

Migration and Political Polarization in the U.S.: An Analysis of the County-level Migration Network

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Abstract

From gridlock in lawmaking to shortened holiday family dinners, partisan polarization pervades social and political life in the United States. We study the degree to which the dynamics of partisan polarization can be observed in patterns of county-to-county migration in the U.S. Specifically, we ask whether migration follows patterns that would lead individuals to homogeneous or heterogeneous partisan exposure, using annual county-to-county migration networks from 2002 to 2015. Adjusting for a host of factors, including geographic distance, population, and economic variables, we test the degree to which migration flows connect counties with similar partisan preferences. Our central finding is that, over the period studied, county-to-county migration flows connect counties with similar partisan voting profiles. Moreover, partisan sorting is most pronounced among the most politically extreme counties. The implication of this finding in the context of partisanship is that U.S. migration patterns reinforce partisan sorting, limiting the degree to which individuals will experience cross-the-aisle local social contacts through spatial interaction. This finding builds on existing research that has documented (1) that individuals prefer to move to and live in locations inhabited by co-partisans, and (2) that local geographic areas have become more polarized in recent decades. Our results indicate that large scale patterns of polarized migration flows serve as a potential mechanism that contributes to geographic partisan polarization.

Introduction

The national political environment in the United States has grown increasingly polarized between Democrats and Republicans in recent years. From the behavior of legislators in the United States Congress [1–3] to individual consumption habits [4], and even the length of family holiday dinners [5], political party affiliation shapes a wide variety of behavioral phenomena. The Democrat / Republican divide does not just represent a national divergence, but is has grown to shape local politics as well [6] suggesting that pockets of divides, and the flows between them, may be a useful way of viewing political polarization. In the current study, we investigate the degree to which geographic migration patterns follow other divides between Democrats and Republicans.

The way in which migration and partisanship are related plays a significant role in shaping the national political landscape in the United States. The national legislature, the presidency, and sub-national elected offices, are allocated according to rules that reflect the geographic distribution of partisan support [7]. For example, representation

in the Senate (entirely) and the Electoral College (in part) are allocated evenly across the states. If politically extreme areas on one side of the partisan aisle cluster into small states, that side of the aisle will be disproportionately represented (relative to the distribution of voters) in the national political landscape [8]. To understand the factors shaping party control in the United States, it is critical that we understand the relationship between internal migration and partisanship.

There is a substantial literature on factors related to the geographic distribution of partisanship. Research to date finds that individuals exhibit a general tendency towards partisan sorting when deciding where to move. Individuals are more likely to move to congressional districts that match their partisan affiliations [9,10]. Individuals value residential real estate more highly when they learn that a property is in a neighborhood populated by co-partisans [11], and are generally more favorable towards areas in which they are in the partisan majority [12]. The literature also indicates that counties and other geographic areas are becoming more polarized along party voting lines—a dynamic that is related to county in- and out-migration rates [13,14]. The existing research has demonstrated a general tendency for individuals to prefer living among co-partisans, and that local areas have grown more partisan in recent years.

These trends raise a question of whether the increasing polarization of local areas is driven by polarized migration flows. To understand whether partisan migration flows serve as a mechanism driving geographic polarization, we need to test for large-scale patterns of sorting via migration flows. We fill this gap in the current research, and study recent historical patterns in county-to-county migration flows. We present an analysis of the association between county-level presidential party voting results and county-to-county annual migration flows from 2002 to 2015. Migration in year i refers to address changes reported to the Internal Revenue Service (IRS) between year $i + 1$ and year i . This period captures two different presidential administrations (George W. Bush and Barack Obama), several changes in party control of Congress, and one redistricting period (2010). It is also influenced by the 2016 election of Donald Trump.

We first visualize migration flows plotted against the partisan vote breakdown in origin and destination counties. We find a consistent and striking pattern in this analysis—that polarized migration flow is common, and that it is strongest among counties at the political extremes. We then use a regression approach to test whether this pattern is consistent after adjustment for other social and economic factors affecting migration, and more precisely, estimate the form of the relationship between partisanship and migration. We find a consistent pattern, wherein migration flows are polarized and the most intense polarization is driven by extremely partisan counties.

We conceptualize the study of county-to-county migration as a network analysis problem. In doing so, we follow a growing body of work that considers migration from a network science perspective [15–17]. We draw upon the network perspective to make use of two concepts. The first is that of “homophily”, or the tendency for units that are alike to interact at greater volumes than those that are dissimilar [18,19]. The second concept upon which we draw is “complex dependence”, a perspective that acknowledges the tendency for relationships (e.g., migration ties) to be dependent upon each other (e.g., one person moving to a county may induce others to move to the same county) [20,21]. Both concepts inform the analysis that we present below.

Materials and methods

We use data from several publicly available sources. We source county-to-county migration flows from the U.S. Internal Revenue Service (IRS) Statistics of Income (SOI) indicators, using number of exemptions to represent migrants. Our data span 14 years, from 2002 to 2015 and are aggregated in two-year summed increments. We use counties

of population 20,000 or more in the 2010 Census for the contiguous 48 states, resulting in 1,834 counties. The 1,834 counties used in our analysis preserves 94.3% of total migration flows (weighted, i.e. migrants) and 88.1% of the total migration connections (un-weighted, i.e. unique network edges) (see [S1 Appendix](#) for more detail).

County-level presidential voting outcomes are sourced from The Guardian and townhall.com for years 2004, 2008, 2012, and 2016 (Fig [1](#)). Data on employment statistics for higher education and military professionals come from the U.S. Bureau of Labor Statistics, using the North American Industry Classification (NAICS) codes 61131 (Colleges and Universities) and 92811 (National Security) for years 2013 and 2016. Data on population, house value, percent of residents with bachelor's degrees, median household income, and unemployment rates were gathered from the U.S. Census American Community Survey (ACS) or Decennial Census for years 2000, 2009, 2012, and 2016. Information on matching between independent variable values for each 2-year migration estimate is detailed in the [S1 Appendix](#). Regarding GIS data, county centroids were computed in ArcMap using county shapefiles from U.S. Census TIGER Line files. We plan to share our dataset on the publicly-available Dataverse (<https://dataverse.org>) upon publication.

To generate heatmaps, we bin counties into 20 bins based on percent votes for GOP candidates, in order to capture differences in the percent votes while preventing an excessive number of empty bins. In terms of statistical methods, we estimate the effects of politics and other variables on migration using multiple ordinary least squares (OLS) regression [\[22\]](#). However, the migrant networks also exhibit network dependencies that violate the independence assumption used for statistical inference with OLS. (That is, they have node-level (e.g. sender effects, receiver effects, and activity effects) and edge-level covariates (e.g. homophily, heterophily, and mixing matrices) that influence the migration patterns.) Thus, we use a network-based permutation testing, specifically, the Quadratic Assignment Procedure (QAP) [\[23\]](#), for the hypothesis testing stage to calculate p-values for the regression coefficients [\[24\]](#).

Fig 1. County-level vote maps. Counties with more than 20,000 residents in 2010 are used in the analysis. The percentage of votes for GOP are mapped for years 2004 (A), 2008 (B), 2012 (C), and 2016 (D), showing regional trends.

Results

Polarized migration patterns

Figures [2](#) – [5](#) describe heatmaps of migration intensity between counties conditioned on the partisan preferences of the origin and destination counties during the two-year periods of 2004–2005, 2008–2009, 2012–2013, and 2014–2015. The four periods correspond to four presidential elections in the years 2004, 2008, 2012, and 2016. Heatmaps for other years are listed in the [S1 Appendix](#). Each figure depicts the relationship based on a different measure of migration flow intensity. In Fig [2](#) the intensity is measured by the average number of migrants for each pair of counties, given the percentage of GOP voters in those counties. In Fig [3](#), the average number of migrants is normalized by origin county population for the given years and in Fig [4](#) by the destination county. In Fig [5](#), intensity is described by the log-scale ratio between the volume of actual migration flows and those estimated using a gravity model (See [S1 Appendix](#) for more detail).

Though the exact structure of homophily varies slightly based on the particular measure of migration intensity, the heatmaps reveal a consistent form of homophily that

Fig 2. Heatmaps based on raw migration data. The following heatmaps depict the average number of migrants from counties with certain GOP presidential voting rates (x axis) to counties with certain GOP rates (y axis).

Fig 3. Heatmaps of migrants normalized by population of origin counties. The following heatmaps depict the average number of migrants from counties with certain GOP presidential voting rates (x axis) to counties with certain GOP rates (y axis). Values are normalized by the population of origin counties.

Fig 4. Heatmaps of migrants normalized by population of destination counties. The following heatmaps depict the average number of migrants from counties with certain GOP presidential voting rates (x axis) to counties with certain GOP rates (y axis). Values are normalized by the population of destination counties.

Fig 5. Heatmaps of migrants normalized by the gravity model. The following heatmaps depict the log-scale ratio between the volume of actual migration flows and those ones estimated using a gravity model.

departs from a conventional homophily pattern. A conventional homophily pattern would indicate that high migration intensity is observed in regions of the plots with similar party voting proportions (e.g., when the proportion voting Republican was nearly equal in both counties). However, for none of the years, and none of the intensity measures, do we observe notably high intensity among moderate counties. Instead, we observe that flows between similar extreme partisan counties are the most intense, and flows involving moderate counties do not exhibit strong homophily. The implication of this pattern is that those moving from moderate partisan counties are equally likely to move to extreme partisan counties as they are to other moderate counties, but those moving from an extreme partisan county are likely to move to a politically similar extreme county. According to this pattern, extremely partisan counties would operate as magnets—drawing population from moderate counties, and then exchanging with other extreme counties. This could serve as a mechanism according to which we observe greater county-level partisan polarization over time. In the next section, we present statistical analyses in which we adjust for other possible explanations of the identified patterns.

Regression Analysis

The patterns in the descriptive heatmaps above suggest homophily in geographic flows originating in extreme partisan counties. However, this finding may be driven by the effects of confounding variables that are not represented in the descriptive analysis. For example, it is well known, and illustrated in Fig 1, that rural areas are more heavily Republican, and densely populated urban areas are more heavily Democratic. The findings documented in the previous section may therefore, for example, be driven by a tendency for people to move from large cities to other large cities. In this section, we present a statistical analysis designed to adjust for confounding factors, and isolate the relationship between the partisanship of origin/destination counties and migration flows.

We use regression methods to account for other factors that may affect migration flows, and isolate the relationship between county partisanship and migration. The linear regression model we estimate takes the form

$$y_{i,j,t} = \beta_{0,t} + \sum_{k=1}^K \beta_{k,t} \times x_{i,j,t}^{(k)} + \epsilon_{i,j,t},$$

where $y_{i,j,t}$ is the migration flow from county i to county j during time period t , $\beta_{0,t}$ is an intercept term that controls the overall level of migration at time t , $x_{i,j,t}^{(k)}$ is one of K predictor variables used to model $y_{i,j,t}$, $\beta_{k,t}$ is a regression coefficient that determines the effect of $x_{i,j,t}^{(k)}$ on $y_{i,j,t}$, and $\epsilon_{i,j,t}$ is an error term that reflects the deviation of $y_{i,j,t}$ from its expected value. Linear regression is a tool that is commonly used to decompose the effects of several variables on migration flows [25–28]. The coefficients are interpreted as measures of the effects of the variables on the expected value of $y_{i,j,t}$, and the performance, or fit, of the model is assessed based on the percentage of the variance in the $y_{i,j,t}$ that can be explained by the independent variables, or adjusted R^2 .

The specified regression model contains features that have been found in the past to affect migration in the United States, including whether the origin and destination counties are in the same state, as well as counties’ population, median age [29,30], median income [25], education (measured by percent of population with a bachelor’s degree) [30], unemployment rate [25], median house price [29], and Haversine distance between county centers. We also introduce a new set of variables regarding the total numbers of jobs in higher education and national defense within each city. We also hypothesize that areas with institutions such as military bases, federal government facilities and universities form connections with other areas with similar facilities. This is well-known theoretically [31], but rarely tested with actual data. Institutions may also spillover with nearby areas [32] or, alternatively, exhibit noisy connectivity patterns without clear signals. Thus, we include variables on the higher education and military occupations because (1) these two industries form networks of populations that involve high rates of intra-industry migration, and (2) these industry occupations are highly correlated with partisan preference. Specifically, military units tend to support GOP candidates and university environments tend to support Democratic candidates [33–35].

For political factors, we include a standard specification for homophily (Table 1) that includes GOP support rate of the origin county (‘GOP_send’), GOP support rate of the destination county (‘GOP_receive’), and the absolute difference of GOP support rate between origin and destination counties (‘GOP_diff’). We also include two more metrics that are designed to model the pattern according to which homophily is more intense among more extreme counties. We refer to these two terms as ‘GOP_shared_bias’ and ‘GOP_prod’. We now define these two terms. First, let the GOP bias of a county be $\tau_i = GOP_i - 0.5$, where GOP_i is the proportion in county i voting for the GOP candidate. We define the ‘GOP_shared_bias’ of county i and j to be $\max(0, \min(\tau_i \cdot \text{sign}(\tau_j), \tau_j \times \text{sign}(\tau_i)))$. For example, if two counties have partisan biases of 0.1 and 0.3, respectively, GOP_shared_bias would be 0.1; if two counties have partisan bias of 0.1 and -0.1, the GOP_shared_bias would be 0. In model 5, we include the shared bias GOP_shared_bias and the product GOP_prod = GOP_shared_bias $\times$ GOP_diff. The GOP_shared_bias measures the degree to which two counties are extreme in the same direction. The GOP_prod conditions the homophily effect on the shared extremeness of the two counties. The vote-related variables are, due to their relationships with each other, difficult to interpret in isolation. We use visualizations of combined effects to understand the patterns according to which voting is relate. In Table 3, we summarize which factors are included in each estimated model.

We use two groups of models in order to test the robustness of the polarization patterns. Models in group A use log-scale migration flows, while all the other variables are in the original format. They also include the product of population in origin/destination counties and inverse distance as the independent variables. Models in group B are based on the log-format gravity model, since gravity model is often used in the log format [36,37] i.e.

$$\log(flow_{ij}) = \alpha_1 \log(P_i) + \alpha_2 \log(P_j) + \beta \log(d_{ij}) + \gamma,$$

Table 1. Explanation of variable terms used in the models

Variable term	Description
GOP_send	Fraction of people who voted for a Republican presidential candidate in the origin county.
GOP_receive	Fraction of people who voted for a Republican presidential candidate in the destination county.
GOP_diff	Absolute value of difference in fraction of people who voted for a Republican presidential candidate in origin vs. destination county.
GOP_shared_bias	Shared deviation in GOP_send and GOP_receive from 0.5 (e.g., if origin is 0.6, and destination is 0.7, shared bias is 0.1; if origin is 0.3, and destination is 0.2, shared bias is 0.2; if origin is 0.6, and destination is 0.3, shared bias is 0).
GOP_prod	$\text{GOP_diff} \times \text{GOP_shared_bias}$ —testing whether homophily is stronger in pairs of counties that are more politically extreme (e.g., is homophily stronger between a 0.9 county and 0.8 county than between a 0.45 county and a 0.55 county).

Table 2. Variables in the two groups of models

Variables	Model Group A	Model Group B
Geographical Effects	Same State	Same State
	Inverse Distance	Log-scale Distance
	Population (send, rec, dist, prod)	Log-scale Population (send, rec, dist)
Fixed County Effects	Median Income (send, rec, dist)	Log-scale Median Income (send, rec, dist)
	Median Age (send, rec, dist)	Median Age (send, rec, dist)
	Pct Bachelor Degree (send, rec, dist)	Pct Bachelor Degree (send, rec, dist)
	Median Housing Value (send, rec, dist)	Log-scale Median Housing Value (send, rec, dist)
Industry Effects	NAICS Military (send, rec, dist)	Log-scale NAICS Military (send, rec, dist)
	NAICS Education (send, rec, dist)	Log-scale NAICS Education (send, rec, dist)

Table 3. Summary of independent variables included in each model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Geographical Effects	Yes	Yes	Yes	Yes	Yes
Fixed County Effects		Yes	Yes	Yes	Yes
Industry Effects			Yes	Yes	Yes
GOP_send				Yes	Yes
GOP_receive				Yes	Yes
GOP_diff				Yes	Yes
GOP_shared_bias					Yes
GOP_prod					Yes

where P_i represents the population for county i , and d_{ij} represent the geographical distance between the county i and county j . We thus use the log format of population

of both origin and destination counties in the model, and also log scale for median income, median home value, employment rates, and quantities of higher education and national defense employment. Other variables, including GOP supporting rate, median age, education, and unemployment rate are represented using the original scale (Table 2). Since network data, such as migration flows, are characterized by complex dependence 15 (e.g., the flow from i to j may depend on the flow from j to i , there may be a tendency for flows to cluster in triads), we use a hypothesis testing method that is robust to network dependence. Quadratic assignment procedure (QAP) is designed for hypothesis-testing for regression with data characterized by network dependence 38. The P-values we report are based on 500 iterations of QAP permutations.

Table 4. Adjusted R^2 values of different models

Model Group	Year	Model 1	Model 2	Model 3	Model 4	Model 5
A	02-03	0.4268	0.4319	0.4436	0.4443	0.4445
	04-05	0.4254	0.4305	0.4418	0.4425	0.4428
	06-07	0.4376	0.4429	0.4529	0.453	0.4533
	08-09	0.361	0.3679	0.3798	0.3799	0.3802
	10-11	0.4441	0.4479	0.4586	0.4587	0.4592
	12-13	0.4389	0.4426	0.4524	0.4524	0.4529
	14-15	0.3851	0.3888	0.3961	0.3961	0.3966
B	02-03	0.2266	0.237	0.2956	0.296	0.2969
	04-05	0.2317	0.2419	0.2987	0.2992	0.3001
	06-07	0.2348	0.2462	0.3026	0.3027	0.3036
	08-09	0.2297	0.2407	0.298	0.2981	0.299
	10-11	0.2356	0.2439	0.3051	0.3052	0.3067
	12-13	0.2226	0.2305	0.2898	0.29	0.2914
	14-15	0.1594	0.1662	0.2137	0.2146	0.2175

In Table 4 we present the adjusted R^2 values for each model estimated. In both model groups, the full model, which includes the complete list of control variables and vote preference effects on migration, provides the best fit to the data. This serves as evidence that we can interpret the relationships between political variables and migration flows as contributing to the models' explanatory power, both across model types and over years.

The results of coefficients for political factors are presented in Table 5. In most models in both groups, the coefficient value of GOP_diff is negative, indicating that migration tends to connect counties with similar voting patterns. Moreover, by calculating the dyadic effects based on GOP_diff, GOP_shared.bias, and GOP_prod, Fig 6 and Fig 7 indicate that the relationship between county migration flows and partisan composition is one of homophily with respect to partisan composition. That is, adjusting for other factors that might affect migration flows, we find that flows are higher between counties with similar partisan compositions, and that this effect is particularly strong for counties with relatively extreme partisan compositions. In addition to the statistical significance of the partisan composition variables, the results we report also show that the model fit, assessed using adjusted R^2 , improves in each year as a result of adding the partisan composition variables 4.

Fig 6. Dyadic effects for model group A. The integrated dyadic terms' effects based on GOP_diff, GOP_shared.bias, and GOP_prod between counties with certain proportion votes supporting the GOP candidate for model group A.

Table 5. Result summary of model groups A and B

Type, Model	Year	GOP diff	GOP send	GOP receive	GOP shared bias	GOP prod
A, 4	02-03	-0.052*	0.096***	0.139***		
	04-05	-0.039·	0.097***	0.163***		
	06-07	0.000	0.008	0.064***		
	08-09	-0.051**	0.009	0.036·		
	10-11	-0.006	0.007	0.038·		
	12-13	0.005	0.011	0.048*		
	14-15	-0.017	-0.039*	-0.020		
A, 5	02-03	-0.089**	0.060*	0.103***	-0.134·	3.087***
	04-05	-0.075*	0.058*	0.124***	-0.127·	3.139***
	06-07	-0.026	-0.001	0.054*	-0.187**	3.184***
	08-09	-0.056·	-0.013	0.014	-0.082	3.029***
	10-11	-0.022	-0.034·	-0.003	-0.107	3.408***
	12-13	-0.014	-0.023·	0.015	-0.117	3.096***
	14-15	-0.030	-0.073***	-0.054***	-0.073·	2.423***
B, 4	02-03	-0.102***	0.033	0.092**		
	04-05	-0.090***	0.042	0.118***		
	06-07	-0.065**	-0.030	0.028		
	08-09	-0.062**	-0.021	0.009		
	10-11	-0.069**	-0.034	-0.002		
	12-13	-0.061**	-0.033	0.008		
	14-15	-0.098***	-0.106***	-0.084***		
B, 5	02-03	-0.068	-0.107**	-0.048	0.187·	4.227***
	04-05	-0.057	-0.100**	-0.025	0.186·	4.339***
	06-07	-0.035	-0.088***	-0.029	0.077	4.253***
	08-09	-0.032	-0.078***	-0.049·	0.073	4.353***
	10-11	-0.019	-0.143***	-0.111***	0.191*	4.252***
	12-13	-0.013	-0.136***	-0.095**	0.184*	3.931***
	14-15	-0.014	-0.252***	-0.230***	0.314***	3.645***

P-values: *** <0.001, ** <0.01, * <0.05, · >0.1

Fig 7. Dyadic effects for model group B. The integrated dyadic terms' effects based on GOP_diff, GOP_shared.bias, and GOP_prod between counties with certain proportion votes supporting the GOP candidate for model group B.

Discussion

In the United States, the representative democratic system is largely based on the geographic distribution of partisan preferences. On the national political stage, representation in both the Senate and the Electoral College are allocated with a bias that favors residents of low-population states. Geographic disparities in partisan preferences, which will persist under the patterns of partisan migration we have documented, exacerbate representational inequality.

We present a comprehensive analysis of the ways in which migration flows between counties are conditioned by the partisan composition of counties. The consistent pattern, which is evident in both bivariate heatmaps and multiple regression models, shows that the migration network is characterized by a lack of homophily among

moderate counties, and strong homophily among extreme counties. This pattern could serve as a mechanism through which partisan polarization of counties is exacerbated, and suggests that those with politically extreme preferences self-select into ideologically homogeneous locales.

In addition, we find that explanatory variables such as the gravity model, and magnetism between places with similar pairs of military, federal and university institutions, help explain higher rates of migration. The gravity model variable emphasizes the convenience of migrating to a nearby location. The self-selection of industry similarities between origins and destinations emphasizes the lack of importance of geographic distance for those who "live life in the network" [39] of military operations and higher education, each of which carries systematic promotion and retention that makes staying in these networks attractive.

Supporting information

S1 Appendix. More information on data, heatmaps, and QAP.

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