The Party Edge:
Consultant-Candidate Networks in American Political Parties

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ABSTRACT

Consultants have become an important part of electoral politics, but we know little about their influence on political campaigns. Using data from *Campaigns & Elections*, we present the first systematic analysis of the networks of Republican and Democratic consultants and their House and Senate general election clients from 1992–2008. After introducing the characteristics of these networks, we estimate a Bayesian spatial autoregressive model demonstrating that campaigns' positions in the consultant-candidate network are associated with the tactics that they employ. We then show that consultants whose clients achieve significant electoral victories become increasingly central to the network in the subsequent election cycle. In this way, consultants play a crucial role in helping parties adapt to changing electoral circumstances.

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1. INTRODUCTION

Parties seem to have greater influence on candidates and elected officials now than at any other point in the post-war era (Aldrich 2011, 255-292), but the precise organizational and institutional mechanisms through they exert influence outside of Congress remain somewhat obscure. This lack of precision is particularly glaring in the study of "parties-as-organizations" (Key 1964). Although formal party organizations exist, their influence and capacity has lagged behind the incredible growth in partisanship we have observed amongst elites in recent decades (Gibson et al. 1983; Aldrich 2000, 1999; Herrnson 2010). One explanation for this discrepancy is that many of the activities of contemporary parties are organized outside of formal party institutions (Monroe 2001; Cohen et al. 2008; Masket 2009). Indeed, a growing body of work shows that party organizations should be viewed not as formal hierarchical institutions, but rather as networks of formal and informal relationships that fulfill the same institutional goals (e.g., Koger, Masket and Noel 2009, 2010).

In this article, we argue that the network of relationships between candidates and their political consultants is an increasingly important component of the informal party-as-organization (see also Doherty 2006, N.d.; Kolodny and Dulio 2003). First, we show that consultants are a key mechanism for diffusing strategies between campaigns. Second, firms that win important races become more central within the network, increasing their ability to disseminate effective tactics within the party. By rewarding success and penalizing failure in this way, parties can facilitate wider adoption of effective campaign strategies.

We begin by describing our theoretical perspective on the role of consultants in party adaptation and specifying three empirical hypotheses. We then describe our source data – listings of consultant-candidate relationships that were published in *Campaigns & Elections* from 1992-2008 — and test our predictions on the candidate-consultant networks we construct. Using spatial autoregressive models, we find support for the hypothesis that candidate strategy is associated with their location in the consultant-candidate network, suggesting that

consultants help to diffuse strategies across campaigns. We then show that consultants become more central within their party's network when they achieve significant electoral victories, which may improve the party's ability to successfully contest future elections. In this way, consultants help parties respond to changing electoral circumstances.

2. RETHINKING THE CONSULTANT-PARTY RELATIONSHIP

Contemporary American political parties face difficult problems of organization and coordination. In an era of candidate-centered elections, they must be able to adapt to changes in the political environment while maintaining message consistency and preserving the party brand (Snyder and Ting 2002; Grynaviski 2010). One approach to these challenges is to rely on formal party organizations, which operate similarly to hierarchically structured firms. In the electoral arena, for instance, the House and Senate campaign committees of the major parties play a crucial role in recruiting candidates, assisting them with their campaigns, and conducting independent expenditures on their behalf.[1]

However, the intense time pressures of modern campaigns and the difficulty of coordinating campaign strategy across hundreds of House and Senate races have largely precluded such a top-down approach. These obstacles are exacerbated by campaign finance laws specifically aimed at curtailing centrally-directed party campaigns. American parties have therefore evolved institutional mechanisms to perform these functions that are very different from the more hierarchical and centralized parties of Western Europe. The contemporary parties in America rely on indirect, informal, and often difficult to observe interactions in which actors at the edges of the formal party organizations provide needed services and information to candidates while facilitating some limited degree of coordination.

Like think tanks, bloggers, interest groups, independent expenditure groups, and cam-

[1]The party campaign committees also employ their own consultants for fundraising, media, etc., but these are outside the scope of our study. See Magleby (2010) for a broader discussion of the role of consultants within contemporary political parties.

paign staff, consultants serve as important conduits for the dissemination of effective tactics and messages despite holding no formal position within party institutions. Rather than passing through formalized channels, strategic insights may instead spread between campaigns through networks of these kinds both within and across election cycles. We argue that consultants are an important mechanism for this diffusion process (see also Darmofal et al. N.d.). They link campaigns across the country, facilitating decentralized exchanges of information within their parties about messaging and strategy. In addition, consultants who are successful gain influence and clients over time, which helps parties to disseminate effective strategies and tactics more widely.

Our view of consultants is consistent with a growing body of theoretical and empirical research that has sought to move beyond formal organizations and rules to focus on the informal means through which American parties operate.[2] This literature argues that research on contemporary party organizations must broaden its focus to include the wider class of agents that coordinate on the task of electing candidates—what Koger, Masket and Noel (2010) call the "expanded party network." This paper seeks to add campaign consultants to the growing list of actors on the party's edge who play a crucial role in contemporary electoral politics.

The argument that campaign consulting firms are a valuable component of parties sharply contrasts with several past studies of consulting firms, which argue that consultants are either a worrying symptom or significant cause of candidate-centered elections, weak party organization, and the growth of mercenary "party-rivaling" organizations such as PACs (Rosenbloom 1973; Sabato 1981; Shea 1996; Nimmo 2001; see also Magleby, Patterson and Thurber 2000). However, we believe that this account takes too narrow a view of party strength (e.g., measuring the strength of party organizations by their budgets and the number of services they provide [Aldrich 2000, 1999; Gibson et al. 1983]). Contemporary parties

[2]See, for instance, Schwartz (1990), Monroe (2001), Bernstein (2003), Dominguez (2005), Bernstein (2005); Skinner (2005), Bawn et al. (2006), Doherty (2006), Heaney and Rojas (2007), Cohen et al. (2008), Koger, Masket and Noel (2009), Herrnson (2009), Grossman and Dominguez (2009), Masket (2009), Masket et al. (2009), and Koger, Masket and Noel (2010).

may be using a less hierarchical approach because it is more effective (Powell 1990; Jung and Lake 2011), not because the parties themselves are weak. Such arrangements can reduce transactions costs and facilitate coordination and cooperation in complex environments without requiring mechanisms for centralized control.

Towards this end, the national campaign committees and state parties often guide candidates to recommended consultants (Herrnson 1986; Kolodny 2000; Dulio 2004) and provide financial support rather than providing services directly. Dulio (2004) argues that this arrangement is the result of concerns about inefficiency:

> In a time of continued technological advancement and when more and more candidates are taking advantage of that technology, parties have discovered that it is inefficient for them to provide all the necessary services to their candidates from inside their headquarters. Therefore, the parties have scaled back tremendously in the services they *provide* to candidates, and have increased the amount of money they spend *paying bills for* their candidates (108–109).

Parties have come to believe in the mantra, "Hire enough professionals ... and provide them with millions of dollars, and they will find a dazzling array of ways to employ their expertise and money" (Aldrich 2011, 272).

Another critique states that consultants pursue their own agenda at the expense of parties (Magleby, Patterson and Thurber 2000). While there are obviously principal-agent issues in these relationships (Walton and Walter 2009), the reputation and profitability of consulting firms are at least partially linked to the electoral success of their clients, which aligns many of their incentives with those of the parties (if not necessarily their clients). Similarly, commercial concerns encourage consulting firms to invest in building their campaign expertise and institutional capacities, creating resources that will help elect party members in the future.

We are not the first to argue that the relationship between parties and consultants is not competitive but rather complementary. Some scholars have argued that the increased use of consultants, while still a sign of weakened political parties, is not a cause of party decline but an effort by parties to adapt to the changing nature of campaigns as well as restrictive electoral and campaign finance laws (Menefee-Libey 2000; Kolodny and Dulio 2003). Others

argued that parties and consultants are engaged in a symbiotic relationship that largely benefits both (e.g., Luntz 1988; Kolodny and Logan 1998; Kolodny 2000; Johnson 2001; Farrell, Kolodny and Medvic 2001; Dulio 2004; Dulio and Nelson 2005). In this view, consultants and parties are allies who specialize in their respective areas of expertise.

However, our stance is stronger. We do not view consultants as party *allies*, but as functional *components* of party organizations. This view rests on the theoretical point that parties are not individual agents with specific goals, but institutions that have evolved to fulfill certain tasks (Aldrich 2011; Masket 2009). To the extent that consulting firms fulfill the aims of institutional parties, they should be evaluated and studied in those terms.

3. CONSULTANTS AS AGENTS OF PARTY ADAPTATION

Our theoretical perspective on the role of consultants in facilitating party adaptation suggests three empirical expectations that we test below.

> *Hypothesis 1: Almost all consulting firms work exclusively with congressional campaigns from only one of the major parties.*

First, we predict that almost all campaign consulting firms are highly partisan.[3] If campaign consulting firms are actors existing at the edge of the party organizations, it seems clear that they cannot cross party lines. Thus, our theory requires that consultants work with clients of one major party.

Note that this prediction is important primarily to establish the basic premise for our study. The consultant-candidate network is widely understood to be partisan. Indeed, this hypothesis has received support in past research, which shows that most consultants work primarily or exclusively with candidates from a single party. For instance, a 1997 survey of consultants by Kolodny and Logan (1998) found that only 8% of general consultants reported

[3]For reasons discussed below, we exclude technical consultants who provide specific services like direct mail and web site design.

working about equally with candidates from both parties. In addition, it is well known that parties purposefully direct candidates towards "loyal" consulting firms and may even premise the distribution of party funds on contracting with approved consultants (Kolodny and Logan 1998).

Hypothesis 2: The tactics used by candidates will be associated with their location in the consultant-candidate network.

Second, we expect that consulting firms influence the messages and tactics employed by their clients. In a general sense, it is clear that consulting firms play a key role in modern elections. Campaigns must organize what is essentially a medium-sized business in the months leading up to Election Day and successfully carry out a series of complex logistical, organizational, and strategic tasks. To be competitive, campaigns must raise hundreds of thousands (or millions) of dollars; field polls; develop mail, TV, and/or radio ads; recruit and coordinate volunteers; and much more. These wild temporal fluctuations in organizational capacity are typically accomplished by relying on the expertise of consultants (Thurber and Nelson 1995; Johnson 2001, 2002), who thus have a great deal of leverage to guide clients toward specific strategies and messages. Consulting firms are likely to recommend certain favored strategies to their clients and to apply new approaches and tactics that seem to work for one client in other campaigns. We therefore expect campaigns' locations in the consultant-candidate network to be associated with the strategies that they employ.

This hypothesis also has some support from prior research and anecdotal accounts. Indeed, consultants were already being criticized for having "helped homogenize American politics... and narrowed the focus of elections" by the early 1980s (Sabato 1981, 7). Subsequent studies found evidence of consultant influence on negative advertising (e.g., Swint 1998; Francia and Herrnson 2007; Grossman N.d.), fundraising (Herrnson 1992; Dulio 2004), electoral outcomes (Medvic and Lenart 1997; Medvic 1998; Dabelko and Herrnson 1997; Dulio 2004), messaging (Johnson 2001), and public policy (Lathrop 2003).

An extreme example of the effect consultants can have on campaign messaging was observed in the 2010 election cycle when Stephen Fincher, a Republican candidate for Congress in Tennessee, and Dorman Grace, a Republican candidate for Alabama Agriculture Commissioner, were discovered to be using almost identical language and visual images in their television commercials. The candidates even shot scenes for their TV ads in the same field using the same tractor as a prop (Weigel 2010). Their consultant, Tommy Hopper, defended the practice (Wilson 2010):

> Hopper said the ads present a good message for both candidates, and that he doesn't see a problem using the same clips and nearly identical scripts. "It saved both candidates a lot of money, and they're running nowhere near the same market," Hopper said.

Hopper was subsequently found to have also used similar phrasing and messaging in an ad for Kansas Congressional candidate Tracey Mann. In an interview with a local newspaper, he again defended the practice, openly admitting that he used similar tactics in his clients' races (Clarkin 2010):

> "We used the (deep roots) theme first for him (Mann), and borrowed it for others," Hopper wrote in an e-mail response. "We use themes that match candidates. The issue is whether they are true to the candidate."

Other recent examples of consultant message recycling include attorney general candidates in California and New York who ran nearly identical biography ads (Katz 2010) and Nevada Assembly candidates who used nearly identical mailers (Ralston 2010).

Of course, the similarities between campaigns that share consulting firms will not always be this stark. Indeed, given the differing electoral circumstances facing each campaign, we expect the patterns to be relatively subtle. However, surveys and in-depth interviews of campaign professionals reveal that there is a great deal of practical wisdom traded and debated within the parties about the messages and strategies that should be used in various electoral scenarios (c.f., Johnson 2011). The spatial statistical methods we use below offer a

method for systematically testing the hypothesis that campaigns sharing consulting firms are more likely to employ similar strategies than we might expect by chance.

> *Hypothesis 3: Consulting firms who are more successful in winning elections become increasingly central in the consultant-candidate network.*

Finally, we expect that the process of strategic adaptation described above will be reinforced by market pressures. Campaigns face strong incentives to retain prominent firms with a track record of recent success. Contracting with respected consultants may not only improve their chances of victory, but also help signal their viability to political elites (Cain 2011). As a result, high-performing firms should acquire more numerous and important clients in subsequent election cycles, increasing their centrality within the consulting network. By contrast, firms that are perceived to have performed poorly are likely to attract fewer and/or less important clients, causing them to become less central to the network (or even to drop out of the network entirely). This selection process is the mechanism by which the interests of consulting firms, candidates, and parties are (imperfectly) aligned. The financial rewards of success encourage consultants to learn about effective strategies and spread them to their clients.

4. DATA, METHODS, AND RESULTS

4.1. *Consultant-candidate network data*

We study consultant-candidate networks for House and Senate general elections during the 1992–2008 period (excluding special elections). The data, which include all major party candidates and incumbents, were gathered from scorecards published at the end of each election cycle in *Campaigns & Elections* (henceforth, *C&E*). The scorecards, which are typically a combination of self-reports by consulting firms and research by the magazine's staff, provide

the most comprehensive information available on consultant-candidate relationships in federal elections. Rather than studying one or two election cycles as in previous research (e.g., Medvic and Lenart 1997; Doherty N.d.), we aggregate these data across nine election cycles.[4] The *C&E* scorecards do not include specifics on the consultant-candidate relationship such as total spending. However, the services provided by each firm are listed. Since our interest is primarily in the substance of campaigns, we restrict our analysis to firms providing general, media, and/or polling consulting;[5] all dyads in which the firm does not provide at least one of those services (typically, specialists in discrete functions such as fundraising, research, direct mail, or voter contact) are excluded.[6] The resulting dataset, which shows general stability in consultant usage over this period,[7] was then merged with election data from CQ's Voting and Elections Collection and processed into a network format for analysis.

4.2. *Hypothesis 1: Cross-party consultants are (virtually) nonexistent*

We now use these data to test the the hypotheses in Section 3. H1 states that consultants will rarely work across party lines. As expected, when we convert these data into network format and plot the results, we find that the consultant-candidate networks of the two major parties do not overlap in any meaningful way, providing powerful support for Hypothesis 1. Figure 1 provides an illustrative example—the 2002 consultant-candidate network. The two largest

[4]We exclude 1990 since there were approximately half as many consultant-candidate dyads as in 1992, which could indicate that the industry had not yet matured or that the data are incomplete. Consulting firms were linked across years when possible (e.g., a new partner was added).

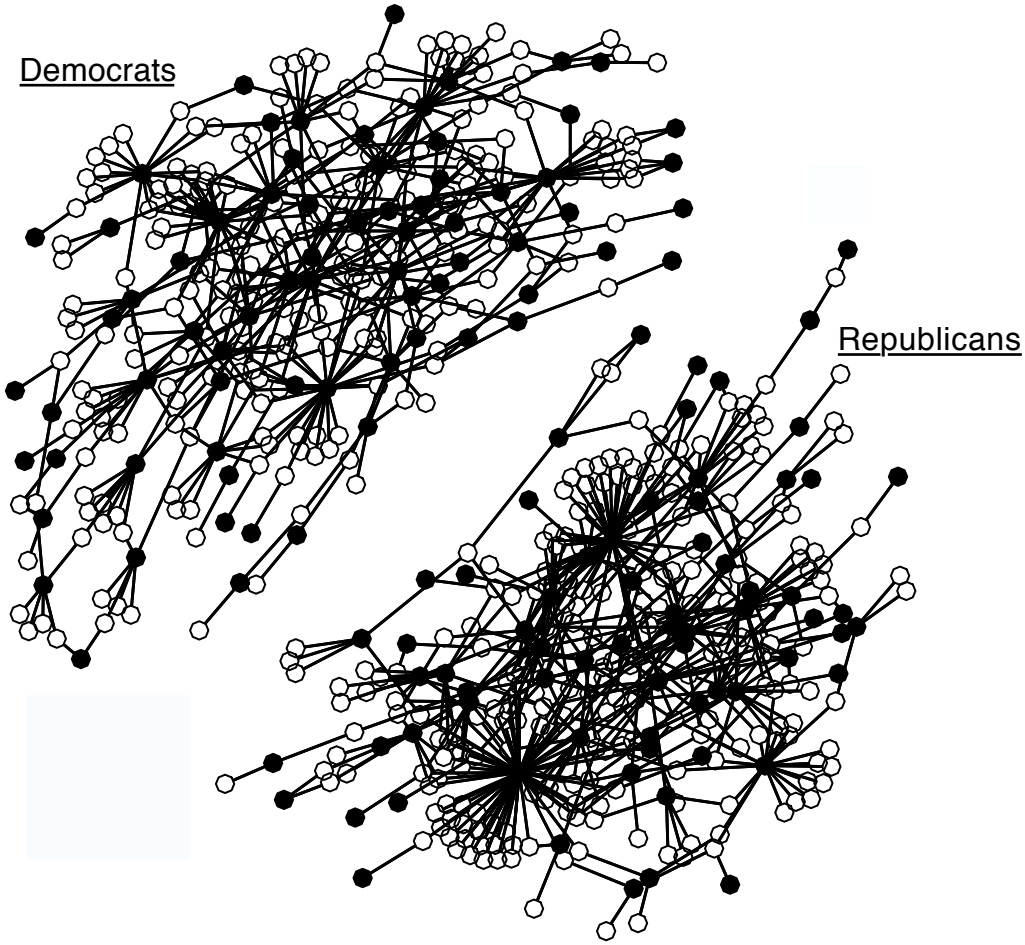
[5]While it might be desirable to further disaggregate our data and look at each type of consultant separately, we lack the sample size necessary to do so. In addition, excluding relevant consultant ties could result in the spatial autoregressive matrix being misspecified.

[6]Firms use a variety of terms to describe the services they provide to *C&E*. A list of the terms that were coded as general, media, and polling consulting is available upon request.

[7]While early studies emphasized the explosive growth of the consulting industry (e.g., Sabato 1981), the industry seems to have subsequently reached maturity; our data indicate that consultant usage was roughly stable in the 1992–2008 period. For instance, the proportion of candidates with one or more consultants whose firms provide general, media, or polling consulting services actually declined slightly. This finding holds when we disaggregate the data by chamber and by party. Consultant usage is also roughly stable over time when we break out the House data by race type (open seat or incumbent) and by the previous electoral experience of the non-incumbent candidate(s) (all results available upon request).

components in the network are portrayed in the figure (consultant nodes are solid black while candidate nodes are unfilled circles). Each connected grouping corresponds to a single party. There is no overlap between the two groups; no consultant worked for candidates from both parties, nor did any candidate hire consultants from both parties.

Figure 1: The 2002 consultant-candidate network



Consultant nodes are solid black circles while candidate nodes are unfilled circles; labels are omitted for legibility. No firms reported working for candidates from both major parties.

Indeed, across nine election cycles, we observe only five cases of general, media, or polling consultants contracting with campaigns in both major parties in the same cycle—a tiny fraction of the observed set of consultant-candidate dyads. This behavior reflects a combination of party loyalty by consultants and market pressure from clients (who are also party

members). For instance, Public Opinion Strategies, a prominent Republican polling firm, preemptively resigned from the Senate campaigns of Pennsylvania senator Arlen Specter and Florida governor Charlie Crist when they left the GOP (Hamby 2009; Halperin 2010).

4.3. *Hypothesis 2: Consultants influence campaign strategy*

Our second goal is to test the extent to which the strategies adopted by campaigns are associated with their location in the candidate-consultant network. Previous studies have primarily focused on whether consultants improve electoral outcomes (e.g., Herrnson 1992; Medvic and Lenart 1997) or affect usage of the specific strategy of "going negative" (e.g., Grossman N.d.). However, consultants are likely to influence many different aspects of campaign strategy such as issue emphasis, policy positions, fundraising tactics, allocation of advertising dollars, and the emphasis placed on grassroots mobilization (Johnson 2011). As such, campaign strategies—and elections in general—cannot be assumed to be independent across districts (as traditional statistical analyses would assume). We instead anticipate that individual campaigns who share consultants will be more likely to use similar tactics and strategies than we would expect by chance (Hypothesis 2).

Unfortunately, there is surprisingly little data on campaign tactics, especially for challengers. One reason is that many campaigns, especially non-competitive races or those that are distant from major media markets, provide little direct evidence by which their activities can be evaluated. These campaigns often receive low levels of media coverage and do not advertise on television. The most comprehensive effort to date to assemble information on campaign messages and strategies is provided by Druckman, Kifer and Parkin (2009, 2010), who collected information from the websites of congressional campaigns during the 2002, 2004, and 2006 general elections. Their data includes all major-party Senate candidates and a random sample of major-party candidates for the House.[8]

[8]Since most campaigns had websites during this period, the potential for selection bias should be lower than comparable television advertising data from the Wisconsin Advertising Project (Goldstein, Franz and Ridout

Druckman, Kifer, and Parkin (hereafter DKP) evaluate campaign websites along numerous dimensions including substantive content. They show that campaign websites accurately represent the more general strategies adopted by campaigns. DKP's data are structured as a rolling cross-section—there is one observation of each website included in the random sample in each cycle. Here, we focus specifically on three indicators of general campaign strategies: (i) issue ownership, (ii) the level of "risk-taking" by the campaign, and (iii) personal negative attacks. The first two are the broadest and richest measures of campaign strategy in the DKP dataset, while the third is a variable that has been the focus of several past studies on consultant influence (e.g., Francia and Herrnson 2007; Grossman N.d.).

Before proceeding, it is worth briefly discussing how these variables are measured. First, DKP provide a general strategy variable referred to as "issue ownership." This variable, which ranges from -20 to 26, is higher for candidates who focus their message on issues that are "owned" by their party (2009, 348). It captures the degree to which campaigns emphasize policy areas in which the candidates' party has a reputational advantage in national polls. This variable is perhaps the best measure of campaign strategy for our purposes since issue emphasis is a strategic choice that consultants are especially likely to influence (Johnson 2011). As Medvic (2001, 433) notes, "Consultants help a candidate select the issues that give the candidate the best chance of winning. These issues will be ones that the public cares about; they will also be issues in which the candidate has a competitive advantage over his or her opponent."

Second, DKP created a scale for the "riskiness" of a given campaign's strategy. This scale, which ranges from -3 to 8, sums a range of indicators for tactics DKP perceive to have uncertain consequences (emphasizing issues, negative information, etc.) and subtracts from that total the number of tactics used that they view as more safe (emphasizing experience as an elected official, personal roots in the community, and the candidate's role in obtaining benefits for their constituents).

2002; Goldstein and Rivlin 2005, 2007).

Our final outcome of interest is whether the campaign website includes negative information about the opponent that is focused on the person rather than issues (e.g., "my opponent is not trustworthy"). The measure is dichotomous and was only collected in 2004 and 2006.[9]

Though DKP have created the best available outcome data for our study, it is worth noting that a cross-sectional snapshot of campaign websites is a relatively crude indicator of Congressional campaign strategy. These variables are likely to be imprecise measures of the true dependent variables of interest, which will inflate the standard errors of our models, biasing our results toward a null finding. As such, positive results should be interpreted as substantial evidence in favor of our theoretical predictions.

Creating the candidate-candidate network: To test H2, it is first necessary to convert our candidate-consultant networks into single-mode networks of campaigns linked by edges with weights representing the number of shared consultants. This process is known as projection and is a standard practice in the social networks literature. For instance, we convert the 2002 Democratic candidate-consultant network in Figure 1 into a network of the 2002 Democratic candidates (the nodes) who are linked by the consultants they shared during that cycle (the edges). The largest connected component of that network is presented in Figure 2.[10]

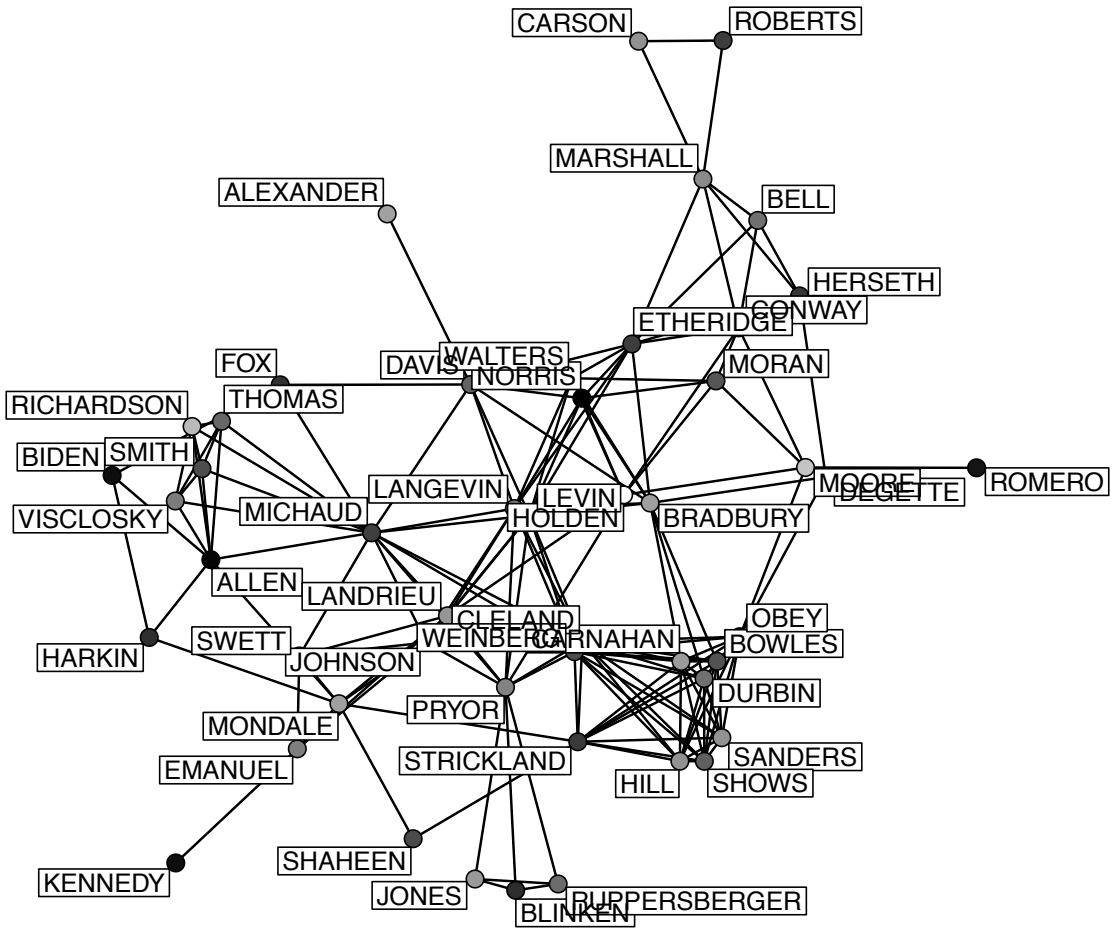
To illustrate the relationships we expect to find, the nodes (which represent 2002 Democratic candidates in the DKP data) are shaded by their values on the DKP's issue ownership variable on a color ramp from white for the minimum value in the component (-13 for Rep. Tim Holden, D-PA) to the maximum (15.6 for John Norris, a challenger in Iowa).

The plot suggests that issue ownership scores are correlated among candidates with shared consultants. For instance, Senator Joe Biden (D-DE), Senator Tom Harkin (D-IA),

[9]The following analyses are not directly related to those conducted by DKP. Readers interested in a more detailed description of their data and coding procedures are directed to the originally published articles and the data documentation on Druckman's website.

[10]As Figure 2 suggests, the candidate networks display high levels of clustering, which is a common artifact of the process of converting ("projecting") so-called two-mode network data into single-mode form (Latapy, Magnien and Vecchio 2008). The conversion process creates cliques among all candidates who share a common consultant. Given the unequal degree distributions of candidate relationships among consultants, large cliques of candidates are formed when the network is projected.

Figure 2: The 2002 Democratic candidate network



Nodes represent the largest connected component in the network of 2002 Democratic Congressional candidates; edges represent shared consultant ties. Nodes are shaded based on the candidate's issue ownership score in the data from Druckman, Kifer and Parkin (2009) on a color ramp from white (minimum) to black (maximum).

and Tom Allen (a Democratic Senate candidate from Maine) appear on the left side of the plot. Biden, Harkin, and Allen share ties because all three used Shrum, Devine & Donilon, the consulting firm of Democratic consultant Bob Shrum, who frequently advocates "union-hall populism" (Fineman and Gegax 2004).[11] All three candidates he advised in 2002 scored very high on the issue ownership variable and thus are shaded nearly black. Among the 49 Democratic candidates in the figure, Allen ranked second, Biden third, and Harkin seventh in

[11] In 2001, for instance, he argued that "if [Democratic candidates] focus on bread-and-butter Democratic issues, they do very well" (House Race Hotline 2001).

the extent to which their websites focused on issues on which Democrats have an advantage.

Spatial autoregressive model: To test Hypothesis 2 formally, we estimate spatial autocorrelation models to examine whether a campaign's location in the consultant-candidate network is associated with the strategies it uses (i.e., the DKP issue ownership, risk-taking, and personal negativity variables described above). In this case, the "space" in question is defined by the candidate-consultant network. The spatial autocorrelation we test for is between observations that are "neighbors" in this network (i.e., candidates who share one or more consultants) rather than in any physical or geographic sense.[12]

Specifically, we estimate Bayesian spatial autoregressive models with covariates (LeSage and Pace 2009).[13] For some continuous outcome y, the model assumes

$$y = \mathbf{X}\beta + \rho\mathbf{W}y + \epsilon \tag{1}$$

$$\epsilon \sim N(0, \sigma^2\mathbf{I_n}). \tag{2}$$

where n represents the number of observations, $\mathbf{X}$ is an $n \times p$ covariate matrix with p covariates (including a constant), and $\mathbf{W}$ is an $n \times n$ weight matrix with zeros along the diagonal. In this case, we specify $\mathbf{W}$ as a matrix of weighted edge values representing shared consultant ties between candidates.[14]

In this framework, the key parameter for testing H2 is the spatial autocorrelation coeffi-

[12]This approach is quite common in the social networks literature. For recent examples, see Mizruchi, Stearns and Marquis (2006) and Papachristos (2009).

[13]All of the analyses in this subsection were conducted in MatLab using the sar_g and sarp_g functions in the Econometrics Toolbox by James P. LeSage. Code and documentation for this package are available at `www.spatial-econometrics.com`. A complete replication file, including data and code, will be made available online when this article is published.

[14]These values are standardized by the total number of consultant ties such that $\sum_j w_{ij} = 1$ for all candidates $i = 1, ..., n$. Thus, if candidate a shared two consultants with candidate b, one with c, and none with d, $w_{ab} = \frac{2}{3}$, $w_{ac} = \frac{1}{3}$, and $w_{ad} = 0$. Substantively, this approach assumes that a candidate will be less likely to resemble other candidates with whom she shares consultants as the number of other candidates with consultants in common increases. For instance, extending the example above, if candidate a also shared two consultants with candidate e and one with f, the weight matrix value w_{ab} that represents the strength of her ties with candidate b would decline from $\frac{2}{3}$ to $\frac{1}{3}$. Conversely, we assume that the similarity between campaigns will be greatest when two candidates share one or more consultants with each other and share consultants with no other campaign.

cient ρ. This term captures the latent tendency of candidates who are "closer" to each other in the network to employ similar campaign tactics (Ward and Gleditsch 2008; LeSage and Pace 2009). In other words, it captures the general tendency for tactics and strategy to covary among campaigns sharing consulting firms. If we constrain ρ to be equal to zero, the model is identical to standard linear regression, which implicitly assumes that tactics and strategies are conditionally independent across campaigns. For instance, incumbent Republicans facing similar electoral environments would be assumed to be equally likely to include personal negative statements on their websites regardless of which consultants they employ. Our theory, on the other hand, suggests that the ρ term should be positive and statistically distinct from zero. A positive spatial autocorrelation coefficient would indicate that campaigns who are neighbors in the network will use similar tactics even after controlling for party, year, district composition, and other covariates. In particular, the individual-level treatment effect of ρ can be interpreted as the predicted change in the outcome y_i for a given unit i as the outcomes for all of its n neighbors $y_1, \ldots, y_n \forall j \neq i$ are exogenously increased by one unit (Ward and Gleditsch 2008, 38).

This spatial autoregressive model for continuous outcomes can be estimated using both maximum likelihood and Bayesian techniques (LeSage and Pace 2009). However, it is somewhat easier to generalize the model for dichotomous outcomes in a Bayesian framework using data augmentation and a probit link function. For the sake of methodological consistency, we therefore fit Bayesian spatial autoregressive models for both the continuous measures of issue ownership and riskiness and the binary measure of personal negativity.[15]

Analysis and results: Following DKP, we include members of both parties and pool across the elections of 2002, 2004, and 2006 in our analyses.[16] We analyze the three dependent

[15]Our analysis is based on uninformative priors. The possible values of ρ were allowed to range from -1 to 1. For the issue salience and risk-taking outcomes, the models were run for 7,000 iterations. Analysis was conducted after discarding the first 1,000 iterations. For the personal negativity outcomes, we ran the model for 5,000 iterations and discarded the first 700. Standard diagnostics indicated these procedures far exceeded what was necessary to ensure convergence and to fully sample the posterior.

[16]Only 21% of candidates appear in the dataset more than once and just 6% appear in all three cycles. As such, we do not include candidate-level random or fixed effects.

variables described earlier: DKP's measure of issue ownership, risk-taking, and personal negativity. (The negativity variable was only collected in 2004 and 2006.)

In addition to the weight matrix constructed from our network data, we include a number of relevant covariates in the models. In each of the analyses below, we include fixed effects for party/year interactions; indicators for gender (women) and chamber (Senate); and indicators for incumbents and open seat candidates (challengers are the reference category). We also include a measure of the percent of the district or state that voted for the presidential candidate from the candidate's party in 2000 (for the 2002 election) or 2004 (for the 2004/2006 elections). This variable serves as our main control for the competitiveness (i.e., general partisan orientation) of the district. Finally, following DKP, we include their measure of "issue salience" as a control variable in the model of issue ownership.[17]

Table 1 presents the results of our spatial autoregressive models for our three campaign strategy variables. Recall that the key parameter for testing Hypothesis 2 is ρ, the spatial autoregressive coefficient that estimates the extent to which candidates who share consultants use more similar strategies than might be expected by chance. We report the point estimates and 95% credible intervals for ρ in the first row of the table.[18] Our expectation is that ρ should be positively signed and statistically distinct from zero.

The first two columns of Table 1 confirm our expectation that campaigns that share consultants are more likely to use similar strategies than we might otherwise expect. The spatial autocorrelation coefficients (ρ) for both the issue ownership and risk-taking measures are positive and statistically distinct from zero. The fourth column shows that this relationship does not hold for the dichotomous personal negativity measure. However, incumbents and non-incumbents differ in the frequency with which they use this strategy. 44% of non-incumbents include such statements on their website while only 13% of incumbents do so.

[17] More information on the measures used in this analysis is available in Druckman, Kifer and Parkin (2009).

[18] Throughout the paper, we report 95% credible or confidence intervals to better represent the statistical uncertainty associated with our parameter estimates in a manner consistent with both Bayesian and frequentist approaches to inference (Gill 1999). Of course, the interpretation of these intervals differs between Bayesian and frequentist models, but in both cases the credible or confidence interval better expresses uncertainty than the associated standard error of the estimate.

Table 1: Spatial autocorrelation regression models of campaign strategy

	Issue ownership	Risk-taking	Personal negativity (non-incumbents)†	Personal negativity (all campaigns)†
Spatial autocorrelation coefficient (ρ)	0.088 [0.010, 0.166]	0.079 [0.000, 0.157]	0.390 [-0.083, 0.764]	-0.074 [-0.284, 0.129]
Senate	-0.524 [-1.445, 0.409]	0.043 [-0.232, 0.315]	0.278 [-0.065, 0.628]	0.234 [-0.048, 0.508]
Female	0.584 [-0.473, 1.663]	0.192 [-0.122, 0.494]	-0.179 [-0.563, 0.212]	0.088 [-0.214, 0.406]
District presidential vote	0.049 [0.007, 0.091]	-0.012 [-0.024, 0.000]	-0.008 [-0.024, 0.007]	-0.022 [-0.034, -0.009]
Open seat	0.036 [-1.221, 1.322]	-0.916 [-1.280, -0.549]	-0.044 [-0.408, 0.343]	-0.033 [-0.405, 0.333]
Incumbent	-0.802 [-1.837, 0.194]	-2.503 [-2.791, -2.216]	–	-0.845 [-1.143, -0.557]
Issue salience	3.954 [1.007, 6.870]	–	–	–
Democrat 2004	4.286 [2.823, 5.797]	1.247 [0.818, 1.667]	0.164 [-0.247, 0.583]	0.207 [-0.160, 0.577]
Democrat 2006	9.743 [8.290, 11.272]	1.670 [1.250, 2.081]	0.750 [0.354, 1.155]	0.721 [0.375, 1.077]
Republican 2006	-11.715 [-13.228, -10.188]	-0.043 [-0.458, 0.356]	0.409 [0.008, 0.832]	0.725 [0.379, 1.085]
Democrat 2002	1.540 [-0.111, 3.216]	0.405 [-0.091, 0.864]	–	–
Republican 2004	-5.331 [-6.793, -3.809]	-0.075 [-0.485, 0.336]	–	–
Constant	-1.066 [-3.558, 1.370]	3.403 [2.755, 4.039]	-0.161 [-0.892, 0.562]	0.308 [-0.301, 0.938]
N	719	710	304	558

95% credible intervals in brackets. † Personal negativity is a dichotomous indicator that was only collected for the 2004 and 2006 elections; models estimated with a probit link function.

We thus estimate a separate model that includes only non-incumbents, which is shown in the third column of Table 1. Among these candidates, the spatial autocorrelation coefficient is again positive. Although the 95% confidence interval includes zero, the 90% interval does not. This is roughly equivalent to finding support for our hypothesis at the $p < 0.10$ level.

In general, these results suggest that consultants play an important role in constructing and disseminating campaign strategy among Congressional candidates in the contemporary era.. Despite our reliance on dependent variables that are likely to be measured imprecisely, campaigns who share consultants are more similar than we would expect by chance even after controlling for factors such as challenger status, year, party, and district characteristics.

Robustness and falsification tests: One potential concern with the results above is that our specification of the weight matrix implies a linear relationship between the number of consulting firms shared by two campaigns and their degree of similarity. The relationship may instead be non-linear (in particular, the marginal effect of having an extra shared consultant may decline as the number of shared consultants increases). It is also possible that some candidates may contract with a single firm for multiple services (e.g., general and media consulting). In that case, the number of shared consultant ties would not accurately capture the association between campaigns. As a robustness check, we re-estimate the models in Table 1 using binary edge weights that are standardized according to the procedure described above (see Footnote 14). The results, which are presented in Appendix A and summarized in the second row of Table 2, are virtually identical to the findings above.

Another possible objection is that consultant ties may be acting as proxies for differences in campaign style across regions of the country. Democrats in the South may campaign differently than those in the Northeast, for instance, and may use consultants who specialize in their region of the country. We therefore re-estimate the models in Table 1 including regional fixed effects and present the results in Appendix A; the resulting spatial autocorrelation coefficients, which are reported in the third row of Table 2, remain consistent with

Table 2: Spatial autocorrelation robustness tests

	Issue ownership	Risk-taking	Personal negativity (non-incumbents)†
ρ Weighted ties (from Table 1)	0.088 [0.010, 0.166]	0.079 [0.000, 0.157]	0.390 [−0.083, 0.764]
ρ Unweighted ties (from Table A.1)	0.087 [0.008, 0.167]	0.080 [0.000, 0.162]	0.410 [−0.076, 0.793]
ρ Regional fixed effects (from Table A.2)	0.085 [0.007, 0.168]	0.079 [0.001, 0.160]	0.375 [−0.085, 0.742]

95% credible intervals are in brackets. † Personal negativity is a dichotomous indicator that was only collected for the 2004 and 2006 elections; models estimated with a probit link function.

H2.[19]

A final objection may be that the spatial autocorrelations reported in Table 1 are not causal. Two similar candidates may be more likely to run similar campaigns *and* to select the same consultants even if neither the consulting firm nor neighboring campaigns have their own effect. Appendix A therefore also reports the results of two falsification tests we conducted to assess the robustness of our results to this concern. In these tests, we created groups of similar candidates and randomly shuffled the consultant ties among them to see if the resulting networks would show evidence of spatial autocorrelation in campaign strategy. If so, it would indicate that our results are the result of similar candidates using similar types of consultants. However, we find little evidence of significant spatial autocorrelation in these tests, which suggests that the estimates in Table 1 are not spurious (although our results indicate that some additional caution is needed in interpreting the results for the issue ownership outcome). Indeed, taken together, the results of these tests and the others described above increase our confidence in the robustness of our findings.

[19]The 90% credible interval for ρ in the personal negativity model is slightly larger in this case $[-0.004, 0.693]$. However, this variable is still significant at $p < .10$ under standard asymptotic assumptions.

4.4. *Hypothesis 3: Consultant victories increase network centrality*

We now turn to H3 and examine changes in consultants' location in the candidate-consultant network over time. (For these analyses, we return to using the complete consultant network dataset spanning the 1992–2008 period.) Do successful consultants become more central in the network and thus more influential in shaping campaign strategies in subsequent election cycles? In particular, do the relative positions of consulting firms change when they win races that are perceived to be important?

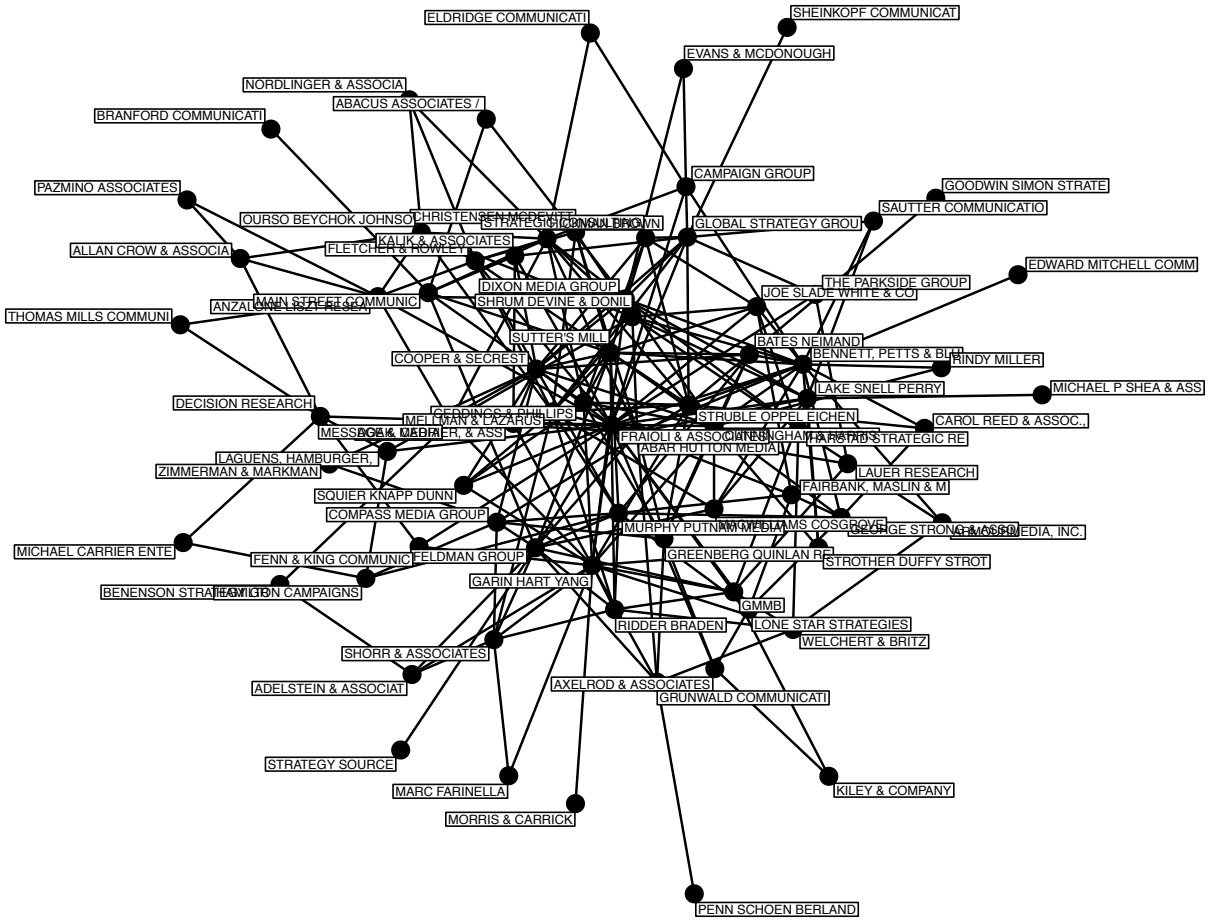
To measure the network positions of consulting firms, we perform the inverse operation from Section 4.3, converting the candidate-consultant network for each party and election cycle to a network of consultants where ties represent shared clients (candidates). For example, the Democratic candidate-consultant network from the 2002 cycle depicted in Figure 1 is converted into the consultant network in Figure 3.

We then operationalize the relative importance of firms within these networks using measures of weighted centrality. Traditional measures of centrality require dichotomous edge values. However, the edge weights in this network reflect the number of candidate clients shared by a given pair of consultants. Substantively, we expect that two firms who share a number of clients to have closer ties than a dyad with only one shared client.[20] We therefore employ generalizations of degree and closeness centrality for weighted networks that combine information about both the number and the strength of the ties to a given node (Opsahl, Agneessens and Skvoretz 2010).[21] Our measure of degree centrality—the simplest measure of consultant importance—is a linear combination of the number of other firms to which a given firm is connected and the total number of ties they have to other firms via shared

[20]There is substantial variation in the number of shared clients. For instance, in the 2002 Democratic consultant network depicted above, there are 472 ties between firms. 378 have a weight of 1 (80.1%), 60 have a weight of 2 (12.7%), 22 have a weight of 3 (4.7%), and so on up to a maximum of seven (the general consulting firm of Shrum, Devine, & Donilon and the media consulting firm of Abar Hutton Media, which was founded by a former member of Shrum's firm [Teinowitz 1999]).

[21]These calculations are conducted using the `tnet` package for R. Note that previous measures for unweighted networks only use information about the number of ties, while previous weighted centrality measures focused only on tie strength with no emphasis on the number of connections.

Figure 3: The 2002 Democratic consultant network



Nodes represent the largest connected component in the network of 2002 Democratic consultants; edges represent shared candidate ties.

clients. While this measure is relatively easy to interpret, it does not account for the structure of the network and firms' location within the network. Our measure of *closeness centrality* captures which firms are the shortest distance from other firms in the network on average using a distance metric that takes into account the number of clients shared by linked firms. Finally, we also estimate the standard measure of eigenvector centrality (Bonacich 1972*a*,*b*) on a bipartite adjacency matrix. (See Appendix B for further details on how the Opsahl, Agneessens and Skvoretz measures are calculated.)

Table 3: The most central Democratic consultants

	Degree	**Eigenvector**	**Closeness**
1992	Cooper & Secrest	Cooper & Secrest	Cooper & Secrest
1994	Cooper & Secrest	Squier Knapp Dunn	Cooper & Secrest
1996	Fenn & King	Fenn & King	Fenn & King
1998	Fraioli & Assoc.	Sutter's Mill	Fraioli & Assoc.
2000	Sutter's Mill	Sutter's Mill	Cooper & Secrest
2002	Fraioli & Assoc.	Cooper & Secrest	Fraioli & Assoc.
2004	Murphy Putnam	Murphy Putnam	Murphy Putnam
2006	Lake Research	Lake Research	Lake Research
2008	Anzalone Liszt	Anzalone Liszt	Anzalone Liszt

Table 4: The most central Republican consultants

	Degree	**Eigenvector**	**Closeness**
1992	Public Opinion Strat.	Public Opinion Strat.	Public Opinion Strat.
1994	Tarrance Group	Public Opinion Strat.	Tarrance Group
1996	Public Opinion Strat.	Public Opinion Strat.	Public Opinion Strat.
1998	Tarrance Group	Keelen Comm.	Tarrance Group
2000	Public Opinion Strat.	Public Opinion Strat.	Public Opinion Strat.
2002	Public Opinion Strat.	Public Opinion Strat.	Public Opinion Strat.
2004	Public Opinion Strat.	Public Opinion Strat.	Public Opinion Strat.
2006	Public Opinion Strat.	Moore Information	Public Opinion Strat.
2008	Public Opinion Strat.	Public Opinion Strat.	Public Opinion Strat.

The most central consulting firms: Table 3 presents the most central Democratic consulting firm by election cycle according to each of the three centrality measures we consider. While the measures are relatively highly correlated (as most centrality measures are), the firms identified as most central within a given election cycle often differ. In only half of the years (1992, 1996, 2004, 2006, and 2008) is the same firm identified as most central by all three measures. The list shows significant turnover—none of the firms identified as most central in the 1990s were among the most central after 2002.

The list of the most central Republican consultants presented in Table 4 suggests a very different pattern. Only four firms appear in the entire table. The list is dominated by the Tarrance Group (which appears to be relatively more central in the 1994 and 1998 election cycles) and Public Opinion Strategies (which began with a position of centrality in 1992 and

largely took over the list starting in 2000).[22]

Electoral success and subsequent network centrality: With these measures in hand, we now turn to testing whether firms' relative positions within the network change depending on their performance. Assessing the effect of consultants on campaign outcomes is a difficult inferential problem for social scientists, but within politics it is an article of faith that "better" consultants improve the chances of victory for their clients. As such, we expect firms will be rewarded for success and penalized for failure. In this way, the decentralized party network can adapt (however imperfectly) to the electoral environment, broadening the usage of tactics and strategies that seem to be working while discarding those that seem less effective.

For instance, the Washington Post described John Anzalone in 2008 as "[t]he best pollster you've never heard of," stating that "The Democratic survey research firm became among the hottest in the nation after the 2006 cycle in which it conducted polling for Reps. Heath Shuler (N.C.), Ron Klein (Fla.), Paul W. Hodes (N.H.) and Jason Altmire (Pa.)—all of whom defeated Republican incumbents" (2008). Anzalone's firm, Anzalone Liszt Research, was subsequently the most central Democratic consulting firm on all three weighted centrality measures during the 2008 cycle.

To test whether consultant success makes them more central over time, we estimate OLS models predicting *changes* in firm centrality based on their record in the previous election cycle.[23] To make centrality measures comparable across election cycles, we first compute each firm's percentile rank on our three centrality measures.[24] For instance, the weighted

[22]These findings support the finding that the Republican consultant network is more centralized than the Democratic one (Grossmann 2009). Indeed, there is much to explore and explain about differences between the two parties in the structure of these networks. However, these inter-party differences are not relevant to the central claims of this paper and we set these issues aside for future research.

[23]Using node-level characteristics as a dependent variable is increasingly common in political science research using social network techniques (Ward, Stovel and Sacks 2011, 251). For examples of other studies that employ a similar approach to ours, see Shah (2000), which looks at changes in normalized measures of network centrality, and Christakis and Fowler (2008), which examines predictors of centrality controlling for centrality in the previous period. Our results are calculated using robust standard errors clustered by firm to account for repeated measurements of the same consulting firm over time.

[24]The data are not strictly censored. For instance, the highest value of the percentile rank measures varies by cycle depending on the number of firms in the data, ties, etc.

degree centrality percentile rank for firm i represents the percentage of all firms within i's party that are less central in a given election cycle.[25] In practice, the percentile ranks in a given year are centered near 50 and range from 0 to 98. However, our interest is in whether *changes* in relative centrality correspond to firm track records. We therefore restrict our sample to firm observations that appear in the data in two or more consecutive election cycles and compute the *change* in each firm's percentile rank between election cycle t and election cycle $t + 1$. In other words, did these surviving firms become more central (positive values) or less central (negative values) conditional on appearing in the data in two or more consecutive cycles? By modeling changes in firm centrality, we partially account for unobservable differences in firm characteristics.[26]

We operationalize electoral success using the number of races in which the firm's candidate won, which is the measure tracked by *C&E* in its scorecards. These win-loss records records play an important role within the industry. However, many consultants represent incumbent clients who are highly likely to win. As such, we disaggregate non-incumbent victories (i.e., wins by challengers and candidates for open seats) from victories by incumbents. Since open-seat and challenger campaigns are typically more difficult to win, a string of victories in such races is especially likely to draw the attention of the political elite.

We also include lagged measures of the firm's centrality percentile rank and *change* in centrality rank to account for the likelihood that highly successful firms will regress toward the mean. For instance, firms that are highly ranked are likely to become less central in future cycles, all else equal. Similarly, firms that increased in centrality in election cycle $t - 1$ are likely to decline in centrality in cycle t (i.e., regress toward the mean).

Table 5 presents the results of these models for Democratic consultants. The total number of non-incumbent victories by a firm is strongly associated with subsequent increases in its

[25] Firms with undefined values for closeness are assumed to be tied as the least central firm.

[26] While we believe that modeling changes in the dependent variable is the most appropriate approach, the results reported below also hold if we use the firm's actual percentile rank in centrality as the dependent variable instead. These results are available upon request.

Table 5: OLS models of changes in centrality rank among Democratic consultants

	Degree	Eigenvector	Closeness
Non-incumbent wins	1.30	1.71	1.50
	[0.49, 2.10]	[0.80, 2.62]	[0.56, 2.44]
Incumbent wins	0.69	0.95	0.56
	[-0.23, 1.62]	[-0.05, 1.95]	[-0.38, 1.49]
Lagged centrality	-0.47	-0.58	-0.46
	[-0.65, -0.29]	[-0.76, -0.41]	[-0.65, -0.28]
Lagged Δ centrality	-0.20	-0.16	-0.18
	[-0.35, -0.04]	[-0.30, -0.01]	[-0.33, -0.03]
Constant	15.67	17.22	14.22
	[8.09, 23.25]	[9.84, 24.60]	[6.98, 21.45]
R^2	0.26	0.30	0.23
N	188	188	188

Dependent variables represent the *change* in percentile rank for each of the centrality measures between election cycles. Models were estimated using robust standard errors clustered by consulting firm. 95% confidence intervals are shown in brackets.

centrality across all three dependent variables ($p < .05$),[27] while the number of incumbent victories is only marginally significant for eigenvector centrality ($p < .10$).[28] The market appears to strongly reward firms like Anzalone Liszt that win a series of non-incumbent races. However, there is much less support for the notion that firms which help incumbents get reelected become more central. In addition, we find (as expected) that firms that are more central are likely to become less central in the next cycle, and that firms that *increased* their centrality in the previous cycle are likely to decrease their centrality in the next ($p < .05$ in each case).

Table 6 shows comparable results for Republican consultants. The GOP results also indicate that the number of non-incumbent victories by a consulting firm is positively related to eigenvector and closeness centrality ($p < .05$) but not the crude degree centrality measure.

[27]One concern is that non-incumbent winners might hire more consultants in their next election, which could spuriously increase the centrality of their original consultants. However, we find that non-incumbent winners who use consultants in both their original race and their re-election campaign actually have *fewer* consultants in their second race ($p < .01$; results available upon request).

[28]One might think that a firm's success rate (rather than the number of wins) would be a better predictor, but results using win rates are inconsistent for both Democratic and Republican firms (available upon request).

Table 6: OLS models of changes in centrality rank among Republican consultants

	Degree	**Eigenvector**	**Closeness**
Non-incumbent wins	0.49	0.99	0.91
	[-0.14, 1.12]	[0.17, 1.82]	[0.11, 1.71]
Incumbent wins	0.43	0.22	0.26
	[-0.04, 0.89]	[-0.25, 0.68]	[-0.21, 0.74]
Lagged centrality	-0.47	-0.57	-0.49
	[-0.65, -0.29]	[-0.81, -0.32]	[-0.72, -0.27]
Lagged Δ centrality	-0.22	-0.23	-0.24
	[-0.42, -0.03]	[-0.41, -0.04]	[-0.43, -0.05]
Constant	21.15	23.35	19.74
	[12.21, 30.09]	[12.56, 34.15]	[9.57, 29.90]
R^2	0.31	0.36	0.34
N	142	142	142

Dependent variables represent the *change* in percentile rank for each of the centrality measures between election cycles. Models were estimated using robust standard errors clustered by consulting firm. 95% confidence intervals are shown in brackets.

As in the Democratic case, there is only modest evidence that incumbent victories lead to increased centrality ($p < .10$ for degree centrality).

In general, these results support the hypothesis that consulting firms' centrality changes meaningfully in response to their track record in previous election cycles. Given the high rates of incumbent re-election we observe in the US, the market appears to particularly reward victories by non-incumbents. Those consultants who win these important races come to hold more influential positions within the party in future elections.

5. CONCLUSION

Thurber (1998) once described scholarship on campaign consultants as "a subfield in search of a theory." In this paper, we set the study of consultants more firmly within the growing body of scholarship on contemporary parties that emphasizes informal organizational structures and patterns of interactions. In this view, consultants are part of a "new equilibrium" in which parties play an informal but important role in elections (Aldrich 2011, 287–292).

Specifically, we theorize that: (i) consulting firms should take on clients primarily within only one party; (ii) firms play an important role in disseminating campaign strategies within the party; and (iii) successful firms become increasingly central in these networks of relationships. We analyze these claims with the most comprehensive dataset on consultant-candidate relationships that has been assembled to date, showing not just that "consultants matter" in a broad sense, but providing evidence that candidate strategy is associated with their location in the party's consultant-candidate network and that consultant success increases their firm's centrality in future election cycles. These results also contribute to the development of social network research in political science. Rather than simply providing a descriptive account of the networks we study, we test theoretically-motivated hypotheses about consultants and party organizations using network data.

In addition, this study suggests a promising approach for future analyses and theorizing about campaigns in the American setting in general and the effect of parties on elections more specifically. Traditional analyses treat elections as independent and identically distributed events (e.g., Ansolabehere, Snyder and Stewart 2001; Canes-Wrone, Brady and Cogan 2002). Implicitly, these statistical models assume that what happens in one campaign has no impact on the others beyond generic year-level effects. By contrast, the results above suggest that the campaigns within each party are neither independent nor uniformly influenced by party organizations. Instead, their fates are likely to be interlinked through consultant ties and other intra-party connections.

Before concluding, it is important to note the limitations of the present study and to discuss improvements that could be made in future research. One limitation is that it is difficult to entirely rule out the possibility that candidates are selecting consulting firms based on the strategies they advocate. The extensive falsification tests presented in Appendix A give us confidence that the spatial autocorrelation reported in Table 1 are not spurious. Nonetheless, candidates may select firms partly as a result of the strategies that firms typically advocate (or vice versa). Future research should investigate this relationship further and test the ro-

bustness of the linkage we find.

A related limitation is the lack of more fine-grained data on campaign strategies. Our current data provides only one observation per election cycle, a level of temporal resolution that makes it impossible to track the spread of specific campaign messages or tactics in the network within a single election cycle. Because consulting firms work with multiple campaigns, they are well-positioned to learn about effective techniques and implement the lessons that have been learned across multiple races within a given election cycle. In addition, consultants may also learn from other consultants retained by their clients. Campaigns frequently hire several consultants who work together in close support of the client. These interactions create a network of professional relationships that facilitates the within-cycle spread of strategies and messages across campaigns. Future studies should therefore seek to study how candidate strategies evolve over the course of a single campaign and to test more directly for the diffusion of strategies through the network.

Despite these limitations, we believe this research provides a new view of consultants as important players in the extended party networks of the contemporary era. Our work shows that they have come to play a key role in diffusing campaign strategies and helping party candidates respond in flexible but relatively coordinated ways to changing electoral circumstances. While the normative consequences of this shift can be debated, the importance of consultants should no longer be ignored.

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APPENDIX A: ROBUSTNESS OF SPATIAL AUTOREGRESSIVE MODELS

Table A.1: Spatial autocorrelation models of campaign strategy (binary adjacency matrices)

	Issue ownership	Risk-taking	Personal negativity (non-incumbents)†	Personal negativity (all campaigns)†
Spatial autocorrelation coefficient (ρ)	0.087 [0.008, 0.167]	0.080 [0.000, 0.162]	0.410 [-0.076, 0.793]	-0.080 [-0.287, 0.133]
Senate	-0.527 [-1.449, 0.395]	0.043 [-0.221, 0.306]	0.281 [-0.049, 0.618]	0.234 [-0.034, 0.504]
Female	0.587 [-0.478, 1.672]	0.189 [-0.114, 0.491]	-0.183 [-0.579, 0.218]	0.096 [-0.210, 0.401]
District presidential vote	0.049 [0.006, 0.091]	- 0.012 [-0.024, 0.000]	-0.008 [-0.024, 0.007]	- 0.021 [-0.034, -0.008]
Open seat	0.042 [-1.239, 1.315]	- 0.916 [-1.273, -0.532]	-0.045 [-0.422, 0.327]	-0.044 [-0.426, 0.317]
Incumbent	-0.785 [-1.790, 0.245]	- 2.500 [-2.785, -2.213]	–	- 0.853 [-1.148, -0.554]
Issue salience	3.966 [0.998, 6.968]	–	–	–
Democrat 2004	4.289 [2.854, 5.783]	1.247 [0.813, 1.676]	0.163 [-0.248, 0.582]	0.198 [-0.180, 0.584]
Democrat 2006	9.768 [8.299, 11.222]	1.671 [1.243, 2.097]	0.747 [0.314, 1.157]	0.730 [0.385, 1.088]
Republican 2006	- 11.699 [-13.210, -10.191]	- 0.043 [-0.456, 0.360]	0.401 [-0.004, 0.833]	0.729 [0.374, 1.095]
Democrat 2002	1.546 [-0.159, 3.253]	0.403 [-0.062, 0.886]	–	–
Republican 2004	-5.281 [-6.744, -3.829]	-0.072 [-0.496, 0.324]	–	–
Constant	-1.075 [-3.545, 1.462]	3.407 [2.765, 4.071]	-0.154 [-0.874, 0.576]	0.287 [-0.330, 0.918]
N	719	710	304	558

95% credible interval in brackets. † Personal negativity is a dichotomous indicator that was only collected for the 2004 and 2006 elections; models estimated with a probit link function.

Table A.2: Spatial autocorrelation models of campaign strategy (regional fixed effects)

	Issue ownership	Risk-taking	Personal negativity (non-incumbents)†	Personal negativity (all campaigns)†
Spatial autocorrelation coefficient (ρ)	0.085 [0.007, 0.168]	0.079 [0.001, 0.160]	0.375 [-0.085, 0.742]	-0.070 [-0.283, 0.129]
Senate	-0.496 [-1.456, 0.429]	0.063 [-0.208, 0.333]	0.248 [-0.099, 0.586]	0.232 [-0.040, 0.498]
Female	0.621 [-0.474, 1.716]	0.190 [-0.113, 0.492]	-0.200 [-0.593, 0.183]	0.093 [-0.219, 0.398]
District presidential vote	0.048 [0.006, 0.090]	- 0.012 [-0.024, 0.000]	-0.007 [-0.022, 0.009]	- 0.021 [-0.035, -0.009]
Open seat	-0.130 [-1.417, 1.153]	- 0.882 [-1.257, -0.505]	-0.012 [-0.401, 0.372]	-0.009 [-0.411, 0.374]
Incumbent	-0.740 [-1.776, 0.266]	- 2.497 [-2.785, -2.216]	–	- 0.858 [-1.158, -0.565]
Issue salience	4.160 [1.154 , 7.071]	–	–	–
Democrat 2004	4.305 [2.814, 5.827]	1.242 [0.835, 1.672]	0.160 [-0.264, 0.613]	0.183 [-0.220, 0.544]
Democrat 2006	9.766 [8.251, 11.227]	1.675 [1.259, 2.099]	0.757 [0.327, 1.188]	0.696 [0.365, 1.056]
Republican 2006	- 11.711 [-13.209, -10.202]	-0.053 [-0.449, 0.364]	0.367 [-0.075, 0.823]	0.692 [0.338, 1.058]
Democrat 2002	1.526 [-0.196, 3.237]	0.398 [-0.060, 0.882]	–	–
Republican 2004	- 5.256 [-6.706, -3.736]	-0.080 [-0.488, 0.342]	–	–
Mid-Atlantic	-0.384 [-2.229, 1.565]	0.088 [-0.467, 0.628]	-0.178 [-0.884, 0.459]	0.084 [-0.435, 0.612]
Midwest	0.950 [-0.811, 2.824]	0.410 [-0.091, 0.941]	-0.086 [-0.714, 0.526]	0.132 [-0.364, 0.664]
Mountain West	0.376 [-1.464, 2.235]	0.253 [-0.256, 0.783]	0.049 [-0.611, 0.699]	0.215 [-0.284, 0.742]
New England	0.397 [-1.698, 2.562]	-0.190 [-0.784, 0.393]	-0.153 [-0.887, 0.595]	-0.143 [-0.754, 0.485]
Prairie	1.598 [-0.417, 3.632]	0.009 [-0.578, 0.574]	-0.167 [-0.867, 0.534]	0.105 [-0.444, 0.653]
South	0.455 [-1.224, 2.194]	0.069 [-0.420, 0.548]	-0.343 [-0.959, 0.264]	-0.121 [-0.601, 0.389]
Border	1.239 [-0.671, 3.149]	0.133 [-0.396, 0.670]	-0.109 [-0.756, 0.565]	0.104 [-0.406, 0.672]
Constant	-1.696 [-4.668, 1.200]	3.267 [2.468, 4.023]	-0.071 [-0.879, 0.745]	0.269 [-0.423, 1.010]
N	719	710	304	558

95% credible interval in brackets. † Personal negativity is a dichotomous indicator that was only collected for the 2004 and 2006 elections; models estimated with a probit link function.

Falsification tests

We conducted two falsification tests in which we divided the candidates in the data into groups of similar candidates and randomly shuffled the consultant ties amongst candidates within those groups. If we continue to observe statistically significant spatial autocorrelation in candidate strategy using these permuted network ties, it would suggest that our results are the spurious result of clustering in consultant selection. By contrast, a lack of significant spatial autocorrelation would increase our confidence in the results in Table 1 and Table 2.

To implement this test, we create two separate partitions of structurally similar candidates. The first partition, which we call candidate-type, separately divides all the candidates by party, year, and race type (e.g., Republicans contesting open seats in 2006). The second partition, which we call region-party, divides all the candidates by region, party, and year (e.g., Democratic candidates in the Northeast in 2002, Democratic candidates in the Mid-Atlantic in 2002, etc.). We then randomly permute the consultant ties for candidates within each partition, creating 500 permuted sets of consultant ties while ensuring that each candidate maintains the same number of ties to other candidates.[29] Table A.3 provides a hypothetical example of how this process works using a group of four Democratic incumbents in 2002. In the example illustrated in the table, the firms contracted by Harkin and Cleland are hypothetically switched, as are the consultants used by Biden and Durbin.

After randomly permuting consultant ties among similar candidates in this way, we then recalculate our projected candidate-candidate adjacency matrix $\mathbf{W}$ and refit the models reported in Table 1 for each set of 500 randomly permuted adjacency matrices.[30] The resulting median estimates of ρ and 95% nonparametric confidence intervals, which are provided in

[29] More precisely, we permute the candidate columns of the bipartite candidate-consultant adjacency matrix, shuffling the vectors representing the consultant ties of the candidates within each grouping.

[30] The well-known quadratic assignment procedure (Mantel 1967; Hubert and Schultz 1976) preserves network topology while shuffling values of the dependent variable to provide a non-parametric sampling distribution for hypothesis tests that would otherwise be distorted by dependence among observations. By contrast, we estimate a statistical model that explicitly accounts for spatial autocorrelation and shuffle the ties between structurally similar individuals as a falsification exercise.

Table A.3: Illustration of random permutation

Actual data

	Firm 1	Firm 2	Firm 3	Firm 4	...
Tom Harkin 2002	1	0	1	0	
Joe Biden 2002	1	0	0	1	
Dick Durbin 2002	0	1	0	0	
Max Cleland 2002	0	0	0	1	
⋮					

Randomly permuted data

	Firm 1	Firm 2	Firm 3	Firm 4	...
Tom Harkin 2002	0	0	0	1	
Joe Biden 2002	0	1	0	0	
Dick Durbin 2002	1	0	0	1	
Max Cleland 2002	1	0	1	0	
⋮					

Table A.4: Spatial autocorrelation falsification tests

	Issue ownership	Risk-taking	Personal negativity (non-incumbents)
ρ Candidate-type permutations	0.016	−0.003	−0.023
	[−0.061, 0.086]	[−0.089, 0.072]	[−0.428, 0.400]
ρ Region-party permutations	0.021	−0.009	−0.038
	[−0.062, 0.096]	[−0.084, 0.065]	[−0.406, 0.342]

95% nonparametric confidence intervals are in brackets.

Table A.4, show little significant evidence of spurious positive spatial autocorrelation.[31]

These results are especially clear for the risk-taking variable. For these models, over 98% of the 500 estimated coefficients are smaller than those reported in Table 1 ($\rho = 0.079$). Examining the results independently, the spatial autocorrelation coefficients are positive and statistically distinguishable from zero no more than we would expect from chance. For instance, using the candidate-type permutations, the spatial autocorrelation coefficient for

[31]Due to convergence issues associated with particular permuted matrices, some could not be included for the personal negativity model. The results below exclude four matrices for the region-party permutations and twelve matrices for the candidate-type permutations.

risk-taking is positive and distinguishable from zero (i.e., the 95% credible intervals do not cover zero) in only twelve out of five hundred cases (results available upon request).

Our falsification test results also support the findings for the personal negativity outcome. In this case, Table 1 reports that the spatial autocorrelation coefficient is marginally distinguishable from zero (the 90% interval does not include zero, but the 95% interval does). The permutation results, reported in the third column of Table A.4, are either similar or stronger. Using the candidate-type permutations, over 98% of the spatial autocorrelation coefficients we estimate are smaller than the estimate reported in Table 1 ($\rho = .390$). Likewise, 97% of estimates from the region-party permutations are smaller than estimate in Table 1.

For the issue ownership variable, however, 7.8% of the spatial autocorrelation coefficients from the the candidate-type permutations are positive and statistically distinguishable from zero, as are 11.2% of the coefficients from the region-party permutations. Both figures exceed what would expect by chance, suggesting that spurious findings of spatial autocorrelation are a possibility. Nonetheless, this result does not by itself undermine our conclusions. The spatial autocorrelation coefficient estimated using the observed network and reported in Table 1 ($\rho = 0.088$) is still very large relative to the estimates generated using the permuted matrices. Just 2% of the estimated coefficients are larger than 0.088 using the candidate-type permutations and 4.4% percent are larger in the region-party permutations.

APPENDIX B: NEW MEASURES OF WEIGHTED CENTRALITY

Opsahl, Agneessens and Skvoretz (2010) define degree centrality as $k \times \left(\frac{s_i}{k_i}\right)^{\alpha} = k_i^{(1-\alpha)} \times s_i^{\alpha}$ where k_i is a simple count of the number of nodes to which node i is connected (the standard measure of degree centrality for node i in an unweighted network), s_i is the sum of all edge weights for node i, and α is a tuning parameter set by the researcher. Setting $\alpha = 0$ returns the standard degree centrality measure, while setting $\alpha = 1$ returns what is called the measure of node strength (Barrat et al. 2004). Values of α between 0 and 1 represent a combination of information about the number of ties to i and the strength of those ties. In the case of our projected consultant networks, we expect consultants who have shared clients with a large number of other firms to be especially important and influential, but we also wish to incorporate information about the strength of those relationships, which are likely to vary depending on the number of clients in common between two firms. We therefore set α to 0.5 to incorporate information from both measures.

Similarly, standard measures of closeness rely on computations of the minimum distance between nodes i and j in unweighted networks where the distances between the nodes in a connected dyad is treated as one unit. Newman (2001) and Brandes (2001) generalize this to weighted networks by treating the distance between nodes i and j as $\frac{1}{w}$ where w is the weight of the edge. Opsahl, Agneessens and Skvoretz propose a generalization in which the distance is instead $\frac{1}{w^{\alpha}}$ where α is again a tuning parameter and $\alpha = 0$ returns the standard unweighted measure. This distance measure is incorporated straightforwardly in the standard definitions of closeness (Freeman 1979; see Opsahl, Agneessens and Skvoretz for details). We again set α to 0.5 to allow both tie strength and the number of ties to influence computations of the minimum distance between nodes. Substantively, consultants that are high on closeness are (on average) not far from most other firms in network terms.