Political Conformity

Event-Study Evidence from the United States

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Abstract

We argue that individuals are influenced by the mainstream political preferences in their group of reference. Combining administrative data from the Federal Election Commission and the United States Postal Service, we identify 45,000 individuals who contributed to the 2008 Obama presidential campaign and changed residence either before or after the 2012 election cycle. We examine whether living in a more Democratic area caused these individuals to contribute more to the Obama campaign in 2012. We disentangle the direction of causality by exploiting the timing of residential mobility in an event-study fashion. We find that conformity effects are statistically and economically significant: living in an area with a 1% higher share of Democrats increases the contribution to Obama by 0.11%. Last, we provide a model that can be combined with the event-study estimates for counterfactual analysis. We find that 27% of the degree of geographic polarization in contributions can be attributed to conformity effects.

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1 Introduction

We argue that individuals are influenced by the mainstream political preferences in their group of reference. For example, when a Democrat belongs to a social network that comprises mostly Republicans, the opposite-minded social context can discourage her political participation. This individual may refrain from publicly endorsing a Democratic candidate to avoid social sanctions from Republican friends (Bernheim, 1994; Perez-Truglia and Cruces, 2014). This person may also feel less excited about the Democratic candidate as a result of exposure to Republican opinions about the candidate (Mutz and Mondak, 2006; Glaeser and Sunstein, 2009).

Other mechanisms may work in the opposite direction. For example, having a majority of Republican friends may reduce the temptation to free-ride on the political participation of other Democrats.[1] Whether the influence of social context is conducive to political conformity is ultimately an empirical question. It is also a difficult question because of the usual challenges associated with identifying peer effects (Manski, 1993; Graham, 2008). Intuitively, it is hard to separate whether Democrats are more politically active when living in a more Democratic area or whether active Democrats are more likely to live in more Democratic areas. This paper estimates conformity effects using an event-study analysis of residential mobility and quantifies the contribution of conformity effects to geographic polarization.

In the first part of the paper, we estimate the magnitude of conformity effects in the context of campaign contributions. Ideally, we would take a sample of contributors and randomize their places of residence. Under the hypothesis of conformity effects, we expect individuals to contribute more when they are randomly assigned to live in areas with a higher share of like-minded social contacts, such as neighbors, friends, and coworkers. Although this ideal experiment is not feasible, we exploit a quasi-experimental design based on the same principle.

We combined data on itemized contributions from the Federal Election Commission (FEC) with data on residential mobility from the National Change of Address database of the United States Postal Service.[2] We identified 45,000 individuals who contributed to Barack Obama's 2008 presidential campaign and changed residence between the end of the 2008 election cycle and the beginning of the 2012 election cycle, or after the end of the 2012

[1]For instance, Perez-Truglia and Cruces (2014) provide evidence consistent with free-riding in the context of campaign contributions. Additionally, being one of the few Democrats in a social group may make attending rallies more attractive, because they can provide a unique opportunity for meeting other Democrats.

[2]To the best of our knowledge, this is the first paper to use the NCOA data for an event-study analysis of residential mobility. This methodology could be used in a number of other applications. In a nutshell, without the help of the NCOA data we could identify individuals who changed residency only if they contributed again in 2012. A similar problem likely arises with many sources of administrative data.

election cycle. These individuals had another opportunity to contribute to Obama, during the 2012 re-election campaign.

Consider a pair of individuals who were observationally identical in the 2008 election (i.e., they contributed a similar amount to Obama in 2008 while living in a similar area). Between the end of the 2008 election and the start of the 2012 election, these two individuals moved to different areas, each with different shares of Democrats. According to the political conformity hypothesis, the individual who moved to a place with a higher share of Democrats should make higher contributions to Obama during the 2012 election, because of the exposure to a more like-minded environment. We find statistically and economically significant evidence in favor of this hypothesis.

However, this estimate of conformity effects relies on the assumption that, for each pair of similar individuals, the likelihood of one moving to a more Democratic area is largely a matter of chance. Of course, this assumption could be violated. The individual who moved to the more Democratic area may have contributed more in 2012 because she was already more strongly affiliated with the Democratic Party in 2008, or because her affiliation had strengthened since 2008. We can use the timing of residential mobility, in an event-study fashion, to test this assumption and validate our estimates.[3]

Consider now a pair of similar individuals who moved after the end of the 2012 election cycle (instead of individuals who moved before the beginning of the 2012 cycle). The conformity hypothesis predicts that the individual moving to the more Democratic area should contribute the same amount during 2012 as the individual moving to the less Democratic area, because these individuals were not exposed to their new social environments during the 2012 election cycle. On the contrary, if the individual moving to the more Democratic area was or had become more Democratic since 2008, then she should contribute more in 2012. As expected, we find that contributions in 2012 are not correlated to the share of Democrats in the area to which the contributor moves after the 2012 election.

Our evidence suggests that conformity effects are economically significant: increasing by 1% the share of Democrats in the 3-digit ZIP code (ZIP-3) increases an individual's contribution to Obama by 0.11% (p-value<0.01). This finding is robust to a number of alternative specifications, such as looking at the extensive versus intensive margins and using counties instead of ZIP-3s in the definition of the reference group.

The main contribution of this paper is to show that location effects constitute a significant force towards conformity. Additionally, we present suggestive evidence about one family of

[3]Others papers have used residential mobility as a source of quasi-experimental variation: e.g., Chetty and Hendren (2015) for measuring the effect of neighborhoods on income mobility. Our research design is also related to Chetty, Friedman and Rockoff (2014), who show that controlling for past behavior (test scores) can be helpful to identify group effects (teacher quality).

plausible mechanisms mediating this relationship: social interaction models. First, these models predict that conformity effects should decay with social distance. Consistent with this prediction, we find that individual contributions are affected by the share of Democrats in the contributor's ZIP-3, but are not affected by the share of Democrats in a more distant reference group: the adjacent ZIP-3s. The social interaction models also predict that conformity effects should intensify as an individual gradually integrates into a new social environment. Consistent with this prediction, conformity effects are 36% higher for individuals who moved a year earlier and thus had an additional year to integrate into their new environments.

Our evidence on political conformity is based on campaign contributions, mainly because of the availability of rich administrative data needed for the event-study analysis. However, similar conformity effects are likely to be present for other forms of political participation with a marked partisan flavor, such as talking about politics, sharing political comments on social networks, attending political rallies, and maybe even registering to vote.

In the second part of the paper, we show that conformity effects play an important role for geographic polarization. In the case of campaign contributions, geographic polarization denotes the extent to which Democrat (Republican) contributors are geographically close to other Democrat (Republican) contributors. This polarization is partly due to the systematic sorting of individuals into areas with a higher share of like-minded people (Bishop, 2009). The conformity effects are bound to exacerbate these sorting effects by inducing higher participation from supporters of the local majority and lower participation from the local minority. To quantify this phenomenon, we estimate a simple model that can be combined with our event-study estimates for counterfactual analysis. We find that a significant portion (27%) of geographic polarization in contributions during the 2012 election can be attributed to conformity effects.[4]

This paper is related to a literature on social effects in political participation (Campbell et al., 1960; Huckfeldt, 1979). Recent literature has focused on the role of social incentives in the decision to turn out to vote (Knack, 1992; Riker and Ordeshook, 1968; Gerber, Green and Larimer, 2008; Funk, 2010; DellaVigna, List, Malmendier and Rao, 2014). In a seminal contribution, Gerber, Green and Larimer (2008) conducted a field experiment in which a group of registered voters were sent letters announcing that they would publicize the recipient's future voting behavior to neighbors. The authors found that these letters had a large positive effect on subsequent turnout. One standard interpretation for this finding is that individuals feel social pressure to vote because the act of voting can signal altruism

[4]This finding implies that geographic polarization may be higher for forms of participation that are more sensitive to conformity effects. Consistent with this implication, Gentzkow and Shapiro (2011) find that segregation in social interactions with neighbors, co-workers and family members is higher than segregation in media consumption.

(Ali and Lin, 2013).[5] Indeed, a similar motive is believed to drive other forms of pro-social behavior, such as charitable giving (Bénabou and Tirole, 2006). However, the act of turning out to vote does not in itself reveal the party or cause that the individual supports. As a result, the mechanisms studied in Gerber, Green and Larimer (2008) and others do not have implications for political conformity.

This study is also related to Perez-Truglia and Cruces (2014), who provide evidence from a field experiment about how individuals interact with supporters of the same and opposite party. They show that the visibility of contributions among social contacts, such as neighbors, affects the amounts contributed, presumably because individuals anticipate social sanctions and social rewards.[6] They also show that contributors care about the contribution behavior of others, presumably because of social norms. Our paper contributes in at least two ways. Most important, we quantify the extent to which social context is conducive to political conformity.[7] Also, we show that the magnitude of social effects is significant in a naturally-occurring context.

Last, the growing concern about polarization has sparked a debate about its possible causes (McCarty et al., 2006; Azzimendi, 2011).[8] We contribute to this debate by showing that social context effects can be important for understanding polarization.

The paper is organized as follows. Section 2 presents the event-study estimates of conformity effects. Section 3 measures the contribution of conformity effects to geographic polarization. The final section concludes.

2 Measuring Conformity Effects

2.1 Data Definitions and Data Sources

2.1.1 Sample of Movers

We use data from the FEC contribution records, which includes all contributions by individuals who gave over $200 in total to a campaign committee in a given election cycle. We start

[5]DellaVigna et al. (2015) estimate the value of this social signal to be between $5 and $15.

[6]Gerber et al. (2013) show that some individuals do not vote because they do not trust the privacy of voting, which might also suggest that individuals do not want to disclose their partisan affiliation to peers. This mechanisms is also consistent with evidence that individuals report to be more sympathetic with supporters of their own political party (e.g., Iyengar, Sood and Lelkes, 2012; Iyengar and Westwood, 2015; Sunstein, 2015).

[7]For example, the comparison channel in Perez-Truglia and Cruces (2014) has mixed predictions regarding political conformity, and there may be other channels that they do not study that may also be driving conformity effects.

[8]For a discussion of sources of spatial auto-correlation in campaign contributions, see for example Cho (2003) and Gimpel, Lee and Kaminski (2006).

with the sample of all individuals who contributed more than $200 to the Obama campaign during the 2008 election cycle (i.e., between January 2007 and December 2008).[9] These individuals had to decide whether to contribute to Obama again during the re-election campaign of 2012.[10]

The research design requires the identification of the Obama contributors who moved after the 2008 election (i.e., after December 31st, 2008) and, for those who moved, when and where they moved. We accomplished this by using data from the National Change of Address database from the United States Postal Service. This database contains information on more than 150 million change-of-address records, including names, addresses, and the dates when the moves became effective.[11] Because we are interested in individuals who changed their social environment, we excluded changes of address for individuals who remained in the same ZIP-3.[12] The National Change of Address database does not cover the totality of residential moves, although it is believed to cover a great majority of them.[13] Although missing some residential moves reduces the size of the final sample, it does not affect the internal validity of the estimates.[14]

A first set of individuals moved in the two years after the 2008 election cycle but before the beginning of the 2012 election cycle (i.e., between January 2009 and December 2010) and stayed in the same address for the duration of the 2012 election cycle.[15] A second set

[9]We cannot reproduce the analysis for individuals contributing during the 2004 election cycle because the NCOA dataset only goes 48 months back. Indeed, to construct our dataset we had to access the NCOA records twice: on January 2013 and January 2015.

[10]One important advantage of focusing on a presidential campaign is that the candidates are the same irrespective of the contributor's area of residence, thereby holding constant the quality of the candidate. If we examined instead contributions to gubernatorial races, then individuals in more Democratic areas may contribute more to Democratic candidates simply because in those areas the Democratic candidates happen to be better.

[11]Doing this with the FEC data alone would be very problematic, because these individuals would appear in the 2012 records only if they contributed again, which would be a smaller and endogenously-selected sample.

[12]We also excluded individuals whose contribution records included multiple addresses in 2008, individuals who contributed to other presidential candidates and individuals whose change of address records corresponded to business addresses. In the final sample, the median (mean) distance traveled was 140 miles (520 miles).

[13]For instance, according to Census Bureau Data, the yearly rate of residential moving in 2011 was 6.2% for Americans aged 40 or above. In comparison, 4.1% of contributors filed change of addresses with USPS during the first year after the end of the 2008 cycle. These figures suggest that the NCOA records include 66% (i.e., 4.1/6.2) of the total residential moves. This coverage rate would be higher if we took into account that contributors are richer and more educated than the average American and thus tend to move less often.

[14]The estimated conformity effects for the subsample of movers with NCOA records may or may not be extrapolated to movers without NCOA records or to non-movers, depending on whether there is substantial heterogeneity in the magnitude of conformity effects across these groups.

[15]If an individual moved more than once between January 2009 and December 2010, we use its last move. If the individual changed residence again during the 2012 cycle (i.e., between January 2011 and December 2012), then we drop her from the sample (i.e., because her last move would have been during the 2012 and

of individuals had not moved by the end of the 2012 election cycle (i.e., December 2012) and then moved during the two years after the end of the 2012 election cycle (i.e., between January 2013 and December 2014).[16] The final sample consists of 45,438 contributors who moved, of which 59% moved before the 2012 election and the remaining 41% moved after the 2012 election.[17] Given that these two groups differ only in the timing of the residential moves, we expect them to have similar characteristics. Appendix A shows that, indeed, these two groups of contributors are similar in many respects, such as gender, race, the share of Democrats in the origin and destination ZIP-3s, and the mean amounts contributed to Obama in the 2012 and 2008 elections.

2.1.2 Dependent Variable and Regression Model

For each of the 2008-contributors, we observe the name and residential address during the 2012 election cycle. Matching these variables to the 2012 FEC records allowed us to measure how much each of the 2008-contributors contributed to Obama in the 2012 campaign. The main dependent variable in the econometric analysis is the amount contributed in 2012. This amount is lower censored at $200 because, for each election cycle, the FEC records include only those individuals who contributed more than $200 in total to the same campaign committee. We use econometric models that account for this lower censoring: a Tobit model and a Poisson model.[18] In both cases, the dependent variable is the contribution amount in excess of $200, so that it takes the value 0 if the individual contributed $200 or less (i.e., if there is no record of a contribution in the FEC records). The Poisson model is our preferred specification, because the coefficients can be directly interpreted as semi-elasticities. Additionally, we present results for the extensive margin (i.e., where the dependent variable is 100 if the individual made a contribution above $200 and 0 otherwise).

Table 1 provides some descriptive statistics about the contribution patterns in the 2008 and 2012 elections. By construction, all individuals in the sample contributed more than $200 to the Obama campaign in 2008. The average amount contributed in 2008 was $651. In 2012, 26.8% of the individuals in the sample contributed more than $200 to Obama, and the average amount contributed was $860.

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not before the 2012 cycle).

[16] Again, if an individual moved more than once during this period, we use its last move.

[17] Of the 600,000 contributors in the initial sample, about 21% of them changed residence at least once in the six years after the end of the 2008 election cycle. However, 65% of these households do not belong to the final sample because they did not satisfy all the requirements (e.g., they moved during the 2012 campaign or moved to an address in the same ZIP-3 of origin).

[18] To accommodate the fixed effects, we use the Tobit estimator proposed by Honoré (1992).

2.1.3 Main Independent Variable: *Share Own-Party*

An individual's reference group comprises all the social contacts that could influence her political participation, including neighbors, friends, relatives, acquaintances, colleagues, bosses, and clients. Because we do not have data on the social networks of the contributors in our sample, we constructed a geographic proxy. This is a common approach in the social interactions literature.[19]

Our baseline specification uses the ZIP-3 where the individual resides as proxy for her reference group. Intuitively, ZIP-3s are probably large enough to include most of the individual's social contacts (e.g., neighbors, friends, coworkers). For example, in Boston, the 021 ZIP-3 covers roughly the same area as the metro area's subway system.[20] For reference, Figure 1 shows the boundaries of the 890 ZIP-3s in the United States (Democratic ZIP-3s are colored with a darker shade). For illustrative purposes, this figure also includes arrows denoting an arbitrary sample of residential moves.

The main independent variable is *Share Own-Party*, which can take values from 0 to 1. In the baseline definition, it is the share of Democrat contributors in the destination ZIP-3 among all the contributors (Democrat and Republican) to presidential campaigns.[21] Below we show that the results are robust using alternative definitions of *Share Own-Party*, such as using counties instead of ZIP-3s and using the share of Democrat voters instead of the share of Democrat contributors. As reported in Table 1, in this sample, the average *Share Own-Party* in the origin ZIP-3 is 0.70. This share is higher than the unweighted average across ZIP-3s (0.61), implying that Democrat contributors are more likely to live in areas with a higher share of Democrats. The average *Share Own-Party* in the destination ZIP-3 (0.69) is almost identical to the average *Share Own-Party* in the origin ZIP-3 (0.70). This implies that individuals, on average, move to ZIP-3s with the same political composition as the origin ZIP-3s. However, the correlation between the share of Democrats in the origin and destination ZIP-3s is 0.36, which is significantly below one and thus indicates that there are substantial changes in the political composition of the reference groups.

2.1.4 Control Variables

The 45,438 contributors are divided into 1,666 groups of individuals who, by the end of the 2008 election, were very similar: they had contributed the same amount to Obama (in $100-intervals), and they were living in a ZIP-3 with the same *Share Own-Party* (in 0.01-intervals).

[19] For a discussion, see for example Perez-Truglia (2013) and Perez-Truglia and Cruces (2014).

[20] In this respect, ZIP-3s have the nice property that they tend to be smaller in more dense areas (Chetty, Friedman and Saez, 2013).

[21] This share is computed using contributions during the 2008, 2004 and 2000 presidential election cycles.

We compare across similar individuals by including group fixed effects in the regressions. The regressions also include as control variables a set of individual characteristics (e.g., gender, race) and characteristics of the destination ZIP-3 (e.g., mean income).[22] For a detailed description of each regression specification, see the notes to the corresponding figure or table.

2.2 Results

2.2.1 Basic Results

Figure 2.a shows in graphical form the results from a regression of the amount contributed during the 2012 cycle (y-axis) on the *Share Own-Party* in the destination ZIP-3 (x-axis). Each dot corresponds to a set of seven dummies for *Share Own-Party*, where the leftmost dot corresponds to the omitted category and thus its corresponding coefficient is normalized to zero.[23] Results are from a Tobit regression with group fixed effects and other control variables as described in the previous subsection (see also the note to the figure for more details).

The red dots in Figure 2.a correspond to individuals who moved after the end of the 2008 cycle but before the beginning of the 2012 cycle. The conformity hypothesis predicts that, within groups of similar individuals, the contributors moving to more Democratic areas should make higher contributions to Obama during the 2012 election cycle, because of the exposure to a more like-minded environment. As expected, the red dots in Figure 2.a show that there is a strong positive relationship between the contribution amount and the share of like-minded individuals. For example, moving an individual from an area with 45% Democrats (corresponding to the leftmost dot) to an area with 90% Democrats (the rightmost dot) would increase her contribution by nearly $250. This effect is equivalent to 29% of the mean amount contributed ($860) among those who contributed more than $200.

These estimates would be a valid measure of conformity effects only if, within each group of similar individuals, which individual ends up in a more Democratic area is largely a matter of chance. Of course, this assumption could be violated. First, the individual who moved to the more Democratic area may have contributed more in 2012 because she was a stronger Democrat in 2008. Second, the individual who moved to the more Democratic area may have contributed more in 2012 because she became a stronger Democrat since 2008. We use the timing of the residential mobility to test this assumption and validate our estimates.

Consider a group of similar individuals who, instead of moving before the beginning of the

[22]For the ZIP-3 characteristics, including *Share Own-Party*, we allow for different coefficients for individuals moving before and after the 2012 cycle. The results are similar if, instead, we run separate regressions for these two groups.

[23]These dummies correspond to the quantiles of the distribution of *Share Own-Party* in the sample.

2012 election cycle, moved after the end of the 2012 election cycle. The conformity hypothesis predicts that the individuals moving to the more Democratic area should contribute the same during 2012 than the individuals moving to the less Democratic area, because during the 2012 election these individuals had not moved yet and thus had not been exposed to their new social environments. On the contrary, if the individuals moving to the more Democratic area were stronger Democrats in 2008 or became stronger Democrats since 2008, we should observe that they contribute more during 2012 than the individuals moving to the less Democratic area.

This falsification test is shown by the blue squares in Figure 2.a. For these individuals, the x-axis corresponds to the *Share Own-Party* in the ZIP-3 to which the individual moved after the end of the 2012 cycle. As expected, individuals moving to the less Democratic areas contribute the same amounts than individuals moving to the more Democratic areas. Moreover, in the next subsection we show that the difference in slopes between the red and blue lines from Figure 2.a is highly statistically significant. This constitutes evidence in favor of the presumed direction of causality: i.e., living in more Democratic areas causes individuals to contribute more to Obama.

One explanation for why this research design works well is that individuals in the sample pool (i.e., individuals who contributed more than $200 to Obama in 2008) probably have a Democratic attachment that is very homogeneous and stable over time, at least relative to the other 99% of the U.S. population who do not contribute. For example, in the general U.S. population, a non-trivial share who voted for Obama in 2008 voted for Romney in 2012. On the contrary, in our sample there were virtually no contributions to Republican presidential candidates in the 2012 election.[24] This view is also consistent with the evidence that contributors tend to be highly partisan (Bonica, 2014) and have a long-standing attachment to their parties (Ansolabehere, de Figueiredo and Snyder, 2003).

It is important to understand the geographic scope of the conformity effects. In particular, the social interaction models (e.g., social pressure, social norms, social learning) predict that participation should be more affected by peers with whom the individuals interacts more often. On average, the frequency of social interactions decays with geographic distance. Then, we should expect smaller conformity effects for reference groups that are further away. In Figure 2.b, the red dots show the effects of *Share Own-Party* in the destination ZIP-3, while the blue squares show the effect of *Share Own-Party* in the "donut" of adjacent ZIP-3s.[25] Both of these variables correspond to individuals who moved before the beginning of

[24] There are, however, some caveats with this estimation, because some individuals may contribute under a different address (in which case it is more difficult to establish that they are the same individual) and the FEC records only include contributions over $200.

[25] We define two ZIP-3s to be adjacent only if their geographic boundaries touch. Our definitions are based

the 2012 election. As expected, the amount contributed is not significantly affected by the political composition in the adjacent ZIP-3s.

2.2.2 Further Results and Robustness Checks

Table 2 presents further regression results. The regression specifications are identical to the one used for Figure 2, except that *Share Own-Party* enters as a single independent variable instead of entering as a set of dummies. Columns (1) through (3) present results from the Poisson model. This is our favorite model because the coefficients can be interpreted as semi-elasticities. *Moved Before Election* shows the coefficient for the subset of individuals who moved before the beginning of the 2012 cycle. In column (1), the estimated coefficient of 0.682 is highly statistically significant (p-value$<$0.01) and also economically significant: moving an individual from a ZIP-3 with 1 percentage point higher share of Democrats would increase the amount contributed by about 0.68%. This effect implies that a move from the 5th-percentile to the 95-percentile of *Share Own-Party*, equivalent to an increase of 41 percentage points, would raise an individual's expected contribution by 32% (i.e., $e^{0.682 \cdot 0.41}$).

Regarding the falsification test, *Moving After Election* shows the coefficient for the subset of individuals who moved after the end of the 2012 cycle. As expected, this coefficient is very close to zero, statistically insignificant, and as precisely estimated as the corresponding coefficient for the group *Moved Before Election*. Table 2 reports the result from a test of the null hypothesis that the coefficients on *Share Own-Party* are equal between the samples *Moved Before Election* and *Moving After Election*. As expected, we can reject the null hypothesis at the 1% level.

The main contribution of this paper is to show that social context has a significant conformity effect on participation, regardless of which combination of mechanisms generate these effects. As a guide, we provide a brief list of plausible mechanisms. First, our favorite family of mechanisms consists of social interaction models, such as social norms, social pressure and social learning. For example, the social pressure model suggests that a Democrat may want to contribute less because she is afraid of social sanctions from her Republican peers. Second, part of the conformity effects may be attributed to differences in fundraising practices across the U.S. geography (Huckfeldt, 1979; Cho, 2003). Indeed, if campaign committees are aware of the power of social incentives, we should expect them to adjust their campaign practices to leverage from these incentives (Gimpel, Lee and Kaminski, 2006). Third, living in a more Democratic area may increase contributions to Obama because those areas are expected to receive preferential treatment from a Democratic president. However, this last mechanism seems at odds with the widespread view that individuals do not make contributions because

on the U.S. Census cartographic data.

of an investment value, but because of a consumption value (Ansolabehere, de Figueiredo and Snyder, 2003).

Columns (2) and (3) from Table 2 provide some suggestive evidence consistent with the social interaction models. First, these models suggest that conformity effects should decay with social distance. Column (2) shows the results for a specification that includes two versions of *Share Own-Party*: one for the destination ZIP-3 and another for the ZIP-3s that are adjacent to the destination ZIP-3. The results confirm that the conformity effects decay with geographic distance: the coefficient for adjacent ZIP-3s is close to zero and statistically insignificant. Furthermore, the difference between the coefficients for the same ZIP-3 and adjacent ZIP-3s is statistically significant (p-value=0.025).

Second, the social interaction models predict that individuals react to the beliefs and actions of peers. Since it takes time to learn about the beliefs and actions of new peers, we should expect conformity effects to grow with the time exposed to the new environment. To explore this conjecture, the specification in column (3) splits the group *Moved Before Election* in two sub-groups: *Two Years Before* refers to contributors who moved two years before the beginning of the 2012 election cycle (i.e., between January and December of 2009), while *One Year Before* refers to contributors who moved one year before the beginning of the 2012 election cycle (i.e., between January and December of 2010). The estimated coefficients of 0.786 and 0.577 suggest that, as expected, the conformity effects were 36% larger for individuals who had an extra year to assimilate into their new environments. This difference is statistically significant at the 1% level and economically significant as well.

It is possible that conformity effects would be even higher for individuals moving three or more years before the start of the election cycle, but we cannot test this hypothesis with our data. Since non-movers tend to be exposed to their environments for much longer than movers,[26] the evidence that longer exposure magnifies the conformity effects also suggests that the estimates of conformity effects for our sample of movers may under-estimate the importance of conformity effects in the general population of contributors.

Columns (4) and (5) from Table 2 present results under alternative specifications for the outcome variable. The specification in column (4) has the dollar amount contributed as dependent variable, but uses a Tobit instead of a Poisson model. The Tobit model changes the assumption that the effects are proportional to the potential amount contributed, but does not throw away any variation in the outcome variable. The results from column (4)

[26]For example, the Census bureau estimates that the yearly rate of residential moving in 2011 was 6.2% for Americans aged 40 or above. If the probability of moving was i.i.d over time, then the expected number of years of exposure to a social environment would be around 16 years (i.e., 1/0.062). In comparison, the average exposure for the sample of movers is between 2 and 4 years (i.e., at the most, an individual lived in the destination ZIP-3 from January 2009 until December 2012).

are qualitatively similar to the results from column (1), suggesting that the results are not sensitive to the choice between Poisson and Tobit models. In column (5), the dependent variable takes the value 100 if the individual contributed more than $200 in the 2012 cycle and 0 otherwise. By looking exclusively at the extensive margin, this specification is throwing away valuable variation in the outcome variable. The coefficient on *Share Own-Party* from column (5) is positive and significant for contributors who moved before the start of the 2012 election and insignificant for contributors who moved after the end of the 2012 election.[27] However, due to the fact that we are throwing away rich variation in the outcome variable, the coefficients are less precisely estimated and, as a result, we cannot reject the hypothesis that the coefficients on *Share Own-Party* are equal across these two groups.

Table 3 presents some additional robustness checks. Column (1) shows results from the baseline specification reported in column (1) from Table 2. Columns (2) and (3) show results for alternative definitions of the reference group. In column (2), we vary the geographic unit of analysis: this specification differs from column (1) in that *Share Own-Party* is defined at the county level rather than at the ZIP-3 level. In column (3), we also vary the data source used to compute *Share Own-Party:* this specification differs from column (2) in that *Share Own-Party* is defined using voting results during the 2008 presidential election rather than using contribution data.

The baseline specification of *Share Own-Party* has at least two advantages over the alternative specifications. First, using ZIP-3s instead of counties can be more reliable because ZIP-3s are smaller on average and they vary less dramatically in size (e.g., some counties have a few hundred inhabitants while others have over ten million). Second, since individuals tend to associate with peers of similar characteristics, the social contacts of contributors are expected to be older, richer and more educated than the average individual from a given area. Thus, using the share of Democrat contributors instead of the share of Democrat voters can provide a better proxy of the political composition of the social contacts of a contributor. In practice, these differences are not that important, to the extent that the results are similar across columns (1), (2) and (3). For instance, the coefficients on *Share Own-Party* from columns (1), (2) and (3) are similar (0.682, 0.714 and 0.788) and their differences are

[27]The magnitudes of the estimates cannot be compared directly across outcome variables. However, we can still provide some suggestive statistics. The coefficient 0.682 from column (1) in Table 2 suggests that a 41 percentage points increase in *Share Own-Party* (i.e., from the 5th to the 95th percentile) would raise the amount contributed by 32% (95% CI: [14%, 44%]). The coefficient 484.941 from column (4) suggests that a 41 percentage points increase in *Share Own-Party* would raise the amount contributed by $198, which is 23% (95% CI: [9%, 37%]) of the mean amount contributed ($870.35) by individuals who contributed over $200 (from Table A.1). The coefficient 6.236 from column (5) suggests that a 41 percentage points increase in *Share Own-Party* would raise the propensity to contribute by 2.56 percentage points, which is 11% (95% CI: [3%, 20%]) of the mean propensity to contribute (23.03%, from Table A.1).

statistically insignificant.

The last two columns from Table 3 explore whether the effects are robust across subgroups of the population. The specification from column (4) is identical to that from column (1) except that it includes two additional variables: the probability that the contributor is female (inferred from data on the joint distribution of first names and gender) and its interaction *Share Own-Party*.[28] The coefficient on this interaction is small and statistically insignificant, suggesting that there are no significant gender differences in conformity effects.[29] Similar to column (4), column (5) includes the interaction between *Share Own-Party* and the probability that the contributor is African-American (inferred from data on the joint distribution of last names and races). The coefficient on this interaction is positive and large (0.328), suggesting that the conformity effects may be more prominent for African-Americans. This could be interpreted as suggestive evidence that African-Americans were more sensitive to social pressure for supporting Obama. However, given that only 12% of the sample is African-American, this difference is not precisely estimated and statistically insignificant (p-value=0.25). Most important, the estimates of the conformity effects are not driven by the subset of African-Americans: the implied coefficient on non-African-Americans (0.648) from column (3) is highly significant and close to the coefficient reported in column (1) for the entire sample (0.682).

3 Measuring the Contribution of Conformity Effects to Geographic Polarization

Geographic polarization (or clustering) in political participation denotes the extent to which active Democrats tend to live close to other active Democrats. The main force behind this polarization is the sorting of individuals into areas with like-minded peers.[30] Additionally, once individuals have been sorted, conformity effects can exacerbate geographic polarization by inducing participation by supporters of the local majority and reducing participation by the local minority. In this section, we quantify the extent to which conformity effects

[28]For example, *Female=0.1* implies that there is a 10% chance that the contributor is female.

[29]However, due to the precision of the estimates, we cannot reject moderate differences. For instance, the 95% confidence interval indicates that the conformity effect for females could be between 73% and 119% of the corresponding effect for males.

[30]This sorting is due to a preference for living next to like-minded individuals combined with a preference for living next to individuals that are similar in other characteristics that are correlated with partisanship. For example, highly educated individuals tend to concentrate geographically, and since more educated individuals are more likely to be Democrats, this sorting on education generates a political sorting. Our paper does not intend to disentangle between these two sources of sorting (for more on this, see Hui, 2013; Cho, Gimpel and Hui, 2013; Gimpel and Hui, 2015).

exacerbate geographic polarization.

3.1 Measuring Geographic Polarization

The histogram from Figure 3 shows the distribution of the share of Democrat contributors (among Democrat and Republican contributors during the 2012 presidential campaign) across ZIP-3s.[31] The average share is 55%. In absence of sorting and conformity effects, we expect the vast majority of ZIP-3s to have a share of Democrat contributors close to 55%. Instead, Figure 3 shows that it is common for ZIP-3s to have a strong majority of Democrat contributors or a strong majority of Republican contributors. This polarization can be very high in some ZIP-3s: e.g., 5% of ZIP-3s have a majority of more than 84% Democrats, and 5% of ZIP-3s have a majority of more than 72% Republicans.

The dispersion of the histogram from Figure 3 is suggestive of geographic polarization. However, part of this dispersion is due to sampling variation: i.e., even if the probability of contributing Democrat was 55% in every in ZIP-3, we should expect that, by chance, the realized proportion of Democrat contributors can be somewhat above or below 55%. The red curve from Figure 3.a shows what the dispersion should have been if it was only due to sampling variation, using predictions from a Binomial model (for more details, see Appendix B). Comparing the red curve to the histogram suggests that sampling variation could only explain a small portion of the dispersion in the histogram.

A simple way of quantifying the dispersion in excess of sampling variation is by fitting a Beta-Binomial model. This model allows for intra-cluster correlation in the probability of contributing Democrat, which can represent a combination of sorting and conformity effects (see Appendix B for more details). The red curve from Figure 3.b corresponds to the prediction of the Beta-Binomial model. Comparing the red curve to the histogram suggests that the Beta-Binomial model fits the data well. With the Beta-Binomial parameters we can estimate the coefficient of intra-cluster correlation. This coefficient can take values from 0 to 1, where a higher value indicates higher geographic polarization.[32] Figure 3.b shows that the estimated intra-cluster correlation coefficient is 0.11 (SE 0.005).[33]

To illustrate the magnitude of this clustering coefficient, Figure 4 provides a comparison with the intra-cluster correlation coefficients for other socio-economic characteristics (also

[31] For the sake of simplicity, in this analysis we take the number of contributors in each ZIP-3 as given. Nevertheless, the results are very similar if we relax this assumption.

[32] A coefficient of 0 would correspond to the extreme case where the probability of contributing Democrat is the same in all ZIP-3s (i.e., the minimum degree of clustering), while a coefficient of 1 would correspond to the extreme case where all ZIP-3s have either a totality of Democrats or Republican contributors (i.e., the maximum degree of clustering).

[33] The results are similar if we use counties instead of ZIP-3s.

obtained by fitting a Beta-Binomial model). As before, *Democrat Contributor* corresponds to the share of Democrat contributors among all contributors in the ZIP-3 (on average, 55%). *Female* corresponds to the proportion of females (on average, 50%). *Age>25* corresponds to the proportion of individuals over 25 years old (on average, 54%). *Income>$30,000* corresponds to the proportion of households with income above $30,000 (on average, 53%). *College Graduate* corresponds to the proportion of College graduates among individuals 25 years old or older (on average, 49%). And *African-American* corresponds to the proportion of African-Americans (on average, 10%).

Figure 4 shows that the intra-cluster correlation is zero for gender, very small for age (0.01), and more significant for income (0.025) and education (0.052). Still, the degree of clustering for *Democrat Contributor* (0.115) is more than four times the degree of polarization in income and two times that of education. Studies of racial segregation suggest that geographic polarization of African-Americans is very high (Cutler, Glaeser and Vigdor, 1999). Consistent with these studies, the intra-cluster correlation coefficient for *African-American* is the highest (0.138). Remarkably, the degree of political polarization is almost as high as the degree of racial polarization.

3.2 A Model for Counterfactual Analysis

3.2.1 Disentangling between Conformity and Sorting

We want to disentangle how much of the coefficient of intra-cluster correlation reported in the previous subsection can be attributed to sorting versus conformity effects. Let $j = 1, ..., J$ denote the geographic areas (e.g., ZIP-3s). Let M_j^D and M_j^R represent the number of sympathizers to the Democratic and Republican Party, respectively (where the total population is $M_j = M_j^D + M_j^R$). A sympathizer of the Democratic party is an individual who, if she was forced to make a choice, would choose the Democratic party over the Republican party. If we observed the distribution of M_j^D, its corresponding coefficient of intra-cluster correlation would measure the contribution of sorting effects to geographic polarization. In practice, individuals are not forced to choose between parties and thus we do not observe the number of sympathizers.

Let p_j^D denote the Bernoulli probability that a Democratic sympathizer from area j makes a campaign contribution, and p_j^R denote the corresponding probability for a Republican sympathizer:

$$\log\left(p_j^D\right) = \gamma \cdot \log\left(\frac{M_j^D}{M_j^R}\right) + \log\left(\tilde{p}_j^D\right) \tag{1}$$

$$\log\left(p_j^R\right) = \gamma \cdot \log\left(\frac{M_j^R}{M_j^D}\right) + \log\left(\tilde{p}_j^R\right) \tag{2}$$

The parameter γ drives the conformity effects: i.e., the elasticity between the probability of making a contribution and the ratio of own-party to opposite-party sympathizers in the reference group. $\tilde{p}_j^D$ and $\tilde{p}_j^R$ are the contribution probabilities in the counterfactual scenario with no conformity effects.

This specification makes two simplifying assumptions. First, since the event-study estimates correspond to a sample of Democrat contributors, we assume that γ is the same for Democrats and Republicans: i.e., $\gamma = \gamma^D = \gamma^R$. This approach will lead to an under-estimation of the importance of conformity effects for polarization if $\gamma^R > \gamma^D$ and an over-estimation if $\gamma^D > \gamma^R$.[34] Second, this specification assumes that individuals are influenced by the composition of sympathizers, $\frac{M_j^D}{M_j^R}$, rather than by the compositions of contributors, $\frac{N_j^D}{N_j^R}$. The latter case would introduce a feedback loop (Manski, 1993) that would exacerbate the conformity effects even further (also known as the social multiplier; Glaeser, Sacerdote and Scheinkman, 1996, 2003). For reference, Appendix C shows one way of extending the model to allow for feedback loops. If anything, our baseline specification without feedback loops can only under-estimate the contribution of conformity effects to geographic polarization.

Note that $p_j^k M_j^k$ is the expected number of contributors to party k in area j (i.e., $E\left[N_j^k\right]$) while $\tilde{p}_j^D M_j^k$ is the equivalent expectation in the counterfactual scenario with no conformity effects. Thus, $\frac{p_j^D M_j^D}{p_j^R M_j^R}$ measure how polarized contributions are expected to be in j, while $\frac{\tilde{p}_j^D M_j^D}{\tilde{p}_j^R M_j^R}$ measures the same polarization in the counterfactual scenario with no conformity effects. Let EP_j be a measure of the excess polarization (in proportional terms) generated by the conformity effects:

$$EP_j = \frac{\frac{p_j^D M_j^D}{p_j^R M_j^R} - \frac{\tilde{p}_j^D M_j^D}{\tilde{p}_j^R M_j^R}}{\frac{\tilde{p}_j^D M_j^D}{\tilde{p}_j^R M_j^R}} = \left(\frac{M_j^D}{M_j^R}\right)^{2\gamma} - 1 \tag{3}$$

Note that EP_j is a function of 2γ instead of γ because conformity effects come in pairs: i.e., they increase the participation rate of the majority party while simultaneously decreasing the participation rate of the minority party. Second, note that the effect of γ depends on $\frac{M_j^D}{M_j^R}$, because conformity effects act by amplifying the polarization in sympathizers. For example, if the sympathizers were exactly even across parties (i.e., $\frac{M_j^D}{M_j^R} = 1$) then there would be no polarization in sympathizers to amplify and the contribution of conformity effects would

[34] For instance, the evidence in Perez-Truglia and Cruces (2014) suggests that Republicans are more sensitive to social pressure, i.e., $\gamma^R > \gamma^D$, which would lead to under-estimation of the importance of conformity effects.

be zero (i.e., $EP_j = 0$) regardless of the value of γ. In an area with 25% Democrats, a conformity effect of $\gamma = 0.11$ would generate an excess polarization of about 27% (i.e., $EP_j = \frac{0.75}{0.25}^{0.22} - 1 = 0.27$).

The overall contribution of conformity effects to polarization can be approximated by the average of EP_j across all j's:

$$EP \equiv \frac{1}{J}\sum_{j=1}^{J} EP_j = \frac{1}{J}\sum_{j=1}^{J}\left(\frac{M_j^D}{M_j^R}\right)^{2\gamma} - 1 \tag{4}$$

This formula shows that the contribution of conformity effects to geographic polarization depends, in addition to γ, on the entire distribution of $\frac{M_j^D}{M_j^R}$, which in turn is driven by the sorting effects. In practice, we do not observe either the actual M_j^D's or the distribution from which they were drawn. Thus, we need to estimate this distribution in order to conduct the counterfactual analysis.

3.2.2 Maximum Likelihood Estimation

For the estimation of the model to be feasible, we need to make a few simplifying assumptions. First, we assume that the distribution of M_j^D is Beta-Binomial. Second, we assume an even distribution of sympathizers in the country as a whole: i.e., $\sum_j M_j^D = \sum_j M_j^R$. This assumption implies that the average probability of the Beta-Binomial distribution must be $\frac{1}{2}$. For this to be true, the two parameters of the Beta-Binomial distribution must be equal. Let θ denote this unique parameter, which implies that the coefficient of intra-cluster correlation is equal to $\frac{1}{1+2\theta}$. Third, let $\tilde{p}_j$ vary freely and assume $\tilde{p}_j^D = \tilde{p}_j$ and $\tilde{p}_j^R = \varphi\tilde{p}_j$. Intuitively, we allow each area j to have its unique average contribution rate as long as the ratio of contribution rates between Democratic and Republican sympathizers is constant.

Take γ as given. Let $y = \left\{M_j, N_j^D, N_j^R\right\}_{j=1}^{J}$ denote the data and let $\Theta = \{\varphi, \theta, \tilde{p}_1, ..., \tilde{p}_J\}$ denote the set of parameters to be estimated. Let $g(k; N, \tilde{p}_j)$ denote the density function of a Binomial distribution with parameter $\tilde{p}_j$, and let $f(k; N, \theta)$ denote the density function of the Beta-Binomial distribution with both parameters equal to θ. The likelihood function is given by:

$$\begin{aligned}\mathcal{L}(y|\Theta) = \prod_{j=1}^{J}\sum_{m=0}^{M_j} g\left(N_j^D; m, \tilde{p}_j\left(\frac{m}{M_j - m}\right)^{\gamma}\right) \times \\ \times\, g\left(N_j^R; M_j - m, \varphi\tilde{p}_j\left(\frac{M_j - m}{m}\right)^{\gamma}\right) f(m; M_j, \theta)\end{aligned} \tag{5}$$

Given a value of γ, we can estimate the parameters in Θ by maximum likelihood and use those estimates to conduct counterfactual analysis. It is straightforward to see where the identification of each parameter comes from. Most important, θ is the degree of sorting that, after being augmented by γ, produces the geographic polarization observed in the data.[35]

3.3 Results

The most straightforward way to estimate the elasticity γ is to estimate the Poisson model with $\log\left(\frac{N_{own}}{N_{opp}}\right)$ as the independent variable.[36] In practice, the correlation coefficient between $\log\left(\frac{N_{own}}{N_{opp}}\right)$ and *Share Own-Party* is 0.99, so this elasticity is approximately a re-scaling of the coefficient on *Share Own-Party* from Table 2. Using the baseline specification from column (1), the estimated elasticity is $\hat{\gamma} = 0.11$: i.e., a 1% increase in $\frac{N_{own}}{N_{opp}}$ increases contributions by 0.11%.

Figure 5 shows the maximum likelihood estimates of $\frac{1}{1+2\hat{\theta}}$ for a range of values of γ from 0 to 0.25. For the particular case $\gamma = 0$, the value of $\frac{1}{1+2\hat{\theta}}$ measures the overall degree of geographic polarization. For $\gamma > 0$, $\frac{1}{1+2\hat{\theta}}$ measures the degree of geographic polarization that would have resulted in absence of conformity effects. Thus, given some $\gamma > 0$, a natural way of measuring the contribution of conformity effects to geographic polarization is by comparing $\frac{1}{1+2\hat{\theta}}$ under $\gamma > 0$ and $\gamma = 0$. According to Figure 5, the intra-cluster correlation coefficients are 0.087 and 0.119 for $\gamma = 0.11$ and $\gamma = 0$, respectively. These estimates imply that 27% of the geographic polarization in contributions can be attributed to conformity effects (i.e., $\frac{0.119-0.087}{0.119}$).[37] The 95% confidence interval for $\hat{\gamma} = 0.11$ goes from 0.05 to 0.18. Reproducing the analysis for those values suggests that conformity effects may explain between 15% and 36% of the geographic polarization in contributions.

Figure 6 provides an alternative illustration of the contribution of conformity effects, using counterfactual simulations. As usual, the x-axis represents the share of Democrat contributors in the 2012 presidential election. The histograms correspond to averages over 1,000 simulations. The solid histogram uses the parameter values estimated under the assumption $\gamma = 0.11$. The hollow histogram uses the same parameter values estimated under $\gamma = 0.11$, except that γ is then set to zero to represent the absence of conformity effects. As

[35] Each $\tilde{p}_j$ is identified mainly by the per capita rate of Democrat contributors in j, while φ is identified mainly by the mean ratio of Republican to Democrat contributors (i.e., the average $\frac{N_j^R}{N_j^D}$ across all j's).

[36] Note that we estimate this equation replacing the unobservable ratio M_j^D/M_j^R by the observable ratio N_j^D/N_j^R. Under the above assumption that $\tilde{p}_j^D = \varphi \tilde{p}_j^R \; \forall j$, then the only bias introduced from this replacement is the attenuation bias due to the sampling variation in N_j^D/N_j^R.

[37] As discussed in the previous subsection, this elasticity may under-estimate the magnitude of conformity effects in the universe of contributors, because non-movers have been living in their environment for much longer than movers. To partially ameliorate this issue we could use instead the estimated elasticity of $\hat{\gamma} = 0.16$ using individuals who moved a year earlier. Combined with Figure 5, it would follow that 32% of the geographic polarization in contributions could be attributed to conformity effects (i.e., $\frac{0.119-0.081}{0.119}$).

expected, the distribution of Democrat contributors is significantly less dispersed under the counterfactual simulations with no conformity effects.

Last, we must note that conformity effects could exacerbate geographic polarization even further through other channels not incorporated in this model. For example, in terms of the social pressure models, Democrats may anticipate that they will be discriminated against in Republican areas, making them more likely to move to more Democratic areas and thus exacerbating the sorting effects.

4 Conclusions

We presented evidence that individuals are influenced by the mainstream political preferences in their group of reference, based on an event-study analysis of residential mobility among campaign contributors. We found evidence of significant conformity effects: increasing by 1% the share of Democrats in the ZIP-3 of residence increases contributions to Obama by 0.11%. We also combined the event-study estimates with a simple model to perform counterfactual analysis. We found that conformity effects are important for understanding geographic polarization, as 27% of polarization can be attributed to conformity effects.

We discussed some mechanisms that could plausibly explain the conformity effects reported in this paper. One avenue for future research could be to disentangle these mediating factors. For instance, according to the social signaling model, a Democrat is less politically active when living in Republican areas to avoid social sanctions, even if personal beliefs about the candidate are unaffected. On the contrary, the social learning model predicts that conformity arises precisely because personal beliefs are shaped by interactions with peers.

A direct way of exploring these additional hypotheses would be to use a similar research design, using beliefs rather than campaign contributions as outcomes. However, to the best of our knowledge, there is not a suitable source of survey data for this purpose. An alternative approach would be to compare the magnitude of social effects across different types of political participation. For instance, the act of turning out to vote does not reveal an individual's partisanship nearly as much as contributing to a candidate does.[38] If social signaling is the main driving force behind the conformity effects, then we expect social context to affect campaign contributions but not voting turnout. On the contrary, if social context affects beliefs about the candidates and policies, then we expect social context to have a significant effect on turnout.

[38] Among other things, campaign contribution records are publicly available and easily accessible, but voting records are not easily accessible and, even if they were accessible, they do not specify the party that the individual voted for.

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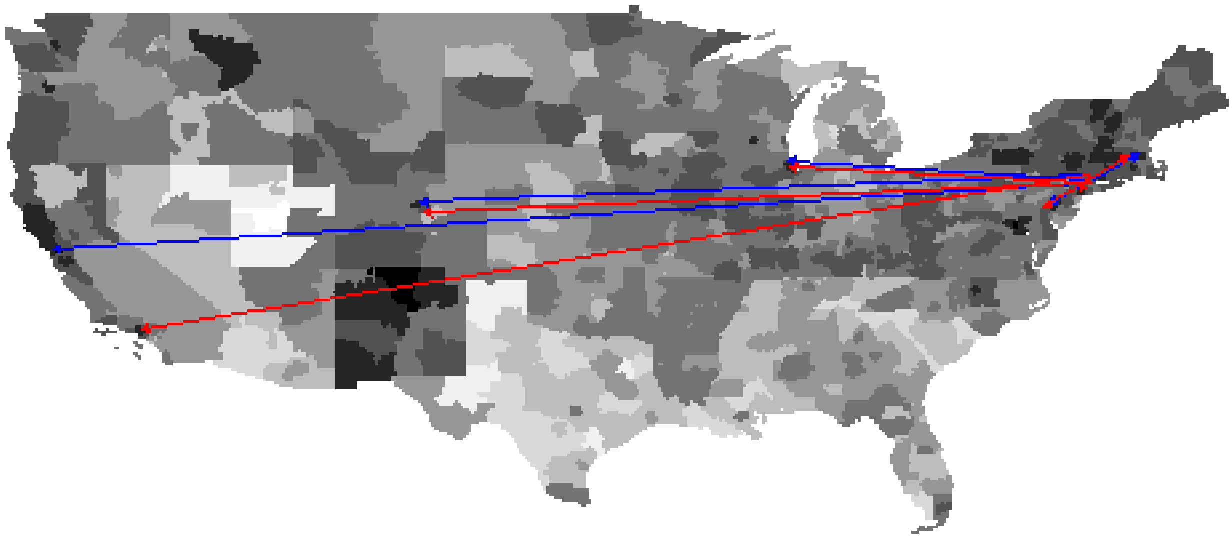
Figure 1: Partisan Affiliation across 3-digit ZIP codes

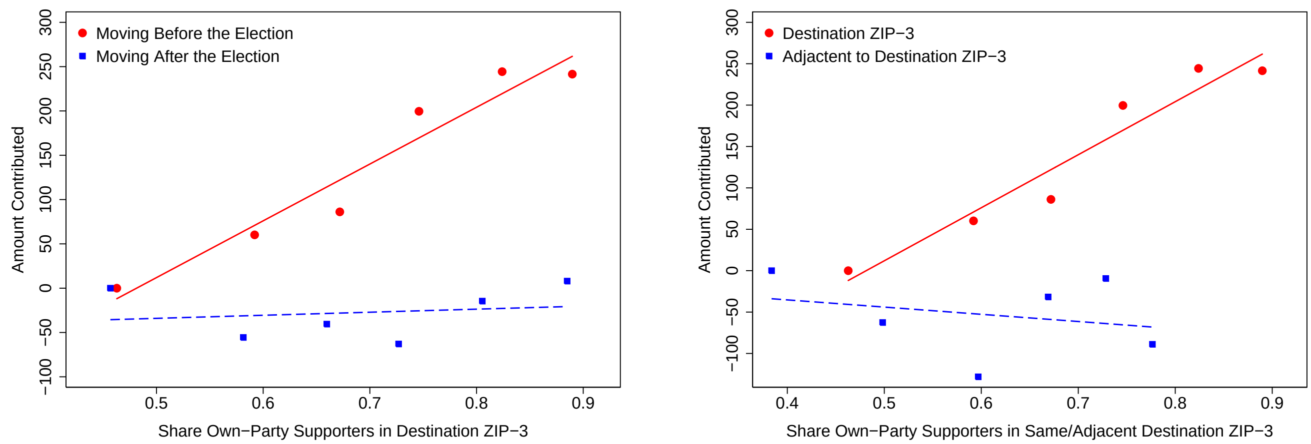


Notes: Map of 3-digit ZIP codes in the contiguous U.S. states. The color of each ZIP-3 denotes its political composition in terms of the share of Democrat contributors among all the contributors to presidential campaigns, with a darker shade denoting a higher concentration of Democrat contributors (using data from the 2000, 2004 and 2008 presidential campaigns). The arrows correspond to an arbitrary sample of contributors who made contributions during the 2008 election cycle to the Obama campaign and changed residence after the end of the 2008 election cycle. All these contributors were living in the same ZIP-3 and made contributions of similar amounts. Each arrow starts in the origin area of residence and points towards the destination area of residence. The red arrows denote individuals moving before the beginning of the 2012 presidential campaign (i.e., contributors who moved between January 2009 and December 2010). The blue arrows denote individuals moving after the end of the 2012 presidential campaign (i.e., contributors who moved between January 2013 and December 2014). Data on contributions from the administrative records of the Federal Election Commission.

Figure 2: Relationship Between Contributions and Political Composition in the Area of Residence

a. Event-study falsification test

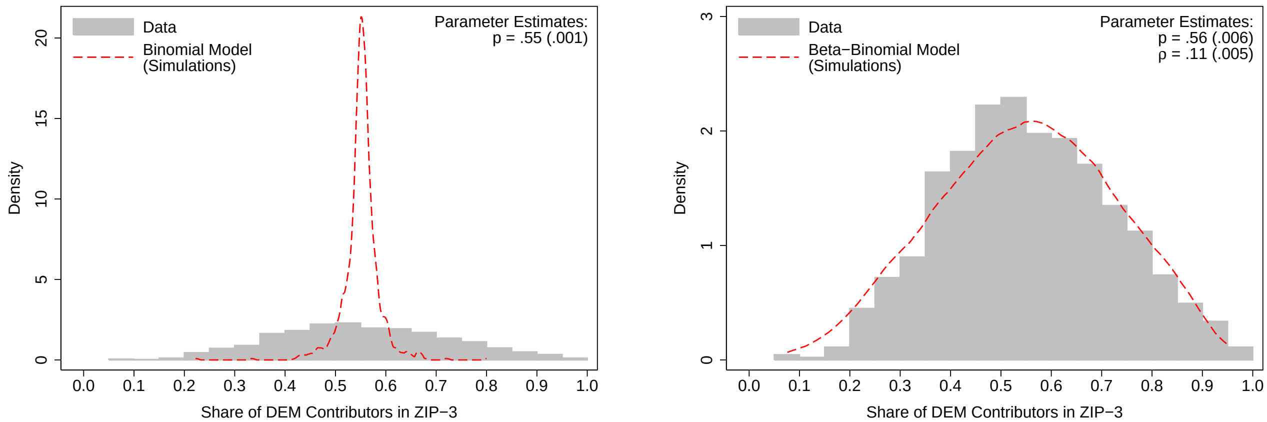
b. Measuring the geographic scope of effects



Notes: Data on 45,438 individuals who contributed to the Obama presidential campaign during the 2008 election cycle and changed residence between January 2009 and December 2010 or between January 2013 and December 2014. All results are from the same Tobit regression, which includes 1,666 group fixed effects, where each group is defined by individuals who contributed a similar amount to the 2008 Obama campaign (i.e., in the same $100-interval) while living in a ZIP-3 with the same political composition (i.e., in the same 0.01-interval). The y-axis corresponds to the amount contributed to Obama during the 2012 presidential campaign (i.e., between January 2011 and December 2012). The x-axis is the share of Democrat contributors among all the contributors to presidential campaigns (using data from the 2000, 2004 and 2008 presidential campaigns). The red dots and blue squares correspond to point estimates from the same regression (and each line corresponds to a linear fit). The red dots correspond to a regression of the amount contributed during the 2012 cycle on the tertiles dummies of the political composition in the ZIP-3 where the individual is living during the 2012 election cycle (for individuals who moved between January 2009 and December 2010). The leftmost dot corresponds to the omitted category, so its coefficient is normalized to zero. In panel (a), the blue squares correspond to the equivalent regressions where the independent variable corresponds to the political composition in the ZIP-3 where each individual is going to move after the end of the 2012 election cycle (for individuals who moved between January 2013 and December 2014). In panel (b), the blue squares correspond to a regression where the independent variable correspond to the political composition in the ring of ZIP-3's that are adjacent to the ZIP-3 where the individual lived during the 2012 cycle (for individuals who moved between January 2009 and December 2010). The regression controls for individual characteristics (amount contributed in 2008, political composition in ZIP-3 during 2008, a dummy variable for whether the individual moved before or after the 2012 cycle, gender and race), and characteristics of the destination ZIP-3 (density, mean gross income, mean age and shares of White, African-American, Hispanic, college graduates and unemployed) interacted with a dummy variable for whether the individual moved before or after the 2012 cycle.

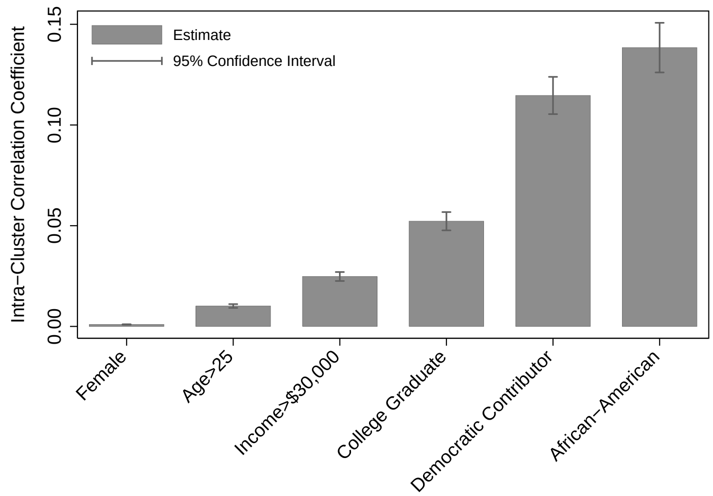
Figure 3: Measuring Geographic Polarization in Campaign Contributions

a. Binomial Model   **b.** Beta-Binomial Model



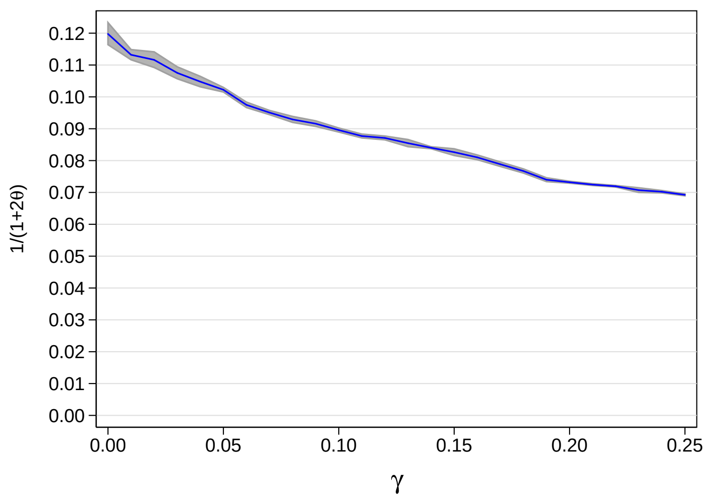
Notes: $N = 890$. The unit of observation is the ZIP-3. The x-axis represents the share of Democrat contributors among all the contributors to presidential campaigns during the 2012 election cycle. The histograms show the actual contribution levels. The red curve corresponds to the Kernel density estimates of the contributions simulated with: the Binomial model in panel a., and the Beta-Binomial model in panel b. In both models the parameter p denotes the probability that a contributor is Democrat. In the Beta-Binomial model, the parameter ρ corresponds to the intra-cluster correlation coefficient. Data on contributions from the administrative records of the Federal Election Commission.

Figure 4: Comparing Political Polarization to Polarization in Other Characteristics



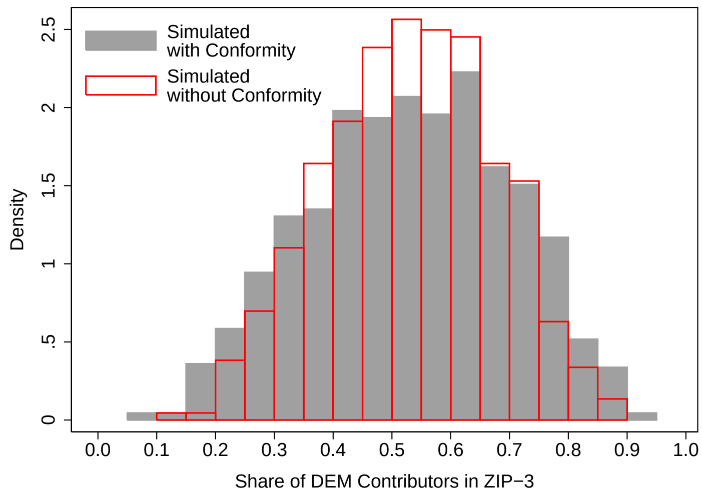
Notes: $N = 890$. The unit of observation is the ZIP-3. For each characteristic listed in the x-axis, the Geographic Polarization Index is estimated by fitting a Beta-Binomial model with parameters $\{\alpha, \beta\}$ through maximum likelihood, and then using those estimates to compute the coefficient of intra-cluster correlation: $\rho = \frac{1}{1+\alpha+\beta}$. Confidence intervals were computed using the Delta Method. *Democrat Contributors*, correspond to the proportion of Democrat contributors among all contributors in the ZIP-3 (on average, 55%). *Female* corresponds to the proportion of females in the ZIP-3 (on average, 50%). *Age>25* corresponds to the proportion of individuals over 25 years old in the ZIP-3 (on average, 54%). *Income>$30,000* corresponds to the proportion of households with income above $30,000 in the ZIP-3 (on average, 53%). *College Graduates* corresponds to the proportion of individuals with College degree among individuals 25 years old or older in the ZIP-3 (on average, 49%). *African-American* corresponds to the proportion of African-American individuals in the ZIP-3 (on average, 10%). Data on contributions from the administrative records of the Federal Election Commission. Data on gender, age, income, education and race from the 2012 American Community Survey.

Figure 5: Contribution of Conformity Effects to Geographic Polarization: Maximum Likelihood Estimates, $\gamma \in [0, 0.25]$



Notes: For each possible value of $\gamma \in [0, 0.25]$ (x-axis), the y-axis shows the intra-cluster correlation coefficient ($\frac{1}{1+2\hat{\theta}}$) for the distribution of Democrat sympathizers, where $\hat{\theta}$ correspond to the maximum likelihood estimates described in section 3.2.2. The blue line corresponds to the point estimate, and the shaded area corresponds to the respective 95% confidence interval.

Figure 6: Contribution of Conformity Effects to Geographic Polarization: Counterfactual Simulations, $\gamma = 0.11$



Notes: Histograms of the share of Democrat contributors among all the contributors to presidential campaigns during the 2012 election cycle: i.e., $\frac{N_j^D}{N_j^D+N_j^R}$. Each observation corresponds to a ZIP-3 share over 1,000 simulations. *Simulated with Conformity* corresponds to simulations using the maximum likelihood estimates obtained under $\gamma = 0.11$ (see section 3.2.2). *Simulated without Conformity* corresponds to the simulations using the same maximum likelihood estimates obtained under $\gamma = 0.11$, but setting $\gamma = 0$ after estimation to represent the absence of conformity effects.

Table 1: Descriptive Statistics for the Main Dependent and Independent Variables

	Average	Std. Dev.	Minimum	Maximum
2008 Election Cycle				
P(Amount>$200)	100.00	0.00	100.00	100.00
Amount ($), if >$200	651.07	711.30	200.01	5,000.00
Share Own-Party (Origin)	0.70	0.14	0.18	0.97
2012 Election Cycle				
P(Amount>$200)	26.77	44.28	0.00	100.00
Amount ($), if >$200	860.79	919.94	200.01	5,000.00
Share Own-Party (Destination)	0.69	0.15	0.18	0.97

Notes: Data on 45,438 individuals who contributed to the Obama presidential campaign during the 2008 election cycle and - according to data from USPS National Change of Address - changed residence between January 2009 and December 2010 or between January 2013 and December 2014. *P(Amount>$200)* takes the value 100 if the individual made a contribution over $200 to the Obama presidential committee during the 2012 election (i.e., between January 2011 and December 2012). *Amount ($), if >$200* corresponds to the amount contributed for those individuals who contributed over $200. *Share Own-Party* is the share of Democrat contributors among all the contributors to presidential campaigns in the origin/destination ZIP-3 (using data from the 2000, 2004 and 2008 presidential campaigns).

Table 2: Measuring Conformity Effects: Main Results

	Amount (semi-elasticity)			Amount ($)	P(A.>$200)
	(1)	(2)	(3)	(4)	(5)
Share Own-Party in ZIP-3					
Moving After Election$^{(i)}$	0.000	-0.003	0.003	1.754	2.648
	(0.172)	(0.172)	(0.172)	(139.691)	(2.844)
Moved Before Election$^{(ii)}$	0.682***	0.759***		484.941***	6.236***
	(0.186)	(0.225)		(147.665)	(2.377)
Two Years Before$^{(iii)}$			0.786***		
			(0.190)		
One Year Before$^{(iv)}$			0.577***		
			(0.186)		
Share Own-Party in Adjacent ZIP-3s					
Moved Before Election$^{(v)}$		-0.143			
		(0.232)			
P-value (i)=(ii)	0.007	0.007		0.019	0.342
P-value (iii)=(iv)			0.002		
P-value (ii)=(v)		0.025			
Model	Poisson	Poisson	Poisson	Tobit	OLS

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors in parenthesis. Data on 45,438 individuals who contributed to the Obama presidential campaign during the 2008 election cycle and changed residence between January 2009 and December 2010 or between January 2013 and December 2014. Each column corresponds to a different regression. All regressions include 1,666 group fixed effects, where each group is defined by individuals who contributed a similar amount to the 2008 Obama campaign (i.e., in the same $100-interval) while living in a ZIP-3 with the same political composition (i.e., in the same 0.01-interval). *Amount (elasticity)* corresponds to the amount contributed to the 2012 Obama presidential campaign (between January 2011 and December 2012), using a Poisson regression model (more precisely, the outcome variable is zero for individuals with no reported contributions and for individuals with reported contributions the outcomes is the amount contributed in excess of $200). *P(A.>$200)* takes the value 100 if the individual made a contribution over $200 to the Obama presidential committee during the 2012 election and 0 otherwise. *Amount Contributed ($)* corresponds to the amount contributed using a Tobit model to take into account that this outcome is lower-censored at $200. *Share Own* is the share of Democrat contributors among all the contributors to presidential campaigns in the destination ZIP-3 (using data from the 2000, 2004 and 2008 presidential campaigns). *Moved Before* is the coefficient for individuals who moved before the start of the 2012 election, so that the *Share Own* corresponds to the political composition in the ZIP-3 where the individual is living during the 2012 election. *Moved After* is the coefficient for individuals who moved after the end of the 2012 election, so that the *Share Own* corresponds to the political composition in the ZIP-3 where the individual is going to live after the 2012 election (i.e., where the individual is not yet living during the 2012 election). *One Year Before* (*Two Years Before*) corresponds to individuals moving in 2010 (2009). *Share Own, Adjacent ZIP-3* is similar to *Share Own*, except that the political composition corresponds to the "ring" of ZIP-3s that are adjacent to the destination ZIP-3. All regressions control for individual characteristics (amount contributed in 2008, political composition in ZIP-3 during 2008, a dummy variable for whether the individual moved before or after the 2012 cycle, gender and race), and characteristics of the destination ZIP-3 (density, mean gross income, mean age and shares of White, African-American, Hispanic, college graduates and unemployed) interacted with a dummy variable for whether the individual moved before or after the 2012 cycle.

Table 3: Measuring Conformity Effects: Additional Robustness Checks

	Amount Cont. (semi-elasticity)				
	(1)	(2)	(3)	(4)	(5)
Share Own-Party					
Moving After Election$^{(i)}$	0.000	0.039	0.181	0.000	-0.007
	(0.172)	(0.161)	(0.192)	(0.172)	(0.173)
Moved Before Election$^{(ii)}$	0.682***	0.714***	0.788***	0.694***	0.648***
	(0.186)	(0.167)	(0.205)	(0.189)	(0.186)
Int. with Female				-0.025	
				(0.085)	
Int. with African-American					0.328
					(0.290)
P-value (i)=(ii)	0.007	0.003	0.040	0.007	0.010
Ref. Group Geography	ZIP-3	County	County	ZIP-3	ZIP-3
Ref. Group Data	Cont.	Cont.	Voting	Cont.	Cont.

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors in parenthesis. Data on 45,438 individuals who contributed to the Obama presidential campaign during the 2008 election cycle and changed residence between January 2009 and December 2010 or between January 2013 and December 2014. Each column corresponds to a different regression. *Amount (elasticity)* corresponds to the amount contributed to the 2012 Obama presidential campaign (between January 2011 and December 2012), using a Poisson regression model (more precisely, the outcome variable is zero for individuals with no reported contributions and for individuals with reported contributions the outcomes is the amount contributed in excess of $200). *Share Own* is the share of Democrat contributors among all the contributors to presidential campaigns in the destination ZIP-3 (using data from the 2000, 2004 and 2008 presidential campaigns). *Moved Before* is the coefficient for individuals who moved before the start of the 2012 election (i.e., between January 2009 and December 2010), so that the *Share Own* corresponds to the political composition in the ZIP-3 where the individual is living during the 2012 election. *Moved After* is the coefficient for individuals who moved after the end of the 2012 election (i.e., between January 2013 and December 2014), so that the *Share Own* corresponds to the political composition in the ZIP-3 where the individual is going to live after the 2012 election (i.e., where the individual is not yet living during the 2012 election). *One Year Before* (*Two Years Before*) corresponds to individuals moving in 2010 (2009). Column (1) reproduces the results from Column (1) in Table 2: for more details about the regression, such as control variables, see note to Table 2. Column (2) deviates from column (1) in that *Share Own-Party* is defined at the county level rather than at the ZIP-3 level. Column (3) deviates from column (1) in that *Share Own-Party* is defined at the county level using voting results during the 2008 presidential election, rather than at the ZIP-3 level using contribution data. Column (4) is identical to column (1) except that it includes two additional variables: the probability that the contributor is female (inferred from data on the joint distribution of first names and gender) and its interaction with *Share Own-Party, Moved Before Election*. Similarly, column (4) is identical to column (1) except that it includes two additional variables: the probability that the contributor is African-American (inferred from data on the joint distribution of last names and races) and its interaction with *Share Own-Party, Moved Before Election*.

Online Appendix: Not For Publication

A Descriptive Statistics about the Sample of Movers

Table A.1 provides descriptive statistics for the sample of movers. Even though the FEC records do not specify the gender and race of the contributors, we can infer that information in a probabilistic sense using complementary data on the distribution of first and last names by gender and race. The last column from Table A.1 show the average characteristics for the entire sample: 48.6% are female, 78% are White, 12.1% are African-American, 4% are Hispanic and the average share of Democrat contributors in the ZIP-3 of residence is 70%.

The first two columns of Table A.1 provide a break-down of the descriptive statistics by the date of residential move. The research design is based on comparing a correlation coefficient (between the amount contributed and the political composition in the ZIP-3) across two groups of individuals: individuals moving after the end of the 2012 cycle, and individuals moving before the beginning of the 2012 cycle. Since we are comparing a correlation coefficient (instead of the average outcome), for the comparison to be valid we do not need these two groups of individuals to be identical. In any case, given that these two groups differ in just the timing of the residential moves, we would still expect small or no differences in characteristics across groups. As expected, the differences in gender, race and political composition of the area of residence are very small: even though some of the pairwise differences are statistically significant, they are always economically small.

Last, Table A.1 also provides a comparison of contribution patterns by date of residential move. The differences are very small with respect to the average amounts contributed during the 2008 and 2012 cycles. This implies that the effects on the amounts contributed can be compared directly across individuals who moved before and after the 2012 cycle. The only important difference is that a higher share of individuals who moved after the end of the 2012 election cycle contributed during 2012. This difference is natural, given that the individuals who moved recently (relative to individuals who had not moved in years) have better information on local opportunities to give and are more likely to be solicited for donations. This difference means that, when looking at the effects on the extensive margin, we need to keep these differences in baseline rates in mind.[i]

[i] Even though the Poisson model also captures effects on the extensive margin, it already takes into account these differences in baseline rates because the coefficients measure semi-elasticities.

Table A.1: Descriptive Statistics by Date of Residential Move

	Moved Before 2012 Election	Moving After 2012 Election	All
Demographic Characteristics			
Percent Female	47.56	50.11	48.60
	(0.28)	(0.34)	(0.22)
Percent White	77.54	78.73	78.03
	(0.14)	(0.15)	(0.10)
Percent African-American	12.19	12.08	12.14
	(0.09)	(0.10)	(0.07)
Percent Hispanic	4.13	3.86	4.02
	(0.08)	(0.09)	(0.06)
Share Own-Party (Origin)	0.70	0.69	0.70
	(0.00)	(0.00)	(0.00)
Share Own-Party (Destination)	0.69	0.68	0.69
	(0.00)	(0.00)	(0.00)
2008 Election Cycle			
Percent Contributed >$200	100.00	100.00	100.00
	(0.00)	(0.00)	(0.00)
Mean Amount ($), if >$200	640.24	666.67	651.07
	(4.28)	(5.31)	(3.34)
2012 Election Cycle			
Percent Contributed >$200	23.03	32.16	26.77
	(0.26)	(0.34)	(0.21)
Mean Amount ($), if >$200	870.35	850.92	860.79
	(11.82)	(11.77)	(8.34)
Observations	26,823	18,615	45,438

Notes: Data on 45,438 individuals who contributed to the Obama presidential campaign during the 2008 election cycle and - according to data from USPS National Change of Address - changed residence between January 2009 and December 2010 or between January 2013 and December 2014. *Moved Before 2012 Election* denotes individuals who moved before the start of the 2012 election (i.e., between January 2009 and December 2010). *Moving After 2012 Election* denotes individuals who moved after the end of the 2012 election (i.e., between January 2013 and December 2014). *Percent Female* computed using data on the joint distribution of first names and gender, and *Percent White*, *Percent African-American* and *Percent Hispanic* inferred from data on the joint distribution of last names and races. *Percent Contributed* is the share that contributed over $200. *Mean Amount ($), if >$200* corresponds to the mean amount contributed for those individuals who contributed over $200. *Share Own-Party* is the share of Democrat contributors among all the contributors to presidential campaigns in the origin/destination ZIP-3 (using data from the 2000, 2004 and 2008 presidential campaigns).

B Measuring Geographic Polarization with the Intra-Cluster Correlation Coefficient

This appendix provides a more technical presentation of the coefficient of intra-cluster correlation.

Let $j = 1, ..., J$ denote the geographic areas. We are interested in measuring the partisan composition of contributors: i.e., the share of Democrat contributors among the total contributors to the Democratic and Republican party. Take as given the number of contributors in area j, N_j, corresponding to the sum of Democrat and Republican contributors: i.e., $N_j = N_j^D + N_j^R$. Given N_j, the probability that one of those contributors contributed to the Democratic (Republican) party is denoted p_j $(1 - p_j)$.[ii]

If the Bernoulli events were independent within areas, i.e., $p_j = p \; \forall j$, then N_j^D would be distributed Binomial(N_j, p). In this case, some areas still would be expected to have a higher share of Democrat contributors than other areas - this variation will correspond purely to sampling variation and will converge to zero as N_j, the number of contributors, becomes large. In the case of campaign contributions, N_j is quite large (median of 500), so this source of variation is expected to be small. The Binomial model precludes the possibility that the probabilities are correlated within ZIP-3's. For example, such intra-cluster correlation can arise due to sorting effects (i.e., Democrats moving close to other Democrats) and conformity effects (i.e., local majorities pressuring the local minority not to contribute). On the contrary, the Beta-Binomial model allows for the Bernoulli events to be correlated between pairs of individuals in the same area. According to this model, $p_j \sim Beta(\alpha, \beta)$. The Beta-Binomial model implies that the average probability of the Bernoulli event is $p = \frac{\alpha}{\alpha+\beta}$ with an intra-cluster correlation coefficient of $\rho = \frac{1}{1+\alpha+\beta}$.

We estimated the Binomial and Beta-Binomial models through maximum likelihood using data from the FEC records on contributions during the 2012 presidential election cycle. Figure 3 uses the estimated parameter values to provide a graphical illustration of how each model fits the data. Figure 3.a shows the simulations from the Binomial model while Figure 3.b shows the simulations from the Beta-Binomial model. In both cases, the histogram shows the actual distribution of the share of Democrat contributors (i.e., $\frac{N_j^D}{N_j^D+N_j^R}$) across ZIP-3's. The curves show kernel density estimators. The blue curve corresponds to the distribution of the actual contribution data, while the red curve corresponds to the contributions simulated with the Binomial (panel a.) and Beta-Binomial (panel b.) models.

Figure 3.a shows that the Binomial model is extremely inaccurate. The Binomial model implies that 90% of the ZIP-3's should have between 50% and 60% Democrat contributors. Instead, the

[ii]For the sake of simplicity, we assume that p_j is independent of N_j. If that assumption was relaxed, at least one extra parameter would be added to the model. However, as shown below, the data fits reasonably well without the need for this extra parameter.

actual data is significantly more dispersed, with 90% of the ZIP-3's having between 28% and 84% Democrat contributors. Figure 3.b shows that, once we take the intra-ZIP-3 correlation in contributions into account, the model fits the data very well. Since the Binomial model is nested within the Beta-Binomial model, we can conduct an LR test between these two models. The LR statistic of 126,603 strongly rejects the null hypothesis that the model is Binomial rather than Beta-Binomial.

The degree of polarization is best interpreted as a property of the underlying beta distribution. The variance of p_j is given by $\frac{\alpha}{\alpha+\beta}\frac{\beta}{\alpha+\beta}\frac{1}{1+\alpha+\beta}$. Since we are interested in comparing the degree of geographic polarization across outcomes that may differ in the mean probability p, we need a normalized measure of dispersion. For a given mean probability $p = \frac{\alpha}{\alpha+\beta}$, the maximum variance that can be attained is $p\,(1-p) = \frac{\alpha}{\alpha+\beta}\frac{\beta}{\alpha+\beta}$. Thus, we can define a normalized version of the dispersion in p_j by dividing the variance in p_j over the maximum possible variance.[iii] This definition results in the coefficient of intra-cluster correlation, $\rho = \frac{1}{1+\alpha+\beta}$. A coefficient of zero would correspond to the extreme case where the proportion of Democrats is exactly the same across all j's. A coefficient of one would correspond to the extreme case where either everyone in j is Democrat or everyone is Republican.

[iii] One important property is that this measure of dispersion will be the same no matter whether we look at the dispersion of p_j or $1 - p_j$. This important property would not satisfied, for example, if we defined the measure of dispersion as the coefficient of variance.

C Introducing Feedback Loops in the Model

In the baseline model, an individual could be influenced by the composition of sympathizers, $\frac{M_j^D}{M_j^R}$. In this appendix, we extend the model so that individuals can be influenced by the compositions of supporters, $\frac{N_j^D}{N_j^R}$. In order to allow for this feedback loop, we can use recursive definitions of p_j^D and p_j^R:

$$\log\left(p_j^D\right) = \gamma \cdot \log\left(\frac{p_j^D M_j^D}{p_j^R M_j^R}\right) + \log\left(\tilde{p}_j\right) \tag{6}$$

$$\log\left(p_j^R\right) = \gamma \cdot \log\left(\frac{p_j^R M_j^R}{p_j^D M_j^D}\right) + \log\left(\varphi\tilde{p}_j\right) \tag{7}$$

Intuitively, $\frac{E\left[N_j^D\right]}{E\left[N_j^R\right]} = \frac{p_j^D M_j^D}{p_j^R M_j^R}$ replaces $\frac{M_j^D}{M_j^R}$ in the baseline specification from equations (6) and (7). After some algebra we get:

$$\log\left(p_j^D\right) = \frac{\gamma}{1-2\gamma}\log\left(\frac{M_j^D}{M_j^R}\right) + \log\left(\varphi^{-\frac{\gamma}{1-2\gamma}}\right) + \log\left(\tilde{p}_j\right) \tag{8}$$

$$\log\left(p_j^R\right) = \frac{\gamma}{1-2\gamma}\log\left(\frac{M_j^R}{M_j^D}\right) + \frac{\gamma}{1-2\gamma}\log\left(\varphi\right) + \log\left(\varphi\tilde{p}_j\right) \tag{9}$$

Comparing (1) and (2) to (8) and (9), the main difference has to do with the terms multiplying $\log\left(\frac{M_j^D}{M_j^R}\right)$ and $\log\left(\frac{M_j^R}{M_j^D}\right)$: while it was γ in the baseline model, in this new specification it is replaced by $\frac{\gamma}{1-2\gamma}$.[iv] Given $\gamma < \frac{1}{2}$, it follows that $\frac{\gamma}{1-2\gamma} > \gamma$. Thus, for a given γ, conformity effects will have a greater effect on polarization in this new specification relative to the baseline specification. The difference between $\frac{\gamma}{1-2\gamma}$ and γ corresponds to the social multiplier. This multiplier is more significant the higher γ: e.g., if $\gamma = 0.05$ then $\frac{\gamma}{1-2\gamma}$ is just 11% higher than γ, but if $\gamma = 0.10$ then $\frac{\gamma}{1-2\gamma}$ is 25% higher than γ.

Finally, we can use (8) and (9) to obtain the new likelihood function:

$$\begin{aligned}\mathcal{L}\left(y|\Theta\right) = \prod_{j=1}^{J}\sum_{m=0}^{M_j} g\left(N_j^D; m, \varphi^{-\frac{\gamma}{1-2\gamma}}\tilde{p}_j\left(\frac{m}{M_j - m}\right)^{\frac{\gamma}{1-2\gamma}}\right) \times \\ \times\, g\left(N_j^R; M_j - m, \varphi^{\frac{1-\gamma}{1-2\gamma}}\tilde{p}_j\left(\frac{M_j - m}{m}\right)^{\frac{\gamma}{1-2\gamma}}\right) f\left(m; M_j, \theta\right)\end{aligned} \tag{10}$$

[iv]The other difference is given by the extra terms $-\frac{\gamma}{1-2\gamma}\log\left(\varphi\right)$ and $\frac{\gamma}{1-2\gamma}\log\left(\varphi\right)$. These terms simply represent that the social multiplier augments the party differences that arise through φ. These terms affect the average participation rates, but do not have a first order effect on geographic polarization.