Immigration, Political Ideologies, and the Polarization of American Politics*

Axel Dreher† Sarah Langlotz‡ Johannes Matzat§ Christopher Parsons¶

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Abstract

We provide causal evidence showing that migration increased the polarization of politicians campaigning for the House of Representatives between 1992 and 2016. Our polarization measures derive from ideology data based on 3 million campaign contributions. Our shift-share estimates hold over the medium-run, although they wane over time. These effects are strengthened should counties host similarly educated or more culturally distant migrants. Contributors' race, employment status and occupations play important roles. Our results hold when focusing specifically upon refugees, where we exploit the spatial and temporal variation stemming from the opening of refugee resettlement centers for the sake of causal identification.

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

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

‡Georg-August University Goettingen: *sarah.langlotz@uni-goettingen.de*.

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

¶University of Western Australia: *christopher.parsons@uwa.edu.au*.

1 Introduction

Traditionally, polarization refers to the ideological distance among the parties along the political spectrum on specific issues (Sani and Sartori 1983). In a two-party electoral system, such as the United States, such polarization is "bedevilling…from institutional gridlock…the degradation of checks and balances…the loss of public faith in election administration, political parties and the political establishment more generally" (Carothers and O'Donohue 2019, p. 66). Ideological polarization increased markedly since the 1970s and accelerated in the 1990s according to a raft of polarization measures.[1] US politics is more polarized today than at any time since the Civil War (Hare and Poole 2014). A 2018 poll of 588 foreign policy opinion leaders identified political polarization as the greatest single threat facing the United States (Busby 2020).

In the largest study of its kind, the PEW Research Centre (PEW 2014) discerned the key compositional shifts in U.S. political ideologies over time, by constructing consistent measures between 1994 and 2014. These include growing minorities holding consistently ideological views, Republicans (Democrats) shifting ideologically to the right (left), raised mutual animosity and the rise of ideological silos, wherein individuals surround themselves with like-minded others. Subsequently, 20% (76%) of conservatives (liberals) desired to live in racially and ethnically diverse communities, whereas 57% (17%) of conservatives (liberals) express preferences for residing where most have shared religious faith.

Historically, votes from both sides of the aisle resulted in significant immigration reform in the U.S.[2] The last time this occurred was in support for the 1990 Immigration Act that was signed into law by (Republican) President Bush. Since then, Democrats and Republicans have diverged significantly on issues of migration, culture and race.[3] Asked whether "immigrants strengthen the country because of their hard work and talents" for example, the difference in responses between Democrats and Republicans increased by an *additional* forty percentage points between 1994 and 2017 (PEW 2017). *A priori*, one might fairly assume therefore that conservatives are on average less amenable to migrants and refugees during our sample period as when compared to liberals—a conjecture supported by recent empirical evidence (Facchini and Steinhardt 2011, Conconi et al.

[1]These include vote shares (Bond and Fleisher 2000, Stonecash et al. 2018); measures of party unity voting (Bond and Fleisher 2000, Stonecash et al. 2018); the voting records of specific interest groups (Stonecash et al. 2018); NOMINATE (D-NOMINATE/DW-NOMINATE) scores based on non-unanimous roll-call votes (Bond and Fleisher 2000, Fleisher and Bond 2004, Poole and Rosenthal 2000, 2001, 2017); campaign contributions (Bonica 2014) and speech patterns (Gentzkow et al. 2019).

[2]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 that led to the passing of the Emergency Quota Act (1921), the Johnson-Reed Act (1924) and the Hart-Cellar Act (1965) that abolished national quotas (Tichenor 2009).

[3]Pat Buchanan's speech on the existence of a culture war for the soul of America is often cited as a relevant turning point in this regard (Fiorina and Abrams 2008).

2020, Mayda et al. 2022).

Polarization broadly pertains to elites or members of the public. Our focus is on the former, which refers to "high levels of ideological distance between parties and high levels of homogeneity within parties" (Druckman et al. 2013). The relationships between elite and mass polarization remain contentious however. This paper accords with Abramowitz's (2010, 2012) perspective, who highlights the pivotal role played by those members of the public most engaged in politics, since these are recognized as the most highly polarized. Carothers and O'Donohue (2019) argue that it is these individuals that transformed American politics from the bottom up. The available evidence suggests it is these groups of 'most consistent' liberals and conservatives that vote more often (especially in primaries), experienced the greatest increases in polarization between 1994 and 2014, are most likely to contact elected officials, attend campaign events and work for a candidate or volunteer for a political campaign. These so-called 'ideologues' also contribute most frequently to political campaigns (PEW 2014).

We explore the causal role of migration in fostering the political ideologies of candidates running for the House of Representatives between 1992 and 2016. Our focus is the United States, which hosts the largest number of migrants globally (Özden et al. 2011), in tandem with suffering some of the highest levels of political polarization (Dimock and Wike 2020). Using data derived from 3 million campaign contributions, we capture the ideology of campaign donors and their political recipients, in turn calculating a raft of polarization measures. We also provide a complementary analysis for the sake of external validity when implementing Twitter data. We subsequently 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 examining the political economy of migrants on aggregate (Mayda 2006, Otto and Steinhardt 2014, Barone et al. 2016, Nikolka and Poutvaara 2016, Halla et al. 2017, Edo et al. 2019, Lonsky 2020, Mayda et al. 2022), and refugees specifically (Campo et al. 2020, Dustmann et al. 2020, Steinmayr 2021) focus on vote shares accruing to (predominantly) far-right parties. As such, they are unable to capture ideological shifts within political parties. Ideologies however significantly change over time, both within and between between political parties (Gerring 2001, PEW 2014). 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. This is what we do in this paper.

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 polarization. According to Bonomi et al. (2021), 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. Migration is therefore expected to affect political polarization more than trade, a proposition we examine conditional on local trade exposure from China.

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 holding extreme positions on wedge issues, like immigration, foster both donations and core supporter turnout, ultimately proving politically polarizing. Migration therefore constitutes one candidate to explain the geographical clustering of political contributions (Hopkins 2017), what has otherwise been termed Partisan sorting (Mason 2015). Indeed, a large literature in social psychology examines how contact with out-groups of various characteristics affect in-groups (Pettigrew and Tropp 2006), insights that lend themselves to providing natural heuristics when interpreting the heterogeneity of our results. Finally, we contribute to the literature that examines the determinants of campaign financing (Brown et al. 1980, Mutz 1995, Gimpel et al. 2006), in our case exploring the role of migration.

Ultimately, we study the ideologies of the universe of candidates running for the House of Representatives as opposed to only those elected to office. Capturing shifts in the prevailing zeitgeist, we leverage "Data on Ideology, Money in Politics, and Elections" (DIME) provided by Bonica (2019) for the 1979-2016 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.[4] 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 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

[4]Findings in McCarty and Rothenberg (1996) and Ensley (2009) support this assumption, for example. We exclude arguably more strategic contributors like Political Action Committees (PACs).

extreme candidates win elections. To test the mechanisms at play, we exploit the differences between residents' characteristics and those of incoming migrants, specifically cultural, educational, occupational and racial disparities.

We identify causal effects using a shift-share instrument, guided by recent advances in the accompanying econometrics literature (Christian and Barrett 2017, Adão et al. 2018, Borusyak et al. 2022, Jaeger et al. 2018, Goldsmith-Pinkham et al. 2020, Mayda et al. 2022). We predict the number of immigrants in a county and year with an interacted instrumental variable comprising two parts. One element serves to *shift* the number of immigrants from year to year. This is calculated as the change in the number of aggregate immigrants from a particular origin to the United States over an electoral cycle. The second element constitutes the pre-sample *share* of migrants in local labor markets, calculated as the share of foreign-born adults from each country of origin in that country's adult population living in U.S. counties in 1980.[5] Our shift-share instrument is then the product of the shift- and share-components summed over all countries of origin.

We examine how changes in foreign populations differentially affect counties with varying initial shares of immigrants in 1980. Network-effects ensure counties with larger historical immigrant shares from certain origins are characterized by larger future shares of incoming immigrants from those origins. Counties with higher initial immigration shares are 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 a battery of controls. This assumption is tested in considerable detail.

Migration on aggregate increases polarization within two years of arrival, inducing political shifts to the ideological 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 elections. 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. They become starker as cultural distances between natives and migrants increase or when education levels are similar, one interpretation of which is that natives resent foreigners from different cultural backgrounds and fear competition, while welcoming immigrants with complementary labor market skills. Unpacking our results from the perspective of campaign donors, we demonstrate that our results are driven by the non-working and retirees, those employed in occupations with high proportions, and yet little contact with immigrants, and predominantly whites. These results are robust to an array of alternative econometric specifications and falsification exercises and when we instead

[5] 1980 constitutes our base year, since it is the first period we observe before our sample period begins. Indeed, the Immigration Act passed in 1990 significantly increased the overall numbers of immigrants permitted to enter the U.S., concurrently introducing family-based immigration, distinct employment visas as well as the diversity lottery.

rely on an alternative measure of elite polarization, one based on Twitter accounts.

In our final analysis, we examine the specific role of refugees in catalyzing ideological polarization (as opposed to migrants on aggregate). This distinction is likely important. Although traditionally constituting only around one tenth of total immigration, refugees receive disproportionate (both positive and negative) media attention, since refugees constitute *"the most visible, challenging, and morally significant of newcomers"* (Haines 2012). In part, this is because refugees often represent new populations through the extensive margin along specific migrant corridors (Bahar et al. 2022). Refugees and other migrants represent fundamentally disparate groups, primarily distinguished by their primary motivation for emigrating (forced vs. unforced), their socioeconomic characteristics and their ethnic backgrounds (Chin and Cortes 2015), in concert with the limited agency refugees have with regards their initial resettlements in the United States.

Whereas immigrants more broadly are free to settle where they choose, refugees, as explained by Bruno (2017), are resettled within 50 or 100 miles—and within the same *state*—as their local 'affiliate', the institution responsible for providing local refugee services.[6] These thresholds do not lend themselves naturally to a Regression Discontinuity design given the paucity of observations around the relevant cut-offs. Instead we divide the U.S. into 52,341 0.15°*0.15° grid cells and exploit novel data on the precise location and timings of the opening of 313 refugee centers across the United States. This approach yields two sets of instrumental variables, both of which predict the number of refugees at the grid cell level before aggregating to the county level. The first set predicts the number of refugees located in each grid cell based on their distance to the nearest refugee resettlement center, allowing for different coefficients in each year and controlling for cells' distances to the nearest Amtrak station, airport and city with a population over 100,000 (see Figure A-7). The second set of instruments represents a melding of our two empirical approaches, one in which the predicted numbers of refugees are implemented as our initial 'shares' of the shift-share approach, whilst considering a number of additional aspects of the refugee allocation process, such as accounting for centers specializing in the resettlement of refugees from specific origins and when individual centers began placing them. Exploring the characteristics of campaign contributors, our results focusing on refugees echo our results for immigrants more broadly.

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

[6]This distance depends upon whether refugees have U.S. ties with friends or family, see Mayda et al. (2022).

2 Data

2.1 Immigrants

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).[7] The U.S. census and ACS report data on the total foreign-born population, which refers to anyone born outside of the U.S., including U.S. citizens born abroad, shorter term migrants (including foreign-born students), humanitarian migrants (including refugees) and some fraction of the illegal migrant population not otherwise captured (Hanson 2006). Origin-specific stocks of immigrants in 1980 capture our initial 'shares', while differences in migrant stocks over two-year periods are employed as instrument 'shifters'. Throughout, the term 'migrants' refers to the aggregate foreign-born population. We present results when specifically analyzing the sub-set of 'refugees' in Section 4.5.

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). 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.

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

2.2 Refugees

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 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.

We geo-code the refugee locations using: Open Street Maps API, Google Maps API, the data science toolkit and manual reviews; relying upon data at the city, county and

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

state levels.[8] To ensure a high degree of accuracy we also reverse geo-code locations, to facilitate comparing the resulting names. Additionally, we manually cross-check a small number of locations receiving at least 10 refugees, in cases in which our county information derived from the raw data conflicted with the county of assigned location. Ultimately, we successfully assign 96.50% of refugees to about 15,200 locations (99.89% at the city-level, the remaining at the county level). These locations are then matched to the county-level, 3,141 in total. We provide these data at https://www.refugeeresettlementdata.com.

Relative to immigrants on aggregate, the share of refugees is substantially lower, decreasing from around 0.0012 in 1990 to 0.0006 in 2018. The dilution of these relatively small numbers of refugees across both time and space results in less than ideal identifying variation, in part thereby explaining the conspicuous absence of papers examining a raft of refugee outcomes in the context of the United States. Figure A-3 illustrates the number of refugees arriving in the United States. Figure A-4 plots the same data highlighting refugees' geo-coded locations. The distribution of refugees is comparable to that of migrants more generally since both migrants and refugees are ultimately attracted to larger, multicultural, urban and often coastal locales.

2.3 Refugee Processing Centers

We obtained data detailing the universe of existing refugee processing centres from the Worldwide Refugee Admissions Processing System (WRAPS) website, previously maintained by the PRM,[9] shortly before they were removed from the public domain during the Tillerson administration. The information provides details of the location of 313 individual refugee resettlement centers run by one of several Voluntary Agencies (Volags) across all U.S. states with the exception of Wyoming.[10] Volags have constituted the backbone of refugee resettlement in the United States from at least 1945, when President Truman passed a directive granting 'Welfare Organisations' the power to sponsor refugees.[11]

The information provides details of the name, address, contact details and voluntary agency to which each processing center is affiliated. Under the Trump administration, dramatic changes were made to the levels and composition of funding to the State

[8] http://www.datasciencetoolkit.org.

[9] Last downloaded 06/10/2017 from: http://www.wrapsnet.org/consolidated-placement-plan.

[10] While it has been commonly reported that Wyoming has never *resettled refugees*, indeed Wyoming did resettle some Vietnamese boat people in 1975. Rather Wyomong never adopted a refugee resettlement program as were ushered in to all other states following the passing of the 1980 Refugee Act. Only very recently have local Wyoming churches taken in Afghan refugees following the refusal of the state Governor to act in this regard (see https://www.churchtimes.co.uk/articles/2021/22-october/news/world/wyoming-churches-take-in-afghan-refugees-after-state-governor-refuses).

[11] This preceded the signing of the Displaced Persons Act of 1948, which acknowledged refugees as a special class of migrant for the first time, together with its extension in 1950, which paved the way for hundreds of thousands of displaced Europeans to subsequently enter the United States.

Department. In turn, the refugee admission ceiling was reduced from 110,000 in the last year of the Obama administration to 45,000 and ultimately slashing that number to 15,000. As such, significant resources had to be dedicated to confirm the continued existence of each affiliate and if not in the affirmative when they closed, if they changed address and/or if any specific center changed their affiliation; as well as to confirm when each center first opened. Once these details were confirmed, each center was assigned a precise geo-location, as shown in Figure A-4 and as explained above.

2.4 Political Ideology and Polarization

We construct several measures capturing political ideologies and polarization from Bonica's (2019) Database on "Ideology, Money in Politics, and Elections" (DIME).[12] These data predominantly leverage campaign contributions registered with the Federal Election Commission (FEC) and state reporting agencies. The data comprise contributors' detailed location, and, for sub-sets of the data, their employment status together with their names and occupations, from which we can subsequently infer their likely origin and degree of contact with immigrants within their workplace. 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 contributors' and candidates' ideologies based on whom they contribute to and from whom they receive contributions, respectively, accounting for factors affecting all contributions across the board, like charisma. The pivotal assumption undergirding these data, and subsequently our analysis therefore, is that contributors donate larger amounts to those candidates they are more ideologically aligned with.[13] Compared to other available data detailing the ideological positions of politicians, those based on roll call votes for example,[14] this approach rather analyzes the entire universe of candidates, including those that failed to win at the ballot. We therefore analyze any and all polarization arising between candidates from the same party, as well as between winning candidates and runners-up from opposing parties. Adopting this methodological approach allows us to capture significant ideological movements *within* parties, even should they fail to win an election. Conversely, omitting losing candidates' ideologies would be akin to treating the 2020 election with Democratic Presidential candidate, Joe Biden—when running against President Trump—as identical to self-styled socialist Bernie Sanders, who would have otherwise run against Trump in Biden's absence.

[12]A number of recent papers implement these data (e.g., Bonica 2013, Thomsen 2014, 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).

[13]A number of articles validate this assumption (e.g., Ensley 2009, Barber et al. 2017).

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

Bonica (2016) calculates a Campaign Finance (CF) score to measure political ideology, based on campaign contributions.[15] He assumes contributors donate based according to their ideal points, 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 calculates ideal points along a single dimension, a typical left-to-right political scale.

This ideological scale is anchored to federal elections. State-level ideological scores are subsequently linked using data on campaign contributors that donate to both federal and state elections. On average between 70 and 90 percent of contributors in any given state contribute to both federal and state election campaigns (Bonica 2014). These observations therefore serve to 'bridge' and in turn harmonize ideological scores across institutions and political hierarchies.[16] What results is a consistent ideological scale across contributors and candidates, institutions and time periods.

The *dynamic* DIME scores that we rely upon in this paper are calculated for each time period separately. This allows for idiosyncratic changes in specific candidate ideology over time. We observe few stark movements in CFscores however. Legislator ideal points—as captured by roll call votes, e.g., DW-NOMINATE—are similarly stable over time (Bonica 2016). Both measures are highly correlated, lending additional plausibility that the CF scores can be interpreted along a liberal-conservative ideological scale. Ideal points, calculated for candidates *prior* to entering office, are typically highly correlated with both candidates' future CFscores as incumbents, as well as their subsequent voting behavior. Bonica (2018) demonstrates DIME scores to accurately predict policy preferences, based on 30 policy items included in the 2012 Cooperative Congressional Election Study (CCES). Candidates' ideal points are also highly correlated with the ideal points of 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 employs biannual changes in migrant stocks. Our focus on the House of Representatives (as opposed to Presidential or Senate elections), is a choice governed by the salience of the topic since for example *"political polarization ... seems to jeopardize Congress's constitutional responsibility for regulatory oversight"* (Farina 2015),

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

[16]As Bonica (2014) explains, he first applies correspondence analysis to federal election data. He then scales the resulting data according to the federal-level ideal points that emerge for each individual state. This exercise is based on data of contributions from donors to both state and federal campaigns. This facilitates anchoring state-level scales, such that the resulting state-level CFscores are all based on the same ideological scale as the federal CFscores. Technically, the correspondence analysis applied by the CFscore method 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.

in addition to the resulting identifying variation, which underpins our empirical analysis. During our sample period, our data comprise ideology estimates for 1,089 candidates and 3,7 million contributions, deriving from 186,209 contributors (173,746 individuals, as opposed to corporate donors).

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 ideological 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 contributions in 1990.[17] We subsequently rank candidates according to their ideology on a left-right scale, binning candidates into terciles. Contributions in the right tail of the scale are termed 'conservative'. In analogy, we define 'liberal' contributions as those located in the left tail. Those remaining in the centermost tercile are deemed 'moderates'. Contributions to moderate candidates, according to this nomenclature, substantially declined over time, at the expense of liberal and in particular conservative candidates (please see Figure 2).[18]

Our *Extreme vs. moderate* measure of polarization is calculated as the difference in contributions donated to the sum of liberal and conservative (*extreme*) candidates relative to those given to moderate candidates. *Winner* focuses on the ideologies of general election winners. Candidates' ideology scores are assigned 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 conditional on them being Republicans (*Winner if Rep.*) or Democrats (*Winner if Dem.*), which facilitates testing for shifts in ideology within parties. *Winner vs. loser* is calculated as the absolute

[17] In essence following Autor et al. (2020).

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

distance between winning candidates and the runners-up. Once again we calculate these at the county-district cell level and aggregated them up to 2010 county boundaries. Digging deeper, we separately analyze 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 compared to the party median in 1990; with the remainder constituting conservative and liberal politicians.

Figure 1 shows that ideological polarization increased over the years of our sample. While the ideology of winners (left axis) exhibits no clear trend, the absolute difference between winners and runners-up increases over time (right axis). Republican winners move to the right, while Democrat winners move to the left (depicted on the left scale).[19] 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.

We draw on individual Twitter accounts in a supplementary analysis. Updated raw data were obtained from Barberá (2015), in which ideological scores for more than 300,000 users are calculated using a Bayesian Spatial Following model. Barberá (2015) assumes that Twitter users are more likely to follow politicians with shared ideologies. The predefined accounts include 318 political accounts of politicians, journalists and political parties, from which 33 million followers are subsequently identified.[20] Ideology scores are subsequently derived from individuals' follower patterns, assuming the existence of a single latent dimension of ideology. The resulting measure is highly correlated with other more established measures (see Barberá 2015). To ensure sufficient numbers of observations per location, we focus on the year 2016. We assign users to counties, based upon the "location" field in their profile, resulting in some 3 million users.[21] We again divide ideological scores into terciles, which we refer to as left, right and moderate users. Our dependent variables detailed at the county level are the shares of extreme users (left or right), left users, right users and moderate users in all Twitter users. Figure A-5 presents these data.[22]

[19]We normalize ideology scores of winning Democrats and Republicans to zero in 1992.

[20]Our sample of Twitter users are clearly unrepresentative of the American population as a whole. They have above average education and take greater interests in politics. Whereas the results from this exercise may be deemed to better accord with a definition of mass polarization, the selected characteristics of the resulting sample are argued to be an additional informative source of elite ideology (Barberá 2015).

[21]Location data are missing or too imprecise for approximately 60 percent of the users in the sample we could retrieve. Figure A-6 shows that the ideology of users with such information has similar distribution in the tails than those without, albeit with lower densities than moderate users.

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

3 Methods

3.1 Migrant Analysis

The endogenous location decision of migrants likely results in them 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 (those that do not). Simply comparing outcomes of locations without recognizing these threats to identification could therefore yield biased estimates.

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. Note that the fixed effects-specification implies that we expect polarization to react to changes in inflows rather than changes in stocks of migrants. This is because we expect populations to become used to levels of migrant inflows, even if these inflows are high, but to react strongest to changes in the flow. In other words, we expect ideology to change temporarily rather than permanently as a consequence of migrant inflows.[23]

In keeping with Mayda et al. (2022), 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).[24] We include a Bartik share control that captures sector-specific local labor market shocks (calculated by Mayda et al. (2022, 365) 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.

We employ the familiar shift-share instrument to address the endogeneity of immigrant

[23]When we control for (predicted) stocks of migrants, our results are unchanged. Results for stocks are qualitatively similar, but statistically weaker).

[24]Our source for these data is Mayda et al. (2022), who take them from the U.S. census and the ACS.

shares in a county's population. In doing so, we closely follow recent work of Mayda et al. (2022).[25] We employ an interacted instrumental variable to predict the 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 $sh_{US,c,80} = \frac{N_{c,80}}{\sum_c N_{c,80}}$.[26] Analogously, 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, $\Delta\widehat{M}_{ce}/(\widehat{M}_{ce} + \widehat{N}_{ce})$.

Our empirical set-up therefore examines 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 any 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. 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. We further examine other potential threats to identification as discussed recently by Christian and Barrett (2017), Adão et al. (2018), Borusyak et al. (2022), Jaeger et al. (2018) and Goldsmith-Pinkham et al. (2020). To this end, we conduct Monte Carlo randomization to test for spurious long-run trends, while accounting for potential adjustment dynamics occurring in those years following earlier migrant inflows.

[25] See Adão et al. (2018), Borusyak et al. (2022), Jaeger 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 this point below.

[26] This is in line with Mayda et al. (2022). We define adults as people over the age of 17.

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).

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).

Motivated by these long-standing hypotheses, we first exploit the richness of our DIME donations data, specifically in terms of splitting our sample along a number of dimensions: donor's names (from which we can infer origins), occupations (from which we can proxy the degree of contact with immigrants), and donors' employment statuses. Employment statuses are categorized as working, non-working, non-working (student) and non-working (retired). For those in employment, we first harmonized the donor occupations to the Standardized Occupation Codes (SOC), through the application of a number of matching tools (e.g., SOCcer) in addition to significant manual matching over an extended period. Once standardized to the SOC, we further disaggregated these occupations according to the skill components of those jobs, using O*NET[27] so as to identify 'high migrant contact' occupations. In turn, we deemed 'high migrant contact' occupations to lie above the top 70th percentile of a 'contact-score' that we calculated based on three constituent factors from O*NET.[28] We define 'high' immigrant share occupations as being equal to or above the 90th percentile in the 1990 U.S. census. Donors' origins were inferred through an examination of donors' surnames in combination with the relevant census information pertaining to the shares of those of differing ethnic backgrounds and their share of surnames in the U.S. census.[29] This information is available for all surnames appearing at least 100 times in the census.

Finally, we examine the potential roles of cultural and educational distances in

[27]O*NET is the Occupational Information Network, see https://www.onetonline.org/.

[28]These are: 1) Work Activity: Developing and Building Teams—Encouraging and building mutual trust, respect, and cooperation among team members, 2) Work Values: Relationships—Occupations that satisfy this work value allow employees to provide service to others and work with co-workers in a friendly non-competitive environment. Corresponding needs are Co-workers, Moral Values and Social Service and 3) Work Context: Interpersonal Relationships: Work With Work Group or Team—How important is it to work with others in a group or team in this job?

[29]Examples include: Anderson= 75% White, Jackson = 53% Black, Garcia = 92% Hispanic, Nguyen = 97% Asian.

mediating the effect of immigration on ideology and polarization with the following regression:

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

where $DIST_{ce}$ is either cultural or educational distance. Cultural distances are based on distinguishing immigrant shares aggregated over individual origins, namely: Western, Latin American, African and Asian countries, all of which are available at the commuting zone level. 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 similarities in geographic origins correlate with these distances. 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.[30]

3.2 Refugee Analysis

The placement of refugees into one of 313 refugee centers lends itself to an alternative identification strategy. First we divide the U.S. into 52,341 equally sized grid cells of $0.15°*0.15°$, which at the equator corresponds to approximately 16.7 km^2. Next we predict the number of refugees located within each grid cell based on their distance to the nearest refugee resettlement center, allowing for annual variations in coefficients (see Figure A-7 for a graphical depiction of refugees by grid cell level, together with the locations of the relevant refugee resettlement centers). Aggregating the predicted number of refugees to the county level, we employ the predicted number of (new) refugees in each year as an instrumental variable. Given that refugees are more likely to settle nearer refugee centers than further away, we expect the instrument to have power. To the extent that the location of refugee centers reflect distances to other locations that might be correlated with polarization through channels other than refugee inflows, this instrument would likely violate the exclusion restriction however. To militate against this possibility, we control for a cell's distance to the nearest Amtrak station, the nearest airport, and the

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

nearest city with a population over 100,000. The zero-stage regression is the following:

$$\mathrm{R}_{gt} = \beta_1 dist_{gt} + \beta_2(dist_{gt} * \lambda_t) + \beta_3 distAmtrak_g + \beta_4 distAirport_g + \beta_5 distCity_g + \mu_c + \lambda_t + \epsilon_{gt}, \quad (4)$$

where R_{gt} is the number of new refugees at the grid-level, $dist_{gt}$ is the distance to the nearest refugee center (in meters), which we include in levels and as interaction with each year λ_t, thereby allowing the effect of distance to vary over time. μ_c are fixed effects for counties. We obtain yearly totals for each county by aggregating the predicted values for incoming refugees based on Equation (4). We then use the predicted county-level refugee inflows over two years as instrument in our first-stage equation (2).[31]

Despite our regressions controlling for other potentially important distances, a skeptical reader might remain unconvinced that distances to the nearest refugee resettlement centers satisfy the exclusion restriction. In response, we estimate several variants of Equation (4), in which we predict the number of incoming refugees at the grid cell level, based on the interaction of distances to a refugee center and the total number of incoming refugees (as variously measured). This approach constitutes a melding of our two empirical approaches, one in which the predicted numbers of refugees are implemented as our initial 'shares'. Additionally, we consider an important aspect of the specific refugee allocation process by taking into account the fact that centers typically specialize in the resettlement of refugees from specific origins.[32]

We estimate three variants of our zero-stage regression, in all cases including grid cell (as opposed to county) fixed effects.[33] Our first variant predicts the number of refugees at the grid-cell level based on a cell's distance to the nearest refugee resettlement center and the *total* number of incoming refugees in a year at the *state-level*. Our second approach considers that some refugee resettlement centers specialize in resettling refugees from specific origins. For each country of origin, we code a binary indicator identifying grid cells that are located within 100 kilometers of a refugee resettlement center that received at least one refugee from that origin in the first year refugees from the country were registered in a state. We then interact this indicator with the number of incoming refugees from that country over the previous election cycle. Aggregating the number of predicted refugees in the same county over all countries of origin yields the total number of predicted

[31] We exclude Alaska since it represents an outlier in terms of the relevant distances given the overall size of the state and the fact that Alaska hosts only one refugee processing center in Anchorage. We also exclude Wyoming from this exercise since the state has never been a part of the U.S. refugee resettlement program.

[32] Of the nine voluntary agencies that currently work to resettle refugees across the U.S. all but one—the International Rescue Committee—are affiliated to a specific religious or alternatively faith-based organization, which in turn has naturally resulted in various voluntary agencies developing expertise for clientele from specific origins (Christensen and Ebrahim 2006). For example, in 1975, the overwhelming majority of Indochinese refugees were resettled by the Catholic Conference (Parsons and Vézina 2018).

[33] Note that these fixed effects capture all relevant time-invariant distances.

refugees at the county level, which we again employ as our instrument. Our third and most conservative approach replaces state-level inflows with (country-of-origin-specific) refugee inflows to the United States at large. The remaining county-level variation is therefore driven exclusively by year-on-year differences in incoming refugees from specific origins to the U.S. and their subsequent allocation across space based on the relative distances to grid cells within 100 kilometers of resettlement centers that had themselves resettled refugees from specific origins in the preceding years. The exclusion restriction is particularly unlikely to be violated in this instance.[34]

4 Results

4.1 Baseline Results

Table 1 reports our baseline results, while omitting coefficient estimates for the control variables for the sake of brevity.[35] Column 1 (Extreme vs. Moderate) adopts the perspective of campaign donors and presents the polarization in donations as the difference in contributions of extreme relative to moderate candidates. Column 2 (Winner) 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 (Winner if Rep/Dem) 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 (Winner vs. Loser). 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 those counties in tandem with larger vote shares for the Republican party. Winning candidates experienced a rightward shift in their ideology. Polarization therefore increased as measured by the ideological distance between the winner relative to the loser. The probability of conservative Republicans winning increased significantly, while

[34]When we construct our instrument in analogy to the analyses of all immigration flows above, results are similar. These results are available on request.

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

conversely, moderate Democrats were less likely to be victorious. There is no significant correlation between immigration and the probability of moderate Republicans or left leaning Democrats being elected. The same holds true for the ideology of Republican winners, while Democratic winners shifted 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 increased polarization.[36] Evaluated at the sample mean, increasing the share of new immigrants in a county by 1 percent raises the difference between extreme and moderate campaign contributions (in dollars) by 0.89 percent. This 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.

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 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

[36]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.

is comparable with Mayda et al. (2022), who focus on immigrant stocks as opposed to shares.[37]

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. 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 of the ideology of Republican winners (which is 0.83 at the 25th and 1.15 at the 75th percentile). 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.[38]

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 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.[39] As expected, we observe

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

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

[39]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 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

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 Alternative Measures

We proceed by testing alternative immigration measures. 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. The figure presents our estimated marginal effects in tandem with the associated 90-percent confidence intervals. The corresponding full regression results are provided in Table A-6 in the Appendix.[40]

Our results for 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 might be suggestive of some underlying process of acceptance.

We further examine our core hypothesis, i.e., whether or not migrants on aggregate affect political polarization using an alternative data set, namely *individual* data deriving from a 2016 cross-section of Twitter accounts. While we would like to apply the same method as before when testing the effects of immigration on polarization, we are restricted by the availability of data. Given the low uptake of Twitter in earlier years we restrict our analysis to a cross-section for the year 2016. We make use of a first stage analogous to those in column 1 of Table 1 (using the full sample) and estimate second-stage regressions with the same set of control variables included.[41]

Table 1 presents the results. Immigration shifts the ideology of Twitter users to the right, concurrently increasing the share of extreme users (and therefore by definition reducing the share of moderate users). In quantitative terms, a typical increase in immigration from the 25th to the 75th percentile increases the share of right Twitter users by 48.6 percentage points resulting in an increase of 28.1 percentage points of extreme Twitter users. These results corroborate those obtained with our campaign donation-based measures of polarization above.[42]

confidence interval.

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

[41]When we estimate the first stage for 2016 alone, the power of our instrument is low given the comparably low number of observations per county. For the same reason the second stage includes fixed effects for states as opposed to counties.

[42]Similarly, analyzing GALLUP data (“How would you describe your political views?—very conservative, conservative, moderate, liberal, very liberal”) provides additional external validity to our baseline results. In particular, the share of very conservative voters increases as a consequence of immigration. These results are available on request.

4.3 Robustness

4.3.1 Shift-share design

We test the plausibility of our exclusion restriction along a number of dimensions, guided by recent advances in the related literature. Figure A-8 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-8 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 (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-8 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.[43] 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 the potential importance of pre-trends, following Mayda et al. (2022) and Goldsmith-Pinkham et al. (2020). First, we provide visual evidence in Figure A-9 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.[44]

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

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

[44] 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 Mayda et al. (2022) 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.

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-7, 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.

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 next is 0.1 (see also Panel A of Figure A-8). 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.[45]

4.3.2 Falsification Exercises

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-10 (based on the specification of column 1 in Table 1) in the Appendix, shows the point estimate 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).

[45] 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.

4.4 Heterogeneous Effects

Our analysis captures the *local* effects of immigration, since any country-wide effects are absorbed into our year fixed effects. Our results can therefore be perceived from the perspective of contact theory (Allport 1954) and group threat theory (Sherif et al. 1961, Campbell 1965), which both provide natural heuristics as a means to further interpret our results. The economics literature in this sphere suggests 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 2020).[46] 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.

To tease out some of the intricacies at play, we continue by splitting our sample along a number of dimensions of campaign contribution donor characteristics, as detailed in Section 3.1. Specifically we exploit donors' employment status, their origins as inferred from their surnames and the degree to which donors likely come into direct contact at work with immigrants as captured by the *nature* of donor's employment in addition to what proportions of immigrants are typically employed in those specific occupations.

These results are presented in Figures 6 to 8. Figure 6 provides some evidence in favor of our *extreme-moderate* measure of political polarization being driven by those not employed and those in retirement. Unpacking our imprecisely estimated occupation estimate from Figure 6, Figure 7 digs a little deeper by examining donations to the political left and right, according to the degree to which donors' employment brings them into direct contact with others in addition to the proportion of immigrants typically employed in those occupations. This analysis reveals that right-wing donations are increasingly driven by donors working in occupations with high proportions of immigrants, and in cases in which such donors have little contact in their daily work-lives with immigrants. Greater interactions with immigrants attenuate this result. Finally, Figure 8 leverages donors' ethnic background, which provides some evidence that our *extreme-moderate* measure of polarization is driven by whites as opposed to other ethnic groups, especially Asians, who rather exert a strong and opposing influence. This result could be explained by Asians having far more familiarity and contact with specific immigrant groups, not least since four Asian countries (Philippines, India, China, and Vietnam) represent four of the top five migrant groups in the United States (with the

[46] Please also refer to Gehring (2022).

other being Mexico).

We continue by testing whether cultural and educational distances between incumbents and immigrants mediate or exacerbate our previous estimates.[47] 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 approach (CFA), the first-stage regressions (and F-statistics) are fundamentally comparable with those reported in Table 1.[48]

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.[49] 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 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

[47]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.

[48]The CFA controls for the first-stage regression residual in the second stages. Alternatives to this approach are 2SLS employing the interaction of our instrument with the distance indicators as additional instruments. This would treat the interactions as separate endogenous variables, which "can be quite inefficient relative to the more parsimonious CF approach" (Wooldridge 2015, p. 429). The resulting increase in efficiency comes at the cost of an additional assumption; that is, we need to assume that the bias does not depend on distance. 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).

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

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).[50] 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 our results are in line with 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 different education reduce the observed shifts to the political right.

4.5 Refugee Results

Panel A of Table 3 reports results for our simple distance-IV. Panels B–D rather report results from our interacted instruments, with grid-cell fixed effects included in the zero-stage regression in Equation (4), and county fixed effects in the first- and second-stage regressions. These regressions employ the absolute numbers of refugees as opposed to population shares. Given that we include fixed effects for counties, population hardly changes from year to year. When we estimate these regressions as population shares, first-stage F-statistics are however weak, so we do not report these results. They are available on request. Though specific levels of significance vary across specifications, we find that refugee inflows increase extreme vs. moderate donations (the exception being the negative coefficient of Panel A), shift the ideology of the winner rightwards and increases the vote share of the Republican party. Republican winners shift to the right, Democratic winners to the left. Winners shift to the right relative to the runner up. Finally, the entire political spectrum moves to the right.

We replicate our donor heterogeneity analysis, assessing which factors play a role in the polarizing response to refugee inflows. This exercise is based on our preferred specification in Panel D. Figures 9 and 10 explore the potential role of contact by exploiting the occupational characteristics of donors. Once again we find that polarization is driven by those retired and unemployed, as we did for immigrants. In contrast however, the average effect on those employed is also significantly positive. Unpacking compositional changes among donations to the ideological right, we find that donors employed in occupations with high proportions of immigrants and infrequent contact with refugees drive our observed effect, although this effect vanishes in cases in which donors are employed

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

in occupations that involve significant refugee contact. Figure 8 reports our results leveraging the ethnic background of donors. These results echo our previous findings for immigrants, highlighting that whites as opposed to other ethnic groups drive the overall polarizing effect in response to refugee inflows. This result is not mechanically determined by whites representing the largest group in our sample.

5 Conclusion

The United States is a nation of immigrants, one profoundly shaped by subsequent arrivals to her shores. Recent decades have ushered in continued high volumes of migrants including refugees, in tandem with significantly diverging, protracted and acute levels of political polarization; so much so, that some argue such polarization represents the single greatest threat to the future of the country. 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.

Implementing various measures of political polarization, we provide causal evidence that political polarization significantly increases in counties that experienced 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 somewhat attenuated over time. We provide some empirical support for the conjecture that polarizing political campaign donations are driven by whites, the unemployed and those in retirement, with right-wing donations in particular driven by those working in occupations with high proportions of immigrants, especially in which donors have little contact with immigrants in their daily lives. Greater interactions with immigrants attenuate these effects. Our baseline findings are starker the greater the cultural distances between incoming migrants and incumbent natives and the more similar the education levels of the two groups.

Though refugees differ from other migrants along a number of dimensions, we uncover similar results for refugees and migrants on aggregate, despite adopting an alternative identification strategy; one that leverages the timing and location of refugee processing centers, in tandem with the fact that specific centers specialize in processing refugees from specific origins.

Portes (2011, 424) 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 some empirical support for the conjecture that this process of acceptance operates more swiftly, but that the local contexts facing immigrants and resettled refugees, including the composition of natives, likely proves pivotal in determining, at least in part, the acute levels of political polarization being witnessed across the United States today.

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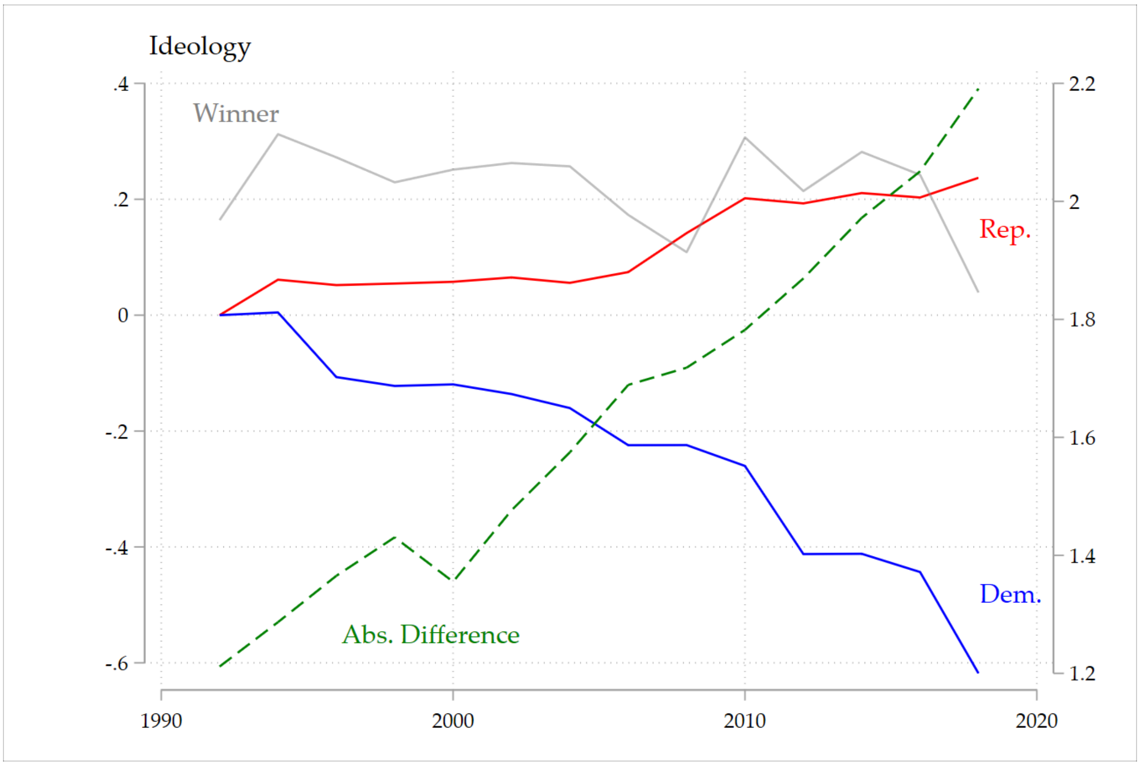
Figures and Tables

Figure 1 – Ideology and Polarization

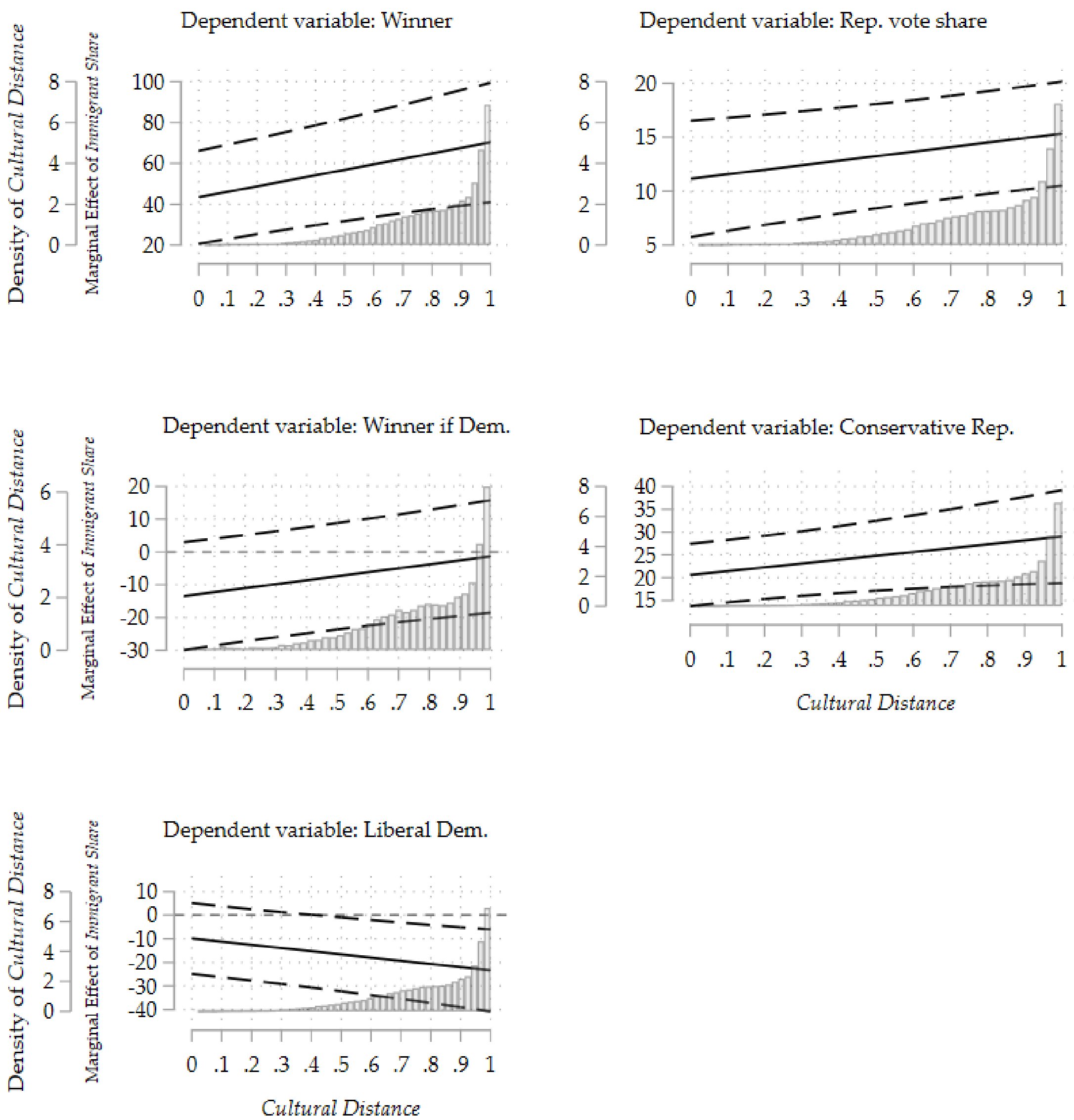


Notes: We depict the ideology of the winners on average (gray line) and by party (red and blue line). Note that we subtract the 1992 party mean of the ideology of the winners by party. The green line depicts the absolute distance between the winner and the runner up. Solid lines refer to the left axis,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

Figure 2 – Share of Contributions to the House of Representatives

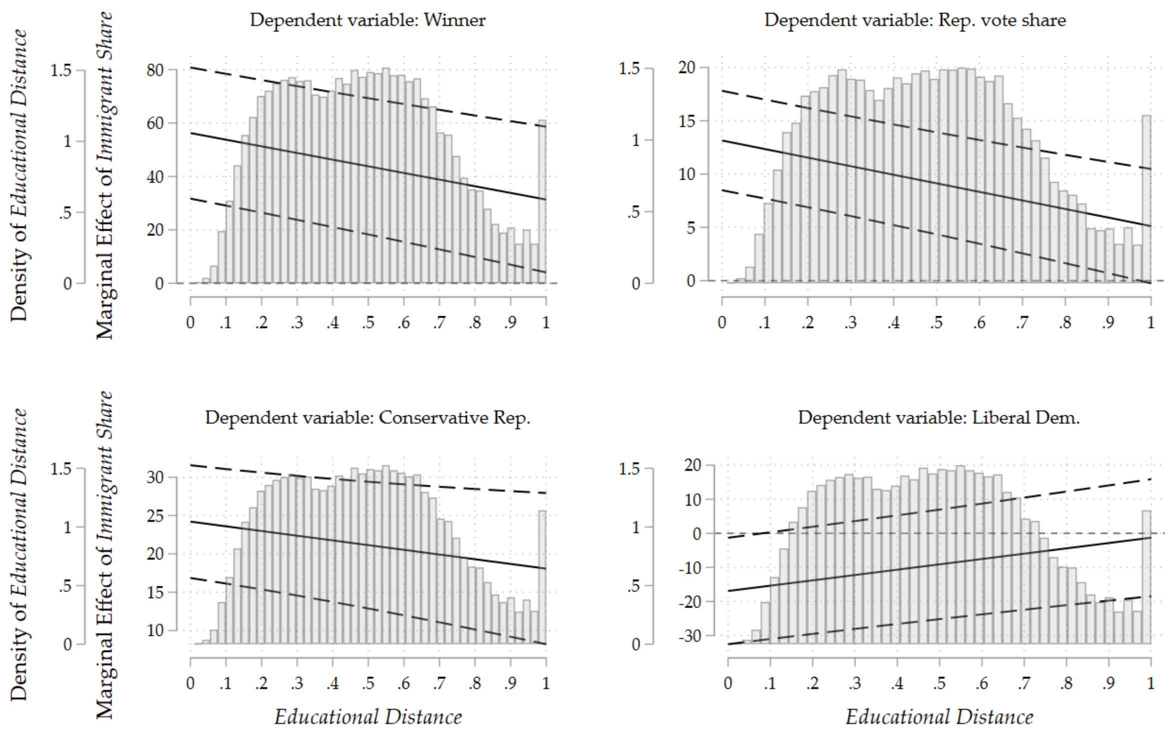
Notes: We rank candidates according to their ideology on the left-right scale and divide the amounts of contributions these candidates received in terciles. For the year 1990, we define the third of the contributions most to the right end of the scale as "conservative" contributions. In analogy, we define "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



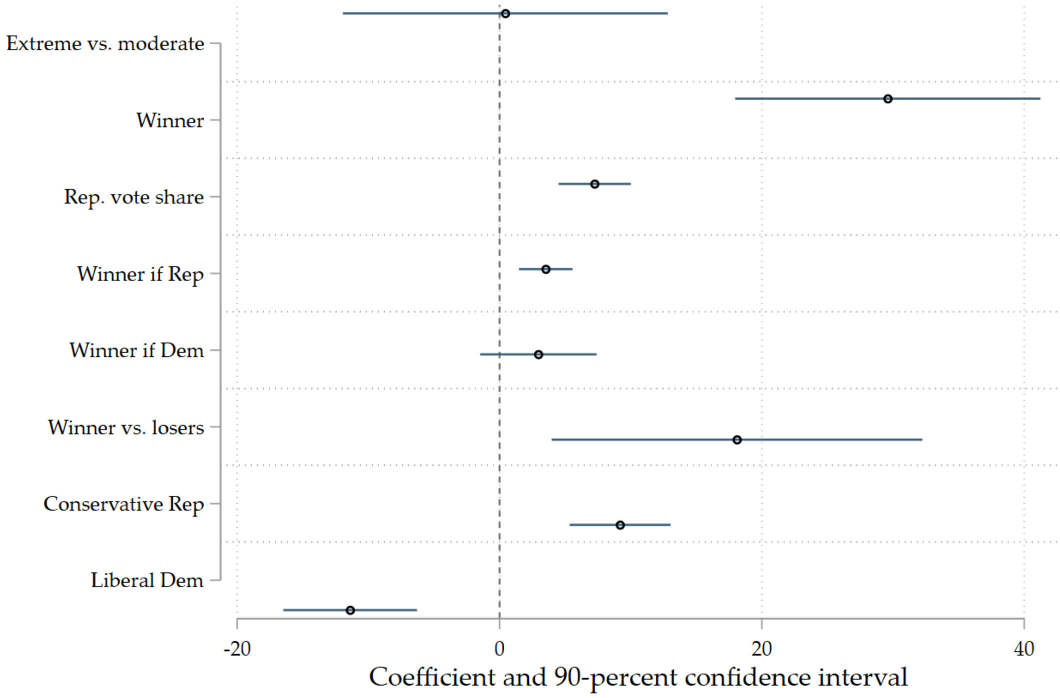
Notes: The figure shows partial leverage plots for the regressions reported in columns 2, 3, 5, 7, and 8 of Table A-4. The dashed lines indicate 90-percent confidence intervals.

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



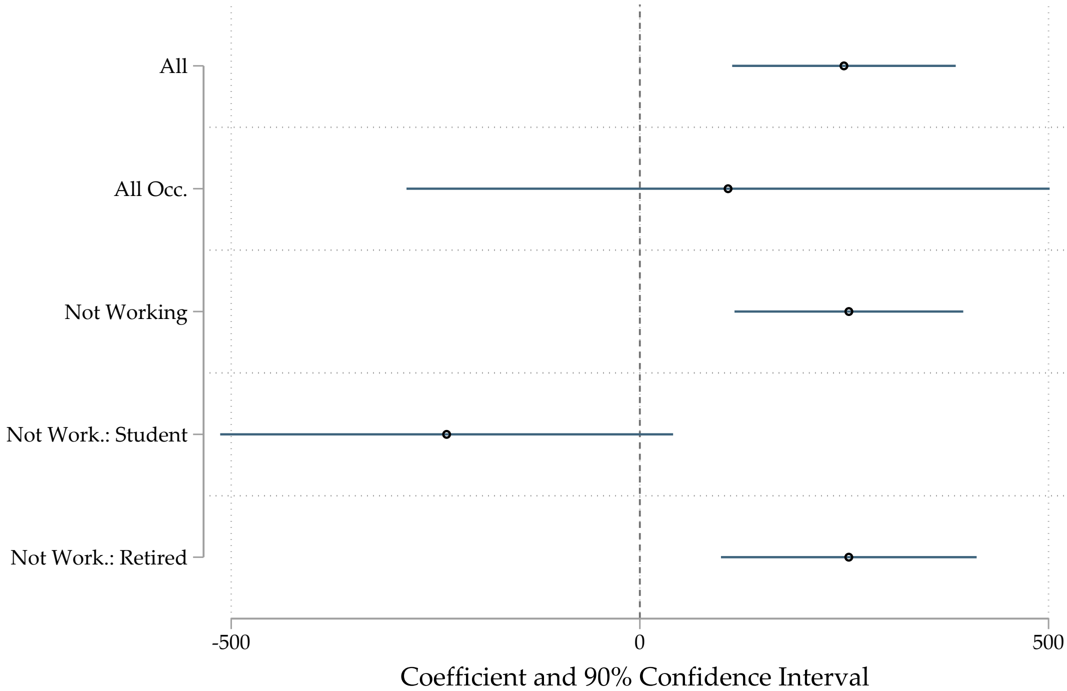
Notes: The figure shows partial leverage plots for the regressions reported in columns 2, 3, 7, and 8 of Table A-5. The dashed lines indicate 90-percent confidence intervals.

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



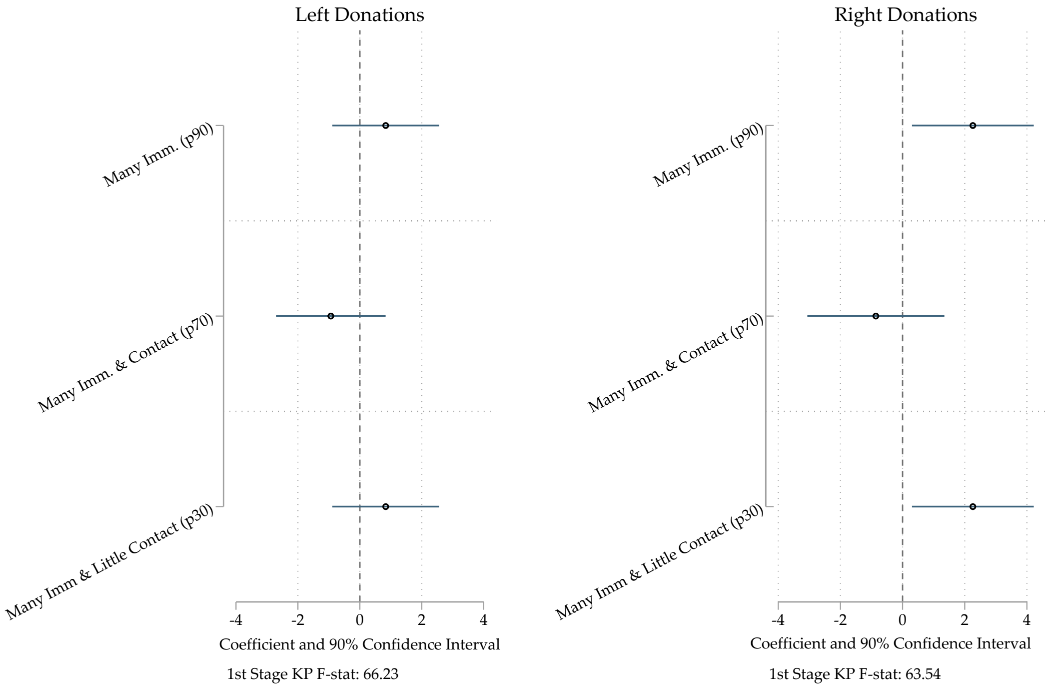
Notes: The figure reports the coefficients of net adult immigration over eight years, in tandem with 90-percent confidence intervals. The coefficient of extreme vs. moderate is multiplied with 0.1. See Table A-6 for details.

Figure 6 – Immigration and Ideology, 1992-2016, Employment Status of Donors



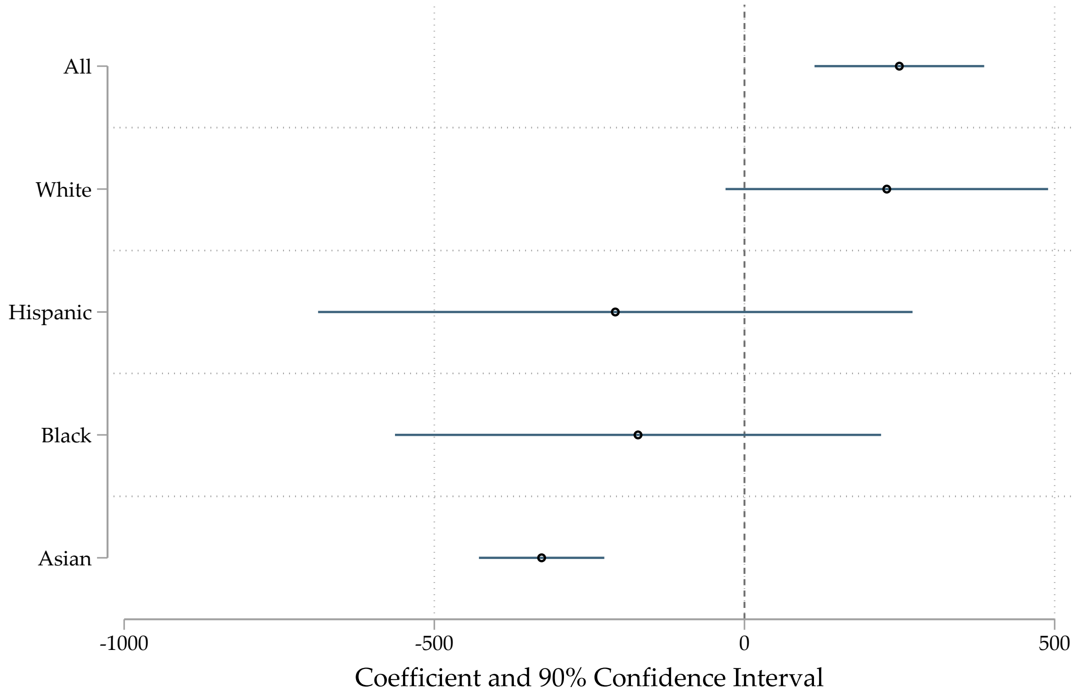
Notes: The figure reports the coefficients of net immigration over two years, in tandem with 90-percent confidence intervals. The outcomes are defined as the inverse hyperbolic sine of the difference of extreme vs. moderate contributions from all, all working, all not working, students and retired contributors respectively. The first stage corresponds to Table 1, column 1.

Figure 7 – Immigration and Ideology, 1992-2016, Likely Contact with Donors



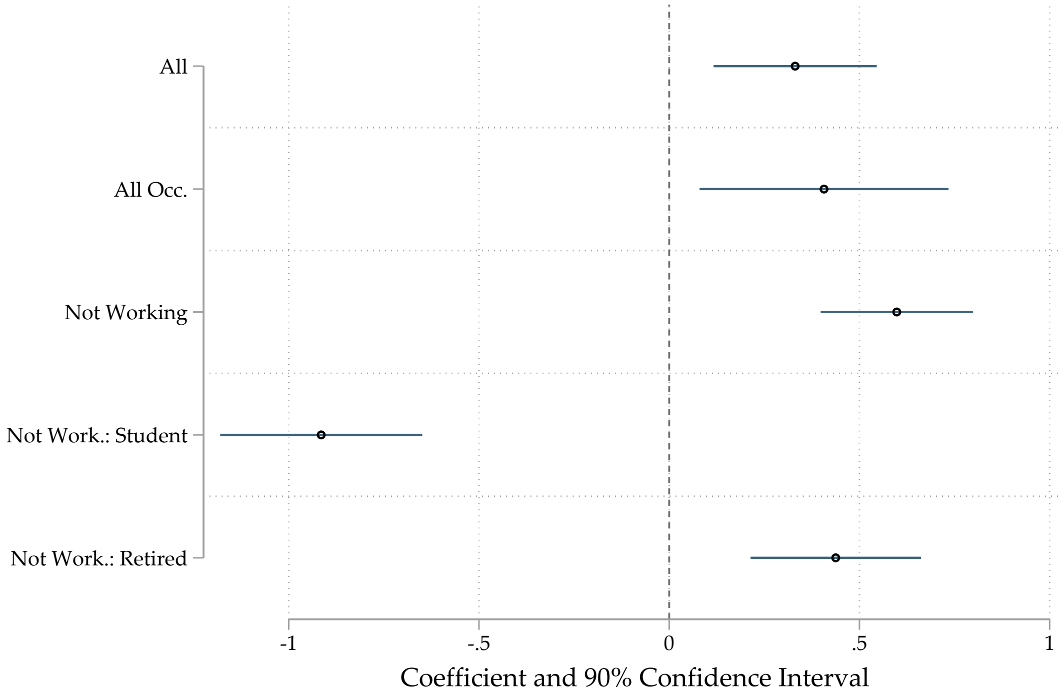
Notes: The figure reports the coefficients of net immigration over two years, in tandem with 90-percent confidence intervals. The outcomes in the left graph are defined as the share of donations among left contributions from donors working in occupations with i) many immigrants (90-percentile), ii) many immigrants and much contact (70-percentile), and iii) many immigrants and little contact (30-percentile) respectively. The Kleibergen-Paap F-statistic for the first stage is 66.23. The right graph repeats the exercise for right donations. The Kleibergen-Paap F-statistic for the first stage is 63.54.

Figure 8 – Immigration and Ideology, 1992-2016, Race of Donors



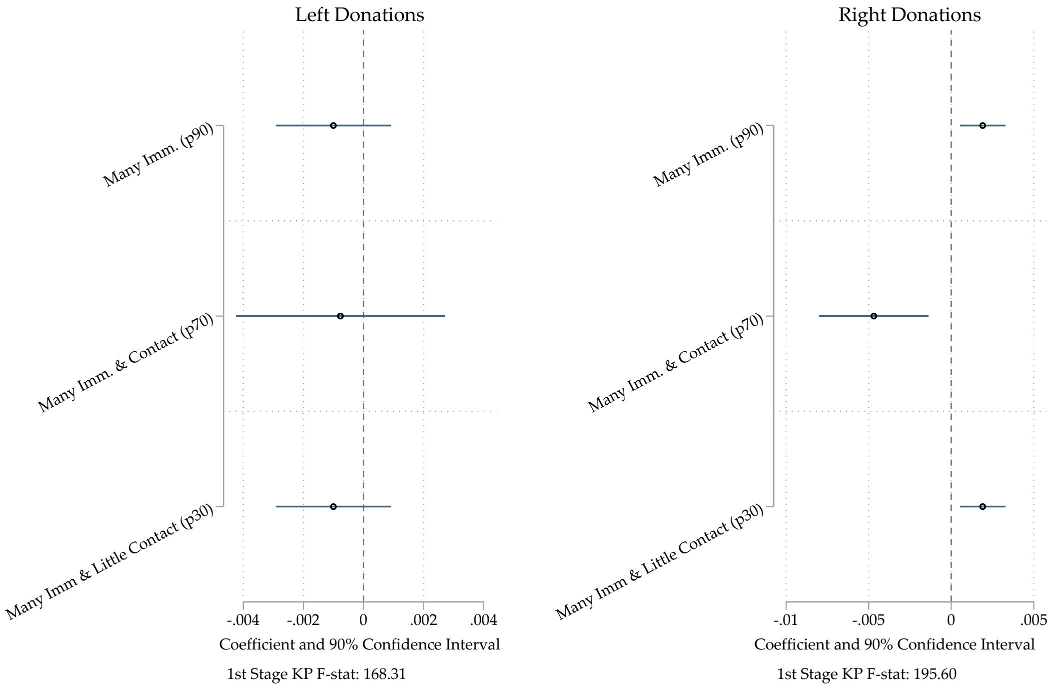
Notes: The figure reports the coefficients of net immigration over two years, in tandem with 90-percent confidence intervals. The outcomes are defined as the inverse hyperbolic sine of the difference of extreme vs. moderate contributions from all, White, Hispanic, Black and Asian contributors respectively. The first stage corresponds to Table 1, column 1.

Figure 9 – Refugees and Ideology, 1992-2016, Employment Status of Donors



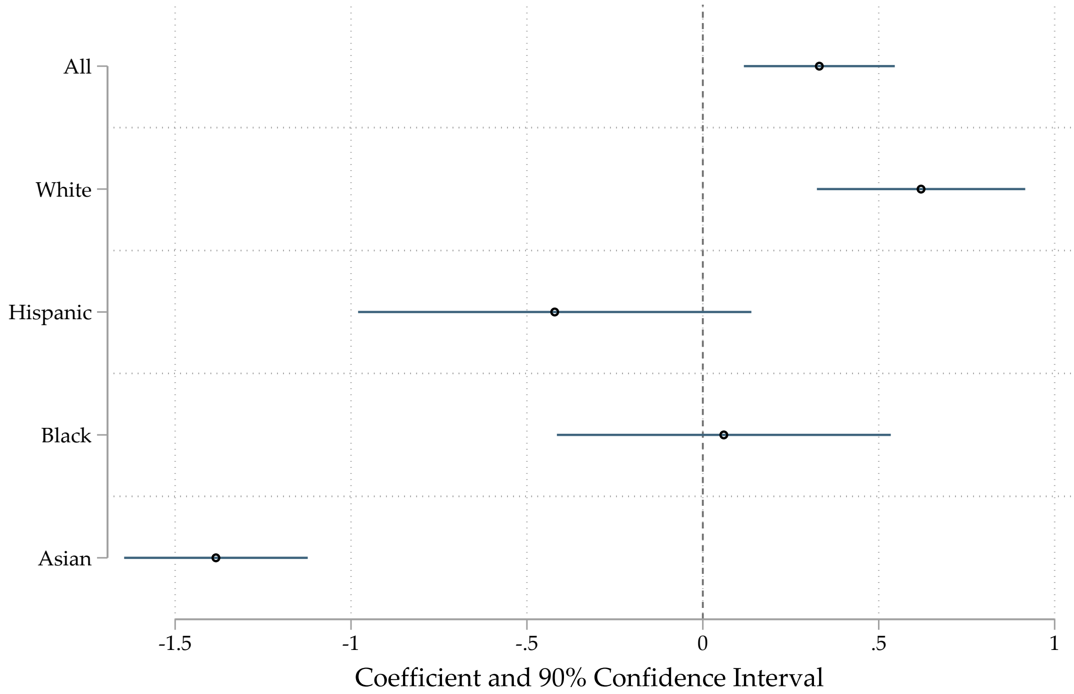
Notes: The figure reports the coefficients of the number of refugees in thousands over two years, in tandem with 90-percent confidence intervals. The outcomes are the inverse hyperbolic sine of the difference of extreme vs. moderate contributions from all, all working, all not working, students and retired contributors respectively. The first stage corresponds to Table 3, Panel D, column 1.

Figure 10 – Refugees and Ideology, 1992-2016, Likely Contact with Donors



Notes: The figure reports the coefficients of the number of refugees in thousands over two years, in tandem with 90-percent confidence intervals. The outcomes in the left graph are defined as the share of donations among left contributions from donors working in occupations with i) many immigrants (90-percentile), ii) many immigrants and much contact (70-percentile), and iii) many immigrants and little contact (30-percentile) respectively. The Kleibergen-Paap F-statistic for the first stage is 168.31. The right graph repeats the exercise for right donations. The Kleibergen-Paap F-statistic for the first stage is 195.60.

Figure 11 – Refugees and Ideology, 1992-2016, Race of Donors



Notes: The figure reports the coefficients of the number of refugees in thousands over two years, in tandem with 90-percent confidence intervals. The outcomes are defined as the inverse hyperbolic sine of the difference of extreme vs. moderate contributions from all, White, Hispanic, Black and Asian contributors respectively. The first stage corresponds to Table 3, Panel D, column 1.

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 – Immigration and Ideology based on Individual 2016 Twitter Accounts

	(1) extreme	(2) right	(3) left	(4) moderate
ΔImmigrant share	66.367***	114.652***	-48.285***	-66.367***
	(11.330)	(21.998)	(11.855)	(11.330)
Constant	0.386***	-0.084	0.470***	0.614***
	(0.093)	(0.150)	(0.071)	(0.093)
Observations	2,529	2,529	2,529	2,529
Kleibergen-Paap F-stat	78.23	78.23	78.23	78.23

Notes: Extreme indicates the share of left and right users in all users in a county. Right/left/moderate are the respective shares in all county Twitter users. The first stage is estimated over the full sample of Table 1, column 1, including control variables, as well as fixed effects for years and counties. The second stage is a cross-section for the year 2016 and includes fixed effects for years and states. We have bootstrapped standard errors and clustered them at the state-level. All regressions include the full set of control variables, population weights and fixed effects for counties and years.

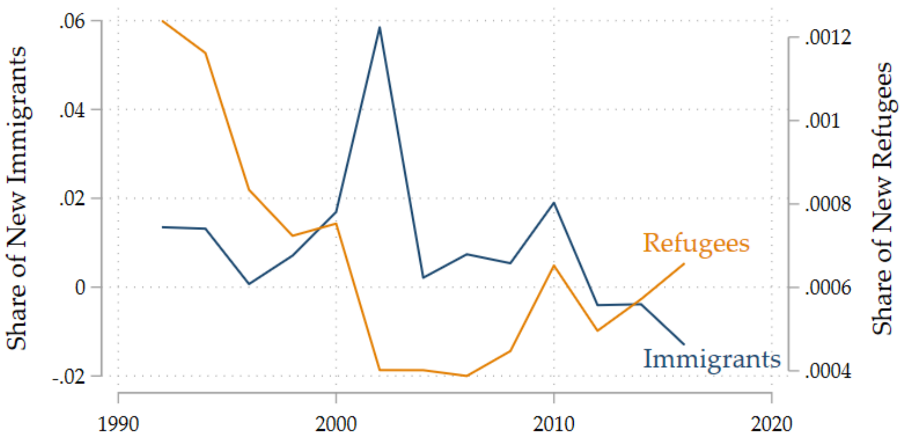
Table 3 – Refugees and Ideology, 1992-2016, Two-year Gross Inflows

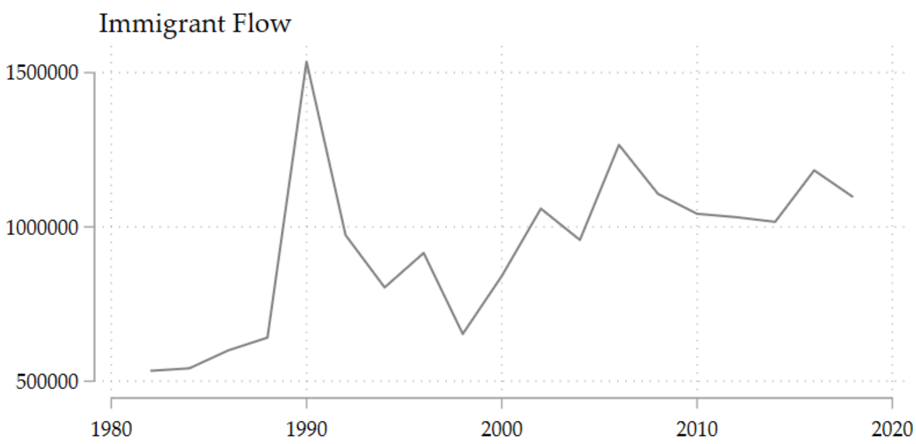
	(1) Extreme vs. moderate	(2) Winner	(3) Rep. vote share	(4) Winner if Rep.	(5) Winner if Dem.	(6) Winner vs. loser	(7) Right Rep.	(8) Mod. Rep.	(9) Mod. Dem.	(10) Left Dem.
Panel A: Distance IV, refugees/population share										
ΔRefugee share	-1190.805	247.595***	112.877***	35.255	-40.472	131.324**	144.622**	15.231	-52.636	-107.160**
	(823.130)	(74.019)	(37.858)	(45.598)	(43.597)	(49.496)	(57.177)	(61.468)	(44.405)	(48.769)
K-P F-stat.	7.07	7.07	7.07	7.62	7.36	6.95	7.09	7.09	7.09	7.09
Panel B: Interacted IV, state totals										
ΔRefugees	0.27590	0.06236***	0.01372***	0.01382***	-0.02220***	0.04378***	0.03846***	0.01427	-0.03449***	-0.01822
	(0.25281)	(0.01724)	(0.00339)	(0.00426)	(0.00574)	(0.01081)	(0.00803)	(0.01112)	(0.00755)	(0.01166)
K-P F-stat.	70.05	68.67	70.05	104.55	35.54	58.91	68.70	68.70	68.70	68.70
Panel C: Interacted IV (origin-specific), state totals										
ΔRefugees	0.62091***	0.11303***	0.02014***	0.01965***	-0.02140***	0.08723***	0.05809***	0.02409**	-0.05847***	-0.02368
	(0.18542)	(0.02844)	(0.00552)	(0.00723)	(0.00736)	(0.01740)	(0.01308)	(0.01189)	(0.01119)	(0.01679)
K-P F-stat.	41.64	40.63	41.64	53.90	21.05	33.22	40.74	40.74	40.74	40.74
Panel D: Interacted IV (origin-specific), U.S. totals										
ΔRefugees	0.32966**	0.09592***	0.02807***	0.00672	-0.02116**	0.06838***	0.02411**	0.03155*	-0.01026	-0.04544***
	(0.12904)	(0.01577)	(0.00602)	(0.00798)	(0.00900)	(0.02288)	(0.00945)	(0.01805)	(0.00789)	(0.01360)
K-P F-stat.	314.95	311.79	314.95	150.90	153.81	260.39	304.41	304.41	304.41	304.41
Observations	39,474	38,966	39,470	26,876	14,466	31,162	39,075	39,075	39,075	39,075

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). ΔRefugees are gross inflows of refugees over the previous two years. ΔRefugee share are refugee inflows as a share of adult population. All regressions include the full set of control variables, population weights and fixed effects for counties and years. In Panel A, the instrumental variable is the predicted number of refugees relative to county population; Panels B–D use the number of predicted refugees as IV. Fixed effects at the zero stage: county level (Panel A), grid cell level (Panels B–D). In Panels B–D, coefficients and standard errors are multiplied with 1,000. Bootstrapped standard errors (with 500 replications) in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Online Appendix

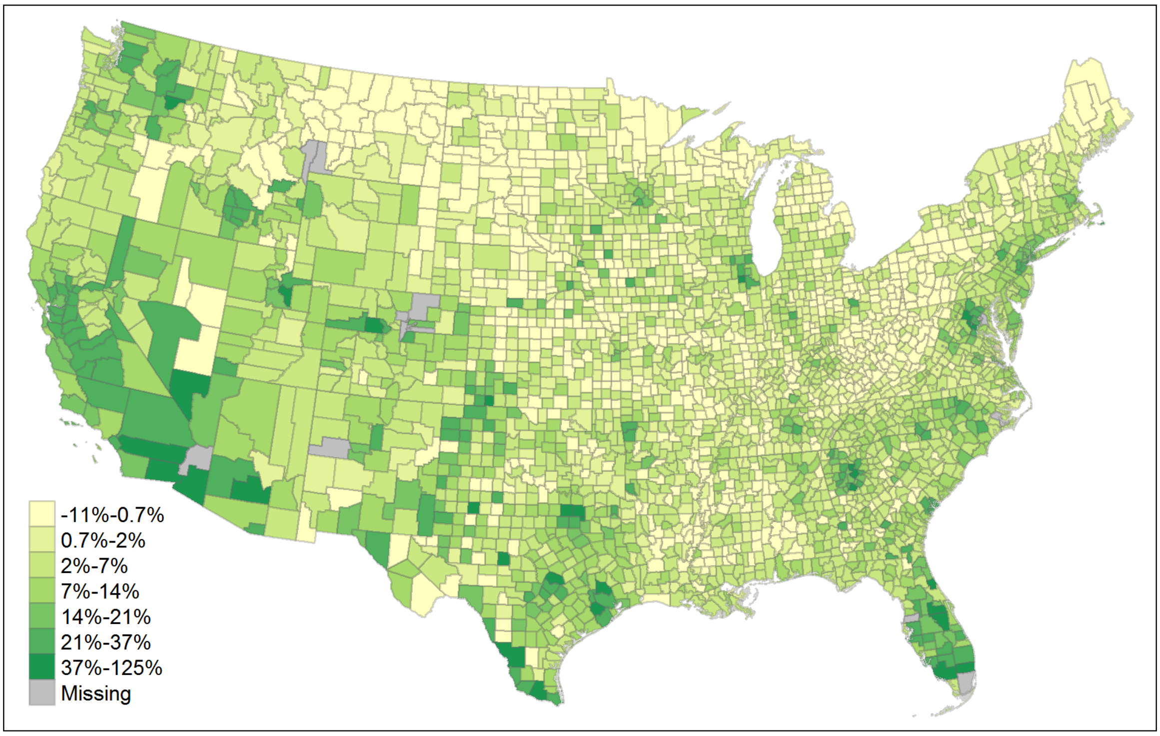
Figure A-1 – Immigrants and Refugees in the United States, 1982-2018, Inflows





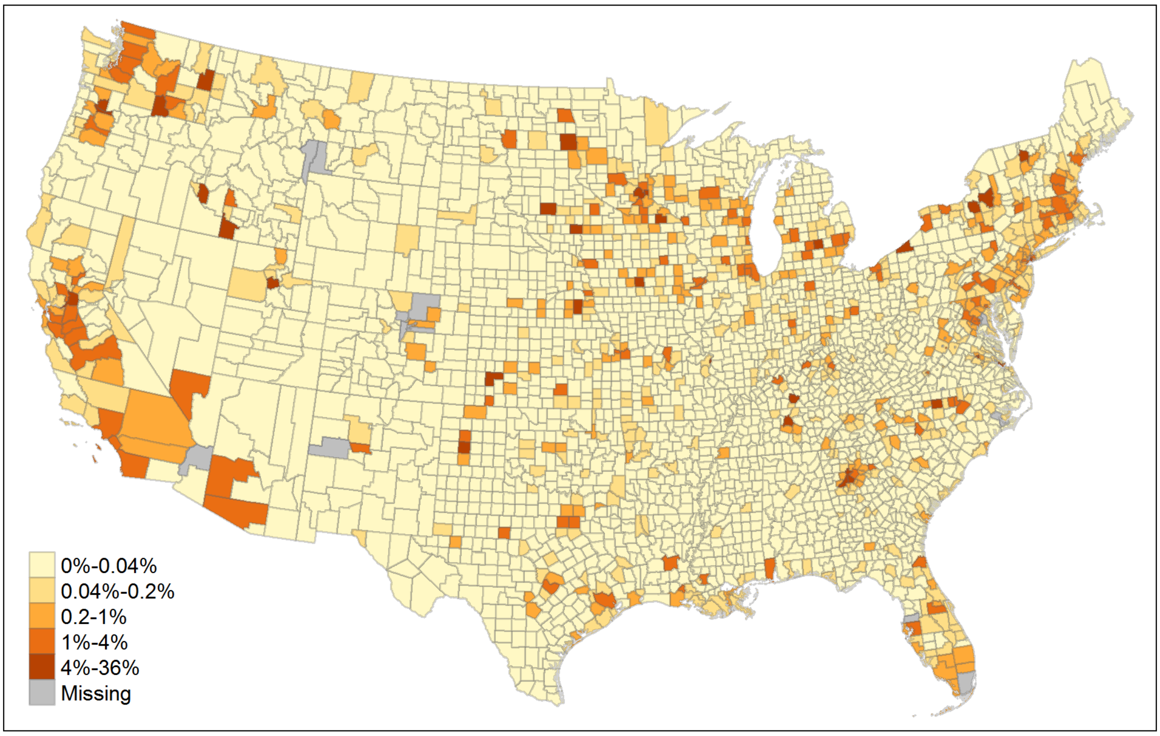
Notes: The upper figure shows net (gross) inflows of adult immigrants (refugees) as a share of the adult population. The lower figure shows the number of foreign nationals that were granted lawful permanent residence.

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



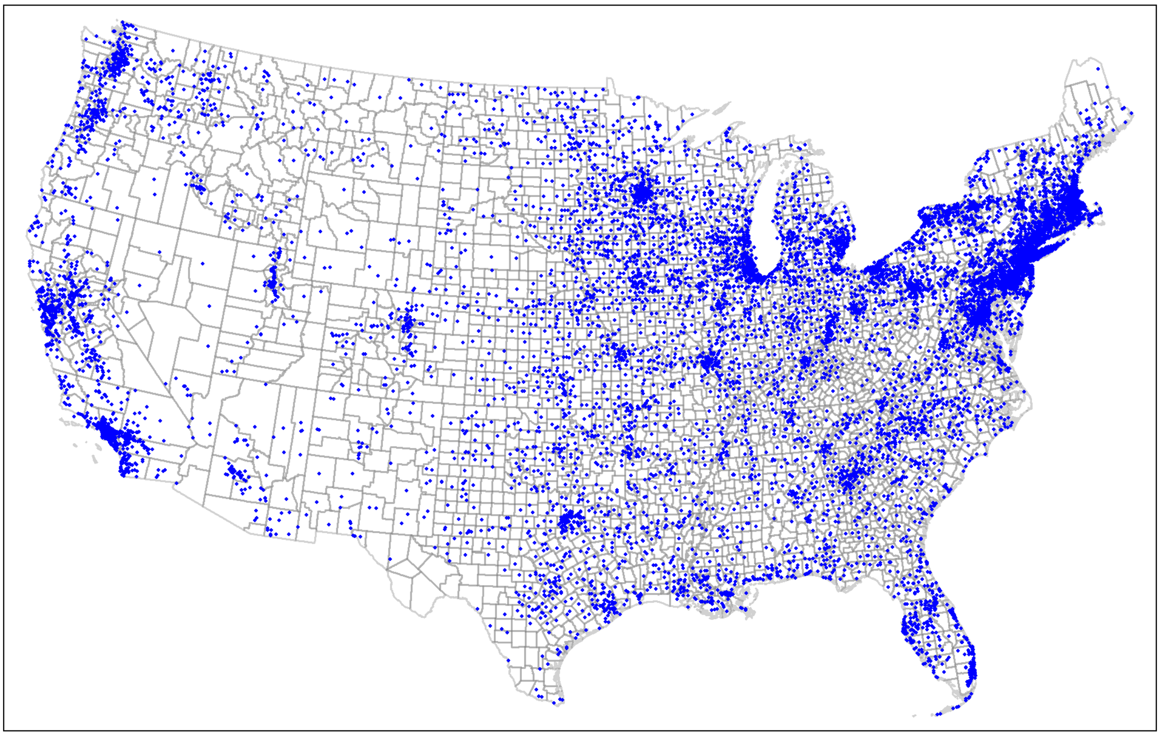
Notes: The map shows the net inflow of adult immigrants over the 1992-2016 period divided by the 1992 adult population. We split groups at the 25th, 50th, 75th, 90th, 95th and 99th percentiles.

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



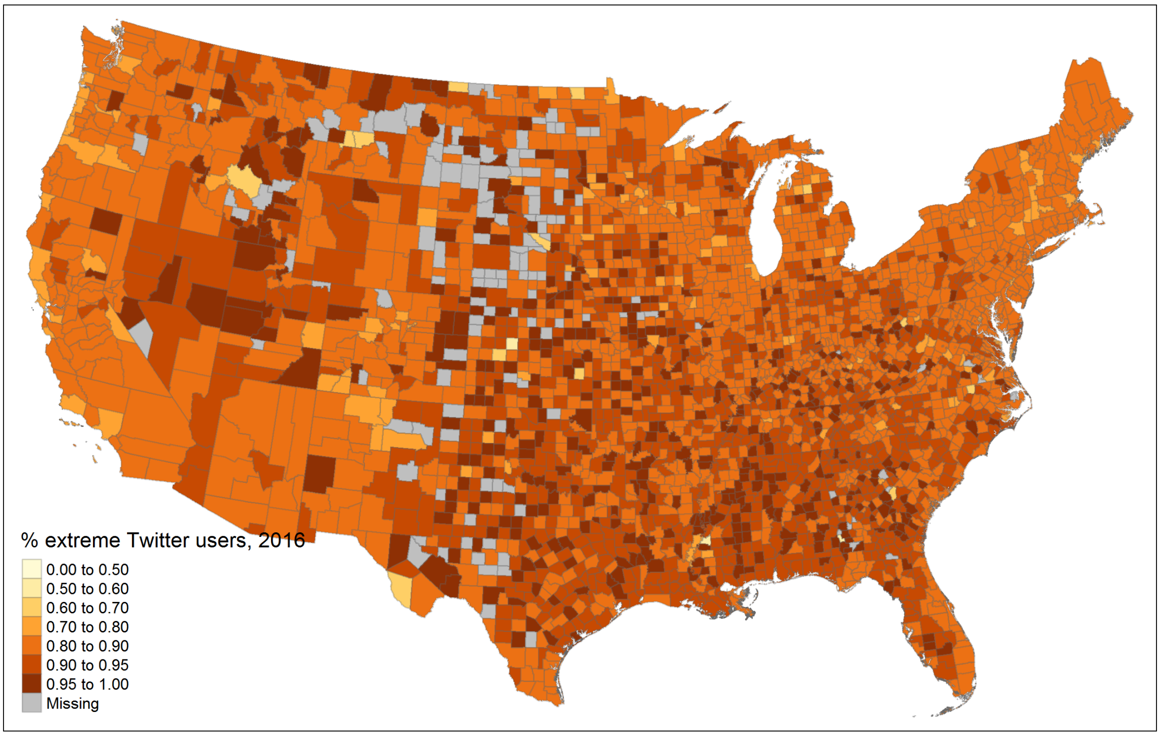
Notes: The map shows the gross inflow of refugees over the 1992-2016 period divided by the 1992 adult population. We split groups at the 75th, 90th, 95th and 99th percentiles.

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



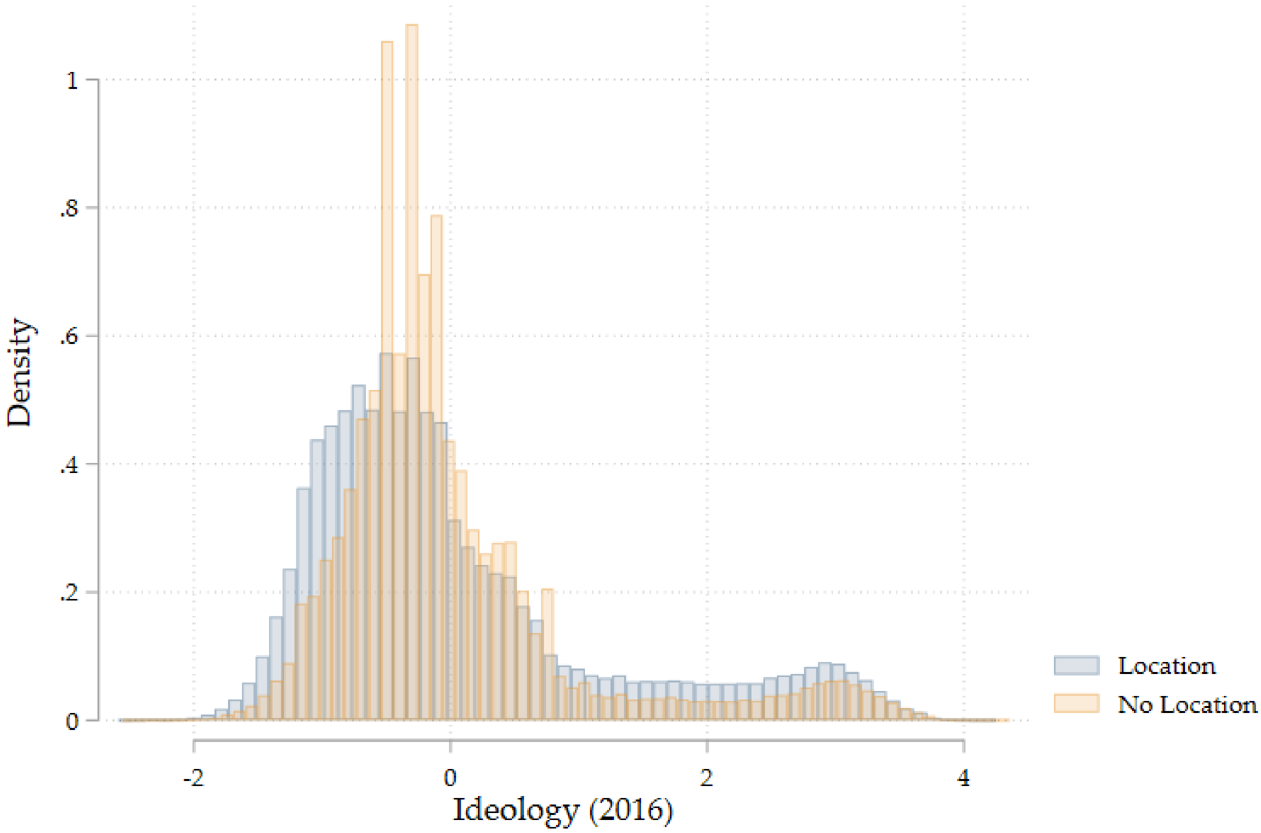
Notes: The map shows the location of first residence of refugees over the 1975-2008 period. We geocoded locations so that they depict a town, city or neighborhood (in large cities). One dot represents one location but can represent several refugees.

Figure A-5 – Twitter polarization 2016



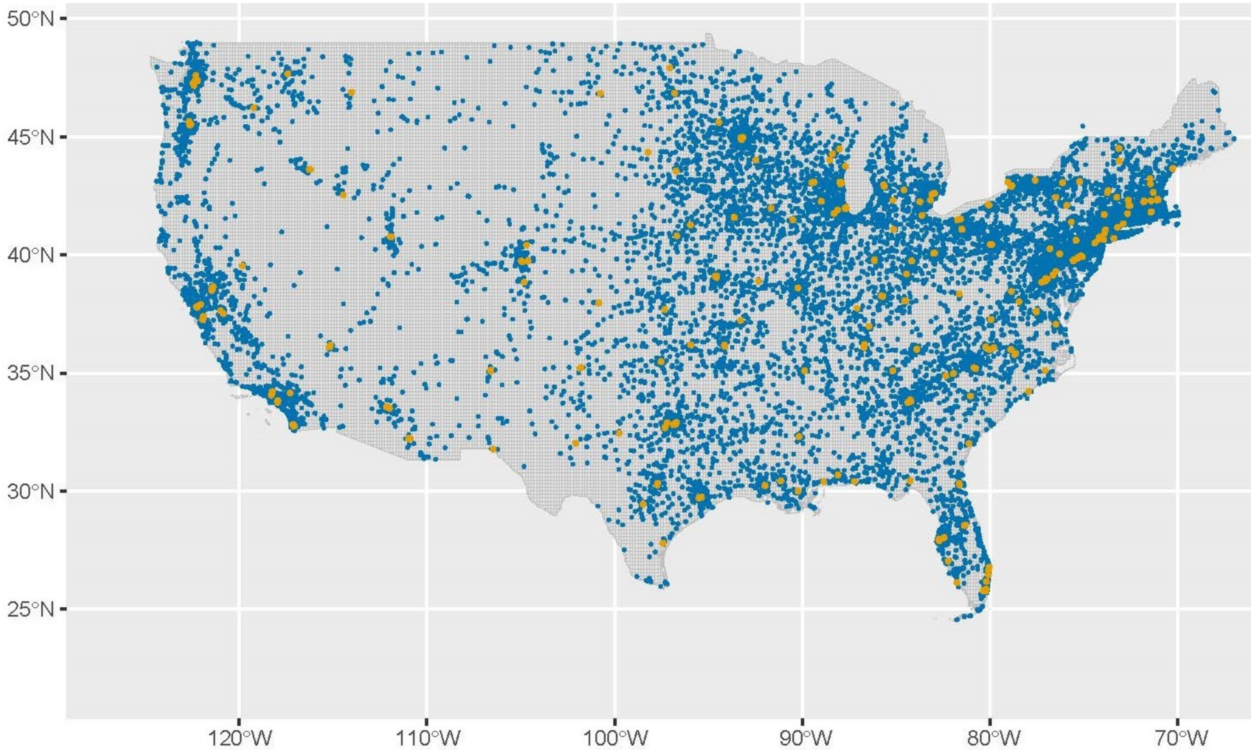
Notes: The map shows extreme Twitter users as a share of all Twitter users at the county level for the year 2016. We get ideology scores of Twitter users from Barberá (2015). We obtain left, right and moderate users by splitting the ideology score into terciles. The map is based on about 3 million Twitter users that provide their location.

Figure A-6 – Distribution of Twitter Accounts with Locational Information



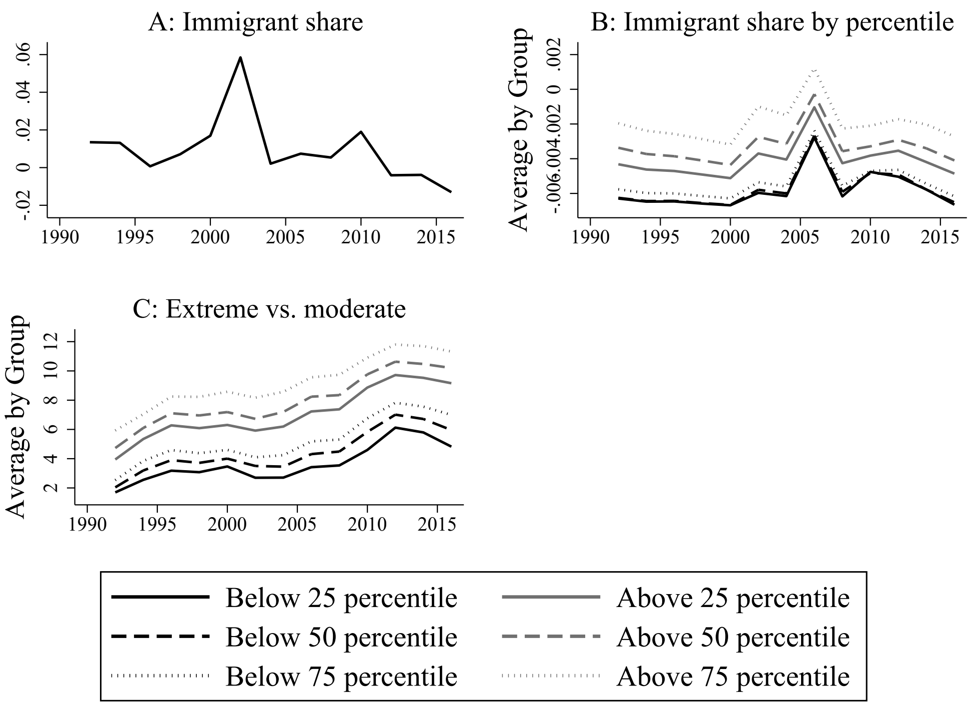
Notes: The graph compares the distribution of ideology scores of Twitter user accounts with county information and accounts with no county information. The graph is based on the full sample of Twitter accounts and their ideology score from the year 2016 that we obtain from Barberá (2015).

Figure A-7 – Refugees and Refugee Resettlement Centers, 0.15° Grid Cells



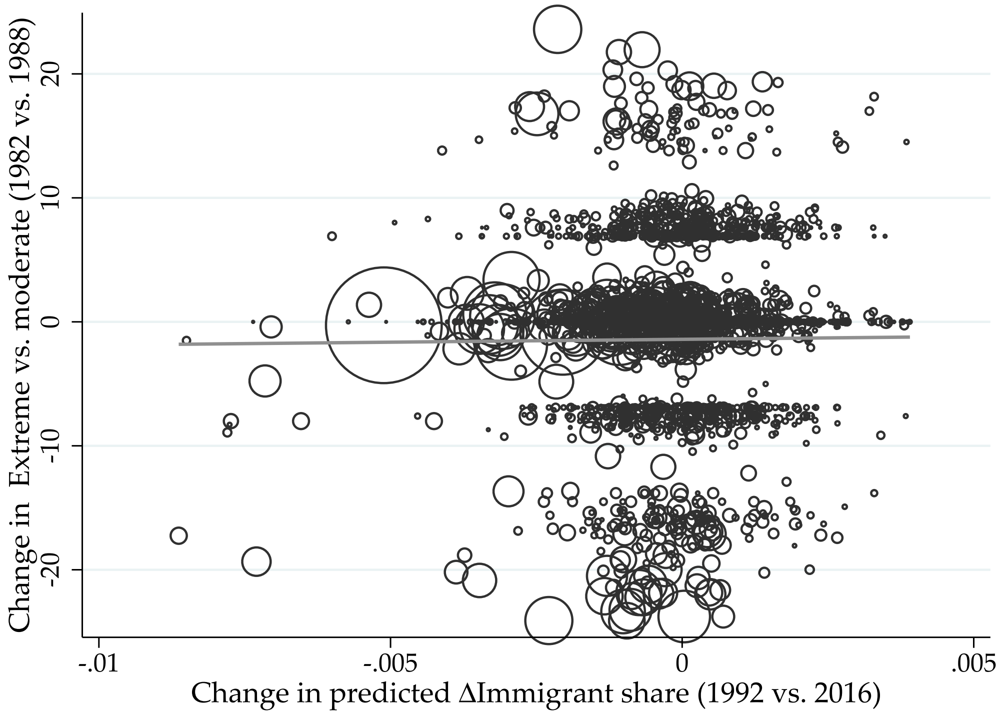
Notes: The map shows the location of first residence of refugees over the 1975-2018 period in blue. The location of active refugee resettlement centers between 1990-2016 is shown in orange. We aggregate the information into 0.15°x0.15° grid cells shown in the background.

Figure A-8 – Parallel Trends—Immigrant Shares by Percentile



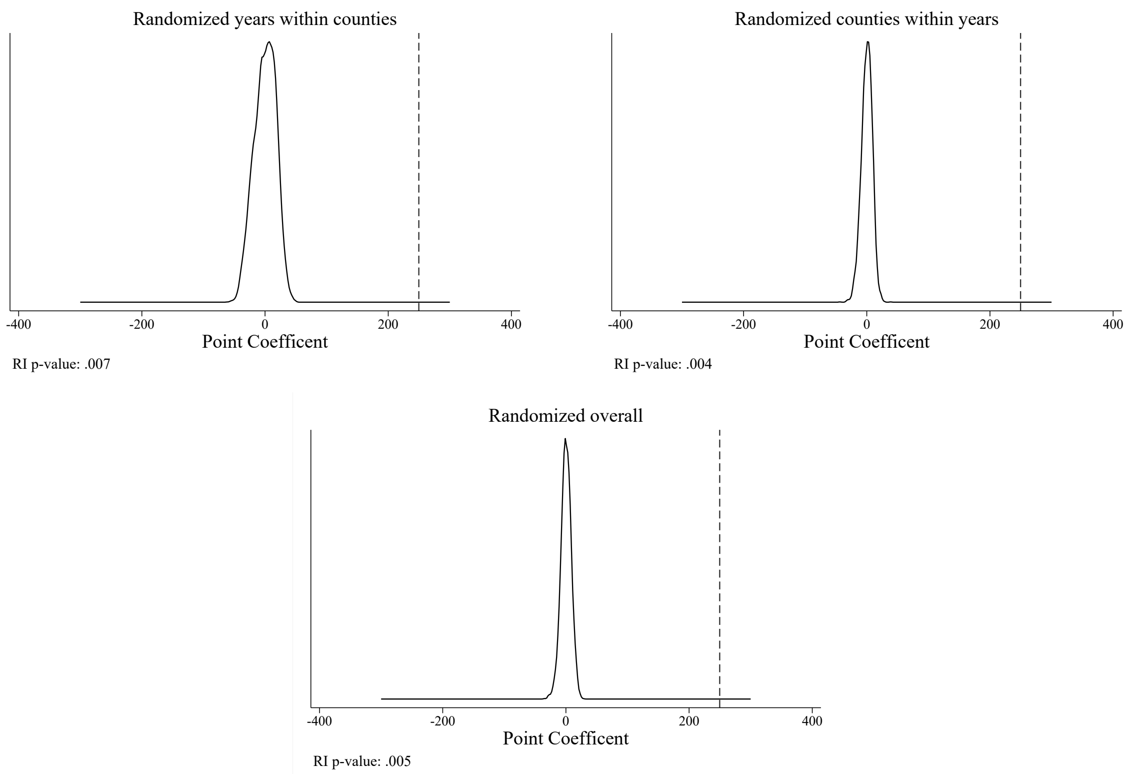
Notes: Panel A shows net inflows of adult immigrants as a share of the adult population. Panel B shows the same variable at the county-level, according to percentiles of the initial share of adult immigrants in the year 1980 (and netting out the effect of the control variables we include in all regressions).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

Figure A-9 – 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, with a slope of 46.21 and standard error of 304.33.

Figure A-10 – 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
Sh. Extreme Twitter	2,529	0.89	0.05	0.00	1.00
Sh. Right Twitter	2,529	0.78	0.10	0.36	1.00
Sh. Left Twitter	2,529	0.11	0.06	0.00	0.45
Sh. Moderate Twitter	2,529	0.11	0.05	0.00	0.37
	Panel B: Control Variables				
Δ Cultural Distance	39936	0.80	0.18	0.02	1.00
Δ Educational 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 (2022) replication materials. Those variables are marked with an asterisk in the table. The sample is based on column 1 of Tables 1 and 2.

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. Winner is the candidate receiving most votes in a county-district cell	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)
Sh. Extreme Twitter	Share of right and left Twitter users in 2016. Thresholds for right, left, moderate users are obtained by splitting the 2012 ideology score into terciles.	Barberá (2015)
Sh. Right Twitter	Share of right Twitter users in 2016.	Barberá (2015)
Sh. Left Twitter	Share of left Twitter users in 2016.	Barberá (2015)
Sh. Moderate Twitter	Share of moderate Twitter users in 2016.	Barberá (2015)
	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 (2022) 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 – 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; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.