DISCUSSION PAPER SERIES

DP15587

IMMIGRATION, POLITICAL IDEOLOGIES AND THE POLARIZATION OF AMERICAN POLITICS

Axel Dreher, Sarah Langlotz, Johannes Matzat, Anna Maria Mayda and Chris Parsons

LABOUR ECONOMICS

PUBLIC ECONOMICS

ISSN 0265-8003

IMMIGRATION, POLITICAL IDEOLOGIES AND THE POLARIZATION OF AMERICAN POLITICS

Axel Dreher, Sarah Langlotz, Johannes Matzat, Anna Maria Mayda and Chris Parsons

Discussion Paper DP15587
Published 22 December 2020
Submitted 16 December 2020

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

IMMIGRATION, POLITICAL IDEOLOGIES AND THE POLARIZATION OF AMERICAN POLITICS

Abstract

We study the extent to which migrant inflows to the United States affect the political polarization of campaign donors and the ideology of politicians campaigning for the House of Representatives in the 1992-2016 period. Implementing various polarization measures based on ideology data derived from 16 million campaign finance contributors, our results show that migrant inflows causally increase the polarization of both campaign donations and leading political candidates. Our estimates hold over the medium-run, although the effects decline over time. The effects of migration are stronger if counties host migrants from more distant cultures, or if incoming migrants are similarly educated. Our main results hold when we focus on refugees as opposed to all immigrants on aggregate.

JEL Classification: J15, F52, F63

Keywords: migration, Refugees, Polarization, Political Ideology, United States

Axel Dreher - mail@axel-dreher.de
University of Heidelberg and CEPR

Sarah Langlotz - sarah.langlotz@uni-goettingen.de
Georg-August University Goettingen

Johannes Matzat - johannes.matzat@uni-goettingen.de
Georg-August University Goettingen; Heidelberg University

Anna Maria Mayda - amm223@georgetown.edu
Georgetown University and CEPR

Chris Parsons - christopher.parsons@uwa.edu.au
UWA

Acknowledgements
We have received helpful comments from Kai Gehring, Gianmarco Ottaviano, Panu Poutvaara and participants at the following conferences and seminars: Georg-August University Goettingen (Development Economics Seminar and CeMig Research Colloquium), Heidelberg University, and International Political Economy Society (IPES, 2020). Thanks! We thank Vasil Yasenov for sharing the PRM refugee data with us. We thank Clara Coelho, Tobias Hellmundt, Kaja Rupieper and Aiko Schmeisser for excellent research assistance. Johannes Matzat acknowledges funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation)-project RTG 1723.

Immigration, Political Ideologies and the Polarization of American Politics*

Axel Dreher[†] Sarah Langlotz[‡] Johannes Matzat[§]
Anna Maria Mayda[¶] Christopher Parsons[‖]

December 16, 2020

Abstract

We study the extent to which migrant inflows to the United States affect the political polarization of campaign donors and the ideology of politicians campaigning for the House of Representatives in the 1992-2016 period. Implementing various polarization measures based on ideology data derived from 16 million campaign finance contributors, our results show that migrant inflows causally increase the polarization of both campaign donations and leading political candidates. Our estimates hold over the medium-run, although the effects decline over time. The effects of migration are stronger if counties host migrants from more distant cultures, or if incoming migrants are similarly educated. Our main results hold when we focus on refugees as opposed to all immigrants on aggregate.

Keywords: Migration, Refugees, Polarization, Political Ideology, United States

JEL classification: J15, F52, F63

*We have received helpful comments from Kai Gehring, Gianmarco Ottaviano, Panu Poutvaara and participants at the following conferences and seminars: Georg-August University Goettingen (Development Economics Seminar and CeMig Research Colloquium), Heidelberg University, and International Political Economy Society (IPES, 2020). Thanks! We thank Vasil Yasenov for sharing the PRM refugee data with us. We thank Clara Coelho, Tobias Hellmundt, Kaja Rupieper and Aiko Schmeisser for excellent research assistance. Johannes Matzat acknowledges funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation)—project RTG 1723.

[†]Alfred-Weber-Institute for Economics, Heidelberg University; KOF Swiss Economic Institute; CEPR; Georg-August University Goettingen; and CESifo; email: *mail@axel-dreher.de.*

[‡]Georg-August University Goettingen; email: *sarah.langlotz@uni-goettingen.de.*

[§]Georg-August University Goettingen; Heidelberg University; email: *johannes.matzat@uni-goettingen.de.*

[¶]Georgetown University; email: *amm223@georgetown.edu.*

[‖]University of Western Australia; email: *christopher.parsons@uwa.edu.au.*

1 Introduction

Modern America was founded by immigrants. All the same, perceptions about how many immigrants the U.S. should welcome to its shores differ widely. At a time the Immigration Act of 1990 increased annual admissions by 40 percent, the U.S. experienced a rapid acceleration in political polarization;[1] at a time immigration to the U.S. subsequently increased, the Republican Party became ideologically more right-leaning, while conversely, the Democratic Party shifted to the left. In other words, political polarization increased.

In this paper, we explore the causal role of immigration in fostering polarization. We investigate both migrants on aggregate as well as refugees separately,[2] the political ideologies of candidates for the House of Representatives, and their respective campaign donors. Our focus is the United States, by-far-and-away the largest destination for immigrants worldwide, between 1992 and 2016, at the county-level. Using ideology data derived from 16 million campaign contributions, we capture the ideology of campaign donors and recipients and calculate a number of polarization measures. Equipped with these measures, we identify causal effects employing the familiar shift-share instrumental variable in conjunction with fixed-effects for counties and years, such that our identifying variation is within counties over time.

The literatures linking total immigrants (including refugees) (Mayda 2006, Otto and Steinhardt 2014, Barone et al. 2016, Nikolka and Poutvaara 2016, Halla et al. 2017, Mayda et al. 2020, Edo et al. 2019, Lonsky 2020) as well as refugees alone (Dustmann et al. 2020, Steinmayr 2016, Campo et al. 2020) to political outcomes typically focus on the vote shares accruing to (predominantly) far-right parties. Historically however it is votes from both sides of the aisle that have resulted in significant immigration reform in the U.S. (Tichenor 2009).[3] It is clear therefore that analyzing the political impact of immigration by examining votes for parties alone, would not only obfuscate times when the two main parties have adopted differing policy stances, but would also crucially fail to account for varying policy stances within parties, which highlights the requirement to

[1]Figure 1 shows this using the differences between the ideologies of Republican and Democratic candidates.

[2]In this paper, the term 'migrants' refers to the total foreign-born population. Distinguishing migrants and refugees has previously been stymied by the paucity of the available data. *A priori* one might expect the impact of migrants and refugees on ideology to differ, since the underlying processes at play are likely highly context-specific, depending on the relative characteristics of refugees, natives and locales. This distinction is likely important, since although traditionally constituting around one tenth of total immigration, refugees receive disproportionate media attention (both positive and negative) as they constitute *"the most visible, challenging, and morally significant of newcomers"* (Haines 2012).

[3]Notable instances of bipartisanship both for and against immigration to the U.S. include the anti-China platforms that both parties adopted in the 1876 and 1880 Presidential elections, which ultimately culminated in the Scott Act of 1888; the eugenicist findings of the Dillingham Commission in 1911 that argued in favor of the racial inferiority of Southern and Eastern Europeans and which resulted in the passing of the Emergency Quota Act (1921), the Johnson-Reed Act (1924) and the Hart-Cellar Act (1965) that abolished national quotas.

account for the political ideologies of individual candidates.[4]

Identifying changes in political ideologies through vote shares therefore proves empirically challenging, not least since ideologies have significantly changed over time both within and between political parties (Gerring 2001). In the 1984 Presidential election, for example, Reagan won 59 percent of the popular vote, while Trump won only 46 percent in 2016. An analysis of the Republican vote share alone might therefore imply that the United States shifted politically to the left, whereas the reason why statements based on these vote shares contradict our observations is because Reagan and Trump did not have the same ideological positions simply because they belonged to the same party. Considering the differences in ideology between Reagan and Trump therefore, as well as those of their opponents (Mondale and H. Clinton respectively), would no doubt provide a more nuanced and comprehensive understanding of the shifting ideological sands over time.[5]

Social psychologists have long examined how out-groups (in our context immigrants and refugees) affect in-groups (natives), although theory is conflicting. Knowing members of out-groups personally likely breeds familiarity and empathy, as argued by proponents of contact theory (Allport 1954). Living in close proximity however, might also result in natives feeling out-competed or threatened, thereby fostering prejudice as proffered by advocates of group threat theory (Sherif et al. 1961, Campbell 1965). The economics literature suggests that the degree to which native populations feel economically threatened by immigrants depends upon the level of competition for jobs between the two groups, as well as the transfers and public services they receive (Mayda 2006, Facchini and Mayda 2009, Cavaille and Ferwerda 2018).[6] Anti-immigration attitudes have also been related to a taste for cultural homogeneity (Card and Preston 2007, Card et al. 2012). Cultural threats may depend on the incompatibility of norms and values as well as the size of the incoming group (Brown 2000, Bansak et al. 2016). Collectively, these theories suggest that migrants can potentially increase prejudice if perceived as competitors, a situation that can be reversed should suitable conditions that enhance knowledge be satisfied.

[4]Overall, except for the 1994-1996 period, both Republicans and Democrats were largely in favor of immigration (Tichenor 2009), although Republicans have also been shown to vote less often for pro-immigration policies (Facchini et al. 2011, Conconi et al. 2019, Mayda et al. 2020). One of the most enduring themes in U.S. politics however is that the majority of the population is largely against all forms of immigration (Simon and Alexander 1993, Tichenor 2009). How individuals ultimately vote therefore, will likely depend upon their local exposure to migrants and refugees, as well as the ideologies of those in the pool of candidates for political office.

[5]Dixit and Weibull (2007) suggest that political polarization arises through differences in prior beliefs about the state of the world. Voters, for example, might agree on a particular objective (e.g., maximizing income) and observe the same evidence (e.g., higher welfare transfers to refugees) and yet nevertheless reach diametrically opposing conclusions about their preferred policies (more vs. fewer restrictive regulations). Inflows of refugees and economic migrants might therefore reinforce political divides, a phenomenon that cannot be captured by vote shares alone.

[6]Also see Gehring (2020).

Resolving this theoretical contention is ultimately an empirical matter. A meta-analysis of 515 studies suggests that the prejudice-reducing effects of contact between in- and out-groups are facilitated by four conditions: i) shared goals, ii) similar status, iii) a non-competitive environment, and iv) common norms and regulations accepted by both groups (Pettigrew and Tropp 2006). These collectively suggest that contact between groups with similar characteristics and yet complementary skills will increase the acceptance of one another. Such potential shifts in attitudes towards migrants then ultimately translate into changes in voters' electoral positions towards them. We refer to this as "political ideology" for short.[7]

Both theories are local in nature, predicting changes in ideology in the immediate neighborhood of migrant inflows. We therefore focus on counties, netting out all effects that change polarization in the entire country in a given year. With migration increasing, debate about migration increases as well, among voters and politicians. Salience leads to citizens identifying with groups who are in favor or rather against migration.[8] The conditions under which contact theory may dominate group threat theory are then non-random, since typically individuals decide whether to engage in meaningful contact with immigrants or not. This selection may widen the ideological distance between these two groups, since in-group members with positive prior beliefs more likely select into contact, as when compared to those in-group members with negative prior beliefs who rather avoid contact. We expect these polarizing views to result in more and larger campaign donations from more extreme voters, to more extreme candidates, who become more likely to win election.

We study the ideologies of all candidates to the House of Representatives rather than just those of elected politicians. In doing so, we capture shifts in the prevailing zeitgeist, also considering the performance of extreme candidates that are unable to win election. To capture ideologies, we leverage "Data on Ideology, Money in Politics, and Elections" (DIME) provided by (Bonica 2019) for the 1979-2018 period. The data exploit patterns in campaign contributions to determine candidates' ideologies. Campaign contributions are premised to be driven by ideologies, such that on average contributors give to ideologically more proximate candidates.[9] Based on contribution patterns (i.e., who gives how much to whom) Bonica estimates ideal points for candidates and contributors. The resulting so-called common-space CFscores "represent the most comprehensive ideological mapping

[7]Political ideology relies on "the knowledge of what goes with what" (Poole 2005) as means to structure and summarize politics systematically.

[8]Contributors might decide to make larger donations to particular candidate types in one moment, while abstaining from donating at others, depending upon the salience of topics in the eyes of a voter. As has been shown in Gennaioli and Tabellini (2019), topics becoming more or less salient over time can result in people switching between those in-groups they identify with, as well as the out-groups they oppose, as their own identity changes over time. This serves to increase polarization along the salient dimension.

[9]Findings in McCarty and Rothenberg (1996) and Ensley (2009) support this assumption, for example. Arguably more strategic contributors like Political Action Committees (PACs) are excluded.

of American political elites to date" (Bonica 2016). We derive a number of polarization measures from these data. Focusing on campaign donors, we measure polarization of campaign finances as donations to extreme candidates relative to moderate candidates. Focusing on candidates, we consider the ideology of election winners, overall, and for Republican and Democratic winners separately. We further measure the ideological distance of election winners relative to losers and the probabilities that moderate or extreme candidates win election. To test the mechanisms at play, we exploit the differences between residents' characteristics and those of incoming migrants, specifically cultural and educational disparities.

We identify causal effects using a Bartik shift-share instrument. That is, we predict the change in the number of immigrants in a county and year with an interacted instrumental variable that consists of one variable that "shifts" the number of immigrants from year to year and a second variable that proxies the "share" of those newcomers that we expect to end up in a particular county.[10] More specifically, the share component of our instrument uses the share of foreign-born adults from each country of origin in that country's adult population living in a U.S. county in 1980. The shift element employs the change in the number of immigrants from that country to the United States over an election cycle. We then sum the interaction of the shift- and share-components over all countries of origin.

The intuition of this interacted instrument follows that of a difference-in-differences approach. We examine how changes in foreign populations differentially affect counties with varying initial shares of immigrants in 1980. Due to network-effects, counties with larger historical immigrant shares from particular origins are likely characterized by larger future shares of incoming immigrants from those origins. Counties with higher initial immigration shares are therefore assumed not to be differentially affected by country-wide changes in immigration as when compared to counties with lower initial shares, other than through the impact of contemporaneous immigration, while controlling for county- and year-fixed effects and our battery of control variables. We test this assumption in considerable detail.

According to our results, immigrants and refugees increase polarization within two years of arrival and induce political shifts to the right. Campaign contributions to extreme candidates increase relative to those for moderates. Election winners become more conservative when they are Republican. Conservative Republicans are more likely to win election. Liberal Democrats less so. Our results are similar when we focus on inflows over eight, as opposed to two year time horizons, although they become smaller in magnitude. Focusing exclusively on refugees, our results are strikingly similar as when compared to those for all immigrants on aggregate in the short-run. These results

[10] As Dustmann et al. (2020) note, most of the literature linking migration and political outcomes fails to identify causal effects. This is largely due to the endogenous location decision of immigrants. Comparing the ideology of areas with more immigrants to areas with fewer immigrants, would therefore likely confound pre-existing differences with any identified effects associated with migrants or refugees.

are weaker over eight-year periods however, which might be suggestive of refugees' high initial rates of internal mobility. Our results become starker as cultural distances between natives and migrants increase. The same holds when education levels are similar. That is, natives seem to resent foreigners from different cultural backgrounds and fear competition, while welcoming immigrants with complementary labor market skills.

Our work is related to Autor et al. (2020) who exploit local trade exposure from China to provide causal estimates of the effects of imports on American political polarization between 2002 and 2016. We rather examine the role of migration in fostering political polarization. *A priori* migration, having profoundly changed American society through the ages, likely constitutes a more salient issue for American voters than does trade (Pew 2016).[11] Migration can therefore be expected to result in greater political polarization when compared with trade.

We also contribute to the literature on interest group politics and political polarization (Cho and Gimpel 2010, Facchini et al. 2011, Barber 2016, Gimpel and Glenn 2019). Glaeser et al. (2005) argue that candidates that hold extreme positions on wedge issues, like immigration, can increase both donations and core supporter turnout, which in turn can be politically polarizing. Migration therefore constitutes one candidate to explain the geographical clustering of political contributions. In examining this dimension, we further contribute to the literature pertaining to the determinants for campaign financing (Brown et al. 1980, Mutz 1995, Gimpel et al. 2006) by empirically examining the role of refugees and migrants in fostering campaign contributions.

The next section introduces our data. Section 3 explains how we estimate causal effects of immigration on polarization and ideology. We discuss our results and their robustness in Section 4. The final section concludes.

2 Data

2.1 Immigrants and Refugees

County-level immigrant stock data are available in 1980, 1990 and 2000 from the U.S. Census, and biannually from the American Community Survey (ACS) for the years 2006-2016 from IPUMS-USA (Ruggles et al. 2020).[12] The U.S. census and ACS report data on the foreign-born population, which refers to anyone born outside of the U.S., including U.S. citizens born abroad, shorter term migrants (such as foreign-born students), humanitarian migrants (such as refugees) and that fraction of the illegal migrant population not otherwise captured (Hanson 2006). We use the stock

[11] According to Gennaioli and Tabellini (2019), respondents to a repeated survey by the Pew Research Center mention "race and immigration"—as opposed to trade—as one of the three most important problems facing the United States with the highest frequency in the 2013-2018 period.

[12] We use linear interpolation to obtain estimates for the years 1992, 1994, 1996, 1998, 2002, 2004.

of immigrants in 1980 to construct our initial 'share', while we use the difference in migrant stocks over two-year periods as the 'shifter' of our Bartik instrument. The term 'migrants' refers to the total foreign-born population, while we focus on the sub-set of 'refugees', in separate analyses.

Our individual-level refugee data derive from two distinct entities of the State Department—the Office of Refugee Resettlement (ORR) and the Bureau of Population, Refugees, and Migration (PRM). The ORR data span the 1975-2008 period and comprise 2.6 million individuals heralding from 136 countries of origin. They are geographically remunerated at the U.S. state, county and city levels. The PRM data comprise 0.6 million individuals from across 99 origin countries between 2009 and 2018. Both data sets are harmonized to the county-level, 3,141 in total.

The number of migrants in the United States increased by 957,554 on average per year between 1990 and 2016. The share of net immigrants relative to the native adult population peaked in the early 2000s (at around 0.06), while turning negative in more recent years (see Figure A-1 in the Appendix). The share of refugees is substantially lower, decreasing from around 0.0012 in 1990 to 0.0006 in 2018. Figure A-2 shows the net increase in the number of immigrants over the years of our sample at the county-level, relative to the adult population in the year 1992, with darker shades indicating greater increases. Figure A-3 similarly illustrates the number of refugees arriving in the United States. Figure A-4 plots the same data, showing their geocoded locations.[13] The distribution of refugees seems to follow a similar pattern as compared to migrants more generally. Migrants and refugees are most attracted to larger, more multicultural urban environments, many of which are located in coastal areas.

Our data from IPUMS-USA also detail immigrants' origins and education levels, which we use to derive proxies for cultural and educational distances to local native populations. By 2016, some 38 percent of migrants heralded from elsewhere in the West, 36 percent came from Latin America, 7 percent from Africa and 20 percent from Asia. Of these, while 32 (21) percent of the immigrants dropped out of (graduated from) high-school, 14 percent spent some time in college, 6 percent graduated from college, and 27 percent have more than college education.

2.2 Political Ideology and Polarization

We use Bonica's (2019) Database on "Ideology, Money in Politics, and Elections" (DIME) to construct measures capturing political ideologies and polarization.[14] These data

[13] We intend to use these data in future iterations of this paper to identify exogenous variation in the flow of refugees.

[14] A number of recent papers use these data (e.g., Bonica 2013, Thomsen 2014, Barberá 2015, Nyhan and Montgomery 2015, Barber 2016, de Benedictis-Kessner and Warshaw 2016, Hollibaugh Jr and Rothenberg 2018, Martin and Peskowitz 2018, Autor et al. 2020).

leverage campaign contributions registered with the Federal Election Commission (FEC) and state reporting agencies, in concert with a number of additional sources. The data comprise contributors' detailed location, and, for sub-sets of the data, their profession and employer. On the receiving end, the data contain information on all candidates running for elected office in the United States that receive such contributions, which arguably holds true for all 'serious' candidates.

Bonica (2019) calculates the ideologies of contributors and candidates based on whom they contribute to and from whom they receive contributions, respectively. He assumes that contributors donate larger amounts to candidates they are more ideologically aligned with.[15]

Compared to data detailing the ideological positions of politicians, which are based on roll call votes of elected politicians in parliament,[16] our approach rather analyzes the entire universe of candidates, including those that failed to win at the ballot. We are therefore able to analyze any polarization that arises between candidates from the same party, as well as between winning candidates and runners-up from different parties.[17]

Bonica (2016) calculates a Campaign Finance (CF) score to measure political ideology, based on campaign contributions.[18] He assumes contributors to donate based on their own ideal point, the candidate's ideal point, the utility they derive from donating and the marginal costs involved. The CFscore method applies correspondence analysis, a method similar to principal components analysis that focuses on relative, as opposed to absolute, differences in ideologies between donors and recipients. Bonica then calculates ideal points along a single dimension, a typical left-to-right political scale.

Bonica subsequently uses federal elections to anchor the ideology score scale. State-level scores in turn are anchored based on data pertaining to those contributors that donate to *both* federal and state elections, since these observations serve to 'bridge' across institutions and levels of politics, so as to introduce a common ideological scale. This is facilitated by the 70 to 90 percent of contributors in any given state who also contribute to federal campaigns (Bonica 2014).[19] The resulting constant scale across contributors

[15]A number of articles validate this assumption (e.g., Ensley 2009).

[16]E.g., DW-NOMINATE (Poole and Rosenthal 1985).

[17]This proves useful for capturing extreme party shifts even if parties fail to win election. Failing to account for losing candidates' ideologies would be akin to treating the election where 2020 Democratic Presidential candidate Biden ran against President Trump as identical to one in which self-styled socialist Bernie Sanders would have run against Trump.

[18]Our description of the CFscores draws from Bonica (2014), see in particular his Supplementary Materials.

[19]As Bonica (2014) explains, he first applies correspondence analysis to federal elections and then scales the resulting federal-level ideal points for each state separately, based on contributions from donors to both state and federal campaigns. This allows to anchor the state-level scaling and calculate CFscores that use the same scale for different types of elections. The correspondence analysis applied by the CFscore methodology scales two-way frequency tables by decomposing a transformed matrix of χ^2 distances (Bonica 2014). As Bonica (2014) explains, this is almost equivalent to a log-linear ideal-point model, but comes at a much-reduced computational cost.

and candidates, institutions and time periods, facilitates meaningful comparisons across these dimensions.

The dynamic DIME scores that we rely upon in this paper are calculated for each time period separately, which allows for changes in candidate ideology over time. We observe few stark movements in CFscores however. The same holds for legislator ideal points when captured by roll call votes, which are also stable over time (Bonica 2016). Both measures are highly correlated, lending plausibility to the interpretation of CF scores as a liberal-conservative scale. Ideal points, calculated for candidates prior to entering office, also correlate strongly with candidates' future CFscores as incumbents as well as their subsequent voting behavior. Bonica (2018) shows that DIME scores accurately predict policy preferences, based on 30 policy items included in the 2012 Cooperative Congressional Election Study (CCES). Ideal points of candidates for office are also highly correlated with the ideal points calculated from these candidates' contributions to the political campaigns of others (Bonica 2016), meaning they seemingly represent genuine expressions of ideological preferences.

We analyze all general elections to the House of Representatives between 1992 and 2016. Our main analysis pertains to biannual changes in migrant stocks.[20] Our focus on the House of Representatives (as opposed to Presidential or Senate elections), is due to the resulting identifying variation.[21] During our sample period, our data comprise ideology estimates for 12,091 candidates and 16 million contributions, deriving from 3.1 million contributors (13 million of which come from 3 million individuals, as opposed to corporate donors or political action committees).

Left-aligned donors include university and college employees, those working in Hollywood and book publishers, as well as the online computer-services industry (Bonica 2016). Right-aligned donors include those in the oil, gas and coal industries, agriculture, mining and construction. During our sample period, among the top three conservative donors are the *Club for Growth* and the *American Future Fund*. Both support a 'conservative and free-market viewpoint'. Among the three largest liberal donors are *For our Future* and *End Citizen United*, which are "committed to serving progressive values and causes" and to limit campaign contributions, respectively. Large donors located in the middle of the ideology distribution include the *American Federation of State County & Municipal Employees*, the *Democratic Congressional Campaign Committee* and the *NEA Fund for Children and Public Education*.

We derive a number of polarization and ideology measures from these data. Focusing on (general election) contributions from donors' in a specific county—those donated to candidates running for the House of Representatives in any electoral district—we define CF scores for liberal, moderate and conservative donations in that county, based on

[20]Refugee data are available from 1979 onward, but we restrict the sample for the sake of comparability.
[21]We however plan to test robustness in future iterations of this paper.

contributions in 1990.[22] We subsequently rank candidates according to their ideology on a left-right scale. We then use this rank to divide campaign contributions into terciles. We refer to contributions located in the right end of the scale as 'conservative'. In analogy, we define 'liberal' contributions as those on the left tail, and consider the remaining tercile as 'moderates'.

Figure 2 shows that the share of contributions to moderate candidates substantially declined over time, at the expense of liberal and in particular conservative candidates.[23] Our first polarization measure (*Extreme vs. moderate*) is the difference in the contributions donated to liberal or conservative ("extreme") candidates added together and those given to moderate candidates.[24]

Our second polarization measure (*Winner*), focuses on the ideologies of general election winners. We assign candidates' ideology score to the county-district cell of their victory. We then take the population-weighted average across all county-district cells within a county. Using population weights, we finally harmonize county borders over time to those of 2010.

We proceed by investigating the ideologies of winners given they are Republicans (*Winner if Rep.*) or Democrats (*Winner if Dem.*) respectively, which facilitates testing for shifts in ideology within parties. The measure *Winner vs. loser* is then the absolute distance between the winning candidate and the runner-up, which we again calculate at the county-district cell level and aggregate to 2010 county boundaries.

We continue by separately analyzing the probabilities that *Conservative Republicans*, *Moderate Republicans*, *Moderate Democrats* or *Liberal Democrats* win at the ballot. We define moderate politicians as centrists within their party, based on their ideology score in 1990 compared to the party median in that year, with the remainder constituting conservative and liberal politicians.[25]

Figure 1 shows that ideological polarization increases over the years of our sample. While the ideology of winners (left axis) exhibits no clear trend, the absolute difference between winners and runner-ups increases over time (right axis). Republican winners move to the right, while Democrat winners move to the left (depicted on the left scale).[26]

Specific candidate ideologies, though estimated for each period separately, do not vary substantially over time. The changes that we observe in the data therefore result from candidates of differing ideologies receiving contributions of varying amounts at different junctures.

---

[22] This broadly follows Autor et al. (2020).

[23] Group-shares are not exactly equal in 1990 given that candidates at tercile cut-offs do not receive equal amounts.

[24] In other words, we sum all contributions that are to the right and left of the cut-offs and deduct the sum of contributions that fall in between.

[25] This broadly follows Autor et al. (2020).

[26] We normalize ideology scores of winning Democrats and Republicans to zero in 1990.

3 Methods

Our aim is to establish causal effects of immigration on political outcomes, while recognizing several threats to identification. The endogenous location decision of migrants likely results in their favoring areas that imbue them with particular advantages, such as better employment prospects. Reverse causality constitutes an additional concern, since newcomers likely choose areas where they are more likely welcomed, as opposed to feared. So too might differential trends exist for treated areas (those that receive immigrants above a particular threshold) and non-treated areas (which do not). Simply comparing such locations could therefore yield biased estimates, since that would necessarily mean comparing measures of ideology and polarization that were anchored at different points in time.

Our main specification is

$$\mathrm{Y}_{ce} = \beta \Delta MS_{ce} + \mu_c + \lambda_e + \mathbf{x}'_{ze}\boldsymbol{\gamma} + \epsilon_{cze}, \tag{1}$$

where Y_{ce} reflects our measures of political ideology and polarization introduced in Section 2 in a county c in election-year e. ΔMS_{ce} is the net change in the number of immigrants relative to (the stock of) a county's adult population. μ_c are county-fixed effects and λ_e are year-fixed effects, which absorb a variety of potential shocks affecting all counties in particular election years. In keeping with Mayda et al. (2020), we include a vector of control variables $\mathbf{x}_{ze}$ (all in differences) at the commuting zone level z. These include the shares of low-skilled natives, males, those married, African-Americans and urban residents, in addition to the unemployment rate, the labor market participation rate and the average income per person in the citizen population together with an index proxying import competition exposure to China as defined in Autor et al. (2016).[27] We also include an indicator variable that we call "Bartik share," and which aims to capture sector-specific local labor market shocks (calculated by Mayda et al. (2020) as the "weighted average of the industry-specific employment in year t, using as weights the employment shares across industries of the commuting zone in 1990.") The error term is ϵ_{cze}. We cluster standard-errors at the state-level and implement population weights in all regressions.

The familiar shift-share instrument is employed to address the endogeneity of immigrant shares in a county's population. In doing so, we closely follow recent work in Mayda et al. (2020).[28] We employ an interacted instrumental variable to predict the

[27] Our source for these data is Mayda et al. (2020), who take them from the U.S. census and the ACS.

[28] See Borusyak et al. (2018), Jaeger et al. (2018), Adão et al. (2018), Goldsmith-Pinkham et al. (2020) for recent contributions. The assumptions discussed in these papers allow us to derive unbiased estimates under assumptions that are, to some extent, weaker than those introduced below. The cost of doing so is in assuming one of the two variables comprising the interacted instrument is exogenous. We return to

change in the number of immigrants in a county and year. We define the number of adults born in the United States that live in county c in the year 1980, as a share of total U.S.-born adults, as $sh_{US,c,80} = \frac{N_{c,80}}{\sum_c N_{c,80}}$.[29] In analogy, we define $sh_{i,c,80} = \frac{M_{i,c,80}}{\sum_c M_{i,c,80}}$ as the share of adults born in country i in that country's adult population living in county c in the year 1980. The number of natives N in county c in year e is then calculated as the product of the county's 1980 population share and the total native adult population in e, $\hat{N}_{ce} = sh_{US,c,80} N_e$. The predicted number of total immigrants residing in a county is $\hat{M}_{ce} = \sum_i sh_{i,c,80} M_{ie}$, the product of the 1980-share of immigrants from a country living in a county in the U.S.-total and the number of immigrants from that country to the United States in e, summed over all countries of origin. Our instrument for the change in the number of immigrants as a share of the adult population is then the change in the predicted share of immigrants in the predicted adult population of a county, $\Delta\widehat{M}_{ce}/(\widehat{M}_{ce} + \widehat{N}_{ce})$.[30]

The intuition of our interacted instrument follows that of a difference-in-differences approach. We investigate how changes in foreign populations over time differentially affect counties with varying shares of immigrants in 1980. Due to network-effects, one would assume that counties with larger historical shares of immigrants from a particular country of origin should receive larger proportions of migrants from the same country of origin in a given year. Simplifying somewhat, the exclusion restriction is that counties with higher shares of immigrants in 1980 are not differentially affected by country-wide changes in immigration, as when compared to counties with low initial shares, other than through the impact of contemporaneous immigration, when controlling for county- and year-fixed effects, in addition to our battery of controls. As in every difference-in-differences estimation, we thus assume that the "treatment" is exogenous when conditioned on the set of fixed effects and controls and that groups with different shares of immigrants are located on parallel trends. Controlling for county- and year-fixed effects—which capture the levels of the variables that comprise our instrumental variable—initial immigrant shares and country-wide immigration cannot be correlated with the error term and are thus indeed (conditionally) exogenous. We visualize and discuss whether and to what extent counties with higher or lower shares of initial immigration adhere to differing trends in terms of polarization below.[31]

this point below.

[29]This is in line with Mayda et al. (2020). We define adults as people above the age of 17.

[30]In our main analysis—where we focus on changes over two-year periods—these changes also refer to periods of two years.

[31]We also examine other potential threats to identification discussed in the recent literature (c.f., Christian and Barrett 2017, Jaeger et al. 2018, Borusyak et al. 2018, Adão et al. 2018 and Goldsmith-Pinkham et al. 2020). To this end, we conduct Monte Carlo randomization tests in order to test for spurious long-run trends, while accounting for potential adjustment dynamics occurring in years following earlier refugee inflows.

Putting these elements together, we estimate the following first-stage regression:

$$\Delta MS_{ce} = \delta \frac{\Delta \widehat{M}_{ce}}{(\widehat{M}_{ce} + \widehat{N}_{ce})} + \omega_c + \phi_e + \mathbf{x}'_{ze}\boldsymbol{\zeta} + \nu_{cze}, \tag{2}$$

where $\mathbf{x}_{ze}$ are the controls from the main equation, ω_c are county-fixed effects, and ϕ_e are year-fixed effects. We then estimate equations (1) and (2) using Two-Stage Least Squares (2SLS).

We next turn to refugees (as opposed to aggregate immigrants), adopting a similar strategy. The key difference in constructing the parallel instrument for refugees, given that we do not have refugee stock data, is that we are unable to adopt exactly the same formulation. Rather, we take the sum of all gross refugee inflows by nationality at the county-level, over the 1980-90 period, and divide it by total refugee inflows of that nationality over the same period.[32]

Further examining the potential roles of cultural and educational distances in mediating the effect of immigration on ideology and polarization, we implement the following regression:

$$\mathrm{Y}_{ce} = \beta \Delta MS_{ce} \times DIST_{ce} + \alpha DIST_{ce} + \mu_c + \lambda_e + \mathbf{x}'_{ze}\boldsymbol{\gamma} + \epsilon_{cze}, \tag{3}$$

where $DIST_{ce}$ is either cultural or educational distance. We calculate distance measures based on comparisons of immigrants' countries of origin and their education levels, relative to those of natives. We calculate immigrant shares distinguishing Western, Latin American, African and Asian countries as aggregate origins, all of which are available at the commuting zone level.[33] County-level shares are proxied by multiplying commuting zone level shares with the overall increase in the county-level flow of immigrants. We then calculate similar measures for the resident population. Shares of Whites, Blacks, Asians and Hispanics in a county's resident population are obtained from the Census Bureau. The absolute differences in the shares of each group comprising our net immigrant flows, as well as the respective shares in resident populations are subsequently computed. The sum of these shares—which we normalize to one—is our proxy for cultural distance, based on the assumption that similarity of geographic origins correlates with this distance. We adhere to the same procedure to proxy educational differences, but rather rely on the shares of immigrant and native populations with differing levels of education, as introduced in Section 2.[34]

We estimate equation (3) with a Control Function (CF) Approach (using bootstrapped

[32]Data are available for 117 countries of origin.

[33]We linearly interpolate the years 1992, 1994, 1996, 1998, 2002 and 2004.

[34]We use information on education at the commuting zone level, for both immigrant flows and native residents.

standard errors with 500 replications), in that we control for the first-stage regression residual (shown in equation (2) above) in our second stages.[35] An alternative to this approach is 2SLS employing the interaction of the instrument with the cultural and educational distance variables as second instruments, but this approach treats the interaction of the endogenous variable as separate, implying it "can be quite inefficient relative to the more parsimonious CF approach" (Wooldridge 2015, p. 429).[36]

4 Results

4.1 Main Results

Table 1 reports our baseline results, while omitting coefficient estimates for the control variables for the sake of brevity.[37] Column 1 adopts the perspective of campaign donors and presents the polarization in donations as the difference in contributions to extreme relative to moderate candidates. Column 2 instead focuses on the ideology of the winning candidates, which we contrast with the share of total votes that goes to the Republican candidate (in a county) for comparison (in column 3). Columns 4 and 5 present results of the ideology of the election winner, given they are Republicans or Democrats respectively. Results defining polarization as the absolute differences between the ideologies of winners and losers are reported in column 6. The remaining columns 7-10 focus on binary variables that indicate whether winning candidates are conservative Republican, moderate Republican, moderate Democrat, or liberal Democrat. As these categories are both exhaustive and mutually exclusive, the coefficients from across the four regressions sum to zero. In concert, these variables allow us to test the effect of immigration on polarization, as well as shifts in the overall ideological spectrum.

We report four specifications in each of the ten columns of Table 1. Panel A presents the results from ordinary least-squares (OLS) regressions that leverage within county variation. Counties experiencing larger net inflows of immigrants relative to their populations become more polarized in terms of campaign donations originating from these counties and vote for the Republican party in larger shares. Winning candidates experience a rightward shift in their ideology. Polarization therefore increases as measured in terms of the distance between the ideology of the winner relative to the loser. The probability of conservative Republicans winning increases significantly, while conversely, moderate Democrats are less likely to be victorious. There is no significant correlation between immigration and the probability of moderate Republicans or left

[35]Note that we also include the respective cultural or educational distance variables in both stages of our regressions.

[36]This increase in efficiency comes at the cost of an additional assumption; that is, we need to assume that the bias is constant for different values of cultural and educational distance.

[37]We show our full results in Table A-3 in the Appendix.

leaning Democrats being elected. The same holds true for the ideology of Republican winners, while Democratic winners shift leftwards.

Panel B reports the reduced-form estimates for the same set of regressions. Here we regress our measures of ideology and polarization on our instrumental variable (in addition to our controls). If our identification strategy holds in the presence of an effect of immigration on ideology, we should also observe strong reduced-form effects. Indeed, there is a sizable and significant effect of the instrument on ideology and polarization in six of the regressions. This effect will be passed through with the same sign if i) the corresponding first-stage regression is sufficiently strong and ii) the coefficients on our instrument are positive. According to our results, there is no significant reduced-form relationship for the election probability of moderate candidates (for both Democrats and Republicans), the ideology of winning candidates from the Democratic party and the ideology of the winner compared to those of the loser. These insignificant results foreshadow the results of the second stage, to which we turn next.

Panel C in Table 1 presents our main results in which we instrument the net inflow of immigrants as a share of the adult population over the two previous years with our shift-share instrument introduced above. As shown in column 1, and in line with our expectations, immigration significantly increases polarization.[38] Evaluated at the sample mean, increasing the share of new immigrants in a county by 1 percent increases the difference between extreme and moderate campaign contributions (in dollar amounts) by 0.89 percent.[39] The coefficient is more than four times the size of the corresponding OLS estimate. Measurement error, reverse causality and omitted variables therefore conspire to bias our OLS coefficients downwards, therein highlighting the need for instrumentation.

Note that our regressions capture the local effects of immigration, since any country-wide effects are absorbed into our year fixed effects. Our results can therefore be interpreted in relation to group threat theory and contact theory. *A priori*, we might expect more left-leaning voters to select into contact more often than right wing voters. Viewed from this perspective, group threat theory can explain our results for Republicans, while contact theory can provide a useful foundation for our results for Democrats.

Column 2 shows that immigration shifts the ideology of the winner rightwards. Specifically, an increase in the share of immigrants from the 25th to the 75th percentiles shifts the ideology of winners by 0.23 points to the right. This represents an increase of approximately 20 percent of the winners' ideological interquartile range (-0.077 and 1.08). The result could reflect one of two things, or a combination thereof. First an increase in the frequency of Republican candidates winning election, with those candidates being to the right of their Democratic counterparts. Alternatively, the result

[38]This result continues to hold when we focus solely on primary elections, if primary and general elections are combined or if we exclusively include individuals as donors. Falls in moderate contributions drive the result.

[39]We report descriptive statistics for all variables in Table A-1 in the Appendix.

could capture the Republican candidate moving to the right of their own party. Indeed, the results in column 3 show that the vote share of the Republican party increases with immigration; an increase in immigration inflows from the 25th to the 75th percentile results in an increase in the Republican vote share by 5.42 percentage points. This result is in line with Mayda et al. (2020), who focus on immigrant stocks as opposed to shares.[40]

To the extent that winning candidates are more likely Republican, the observed rightward shift in ideology in column 2 could follow mechanically. Our results in column 4 however show that the ideology of winning Republicans also moves further to the right. Contrasting the magnitudes of the coefficients in columns 2 and 4 proves informative. The large observed effects in column 2 can be explained by a combination of more Republican candidates winning, in tandem with those winners moving further to the political right.[41] Column 5 demonstrates that the ideology of winning Democratic candidates shifts to the left with larger immigration, although that coefficient is imprecisely estimated.

The same holds for our second measure of polarization, the absolute difference between the ideologies of the winners and losers. According to column 6, the coefficient is positive and substantive, but not significant at conventional levels. The remaining columns of Table 1 show that the political spectrum shifts to the right in counties experiencing larger immigration inflows. The probability of conservative Republican candidates winning election increases by more than 10 percentage points when our measure of immigration rises from the 25th to the 75th percentile. This comes at the expense of liberal Democrats, whose probability of winning declines by almost 7 percentage points.[42]

In summary, we provide evidence in line with immigration polarizing campaign donors' contributions, and shifting ideologies politically rightward, particularly among Republican election winners. Given that more extreme Republican candidates also enter office more frequently in response to increased immigration, overall the ideologies of elected politicians turn substantially rightwards. Comparing our second-stage coefficients to our OLS results in Panel A shows they both operate are in the same direction, although the OLS coefficients are smaller in absolute terms.

Panel D in Table 1 reports our corresponding first-stage regressions. Reassuringly, none of our estimates suffer from a weak-instrument problem. The coefficients are highly significant and all associated first-stage F-statistics exceed 40.[43] As expected, we observe

[40]According to their results, an increase in low-skilled immigrants of one percent of the population increase the Republican vote share by more than three percentage points (while high-skilled immigrants reduce the Republican vote share).

[41]Increasing the immigrant share from the 25th to the 75th percentile shifts the ideology of Republican winners to the right by around 0.06. This is approximately 20 percent of the interquartile range in the ideology of Republican winners (which is 0.83 at the 25th and 1.15 at the 75th percentile).

[42]While we also observe small gains for moderate Republicans in tandem with (more substantial) losses for moderate Democrats, these effects are imprecisely estimated.

[43]They are thus considerably larger than the conventional rule-of-thumb value of 10. They remain strong when we compute F-statistics that are robust to heteroskedasticity, autocorrelation, and clustering (Olea and Pflueger 2013). The Montiel-Pflueger effective F-statistic for column 1, for example, is

a positive relationship between the shift-share instrument and immigration flows. A typical (one-standard deviation) increase in our instrument—equivalent to around 0.01—increases net immigrant flows by about 4,613 immigrants in a county hosting 109,183 immigrants (the 99th percentile in 1992), but only by approximately 10 immigrants in a county with a stock of 237 immigrants (the median in 1992).

4.2 Heterogeneous Effects

We continue by testing whether cultural and educational distances between incumbents and immigrants mediate or exacerbate our previous estimates.[44] To this end we interact the share of immigrants arriving in a county with indicators of cultural and educational distance (focusing on net immigration inflows over a two year time horizon). We provide full regression results in the Appendix (in Tables A-4 and A-5) and illustrate the results for significant interactions in figures. Since we adopt a control function specification, the first-stage regressions (and F-statistics) are fundamentally comparable with those reported in Table 1. Note that the number of observations falls because we do not have complete data for either distance. Our first stages consequently differ too, but first-stage F-statistics remain sufficiently high (as shown in the Appendix).

The effects of immigration on rightward shifts in ideology become more pronounced when cultural distances are greater, since the ideologies of winners shift further to the political right. This effect is due to the increased probability of conservative Republicans winning elections. As shown in Figure 3, these interactions result in marginal effects that are significant throughout the ranges of cultural distance for the ideologies of winners and the probabilities of conservative Republicans winning. An increase in immigration from the 25th to the 75th percentile for example increases the probability of a conservative Republican winning by 9.57 percentage points if immigrants are culturally similar to the resident population (the 25th percentile of the distance variable). This effect increases to 12.13 percentage points however when the cultural distance between the two groups increases to the 75th percentile.[45] An increase in immigration over the same interquartile range similarly results in rightward ideological shifts of winners by between 0.21 and 0.29 points, while concurrently increasing the Republican vote share by 5.15 and 6.42 percentage points, respectively.

Increases in educational distance rather operate in the opposite direction. Figure 4 plots the marginal effects for our significant interactions. These show that the probability of conservative Republicans winning election is significant across the full range of

above the corresponding critical value for a 5-percent "worst-case" bias at the 1-percent confidence level (Olea and Pflueger 2013). The coefficient in column 1 falls also within the Anderson–Rubin 95-percent confidence interval.

[44] In these additional regressions we no longer report results for the (insignificant) effects of ideology on the probability of moderate candidates winning, to reduce clutter.

[45] Cultural distance takes on the value of 0.24 at the 25th percentile and 0.96 at the 75th percentile.

our educational distance measure. An increase in immigration from the 25th to the 75th percentile increases the probability of a conservative Republican winning by 9.47 percentage points, if immigrants have a similar educational background compared to the resident population (the 25th percentile of the distance variable). This increase is 8.57 percentage points if immigrants rather herald from different educational backgrounds as when compared to resident populations (the 75th percentile of the distance variable). Similarly, the effect of immigrants on the Republican vote share is positive unless educational distance exceeds about 0.98 (which only holds for some 2.6 percent of our observations). Conversely, the probability that liberal Democrats win elections declines with educational distance (until this distance is smaller than 0.06, which is the case in 0.1 percent of the observations).[46] Similarly, the rightward shift of the winner declines with decreasing similarity in educational background amounting to 0.21 points at the 25th percentile and 0.17 points at the 75th percentile of the distance variable.

Taken collectively and viewed through the lenses of our underlying hypotheses our results provide support for both contact theory and group threat theory. Natives engage more with culturally closer immigrants, while feeling more threatened by newcomers from more distant cultures. Conversely, labor-market complementarities and reduced labor market competition among people with similar education drives the observed shifts to the political right.

4.3 Alternative Measures

We proceed by testing alternative immigration measures.[47] Figure 5 illustrates results of estimates analogous to our baseline in Table 1, focusing instead on changes in the stock of immigrants over eight year periods. Figure 6 estimates gross as opposed to net immigrant flows (over two year periods). Both figures present our estimated marginal effects in tandem with the associated 90-percent confidence intervals. The corresponding full regression results are provided in Tables A-6 and A-7 in the Appendix.[48]

Our results for net immigration over eight years, as opposed to just two, are broadly similar to our baseline estimates, although the coefficients are smaller in magnitude. The polarizing effects of immigration are therefore attenuated over time, which is suggestive of some underlying process of acceptance. Turning to gross flows, while the coefficients align in the same direction as compared to our baseline results, they are less precisely estimated, largely resulting in insignificant coefficients. One notable exception is in terms of gross immigration increasing polarization as measured by the absolute distance in ideology

[46]Educational distance takes on the value of 0.30 at the 25th percentile and 0.65 at the 75th percentile.

[47]Our results are robust to estimating migrant stocks as opposed to shares. In that case however, the first-stage F-statistics are lower, although they remain above 15 throughout.

[48]The first-stage F-statistics remain strong in these regressions with the exception of those in column 5 of Table A-6.

between election winners and losers.[49] Net flows over the previous two years therefore exert the greatest impacts on political polarization in the United States.

Finally, we empirically examine the impact of refugees alone—as opposed to migrants on aggregate—over two and eight year time horizons. Recall that our refugee data refer to gross flows. While refugees traditionally constitute around one tenth of total immigration only, they receive disproportionate media attention. Perhaps above all however, refugees and migrants constitute two fundamentally disparate groups, most importantly distinguished by their primary motivation for migrating (forced vs. unforced), their socio-economic characteristics, country of origin and ethnic background (Chin and Cortes 2015). Indeed, of those individuals deemed 'most vulnerable' in U.S.-run off-shore processing camps, which signifies individual's eligibility for subsequent resettlement in the U.S., less than one percent are actually resettled. This constitutes an additional barrier to selection to emigrating (Mayda et al. 2019). The resettlement process also results in long delays, often of many years, resulting in uncertainty in relation to the timing of any resettlements (Beaman 2012). The circumstances of refugees' departures also typically mean refugees are unable to take capital with them. Refugees and migrants also face different incentives to invest in human capital at destination driven by the possbility of their not being able to return home.

As opposed to migrants more broadly, who have agency to decide where they will live, refugees are instead mandated to locate near co-nationals or refugee resettlement centres initially (Mayda et al. 2019). As such they are more reliant upon their initial networks, not least since refugees are less likely to speak English on arrival (Haines 2012).

Table 2 replicates the analysis of Table 1 for refugees.[50] The Appendix reports results for the eight- as opposed to the two-year period (Table A-9). The results for gross refugee inflows over two years are strikingly similar to those of aggregate (net) immigration, both in terms of magnitude and statistical significance. In particular, we find that larger (gross) refugee inflows increase the polarization of campaign donations, shift winner's ideology rightwards, expand the Republican vote share and raise the probability that conservative Republicans win election at the expense of liberal Democrats.

No longer do we uncover any effect of refugees on the ideology of winners should they be Republican however (though the coefficient stays positive). Neither are we able to find any statistical evidence in line with refugees affecting ideologies nor polarization over an

[49]To reduce measurement error we only consider immigrants in the census/survey which entered the United States after the last census/survey in our data, which implies that we have a maximum of 10 years between the year of arrival and the year for which we have the location of an immigrant for the 1990s, a maximum of 6 years in the early 2000s and 1 year gaps afterwards. Please note that our gross flow data are measured at the time of refugee placement, as opposed to immigrants' locations in the United States more broadly being recorded at the time of the census or survey, which may or may not correspond to the migrants' first location after they entered the United States. This additional noise could explain the imprecisely estimated coefficients.

[50]See Table A-8 for the full set of 2SLS results.

eight-year time horizon, across most of our regressions (Table A-9). Refugees are unlikely to remain in counties of initial allocation for extended periods of time however, such that previous arrivals might result in lower anxiety. As in the polarizing case of migrants, any polarizing effect of refugees might be attenuated over time by some undergirding process of acceptance by the native population. Note however that there is one important exception to this pattern: As column 1 shows, extreme versus moderate contributions increase significantly with larger refugee flows, potentially highlighting the politicization of refugees in U.S. politics.

4.4 Robustness

We test the plausibility of our exclusion restriction along a number of dimensions, guided by recent advances in the related literature. Figure A-5 in the Appendix focuses on non-linear trends. While linear trends would be captured by our set of fixed effects, Christian and Barrett (2017) have shown that non-linear trends can lead to spurious inference, in a setting broadly related to ours. Following Christian and Barrett (2017), we plot the variation in immigration and polarization for different groups that are defined according to the percentiles of the immigrant shares in 1980, in tandem with the yearly values of net immigration. Specifically, Panel A of Figure A-5 presents immigrant net inflows as a share of the adult population. Panel B shows the same variable at the county-level, according to percentiles of the initial share of immigrants in 1980 (and netting out the effects of our control variables that we include in all regressions). Panel C focuses on extreme versus moderate campaign contributions for the same percentiles. Figure A-5 provides no basis to believe that we violate the parallel trends assumption. The trends in immigration and moderate versus extreme campaign contributions, respectively, do indeed appear parallel across percentiles.[51] Neither are non-linear trends apparent. Reassuringly, no non-linear trend overlaps the trend in net immigration at the county-level (a common trend in all variables that is otherwise indifferent across percentiles would be captured by our year-fixed effects).

We further test for the potential importance of pre-trends, following Mayda et al. (2020) and Goldsmith-Pinkham et al. (2020). First, we provide visual evidence in Figure A-6 that plots the correlation between the change in predicted net immigration (1992-2016) and the change in our outcome measure "Extreme vs. moderate" in earlier years (1982-1988). The straight line indicates that the correlation is essentially zero; it is also insignificant at conventional levels. This demonstrates an absence of pre-trends in our outcome which are correlated with changes in predicted immigration.[52]

[51] The same holds for our other outcome variables, although we do not report them for the sake of brevity.

[52] We also calculate the correlation between the country-of-origin-specific initial shares in 1980 and changes in local economic, demographic and ideology variables over the 1980-1990 period. Following

Second, reverse causality or trends in other variables that are correlated with changes in our instrumental variable could bias our coefficients. Larger Republican vote shares for example could reduce immigration, which in turn could affect the Republican vote share. We therefore test the effect of changes in the same set of (local economic, demographic and ideology) variables over the 1980-1990 period on changes in the shift-share instrument in two-year increments. We again focus on the 1992-2016 period and include the same set of control variables as in the main regressions in addition to year-fixed effects. According to column 1 of Table A-10, the correlations between the changes in our instrumental variable and polarization and ideology measured as the differences between 1982 and 1988 are small and insignificant at conventional levels. The one exception is the difference in "Winner if Republican" between 1982 and 1988, which is marginally significant. Note however that with a 10-percent significance level, one of the 10 regressions in column 1 is significant by chance. Column 2 rather presents analogous (conditional) correlations between changes in our instrumental variable and eleven economic and demographic variables measured as the differences between 1980 and 1990. All are insignificant.

We continue by testing whether our results are driven by omitted variables that are systematically correlated with immigration over time within counties, or across counties at specific points in time. To this end, we randomly assign immigrants across these two dimensions. First, we assign immigrants of each particular year to a random year for the same county. Second, we assign immigrants of one county in each year to a random county in the same year. Third, we randomly assign immigrants across counties and years simultaneously. Figure A-7 (based on the specification of column 1 in Table 1) in the Appendix, shows the point coefficients resulting from 5,000 such randomizations for each of the three procedures, in concert with the p-values, which we calculated as the proportion of times that the absolute value of the t-statistics in the simulated data exceeds the absolute value of the original t-statistic. The coefficients are clearly centered around zero and rarely exceed the coefficient of column 1 in Table 1 (which is indicated by the dashed vertical lines).

Finally, we consider how the dynamics of our instrumental variable could threaten identification. According to Jaeger et al. (2018), the analysis of immigration responses based on shift-share instruments may conflate the short- and long-run effects of immigration. Jaeger et al. (2018) argue that in order for the instrument to be valid, there should be either no dynamic adjustment process in the outcome variable, or the shifts in (changes of) immigration at the national-level should not be serially correlated. In our sample, the correlation of net immigration at the county-level from one year to the

Mayda et al. (2020) we focus on 14 groups of origin countries to calculate these shares: Mexico, Canada, Rest of Americas, Western Europe, Eastern Europe, China, Japan, Korea, Philippines, India, Rest of Asia, Africa, Oceania and Others. The correlations of these shares with the pre-determined changes in outcome measures are close to zero. All correlations between these shares and the pre-determined local economic and demographic characteristics are smaller than 0.18.

next is 0.1 (see also Panel A of Figure A-5). When we further include the instrumental variable in t and $t-1$ in our reduced-form regressions, as in column 1 of Panel B in Table 1, we find the contemporaneous effect remains significant, while the coefficient of the lagged instrument is insignificant.[53]

5 Conclusion

The United States is a nation of immigrants which has been profoundly shaped by subsequent arrivals to her shores. While immigration has long been welcomed by large shares of the population, recent history has witnessed more polarized views. In this paper we test whether migration causally affects political polarization in the United States. Our data comprise the universe of migrants and refugees as well as the ideologies of 16 million campaign donors and politicians campaigning for election to the House of Representatives in the 1992-2016 period.

Our identification strategy exploits within county variation, such that our results can be interpreted through the lenses of contact and group threat theory. Implementing various polarization measures, we find that political polarization significantly increases in counties that experience greater inflows of immigrants over a two-year time horizon. These effects also hold over the longer run, i.e., periods of eight years, although the estimated effects are smaller. One explanation for this finding can be ascribed to Portes (2011, 424) who argues that new immigration is first "reviled when it is actually taking place and celebrated after a period of time, when the first generation has passed from the scene." Our results provide empirical support that this process of acceptance operates more quickly than previously thought.

Our findings are starker the greater the cultural distances between incoming migrants and incumbent natives, which we interpret as evidence in support of contact theory: In-group (i.e., incumbent) members with negative prior beliefs likely select into avoiding contact with those from culturally more distant backgrounds. As a consequence, only more left-leaning voters get in contact with newcomers and in turn become more accepting. Voters further to the right avoid contact and—in line with group threat theory—further move to the right. The polarizing effects of migration also become stronger when the education levels of newcomers and natives are more similar. This is again in line with group threat theory, since natives become more polarized when they feel more threatened in local labor markets.

Though refugees differ from other migrants along a number of dimensions, we uncover similar results for refugees and migrants on aggregate, although the estimated effects of refugees fall more starkly over time. This is likely the result of refugees' secondary

[53] The coefficient of the contemporaneous instrument falls from 9.89 to 6.35. We do not report these results in a table—details of which are available on request.

migrations within the United States after having been initially resettled, in addition to some undergirding process of acceptance by the host population.

References

Adão, R., M. Kolesár, and E. Morales (2018). Shift-Share Designs: Theory and Inference. NBER Working Paper No. 24944, National Bureau of Economic Research.

Allport, G. (1954). *The Nature of Prejudice*. Addison-Wesley, Oxford.

Autor, D., D. Dorn, G. Hanson, and K. Majlesi (2020). Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure. *American Economic Review 110*(10), 3139–3183.

Autor, D. H., D. Dorn, and G. H. Hanson (2016). The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade. *Annual Review of Economics 8*, 205–240.

Bansak, K., J. Hainmueller, and D. Hangartner (2016). How Economic, Humanitarian, and Religious Concerns Shape European Attitudes Toward Asylum Seekers. *Science 354*(6309), 217–222.

Barber, M. (2016). Ideological Donors, Contribution Limits, and the Polarization of American Legislatures. *Journal of Politics 78*(1), 296–310.

Barberá, P. (2015). Birds of the Same Feather Tweet Together: Bayesian Ideal Point Estimation Using Twitter Data. *Political Analysis 23*(1), 76–91.

Barone, G., A. D'Ignazio, G. De Blasio, and P. Naticchioni (2016). Mr. Rossi, Mr. Hu and Politics. The Role of Immigration in Shaping Natives' Voting Behavior. *Journal of Public Economics 136*, 1–13.

Beaman, L. (2012). Social Networks and the Dynamics of Labour Market Outcomes: Evidence from Refugees Resettled in the U.S. *Review of Economic Studies 79*(1), 128–161.

Bonica, A. (2013). Ideology and Interests in the Political Marketplace. *American Journal of Political Science 57*(2), 294–311.

Bonica, A. (2014). Mapping the Ideological Marketplace. *American Journal of Political Science 58*(2), 367–386.

Bonica, A. (2016). *Database on Ideology, Money in Politics, and Elections: Public Version 2.0.* Stanford, CA: Stanford University Libraries.

Bonica, A. (2018). Are Donation-Based Measures of Ideology Valid Predictors of Individual-Level Policy Preferences? *Journal of Politics 81*(1), 327–333.

Bonica, A. (2019). *Database on Ideology, Money in Politics, and Elections: Public Version 3.0.* Stanford, CA: Stanford University Libraries.

Borusyak, K., P. Hull, and X. Jaravel (2018). Quasi-experimental Shift-Share Research Designs. Working Paper 24997, National Bureau of Economic Research.

Brown, C., R. Hedges, and L. Powell (1980). Modes of Elite Political Participation: Contributors to the 1972 Presidential Candidates. *American Journal of Political Science 24*(2), 259–290.

Brown, R. (2000). Social Identity Theory: Past Achievements, Current Problems and Future Challenges. *European Journal of Social Psychology 30*(6), 745–778.

Campbell, D. T. (1965). Ethnocentric and Other Altruistic Motives. In D. Levine (Ed.), *Nebraska Symposium on Motivation*. Lincoln: University of Nebraska Press.

Campo, F., S. Giunti, and M. Mendola (2020). The Political Impact of Refugee Migration: Evidence from the Italian Dispersal Policy. CefES Working Paper 456. Center for European Studies.

Card, D., C. Dustmann, and I. Preston (2012). Immigration, Wages and Compositional Amenities. *Journal of International Economics 10*(1), 78–119.

Card, D. and I. Preston (2007). Racial and Economic Factors in Attitudes to Immigration. *The B.E. Journal of Economic Analysis & Policy 7*(1).

Cavaille, C. and J. Ferwerda (2018). How Distributional Conflict over In-Kind Benefits Generates Support for Anti-Immigrant Parties. Working Paper.

Chin, A. and K. Cortes (2015). The Refugee/Asylum Seeker. In B. Chiswick and P. Miller

(Eds.), *Handbook of the Economics of International Migration.* Volume 1. North-Holland, 585-658.

Cho, W. and J. Gimpel (2010). Rough Terrain: Spatial Variation in Campaign Contributing and Volunteerism. *American Journal of Political Science 54*(1), 74–89.

Christian, P. and C. Barrett (2017). Revisiting the Effect of Food Aid on Conflict: A Methodological Caution. *Policy Research Working Paper 8171.*

Conconi, P., G. Facchini, M. Steinhardt, and M. Zanardi (2019). The Political Economy of Trade and Migration: Evidence from the U.S. Congress. *Economics & Politics 32*(2), 250–278.

de Benedictis-Kessner, J. and C. Warshaw (2016). Mayoral Partisanship and Municipal Fiscal Policy. *Journal of Politics 78*(4), 1124–1138.

Dixit, A. and J. Weibull (2007). Political Polarization. *Proceedings of the National Academy of Sciences 104*(18), 7351–7356.

Dustmann, C., K. Vasilijeva, and A. Piil Damm (2020). Refugee Migration and Electoral Outcomes. *Review of Economic Studies 86*(5), 2035–2091.

Edo, A., Y. Giesing, J. Öztunc, and P. Poutvaara (2019). Immigration and Electoral Support for the Far-Left and the Far-Right. *European Economic Review 115*, 99–143.

Ensley, M. J. (2009). Individual Campaign Contributions and Candidate Ideology. *Public Choice 138*(1–2), 221–238.

Facchini, G. and A. Mayda (2009). Does the Welfare State Affect Individual Attitudes Toward Immigrants? Evidence Across Countries. *Review of Economics and Statistics 91*(2), 295–314.

Facchini, G., A. Mayda, and P. Mishra (2011). Do Interest Groups Affect US Immigration Policy? *Journal of International Economics 85*(1), 114–128.

Gehring, K. (2020). External Threat, Group Identity, and Support for Common Policies—The Effect of the Russian Invasion in Ukraine on European Union Identity. CESifo Working Paper 8061, CESifo.

Gennaioli, N. and G. Tabellini (2019). Identity, Beliefs, and Political Conflict. CESifo Working Paper No. 7707.

Gerring, J. (2001). *Party Ideologies in America, 1828-1996.* Cambridge University Press.

Gimpel, J. and J. Glenn (2019). Racial Proximity and Campaign Contributing. *Electoral Studies 57*, 79–89.

Gimpel, J., F. Lee, and J. Kaminski (2006). The Political Geography of Campaign Contributions in American Politics. *Journal of Politics 68*(3), 626–639.

Glaeser, E., G. Ponzetto, and J. Shapiro (2005). Strategic Extremism: Why Republicans and Democrats Divide on Religious Values. *Quarterly Journal of Economics 120*(4), 1283–1330.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review 110*(8), 2586–2624.

Haines, D. W. (2012). *Safe Haven? A History of Refugees in America.* Kumarian Press.

Halla, M., A. Wagner, and J. Zweimüller (2017). Immigration and Voting for the Far Right. *Journal of the European Economic Association 15*(6), 1341–1385.

Hanson, G. H. (2006). Illegal Migration from Mexico to the United States. *Journal of Economic Literature 44*(4), 869–924.

Hollibaugh Jr, G. E. and L. S. Rothenberg (2018). The Who, When, and Where of Executive Nominations: Integrating Agency Independence and Appointee Ideology. *American Journal of Political Science 62*(2), 296–311.

Jaeger, D., J. Ruist, and J. Stuhler (2018). Shift-Share Instruments and the Impact of Immigration. NBER Working Paper No. 24285, National Bureau of Economic Research.

Lonsky, J. (2020). Does Immigration Decrease Far-Right Popularity? Evidence from Finnish Municipalities. GLO Discussion Paper Series 540, Global Labor Organization (GLO).

Martin, G. and Z. Peskowitz (2018). Agency Problems in Political Campaigns: Media Buying and Consulting. *American Political Science Review 112*(2), 231–248.

Mayda, A. (2006). Who Is Against Immigration? A Cross-Country Investigation Of Individual Attitudes Toward Immigrants. *Review of Economics and Statistics 88*(3), 510–530.

Mayda, A., G. Peri, and W. Steingress (2020). The Political Impact Of Immigration: Evidence From The United States. *American Economic Journal: Applied Economics* (Forthcoming).

Mayda, A. M., C. R. Parsons, H. Pham, and P.-L. Vézina (2019). Refugees and Foreign Direct Investment: Quasi-experimental Evidence from US Resettlements. CEPR Discussion Paper No. 14242.

McCarty, N. and L. S. Rothenberg (1996). Commitment and the Campaign Contribution Contract. *American Journal of Political Science 40*(3), 872–904.

Mutz, D. (1995). Effects of Horse-Race Coverage on Campaign Coffers: Strategic Contributing in Presidential Primaries. *Journal of Politics 57*(4), 1015–1042.

Nikolka, T. and P. Poutvaara (2016). Brexit—Theory and Empirics. *CESifo Forum 17*(4), 68–75.

Nyhan, B. and J. Montgomery (2015). Connecting the Candidates: Consultant Networks and the Diffusion of Campaign Strategy in American Congressional Elections. *American Journal of Political Science 59*(2), 292–308.

Olea, J. L. M. and C. Pflueger (2013). A Robust Test for Weak Instruments. *Journal of Business & Economic Statistics 31*(3), 358–369.

Otto, A. and M. Steinhardt (2014). Immigration and Election Outcomes: Evidence from City Districts in Hamburg. *Regional Science and Urban Economics 45*, 67–79.

Pettigrew, T. and L. Tropp (2006). A Meta-Analytic Test of Intergroup Contact Theory. *Journal of Personality and Social Psychology 90*(5), 751–783.

Pew (2016). *2016 Campaign: Strong Interest, Widespread Dissatisfaction.* Pew Research Center Washington, DC.

Poole, K. (2005). *Spatial Models of Parliamentary Voting.* Cambridge University Press.

Poole, K. T. and H. Rosenthal (1985). A Spatial Model For Legislative Roll Call Analysis. *American Journal of Political Science 29*(2), 357–384.

Portes, A. (2011). America and Its Immigrants: A Game of Mirrors. *Proceedings of the American Philosophical Society 155*(4), 418–32.

Ruggles, S., S. Flood, R. Goeken, J. Grover, E. Meyer, J. Pacas, and M. Sobek (2020). IPUMS USA: Version 10.0 [dataset]. Minneapolis, MN: IPUMS, https://doi.org/10.18128/D010.V10.0.

Sherif, M., O. Harvey, B. White, W. Hood, and C. Sherif (1961). *Intergroup Conflict and Cooperation: The Robbers Cave Experiment. Vol 10.* Norman, OK: University Book Exchange.

Simon, R. J. and S. H. Alexander (1993). *The Ambivalent Welcome: Print Media, Public Opinion, and Immigration.* Praeger Publishers.

Steinmayr, A. (2016). Exposure to Refugees and Voting for the Far-Right: (Unexpected) Results from Austria. *IZA DP 9790.*

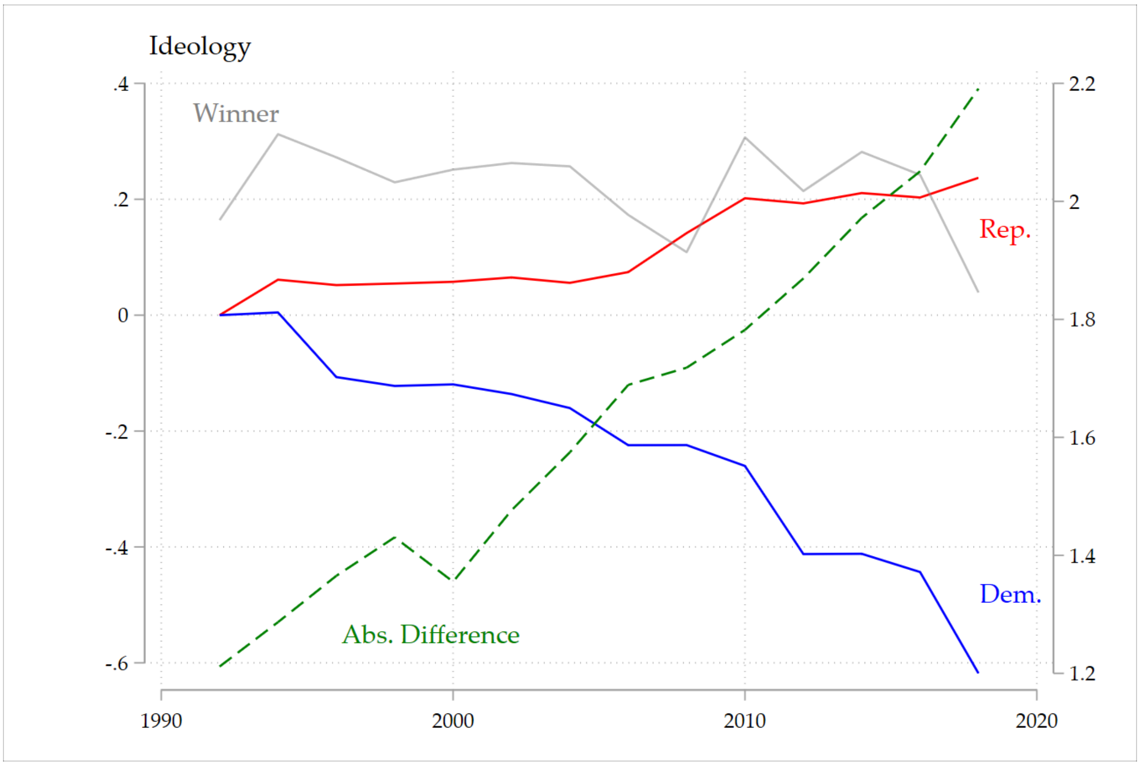
Thomsen, D. (2014). Ideological Moderates Won't Run: How Party Fit Matters for Partisan Polarization in Congress. *Journal of Politics 76*(3), 786–797.

Tichenor, D. J. (2009). *Dividing Lines: The Politics of Immigration Control in America*, Volume 104. Princeton University Press.

Wooldridge, J. (2015). Control Function Methods in Applied Econometrics. *Journal of Human Resources 2*, 420–425.

Figures and Tables

Figure 1 – Ideology and Polarization

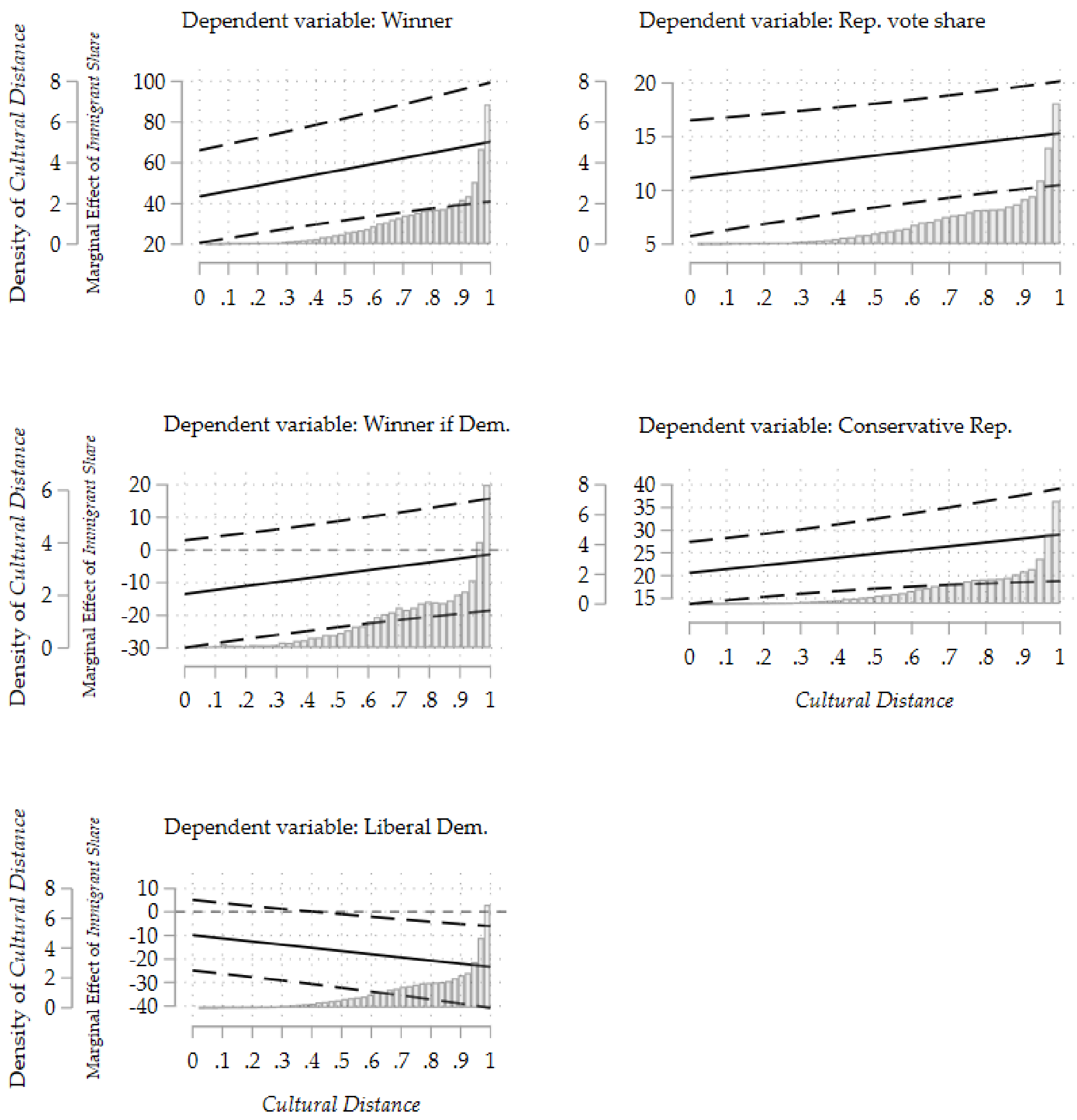


Notes: We depict the ideology of the winners on average (gray line) and by party (red and blue line). Note that we subtract the 1992 party mean of the ideology of the winners by party. The green line depicts the absolute distance between the winner and the runner up. Solid lines refer to the left axis, the dashed line refers to the right axis (both axes represent the ideology score).

Figure 2 – Share of Contributions to the House of Representatives

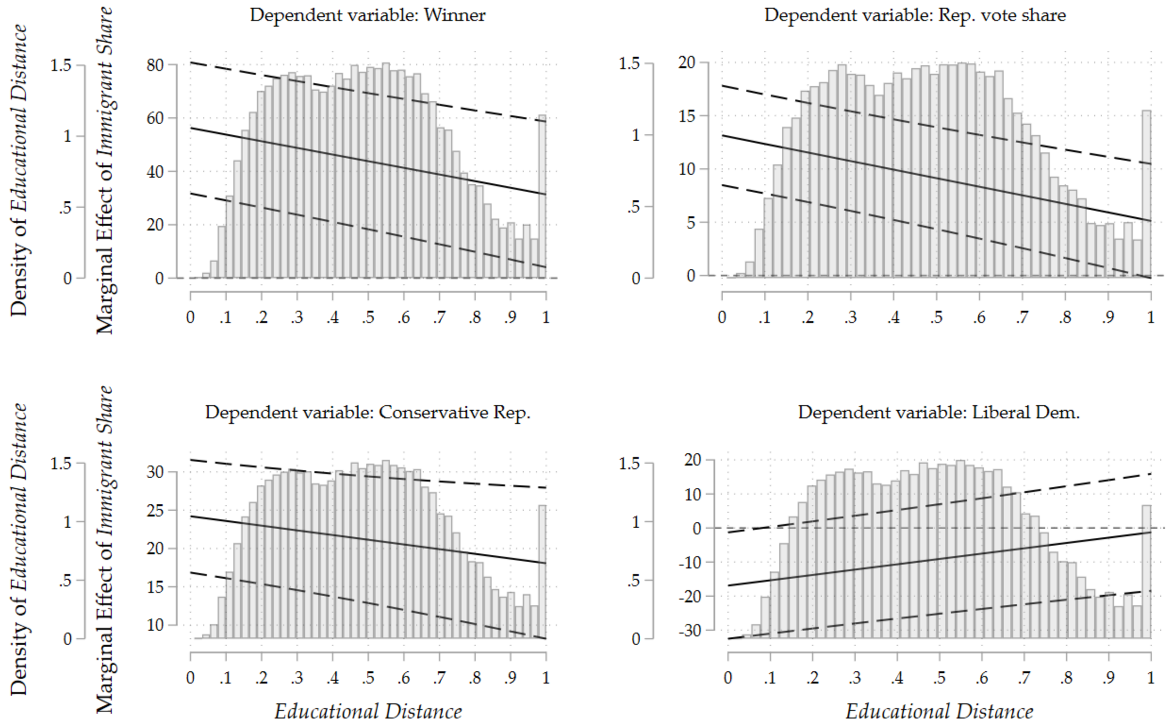
Notes: We rank candidates according to their ideology on the left-right scale and divide the amounts of contributions these candidates received in terciles. For the year 1990, we define the third of the contributions most to the right end of the scale as "conservative" contributions. In analogy, we define "liberal" contributions as those on the left end of the scale and the remaining tercile as "moderates." We then use the resulting cut-offs for ideology scores to categorize amounts of contributions into these three categories of CFscores in each year in our sample.

Figure 3 – Immigration, Ideology and Cultural Distance, 1992-2016, Two-year Net Inflows



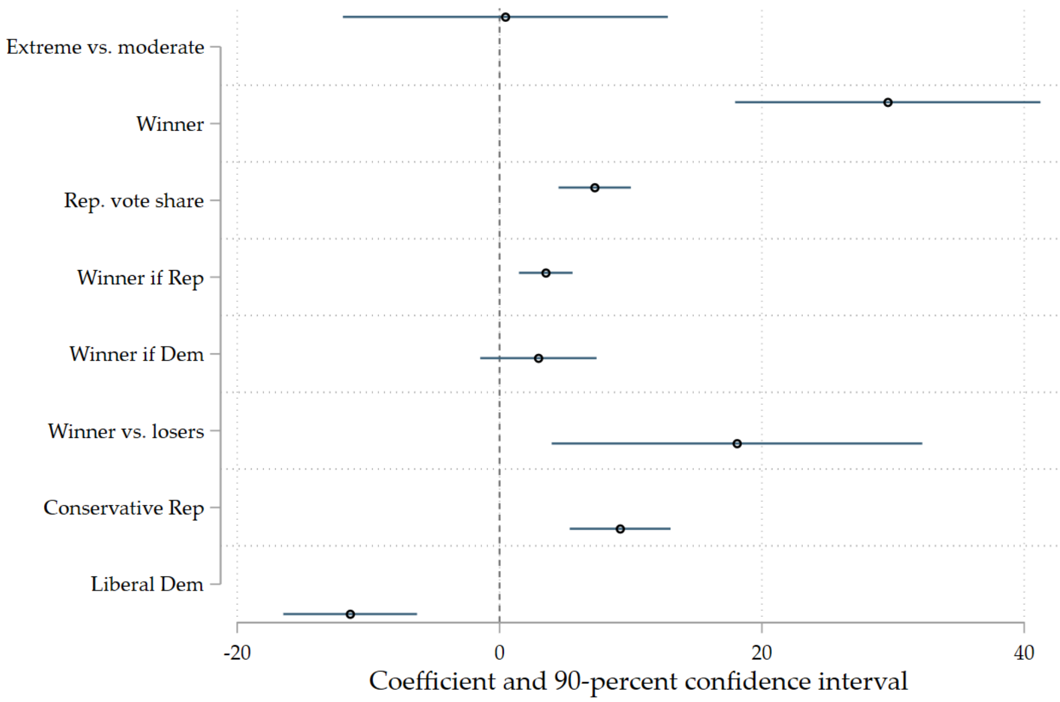
Notes: The figure shows partial leverage plots for the regressions reported in columns 2, 3, 5, 7, and 8 of Table A-4. The dashed lines indicate 90-percent confidence intervals.

Figure 4 – Immigration, Ideology and Educational Distance, 1992-2016, Two-year Net Inflows



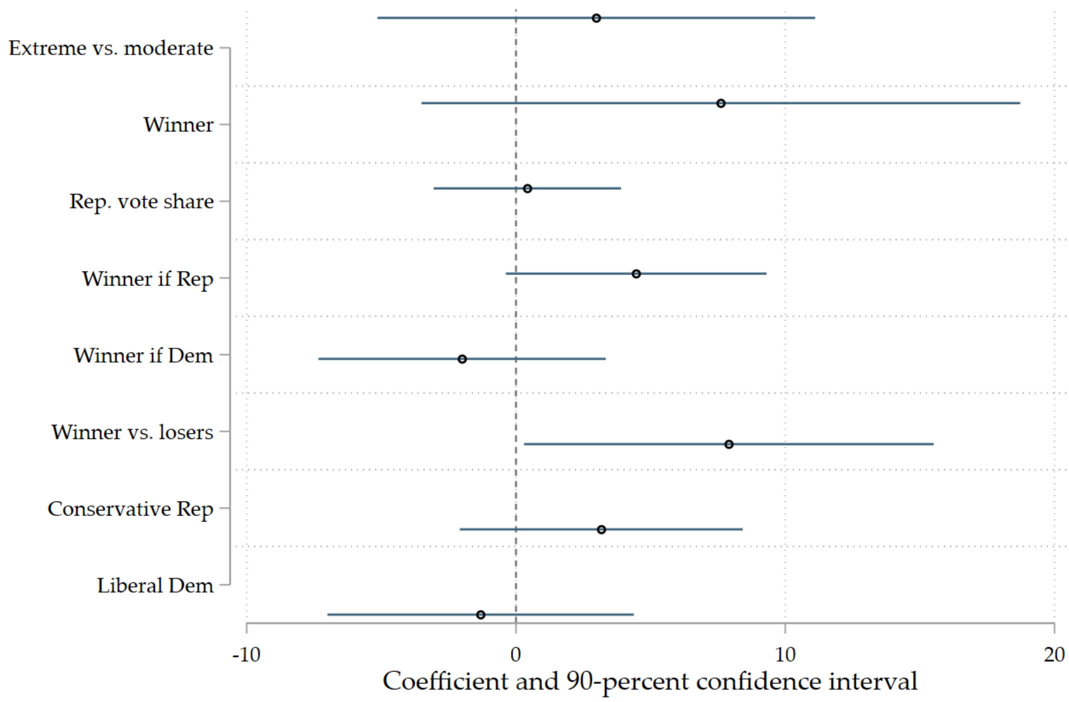
Notes: The figure shows partial leverage plots for the regressions reported in columns 2, 3, 7, and 8 of Table A-5. The dashed lines indicate 90-percent confidence intervals.

Figure 5 – Immigration and Ideology, 1992-2016, Eight-year Net Inflows



Notes: The figure reports the coefficients of net adult immigration over eight years, in tandem with 90-percent confidence intervals. The coefficient of extreme vs. moderate is multiplied with 0.1. See Table A-6 for details.

Figure 6 – Immigration and Ideology, 1992-2016, Two-year Gross Inflows



Notes: The figure reports the coefficients of gross immigration over two years, in tandem with 90-percent confidence intervals. The coefficient of extreme vs. moderate is multiplied with 0.1. See Table A-7 for details.

Table 1 – Immigration and Ideology, 1992-2016, Two-year Net Inflows

	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Right Rep.	(8) Mod. Rep.	(9) Mod. Dem.	(10) Left Dem.
Panel A: OLS estimates										
ΔImmigrant share	56.858*	8.440**	3.101***	1.759	-3.437**	5.158*	4.557***	1.309	-3.677***	-2.158
	(30.728)	(3.420)	(0.847)	(1.387)	(1.644)	(2.814)	(1.213)	(1.993)	(1.247)	(2.115)
Panel B: Reduced-form estimates										
Immigrant share IV	9.891***	2.181***	0.507***	0.555***	-0.319	1.217	0.946***	0.082	-0.390	-0.644***
	(2.711)	(0.450)	(0.125)	(0.157)	(0.253)	(0.853)	(0.162)	(0.319)	(0.372)	(0.212)
Panel C: Second-stage estimates										
ΔImmigrant share	249.685***	55.130***	12.804***	14.488***	-8.667	30.963	23.880***	2.077	-9.840	-16.260***
	(81.515)	(14.404)	(3.805)	(4.388)	(7.850)	(23.902)	(4.727)	(8.177)	(9.958)	(5.507)
Panel D: First-stage estimates										
Immigrant share IV	0.040***	0.040***	0.040***	0.038***	0.037***	0.039***	0.040***	0.040***	0.040***	0.040***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	40,023	39,514	40,019	27,181	14,287	31,618	39,624	39,624	39,624	39,624
K-P F-stat.	78.22	76.93	78.24	103.6	42.02	66.25	78.68	78.68	78.68	78.68

Notes: The dependent variables are the difference in contributions to extreme compared to moderate candidates (1), ideology of the winning candidates (2), share of total votes that goes to the Republican candidate (3), ideology of the election winner given that they are Republicans (4) or Democrats (5), absolute difference between the ideology of the winner and loser (6), probability the winning candidate is a conservative Republican (7), moderate Republican (8), moderate Democrat (9), or liberal Democrat (10). ΔImmigrant share measures the net inflow of adult immigrants as a share of adult population over the previous two years. All regressions include the full set of control variables, population weights and fixed effects for counties and years (see Table A-3 for the full set of 2SLS results including control variables). Standard errors clustered at the state-level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

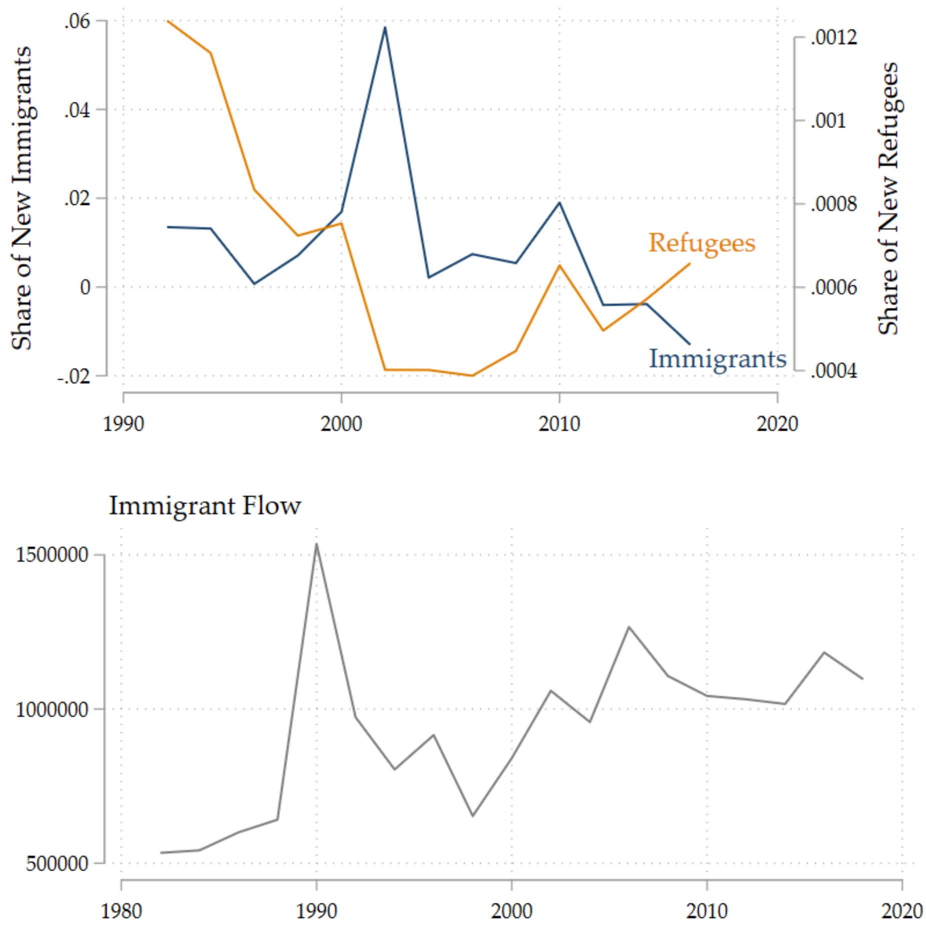
Table 2 – Refugees and Ideology, 1992-2016, Two-year Gross Inflows

	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Right Rep.	(8) Mod. Rep.	(9) Mod. Dem.	(10) Left Dem.
Panel A: OLS estimates										
ΔRefugee share	208.881*	5.141	5.653**	1.001	-9.492**	21.818**	11.587	-5.182	-4.555	-1.786
	(104.410)	(10.972)	(2.163)	(5.534)	(4.512)	(10.065)	(7.709)	(5.656)	(6.045)	(8.011)
Panel B: Reduced-form estimates										
Refugee share IV	189.726***	17.583**	6.282***	7.172	-3.502	0.372	12.505**	-1.189	1.930	-13.222***
	(57.984)	(8.607)	(2.091)	(6.390)	(3.033)	(10.406)	(5.635)	(4.051)	(4.230)	(3.523)
Panel C: Second-stage estimates										
ΔRefugee share	593.390***	54.672**	19.646***	26.927	-9.433	1.115	39.125**	-3.720	6.040	-41.368***
	(188.796)	(26.342)	(6.597)	(21.589)	(8.275)	(31.228)	(15.344)	(12.288)	(13.145)	(11.531)
Panel D: First-stage estimates										
Refugee share IV	0.320***	0.322***	0.320***	0.266**	0.371***	0.333***	0.320***	0.320***	0.320***	0.320***
	(0.062)	(0.063)	(0.062)	(0.107)	(0.033)	(0.064)	(0.062)	(0.062)	(0.062)	(0.062)
Observations	40,044	39,533	40,040	27,198	14,302	31,633	39,643	39,643	39,643	39,643
K-P F-stat.	26.31	26.43	26.31	6.188	125.9	27.37	26.33	26.33	26.33	26.33

Notes: The dependent variables are the difference in contributions to extreme compared to moderate candidates (1), ideology of the winning candidates (2), share of total votes that goes to the Republican candidate (3), ideology of the election winner given that they are Republicans (4) or Democrats (5), absolute difference between the ideology of the winner and loser (6), probability the winning candidate is a conservative Republican (7), moderate Republican (8), moderate Democrat (9), or liberal Democrat (10). ΔRefugee share measures the gross inflow of refugees as a share of adult population over the previous two years. All regressions include the full set of control variables, population weights and fixed effects for counties and years (see Table A-8 for the full set of 2SLS results including control variables). Standard errors clustered at the state-level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

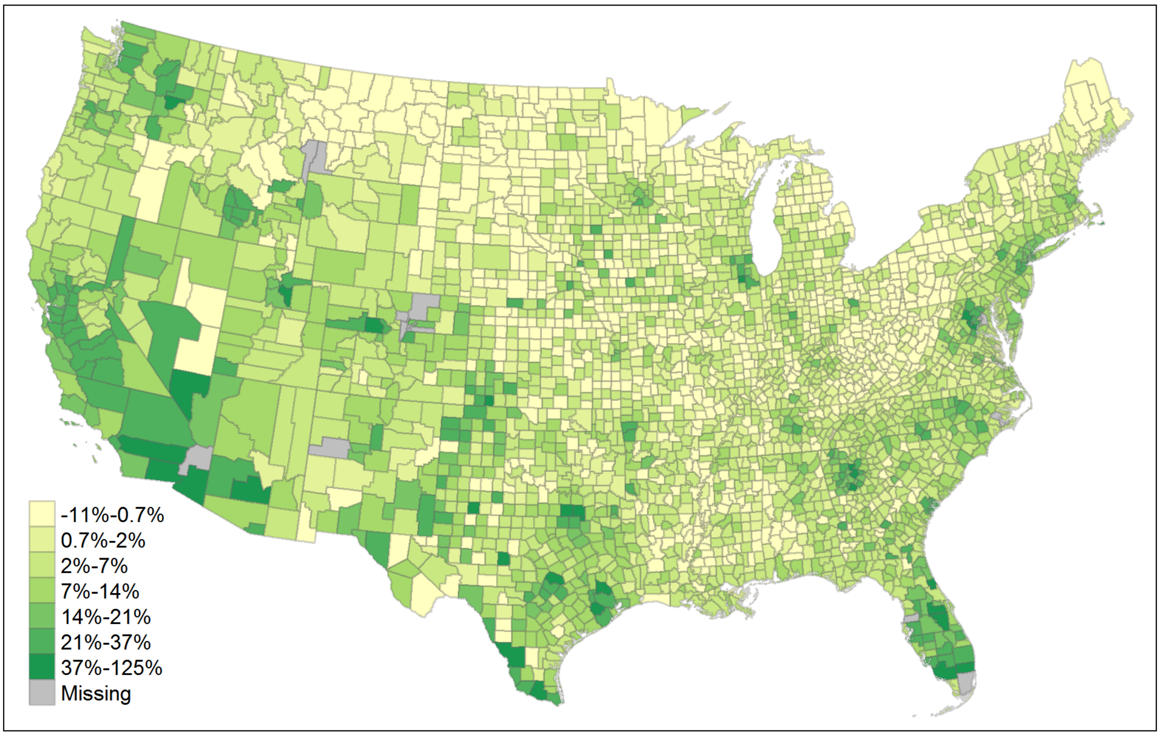
Appendix

Figure A-1 – Immigrants and Refugees in the United States, 1982-2018, Inflows



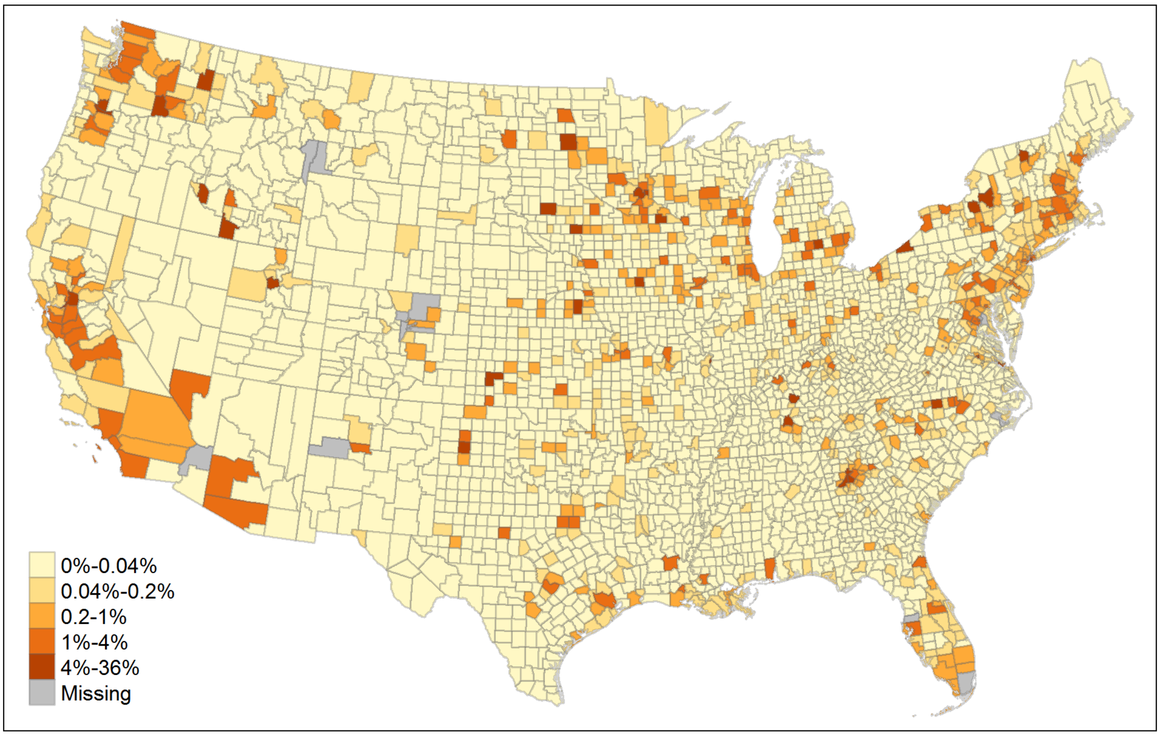
Notes: The upper figure shows net (gross) inflows of adult immigrants (refugees) as a share of the adult population. The lower figure shows the number of foreign nationals that were granted lawful permanent residence.

Figure A-2 – Immigrants in the United States by County, 1992-2016, Net Inflows



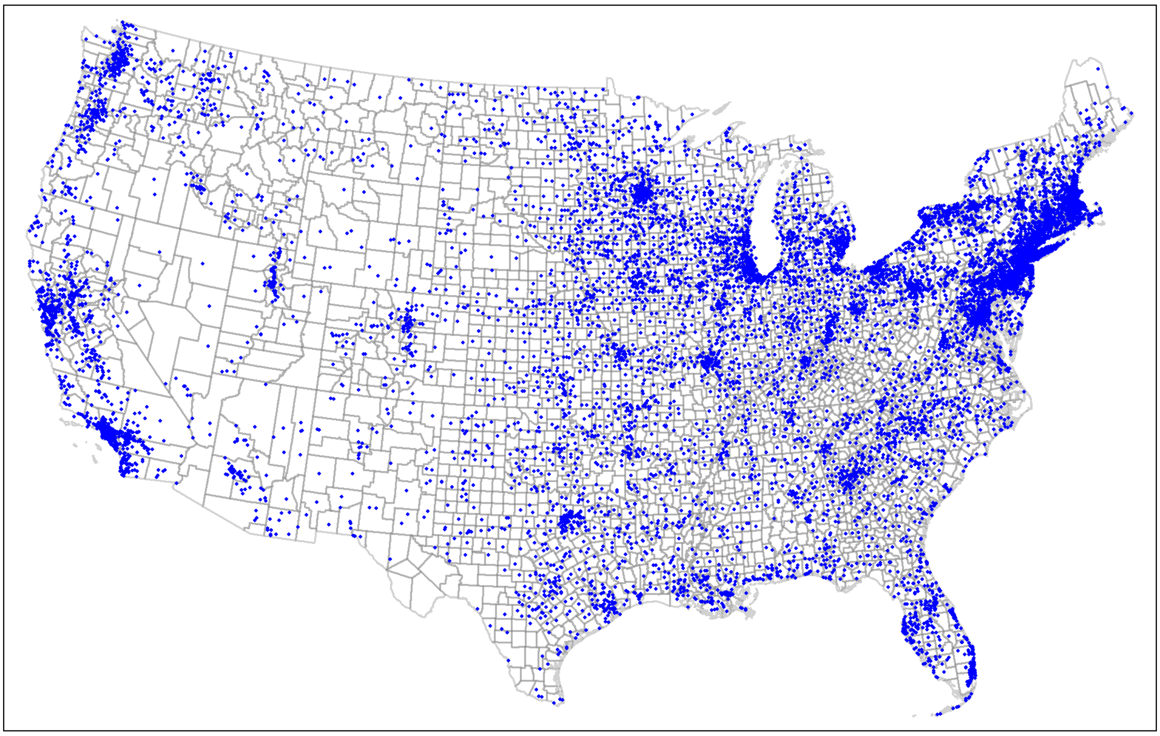
Notes: The map shows the net inflow of adult immigrants over the 1992-2016 period divided by the 1992 adult population. We split groups at the 25th, 50th, 75th, 90th, 95th and 99th percentiles.

Figure A-3 – Refugees in the United States by County, 1992-2016, Gross Inflows



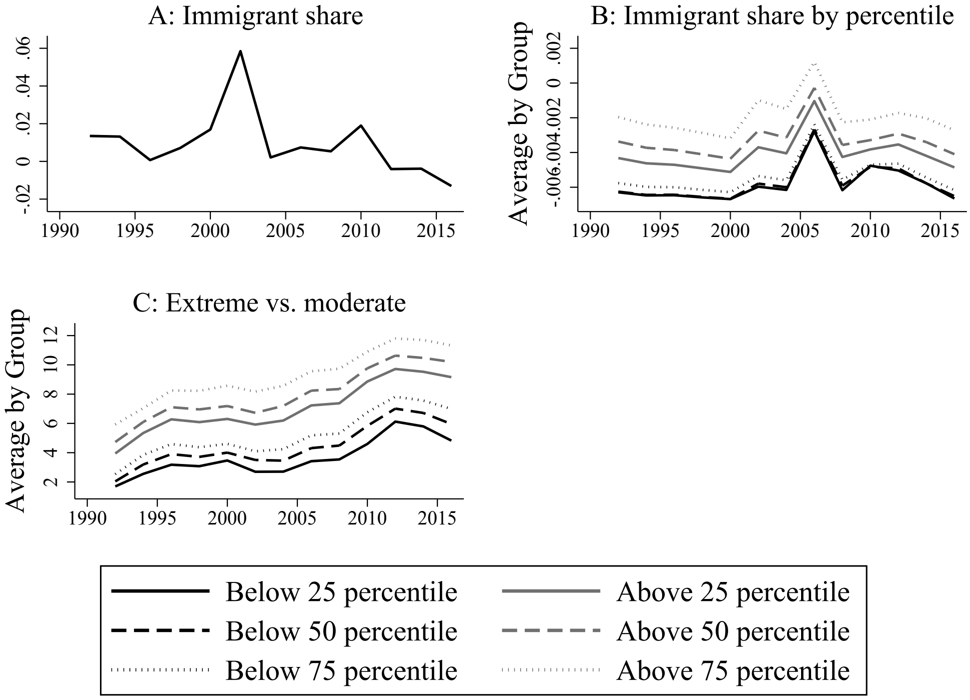
Notes: The map shows the gross inflow of refugees over the 1992-2016 period divided by the 1992 adult population. We split groups at the 75th, 90th, 95th and 99th percentiles.

Figure A-4 – Refugees in the United States by County, 1975-2008, Gross Inflows, Geocoded



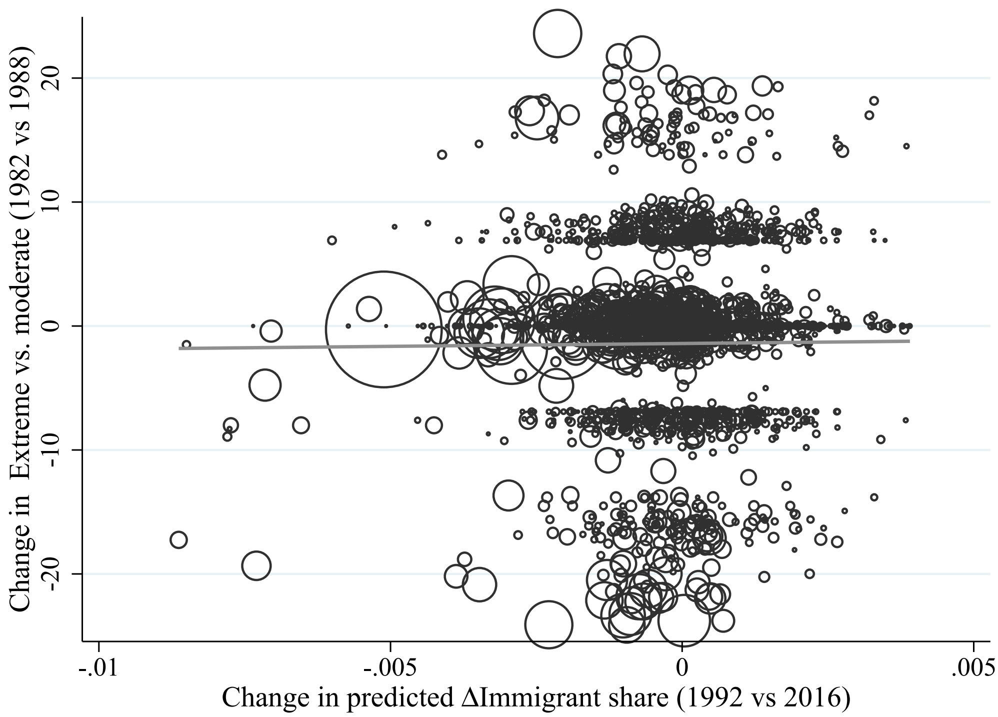
Notes: The map shows the location of first residence of refugees over the 1975-2008 period. We geocoded locations so that they depict a town, city or neighborhood (in large cities). One dot represents one location but can represent several refugees.

Figure A-5 – Parallel Trends—Immigrant Shares by Percentile



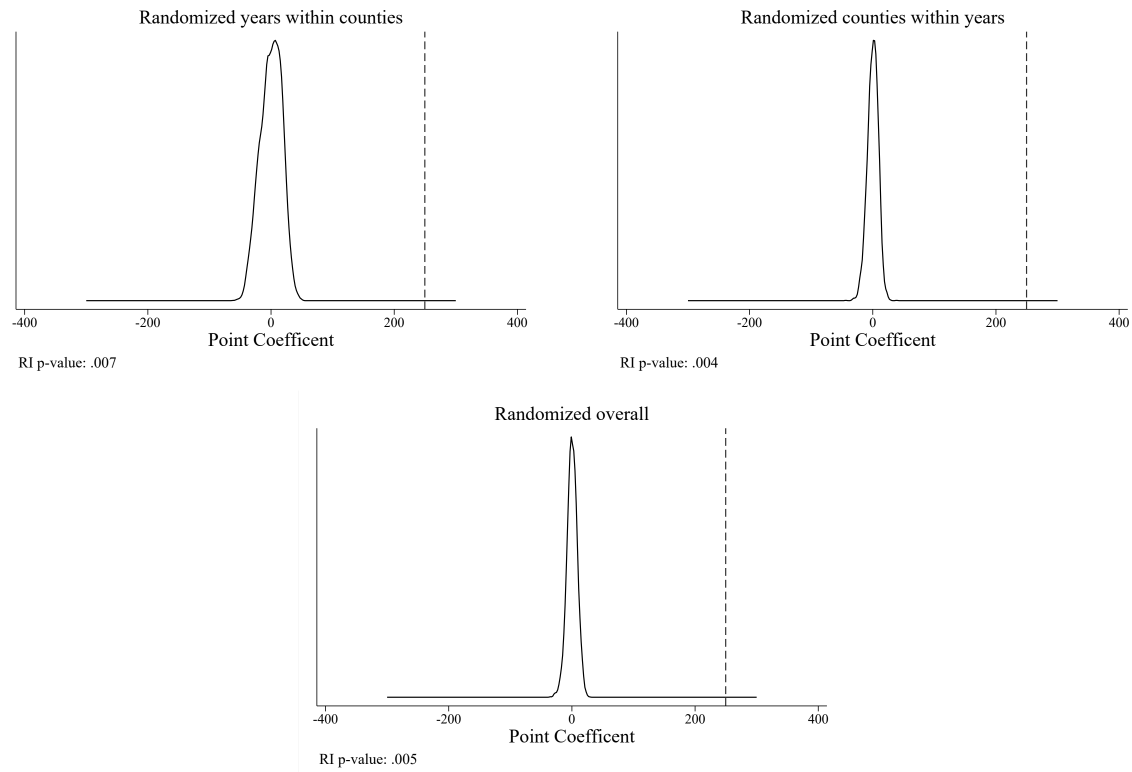
Notes: Panel A shows net inflows of adult immigrants as a share of the adult population. Panel B shows the same variable at the county-level, according to percentiles of the initial share of adult immigrants in the year 1980 (and netting out the effect of the control variables we include in all regressions). Panel C shows extreme versus moderate campaign contributions for the same percentiles.

Figure A-6 – Correlation Between Extreme vs. Moderate Contributions and Changes in Immigration



Notes: The figure shows the correlation between the change in net adult immigration (1992-2016) and the change in extreme vs. moderate campaign contributions (1982-1988). The straight grey line represents fitted values weighted by population: slope is 46.21 and standard error 304.33.

Figure A-7 – Randomized Immigrants, Extreme vs. Moderate Contributions



Notes: The figures show results from regressions based on column 1 in Table 1. Each figure graphically represents the coefficients of 5,000 regressions, where we have randomized immigration shares (i) across years within the same county, (ii) across counties within the same year, and (iii) across space and time. The dashed vertical line shows the coefficient for net adult immigration from column 1 of Table 1. We calculate the randomization inference (RI) p-value as the proportion of times that the absolute value of the t-statistic in the simulated data exceeds the absolute value of the original t-statistic.

Table A-1 – Descriptive Statistics

	Obs.	Mean	SD	Min	Max
	Panel A: Immigrants and Refugees				
Δ Immigrants*	40023	623.7443	3376.97	-377.1992	126924.00
Δ Immigrant share*	40023	0.0035	0.01	-0.0276	0.12
Immigrant share IV*	40023	0.0024	0.01	-0.0818	0.22
Δ Immigrants (gross)	40023	846.4581	5411.54	0.0000	284252.00
Δ Immigrant share (gross)	40023	0.0051	0.01	0.0000	0.07
Immigrant share (gross) IV	40023	0.0039	0.01	0.0000	0.10
Δ Refugees	40023	44.1943	362.89	0.0000	24549.00
Δ Refugee share	40023	0.0001	0.00	0.0000	0.07
Refugee share IV	40023	0.0001	0.00	0.0000	0.06
	Panel B: Political Outcomes				
Extreme vs. moderate	40023	6.22	5.95	-16.05	17.67
Winner	39514	0.55	0.67	-2.54	2.02
Rep. vote share	40019	0.57	0.22	0.00	1.00
Winner if Rep.	27240	0.98	0.24	-0.90	2.02
Winner if Dem.	14666	-0.32	0.40	-2.54	1.30
Winner vs. loser	31618	1.58	0.56	0.00	5.77
Conservative Rep.	39624	0.20	0.39	0.00	1.00
Mod. Rep.	39624	0.17	0.37	0.00	1.00
Mod. Dem.	39624	0.14	0.34	0.00	1.00
Liberal Dem.	39624	0.49	0.49	0.00	1.00
	Panel B: Control Variables				
Δ Cultural Distance	39936	0.80	0.18	0.02	1.00
Δ Cultural Distance	39955	0.49	0.23	0.01	1.00
Income*	40023	2.34	0.43	1.35	4.39
Share Afr.-American*	40023	0.10	0.12	0.00	0.65
Share urban*	40023	0.21	0.28	0.00	1.00
Unemployment*	40023	0.04	0.01	0.01	0.12
Share male*	40023	0.49	0.01	0.36	0.56
Share married*	40023	0.57	0.06	0.33	0.71
Import competition*	40023	0.06	0.06	0.00	1.12
Labor participation*	40023	0.63	0.05	0.40	0.84
Share low-skilled*	40023	0.17	0.07	0.04	0.46
Bartik share*	40023	0.01	0.01	0.00	0.13

Notes: We take parts of our data from Mayda et al.'s (2020) replication materials. Those variables are marked with an asterisk in the table. The sample is based on column 1 of Table 1.

Table A-2 – Description and Sources

	Description	**Source**
	Panel A: Immigrants and Refugees	
Δ Immigrants (gross)	Change in the county stock of adult immigrants	Census, ACS
Δ Immigrant share (gross)	Change in the county stock of adult immigrants divided by county adult population	Census, ACS, Mayda et al.
Immigrant share (gross) IV	Sum of 1980 share of adult immigrants by country*net flow of immigrants by country divided by 1980 share of adult population*total population	Census, ACS, Mayda et al.
Δ Refugees	Number of new refugees	ORR, PRM
Δ Refugee share	Number of new refugees divided by county adult population	ORR, PRM, Mayda et al.
Refugee share IV	Sum of 1980-90 share of refugees by country*number of new refugees by country divided by 1980 share of adult population*total population	ORR, PRM, Mayda et al.
	Panel B: Political Outcomes	
Extreme vs. moderate	Inverse hyperbolic sine of the difference between extreme and moderate contributions (based on dollar-weighted terciles in 1990)	Bonica (2019)
Winner	Ideology of winner	EDS, Bonica (2019)
Rep. vote share	Republican vote share	EDS
Winner if Rep.	Ideology of Republican winners	EDS, Bonica (2019)
Winner if Dem.	Ideology of Democratic winners	EDS, Bonica (2019)
Winner vs. loser	Absolute ideological distance between winner and runner up	EDS, Bonica (2019)
Conservative Rep.	Dummy = 1 if winner is a Republican and right of 1990 party median	EDS, Bonica (2019)
Mod. Rep.	Dummy = 1 if winner is a Republican and left of 1990 party median	EDS, Bonica (2019)
Mod. Dem.	Dummy = 1 if winner is a Democrat and right of 1990 party median	EDS, Bonica (2019)
Liberal Dem.	Dummy = 1 if winner is a Democrat and left of 1990 party median	EDS, Bonica (2019)
	Panel C: Control Variables	
Δ Cultural Distance	Sum of the the absolute differences between the share of Latinos, Asians, Africans and Westerners among residents and new immigrants	Census, ACS, Mayda et al.
Δ Educational Distance	Sum of the the absolute differences between the share of high-school dropouts, high-school graduates, people with some college, college graduates and people with more than college among residents and new immigrants	Census, ACS, Mayda et al.

Notes: We take parts of our data from Mayda et al.'s (2020) replication materials (marked with an asterisk in Table A-1). ACS = American Community Survey, ORR = Office of Refugee Resettlement, EDS = Election Data Services, PRM = Bureau of Population, Refugees, and Migration.

Table A-3 – Immigration and Polarization, 1992-2016, Two-year Net Inflows

	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Cons. Rep.	(8) Mod. Rep.	(9) Mod. Dem.	(10) Liberal Dem.
ΔImmigrant share	249.685***	55.130***	12.804***	14.488***	-8.667	30.963	23.880***	2.077	-9.840	-16.260***
	(81.515)	(14.404)	(3.805)	(4.388)	(7.850)	(23.902)	(4.727)	(8.177)	(9.958)	(5.507)
ΔIncome	-0.155	-0.030	0.024	-0.104**	0.147	-0.228	-0.114	0.173**	0.006	-0.066
	(1.061)	(0.132)	(0.037)	(0.047)	(0.105)	(0.205)	(0.069)	(0.079)	(0.086)	(0.068)
ΔShare Afr.-American	6.688	0.198	-0.257	-0.383	0.497	-1.558	-0.576	1.428**	-0.694	-0.118
	(11.348)	(1.153)	(0.285)	(0.686)	(1.167)	(2.397)	(0.743)	(0.705)	(0.540)	(0.641)
ΔShare urban	-1.017	-0.054	0.027	0.116*	-0.050	-0.041	0.054	-0.087	-0.062	0.095
	(1.080)	(0.171)	(0.039)	(0.058)	(0.114)	(0.138)	(0.103)	(0.101)	(0.070)	(0.086)
ΔUnemployment	-2.630	1.395	0.732	-1.196**	-0.819	-0.011	-0.720	2.824***	-0.636	-1.475*
	(8.333)	(1.105)	(0.447)	(0.534)	(1.125)	(1.855)	(0.617)	(0.898)	(0.797)	(0.817)
ΔShare male	24.391	-0.999	-0.865*	1.457**	-0.288	3.277	-0.108	-1.654	0.420	1.336*
	(16.328)	(1.498)	(0.433)	(0.625)	(0.915)	(2.010)	(1.202)	(1.115)	(0.874)	(0.676)
ΔShare married	-8.358**	-0.523	-0.071	-0.432**	0.189	-1.309*	-0.784***	0.607**	0.212	-0.038
	(3.662)	(0.451)	(0.137)	(0.177)	(0.431)	(0.774)	(0.268)	(0.260)	(0.248)	(0.266)
ΔImport competition	-9.630*	-0.542	-0.208*	0.514**	-0.038	0.357	-0.324	-0.180	0.325	0.171
	(4.876)	(0.362)	(0.118)	(0.212)	(0.478)	(0.771)	(0.346)	(0.226)	(0.293)	(0.190)
ΔLabor participation	18.391*	1.568	0.235	0.772*	-0.316	3.427	1.509**	-1.353*	0.218	-0.381
	(9.987)	(1.363)	(0.404)	(0.445)	(1.025)	(2.087)	(0.601)	(0.751)	(0.692)	(0.554)
ΔShare low-skilled	-10.063	-0.451	0.275	-0.186	-1.692*	-0.141	0.410	0.288	-0.825	0.143
	(8.944)	(0.725)	(0.265)	(0.266)	(0.954)	(1.834)	(0.579)	(0.576)	(0.543)	(0.401)
ΔBartik share	-13.745	-0.902	-0.574	-1.503	5.696***	-0.239	-1.799	0.459	0.508	0.806
	(18.406)	(1.813)	(0.528)	(1.239)	(1.437)	(2.300)	(1.209)	(1.247)	(1.290)	(1.087)
Observations	40,023	40,019	39,514	27,181	14,287	31,618	39,624	39,624	39,624	39,624
R-squared	-0.017	-0.063	-0.134	-0.085	0.007	-0.035	-0.043	0.006	-0.002	-0.032
K–P F-stat.	78.22	78.24	76.93	103.6	42.02	66.25	78.68	78.68	78.68	78.68

Notes: The table shows the second stages of 2SLS regressions; all regressions include population weights and fixed effects for counties and years; standard errors clustered at the state-level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A-4 – Immigration, Ideology and Cultural Distance, 1992-2016, Two-year Net Inflows

	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Cons. Rep.	(8) Liberal Dem.
ΔImmigrant share	181.751	43.415***	11.152***	16.903***	-13.466	37.614**	20.567***	-9.854
	(143.861)	(13.827)	(3.274)	(6.401)	(10.010)	(16.713)	(4.177)	(9.122)
ΔImmigration * ΔCultural Dist.	145.097	26.852***	4.184**	-4.219	12.108**	-13.084	8.435*	-13.529**
	(116.131)	(9.208)	(2.022)	(4.762)	(5.282)	(15.809)	(4.950)	(5.299)
ΔCultural Distance	-0.425	-0.025	0.008	0.020	-0.053	0.068	0.014	0.044
	(0.602)	(0.057)	(0.013)	(0.024)	(0.047)	(0.071)	(0.030)	(0.033)
ΔIncome	-0.398	-0.080	0.014	-0.101	0.110	-0.209	-0.133*	-0.045
	(1.012)	(0.170)	(0.031)	(0.063)	(0.105)	(0.168)	(0.074)	(0.084)
ΔShare African-American	6.199	0.120	-0.266	-0.356	0.423	-1.487	-0.602	-0.072
	(12.867)	(1.238)	(0.259)	(0.561)	(1.010)	(1.789)	(0.785)	(0.724)
ΔShare urban	-1.040	-0.058	0.026	0.114**	-0.043	-0.039	0.053	0.098
	(1.058)	(0.169)	(0.034)	(0.049)	(0.090)	(0.169)	(0.074)	(0.092)
ΔUnemployment	-3.810	1.129	0.669**	-1.191***	-0.973	0.040	-0.829	-1.384**
	(9.244)	(1.089)	(0.272)	(0.387)	(1.153)	(1.756)	(0.631)	(0.695)
ΔShare male	26.671**	-0.437	-0.745**	1.429**	-0.038	3.088	0.114	1.130
	(11.682)	(1.396)	(0.315)	(0.588)	(1.139)	(2.204)	(0.840)	(0.767)
ΔShare married	-8.497**	-0.566	-0.081	-0.426***	0.217	-1.318**	-0.804***	-0.029
	(4.271)	(0.431)	(0.109)	(0.136)	(0.378)	(0.641)	(0.246)	(0.239)
ΔImport competition	-9.817*	-0.559	-0.208**	0.522**	-0.101	0.389	-0.324	0.189
	(5.012)	(0.480)	(0.100)	(0.205)	(0.319)	(0.578)	(0.310)	(0.235)
ΔLabor market participation	20.181**	1.944*	0.304	0.741*	0.037	3.290**	1.645***	-0.542
	(9.109)	(0.993)	(0.271)	(0.392)	(1.099)	(1.676)	(0.467)	(0.618)
ΔShare low-skilled	-10.848	-0.669	0.227	-0.181	-1.798**	-0.098	0.314	0.213
	(7.850)	(0.723)	(0.199)	(0.287)	(0.735)	(1.587)	(0.474)	(0.459)
ΔBartik share	-11.676	-0.398	-0.472	-1.535	5.958***	-0.376	-1.600*	0.609
	(10.735)	(1.590)	(0.336)	(1.071)	(1.283)	(2.992)	(0.954)	(1.029)
Observations	39,936	39,430	39,932	27,108	14,273	31,560	39,538	39,538
Kleibergen-Paap F	52.21	51.15	52.22	56.89	20.72	41.85	52.28	52.28

Notes: The table shows the second stages of Control Function Approach regressions, including the residual from the first-stage regressions; population weights and fixed effects for counties and years; bootstrapped standard errors clustered at the state-level in parentheses (500 repetitions); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A-5 – Immigration, Ideology and Educational Distance, 1992-2016, Two-year Net Inflows

	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Cons. Rep.	(8) Liberal Dem.
ΔImmigrant share	249.909**	56.269***	13.152***	13.884	-8.660	29.886	24.207***	-16.918*
	(120.949)	(14.925)	(2.836)	(13.092)	(9.578)	(18.335)	(4.469)	(9.500)
ΔImmigration * ΔEducational Dist.	11.190	-24.915***	-8.034***	5.512	-3.727	19.468*	-6.132*	15.653***
	(66.579)	(5.855)	(1.872)	(3.708)	(4.372)	(11.647)	(3.286)	(4.016)
ΔEducational Distance	0.935	0.420***	0.100***	0.035	-0.061	0.319*	0.194***	-0.141**
	(0.849)	(0.098)	(0.027)	(0.044)	(0.093)	(0.177)	(0.042)	(0.059)
ΔIncome	-0.267	-0.019	0.030	-0.118	0.165	-0.305*	-0.120*	-0.084
	(1.024)	(0.157)	(0.030)	(0.083)	(0.103)	(0.174)	(0.069)	(0.083)
ΔShare African-American	7.955	0.521	-0.198	-0.283	0.342	-1.052	-0.380	-0.168
	(12.521)	(1.098)	(0.240)	(0.529)	(0.965)	(1.769)	(0.746)	(0.667)
ΔShare urban	-1.071	-0.077	0.022	0.115**	-0.048	-0.061	0.043	0.103
	(1.047)	(0.155)	(0.031)	(0.055)	(0.097)	(0.159)	(0.071)	(0.086)
ΔUnemployment	-1.940	1.653	0.790***	-1.142**	-0.870	0.360	-0.593	-1.552**
	(8.885)	(1.050)	(0.255)	(0.464)	(1.062)	(1.685)	(0.611)	(0.670)
ΔShare male	23.006**	-1.187	-0.880***	1.331**	-0.092	2.415	-0.268	1.307*
	(10.645)	(1.292)	(0.290)	(0.610)	(0.965)	(1.940)	(0.818)	(0.720)
ΔShare married	-7.938*	-0.462	-0.063	-0.394**	0.151	-1.091*	-0.735***	-0.026
	(4.131)	(0.414)	(0.102)	(0.163)	(0.384)	(0.611)	(0.242)	(0.235)
ΔImport competition	-9.717*	-0.500	-0.194**	0.502**	0.008	0.271	-0.323	0.140
	(5.019)	(0.449)	(0.096)	(0.230)	(0.353)	(0.568)	(0.300)	(0.225)
ΔLabor market participation	17.732**	1.409	0.211	0.724*	-0.208	3.094**	1.412***	-0.363
	(8.385)	(0.866)	(0.244)	(0.379)	(0.928)	(1.458)	(0.433)	(0.568)
ΔShare low-skilled	-9.973	-0.234	0.338*	-0.196	-1.709***	-0.161	0.476	0.034
	(7.574)	(0.683)	(0.183)	(0.327)	(0.641)	(1.422)	(0.453)	(0.438)
ΔBartik share	-11.804	-0.401	-0.481	-1.326	5.618***	0.471	-1.503	0.722
	(11.813)	(1.573)	(0.312)	(1.055)	(1.326)	(3.062)	(0.949)	(1.025)
Observations	39,955	39,449	39,951	27,124	14,279	31,574	39,557	39,557
Kleibergen-Paap F	86.04	84.39	86.04	101.6	36.46	68.53	86.72	86.72

Notes: The table shows the second stages of Control Function Approach regressions, including the residual from the first-stage regressions; all regressions include population weights and fixed effects for counties and years; bootstrapped standard errors clustered at the state-level in parentheses (500 repetitions); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A-6 – Immigration and Polarization, 1992-2016, Eight-year Net Inflows

	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Cons. Rep.	(8) Liberal Dem.
ΔImmigrant share	4.430	29.599***	7.255***	3.524***	2.962	18.103**	9.193***	-11.388***
	(73.814)	(6.936)	(1.643)	(1.216)	(2.640)	(8.416)	(2.291)	(3.038)
ΔIncome	3.272*	-0.085	0.010	-0.031	-0.116	-0.136	-0.083	-0.021
	(1.899)	(0.175)	(0.054)	(0.072)	(0.123)	(0.265)	(0.085)	(0.106)
ΔShare African-American	-8.573	-1.020	-0.099	-1.473***	-0.965	-2.278	-1.288	-0.672
	(11.801)	(1.456)	(0.473)	(0.453)	(1.366)	(2.671)	(1.248)	(0.854)
ΔShare urban	-0.828	0.068	0.015	0.054	0.040	0.045	-0.006	-0.027
	(0.516)	(0.109)	(0.025)	(0.033)	(0.093)	(0.108)	(0.044)	(0.052)
ΔUnemployment	29.897	-2.848	0.562	-1.777***	-3.985**	-4.973*	-2.242*	2.090*
	(21.567)	(1.876)	(0.615)	(0.649)	(1.501)	(2.472)	(1.273)	(1.142)
ΔShare male	12.179	3.773	0.661	1.177	-1.015	7.653**	1.874	-0.395
	(11.273)	(3.454)	(1.101)	(0.820)	(2.093)	(3.409)	(1.464)	(1.574)
ΔShare married	-15.352***	-0.914	-0.301	-0.460	-0.763	-1.618	-0.577	0.357
	(5.342)	(0.866)	(0.265)	(0.275)	(0.821)	(1.179)	(0.531)	(0.466)
ΔImport competition	-4.125*	-0.439	-0.173	0.136	-0.441	-0.908	-0.053	0.318*
	(2.420)	(0.492)	(0.118)	(0.139)	(0.518)	(0.931)	(0.385)	(0.172)
ΔLabor market participation	-8.554	3.900	0.978	0.706	1.954	4.644*	1.674*	-1.303
	(13.091)	(2.638)	(0.644)	(0.454)	(1.395)	(2.629)	(0.869)	(1.361)
ΔShare low-skilled	-4.636	-2.231	-0.432	0.090	-1.922	-1.750	0.255	0.997
	(13.469)	(2.229)	(0.548)	(0.402)	(1.624)	(2.455)	(1.043)	(0.840)
ΔBartik share	-5.509	-3.841*	-0.643	-0.279	6.298***	-0.177	-3.927***	1.779
	(25.575)	(1.989)	(0.458)	(1.033)	(1.878)	(2.947)	(1.078)	(1.357)
Observations	9,236	9,138	9,235	5,898	2,408	6,226	9,161	9,161
R-squared	0.020	-0.706	-0.477	-0.040	0.008	-0.140	-0.113	-0.322
Kleibergen-Paap F	18.25	18.16	18.25	15.85	8.744	11.43	18.13	18.13

Notes: The table shows the second stages of 2SLS regressions; all regressions include population weights and fixed effects for counties and years; standard errors clustered at the state-level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A-7 – Immigration and Polarization, 1992-2016, Two-year Gross Inflows

	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Cons. Rep.	(8) Liberal Dem.
ΔImmigrant share	29.830	7.608	0.424	4.465	-2.000	7.906*	3.169	-1.313
	(48.443)	(6.626)	(2.075)	(2.886)	(3.180)	(4.533)	(3.131)	(3.391)
ΔIncome	0.856	0.186	0.085**	-0.078	0.101	-0.125	-0.020	-0.137**
	(1.107)	(0.125)	(0.037)	(0.052)	(0.094)	(0.136)	(0.071)	(0.066)
ΔShare African-American	7.327	0.373	-0.203	-0.378	0.498	-1.417	-0.492	-0.193
	(10.883)	(1.408)	(0.373)	(0.699)	(1.169)	(2.536)	(0.803)	(0.667)
ΔShare urban	-1.172	-0.091	0.022	0.087*	-0.027	-0.075	0.038	0.104
	(1.001)	(0.136)	(0.035)	(0.050)	(0.120)	(0.149)	(0.089)	(0.074)
ΔUnemployment	5.716	3.202**	1.200***	-0.874*	-1.166	0.945	0.060	-2.037**
	(8.743)	(1.547)	(0.397)	(0.512)	(1.053)	(1.746)	(0.753)	(0.896)
ΔShare male	18.225	-2.325**	-1.204***	1.276*	-0.119	2.540	-0.677	1.741**
	(13.561)	(1.119)	(0.334)	(0.683)	(0.855)	(1.785)	(1.184)	(0.665)
ΔShare married	-8.816**	-0.636	-0.084	-0.420**	0.275	-1.500**	-0.833***	-0.013
	(3.840)	(0.473)	(0.135)	(0.179)	(0.388)	(0.741)	(0.278)	(0.267)
ΔImport competition	-8.403*	-0.271	-0.143	0.594***	-0.140	0.552	-0.207	0.089
	(4.945)	(0.373)	(0.121)	(0.211)	(0.416)	(0.776)	(0.355)	(0.219)
ΔLabor market participation	-20.549	-2.402	-0.938*	-1.786	5.892***	-1.042	-2.435*	1.249
	(17.562)	(1.855)	(0.508)	(1.282)	(1.435)	(2.389)	(1.281)	(1.154)
ΔShare low-skilled	5.683	-1.196*	-0.477**	0.349	0.427	1.859*	0.307	0.485
	(6.645)	(0.683)	(0.201)	(0.403)	(0.652)	(0.982)	(0.460)	(0.486)
ΔBartik share	-1.140	1.518*	0.764***	0.224	-2.184***	1.091	1.260*	-0.460
	(7.765)	(0.843)	(0.239)	(0.256)	(0.658)	(0.904)	(0.631)	(0.451)
Observations	40,023	39,514	40,019	27,181	14,287	31,618	39,624	39,624
R-squared	0.001	-0.000	0.008	0.000	0.014	0.003	0.002	0.003
Kleibergen-Paap F	103.7	103.7	103.6	182.5	75.37	106.4	103.4	103.4

Notes: The table shows the second stages of 2SLS regressions; all regressions include population weights and fixed effects for counties and years; standard errors clustered at the state-level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A-8 – Refugees and Ideology, 1992-2016, Two-year Gross Inflows

	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Cons. Rep.	(8) Mod. Rep.	(9) Mod. Dem.	(10) Liberal Dem.
ΔRefugee share	591.695***	54.394**	19.536***	26.857	-9.339	0.894	38.825**	-3.602	6.197	-41.343***
	(188.464)	(26.204)	(6.551)	(21.566)	(8.264)	(31.167)	(15.279)	(12.317)	(13.188)	(11.500)
ΔIncome	0.890	0.230**	0.081**	-0.049	0.083	-0.055	-0.007	0.185***	-0.046	-0.133**
	(1.024)	(0.094)	(0.034)	(0.046)	(0.085)	(0.117)	(0.067)	(0.066)	(0.066)	(0.056)
ΔShare Afr.-American	5.718	0.311	-0.267	-0.384	0.525	-1.150	-0.575	1.455**	-0.780	-0.062
	(10.898)	(1.402)	(0.347)	(0.706)	(1.166)	(2.515)	(0.784)	(0.701)	(0.585)	(0.655)
ΔShare urban	-1.698	-0.126	0.003	0.072	-0.020	-0.051	0.007	-0.084	-0.065	0.143*
	(1.084)	(0.144)	(0.035)	(0.053)	(0.105)	(0.142)	(0.093)	(0.101)	(0.081)	(0.077)
ΔUnemployment	3.846	3.203*	1.117***	-0.877*	-1.227	1.257	-0.013	2.920***	-1.036	-1.883**
	(8.654)	(1.601)	(0.382)	(0.503)	(0.984)	(1.865)	(0.751)	(0.831)	(0.642)	(0.915)
ΔShare male	24.192*	-1.880	-0.995***	1.407*	-0.177	2.335	-0.314	-1.749	0.750	1.313*
	(14.229)	(1.167)	(0.321)	(0.702)	(0.891)	(1.669)	(1.107)	(1.063)	(0.752)	(0.715)
ΔShare married	-8.157**	-0.529	-0.067	-0.382*	0.203	-1.373*	-0.777***	0.603**	0.223	-0.052
	(3.816)	(0.439)	(0.127)	(0.192)	(0.426)	(0.788)	(0.272)	(0.260)	(0.258)	(0.252)
ΔImport competition	-9.143*	-0.327	-0.169	0.576**	-0.129	0.574	-0.252	-0.164	0.264	0.143
	(4.977)	(0.367)	(0.121)	(0.217)	(0.401)	(0.798)	(0.346)	(0.200)	(0.252)	(0.216)
ΔLabor participation	7.465	-1.300*	-0.388**	0.201	0.503	1.378	0.356	-1.494**	0.822*	0.318
	(6.963)	(0.660)	(0.191)	(0.420)	(0.528)	(0.935)	(0.477)	(0.567)	(0.420)	(0.455)
ΔShare low-skilled	-2.930	1.500	0.689***	0.292	-2.235***	1.407*	1.178*	0.386	-1.241***	-0.313
	(8.105)	(0.973)	(0.247)	(0.290)	(0.675)	(0.756)	(0.657)	(0.517)	(0.338)	(0.474)
ΔBartik share	-17.545	-2.197	-0.832	-1.711	5.843***	-1.126	-2.254*	0.379	0.821	1.031
	(17.908)	(1.855)	(0.510)	(1.289)	(1.482)	(2.413)	(1.286)	(1.124)	(1.262)	(1.101)
Observations	40,044	39,533	40,040	27,198	14,302	31,633	39,643	39,643	39,643	39,643
R-squared	-0.002	-0.005	-0.000	-0.009	0.016	0.003	-0.002	0.006	0.002	-0.013
K-P F-stat.	26.31	26.43	26.31	6.188	125.9	27.37	26.33	26.33	26.33	26.33

Notes: The table shows the second stages of 2SLS regressions; all regressions include population weights and fixed effects for counties and years; standard errors clustered at the state-level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A-9 – Refugees and Ideology, 1992-2016, Eight-year Gross Inflows

	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Cons. Rep.	(8) Liberal Dem.
ΔRefugee share	210.667***	0.358	4.234	2.003	4.190	26.486	8.574	-7.844
	(66.655)	(8.341)	(3.119)	(4.295)	(4.629)	(25.109)	(7.970)	(9.903)
ΔIncome	3.016**	0.475***	0.139***	0.013	-0.040	0.195	0.074	-0.220***
	(1.375)	(0.097)	(0.036)	(0.068)	(0.082)	(0.175)	(0.072)	(0.073)
ΔShare African-American	-11.297	-1.166	-0.205	-1.528***	-0.995	-2.028	-1.471	-0.481
	(11.796)	(1.149)	(0.348)	(0.490)	(1.307)	(2.512)	(1.215)	(0.620)
ΔShare urban	-1.089**	0.038	0.003	0.048**	0.020	-0.016	-0.025	-0.006
	(0.526)	(0.097)	(0.024)	(0.024)	(0.111)	(0.141)	(0.036)	(0.060)
ΔUnemployment	27.013	1.084	1.454***	-1.522**	-3.373**	-2.866	-1.150	0.693
	(17.586)	(1.769)	(0.529)	(0.669)	(1.341)	(2.150)	(1.441)	(1.097)
ΔShare male	20.043**	1.396	0.225	1.088	-0.973	7.952**	1.477	0.205
	(8.898)	(1.894)	(0.863)	(0.891)	(1.841)	(3.185)	(1.343)	(1.226)
ΔShare married	-14.238***	-1.012	-0.295	-0.418	-0.711	-1.361	-0.555	0.345
	(5.288)	(0.802)	(0.293)	(0.254)	(0.839)	(1.136)	(0.531)	(0.466)
ΔImport competition	-4.974*	-0.088	-0.106	0.166	-0.331	-0.617	0.021	0.214
	(2.853)	(0.308)	(0.103)	(0.129)	(0.454)	(0.827)	(0.349)	(0.163)
ΔLabor market participation	-7.011	-1.547**	-0.296	0.128	1.082	0.960	0.080	0.702
	(6.827)	(0.734)	(0.265)	(0.491)	(0.753)	(1.141)	(0.674)	(0.540)
ΔShare low-skilled	-6.672	3.203**	0.823**	0.697	-1.033	1.827	1.807**	-0.962
	(9.032)	(1.520)	(0.373)	(0.439)	(1.636)	(1.602)	(0.882)	(0.687)
ΔBartik share	-2.181	-4.204**	-0.687	-0.511	6.425***	0.789	-3.930***	1.827
	(24.067)	(1.871)	(0.485)	(0.896)	(2.012)	(3.113)	(1.137)	(1.438)
Observations	9,236	9,138	9,235	5,898	2,408	6,226	9,161	9,161
R-squared	0.019	0.031	0.031	0.037	0.055	0.015	0.010	0.014
K-P F-stat.	18.25	24.04	23.14	2.841	127.4	32.11	23.10	23.10

Notes: The table shows the second stages of 2SLS regressions; all regressions include population weights and fixed effects for counties and years; standard errors clustered at the state-level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A-10 – Pre-trends, Shift-Share Instrument

	(1)	obs.		(2)	obs.
Extreme vs. moderate	4.86e-06	36,916	Income	0.000857	36,940
	(1.56e-05)			(0.000548)	
Winner	-0.000172	32,680	Afr.-American	0.00779	36,940
	(0.000169)			(0.0237)	
Rep. vote share	0.000605	36,916	Share urban	0.000265	36,940
	(0.000708)			(0.000832)	
Winner if Rep.	0.00131*	13,772	Unemployment	-0.0259	36,940
	(0.000663)			(0.0216)	
Winner if Dem.	-0.00154	18,908	Share male	-0.0948	36,940
	(0.00110)			(0.0801)	
Winner vs. loser	0.000731	25,950	Share married	0.0139	36,940
	(0.000453)			(0.0197)	
Conservative Rep.	-0.000220	34,840	Import competition	0.00303	36,940
	(0.000301)			(0.00548)	
Mod. Rep.	2.54e-06	34,972	Labor participation	0.0156	36,940
	(0.000245)			(0.00939)	
Mod. Dem.	0.000414	34,840	Share low-skilled	-0.000339	36,940
	(0.000268)			(0.00337)	
Liberal Dem.	0.000135	34,972	Share white low-skilled	0.00511	36,940
	(0.000158)			(0.00413)	
			Share of white male low-skilled	0.0340	36,940
				(0.0216)	

Notes: We define the pre-trend variables as the difference between 1982 and 1988 for column 1 and changes between 1980 and 1990 for column 2, while the dependent variable is the two-year difference of the shift-share instrument in the 1992-2016 period. All specifications include the same control variables as in Table A-3, year-fixed effects (we omit county-fixed effects) and population weights. Each line represents a separate regression with the variables listed as the explanatory variables of interest. Standard errors clustered at the state-level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.