POLITICAL CONFORMITY: EVENT-STUDY EVIDENCE FROM THE UNITED STATES

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Abstract—We propose that individuals are more politically active in more like-minded social environments. To test this hypothesis, we combine administrative data from the Federal Election Commission and the U.S. Postal Service. We identify 45,000 individuals who contributed to Barack Obama's 2008 presidential campaign and changed residences either before or after the 2012 election cycle. We examine whether living in an area with a higher share of Democrats causes higher contributions to Obama. We find that conformity effects are economically significant. Additionally, we conduct counterfactual analysis that shows that these effects are important for understanding geographic polarization.

I. Introduction

POLITICAL participation can be influenced by the political preferences and political participation of peers. Some mechanisms may encourage individuals to participate when they live in areas with other like-minded individuals, a phenomenon that we dub political conformity. For example, a Democrat with a majority of Democratic friends may gain social rewards by publicly endorsing a Democratic candidate (Bernheim, 1994; Perez-Truglia & Cruces, 2017).[1] However, other mechanisms may work in the opposite direction. For instance, having more Democratic friends may introduce the temptation to free-ride on their participation.

Whether peer effects are 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 likely to live in more Democratic areas. This paper measures political conformity using an event-study analysis of residential mobility. Moreover, we quantify the contribution of conformity to geographic polarization.

In the first part of the paper, we estimate the magnitude of conformity effects in the context of campaign contributions. An ideal approach would be to take a sample of contributors and randomize their places of residence. Under the hypothesis of conformity effects, individuals should contribute more when they are randomly assigned to live in areas with a high share of like-minded social contacts, such as neighbors, friends, and coworkers. This ideal experiment is infeasible, so we exploited a quasi-experimental design based on the same principle.

We combined data on itemized contributions from the Federal Election Commission with data on residential mobility from the National Change of Address database of the U.S. Postal Service. We identified around 45,000 individuals who contributed to Barack Obama's 2008 presidential campaign and changed residences between the end of the 2008 election cycle and the beginning of the 2012 election cycle or after the end of the 2012 election cycle. These individuals had another opportunity to contribute to Obama during the 2012 reelection campaign.[2]

Consider a pair of individuals who were observationally identical in the 2008 election: they contributed similar amounts to Obama in 2008 while living in similar areas. Between the end of the 2008 election and the start of the 2012 election, these two individuals moved to areas with different shares of Democrats. According to the political conformity hypothesis, relative to the individual moving to the less Democratic area, the individual who moved to the more Democratic area should make higher contributions to Obama during the 2012 election because of the exposure to a more like-minded environment. We present 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 that person was more strongly affiliated with the Democratic Party in 2008 or because that person's 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]

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[1] Among other examples, this Democrat also may feel more excited about the Democratic candidate as a result of exposure to the opinions about the candidate of Democratic peers (Mutz & Mondak, 2006; Glaeser & Sunstein, 2009).

[2] This methodology allowed us to identify individuals who made contributions only to the 2008 election cycle and not the 2012 election cycle. To the best of our knowledge, this is the first paper to exploit the NCOA data for an event-study analysis of residential mobility, a methodology that can be applied in many other contexts.

[3] Other papers have used residential mobility as a source of quasi-experimental variation—for example, Chetty and Hendren (2017) for measuring the effect of neighborhoods on income mobility. Our research design also is 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).

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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 does not predict that the individual moving to the more Democratic area should contribute more during 2012 than 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 that person should contribute more in 2012 than the individual moving to the less Democratic area. We show that contributions in 2012 were not correlated to the share of Democrats in the area to which the contributor moved after the 2012 election. This evidence supports the presumed direction of causality, according to which living in more Democratic areas causes individuals to contribute more to Obama.

Our evidence suggests that conformity effects are economically significant. Increasing the share of Democrats in the three-digit postal code (ZIP-3) where an individual lives by 1 percentage point increases the amount contributed to Obama by 0.67% (p-value < 0.01). This finding is robust to several alternative specifications, such as looking at the extensive versus intensive margins, using different regression specifications and control variables, and using counties instead of ZIP-3s to define reference groups.

Several mechanisms may explain these conformity effects. Our favorite interpretation relies on social interaction models, such as social pressure, social learning, and social norms. We present two pieces of suggestive evidence. First, social interaction models predict that peer effects should decrease with social distance. Consistent with this prediction, we find that the share of Democrats in the contributor's ZIP-3 affects that person's contributions but that the share of Democrats in a more distant reference group, the adjacent ZIP-3s, does not affect that person's contributions. Second, social interaction models predict that the magnitude of peer effects should increase with the time that individuals spend in a new peer group. Consistent with this prediction, increasing the exposure time from 0 to 24 months increases the magnitude of conformity effects by 59%.

In the second part of the paper, we show that these conformity effects can have important implications for geographic polarization. In a nutshell, geographic polarization denotes the extent to which Democratic contributors tend to be located near other Democratic contributors. This polarization arises in part because Democrats tend to move to like-minded areas (Bishop, 2008). Conditional on how potential contributors are sorted, conformity effects increase the participation from supporters of the local majority and reduce participation from the local minority, thus resulting in higher polarization. We estimated a simple maximum likelihood model that can be combined with our event-study estimates for counterfactual analysis. We show that a significant portion (27%) of geographic polarization in contributions during the 2012 election can be attributed to conformity effects.

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 partisanship, such as talking about politics, sharing political comments on social networks, attending political rallies, and maybe even registering to vote.

This paper is related to a literature on social effects in political participation (Campbell et al., 1960; Huckfeldt, 1979; Weatherford, 1982). Recent literature has focused on the role of social incentives in the decision to turn out to vote (Knack, 1992; Riker & Ordeshook, 1968; Gerber, Green, & Larimer, 2008; Funk, 2010; Dellavigna et al., 2017). In a seminal contribution, Gerber et al. (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 (Ali & Lin, 2013). Indeed, a similar motive is believed to drive other forms of pro-social behavior, such as charitable giving (Bénabou & 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 et al. (2008) and others are not expected to cause political conformity.

This study is also related to Perez-Truglia and Cruces (2017), who provide evidence from a field experiment about how individuals interact with supporters of the same and opposite parties. They show evidence about the mechanism through which peers may influence partisanship. In particular, they show that increasing the visibility of contributions among social contacts leads to political conformity by increasing contributions to the local majority party and decreasing contributions to the local minority, which the authors interpret as evidence of partisan social pressure. This interpretation also is consistent with evidence that individuals report to be more sympathetic to supporters of their own party, relative to supporters of their opposite party (Iyengar, Sood & Lelkes, 2012; Iyengar & Westwood, 2015). Our paper contributes in at least two ways. More important, we quantify the extent to which social context is conducive to political conformity. Also, we show that the magnitude of social effects is significant in a naturally occurring context.

Finally, the growing concern about polarization has sparked a debate about its possible causes (McCarty, Poole, & Rosenthal, 2006), including the analysis of geographic polarization. For instance, Cho (2003) and Gimpel, Lee, and Kaminski (2006) study the spatial autocorrelation in campaign contributions. We contribute to this debate by showing that social context effects can be important for understanding geographic polarization.

The paper is organized as follows. Section II presents the data. Section III discusses the estimates of conformity effects from the event-analysis. Section IV discusses the contribution of conformity effects to geographic polarization by means of a counterfactual analysis. Section V concludes.

II. Data Sources and Identification Strategy

A. Data Sources

We use data from the Federal Election Commission (FEC) contribution records, which includes all contributions by individuals who gave more than $200 to a campaign committee in a given election cycle. We start with the sample of all individuals who contributed more than $200 to the Obama campaign during the 2008 election cycle (between January 2007 and December 2008).[4] These individuals had to decide whether to contribute to Obama again during the reelection campaign of 2012. One important advantage of focusing on a presidential campaign is that the candidates are the same regardless of the contributor's area of residence, and thus we do not have to worry about confounding the effects of the location of residence with candidate effects.[5]

The research design requires the identification of Obama contributors who moved after the 2008 election (i.e., after December 31, 2008), as well as when and where they moved. We accomplished this by using data from the National Change of Address (NCOA) database from the U.S. Postal Service (USPS). This database contains information on more than 150 million change-of-address records, including names, addresses, and the dates when the moves became effective. We excluded individuals who remained in the same ZIP-3 because we need individuals to change their social environment to provide useful variation for the event-study analysis.[6] In the final sample, the median (mean) distance between origin and destination addresses was 140 miles (520 miles).

The NCOA database does not cover the totality of residential moves, although we suspect that it covers the majority of moves in our sample of contributors. In our sample, 4.1% of contributors filed changes of address with the USPS during the first year after the end of the 2008 cycle. In contrast, U.S. Census Bureau data for 2011 suggest that 6.2% of Americans aged 40 or above changed residences, implying that the NCOA records includes 66% of these moves (4.1/6.2 = 0.66). Moreover, the implied coverage rate is significantly higher if we account for the fact that contributors are, on average, wealthier and more educated than the U.S. average and thus less likely to move. Missing some residential moves reduces the final sample size and therefore the statistical precision, but it should not affect the internal validity of the estimates (see section IIIC for a discussion of the implications for external validity).

B. Timing of Residential Moves

The event-study analysis is based on the comparison between two sets of individuals: those who moved before the 2012 election cycle and those who moved after the 2012 election cycle. Let *Moved before 2012 Cycle* denote the set of individuals who did not move from the beginning to the end of the 2008 election cycle (January 2007–December 2008), then moved in the two years between the end of the 2008 cycle and before the beginning of the 2012 cycle (between January 2009 and December 2010), and then stayed in their new residences for the duration of the 2012 election cycle. For individuals who moved more than once between January 2009 and December 2010, we used their last move. Let *Moved after 2012 Cycle* denote the set of individuals who did not move from the beginning of the 2008 cycle (January 2007) until the end of the 2012 cycle (December 2012) and then moved during the two years after the end of the 2012 cycle (i.e., between January 2013 and December 2014). Again, for individuals who moved more than once during this period, we used their last move. The final sample consisted of 45,108 contributors who moved, of whom 59% moved before the 2012 election and the remaining 41% moved after the 2012 election.[7]

C. Outcome of Interest: 2012 Contributions

For all 2008 contributors, we observed their names and residential addresses during the 2012 election cycle. Matching these variables to the 2012 FEC records allowed us to measure whether they contributed to Obama in the 2012 campaign. Column 1 of table 1 provides some descriptive statistics about contributions to the 2008 and 2012 Obama campaigns. All individuals in the sample contributed more than $200 to the Obama campaign in 2008, and the average amount contributed was $644. In 2012, 26.7% of the individuals in the sample contributed more than $200 to Obama. Among those who contributed more than $200, the average amount contributed was $854.

The main outcome of interest is the amount contributed in 2012. This amount is lower-censored at $200 because, for each election cycle, the FEC records include only individuals who contributed more than $200 to a given committee. When analyzing this outcome, we used two econometric models that account for the censored nature of the dependent

[4] We cannot reproduce the analysis for individuals contributing during the 2004 election cycle, because the data on residential mobility did not go far back enough.

[5] For example, if we examined contributions to gubernatorial races, then individuals in more Democratic areas may contribute more to Democratic candidates simply because the Democratic candidates happen to be better in those areas.

[6] 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.

[7] More precisely, of the approximately 600,000 contributors in the sample of contributors to Obama in 2008, about 85,000 moved in the two years preceding or the two years following the 2012 cycle. However, only 45,000 of them moved to a different ZIP-3.

TABLE 1.—BASIC CONTRIBUTION PATTERNS, BY DATE OF RESIDENTIAL MOVE

		By Date of Move		
	All	Before 2012 Cycle	After 2012 Cycle	p-value of Difference
2008 Cycle				
Percent contributed > \$200	100.00	100.00	100.00	
	(0.00)	(0.00)	(0.00)	
Mean amount (\$), if > \$200	643.52	634.24	656.94	<0.01
	(3.29)	(4.24)	(5.24)	
2012 Cycle				
Percent contributed > \$200	26.67	22.95	32.05	<0.01
	(0.21)	(0.26)	(0.34)	
Mean amount (\$), if > \$200	854.46	864.73	843.84	0.21
	(8.32)	(11.77)	(11.76)	
Observations	45,108	26,661	18,447	

Data for individuals who contributed to Obama's presidential campaign during the 2008 election cycle and changed residences between January 2009 and December 2010 (*Moved before 2012 Cycle*) or between January 2013 and December 2014 (*Moved after 2012 Cycle*). *2008 Cycle* corresponds to contributions to Obama between January 2007 and December 2008, and *2012 Cycle* corresponds to contributions to Obama between January 2011 and December 2012. *Percent Contributed > \$200* is the share of individuals contributing over \$200. *Amount (\$), if > \$200* corresponds to the amount contributed for those individuals who contributed over \$200.

variable: the Tobit model (Honoré, 1992) and the Poisson model. In both cases, the dependent variable is defined as 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 baseline results are based on the Poisson estimates, because the coefficients can be directly interpreted as semielasticities and are thus easier to analyze. Additionally, we used Logit regressions to measure the effects on the extensive margin.

D. *Main Independent Variable: Share Democrat*

An individual's reference group comprises all social contacts that could influence her political participation: neighbors, friends, relatives, acquaintances, colleagues, bosses, and clients. Because we did not have data on the social networks of the contributors in our sample, we followed the common approach in the social interactions literature by relying on a geographic proxy (for a discussion, see Perez-Truglia, 2013). More specifically, our baseline specification uses the individual's ZIP-3 of residence as a proxy for that individual's reference group. Intuitively, ZIP-3s are probably large enough to include most of the individual's social contacts. For example, the 021 ZIP-3 in Boston covers roughly the same area as the metropolitan area's subway system, thus covering individuals who live and work near each other (Chetty et al., 2013).

The main independent variable, *Share Democrat*, equals the share of Democratic contributors in the destination ZIP-3 among all contributors (Democrats and Republicans), using data from the FEC for the 2000–2008 presidential election cycles. By construction, *Share Democrat* can take values from 0 to 1. Table 2 shows that in our sample of movers, the average *Share Democrat* in the origin ZIP-3 is 0.69. For reference, figure D.1 shows a map with the distribution of *Share Democrat* across ZIP-3s. Moving from the 5th percentile to the 95th percentile of *Share Democrat* would amount to an increase of 41 percentage points, indicating a substantial amount of variation in this variable.

TABLE 2.—CHARACTERISTICS OF CONTRIBUTORS, BY DATE OF RESIDENTIAL MOVE

		By Date of Move		
	All	Before 2012 Cycle	After 2012 Cycle	p-value of Difference
Individual characteristics				
Percent female	48.61	47.57	50.12	<0.01
	(0.22)	(0.28)	(0.34)	
Percent white	78.02	77.53	78.73	<0.01
	(0.10)	(0.14)	(0.15)	
Percent African American	12.14	12.18	12.08	0.46
	(0.07)	(0.09)	(0.10)	
Percent Hispanic	4.02	4.14	3.85	0.02
	(0.06)	(0.08)	(0.09)	
ZIP-3 characteristics				
Mean income (\$10,000s)	72.28	72.26	72.33	0.84
	(0.17)	(0.22)	(0.27)	
Percent college	58.17	58.15	58.21	0.60
	(0.05)	(0.07)	(0.08)	
Percent Democrat (Origin)	69.94	70.40	69.28	<0.01
	(0.07)	(0.09)	(0.10)	
Percent Democrat (Destination)	68.67	69.19	67.91	<0.01
	(0.07)	(0.09)	(0.11)	
Observations	45,108	26,661	18,447	

Data for individuals who contributed to Obama's presidential campaign during the 2008 election cycle and changed residences between January 2009 and December 2010 (*Moved before 2012 Cycle*) or between January 2013 and December 2014 (*Moved after 2012 Cycle*). *Percent Female* was inferred from data on the joint distribution of first names and gender, and *Percent White*, *African American*, and *Hispanic* were inferred from data on the joint distribution of last names and races. *Mean Income, Percent Unemployed*, and *Share College* are averages at the origin ZIP-3. *Share Democrat* is the share of Democratic presidential contributors in the origin/destination ZIP-3 during 2000 to 2008.

The average of *Share Democrat* among Democratic contributors (0.69, from table 1) is higher than the population-weighted average across ZIP-3s (0.60), suggesting that Democratic contributors tend to live in more Democratic areas than the average individual. The average *Share Democrat* in the destination ZIP-3 (0.69, from table 1) is almost identical to the average *Share Democrat* in the origin ZIP-3 (0.70, from table 1). This implies that individuals, on average, move to ZIP-3s with the same political composition as their origin ZIP-3s. However, the persistence of *Share Democrat* is far from perfect, leaving substantial changes in the political composition of reference groups over time. For instance, the correlation between origin and destination ZIP-3s is just 0.36. Furthermore, after controlling for *Share Democrat* in the origin ZIP-3, the standard deviation of *Share Democrat* in the destination ZIP-3 is 0.14.

E. *Regression Specification*

Let $c_{i,k}^{12}$ denote a measure of individual i's contribution during the 2012 cycle. The subscript k denotes whether the individual moved before the 2012 cycle ($k = Bef$) or after it ($k = Aft$). Let $S_{i,k}^{Bef}$ be a variable that takes the value *Share Democrat* in the destination ZIP-3 when $k = Bef$ and 0 otherwise. Let $S_{i,k}^{Aft}$ take the value *Share Democrat* in the destination ZIP-3 when $k = Aft$ and 0 otherwise. That is, when $k = Bef$, $S_{i,k}^{Bef}$ is the *Share Democrat* where the individual lived during the 2012 cycle, and when $k = Aft$, $S_{i,k}^{Aft}$ is the *Share Democrat* where the individual moved after the end of the 2012 cycle. Let $Z_{i,k}^{Bef}$ and $Z_{i,k}^{Aft}$ be vectors with elements defined as $S_{i,k}^{Bef}$ and $S_{i,k}^{Aft}$, but for other characteristics of the ZIP-3 instead of *Share Democrat*, such as the mean income. Finally, let $X_{i,k}$ be a vector of additional controls. The baseline regression specification is given by

$$c_{i,k}^{12} = \alpha_{Bef} \times S_{i,k}^{Bef} + \alpha_{Aft} \times S_{i,k}^{Aft} + \beta_{Bef} \times Z_{i,k}^{Bef} + \beta_{Aft} \times Z_{i,k}^{Aft} + \mu \times I_{\{k=Bef\}} + \delta X_{i,k} + \epsilon_{i,k}. \quad (1)$$

To compare between pairs of similar individuals, the 45,108 contributors are divided into 1,399 groups of individuals who contributed the same amount to Obama's 2008 campaign (in \$100 intervals) while living in a ZIP-3 with the same *Share Democrat* (in 0.01 intervals). The vector of controls $X_{i,k}$ includes the set of 1,399 group dummies. Additionally, $X_{i,k}$ includes the 2008 contribution amount; the *Share Democrat* in the origin ZIP-3; the probability that the contributor is female (inferred from U.S. Census Bureau's data on the joint distribution of first names and gender); and the probabilities of being white, African American, or Hispanic (inferred from U.S. Census Bureau's data on the joint distribution of last names and ethnicities). Finally, in the baseline specification, $Z_{i,k}^{Bef}$ and $Z_{i,k}^{Aft}$ include the following ZIP-3 characteristics: mean gross income; unemployment rate; share of college graduates; total population; share of individuals 25 years old or younger; percentages of whites, African Americans, and Hispanics; and the coefficient of ethnic fractionalization.[8]

The two coefficients of interest are α_{Bef} (the association between the contribution amount and the current *Share Democrat*) and α_{Aft} (the association between the contribution amount and the future *Share Democrat*). In our event-study framework, finding that $\alpha_{Bef} > 0$ and $\alpha_{Aft} = 0$ would suggest that increasing the share of Democratic peers causes higher contributions to Obama.

F. *Comparing Individuals Who Moved before and after the 2012 Cycle*

Given that the identification strategy relies on the comparison between α_{Bef} and α_{Aft}, a potential concern is that these coefficients may be dramatically different—not because of the timing of the residential moves but because of differences in characteristics between individuals who moved before and after the 2012 cycle. What matters the most is not whether these differences are statistically significant but whether these differences are economically large enough to explain the difference between α_{Bef} and α_{Aft}.

Table 2 compares a series of individual and ZIP-3 characteristics between the groups of individuals who moved before and after the 2012 cycle. For both groups, these are premove characteristics, that is, outcomes that could be measured before the individuals moved. The large sample size provides enough statistical power to distinguish statistically even tiny differences. Although some differences in individual and ZIP-3 characteristics are highly statistically significant, all are economically very small: 47.6% versus 50.1% female, 77.5% versus 78.7% white, 12.2% versus 12.1% African American, 4.1% versus 3.9% Hispanic, \$72,260 versus \$72,330 mean ZIP-3 income, 58.2% versus 58.2% college graduates, and 70.4% versus 69.3% *Share Democrat*.

The top half of table 1 compares another premove characteristic: the amount contributed to the 2008 Obama campaign between individuals who moved before and after the 2012 cycle. By construction, all individuals in the sample contributed more than \$200 in 2008. The average contribution amount was \$23 lower for individuals who moved before the 2012 cycle, relative to individuals who moved after the 2012 cycle (\$634 versus \$657, or 3.5% lower). Again, this difference is highly statistically significant but economically small. These small differences in premove characteristics and contributions are not surprising given the short period of time separating individuals who moved before and after the 2012 cycle. Most important, these small differences in premove characteristics and contributions are unlikely to explain large difference between α_{Bef} and α_{Aft}.

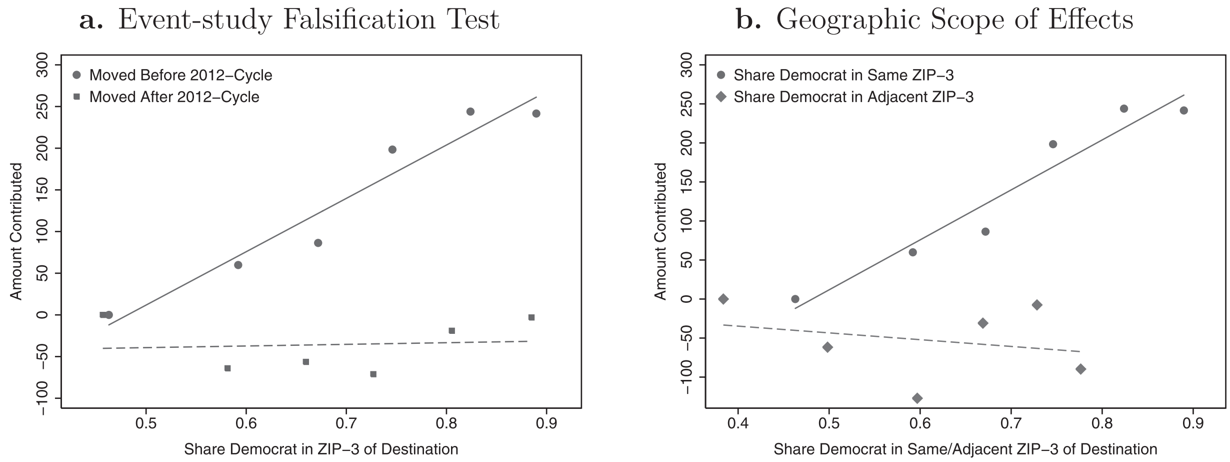
The bottom half of table 1 compares the 2012 contributions between individuals who moved before and after the 2012 cycle. It is crucial to note that the 2012 contributions are a postmove characteristic for individuals who moved before the 2012 cycle and a premove characteristic for individuals who moved after the 2012 cycle. Thus, by construction, any differences in 2012 contributions between these two groups pick up the effect of moving. The probability of contributing in the 2012 cycle is 23% for individuals who moved before the 2012 cycle and 32% for individuals who moved after the 2012 cycle. This difference is both statistically and economically significant. Given the similarity of premove characteristics and premove contributions, this significant difference in postmove contributions is most likely due to the effect of moving.

At least two factors can explain the negative effect of moving on the probability to contribute. First, when individuals move, the time it takes to find local opportunities to give can reduce the likelihood of contributing. This effect also has been documented for other forms of political behavior. For example, Squire, Wolfinger, and Glass (1987) show that the probability of voting decreases significantly after individuals move, among other factors, because of the need to register to vote in the new location.[9] Second, solicitation can be another

[8] Data on ZIP-3 characteristics from the Census Bureau's 2008–2012 American Community Survey five-year estimates and the Internal Revenue Service's 2008 Statistics of Income.

[9] For instance, they report that individuals who moved in the last 0 to 2 years have a 10 percentage point lower probability of voting relative to individuals who moved 3 to 5 years ago.

FIGURE 1.—RELATIONSHIP BETWEEN CONTRIBUTIONS AND *SHARE DEMOCRAT*



Data on 45,108 individuals who contributed to Obama's presidential campaign during the 2008 election cycle and changed residences between January 2009 and December 2010 (group *Moved before 2012 Cycle*) or between January 2013 and December 2014 (group *Moved after 2012 Cycle*). The *y*-axis corresponds to the amount contributed in excess of $200 to Obama during the 2012 cycle (January 2011–December 2012). The *x*-axis corresponds to the share of Democratic contributors among all the contributors to presidential campaigns in the same or adjacent destination ZIP-3 (using data from the 2000 to 2008 presidential election cycles). All results come from a single Tobit regression. The dots correspond to the effects of six *Share Democrat* dummies on the 2012 contributions among the group *Moved before 2012 Cycle* (the left-most dot was normalized to 0). The squares differ from the dots in that they use the group *Moved after 2012 Cycle* instead of *Moved before 2012 Cycle*. The diamonds differ from the dots in that they use *Share Democrat* in the ZIP-3s adjacent to the destination ZIP-3 instead of the same destination ZIP-3 (for the group *Moved before 2012 Cycle*, and controlling for a set of characteristics of this adjacent-ZIP-3). See section IIE for more details about the regression specification, including the full list of control variables.

factor that may contribute to the the negative effect of moving on the probability to contribute. According to a survey by Pew Research, 67% of individuals who contributed to presidential candidates in 2012 made their contributions in person, over the telephone, or through the mail (Smith & Duggan, 2012), all channels used intensively by the campaigns to solicit contributions. After individuals move, the campaigns need time to identify their new mail addresses and telephone numbers, which can lead to a reduction in solicitation and thus a drop in contributions.

This effect of moving on 2012 contributions does not present a challenge to the identification strategy. However, because the 2012 contributions are the dependent variable in the regression analysis, when comparing the coefficients between individuals who moved before and after the 2012 cycle, we must account for differences in baseline levels. In the Poisson and Logit models, the conformity effects are estimated as semielasticities, which accounts for differences in baseline levels. In the Tobit model, there are no baseline differences to account for because, according to the last row in table 1, the differences in postmove contributions are not significant in the conditional contribution amount. In practice, the coefficient α_{Aft} is close to 0, and as a result, accounting for differences in baseline levels does not make any difference.

III. Results from the Event-Study Analysis

A. *Main Results*

To get a less parametric look at the data, figure 1 shows a binned partial regression plot of the effect of *Share Democrat* in the destination ZIP-3 (*x*-axis) on the amount contributed during the 2012 cycle (*y*-axis). For this, *Share Democrat* is split into six groups of equal size. The horizontal location of the six dots, squares, and diamonds in figure 1 corresponds to the average of *Share Democrat* in each of these six groups. Their vertical location corresponds to the effect of belonging to that group on the 2012 contributions, with the left-most dot, square, or diamond normalized to 0. All results were obtained from a Tobit regression using the baseline specification described in section IIE.

The dots in figure 1a 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 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. Consistent with this prediction, the dots in figure 1a show a strong positive relationship between the amount contributed and the share of like-minded individuals. For example, moving an individual from an area with 45% Democrats (corresponding to the left-most dot) to an area with 90% Democrats (the right-most dot) increases that individual's contribution by nearly $250. This effect is equivalent to 29% of the mean amount contributed among those who contributed more than $200 ($854, from table 1).

For a more formal test of this hypothesis, column 1 of table 3 presents the baseline Poisson regression. For the group *moved before 2012 Cycle*, the coefficient on *Share Democrat* (0.674) is highly statistically significant (p-value$<$ 0.01). This coefficient can be interpreted as a semielasticity: increasing *Share Democrat* by 1 percentage point would increase the amount contributed by an economically significant 0.67%.

These estimates are a valid measure of conformity effects only if, conditional on the control variables, the political composition of the area of destination is exogenous. Of

TABLE 3.—MAIN REGRESSION RESULTS: MEASURING CONFORMITY EFFECTS

	Amount Contributed ($)					
	(1)	(2)	(3)	(4)	(5)	(6)
Share Democrat in Same ZIP-3						
Moved after 2012 Cycle[i]	−0.022	−0.026	−0.019	0.011	−0.022	−0.019
	(0.173)	(0.173)	(0.173)	(0.175)	(0.173)	(0.174)
Moved before 2012 Cycle[ii]	0.674***	0.773***	0.528***	0.652***	0.678***	0.702***
	(0.187)	(0.227)	(0.203)	(0.191)	(0.197)	(0.186)
Interaction with *Exposure Time*			0.013**			
			(0.006)			
Interaction with *Same-State Dummy*				0.064		
				(0.088)		
Interaction with *Female*					−0.009	
					(0.085)	
Interaction with *Nonwhite*						−0.142
						(0.203)
Share Democrat in Adjacent ZIP-3s						
Moved before 2012 Cycle[iii]		−0.184				
		(0.236)				
p-value i = ii	0.007	0.005				
p-value ii = iii		0.020				

Significant at *10%, **5%, and ***1%. Standard errors in parentheses, clustered at the group-level (i.e., individuals with similar origin and 2008-contribution). Data on 45,108 individuals who contributed to Obama's presidential campaign during the 2008 election cycle and changed residences between January 2009 and December 2010 (group *Moved before 2012 Cycle*) or between January 2013 and December 2014 (group *Moved after 2012 Cycle*). Each column corresponds to a different regression. *Amount ($)* is the amount contributed in excess of $200 to Obama during the 2012 cycle (January 2011–December 2012). *Exposure Time* is the number of months between the date of the move and the beginning of the 2012 cycle (from 0 to 23). *Same-State Dummy* takes the value 1 if the individual moved between two ZIP-3s belonging to the same state. *Female* is the probability of being female (from 0 to 1) inferred from data on the joint distribution of first names and gender. *Nonwhite* is the probability of not being white (from 0 to 1) inferred from data on the joint distribution of last names and ethnicities. See section IIE for more details about the regression specification, including the full list of control variables.

course, this assumption could be violated. First, individuals who moved to a more Democratic area may have contributed more in 2012 because they were stronger Democrats in 2008. Second, individuals who moved to a more Democratic area may have contributed more in 2012 because they became stronger Democrats since 2008.

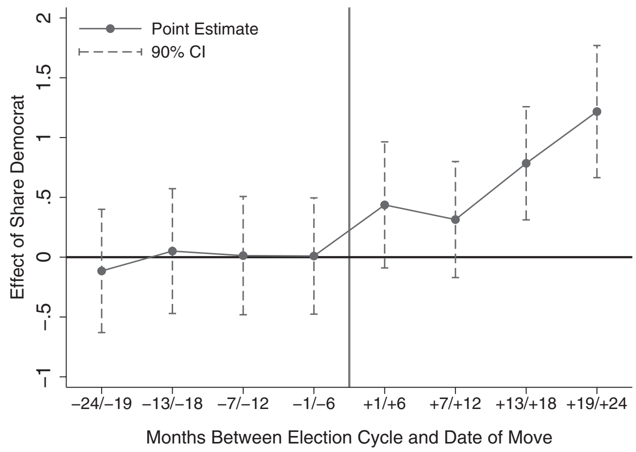
We used the timing of residential mobility to test this identification assumption and validate our estimates. Consider a group of similar individuals who, instead of moving before the beginning of the 2012 election cycle, moved after the end of the 2012 election cycle. During the 2012 election, these individuals had not moved yet and thus had not been exposed to their new social environments. Thus, the conformity hypothesis does not predict that individuals who moved to a more Democratic area contributed more during 2012. On the contrary, if the individuals moving to the more Democratic area were already stronger Democrats in 2008 or became stronger Democrats between 2008 and 2012, then we should observe that they contribute more, even during the 2012 cycle.

The squares in figure 1a show the association between the 2012 contributions and the *Share Democrat* where individuals moved after the end of the 2012 cycle. Consistent with our hypothesis, relative to individuals who moved to less Democratic areas after 2012, individuals who moved to more Democratic areas after 2012 did not contribute more during 2012. For a more formal version of the falsification test, column 1 of table 3 presents the coefficients for the groups *Moved before 2012 Cycle* (α_{Bef}) and for the group *Moved after 2012 Cycle* (α_{Aft}). Whereas the coefficient on *Share Democrat* (0.674) is statistically and economically significant for the group *Moved before 2012 Cycle*, the corresponding coefficient for *Moved after 2012 Cycle* (-0.022) is equally precisely estimated, very close to 0, and statistically insignificant. Additionally, table 3 reports the test of the null hypothesis that the coefficients on *Share Democrat* are equal between *Moved before 2012 Cycle* and *Moved after 2012 Cycle* ($\alpha_{Bef} = \alpha_{Aft}$). We can reject this null hypothesis at the 1% level. This evidence supports the presumed direction of causality, according to which living in more Democratic areas causes individuals to contribute more to Obama.

Share Democrat may affect contributions through several mechanisms. Our preferred explanation is based on social interaction models, such as social norms, social pressure, and social learning. We present two pieces of suggestive evidence in favor of this interpretation.

A first piece of suggestive evidence is based on the prediction that participation should be more affected by peers with whom an individual interacts more often. Because the frequency of social interactions decays with geographic distance, the social interaction models predict smaller effects of *Share Democrat* for reference groups that are farther away. In figure 1b, the diamonds are defined in the same way as the dots, except that *Share Democrat* is computed in the "doughnut" of ZIP-3s that are adjacent to the destination ZIP-3 instead of the destination ZIP-3 itself. Consistent with our hypothesis, the amount contributed does not seem to be affected by the political composition in the adjacent ZIP-3s. For a more formal test of this hypothesis, column 2 of table 3 shows the results from a regression that includes two variables: *Share Democrat* in the destination ZIP-3 and *Share Democrat* in the adjacent ZIP-3s. The coefficient on the adjacent ZIP-3s is small and statistically insignificant, and the difference between the coefficients for the same ZIP-3 and adjacent ZIP-3s is statistically significant (p-value $= 0.02$).

FIGURE 2.—EVENT-STUDY ANALYSIS OF THE EFFECT OF *SHARE DEMOCRAT* ON CONTRIBUTIONS



Data on 45,108 individuals who contributed to Obama's presidential campaign during the 2008 election cycle and changed residence between January 2009 and December 2010 or between January 2013 and December 2014. Results from a single Poisson regression of the 2012 contribution amount on *Share Democrat*, following the baseline specification described in section IIE (including the full list of control variables), with the only difference that *Share Democrat* is interacted with eight dummies corresponding to the number of months between the 2012 election cycle and the date of move. For instance, the group +1/+6 corresponds to individuals who moved between July 2011 and December 2011, and the group −24,−19 corresponds to individuals who moved between July 2014 and December 2014. The dots correspond to the coefficients on these eight interaction terms, with confidence intervals constructed with clustered standard errors.

A second piece of suggestive evidence in favor of social interaction models is based on the timing of the effects. After an individual moves into a new reference group, it takes time to learn the beliefs, preferences, and actions of new peers. Thus, social interaction models predict that at least for an initial period, peer influence should increase over time. To test this hypothesis, we split the sample of movers in six-month intervals according to the date when they moved. Figure 2 reports the Poisson coefficients corresponding to the conformity effects for each of these subgroups. Consistent with the previous event-study analysis, the coefficients are consistently close to 0 for individuals who moved 1 to 6, 7 to 12, 13 to 18, and 19 to 24 months after the 2012 election (the coefficients to the left of the vertical line), whereas they are consistently positive for individuals who moved after the 2012 election (the coefficients to the right of the vertical line). Most important, consistent with the social interaction models, the magnitude of conformity effects increases with the the time spent in the destination ZIP-3s before the beginning of the 2012 cycle.

Column 3 of table 3 presents a more formal test of this hypothesis. This Poisson regression includes an interaction between *Share Democrat* and the number of months between the date of the move and the beginning of the 2012 cycle, from 0 to 23, which we denote as *Exposure Time*. The coefficient on *Share Democrat* corresponds to the conformity effect for individuals who spent less than one month in the destination ZIP-3 before the 2012 cycle started.[10] This coefficient of 0.528 implies that a 1 percentage point increase in *Share Democrat* would increase the amount contributed by about 0.528%. The coefficient on the interaction between *Share Democrat* and *Exposure Time* (0.013) is positive and statistically significant at the 5% level, indicating that the magnitude of conformity effects increases with exposure time. This difference is economically significant, as increasing exposure time by two years (from 0 to 24 months) increases the magnitude of conformity effects by 59% (i.e., from 0.528 to 0.840).

[10] Nevertheless, most contributors do not start making contributions until several months after the beginning of the election cycle, so in practice, the exposure time before the first contribution is made is greater.

B. Robustness Checks

The last three columns of 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: a dummy variable indicating whether the contributor moved between two ZIP-3s located in the same state (about 45% of movers) and its interaction with *Share Democrat*. The coefficient on this interaction (0.064) is small and statistically insignificant, suggesting that the conformity effects are not significantly different between in-state and out-of-state movers. However, due to the precision of the estimates, we cannot reject moderate differences (e.g., the 95% confidence interval suggests that conformity effects could be between 15% lower and 24% higher for in-state relative to out-of-state movers).

Column 5 includes the interaction between *Share Democrat* and the probability that the contributor is female (inferred from data on the joint distribution of first names and gender). For example, *Female* $= 0.1$ implies a 10% chance that the contributor is female. The coefficient on this interaction (-0.009) is very small and statistically insignificant, suggesting that there are no significant gender differences in conformity effects. However, due to the precision of the estimates, we cannot rule out the possibility of small differences. Column 6 includes the interaction between *Share Democrat* and the probability that the contributor is not white (inferred from data on the joint distribution of last names and ethnicities). The coefficient on this interaction (-0.142) is statistically insignificant, but due to the limited variation in ethnicity, the coefficient is not precisely estimated and thus not very informative.

Table 4 presents results under alternative specifications for the outcome variable. The specifications in columns 1 and 2 use the amount contributed as the dependent variable and correspond to the Poisson and Tobit models, respectively. The main difference between the Poisson and Tobit models is that the Poisson model assumes that the effects are proportional to the expected contribution amount. The results from columns 1 and 2 are identical in terms of signs and statistical significance of the coefficients, indicating that the results are not qualitatively sensitive to the choice between Poisson and Tobit models. Regarding magnitudes, the Poisson coefficient (0.674, from column 1) suggests that a 1 percentage point increase in *Share Democrat* would increase the expected

TABLE 4.—ROBUSTNESS TEST: ALTERNATIVE DEFINITIONS OF THE OUTCOME VARIABLE

	Amount ($)		P(A>$200)	P(A>$325)	P(A>$500)	P(A>$1,000)
	(1)	(2)	(3)	(4)	(5)	(6)
Share Democrat in ZIP-3						
Moved after 2012 Cycle[i]	−0.022	0.135	0.101	0.039	0.032	0.020
	(0.173)	(141.882)	(0.104)	(0.174)	(0.181)	(0.287)
Moved before 2012 Cycle[ii]	0.674***	437.523***	0.367***	0.504***	0.560***	0.820***
	(0.187)	(136.447)	(0.129)	(0.146)	(0.130)	(0.198)
p-value i = ii	0.007	0.043	0.119	0.038	0.019	0.013
Model	Poisson	Tobit	Logit	Logit	Logit	Logit

Significant at *10%, **5%, and ***1%. Standard errors in parentheses (clustered in column 1, and bootstrapped in columns 2 through 6). Data on 45,108 individuals who contributed to Obama's presidential campaign during the 2008 election cycle and changed residences between January 2009 and December 2010 (group *Moved before 2012 Cycle*) or between January 2013 and December 2014 (group *Moved after 2012 Cycle*). Each column corresponds to a different regression. *Amount ($)* is the amount contributed in excess of $200 to Obama during the 2012 cycle (January 2011–December 2012). *P(A>$X)* is a dummy that takes the value 1 if the individual made a contribution over $X and 0 otherwise. *Share Democrat* is the share of Democratic contributors in the same or adjacent destination ZIP-3. The results shown correspond to the raw coefficients from Poisson, Tobit, and Logit regressions.

TABLE 5.—ROBUSTNESS TEST: ALTERNATIVE DEFINITIONS OF THE GROUP DUMMIES

	Amount Contributed ($)				
	(1)	(2)	(3)	(4)	(5)
Share Democrat in ZIP-3					
Moved after 2012 Cycle[i]	−0.022	−0.093	0.102	−0.022	0.011
	(0.173)	(0.197)	(0.331)	(0.200)	(0.172)
Moved before 2012 Cycle[ii]	0.674***	0.482**	0.700**	0.601***	0.612***
	(0.187)	(0.210)	(0.347)	(0.205)	(0.185)
p-value i = ii	0.007	0.041	0.191	0.030	0.017
Group dummies definition					
Amount Pairing	$100 interval	$100 interval	$100 interval	$10 interval	None
Origin Pairing	0.01 interval Share Democrat	Same ZIP-3	Same ZIP-5	0.01 interval Share Democrat	None
Observations	45,108	42,120	26,247	42,518	45,630
Numer of Groups	1,399	4,456	7,767	4,074	

Significant at *10%, **5%, and ***1%. Clustered standard errors in parentheses. Data on 45,108 individuals who contributed to Obama's presidential campaign during the 2008 election cycle and changed residences between January 2009 and December 2010 (group *Moved before 2012 Cycle*) or between January 2013 and December 2014 (group *Moved after 2012 Cycle*). *Amount ($)* is the amount contributed in excess of $200 to Obama during the 2012 cycle. Different columns correspond to Poisson regressions with different group fixed effects: (a) individuals who contributed an amount to the 2008 Obama campaign in the same $100 interval while living in a ZIP-3 in the same 0.01 interval of *Share Democrat*; (b) individuals who contributed in the same $100 interval while living in the same ZIP-3; (c) individuals who contributed in the same $100 interval while living in the same ZIP-5; (d) individuals who contributed in the same $10 interval while living in a ZIP-3 in the same 0.01 interval of *Share Democrat*; (e) no group fixed effects. See section E for more details about the regression specification.

contribution amount by 0.67%. The Tobit coefficient from column 2 implies that the same 1 percentage point increase in *Share Democrat* would raise the contribution amount by $4.37, a 0.51% increase, relative to the average contribution for that group ($854, from table 1). This difference in magnitudes (0.67% versus 0.51%) is statistically insignificant at the 10% level, suggesting that the results are quantitatively robust across the Poisson and Tobit models.

Column 3 of table 4 corresponds to a Logit regression, where the dependent variable indicates if the individual contributed more than $200 during the 2012 cycle. Columns 4 to 6 are similar to column 3, but instead of $200, they use the thresholds $325, $500, and $1,000, respectively. These three thresholds split the distribution of contribution amounts over $200 in four quartiles. The coefficients on columns 3 through 6 are consistent in sign and statistical significance to the baseline results from column 1. The Logit coefficients can be interpreted as semielasticities, that is, as the proportional effect on the odds ratio. The semielasticity is 0.367 for the $200 threshold, 0.504 for the $325 threshold, 0.560 for the $500 threshold, and 0.820 for the $1,000 threshold, suggesting a larger magnitude of conformity effects for larger thresholds. However, only one of the pairwise differences between those coefficients, corresponding to thresholds $200 and $1,000, is statistically significant at the 10% level.

Regarding the comparison of magnitudes between the Logit and Poisson results, these are not directly comparable, because the Logit coefficients correspond to the proportional effects on the odds ratio, whereas the Poisson coefficients correspond to the proportional effects on the amount contributed. With this caveat in mind, all pairwise differences between the Poisson coefficient (0.674, from column 1) and each of the Logit coefficients (0.367, 0.504, 0.560, and 0.820, from columns 3 through 6) are statistically insignificant at the 10% level.

Table 5 assesses the robustness of the results to alternative definitions of the group dummies. Column 1 corresponds to the baseline results, in which individuals are grouped together if in 2008 they made contributions in the same $100 interval while living in a ZIP-3 in the same 0.1 interval of *Share Democrat*. Relative to column 1, the specification in column 2 groups individuals only if they lived in the same ZIP-3 rather than in ZIP-3s in the same 0.1 interval of *Share Democrat*. The specification from column 3 is even stronger than that of column 2 by pairing individuals only if they lived

TABLE 6.—ROBUSTNESS TEST: ALTERNATIVE SETS OF ZIP-3 CONTROLS

	Amount Contributed ($)				
	(1)	(2)	(3)	(4)	(5)
Share Democrat in ZIP-3					
Moved after 2012 Cycle[i]	−0.022	0.077	0.111	0.043	0.021
	(0.173)	(0.169)	(0.170)	(0.191)	(0.219)
Moved before 2012 Cycle[ii]	0.674***	0.641***	0.624***	0.672***	0.575**
	(0.187)	(0.173)	(0.167)	(0.200)	(0.233)
p-value i = ii	0.007	0.022	0.035	0.024	0.086
ZIP-3 controls					
Economic	Yes	Yes	Yes	Yes	Yes
Demographic	Yes	Yes	No	Yes	Yes
Racial	Yes	No	No	Yes	Yes
Redistribution	No	No	No	Yes	Yes
Family	No	No	No	No	Yes

Significant at *10%, **5%, ***1%. Clustered standard errors in parentheses. Data on 45,108 individuals who contributed to Obama's presidential campaign during the 2008 election cycle and changed residences between January 2009 and December 2010 (group *Moved before 2012 Cycle*) or between January 2013 and December 2014 (group *Moved after 2012 Cycle*). Each column corresponds to a different Poisson regression. *Amount ($)* is the amount contributed in excess of $200 to Obama during the 2012 cycle. See section IIE for more details about the regression specification, including the full list of control variables. Column 1 includes as controls all the ZIP-3 characteristics listed in section IIE. Columns 2 and 3 exclude some of these ZIP-3 characteristics, and columns (4) and (5) include additional ZIP-3 characteristics. *Economic* includes gross income per 1040 form, unemployment rate, and percent of college graduates; *Demographic* includes population and percent of individuals 25 years old or younger; *Racial* includes percent white, percent African American, percent Hispanic, and the coefficient of ethnic fractionalization; *Redistribution* includes average effective tax rate from 1040 forms and percent of 1040 forms claiming Earned Income Tax Credit; and *Family* includes percent of married households and percent of households with school-aged children.

in the same ZIP-5. Relative to column 1, the specification in column 4 pairs individuals if they contributed amounts in the same $10 interval rather than the same $100 interval. Finally, column 5 excludes the group fixed effects altogether. The results from columns 2 through 5 are consistent in sign and statistical significance to the results from the baseline specification in column 1. The coefficients are also quantitatively robust: from a coefficient of 0.674 in column 1 to coefficients of 0.482, 0.700, 0.601, and 0.612 in columns 2 through 5, with all pairwise differences being statistically insignificant at the 10% level.

Another concern is that although the event-study analysis addresses the problem of reverse causality, it does not address the problem of omitted variable bias from omitted ZIP-3 characteristics. On the one hand, the effect of *Share Democrat* could be partially or entirely driven by some omitted ZIP-3 characteristic that correlates with *Share Democrat*. On the other hand, it is possible that omitted ZIP-3 characteristics lead to an underestimation of the magnitude of conformity effects.

To address this concern, table 6 assesses the robustness of the findings to alternative sets of ZIP-3 controls. Column 1 corresponds to the baseline specification, which includes the full set of ZIP-3 controls listed in section IIE. Relative to column 1, column 2 excludes the racial ZIP-3 characteristics, and column 3 excludes both the racial and demographic ZIP-3 characteristics. Relative to column 1, column 4 includes additional ZIP-3 controls related to income redistribution: the average effective tax rate and the percentage claiming an earned income tax credit, according to IRS data on 1040 forms. In addition to the extra controls from column 4, column 5 includes two ZIP-3 characteristics related to family composition: the share of married households and the share of households with school-aged children. The results from columns 2 through 5 are consistent in sign and statistical significance to the results from the baseline specification in column 1. The coefficients are also quantitatively robust: from a coefficient of 0.674 in column 1 to coefficients of 0.641, 0.624, 0.672, and 0.575 in columns 2 through 5, with all pairwise differences being statistically insignificant at the 10% level. The fact that the estimates are so robust to alternative sets of ZIP-3 does not eliminate the possibility of bias from omitted ZIP-3 characteristic, but it mitigates this concern.

Appendix A presents further robustness checks. Appendix A.1 reproduces the event-study analysis using alternative definitions of *Share Democrat*, such as defining the reference group at the county level instead of the ZIP-3 level. The results are qualitatively and quantitatively similar. Appendix A.2 reproduces the event-study analysis using supporters of Mitt Romney's presidential campaigns. The sample of contributors to Romney is much smaller, so the results are much less precisely estimated. In spite of this, the conformity effects are statistically indistinguishable between the two samples.

C. *Discussion*

In this section, we discuss some nuances of the interpretation of the results.

We must emphasize that although our preferred interpretation comprises social interaction models, *Share Democrat* may affect contributions through alternative mechanisms. For example, part of the conformity effects may be attributed to differences in fundraising practices in the United States (Huckfeldt, 1979; Cho, 2003). Indeed, if campaign committees understand the power of social incentives, we should expect them to adjust their campaign practices to leverage these incentives (Gimpel et al., 2006). Also, 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 of an investment value, but because of a consumption value (Ansolabehere, de Figueiredo, & Snyder, 2003).

Regarding the external validity of our estimates, given that the NCOA records omit some residential moves, we would like to extrapolate the magnitude of conformity effects from the subsample of movers with NCOA records to all movers. This external validity depends on whether contributors with missing NCOA records are a random subset of all movers or whether they are systematically different in characteristics that mediate the conformity effects. For instance, mailing professionals claim that younger individuals are less likely to use mail forwarding and, as a result, are less likely to show up in the NCOA records. Thus, if younger individuals were less (more) sensitive to conformity effects, our results would underestimate (overestimate) the magnitude of conformity effects in the population of movers.

The magnitude of conformity effects that we estimated with the sample of recent movers may or may not be extrapolated to the general population. On the one hand, the facts that less recent movers have been exposed to their environment for much longer than recent movers[11] and that longer exposure magnifies the conformity effects imply that our results would underestimate the magnitude of conformity in the general population. On the other hand, if more frequent movers are more willing to conform (which could be why they were more willing to move in the first place), then our estimates for recent movers would overestimate the magnitude of conformity effects in the general population.

Finally, the insignificant coefficient on *Share Democrat* for the group *Moved after 2012 Cycle* does not imply that individuals in this sample do not sort into like-minded areas. As a group, there is substantial sorting in this sample. These contributors moved to ZIP-3s with an average *Share Democrat* of 68.67% (from table 2), which is significantly higher than the population-weighted U.S. average of 60.08%. Within our sample of movers, our evidence indicates that conditional differences in 2012 contribution amounts do not predict the *Share Democrat* after 2012. This evidence does not imply that stronger Democrats do not move to more Democratic areas. Indeed, the lack of correlation between conditional contribution amounts and partisanship is consistent with the widespread view that contributors who donate large sums have a partisan affiliation that is largely homogeneous (Bonica, 2014) and stable (Ansolabehere et al., 2003).[12]

IV. Measuring the Contribution of Conformity Effects to Geographic Polarization

Geographic polarization in contributions denotes the extent to which Democratic contributors tend to live close to other Democratic contributors. This polarization is partly generated by the sorting of individuals into areas with like-minded peers.[13] 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 the remainder of the paper, we quantify the extent to which conformity effects exacerbate geographic polarization.

A. *Measuring Geographic Polarization in Contributions*

To study the contribution of conformity to geographic polarization, we must start by choosing a measure of geographic polarization. We use the intracluster correlation coefficient, which can be obtained by estimating the beta-binomial model. This coefficient can take values from 0 to 1, where a higher value indicates higher geographic polarization. A coefficient of 0 would correspond to the extreme case where the probability of being a Democratic contributor is the same in all ZIP-3s (the minimum degree of clustering), while a coefficient of 1 would correspond to the extreme case where all ZIP-3s have exclusively Democrat or Republican contributors (i.e., the maximum degree of clustering).

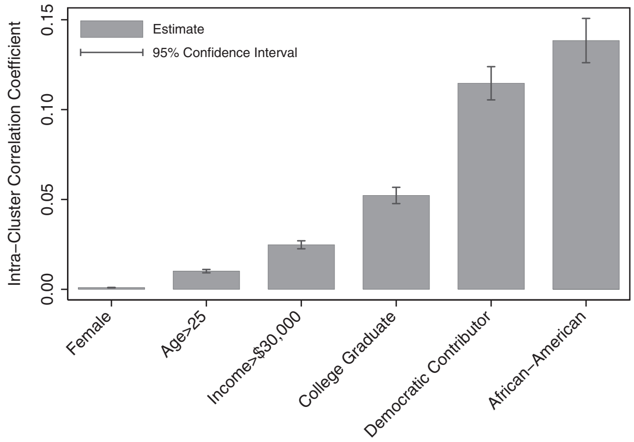
Using data on individual contributions to the 2012 presidential candidates, we find an estimated intracluster correlation coefficient at the ZIP-3 level of 0.11 (SE 0.005) (for a formal definition of this correlation coefficient and details of the estimation results, see appendix B). To illustrate how economically significant this coefficient is, figure 3 shows the corresponding coefficients of intracluster correlation for other socioeconomic characteristics. The degree of clustering for *Democratic Contributor* (0.115) is significantly higher than the clustering for gender ($<$ 0.01), age (0.01), income (0.025), and education (0.052). Only the racial clustering (African Americans, 0.138) is somewhat higher than the partisan clustering, with the difference being statistically significant but economically not large. Given the consensus that racial segregation is very high in the United States (Cutler, Glaeser, & Vigdor, 1999), this benchmark suggests a high degree of partisan polarization.

[11] 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 (1/0.062). In comparison, our sample of movers have been exposed between 0 and 23 months.

[12] For example, in the general U.S. population, a nontrivial share who voted for Obama in 2008 voted for Romney in 2012. On the contrary, in our sample there were virtually no individuals contributing to Obama in 2008 and Romney in 2012. 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 include only contributions over $200.

[13] Individuals may have a preference for living next to like-minded individuals, or they may have a preference for other place characteristics that are correlated with partisanship (for more on this, see Hui, 2013; Cho, Gimpel, & Hui, 2013; Gimpel & Hui, 2015).

FIGURE 3.—COMPARING POLITICAL POLARIZATION TO POLARIZATION IN OTHER CHARACTERISTICS



Data on 890 three-digit ZIP codes. For each characteristic listed on 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 intracluster correlation: $\rho = \frac{1}{1+\alpha+\beta}$. Confidence intervals were computed using the delta method. *Democratic Contributors* corresponds to the proportion of Democratic contributors among all contributors in the ZIP-3 during the 2012 presidential election (on average, 55%). *Female* corresponds to the proportion of women 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 degrees among all individuals 25 years and 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%).

Source: Contribution data from Federal Election Commission records in the 2012 cycle and data on gender, age, income, education and race from the 2012 American Community Survey.

B. *The Maximum Likelihood Model for Counterfactual Analysis*

We want to disentangle how much of the coefficient of intracluster correlation reported in the previous section can be attributed to sorting versus conformity effects. Let $j = 1, \ldots, J$ 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 parties, with the total population given by $M_j = M_j^D + M_j^R$. 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 intracluster 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 in each area.

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:

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

$$\log\left(p_j^R\right) = \gamma \cdot \log\left(\frac{M_j^R}{M_j^D}\right) + \log\left(\tilde{p}_j^R\right). \tag{3}$$

The parameter γ drives the conformity effects—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.

Note that $p_j^k M_j^k$ is the expected number of contributors to party k in area j $\left(E\left[N_j^k\right]\right)$ 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:

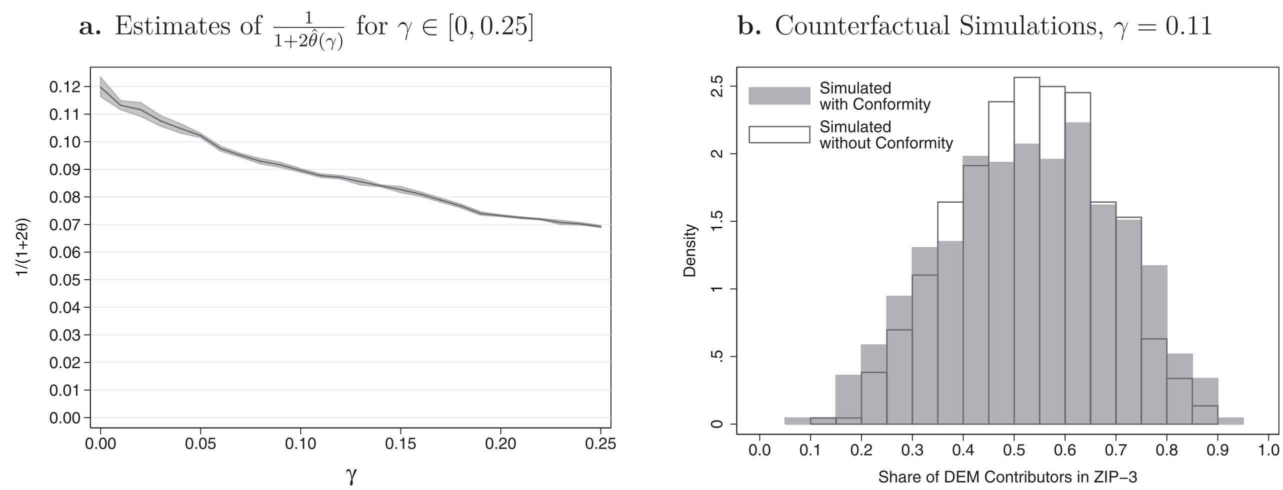
$$EP_j = \frac{\frac{p_j^D M_j^D}{p_j^R M_j^R} - \frac{\tilde{p}_j^D M_j^D}{\tilde{p}_j^R M_j^R}}{\frac{\tilde{p}_j^D M_j^D}{\tilde{p}_j^R M_j^R}} = \left(\frac{M_j^D}{M_j^R}\right)^{2\gamma} - 1. \tag{4}$$

Note that EP_j is a function of 2γ instead of γ because conformity has a double effect, by increasing 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 $\left(\frac{M_j^D}{M_j^R} = 1\right)$, there would be no polarization in sympathizers to amplify, and the contribution of conformity effects would be 0 regardless of the value of γ ($EP_j = 1^{2\gamma} - 1 = 0$). In an area with 25% Democrats, a conformity effect of $\gamma = 0.11$ would generate an excess polarization of about 27% $\left(EP_j = \frac{0.75}{0.25}^{0.22} - 1 = 0.27\right)$.

The overall contribution of conformity effects to polarization would be given by the average of EP_j across all j's. This average, in addition to γ, depends on the entire distribution of $\frac{M_j^D}{M_j^R}$, which is driven by the sorting effects. In practice, we do not observe the distribution of M_j^D's, so we need to estimate it. To make this estimation possible, we make three 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: $\sum_j M_j^D = \sum_j M_j^R$. This assumption implies that the average probability of the beta-binomial distribution must be $\frac{1}{2}$, which happens if and only if the two parameters of the beta-binomial distribution are equal. Let θ denote this unique parameter, which implies that the coefficient of intracluster 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 $\Theta = \{\varphi, \theta, \tilde{p}_1, \ldots, \tilde{p}_J\}$ denote the set of parameters to

FIGURE 4.—CONTRIBUTION OF CONFORMITY EFFECTS TO GEOGRAPHIC POLARIZATION, MAXIMUM LIKELIHOOD ESTIMATES



(a) For each possible value of $\gamma \in [0, 0.25]$ (x-axis), the y-axis shows the intracluster correlation coefficient $\left(\frac{1}{1+2\hat{\theta}}\right)$ for the distribution of Democratic sympathizers, where $\hat{\theta}$ correspond to the maximum likelihood estimates described in section IVB. The line corresponds to the point estimate, and the shaded area corresponds to the respective 95% confidence interval. (b) Histogram of the share of simulated Democratic contributors among all the contributors to presidential campaigns during the 2012 election cycle across the 890 3-digit ZIP codes. *Simulated with Conformity* corresponds to 1,000 simulations using the maximum likelihood estimates obtained under $\gamma = 0.11$ (see section IVB). *Simulated without Conformity* corresponds to 1,000 simulations using the same maximum likelihood estimates obtained under $\gamma = 0.11$, except for γ, which is set to 0 after estimation to represent the absence of conformity effects.

be estimated. Let $g\left(k; N, \tilde{p}_j\right)$ 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

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

For a given value of γ, we can estimate the set of parameters 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. Each $\tilde{p}_j$ is identified mainly by the per capita rate of Democratic contributors in j. φ is identified mainly by the average of $\frac{N_j^R}{N_j^D}$ across all j's. Most important, θ is the degree of sorting that, after being augmented by γ, produces the polarization of contributions observed in the data.

C. *Results from the Counterfactual Analysis*

Figure 4a shows the maximum likelihood estimates of $\frac{1}{1+2\hat{\theta}(\gamma)}$ for a range of values of γ from 0 to 0.25. The value of $\frac{1}{1+2\hat{\theta}(0)}$ (when $\gamma = 0$) measures the overall degree of geographic polarization. For $\gamma > 0$, $\frac{1}{1+2\hat{\theta}(\gamma)}$ measures the degree of geographic polarization that would have resulted in the absence of conformity effects of magnitude γ. Thus, given some $\tilde{\gamma} > 0$, a natural way of measuring the contribution of conformity effects to geographic polarization is by comparing $\frac{1}{1+2\hat{\theta}(\tilde{\gamma})}$ with $\frac{1}{1+2\hat{\theta}(0)}$: $\frac{\frac{1}{1+2\hat{\theta}(0)} - \frac{1}{1+2\hat{\theta}(\tilde{\gamma})}}{\frac{1}{1+2\hat{\theta}(0)}}$.

The last step is to obtain an estimate of γ. As defined in equations (2) and (3), γ correspond to the effect of $\log\left(\frac{N_j^{own}}{N_j^{opp}}\right)$ on own contributions. For our sample of Democratic contributors, this elasticity can be obtained from a Poisson regression of own contribution on $\log\left(\frac{N_j^D}{N_j^R}\right)$, using the event-study specification from equation (1).[14] Using the same specification as column 1 of table 3, the estimated elasticity is $\hat{\gamma} = 0.11$: a 1% increase in $\frac{N_j^{own}}{N_j^{opp}}$ increases contributions by 0.11%.[15] According to figure 4a, the intracluster correlation coefficients are 0.087 for $\gamma = 0.11$ and 0.119 for $\gamma = 0$. These estimates imply that 27% of the geographic polarization in contributions can be attributed to conformity effects $\left(\frac{0.119-0.087}{0.119}\right)$. Reproducing the analysis with the 95% confidence interval of $\hat{\gamma}$, [0.05, 0.18], it follows that conformity effects could explain between 15% and 36% of the geographic polarization in contributions.

Figure 4b provides an alternative illustration of the contribution of conformity effects, based on counterfactual simulations. The solid histogram shows the distribution of the share of Democratic contributors averaged over 1,000

[14] 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 $\tilde{p}_j^D = \varphi\tilde{p}_j^R\ \forall j$, the only bias introduced from this replacement is the attenuation bias due to the sampling variation in N_j^D/N_j^R.

[15] In practice, $\log\left(\frac{N_j^D}{N_j^R}\right)$ approximately a linear transformation of *Share Democrat* (their correlation coefficient is 0.99), so this elasticity is approximately a rescaling of the coefficient on *Share Democrat* from column 1 of table 3.

simulations using the maximum likelihood estimates for $\gamma = 0.11$. The hollow histogram uses the same parameter values estimated under $\gamma = 0.11$, except for γ, which is set to 0 after estimation to represent the absence of conformity effects. Consistent with the counterfactual calculations from the previous paragraph, figure 4b shows that the distribution of Democratic contributors is noticeably less dispersed under the counterfactual simulations with no conformity effects.

Finally, we can discuss the implications of some of the simplifying assumptions introduced in the maximum likelihood model. First, since the event-study estimates correspond to a sample of Democratic contributors, we implicitly assumed that γ is the same for Democrats and Republicans: $\gamma = \gamma^D = \gamma^R$. If conformity effects are stronger for Republicans, this approach leads to an underestimation of the importance of conformity effects for polarization, but if the conformity effects are stronger for Democrats, this approach leads to an overestimation. The evidence from appendix A.2 suggests that the magnitude of conformity effects may be similar among Democrats and Republicans and, if anything, it may be stronger among Republicans. Second, our model assumed 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) or social multiplier (Glaeser, Sacerdote, & Scheinkman, 2003) that would exacerbate the conformity effects even further. If anything, our baseline specification without feedback loops can only underestimate the contribution of conformity effects to geographic polarization. For reference, appendix C shows one way of extending the model to allow for feedback loops, which could augment the magnitude of conformity effects by about 28%.[16]

V. Conclusion

We presented evidence that individuals are influenced by the mainstream political preferences in their groups of reference, based on an event-study analysis of residential mobility among campaign contributors. We found evidence of significant conformity effects: increasing by 1 percentage point the share of Democrats in the ZIP-3 of residence increases the amount contributed to Obama by 0.67%. 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 so as to avoid social sanctions, even if her or his 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.

One strategy to study these additional hypotheses would be to use a similar research design that instead focuses on partisan beliefs rather than partisan behavior. Another 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, because the turnout records do not specify the party that the individual voted for and also because they are not as easily accessible as the contribution records. If social signaling was the main driving force behind the conformity effects, then we would expect social context to affect campaign contributions but not voting turnout.[17] On the contrary, if social context affected beliefs about the candidates and policies, then we would expect social context to have a significant effect on turnout as well.

[16] Additionally, conformity effects may exacerbate geographic polarization even further by causing higher sorting. For instance, individuals may anticipate that they will be treated better in like-minded areas, making them more likely to move to those areas.

[17] Relatedly, Gentzkow and Shapiro (2011) find that segregation in social interactions with neighbors, coworkers, and family members is higher than segregation in media consumption.

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