Parties and Electoral Performance in the Market for Political Consultants*

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Abstract

We investigate whether the hiring relationships of candidates and political consulting firms better resembles the predictions of the "adversarial" or "allied" models of consultant-party interaction. We find that the highest-quality consultants are not allocated to the most competitive races, consultant-candidate relationships persist even as candidates' electoral prospects change, and firms who work for challengers face a higher risk of market exit than firms working for incumbents. The market focuses entirely on win-loss records and ignores the information on consultant performance available in candidates' vote shares. These findings depict a market driven by individual candidate, rather than aggregate party, goals.

Political consultants are the architects of contemporary congressional campaign strategy. Consultants help candidates develop advertisements, shape campaign platforms, and allocate scarce resources across different campaign activities (Sabato, 1981; Shea, 1996; Medvic, 2001). Consultants play an important role in disseminating knowledge about effective campaign strategies (Nyhan and Montgomery, Forthcoming). As a result, almost all competitive candidates hire at least one consulting firm to provide expert guidance. A major debate in the literature on political consultants concerns the nature of the relationship between consulting firms and political parties. Some of the leading scholars in the field have argued that consultants act as "surrogates" for parties (Kolodny and Dulio, 2003) (p. 733). Other scholars contend that consultants and parties have a more conflictual relationship (Sabato, 1981; Shea, 1996; Friedenberg, 1997; Plasser, 2001). The distinction between the two views is clearly presented by Kolodny and Logan (1998), who distinguish between "adversarial" and "allied" models of party-consultant relations. The adversarial model stipulates that consultants offer competing services to candidates and have supplanted party organizations in providing campaign services to candidates. In contrast, the allied model stipulates that political consultants internalize the objectives of their political party and advance these goals in the electoral arena through their campaign work.

We contribute to this literature through a series of analyses. Our theoretical point of departure is the fundamental conflict between the goals of individual Congressional candidates and the goals of their party as a whole. We argue that these conflicts raise doubts about the strength of the nexus between consultants and parties. If candidates are primarily concerned with their own individual electoral prospects (Mayhew, 1974) as opposed to the electoral goals of their party, there is wide scope for these disagreements. In an environment where effective consultants are scarce, this observation immediately leads to a conflict between the objectives of candidates and those of the parties. Parties prefer to allocate the most-effective consultants to work in the races with highest ex ante levels of competitiveness, where consultants' potential marginal impact is highest. If we think of high-quality consultants as a generic campaign resource in a resource-allocation model like that of Snyder (1989), the prediction that parties should target them to the most competitive races emerges if parties attempt to maximize the expected number of legislative seats won or the probability of securing a majority. Individual candidates, on the other hand, prefer to minimize the risk of losing their own campaign by employing the highest-quality consultants available, regardless of their current electoral circumstances. In particular, risk-averse incumbents in safe seats may still want to hire high-quality consultants for their campaign even if their actual chance of losing reelection is small. Consultants themselves may also choose to pursue individual objectives - such as maximizing their firm's revenues or profits - even in cases where these objectives conflict with those of their party.

We investigate whether the observed matches between individual congressional candidates and consulting firms better reflect the predictions of the allied or the adversarial models of party-consultant linkages. Our analysis examines both sides of the consultant-candidate marketplace: the supply-side interests of consulting firms and the demand-side interests of congressional candidates and parties. Empirically, we show that the conflict between candidate and party goals manifests itself in the allocation of consultants to candidates. First, we confirm the results of prior research that the majority of political consulting firms work exclusively for candidates from one major party. Second, using a variety of methods and specifications, we show that the highest-quality consultants are in general not allocated to the most competitive campaigns, where these consultants would have the highest marginal value to the parties, but instead disproportionately work for candidates with secure electoral prospects. Moreover, relationships between consulting firms and candidates are remarkably persistent over time. Even as candidates' electoral prospects change, consulting firms and candidates continue to work with one another. Together, these findings depict a market for political consultants that is broadly organized along partisan lines, but in which specific firm-candidate pairings are primarily driven by the relationships between individual candidates and political consulting firms, rather than central party organizations.

We also document powerful informational frictions in the marketplace for political consultants that further limit the potential for alignment in party and consultant objectives. We show that candidates and parties use "unanticipated" victories of consultants' clients to make inferences about the quality of consulting firms and guide their hiring decisions. However, they appear to ignore the unanticipated portion of vote share outcomes, which are strictly more informative than the binary win-loss outcome. Consulting firms' revenue in the next cycle jumps if their clients win unexpected victories, but there is no response to increases in unanticipated vote share. This result implies that clients' ability to learn about which firms are more effective than others is censored in an important way.

Given the winner-take-all nature of politics, it is not irrational for candidates to care more about crossing the 50 percent threshold than about inframarginal gains in vote share (Milyo, 2001). However, the problem of deciding what actions to take in an individual candidate's campaign is quite distinct from the problem of evaluating the usefulness of consultants based on their performance in other campaigns. Focusing entirely on wins is a natural approach in the former problem but not in the latter. Because most Congressional races are not competitive, candidates are effectively throwing away the majority of available information on consultant performance when they ignore the vote share productivity of consulting firms. A consulting firm with sufficient prestige to have some discretion over which clients to accept or reject could manipulate this learning process by choosing to work only for likely winners.[1] This market environment makes it much riskier for consultants to work in the most competitive congressional races as compared to more electorally secure races. Even though participating in more competitive elections would have a larger marginal effect on the party's expected seat share in Congress, the financial incentives for consulting firms appear to push them in the opposite direction, toward safe seats.[2]

The censored learning process we document has important implications for the composition of the political consulting market. As the unconditional reelection probability of House incumbents is in the neighborhood of 90 percent (Diermeier, Keane and Merlo, 2005), there is little chance of an incumbent generating a negative shock to the firm's reputation. We find evidence consistent with this pattern in, by showing that firms who work for challenger clients are much more likely to exit the market in the next election cycle than are firms who work preferentially for incumbents. The uncompetitiveness of most Congressional races limits the degree to which a high-quality entrant could capture market share from established firms, and hence may allow unproductive firms to persist in the market over long periods of time. With less-than-perfect information about consultant effectiveness available, candidates may rely more strongly on other factors such as personal connections in making hiring decisions.

Together, our findings suggest a somewhat different picture of the role of consultants than currently emphasized in party-based accounts of the market for political consultants. While the consulting marketplace is effectively partitioned into two distinct partisan groups of consultants, individual candidate goals and their previous relationships with consulting firms, as opposed to the electoral goals of the major parties, best explain the matches that we observe between candidates and consultants. While there are surely areas where candidates' and parties' interests are aligned with one another, in instances where these objectives are in conflict with one another it is the interests of individual candidates, as opposed to the parties, that drive the allocation of scarce consulting resources.

Background

The early literature on the party-consultant nexus contended that the rise of political consultants had weakened parties by creating a locus of campaign expertise that was independent of formal party structures (Sabato, 1981). Consultants were often depicted as having usurped campaign management and resource-allocation functions traditionally provided by the central party organizations, weakening the parties' influence over campaign strategy (Friedenberg, 1997). In response, more recent scholarship has focused on documenting the close links between consulting firms and the party organizations, arguing that the relationships between consultants and candidates are mediated by the parties and do not simply bypass the major party organizations (Kolodny and Dulio, 2003; Cain, 2013).

The empirical evidence used to support the party-centered characterization of the consultant marketplace typically consists of documentation of links between parties and consultants. Consultants and formal party organizations have close links, as evidenced by the large number of consultants who move back and forth from party organizations to private consulting firms. For example, Farrell, Kolodny and Medvic (2001) argue that a common career trajectory for political consultants includes service in national and state party organizations.[3] Doherty (2006) investigates party-consultant links in state-level politics in California, arguing that each party's network of consultants comprises an informal party organization that "facilitates the efficient transfer of information and resources among campaigns" (p. xi) in a manner consistent with formal party goals. Kolodny and Logan (1998) use interviews with consultants to reach similar conclusions.

This form of evidence does not definitively establish the allied model of party-consultant relations. Though consultants may be sympathetic to the broad goals of a party, the marketplace for consultants may still systematically deviate from the expectations of the allied model. For example, consultants may choose to work for the candidates who will be the most remunerative for the firm and not necessarily those candidates who will have the highest expected benefit for the party as a whole. A similar logic also applies to the interests of individual candidates. Candidates may support the goal of maximizing their party's legislative seats or probability of holding a majority in principle, but they may not be willing to weaken or sacrifice their own electoral prospects to achieve these goals.

In contrast to much of the previous literature, we allow consulting firm quality to vary across firms and illustrate that these quality differentials manifest themselves in heterogeneous impacts on candidates' electoral performance. Our approach is to first estimate models of the electoral performance of congressional candidates. To guard against omitted variable bias, we control for baseline expectations of candidate electoral performance using the Cook Political Report, incumbency, and national partisan swings. We then use the residuals from these models, divided by the firms' revenues, as measures of consultant productivity.[4] By averaging these residuals across all of a consulting firm's candidate clients we are able to obtain an estimate of each consulting firm's productivity.

A recent article by Nyhan and Montgomery (Forthcoming) convincingly demonstrates that candidates who share consulting firms use more similar campaign strategies than would be expected on the basis of candidate attributes and electoral circumstances alone. This result implies that different firms have distinctive, and measurably different, approaches to campaign strategy. Hence, Nyhan and Montgomery provide a plausible mechanism for heterogeneity in effectiveness or quality across firms, as some choices of tactics may be consistently more effective, or more well-adapted to particular campaign circumstances, than others. Our estimates of consulting firm quality could be used to determine which campaign strategies and practices are associated with increased consultant quality.

Data

To implement our analyses, we collected a novel data set of federal candidates' expenditures on political consultants. We began by gathering names of consulting firms from the trade magazine *Campaigns & Elections*, examining both mentions of firms in back issues and the current electronic database of firms maintained by the magazine.[5] We then searched for every payment made to any firm in our sample by a candidate in a federal election, using the database of campaign expenditures maintained by the Center for Responsive Politics.

The resulting dataset contains each firm's complete set of federal-level clients, as well as the revenues earned from each client, from 2002-2010. We are able to match each candidate with the consulting firms (if any) that the candidate hired, and identify the amount the candidate paid to each firm. The dyadic nature of the dataset allows us to disaggregate consultant spending to the firm level and consider the possibility that electoral effectiveness may vary by firm. In the remainder of this section, we describe the construction of the dataset in more detail and present some descriptive statistics.

Identifying the Set of Political Consulting Firms

To construct our database of congressional candidates' consulting expenditures, we searched through federal campaign expenditure reports for names of consulting firms. We identified the names of political consulting firms using the end-of-cycle election summaries published by *Campaigns & Elections* magazine in the 2002-2010 cycles, as well as the magazine's current on-line database of active firms.[6] After every two-year election cycle, the magazine published a feature called "Win-Loss." This feature included a list of the firms who worked for active campaigns that cycle, along with a brief description of their expertise, partisan affiliation, and the win-loss record of their clients in that year's elections. Note that we do not use the self-reported *Campaigns & Elections* list to measure the consultant-candidate pairings, or which firms were active in which cycles, because of the possibility for misreporting, selective censoring, or measurement error in the listings. As described below, we simply extracted names of consulting firms and then matched these names to the *Center for Responsive Politics* (2013) database of federal campaign expenditures to generate our measure of which consultants worked with which candidates in which cycles.

Firm Names. We took the names of consulting firms listed in *Campaigns & Elections*, and standardized them by removing punctuation, common abbreviations such as "Inc.," "Co.", etc., and varying capitalization. We then performed a manual check for firms that changed their names during the sample period. This process yielded a set of 1275 unique firms.

Candidate Expenditures on Consulting Firms

We identify candidates' relationships with consulting firms using the Federal Election Commission's campaign expenditures dataset, as organized and published by the *Center for Responsive Politics* (2013). Using the set of consulting firm names identified in the previous section, we scan the individual expense transactions of all candidates for recipient names matching any of our list of firms. We keep the amounts of each transaction and aggregate to the firm-candidate level, so that our final dataset has, for every candidate, a list of each firm hired and the amount spent on each. We consider a candidate to have hired a firm if the candidate reported any expenses paid to that firm in a given election cycle.[7]

Of the 1275 firms searched for, we located 802 that earned revenues from federal candidates during our sample period.[8] Because our analysis focuses on congressional general elections, we limited our dataset to expenditures by the ultimate general election candidate in Senate and House races. This restriction further limited the sample to a total of 645 firms. Tables 1 and 2 report summary statistics on the number of firms operating and total revenues earned by the industry in each election cycle. Our sample contains close to 400 unique firms operating in each cycle, indicating significant turnover cycle-to-cycle in the composition of the industry. In the aggregate, the firms we investigate earn revenues in the hundreds of millions of dollars each cycle, with an upward trend over time.[9] However, the distribution of earnings across the various firms in the industry is far from even. Figure 4 of the Online Supporting Appendix shows the distribution of per-client revenues in our sample. The median firm bills about $23,000 per client, and works with two campaigns per cycle. However, there is a substantial group of firms charging in the $100,000 - $1 million range per client. A quarter of the sample group works on at least five different congressional campaigns per cycle.

[Table 1 About Here]

[Table 2 About Here]

Firm Expertise. The descriptions of firms' expertise given by *Campaigns & Elections* are non-standard and not consistent over time. However, drawing on typologies of firms found in the existing literature (Friedenberg, 1997; Medvic, 2001; Magleby, 2010), we were able to group the expertise labels into several broad categories reflecting the different functions of consulting firms.[10] We make use of the firms' expertise in regressions where consulting firms' market share, defined within expertise categories, is the dependent variable. We define market share for a given firm as the firm's total revenues from all clients in a given cycle, divided by the sum of revenues earned that cycle by all firms in the same expertise category and the same party.

Partisan Affiliation. The vast majority of the firms in the universe of 802 that appear in both *Campaigns & Elections* and in the FEC expenditures data over the sample period have a strict partisan affiliation; i.e. a firm either works only for Democrats or only for Republicans. This feature of the market is interesting in that it indicates that party affiliation has a strong influence in the matching of candidates to firms and the development of firms' reputations. Though this feature does not directly demonstrate influence by party organizations, it is at least consistent with the hypothesis that political parties may act as intermediaries between consulting firms and congressional candidates. The segregation by party means that Republican candidates and Democratic candidates choose consultants from nearly disjoint sets of firms. When constructing our firm market share variable in the analysis, we therefore define market share separately within Democratic and Republican candidates.

Television Advertising Prices

In some of our specifications, we predict the amount paid by a candidate to a firm given various firm- and candidate-specific covariates. Because in many cases consulting firms make purchases of advertising time on behalf of their clients, one important driver of candidate-to-firm payments might be the cost of television advertising in the candidate's region (Martin, 2013). We collected data on advertising prices, in dollars per ratings point, in each of the 210 Designated Market Areas in the United States from the Media Market Guides published by Spot Quotations and Data. We recorded the prices prevailing in the third quarter of each election year from 2002 to 2010. Because congressional districts and media markets do not perfectly align (Snyder and Strömberg, 2010), we constructed, for each congressional district, a weighted-average price of all the markets with which the district overlaps. We weighted the prices by the fraction of the population in the district residing in a given media market.

Results

We employ several empirical analyses motivated by our theoretical perspective. First, we examine the relationship of electoral competitiveness to spending on consultants. Second, we construct a measure of firms' productivity based on the portion of their clients' election outcomes that are not predictable using commonly known ex-ante predictors. We look at how these measures of productivity relate to firms' market share. Third, we examine clients' responses to available information about firms' performance by exploring how a firm's revenue in future elections responds to successes in the current election.

Strategic Hiring of Consultants

Past analyses of the electoral impact of consultants (Medvic and Lenart, 1997) have relied on an assumption of exogeneity between spending on consultants and the electoral environment in which a candidate competes. However, if candidates see hiring consultants as a means to achieving an end - namely, winning office - then there is good reason to expect that candidates' choices of consultants will depend strongly on their assessments of the prior likelihood of success. A candidate who foresees an easy victory has little reason to spend scarce campaign resources on high-priced consultants, whereas a candidate engaged in a close-fought battle has strong incentive to take any available action that might win him marginal votes, even if the cost is high.

Figure 1 shows that this pattern is indeed clearly evident in the data. We plot a well-known measure of competitiveness against total consultant expenditures, and reveal a clear pattern that candidates in more competitive races spend more money on consultants. We measure competitiveness using the Cook Political Report's initial forecasts of election outcomes.[11] The figure shows that expenditures are highest in races projected to be the most competitive.

[Figure 2 About Here]

However, the cross-tabulation shown in figure 1 overstates the degree to which candidates change their spending patterns as a function of changes in expected competitiveness: much of the variation visible in the figure is cross-sectional rather than within-candidate. Table 3 demonstrates this clearly: the OLS estimate of the expected differential in spending between a race rated "Tossup" and one rated "Solid Democrat" is over $700K, and statistically distinguishable from all the other categories. When we include candidate fixed effects in the regression, that estimate drops by nearly two-thirds. Estimates for the other categories fall as well, to the point that only the two least competitive categories are statistically significant predictors of lower consultant expenditures. The candidate fixed effects are much better predictors of consultant expenditures than are within-candidate changes in expected competitiveness.

[Table 3 About Here]

Table 4 shows another consequence of candidates' measurable but fairly limited response to changes in electoral conditions. This table reports a fixed-effects regression where the dependent variable is an indicator for a particular firm being hired by a particular candidate.[12] We estimate the effect of changes in expected competitiveness on the probability of hiring, within a candidate-firm pair. Only the two least competitive categories ("Solid Democrat" and "Solid Republican") significantly reduce the probability of a firm being hired, relative to the omitted "Tossup" category. Even in these cases, the substantive impact is small - the probability of a given firm being hired declines by only 12-15% relative to the probability of hiring in the most competitive contests. Hence, once firm-candidate relationships have formed, they are very likely to persist over time, regardless of changes in the candidate's electoral circumstances.

[Table 4 About Here]

Furthermore, ex-ante competitiveness is far from a perfect predictor of candidates' expenditures on consulting firms. Many candidates in clearly uncompetitive races - those rated by Cook as "Solid Republican" or "Solid Democrat" - are paying substantial amounts to consulting firms. This pattern may arise due to incumbents' natural risk aversion: even a small chance of losing a reelection campaign may be enough to induce an incumbent to spend on consultants. Such high-marginal-cost, low-marginal-return behavior is optimal from the point of view of an individual candidate - though not, of course, from the point of view of the party as a whole. Another possibility is that candidates may have secondary objectives other than winning election in mind when hiring consultants. For example, candidates may use payments to consulting firms as a means to direct patronage to past supporters or staffers.

Measures of Consultant Quality

In this section we construct measures of consulting firms' productivity in generating electoral impact. Because it is possible that firms may be selecting candidates to accept as clients on the basis of their likely performance, it is not sufficient to look at raw outcomes such as firms' win/loss records or the average vote shares of their clients. Such measures will be biased due to selection if, for example, some firms disproportionately work for clients in uncompetitive races. Instead, we first condition on commonly-known predictors of electoral performance, and extract the residual or "unexpected" portion of each candidate's electoral result. We then average this residual across all of the races in which a particular firm participates in a given cycle to yield our firm-level measure of productivity.

One potential objection to this measure is that the election residuals absorb many unobserved (by the analyst) factors not properly attributed to consultant performance.[13] Our measure employs multiple races to quantify the electoral performance of consultants. Averaging across races allows us to capture the persistent contribution of the firm to its clients' electoral performance and remove the idiosyncratic component of an individual candidate's electoral performance. While any individual candidate's electoral performance has a random component, by averaging across a large number of races we are able to identity asymptotically the component of electoral performance that can be attributed to the consulting firm. Of course, the variance of this measure decreases as a consulting firm's number of clients increases. For firms with a very small number of candidate clients, the measure will be noisy. Hence, our reported results that use our residual-based productivity measure restrict the sample to the subset of consulting firms that worked in at least five races in a given cycle.

Another potential objection is that consultants may have additional information about the viability of candidates before agreeing to work with candidates. While our method accounts for elite expectations by including the Cook forecast, consulting firms may have additional information at their disposal. If a particular consulting firm refuses to work with a candidate because the firm correctly believes that the candidate will perform below expectations, then the measure will be biased for this firm. There are several reasons to believe that this possible bias is not a serious issue in our application. First, unforeseeable scandals, gaffes, and campaign miscues will be absorbed into the error term and will not bias the quality measure. Second, consultant-client relationships are typically long lived and persist over multiple campaign cycles. While it may be possible for a consulting firm to obtain additional information about the electoral prospects of a candidate in a particular cycle, it is unlikely that this information alone will drive the firm's selection of clients, given the observed persistence of firm-client relationships.[14] Finally, the most plausible bias is that our measure polarizes the true level of consultant quality. If high-quality consulting firms refuse to work for candidates with unanticipated negative electoral shocks, then these firms will appear to be higher quality than they actually are. Similarly, if low-quality consulting firms are stuck working with candidates with negative electoral shocks, these firms will be estimated as lower quality than they actually are. While this polarization scenario would overestimate the magnitudes of the coefficient estimates of our regressions, it will not affect the sign of the estimates. For this reason, such bias will not affect the qualitative conclusions about the assignment of firms of varying quality to races of varying competitiveness that are the focus of the article.

Our set of performance predictors is straightforward but nonetheless generates quite accurate predictions. Our independent variables are the forecasts of the Cook Political Report plus cycle fixed effects, dummy variables for incumbency, and in some cases the log of total expenditures reported by each candidate in the race (Jacobson, 2012). The first panel of Table 5 reports a regression in which the dependent variable is Democratic vote share; each observation is a single election. The predictive power of this set of covariates is quite high. R^2 values in the basic OLS specifications exceed 80 percent, and when district fixed effects are included they approach 95 percent. The fact that election outcomes are so predictable implies that observers in the market for consultants - even those making less sophisticated heuristic assessments - ought to be able to account for factors other than firm skill when assessing the performance records of a firm's clients.

Formally, we estimate the models defined in equations 1 and 2. In both equations, k indexes elections, t indexes cycles, and x is a vector of regressors, including cycle dummies, the Cook ratings, and incumbency status. $\Phi(\cdot)$ is the standard normal CDF.

$$DemShare_{tk} = x'_{tk}\beta^{VS} + r^{VS}_{tk} \quad (1)$$

$$\mathbb{P}(DemWin_{tk}) = \Phi(x'_{tk}\beta^{Win}) \quad (2)$$

After estimating the parameter vectors β^{VS}, β^{Win}, we computed vote-share and win residuals respectively as:

$$\begin{aligned} r_{tk}^{VS} &= DemShare_{tk} - x_{tk}'\beta^{VS} \\ r_{tk}^{Win} &= s_{tk}\sqrt{-2\left(DemWin_{tk}\log\Phi(x_{tk}'\beta^{Win}) + (1 - DemWin_{tk})\log\left(1 - \Phi(x_{tk}'\beta^{Win})\right)\right)} \end{aligned}$$

where $s_{tk} = sign(DemWin_{tk} - \Phi(x_{tk}'\beta^{Win}))$.

Among the best predictors of Democratic vote share are the Cook forecasts; the "Solid Democrat (D3)" rating is associated with a 17-point Democratic advantage.[15] The incumbent party receives a 2-to-4 point advantage - somewhat smaller than what is typically estimated for House races (Lee, 2008) due to the fact that the Cook forecasters use incumbency information in assigning their ratings. The Democratic waves of 2006 and 2008 are reflected in the dummy variable coefficient estimates for those cycles.

[Table 5 About Here]

The second panel of Table 5 reports a regression with the same covariates, but this time using a dummy for Democratic victory as the dependent variable. Results are quite similar to those in the vote-share version, though with slightly lower (pseudo-)R^2.

To construct our measures of consultant productivity, we extracted the residuals from the regressions reported in Table 5.[16] In the vote share case, the residual is the portion of the vote share not explained by easily-available predictors. The residual in the win-probability version represents the "surprise" of an election result; positive if a candidate won and negative if he/she lost.

Note that the residuals from the regressions given by equations 1 and 2 are defined at the level of the election - the dependent variable in each is either the Democratic candidate's vote share or a dummy for the Democrat winning. Since there are two candidates in each election, we assigned the residual r_{tk} to firms working for the Democratic candidate, and the same magnitude but opposite sign ($-r_{tk}$) to firms working for the Republican candidate. Hence, underperformance relative to expectations by a Democratic candidate implies relative overperformance by the opposing Republican candidate, and vice versa.

Because consultants often work for more than one candidate in a given election cycle, and candidates often hire more than one consultant, it was necessary to aggregate the candidate-level residuals in some fashion in order to construct a firm-level productivity measure. We carried out this aggregation as follows.

First, we apportioned each candidate's residual to the firms hired by that candidate on the basis of the candidate's payments to each hired firm. So if candidate X spent \$10,000 on firm A and \$5,000 on firm B, we assigned two-thirds of X's residual to firm A and one-third to firm B. In equation form:

$$\bar{r}_{tfk} = \frac{p_{tfk} r_{tk}}{\sum_{f'} p_{tf'k}} \tag{3}$$

Where in the above, r_{tk} is the residual of candidate k in election t, and p_{tfk} is the payment from candidate k to firm f in election t. Second, we constructed a firm-level weighted average of the apportioned residuals constructed in the first step for each firm. We used weights based on the revenues received from each client as a share of the firm's total revenues. So if firm A earned \$10,000 from candidate X and \$10,000 from candidate Y, we assigned firm A the average of the residuals from candidates X and Y. In other words:

$$\hat{r}_{tf} = \frac{p_{tfk} \bar{r}_{tfk}}{\sum_{k'} p_{tfk'}} \tag{4}$$

Finally, we divided this weighted-average residual by the firm's total billings in a given cycle ($\sum_k p_{tfk}$), to arrive at our measure of productivity. The measure is in units of electoral impact - either in vote-share or win-probability terms - per dollar.

The weighted-average vote-share residuals among firms with at least five clients in a cycle range from a minimum of -10.3 to a maximum of +14.2, with mean of 0.27.[17] When we divide by firm revenues (in dollars) to arrive at our estimate of productivity, the resulting measure has mean of 4.9×10^{-6}; hence, the average firm requires \$100,000 to produce a half-point increase in its client's vote share relative to expectations. The weighted-average residuals in win probability terms have more limited range, with minimum of -1.39, maximum of 1.47, and mean of 0.03. The two measures have positive but imperfect correlation, with a correlation coefficient of 0.49, and are capturing distinct notions of consultants' contribution to the electoral performance of candidates.[18]

Parties' most impactful consultants do not appear to be allocated to races where they have the highest marginal impact on the parties' overall electoral fortunes. Although the results in Figure 1 demonstrate that the *quantity* of spending on consultants is highest in the races deemed most competitive ex-ante, a similar relationship does not appear to hold for the *quality* of that spending. Figure 2 documents an essentially null relationship between the average quality[19] of firms assigned to a race and that race's ex-ante competitiveness. Among Democratic candidates, the quality of firms working on races rated "Likely Democrat" by Cook is statistically indistinguishable from the quality of firms working on races rated "Tossup," even though Democratic candidates are likely to win races in the former category without any expert intervention. A similar pattern holds for Republicans: there the most effective firms are actually assigned to the "Solid Republican" category.

Why is the allocation of consultant quality quite different from the predictions of a party-centered model? We suspect that this pattern arises due to long-term relationships between candidates and consultants that are not mediated by the party organizations. As we document in section and again in the next section, the specific candidate-to-firm matches are highly persistent over time. Hence, it is likely that an upstart candidate in a close race who is matched to a prestigious firm will, should she win, continue to work with the same firm in later elections. The working relationship between candidate and consultant is likely to persist long after she has established herself as an incumbent and no longer "needs" the firm's assistance, in the sense of maximizing the overall party's chances at securing a majority in Congress. If these individual relationships are strong - and they appear to be - over time the party's best consultants will become dispersed across races of varying competitiveness, in spite of the party's best efforts to allocate them strategically.

[Figure 3 About Here]

Informational Frictions

With our productivity measures in hand, we investigate how productivity in the previous electoral cycle influences firms' market performance in the current cycle. As we formalize in the model presented in Appendix A in the Online Supporting Material, clients cannot observe firms' quality directly; they must rely on the observed outcomes of elections in which the firm participates in order to infer latent consultant quality. Good news - a firm's client winning his election - ought to cause clients to raise their perceptions of the firm's quality, and similarly bad news ought to depress candidate perceptions. These changes in beliefs over time should manifest themselves in the marketplace with positive shocks to clients' beliefs about quality resulting in more firm revenue.

Before proceeding with the more sophisticated measures of firm performance described in section , we first looked at how a firm's revenues in future elections respond to electoral success in the current election with a simple fixed-effects regression.[20] Column (1) of Table 6 shows that for the average firm, an additional client winning her campaign produces a statistically significant \$15,000 in additional expected revenues in the next cycle. Given the typical size of firms in the industry - where the median firm earns around \$70,000 per cycle from Congressional campaigns - this is a moderate and non-negligible increase in revenue.

The base specification of column (1) assumes that all wins influence perceptions of the firm's quality equally, which is unlikely. For instance, some incumbent candidates in safe districts are so heavily favored to win that having worked on a successful campaign for them does not provide much of a signal of a firm's ability. In column (2) we split out races in which the firm's client was an incumbent running against a challenger who had not held prior elective office, a case in which prior research on congressional elections has shown the incumbent to be heavily favored (Jacobson, 2012). The difference between the two cases is quite dramatic. The "expected" wins produce an impact on future revenues that is estimated to be negative (but not significantly different from zero).[21] The "unexpected" wins, on the other hand, produce a positive impact of over \$80,000 in expected revenue in the next cycle. Although the coefficient estimates are somewhat imprecise, an F-test rejects the hypothesis of equality of the expected and unexpected win coefficients at the 99% level. The final two columns of the table repeat columns (1) and (2) with the addition of cycle fixed effects. The coefficient estimates are quite similar in this case.

[Table 6 About Here]

Given the evidence from this simple specification that firms' market outcomes respond very differently to surprising election outcomes than to unsurprising ones, we next proceed to investigate the impact of our measures of consulting firms' electoral impact from section . Our first specification models a firm's market share in the current period as a function of the productivity measures described above (in both win- and vote-share terms) in the previous period.

We constructed market shares as a firm's share of the total revenues going to all firms in the same expertise category from candidates with the same party affiliation. We regressed each firm's market share in period $t+1$ on its market share in period t and the firm's productivity in period t. Because the productivity measure is an estimated quantity, the usual standard error calculation is inappropriate. Instead we computed bootstrap standard errors by resampling from the election dataset, re-estimating the regressions in Table 5, re-computing productivity, and finally estimating the second-stage regression of market share on estimated productivity. Bootstrapped standard errors computed from 2500 bootstrap resamples are reported in Table 7.

The first six columns of Table 7 are OLS regressions, using the firm's previous-period market share as a regressor to account for persistence over time. Market shares exhibit strong persistence; on average, a firm retains close to 90 percent of its previous-period share. Insofar as firms' market shares are a function of clients' perceptions of firms' electoral impact, this persistence indicates that clients' beliefs change relatively slowly. The seventh column accounts for persistence using firm fixed effects. In columns (1) and (2) we estimate the effect of previous-cycle productivity in terms of surprise wins and unexpected vote share, respectively. The surprise-win measure has a strong positive effect; the unexpected-vote-share measure has an effect that is positive but not statistically different from zero. The measures in columns (1) and (2) are our per-dollar productivity measures. It is possible that certain kinds of firms (say, media firms, which purchase expensive television advertising spots for their clients) may earn higher revenues than those in other categories. Or, since more money is generally spent on consultants in close races, firms working in close races may earn higher revenues and hence register as lower-productivity according to our method. To demonstrate that our results are driven not by variation in billings but by variation in the underlying measures of performance, in columns (3) and (4) we estimate the same regressions but using the win- and vote-share-residuals directly, without dividing by revenues. The scale of the coefficients is different due to the rescaling of the independent variable, but the substantive conclusions are the same. A one-standard-deviation increase in a firm's win-residual generates a (statistically significant) market share increase of 1.6 percentage points in the next period; a one-standard-deviation increase in a firm's vote-share-residual generates a (not statistically significant) market share increase of 0.4 percentage points.

Columns (5) and (6) include both measures of productivity in the same regression. When both are included together, the point estimate on the vote-share version becomes negative (though it remains statistically indistinguishable from zero). This is further evidence that unexpected wins are the driver of firms' revenues; all of the action is coming from close wins near 50 percent, and further increases in vote share beyond that have no effect. Finally, column (7) includes firm-level fixed effects. Though adding fixed effects decreases the precision of these estimates relative to the OLS versions, the directional conclusions are the same.

[Table 7 About Here]

Table 8 reports results of a similar regression exercise with a different dependent variable. Here, each observation is a firm-candidate pair, and the dependent variable is the amount of the payment made from the candidate to the firm (p_{tfk}). This specification allows us to include some candidate-specific controls that are likely to influence how much revenue a firm earns and were by necessity omitted from the firm-level regression in Table 7. We include the Cook forecast for the candidate's race, the candidate's total funds raised in the cycle from individual donors, and the measure of the cost of television advertising described above. Candidates in races predicted to be uncompetitive spend less on consultants, even within the subset of candidates who chose to hire at least one firm. The coefficient on fundraising is positive, indicating that the typical consultant captures between 6 and 8 percent of its clients' total fundraising dollars. The advertising price coefficient is negative in the OLS specifications but positive in the fixed effects specification, suggesting that increases in underlying costs are passed on to clients.

Again, we account for the observed high degree of persistence in the dependent variable in two ways. In the first five columns, we include as a regressor the payment made between the same pair of candidate and firm in the previous cycle. The typical firm can expect to receive about 37 cents from a candidate in the current cycle for every dollar in contracts it earned from that candidate in the previous cycle, suggesting substantial persistence in relationships between firms and candidates. In the last column, we include candidate-firm fixed effects to account for this persistence. The main result in this specification is similar to the last; increases in productivity in "surprise win" terms predict increases in the price a firm is able to charge its clients, indicating that clients are paying attention to firms' win and loss records and consider them an indication of quality. Increases in productivity in vote share terms here are statistically insignificant (with negative point estimate) when included in the regression alone, and when included together with the win-productivity measure actually *decrease* the price that firms can command.

[Table 8 About Here]

This apparent distinction between victories and vote share performance is indicative of clients ignoring a great deal of information about consultant quality, and may have important consequences for the behavior of consulting firms in campaigns. Because marginal increases in vote share are worth little while crossing the threshold of 50 percent is worth a lot, consultants for underdog candidates are likely to be risk-loving: faced with a choice of a low-variance strategy versus a high-variance one, the consultant may well prefer the high-variance strategy even if it is dominated in expected value terms. The incentives are reversed for consultants working for favored candidates.

These results suggest that clients believe that firms possess persistent differences in their ability to impact elections, and are willing to pay more for firms with higher perceived ability. They appear to use the firm's record of election wins and losses - rather than how well its clients perform relative to expectations - to infer this ability. For this purpose, some elections are much more informative than others. It is very difficult to learn about firms that work for incumbents from win-loss information alone, as incumbents tend to be very likely to win their races with or without the participation of consultants. Appendix A in the Online Supporting Material presents a simulation exercise demonstrating the difficulty of learning from rare events, such as incumbent losses, relative to learning from vote share information. Combining this theoretical observation with the empirical results presented here, one should expect that incumbent clients, whose unconditional reelection probabilities are quite high, ought to provide little information on a firm's quality to observers.

Table 9 shows some evidence consistent with this hypothesis. The table reports three variants of a firm-level regression where the dependent variable is the firm exiting the market.[22] As one might expect, larger firms (those with more clients in one cycle) are less likely to exit the market in the next cycle. However, the marginal effects of having additional incumbent clients and having additional challenger clients have opposite signs. While having additional incumbent clients reduces the likelihood of exit in the next period, having additional challenger clients actually *increases* it. This pattern holds cross-sectionally, within firms, and in a Cox proportional hazard specification where we allow the baseline exit hazard to vary by firm. These differential effects are consistent with a world where incumbent races are much less likely to reveal (possibly negative) information about the firm's ability.

[Table 9 About Here]

Discussion

We have examined the market for political consulting firms in Congressional elections. Although there is a clear partisan organization to the market, and many individual consultants have close professional ties to the parties, the market incentives for consulting firms are not well aligned with partisan electoral goals. In particular, the predominant driving factor in the assignment of firms to candidates appears to be long-lived candidate-consultant relationships, which persist in the face of significant changes in candidates' electoral prospects over time. As a result, each party's most electorally impactful consultants are distributed more or less at random across races of varying competitiveness, rather than concentrated in close races where they would have the greatest impact on the party's overall electoral success. Our analysis suggests that while parties and consultants may not be adversaries, they are not necessarily the close allies that some scholars have depicted (Kolodny and Logan, 1998).

This individualistic assignment of firms is supported by an informational environment that rewards consulting firms for wins (and, correspondingly, punishes them for losses) but ignores overperformance relative to expectations in losing contests (and underperformance relative to expectations in winning ones). We demonstrate that clients appear to use only unanticipated victories and losses as a gauge of consultant quality, an incentive structure that makes working for candidates with safe seats much less risky for firms' reputations than working in contested races. One consequence of this riskiness is that firms who work for challenger clients in one cycle are much more likely to exit the market in the next than are firms who work preferentially for incumbents, who tend to win their races with high probability.

The fact that clients use only limited and coarse information on electoral performance in making hiring decisions, combined with the uncompetitiveness of most Congressional races, leaves substantial slack available for unproductive firms who happen to be well-connected to established candidates to persist in the market over long periods of time. If, as we argue, individual candidate-consultant relationships are the primary driver of observed matches between firms and candidates, a natural question arises as to the determinants of these relationships. While such questions would take us beyond our focus on firms' electoral performance, they present an intriguing avenue for future research. Is there a "revolving door" relationship between Congressional staff networks and firms similar to that documented in the lobbying industry (Vidal, Draca and Fons-Rosen, 2012)? If candidates and parties are not fully optimizing on electoral performance, might they be weighting some other dimension, such as the ability to use consulting expenditures to direct patronage to supporters and friends? We leave such questions for future work.

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Notes

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[1]The incentive to work for favorites arises not simply because a winning client is likely to generate repeat business in the next cycle, but also because of the inferences about the firm's effectiveness that other participants in the market will draw upon observing a client win.

[2]There are other structural reasons to expect that consulting firms would rather work for electorally safe clients and have quite different objectives than the parties. Secure congressional candidates have a higher expected number of future campaigns before exiting office, which makes these candidates more valuable for consulting firms in the future. Additionally, electorally weak candidates who lose may be so financially constrained after the election that they are unable to reimburse consultants for services rendered during the campaign. We thank an anonymous referee for suggesting these points.

[3]In related work, Skinner, Masket and Dulio (2012) find that major parties and 527s have close ties in employed personnel and Bernstein (1999) finds that consultant firm staff are primarily recruited from party backgrounds, including formal party organizations and other same-party campaigns.

[4]We define a more productive firm as one that generates more electoral impact at lower cost; thus our productivity measures are all defined in per-dollar terms.

[5]Cain (2013) and Nyhan and Montgomery (Forthcoming) also employ *Campaigns & Elections* to generate a list of consulting firm names.

[6]The database is available at `https://www.politicalpagesdirectory.com/`.

[7]The CRP identifies expenses as associated with a given election cycle, and we follow their classification. Generally, they consider expenses paid between January 1 of the calendar year before the election year and December 31 of the election year to belong to that cycle.

[8]The remaining firms are primarily specialists in state, local, and ballot initiative campaigns and do not appear in the FEC expenditures data.

[9]Note that all dollar figures used in our tables and analyses are deflated to constant, 2000 dollars. The upward trend over time is thus due to real growth in the size of the industry over time, rather than inflation.

[10]These categories, in order of frequency of their occurrence in the data, are: Media and advertising (TV, radio, print), general or full-service strategy, direct mail, polling, fundraising, telemarketing, Internet and technology specialists, get out the vote, opposition research, and legal/accounting.

[11]The Cook report classifies congressional races into one of eight categories.

These are Solid Republican, Likely Republican, Lean Republican, and Toss-Up Republican, plus the same four categories on the Democratic side. We collapse the two "toss-up" categories into one, labeled "T" in the plot. The categories are ordered left to right in order of their favorability to Democratic candidates.

[12]Hence, an observation in this regression is a candidate-firm-cycle.

[13]One important electoral factor that should not be attributed to consultants, national partisan swing, is purged from the productivity measure with the inclusion of year fixed-effects in our regression specifications.

[14]For this kind of bias to be a problem, firm-candidate relationships would have to be responsive to changes in unobservable candidate prospects. We cannot test this conjecture directly, but table 4 shows that firm-candidate relationships are not very responsive to changes in *observable* candidate prospects.

[15]The omitted category is races rated "Tossup."

[16]Residuals were constructed using the model reported in columns (1) and (5), respectively.

[17]Note that the units here are percentage points of vote share.

[18]In Appendix B in the Online Supporting Material, we include a series of robustness checks that employ alternative versions of our productivity measure. We estimate versions of the win-share productivity measure using linear probability models instead of the discrete generalized linear model that we use here. We also construct a more flexible measure of consultant productivity that allows firms' productivity to vary across Cook forecast categories. Finally, we also restricted the analysis to the sample of "media" firms due to the possibility that

media firms use different compensation schemes, based on partial rebates for advertising purchases, than the other consulting firms in our sample.

[19]We measure the quality of the firms assigned to a race in a given election cycle using the firms' vote-share residuals from the previous election cycle, whose construction was described previously. If there are multiple firms assigned to the same race, we compute a weighted average value, using the amount (in dollars) paid to each firm as the weights.

[20]We use firm-level fixed effects, so that only within-firm variation in revenues affects the coefficient estimate.

[21]Such a victory counts as both a win and an expected win, so the total impact is the sum of the two coefficients given in Table 6.

[22]Each observation here is a firm-election cycle. We classify a firm as exiting the market if it appears in our dataset in one election but does not in the next.

References

Bernstein, Jonathan H. 1999. The Expanded Party in American Politics. PhD thesis University of California, Berkeley.

Cain, Sean A. 2013. "Political Consultants and Party-Centered Campaigning: Evidence from the 2010 U.S. House Primary Election Campaigns." *Election Law Journal* 12(1):3–17.

Center for Responsive Politics. 2013. `http://www.opensecrets.org/resources/create/data.php`.

Diermeier, Daniel, Michael Keane and Antonio Merlo. 2005. "A Political Economy Model of Congressional Careers." *American Economic Review* 95(1):347–373.

Doherty, Joseph William. 2006. The Candidate-Consultant Network in California Legislative Campaigns: A Social Network Analysis of Informal Party Organization. PhD thesis University of California, Los Angeles.

Farrell, David M., Robin Kolodny and Stephen Medvic. 2001. "Parties and Campaign Professionals in a Digital Age: Political Consultants in the United States and Their Counterparts Overseas." *Harvard International Journal of Press/Politics* 6(4):11–30.

Friedenberg, Robert V. 1997. *Communication Consultants in Political Campaigns: Ballot Box Warriors*. Westport, Conn.: Praeger.

Jacobson, Gary C. 2012. *The Politics of Congressional Elections, 8th Edition*. New York: Pearson.

Kolodny, Robin and Angela Logan. 1998. "Political Consultants and the Extension of Party Goals." *PS: Political Science and Politics* 31(2):155–159.

Kolodny, Robin and David A. Dulio. 2003. "Political Party Adaptation in U.S. Congressional Campaigns: Why Political Parties Use Coordinated Expenditures to Hire Political Consultants." *Party Politics* 9(6):729–746.

Lee, David S. 2008. "Randomized Experiments from Non-Random Selection in U.S. House Elections." *Journal of Econometrics* 142:675–697.

Magleby, David B. 2010. Political Parties and Consultants. In *The Oxford Handbook of American Political Parties and Interest Groups*, ed. L. Sandy Maisel and Jeffrey M. Berry. Vol. 1 Oxford University Press.

Martin, Gregory J. 2013. "The Informational Content of Campaign Advertising." Working paper, Emory University.

Mayhew, David R. 1974. *Congress: The Electoral Connection*. Yale University Press.

Medvic, Stephen K. 2001. *Political Consultants in U.S. Congressional Elections*. Columbus, Ohio: The Ohio State University Press.

Medvic, Stephen K. and Silvo Lenart. 1997. "The Influence of Political Consultants in the 1992 Congressional Elections." *Legislative Studies Quarterly* 22(1):61–77.

Milyo, Jeffrey. 2001. "What Do Candidates Maximize (and Why Should Anyone Care)?" *Public Choice* 109(1-2):119139.

Nyhan, Brendan and Jacob M. Montgomery. Forthcoming. "Connecting the Candidates: Consultant Networks and the Diffusion of Campaign Strategy in American Congressional Elections." *American Journal of Political Science* .
URL: *http://www.dartmouth.edu/ nyhan/consultant-networks.pdf*

Plasser, Fritz. 2001. "Parties' Diminishing Relevance for Campaign Professionals." *Harvard International Journal of Press/Politics* 6(4):44–59.

Sabato, Larry J. 1981. *The Rise of Political Consultants: New Ways of Winning Elections*. New York: Basic Books.

Shea, Daniel M. 1996. *Campaign Craft: The Strategies, Tactics, and Art of Political Campaign Management*. Westport, Conn.: Praeger.

Skinner, Richard M., Seth E. Masket and David A. Dulio. 2012. "527 Committees and the Political Party Network." *American Politics Research* 40(1):60–84.

Snyder, James M. 1989. "Election Goals and the Allocation of Campaign Resources." *Econometrica* 57(3):637–660.

Snyder, Jr., James M. and David Strömberg. 2010. "Press Coverage and Political Accountability." *Journal of Political Economy* 118(2):355–408.

Vidal, Jordi Blanes I., Mirko Draca and Christian Fons-Rosen. 2012. "Revolving Door Lobbyists." *American Economic Review* 102(7):37313748.

Cycle	All Federal Candidates	Gen Election Congressional
2002	$ 204M	$ 127M
2004	$ 624M	$ 132M
2006	$ 300M	$ 170M
2008	$ 907M	$ 168M
2010	$ 402M	$ 255M

Table 1: Total expenditures on consulting firms in federal elections, 2002-2010 (in real 2000 dollars)

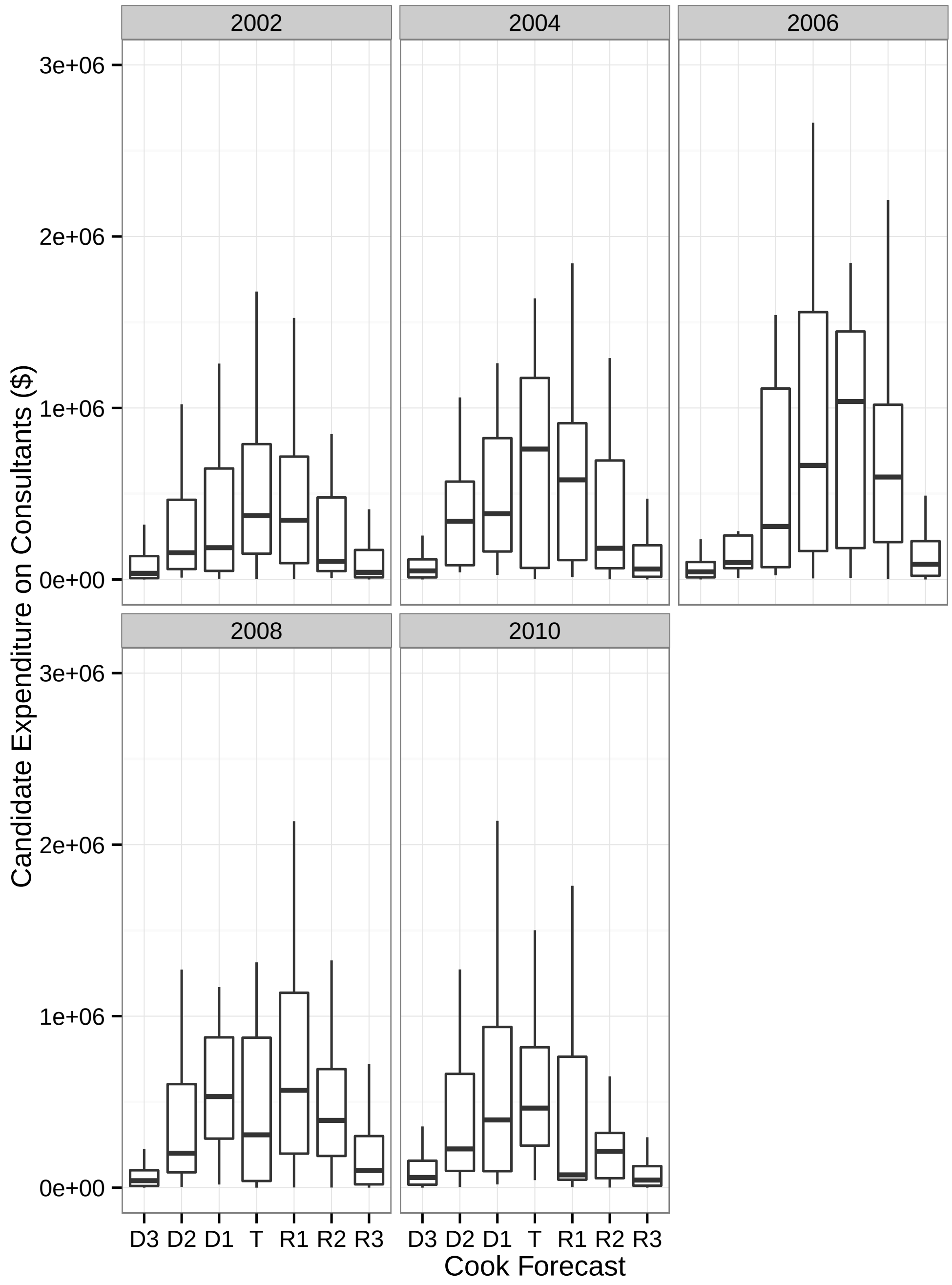

Figure 1: Consultant expenditures by Cook election forecast

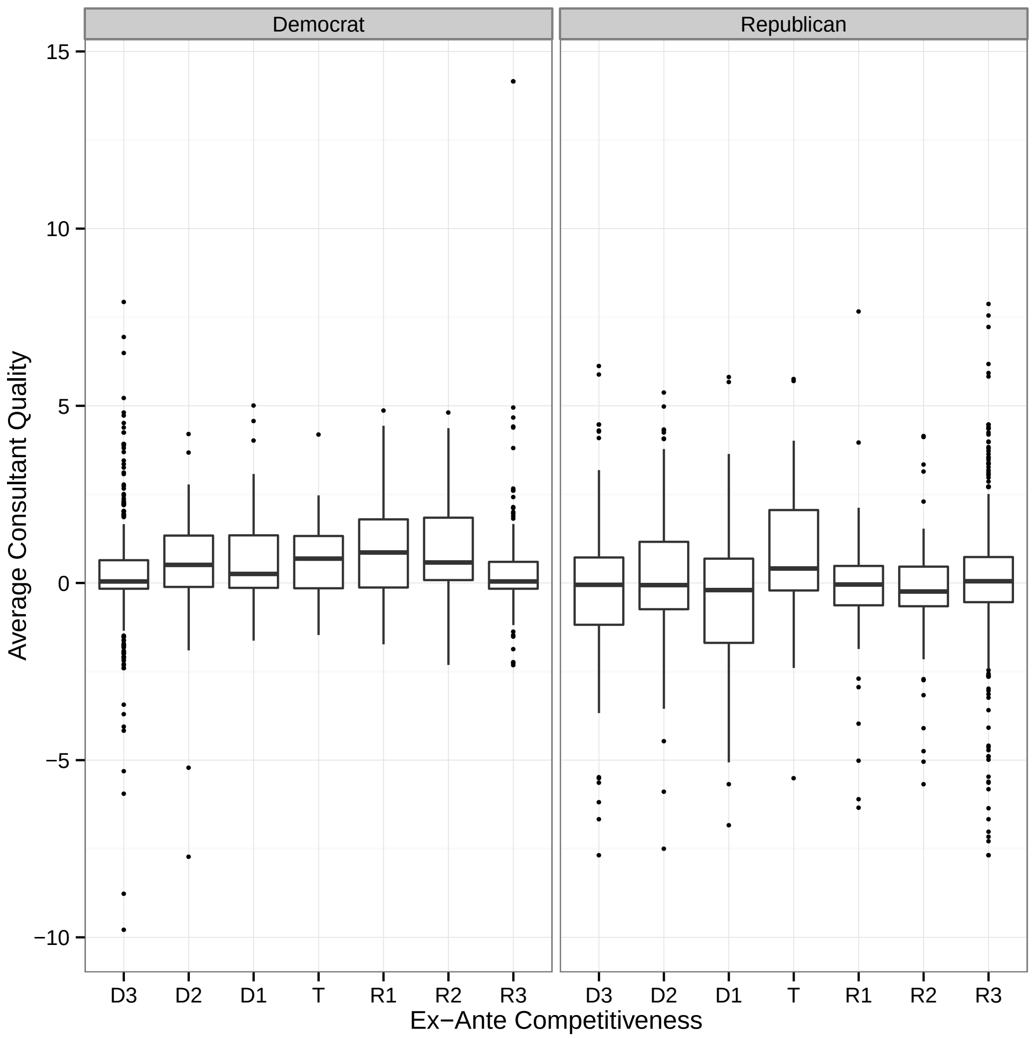

Figure 2: Box plot of ex-ante race competitiveness against the previous election cycle vote share residual of firms assigned to that race in the current cycle.

Cycle	All Federal Candidates	Gen Election Congressional
2002	461	381
2004	502	374
2006	491	387
2008	530	396
2010	494	395

Table 2: Active consulting firms in federal elections, 2002-2010

Coefficient	OLS	FE
(Intercept)	825,495	
	(100,946)	
Cook Forecast: D3	-718,983	-249,380
	(99,562)	(116,532)
Cook Forecast: D2	-436,364	-104,792
	(103,377)	(121,338)
Cook Forecast: D1	-281,181	-20,426
	(109,178)	(123,799)
Cook Forecast: R1	-155,322	9,478
	(114,496)	(129,702)
Cook Forecast: R2	-335,998	-38,581
	(111,489)	(125,727)
Cook Forecast: R3	-650,561	-222,997
	(97,586)	(128,872)
Incumbent	31,816	-119,338
	(18,197)	(62,175)
Republican	-26,221	
	(18,519)	
Candidate Fixed Effects?	N	Y
R^2	0.181	0.733
N	2688	2688

Table 3: Regression of House candidates' total expenditures on consulting firms as a function of ex-ante competitiveness.

Coefficient	Hiring Probability
Cook Forecast: D3	-0.154
	(0.037)
Cook Forecast: D2	-0.035
	(0.037)
Cook Forecast: D1	-0.031
	(0.038)
Cook Forecast: R1	-0.044
	(0.040)
Cook Forecast: R2	-0.006
	(0.038)
Cook Forecast: R3	-0.128
	(0.036)
Candidate-Firm Fixed Effects?	Y
R^2	0.430
N	17,526

Table 4: Fixed-effects regression of probability of hiring a consulting firm on ex-ante competitiveness.

Coefficient	Vote Share OLS 1	OLS 2	FE 1	FE 2	Win Probability Probit	FE 1	FE 2
(Intercept)	47.830	48.869			-0.195		
	(0.899)	(1.982)			(0.205)		
Cook Forecast: D3	17.921	13.584	4.593	3.911	2.030	0.126	0.115
	(1.219)	(1.287)	(1.428)	(1.595)	(0.254)	(0.075)	(0.084)
Cook Forecast: D2	5.472	4.362	1.320	1.165	0.731	0.023	0.008
	(1.282)	(1.278)	(1.302)	(1.404)	(0.260)	(0.078)	(0.086)
Cook Forecast: D1	1.758	1.938	0.704	0.668	0.142	0.016	-0.014
	(1.298)	(1.297)	(1.437)	(1.563)	(0.263)	(0.080)	(0.088)
Cook Forecast: R1	-1.882	-2.191	-0.802	-0.721	-0.491	-0.084	-0.080
	(1.113)	(1.192)	(1.211)	(1.289)	(0.256)	(0.078)	(0.087)
Cook Forecast: R2	-4.623	-4.068	-2.562	-1.840	-0.640	-0.058	-0.055
	(1.174)	(1.226)	(1.272)	(1.307)	(0.248)	(0.069)	(0.081)
Cook Forecast: R3	-13.034	-10.408	-7.956	-5.745	-2.013	-0.239	-0.217
	(1.117)	(1.220)	(1.201)	(1.284)	(0.239)	(0.062)	(0.072)
2004 Cycle	1.324	1.633	1.627	1.860	-0.031	-0.010	-0.001
	(0.509)	(0.475)	(0.343)	(0.386)	(0.199)	(0.011)	(0.013)
2006 Cycle	5.057	4.240	5.703	5.157	1.114	0.073	0.073
	(0.539)	(0.503)	(0.404)	(0.427)	(0.202)	(0.016)	(0.018)
2008 Cycle	3.771	3.850	5.411	5.087	0.646	0.090	0.091
	(0.530)	(0.508)	(0.411)	(0.422)	(0.199)	(0.018)	(0.019)
2010 Cycle	-3.552	-2.760	-2.581	-2.649	-1.227	-0.086	-0.089
	(0.559)	(0.545)	(0.429)	(0.468)	(0.197)	(0.017)	(0.020)
Incumbent Democrat	2.890	1.707	4.401	3.980	0.818	0.115	0.102
	(1.176)	(1.134)	(0.819)	(0.841)	(0.206)	(0.041)	(0.044)
Incumbent Republican	-2.035	-1.470	-2.550	-2.124	-0.403	-0.019	-0.045
	(0.870)	(0.755)	(0.725)	(0.656)	(0.194)	(0.036)	(0.036)
Log Democratic Expenditures		1.047		0.803			0.009
		(0.098)		(0.107)			(0.003)
Log Republican Expenditures		-1.094		-0.397			-0.001
		(0.078)		(0.063)			(0.002)
District Fixed Effects?	N	N	Y	Y	N	Y	Y
(Pseudo-)R^2	0.816	0.848	0.943	0.949	0.806	0.846	0.848
N	1974	1798	1974	1798	1974	1974	1798

Dependent variable for columns (1)-(4) is Democratic share of the two-party vote. Dependent variable for columns (5)-(7) is a dummy for a Democratic win. Column (5) is a probit regression; (6) and (7) are linear probability models. The R^2 row is a psuedo-R^2 for the probit model in column (5). Robust standard errors are in parentheses.

Table 5: Models of candidates' vote share

Coefficient	(1)	(2)	(3)	(4)
Last Cycle Wins	15,082	82,912	14,034	87,804
	(6,490)	(58,899)	(6,368)	(60,537)
Last Cycle Expected Wins		-92,389		-101,262
		(62,845)		(65,447)
Cycle Fixed Effects?	N	N	Y	Y
Firm Fixed Effects?	Y	Y	Y	Y
R^2 (Within)	0.007	0.016	0.016	0.027
R^2 (Total)	0.746	0.746	0.748	0.749
N	1,564	1,514	1,564	1,514

Dependent variable is current cycle revenues. Standard errors (in parentheses) are robust and clustered at the firm level. "Last Wins" is number of clients worked for in the previous cycle who won their campaign. "Last Expected Wins" is the same but includes only incumbent clients running against challengers who had not held previous elective office.

Table 6: Fixed-effects regression of firm revenues on previous wins.

Coefficient	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prev. Cycle Productivity (Win)	7,479				8,078	8,040	5,488
	(1,838)				(2,077)	(2,080)	(4,424)
Prev. Cycle Productivity (VS)		168.702			-34.942	-45.207	-9.500
		(101.283)			(115.161)	(118.573)	(176.816)
Prev. Cycle Average Residual (Win)			0.070				
			(0.012)				
Prev. Cycle Average Residual (VS)				0.002			
				(0.001)			
Prev. Cycle Market Share	0.865	0.867	0.863	0.866	0.865	0.865	
	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	
Cycle Fixed Effects?	N	N	N	N	N	Y	Y
Firm Fixed Effects?	N	N	N	N	N	N	Y

Note: Bootstrapped standard errors in parentheses.

Table 7: Second stage regression of firms' market share on productivity measures.

Coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Productivity (Win)	1.980E+10		2.384E+10	2.419E+10	2.413E+10	1.184E+10
	(4.924E+09)		(5.246E+09)	(5.000E+09)	(5.142E+09)	(6.859E+09)
Productivity (VS)		-1.386E+08	-2.716E+08	-3.345E+08	-3.118E+08	8.282E+07
		(1.003E+08)	(1.258E+08)	(1.386E+08)	(1.343E+08)	(1.567E+08)
Prev. Cycle Payment	0.371	0.371	0.370	0.370	0.370	
	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	
Fundraising Total	0.061	0.061	0.061	0.062	0.063	0.084
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.011)
Cook Forecast - D3	-53,231	-53,384	-52,648	-48,645	-46,226	-37,783
	(8,757)	(8,622)	(8,848)	(8,583)	(8,634)	(17,395)
Cook Forecast - D2	-27,007	-27,845	-26,851	-20,880	-19,879	-15,975
	(8,698)	(8,645)	(8,992)	(8,247)	(8,321)	(13,051)
Cook Forecast - D1	-44,751	-45,300	-44,595	-38,360	-38,246	-26,175
	(8,323)	(8,303)	(8,407)	(8,182)	(8,127)	(13,414)
Cook Forecast - R1	-27,049	-27,345	-26,963	-24,430	-23,955	-37,500
	(9,009)	(9,073)	(9,045)	(8,833)	(8,847)	(16,370)
Cook Forecast - R2	-52,079	-52,511	-51,844	-47,835	-47,040	6,729
	(9,697)	(9,567)	(9,826)	(9,672)	(9,769)	(12,995)
Cook Forecast - R3	-49,180	-49,624	-49,056	-46,628	-45,729	-14,903
	(8,407)	(8,286)	(8,564)	(8,395)	(8,351)	(14,085)
TV Advertising Price Index					-8.014	42.998
					(1.914)	(12.248)
Cycle Fixed Effects?	N	N	N	Y	Y	Y
Firm-Candidate Fixed Effects?	N	N	N	N	N	Y

Note: Bootstrapped standard errors in parentheses.

Table 8: Second stage regression of candidate-to-firm payments on productivity measures.

Coefficient	OLS	FE	Cox Hazard
(Intercept)	0.259		
	(0.009)		
Prev. Cycle # Incumbent Candidates	-0.009	-0.006	-0.031
	(0.002)	(0.003)	(0.010)
Prev. Cycle # Challenger Candidates	0.018	0.025	0.063
	(0.004)	(0.005)	(0.015)

Notes: N=2690. Standard errors in parentheses.

Table 9: Regressions of firm exit on number of incumbent and challenger clients.