

The Partisan Ties of Lobbying Firms

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Abstract

Organized interests commonly face principal-agent problems in attempting to control the lobbyists under their employ. This article explains how lobbying firms help to curtail these problems by reducing the degree of asymmetric information between lobbyists and their clients. It shows that lobbying firms' partisan identities provide informative signals about lobbyists' loyalties. Using data from lobbying records released under the Lobbying Disclosure Act, as well as original data collected on lobbying firms, this article examines the effects of partisan ties on firms' lobbying revenues. The results demonstrate that partisan ties with the majority party of the House of Representatives translate into higher lobbying revenues, but ties with the Senate's majority party make no significant difference for revenue. These findings provide evidence of the political market value of partisan ties, as well as evidence of perceived differences in the institutional vulnerability of the House and Senate to interest group pressure.

Keywords

Lobbying firm, Congress, partisanship, credence good, principal-agent problem

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Lobbyists are individuals who contact representatives of the government on behalf of others who have an interest in influencing government policies. Lobbying is big business in the United States. More than 11 thousand individuals registered as lobbyists at the federal level in 2016, while organizations across the political spectrum reported spending more than \$3 billion on federal lobbying in the same year (Center for Responsive Politics 2017).¹ Federal lobbying expenditures are about five times greater than campaign contributions to candidates through Political Action Committees (PACs) in a typical year (Milyo et al. 2000). These expenditures can yield substantial financial returns for the organizations that make them (de Figueiredo and Richter 2014; Goldman et al. 2009; Richter et al. 2009).

One of the fundamental problems that organizations face when they hire lobbyists is that lobbyists work in an arena in which they inherently have conflicting interests. Along these lines, Ainsworth and Sened (1993) described lobbyists as “entrepreneurs with two audiences.” Lobbyists have an interest in satisfying the organizations that employ them. Yet they also have an interest in currying favor with the government officials that they meet with; lobbyists need to keep the goals of these officials in mind if they wish to continue to have access to them. As they navigate between the gauze of employing organizations and their governmental targets, lobbyists carve out a zone of autonomy in which they decide how to conduct their lobbying (Kersh 2000). Consequentially, neither employing organizations nor government officials are entirely sure of

¹ This amount only includes dollars reported under the Lobbying Disclosure Act (LDA), which does not require reporting spending below certain thresholds or spending that takes places at the state or locals levels. Thus, it reflects a minimum amount spent on lobbying, rather than a maximum.

the extent to which lobbyists can be trusted; both confront *asymmetric information* in their dealings with lobbyists.

The relationship between lobbyists and their clients is additionally complicated by the fact that lobbying is a *credence good*. A credence good is one in which the buyer has to rely on the seller to know how much of the good the buyer needs (Darby and Karni 1973). Lobbyists are in the position of advising their clients about whom they need to lobby. The two-audiences problem, asymmetric information, and the credence qualities of lobbying combine to create *principal-agent problems* for organizations managing their relationships with lobbyists (Holyoke 2017; Lowery and Marchetti 2012; Stephenson and Jackson 2010).

Organizations may be able to take steps to address principal-agent problems vis-a-vis their lobbyists. As is the case with many credence goods, two potential solutions are *vertical integration* and *reputation* (Darby and Karni 1973). Vertical integration is achieved under these circumstances by making lobbyists permanent employees of the organization – that is, by hiring them as *in-house* rather than *contract* lobbyists. Doing so is likely to allow the client to increase its effectiveness in monitoring lobbyists' work (Williamson 1981). The in-house solution may work for a large number of lobbyists, but not for all of them. Drutman (2015) argued that in-house lobbyists are preferred when an organization is interested principally in a particular policy area, seeks industry-specific expertise, or is in the process of establishing a permanent presence in Washington. But, when an organization is concerned more with the vicissitudes of the political process (e.g., how to influence a particular congressional committee), contract lobbyists are often preferred (see also Nownes 2006, 96). Contract lobbyists are especially valued for their knowledge of the intricacies of how government makes policy, as well as their relationships with people who are still inside the process.

Although many organizations lean heavily on the expertise of contract lobbyists, doing so may involve a considerable amount of trepidation (Drutman 2015). If contract lobbyists are selected because of their closeness to the policy process and its protagonists, how can employing organizations be confident that contract lobbyists will represent their clients authentically and not defer to their close contacts in government? The question may be especially pertinent for organizations that do not have a Washington headquarters (as is the case for many corporations) or those that are not otherwise major players on the Washington scene. How are organizations that are relatively distant from policy arenas supposed to adequately vet and monitor contract lobbyists?

A second potential solution to the agency problems associated with hiring contract lobbyists is to rely on reputation. We argue that hiring contract lobbyists through *lobbying firms* with known reputations helps clients to find lobbyists that will represent their interests well. Organizations in the market to hire lobbyists may not be able to judge the reliability of every individual contract lobbyist available for hire, but they may be able to learn the reputations of some of the firms that manage them. The nature and qualities of firms' brands may provide important signals of the loyalties, reliability, and expertise of contract lobbyists, thus reducing the uncertainty that organizations face when making contracting decisions.

Despite the potentially critical role that lobbying firms play in the conduct of lobbying, the extant empirical literature contains scant evidence on how lobbying *firms* affect the lobbying process. Research has tended to focus on *lobbyists as individuals* and/or on the *clients they serve*, such as interest groups and corporations (Baumgartner et al. 2009; Kersh 2002; Milbrath 1963). For example, Bertrand et al. (2014) examined whether lobbyists are rewarded more for their policy expertise or for their professional connections. LaPira and Thomas (2017)

investigated the similarities and differences between lobbyists that had worked in government (i.e., “revolving door” lobbyists) and those that did not have this experience (see also Lazarus et al. 2016). Hall and Deardorff (2006) explained how lobbyists subsidize attention by members of Congress to lobbyists’ issues, while Ringe et al. (2015) demonstrated how the information provided by lobbyists helps to reinforce legislators’ views on these issues. While these studies yield a great deal of insight into how *individuals* perform lobbying and its effects on policy, they are generally silent on how lobbying *firms* may help to steer this work (but see Brasher 2014, 179-191).

By neglecting to examine the role of lobbying firms, the extant literature implicitly presumes that their role is politically neutral. Yet, we argue that like firms in the political consulting industry (Sheingate 2016), lobbying firms have identities that are politically relevant and consequential. This article examines, in particular, the extent to which the lobbying firms’ *partisan ties* signal firms’ political loyalties. To evaluate the political market value of lobbying firms’ partisanship, we analyze Lobbying Disclosure Act (LDA) data on lobbying firms from 2008 to 2016, as well as original data that we compiled on the characteristics of lobbying firms active during this period. In particular, we analyze how variations in the alignment between the partisan ties of the founders of lobbying firms and the majority party in Congress correspond to the ability of firms to generate revenue from lobbying contracts.

Our investigation yields several contributions to the scholarly literatures on lobbying, political parties, and legislative politics. First, we report the results of one of the first systematic analyses of the role of lobbying firms in American politics, establishing the effects of government institutions, political parties, and client diversity. Second, we provide empirical evidence on how lobbying in the U.S. House and Senate is perceived differently between

chambers, thus expanding knowledge on how Congress and lobbyists interact. Third, we add to a growing body of knowledge on the interactions between political parties and interest group politics (Beyers, De Bruycker, and Baller 2015; Fraussen and Halpin 2016; Heaney 2010) by showing how lobbying firms help to tie lobbyists to parties, thus connecting firms to extended party networks (Koger et al. 2009). In making these contributions, this article sets the stage for a new line of inquiry into the politics of lobbying firms.

Making Sense of Lobbying Firms

Washington, DC has witnessed a tremendous growth in lobbying over the past several decades (Holyoke 2015; Leech et al. 2005). This growth has been fueled in no small part by the considerable incomes that can be earned in this profession (Birnbaum 2005; LaPira and Thomas 2017). As a prominent lobbyist told us, “once it became lucrative, every staffer – not just Member – every staffer on [Capitol] Hill who had two or three years of experience went out and hung up a shingle” (anonymous interview). While this lobbyist’s statement is somewhat hyperbolic, it nonetheless reflects the eagerness and energy with which many people have moved from government positions to lobbying in recent years.

With the rush of former government employees to become lobbyists, the question immediately arises as to how potential clients make sense of this onslaught. One answer is that the principal founding partners of firms play an enormous role in establishing firms’ identities. For example, The Livingston Group, founded by former House Appropriations Committee Chairman Bob Livingston (R-LA), has become well known for appropriations lobbying. The McManus Group, founded by former House Ways and Means Committee Republican staff director John McManus – who was a key participant in writing the Medicare Prescription Drug,

Improvement, and Modernization Act of 2003 – has become known with a niche for health policy lobbying. Indeed, the potential for forming niches is quite extensive, as firm identities could be based on multiple dimensions, such as targeted government institution, policy area, geography, gender, client type, or political party (Heaney 2004).

In this article, we focus on partisan ties as a key feature of a lobbying firm's identity. In doing so, we do not deny that other dimensions – such as policy area and geography – can be quite important. Rather, we maintain that partisan ties are readily observable, easily understandable, and likely consequential in this age of intense partisan polarization (Koger and Victor 2009; Sinclair 2006). Potential clients can observe the partisan ties of the founders and very likely learn something useful and relevant about the firm. This information may help them to discern if the firm is or is not likely to serve the client's interests well.

Firms may opt to brand themselves as either partisan or bipartisan. For example, The Podesta Group, founded by brothers John and Tony Podesta, is known as a major Democratic lobbying firm. Both brothers have worked for a variety of Democratic politicians, with John Podesta having held prominent positions in the administrations of presidents Bill Clinton and Barack Obama, as well as presidential candidate Hillary Clinton. Representation by the Podesta Group promises access to Democratic politicians and credibility on liberal issues. However, the value of this representation likely fluctuates with the status of Democrats in government, being worth more when Democrats are in power and less when they are out. The same is true for Republican-identified firms. As the founder of a major Republican firm told us:

. . . when I started – certainly during the Bush years – it was a pretty lucrative business for Republicans. For us, under Obama, he hated lobbyists. He ran against lobbyists, except for his [party's] lobbyists. If you're one of his lobbyists,

you still did very well. I'll just refer you to Tony Podesta. You can take a look at his growth. Ours did not. Ours went down like that [motioning a sharp decline] (anonymous interview).

According to this view, lobbying firms are an extension of a party's network. Lobbying firms and parties lean on one another to advance the party's agenda and to line the pockets of the party's supporters. Thus, we claim that lobbying firms should be added to the list of actors that are traditionally examined in party networks research (see, inter alia, Heaney et al. 2012; Koger et al. 2009; Loomis 2007).

Not all lobbying firms choose to adopt a partisan brand. Some firms may instead choose to brand themselves explicitly as bipartisan.² This branding signals that the firm is willing and able to work across the aisle to try to find nonpartisan and/or bipartisan solutions to policy problems. For example, Nathanson + Hauck was co-founded by a Democrat, Melanie Nathanson, and a Republican, Megan Hauck. They feature their bipartisan status in advertising the firm (Nathanson + Hauck 2017). Founded in 2011, the firm's revenues so far do not appear to have been markedly affected as a result of the changing electoral fortunes of the parties (Center for Responsive Politics 2017).

Based on these considerations, we state the *Partisan Ties Hypothesis*: When a lobbying firm is identified with a particular political party, it experiences financial gains when that party

² The existence of a meaningful bipartisan option with lobbying firms stands in contrast to the political consulting industry, where the firms are exclusively identified as Republican or Democratic (Sheingate 2016).

controls government and is at a financial disadvantage when that party does not control government, other things equal.

Institutional Vulnerability

The Partisan Ties Hypothesis is stated with respect to partisan control of government writ large. In the American system, one political party may gain or lose control of different institutions at different times, as separate elections are held for the presidency (which controls the executive branch), House, and the Senate. Without in any way diminishing the importance of lobbying the executive branch (see McKay 2011; Yackee and Yackee 2006), this article considers how partisan ties may matter differently when lobbying the House and Senate.

Relatively little empirical research examines differences between lobbying the House and Senate. A reason for this lacuna may be that the joint production of policy outcomes (i.e., the House and Senate work together to enact legislation) makes it difficult to identify differential effects of lobbying between the chambers. Nonetheless, variations in the institutional design of the two chambers may provide clues as to how lobbying is likely to work differently in the House and Senate.

Moosbrugger (2012) argued that the ability of interest groups to exert pressure effectively on a governmental body depends on the degree to which institutional design leaves members of the government *vulnerable* to targeting by those interests. According to her argument, vulnerability is the extent to which politicians can be individually *identified* as being responsible for policy outcomes and can be held *accountable* for those outcomes at the ballot box. Identifiability is affected by the extent to which an institution uses majoritarian or supermajoritarian decision rules, with majoritarian rules making actions more identifiable and

supermajoritarian rules making them less so. Accountability is affected by the frequency of elections, with more frequent elections yielding greater accountability and less frequent elections suggesting reduced accountability.

Although Moosbrugger did not consider the United States as one of her cases, her analysis can be applied straightforwardly to the American context. House rules contain strong majoritarian elements, while the Senate has a heavier reliance on supermajoritarian procedures, such as cloture and the filibuster (Koger 2010), suggesting that identifiability is greater in the House. House members are subject to more regular elections than are Senators (every two years, rather than every six years), and usually face a smaller constituency than do Senators (except in very small states, such as Wyoming), making them generally more electorally accountable than Senators. Together, these factors point strongly in the direction of members of the House being more vulnerable to interest group pressure than are members of the Senate.

Some limited empirical evidence supports the relevance of institutional vulnerability to American lobbying. Baker (2008, 144-151) interviewed 12 lobbyists and asked them about their perceptions of differences in lobbying the House and Senate. The results of his interviews are consistent with the prediction that interest groups are able to exert greater pressure in the House than the Senate. Respondents described Senators as being harder to lobby than House members because they are more cross-pressured by their diverse constituencies, because they are more concerned with national issues, and because they are less attentive to the technical details of legislation. In contrast, they saw House members as more attentive to the narrow constituencies in their districts and more willing to work with them on the technical aspects of legislation.

Considering Moosbrugger's analysis of institutional vulnerability and evidence from Baker's interviews, we state the *Institutional Vulnerability Hypothesis*: When a lobbying firm is

aligned with the party that controls the House of Representatives, that is of greater financial value to the firm than being aligned with the party that controls the Senate.

Data and Research Design

In 1995, Congress passed and President Bill Clinton signed the LDA, Public Law 104-65. The LDA was intended to increase transparency in the practice of lobbying by clarifying the rules as to what constitutes lobbying and how it should be disclosed to the public. It required lobbyists to register and report their lobbying activities and payments received on a semiannual basis to Clerk of the House of Representatives and the Secretary of the Senate, unless those activities constitute less than 20 percent of time spent providing services to the client over a six-month period. The House and Senate then make these reports available to the public. The Center for Responsive Politics (2017) collects these reports and formats them for data analysis, which yields the core data that we analyze in this article.

In 2007, Congress passed and President George W. Bush signed the Honest Leadership and Open Government Act (HLOGA), Public Law 110-81. HLOGA amended the LDA with the purpose of closing some of the loopholes embedded in the LDA. Among other things, it placed new restrictions on lobbying by former government employees in the form of a “cooling off” period, increased the frequency of reporting from semiannually to quarterly, and expanded the types of entities required to report to include those that coordinate coalition activities. The provisions of HLOGA took effect in January 2008.

The enactment of HLOGA created significant changes in the nature of the lobbying data generated by the LDA. By placing restrictions on who could serve as a lobbyist, it disincentivized registration for individuals who might be interested in moving through the

revolving door between lobbying and government. Since the LDA imposed no costs on lobbying, individuals had an incentive to register if the need to register might be in doubt. By imposing potential opportunity costs on registration, HLOGA has led to reductions in lobbyist registrations (LaPira and Thomas 2017). A study by Auble (2013) presented evidence that HLOGA led approximately 3,400 lobbyists to deactivate their registrations – even though most of these people remained employed by the same organization in 2011 and 2012 – suggesting that they began lobbying in the shadows of the law. These changed incentives, along with quarterly reporting requirements and reporting by new entities, make data generated since the enforcement of HLOGA not directly comparable with data generated earlier. As a result, this article only analyzes data generated since 2008.

We analyze quarterly data reported by an unbalanced panel of 1,603 lobbying firms from the first quarter of 2008 through the third quarter of 2016. To be included in the panel, registrants were taken from lobbying activity reports where the registrant and the client differed – indicating that the registrant was a contract lobbyist or firm hired by a client.³ To count as a firm for this article, this registrant had to, at some point, list at least two lobbyists as active in the same quarter, and have at least two quarters in which it reported activity valued at more than zero dollars.

The goal of our analysis is to evaluate the determinants of variation in the quarterly revenues of lobbying firms. We model *Revenue per Lobbyist*, which reflects the profitability of

³ The Center for Responsive Politics (2017) records these differences in its data, which we use.

the firm's lobbying accounting for its entire lobbying staff.⁴ Our focal independent variables are *Firm Aligned with House Leadership* and *Firm Aligned with Senate Leadership*. We do not consider bipartisan firms or those without clear partisan identifications to be aligned with either chamber. These variables were measured through original research on the partisan affiliations of the firms' founders. Research assistants were instructed to look at the professional histories of founders' prior employment on legislative staff, campaigns, or in the administrations of partisan officials. For example, working for a Republican Senator would earn a founder a Republican label. If no partisan work history was found, research assistants turned to campaign finance data. If over 90 percent of donations from a founder were given to one party, they were labeled as affiliated with that party (see Koger and Victor 2009). Founders that did not meet either of these criteria were categorized as not having established a partisan reputation. It is important to note that we do not suggest that these firms are *nonpartisan*, only that their partisanship has not become publicly and widely known.

We collected data on several control variables intended to account for alternative explanations for why firms may generate revenue. First, we drew *Number of Clients* directly from the lobbying reports. This variable accounts for the fact that larger firms are better known, more prestigious, and thus more capable of demanding higher payments for their services than are firms with fewer clients, as well as for the possibility that there are *economies of scale* in managing clients (Koshal 1972).

⁴ We adjust for inflation using the *Consumer Price Index for All Urban Consumers: All Items* (FRED 2017).

Second, we calculated *Client Diversity* based on the distribution of the firm’s reported lobbying activity across issues and industries. We include a measure of diversification because of the long-standing expectation in economics that diverse investment portfolios perform better than more homogenous portfolios (Markowitz 1959). It is calculated using Simpson's Reciprocal Index (Simpson 1949):

$$\left[\sum_{i=1}^z \left[\left(\frac{n_i}{N} \right)^2 \right] \right]^{-1}$$

where n_i is the total dollars reported with that industry or issue for the firm in a given quarter and N is all dollars on reported by the firm in a quarter. Thus, n_i/N is the proportional abundance of contract dollars for a particular industry or issue in a given quarter for a firm. It can be understood as weighted degree in the firm-industry or firm-issue bipartite networks (Newman 2001). This measure is similar to “effective number of parties” estimates commonly used in electoral research (Laakso and Taagepera 1979). It is preferable to alternative measures of diversity, such as the Herfindal Index (Herfindahl 1950) or Shannon's H (Shannon 1948), because it is more intuitively interpretable. The minimum value is 1, when all of the activity is concentrated in a single industry or issue, and the maximum value is equal to the number of industries or issues when all activity is distributed equally across all possible industries or issues. We add the diversity measure based on issues to the diversity measure based on industries to obtain a single measure of *Client Diversity*.⁵

⁵ We considered specifying our models to separate measures of client diversity based on issues and industries. These separate estimates had a Cronbach’s α of 0.803, which suggested

Third, we used firms' web pages to collect information on a variety of characteristics of firms. *Law Firm* takes the value of one if a lobbying firm is a law firm, zero otherwise. *International Office* takes the value of one if a lobbying firm has an affiliated international office, zero otherwise. *Number of Domestic Offices* is a count of the number of domestic office locations listed on the firm's website. *Firm Age* is the number of year's since the firm's founding.⁶ These variables are intended to account for variations in firm structure and/or prestige that may correspond with a firm's revenue-earning potential.

Some readers may wonder if we should also include a direct measure of lobbying firm prestige in the model. In investigating this possibility, we found that the most commonly referenced measures of lobbying firm prestige are based strictly on firm revenue (see, for example, Center for Responsive Politics 2017; Staff 2012; Bloomberg Government 2015). Hence, by relying on revenue for our dependent variable, we have implicitly incorporated prestige considerations into our analysis. Further, we believe that our independent variables on

that they measure the same underlying concept (Cronbach 1951). Hence, we determined that using a diversity index that combined these measures is preferable.

⁶ Research assistants were instructed to look for the year in which a firm was founded in the "About," "Firm History," or similar section of firms' websites. An age variable was calculated by subtracting this founding year from the year of the panel observation. In instances where no founding year was identified, we used the first year that the firm appears in lobbying disclosure data since 1998 (the first year of data available). If the first year the firm appeared was 1998, indicating that it may have proceeded the first public disclosures, it was left as missing.

Number of Clients and *Firm Age* capture important aspects of prestige. As a result, we have not opted to include a separate variable for prestige in our analysis.⁷

Statistical Analysis

The data collected in this research allows us to report the partisan distribution of firms and their revenues over time. Figure 1 shows the partisan distribution of firms. Of the firms whose partisan identities we could discern, only 34 (7.62%) identified explicitly as bipartisan. Democratic and Republican firms are roughly at parity. We found 201 (45.07%) Democratically-identified firms and 211 (47.31%) Republican-identified firms.

INSERT FIGURE 1 HERE

Despite the fact that bipartisan firms are less numerous than partisan-leaning firms, Figure 2 indicates that bipartisan firms command consistently greater payments than do their partisan-leaning competitors. Republican and Democratic firms are roughly at parity with one another over time. However, a marginal advantage trades back and forth that corresponds with control of Congress. Democratic firms earned higher average revenue when Democrats held congressional majorities from 2008 to 2010. On the other hand, Republican firms earned more when Republicans reclaimed congressional control, from 2011 through 2016. Firms without clearly identifiable partisan identities – which are not depicted in Figure 2 – receive consistently lower marginal payments than those received by partisan and bipartisan firms.

⁷ Further, the time-invariant component of firm prestige is captured by the fixed effects, random effects, and first differences specifications, described below, all of which are ways to account for unobserved heterogeneity across firms.

INSERT FIGURE 2 HERE

In order to explain the variation in the quarterly revenues of lobbying firms, we turn to a multiple-regression framework. In Model 1, we estimate a regression of *Revenue per Lobbyist* on *Firm Aligned with House Leadership*, *Firm Aligned with Senate Leadership*, *Number of Clients*, and *Client Diversity*. These are the variables for which we have complete data. We estimate Model 1 using a Panel Linear Model with two-way fixed effects (Wooldridge 2002; Croissant and Millo 2008). The firm-level fixed effects account for time-invariant unobserved heterogeneity, while the year fixed effects account for temporal variation in the dependent variable. This approach leverages within-firm variation in the dependent variable while accounting for aggregate temporal trends. We report HC3 Arellano standard errors clustered by firm that are robust to heteroscedasticity and serial autocorrelation (Arellano 1987). The results of Model 1 are reported in Table 1.

INSERT TABLE 1 HERE

The estimates of Model 1 provide support for the Partisan Ties Hypothesis with respect to the House, but not to the Senate. Being aligned with the House leadership corresponds with a higher revenue of about \$6,000 per lobbyist per quarter. Average revenues are not significantly higher when a firm is aligned with the Senate leadership. Thus, these results support the Institutional Vulnerability Hypothesis: firms benefit more financially by being aligned with the House than the Senate. With respect to the control variables, *Number of Clients* has a positive, significant relationship with *Revenue per Lobbyist*, which indicates that larger and more prestigious firms tend to have higher revenues per lobbyist, other things equal. Also, *Client Diversity* corresponds positively and significantly with *Revenue per Lobbyist*, which reveals that

lobbying firms experience the typical economic benefits associated with diversification (Markowitz 1959).

In Model 2, we estimate a Panel Linear Model that includes the same variables as Model 1, while also including variables on firm characteristics: *Law Firm*, *International Office*, *Number of Domestic Offices*, and *Firm Age*. Each of these variables contains significant missing data, which we impute using multiple imputation (King et al. 2001).⁸ This model is estimated using random effects for firms and fixed effects for years because two-way fixed effects cannot be computed with the inclusion of the new time-invariant control variables. We follow the same procedures for estimating standard errors as we do in Model 1.

Despite the inclusion of new variables, the results of Model 2 are consistent with those of Model 1. *Firm Aligned with House Leadership*, *Number of Clients*, and *Client Diversity* have positive, significant coefficients, while *Firm Aligned with Senate Leadership* is insignificant. These results further support the Partisan Ties Hypothesis for the House, as well as the Institutional Vulnerability Hypothesis.

The added variables in Model 2 yield further insights on the correlates of *Revenue per Lobbyist*. The coefficient on *Law Firm* is significant and negative. This result may stem from the fact that law firms use their lobbyists to serve a wider variety of clients than do other lobbying firms, such that some clients demand lobbying and others require other kinds of services (e.g., legal representation, government contract business development, comments on proposed regulatory rules). *Number of Domestic Offices* is significant and negative. This result likely reflects that fact that firms with multiple domestic offices tend to turn their attention away

⁸ These procedures are explained in detail in Appendix A.

from Washington, DC at the margins and toward other types of business. *International Office* and *Firm Age* are not statistically significant.

In Model 3, we estimate a Panel Linear Model using a *first differences* specification of the regression. Change in *Revenue per Lobbyist* is regressed on change in each of the independent variables in Model 1. The advantage of estimating a first differences model is “it removes the latent heterogeneity from the model whether the fixed or random effects model is appropriate” (Greene 2012, 356). However, the first-differences approach also removes time-invariant firm-level independent variables from the model (*Law Firm*, *International Office*, *Number of Domestic Offices*), since these variables have $\Delta X = 0$ in all cases, as well as *Firm Age*, since $\Delta X = 1$, yielding a constant. We follow the same procedures for estimating standard errors as in Models 1 and 2.

This analysis yields the same pattern of support for our hypotheses, while tempering concerns that latent heterogeneity may be an explanation for our findings. Of particular note is the finding that when a firm becomes newly aligned with the House, it benefits from a boost in revenue; on the other hand, a firm that dealigns with the House majority party suffers a drop in revenue. The one notable difference between the results in Model 3 and those in Models 1 and 2 is that *Client Diversity* is no longer statistically significant in Model 3; that is, changes in client diversity do not correspond significantly with changes in revenue.

We conducted robustness analysis to determine if our conclusions about our hypothesis tests withstand variations in the specification of Models 1 and 3, reported in Appendix B. In Model 4, we estimate Model 1 without *Firm Aligned with Senate Leadership*. In Model 5, we estimate Model 1 without *Firm Aligned with House Leadership*. In Model 6, we estimate Model 1 without *Number of Clients* and *Client Diversity*. We repeat this series of permutations on

Model 3 for Models 7, 8, and 9. The analyses show that the results reported in Models 1 and 3 are robust to variations in specification; multicollinearity does not alter the conclusions that we draw about our hypotheses.

The evidence presented in Table 1 (Models 1 to 3), as well as the robustness analysis presented in Appendix B (Models 4 to 9), demonstrates that there is a robust, positive association between a lobbying firm's alignment with the House majority party and its revenues. These results establish a clear correlation between lobbying revenue and control of the House, but not necessarily causation. Does alignment with the House *cause* a lobbying firm's revenue to rise and dealignment *cause* it to fall? We answer this question by exploiting changes in House and Senate party leadership as temporal interventions.

We use a *difference-in-differences estimator* to test temporal causality in both institutions, which occurred as a result of separate electoral cycles. Specifically, we exploit the exogenous shocks created by the changing control of the House in 2011 (from Democratic to Republican) and the Senate in 2015 (from Democratic to Republican). Blanes i Vidal et al. (2012) and de Figueiredo and Richter (2014) recommend the difference-in-differences approach when dealing with panel datasets on lobbying because it effectively addresses persistence issues that commonly affect these data.

Identification with a difference-in-differences estimator relies on a parallel trends assumption. That is, identification assumes that the average change in the potential outcomes between the treatment and control units between two time periods would be the same, and the difference in the change across the two groups can be attributable to the intervention on the treatment units (Ashenfelter and Card 1985).

In this article, we estimate the causal effect of the party of affiliation of a lobbying firm gaining control over a chamber of Congress. In this case, a firm is “treated” when the party is it aligned with gains control of a chamber. These firms are compared to the newly out-party firms. Lobbying firms do not appear to exhibit parallel trends clearly, however, as their fortunes are tied to numerous other factors, such as issue and industry portfolios, as well as how these factors interact with the legislative agenda. Abadie (2005) addressed how the parallel-trends identifying assumption may be implausible when there are imbalances in pre-treatment covariates that might be associated with outcomes. To address this irregularity, we use a kernel-weighting procedure developed by Hazlett (2016) that allows for consistent, non-biased estimation of the Average Treatment Effect on the Treated under these conditions. We further detail the procedure in Appendix C.

We estimate the difference in differences between Republican and Democratic firms for 2010-2011 and 2014-2015, when chambers changed partisan control, as well as 2009-2010 and 2013-2014, to provide baselines for comparison. In each case, Republican firms are considered the “treated” units and the Democratic firms are weighted to make them as comparable to Republican firms as possible.

INSERT TABLE 2 HERE

The results of this estimation are reported in Table 2.⁹ We do not find significant changes in baseline years. In 2010-2011, we observe a significant, positive effect of the treatment (Republicans assuming control of the House) on *Revenue per Lobbyist*. In 2014-2015,

⁹ Examination of the parallel-trends assumption and other details of the estimation process are provided in Appendix C.

however, we do not observe a significant effect of the treatment (Republicans assuming control of the Senate) on *Revenue per Lobbyist*.

The contrast between 2010-2011 and 2014-2015 is clearly reflected in Figure 3. As panel 3A reveals, Republican firms received a boost in 2011 over 2010 when compared to Democratic firms, which suffered a significant decline, on average. In contrast, panel 3B reveals no significant difference between Democratic and Republican firms in their 2014-2015 changes. Thus, assuming control of the House appears to have benefited Republican firms in a way that assuming control of the Senate did not.¹⁰

INSERT FIGURE 3 HERE

Discussion

Although they have been almost entirely neglected in the study of interest group politics, lobbying firms are consequential institutions involved in the lobbying process in the United States. Lobbying firms screen lobbyists, assess their credentials and political connections, and organize them into groupings that help potential clients make more informed decisions about how they will be represented in Washington. This article shows that the partisanship of the founders of lobbying firms is one important signal that informs prospective clients about lobbyists. The results demonstrate that when the founders of a lobbying firm have ties to the political party that controls the House of Representatives, the firm is able to command higher fees for its services. During the period under investigation in this study (2008-2016), the political market value of these ties was, on average, about \$6,000 per lobbyist per quarter (see

¹⁰ Computer code to replicate all analyses in this article appears in Appendix D.

Table 1, Model 1). For 2011, the year after the Republicans regained control of the House, these ties led to an average increase in revenue of about \$37,000 per lobbyist per quarter (see Table 2). This analysis complements prior research that estimates financial benefits to members of Congress from holding majority status (Cox and Magar 1999).

Knowing the partisan ties of the founders of lobbying firms reduces the degree to which potential lobbying clients face asymmetric information in hiring lobbyists. These ties reveal something important about where lobbyists' loyalties and connections lie. They shed light on where they will have access and where they will be shut out of the room. In response, potential clients adjust their willingness to pay for lobbying by increasing fees paid to affiliates of the party in power and reducing their payments to affiliates of the out party.

Partisan reputations help to reduce the principal-agent problem between lobbyists and their clients by revealing key information about lobbyists' loyalties. Lobbyists have more credibility in selling access to their co-partisans and less credibility in persuading potential clients that they will have access to their partisan opponents. Of course, reputation by no means eliminates all principal-agent problems. Indeed, relying on partisan reputations may make principal-agent problems worse along some dimensions. For example, at times, leaders of the party in power may attempt to systematically exploit their ties with lobbyists in a way that is adverse to the interests of lobbyists' clients. Republican leaders employed this tactic with questionable success in the early 2000s as part of the so-called "K Street Project" (Loomis 2007). Still, *knowing* the partisan ties of lobbyists alerts clients to this possibility, allowing clients to adjust their willingness to pay for lobbyists' services.

Our findings speak not only to the market value of partisan ties (i.e., the Partisan Ties Hypothesis), but also to differences in the market value of lobbying the House versus the Senate.

Becoming aligned with the House had a higher market value than becoming aligned with the Senate during the period of our study. Democrats losing control of the House in 2011 was costly to Democratic lobbying firms and created a windfall for Republican lobbying firms. However, Democrats losing control of the Senate in 2015 had no significant effect on the bottom lines of Democratic or Republican lobbying firms. These findings are supportive of the view that members of House are perceived to be more vulnerable to interest group pressure than are members of the Senate (i.e., the Institutional Vulnerability Hypothesis). Lobbyists may be able to make more credible promises that they will obtain favors from their co-partisans in the House than that they will obtain similar favors from their allies in the Senate.

At the same time, we are mindful of the fact that our data span only a nine-year time period. It is possible that the relative value of ties to the House and Senate changes over time. For example, if one party held a supermajority in the Senate, the relative market value of ties to that party might increase substantially. Under these circumstances, potential clients might come to believe that supermajority status allows Senators to have a freer hand in responding to special interests than they had with only a simple majority. Alternatively, if the Senate eliminated some of its distinctive supermajoritarian rules, such as the filibuster, that might increase the value of lobbying firms' partisan ties to the Senate. It is also possible that the relative market value of ties to the House and Senate depends on the degree of cooperation between the leaders of these bodies. Questions along these lines could be examined in future studies that followed additional variations in chamber control or modifications of chamber rules.

Conclusion

This article lays the groundwork for a new empirical agenda on the study of lobbying by demonstrating that lobbying firms are a relevant unit of analysis. Our investigation shows that

the partisan ties of lobbying firms is one factor that narrows the asymmetric information gap between lobbyists and their clients. Future research might question whether other aspects of firms' identities send similarly relevant signals. For example, what is communicated by the policy niches of lobbying firms? Are niches in prime policy areas, such as health and defense, more informative than less-demanded niches, such as social welfare and transportation? How are these identities related to the growth and death of lobbying firms over time? Do firm identities modulate growth in ways that are similar to the identities of their interest group counterparts (see Lowery and Gray 1995; Nownes and Lipinski 2005)? Or are their identities more fluid because of the way that lobbying firms depend on lobbyists who are continually passing through vacancy-chain networks (see Padgett 1990)?

Our analysis points to differences in the abilities of lobbying firms to sell representation to the House and Senate. Are there similarly differences in lobbying firms' abilities to market representation to committees and other institutions within Congress? How does the value of lobbying firms' access to major committees – such as Ways and Means, Appropriations, and Finance – compare to the value of lobbying firms' access to more specialized committees, such as Veterans' Affairs and Small Business? Research into these questions could complement prior studies that investigated the strategies of interest groups in lobbying committees (see Hojnacki and Kimball 1999).

We point to the credence qualities of lobbying and explain how lobbying firms serve to establish lobbyists' credibility. This analysis is strictly empirical. Yet there are also normative dimensions to this issue that are worth exploring. Recent work by Holyoke (2017) points to how principal-agent problems shape lobbyists' behavior in ways that create ethical dilemmas. He explores ethical implications of the willingness of lobbyists to compromise their issue positions

in response to pressure from legislative allies. To what extent do lobbying firms ameliorate or amplify these problems? Under what conditions do lobbying firms create countervailing pressures to uphold client interests, and under what conditions do they promote catering to legislative allies?

Perhaps most significantly, this article points to lobbying firms as a neglected actor in the arsenal of political parties. Lobbying firms are a place for party loyalists when they have finished – or taken a break from – government service. Parties may attempt to use firms to reward their supporters. Or, they may turn to firms as ways of influencing the legislative process. For example, parties may seek to guide lobbyists in the arguments they make, the tactics they use, and which legislators they choose as their targets. Lobbying firms reflect and reinforce the partisanship of the policy process. As a result, lobbying firms deserve more systematic attention from scholars of party networks, interest group politics, and the policy process more generally.

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Table 1. Determinants of Firm Revenue – Panel Linear Models

<i>Variable</i>	Model 1 <i>Revenue per Lobbyist</i>	Model 2 <i>Revenue per Lobbyist</i>	Model 3 <i>Change in Revenue per Lobbyist⁺</i>
	Coefficient (Standard Error)		
<i>Firm Aligned with House Leadership</i>	5982* (2181)	6226* (2164)	4079* (2022)
<i>Firm Aligned with Senate Leadership</i>	574 (1804)	637 (1781)	1083 (1600)
<i>Number of Clients</i>	1820* (253)	1643* (248)	3118* (316)
<i>Client Diversity</i>	1135* (331)	1334* (323)	-658 (395)
<i>Law Firm</i>		-7927* (2436)	
<i>International Office</i>		-1017 (2608)	
<i>Number of Domestic Offices</i>		-842* (391)	
<i>Firm Age</i>		-35 (30)	
<i>Constant</i>		51203* (2776)	-180* (68)
N	33,243	33,243	31,640
Firms	1,603	1,603	1,603
T	2 to 35	2 to 35	2 to 35
F-statistic	566*	305*	381*
F degrees of Freedom	5, 31601	5, 31634	42, 33200
Method	Panel Linear Model with two-way fixed effects	Panel Linear Model with firm random effects, temporal fixed effects	Panel Linear Model with first differences, i.e., ΔY on ΔX

Note: * $p \leq 0.05$.

⁺ Independent variables in Model 3 are first differences, ΔX .

Table 2. Difference-in-Differences Estimates for Change in Chamber Majority

<i>Year</i>	Control Status	Coefficient (Standard Error)
2009-2010	Baseline	21,105 (12,258)
2010-2011	House Change	37,213* (16,523)
2013-2014	Baseline	4,277 (14,457)
2014-2015	Senate Change	-15,020 (24,967)

Note: * $p \leq 0.05$.

Figure 1. Distribution of Lobbying Firms by Partisan Ties

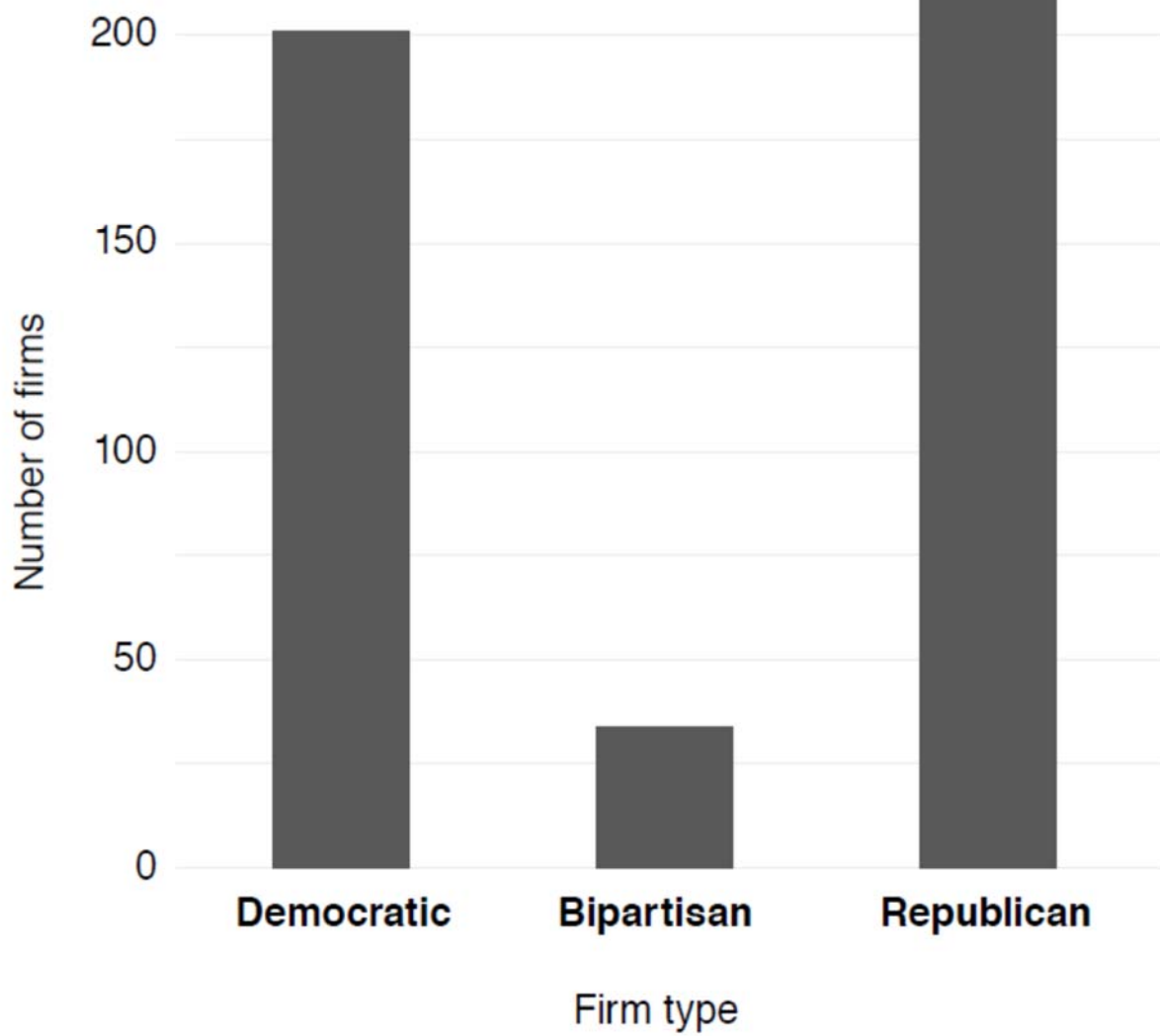


Figure 2. Trends in Revenues for Partisan and Bipartisan Lobbying Firms

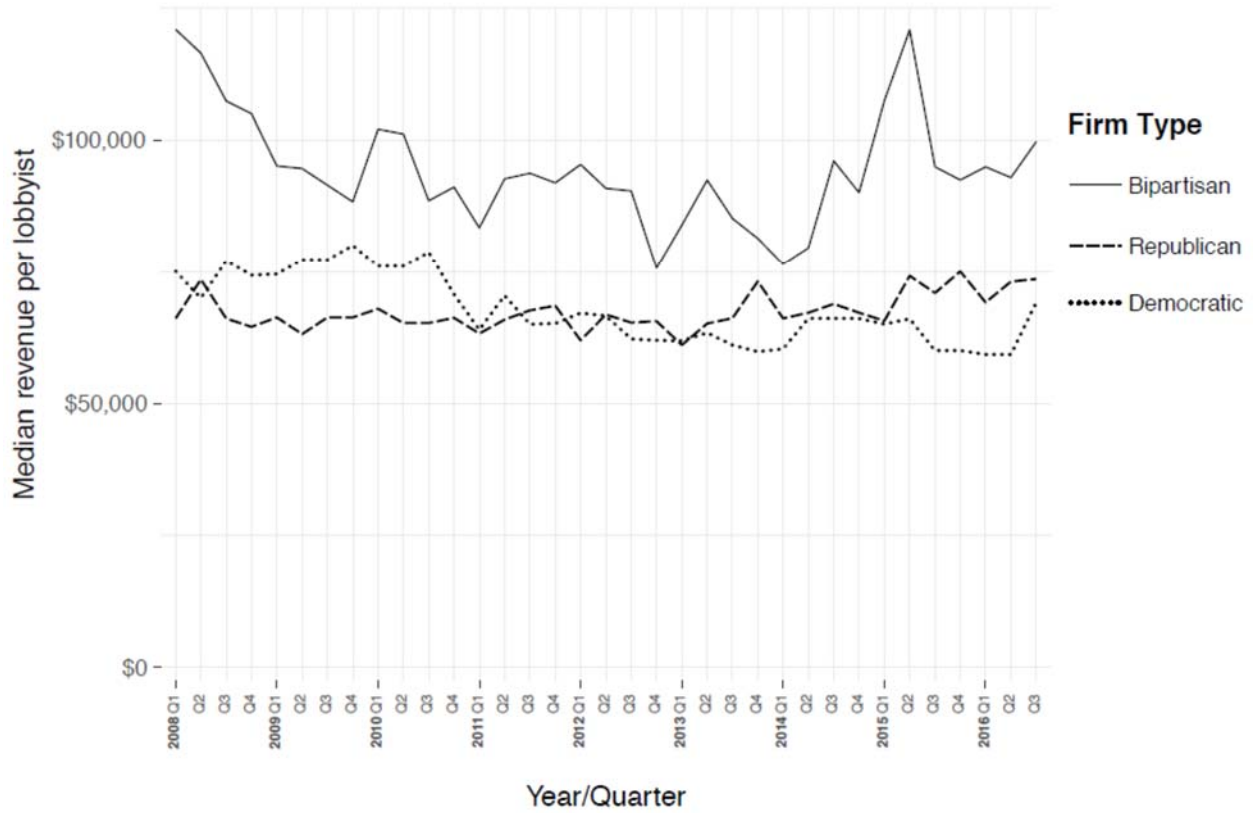
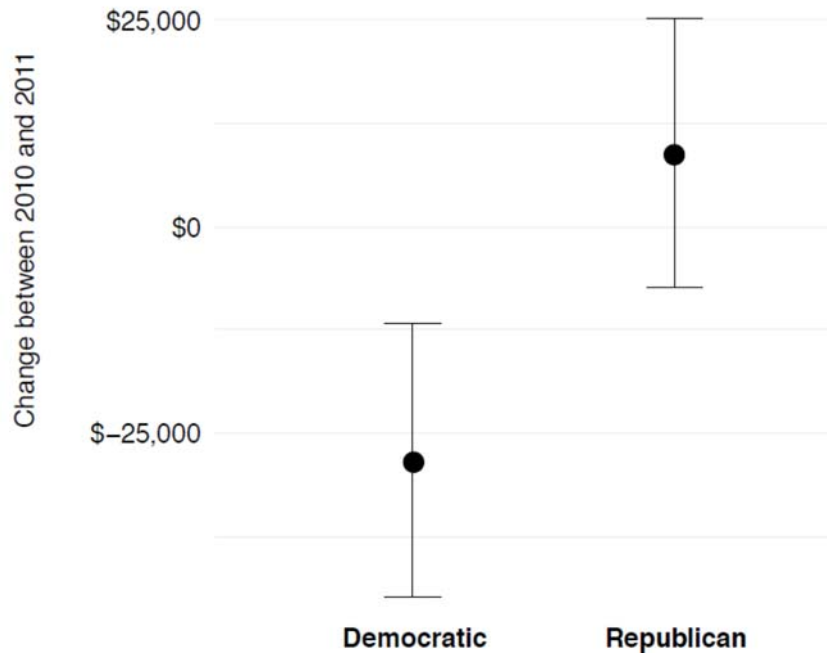
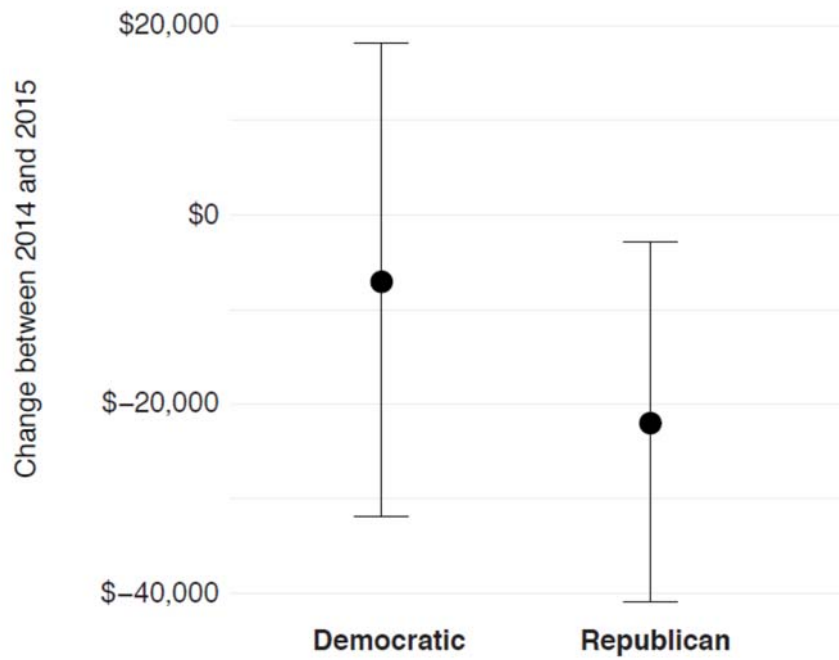


Figure 3. Difference in Differences Revenue Plots

3A. Revenue per Lobbyist Difference in Differences for 2010 to 2011



3B. Revenue per Lobbyist Difference in Differences for 2014 to 2015



Appendix

- A. Multiple Imputation
- B. Robustness Analysis
- C. Difference-in-Differences Analysis
- D. Computer Code (R Script)

Appendix A. Multiple Imputation

When limited to the scope of variables derived from lobbying disclosure records, our regression models contain no missing data. Models 1 and 3 reported in the article (the two-way fixed effects and first-differences models), use only independent variables derived from Lobbying Disclosure Act (LDA) data and account for firm and year effects through the structure of the estimators. The firm random-effects estimator (Model 2) includes independent variables derived from coding firm websites and other sources, which contain missing data. The extent of missingness is detailed in Table A.1.

Table A.1. Prevalence of Missing Data across Variables

Variable	Annual Percent Missing	Quarterly Percent Missing
<i>Law Firm</i>	35.22%	34.42%
<i>International Office</i>	36.52%	35.74%
<i>Number of Domestic Offices</i>	34.29%	33.48%
<i>Firm Age</i>	9.32%	9.33%
<i>Total Campaign Finance Contributions</i>	0.03%	2.46%
<i>Total Campaign Finance Contributions to Republicans</i>	0.02%	1.11%

To address the substantial missing data in our hand-coded variables, we adopted a multiple-imputation approach using Amelia in R (King et al. 2001; Honaker et al. 2011). Multiple imputation with Amelia relies on the assumption that data are missing at random. That is, it assumes that the missingness is a function of observed variables, rather than of other missing variables. Because of this assumption, it is standard practice to include more variables in the matrix for imputation than what one will ultimately include in models for estimation. We used *Revenue per Lobbyist* (in 2015 dollars), *Number of Clients*, *Number of Lobbyists*, *Client Diversity*, *Law Firm*, *International Office*, *Number of Domestic Offices*, *Firm Age*, *Total Campaign Finance Contributions*, *Total Campaign Finance Contributions to Republicans*, *Has a*

Website, Number of Republican Founders Identified, Number of Democratic Founders Identified, Democratic Firm, Republican Firm, and Bipartisan Firm. We ran this imputation process at both the firm-year and firm-quarter levels.

Because imputation assumes multivariate normality, we logged *Number of Lobbyists, Number of Clients, Client Diversity, Number of Domestic Offices, Total Campaign Finance Contributions, and Total Republican Campaign Finance Contributions*, which were all substantially skewed right. It is worth noting that simple multivariate normal imputation models tend to perform as well as more complicated models, even though multivariate normal distributions may poorly approximate the distributions of mixed data (King et. al. 2001; Schafer 1997; Schafer and Olsen 1998). For the imputation, logical bounds of [0,1] were imposed on all dichotomous variables, while *Firm Age* was bounded at the minimum and maximum observed values, and both campaign finance variables were bounded at the minimum and maximum of the observed total contribution variable. As Honaker et al. (2011) suggest, we allow missing ordinal variables to take continuous values from the imputation, as these estimates more accurately convey the uncertainty of the imputation than would forcing integer values.

Figures A.1 and A.2 show the distributions of imputed data (red lines) plotted in comparison to the kernel density estimates of distributions for observed variables (black lines) for the year and quarterly panels. We should not expect these densities to match exactly, unless data were missing completely at random. Indeed, the fact that they may not match is the reason to impute values in the first place. For dichotomous variables (i.e., *Law Firm* and *International Office*), the imputed distributions appear between the modes of the kernel density estimates, proportionately closer to the larger modes. For the continuous variables, the imputed distributions appear coterminous to, or slightly to the right of, the kernel density estimates.

Figure A.1. Observed versus Imputed Densities for Quarterly Data

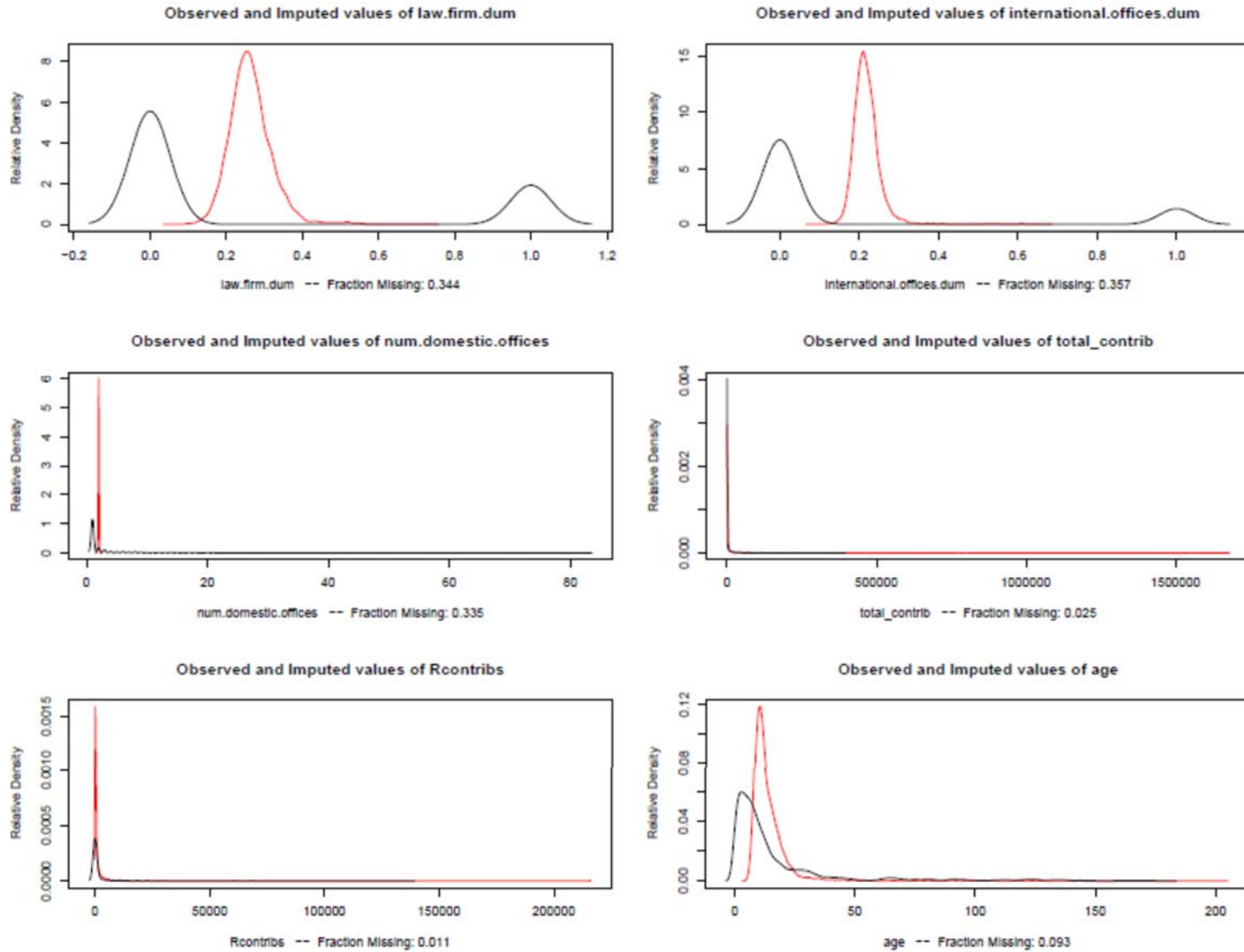
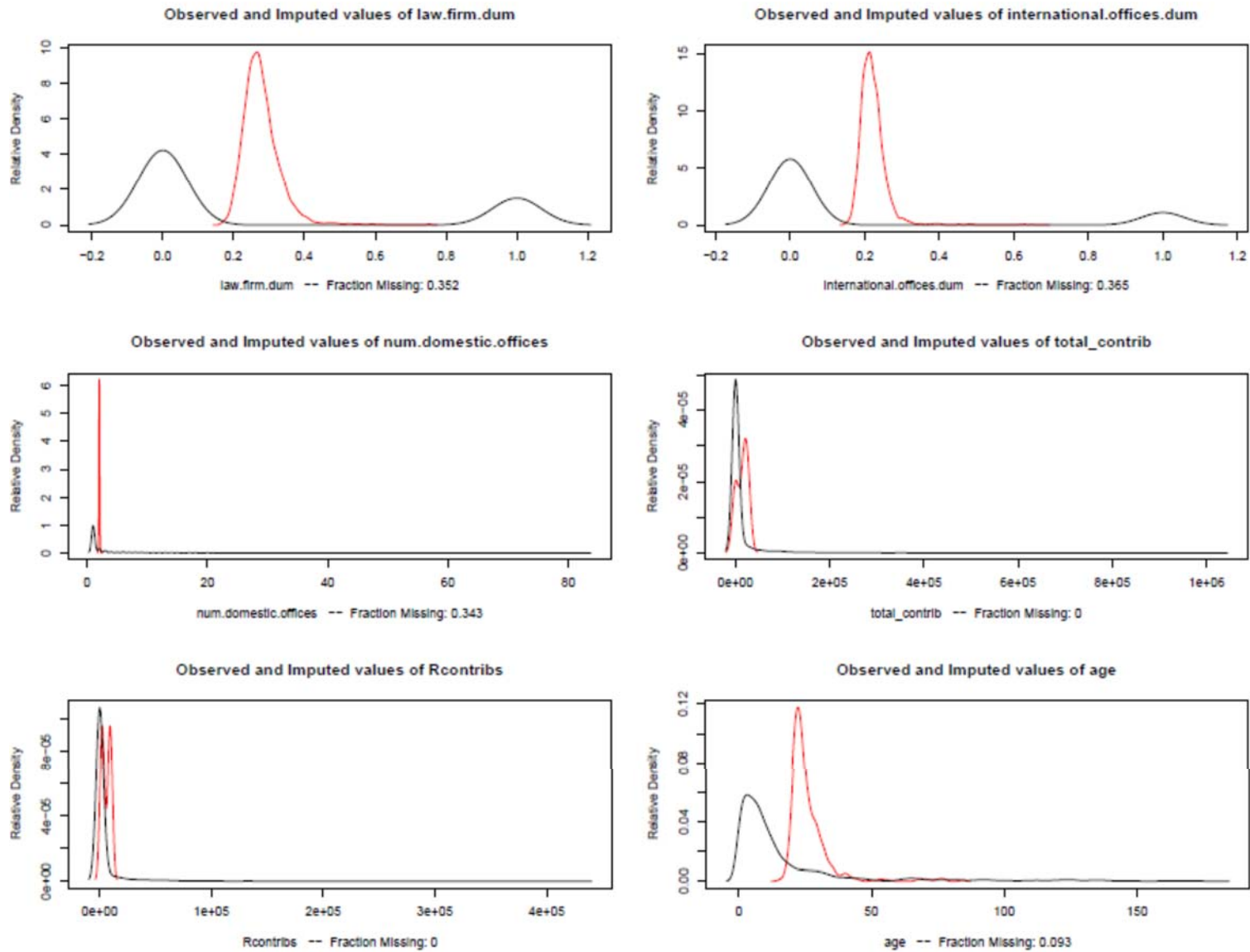


Figure A.2. Observed versus Imputed Densities for Yearly Data



The paths of the expectation-maximization chains in Figures A.3 and A.4 demonstrate convergence towards the same principal component from dispersed starting values (represented by different color lines). This convergence indicates a well-behaved likelihood function by showing that variations in the starting values do not yield considerable differences in results.

Figure A.3. Paths of the Expectation-Maximization Chains for Quarterly Data

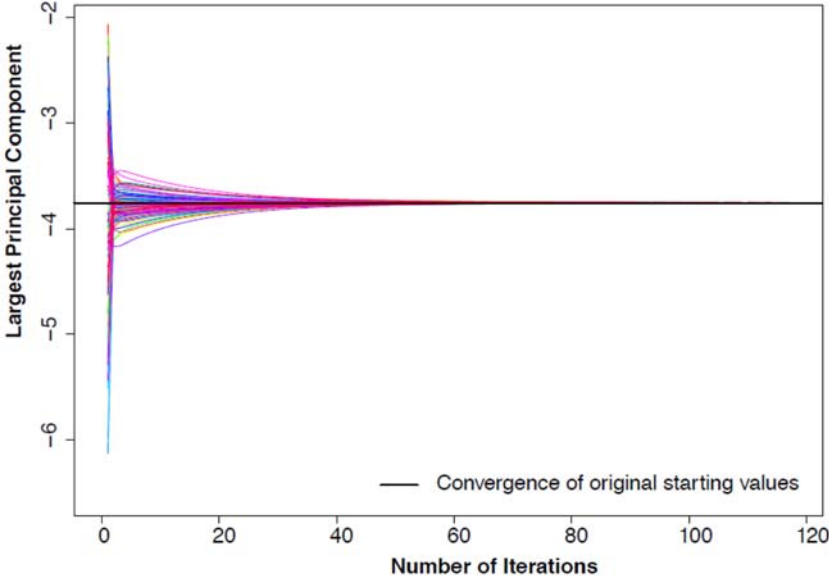
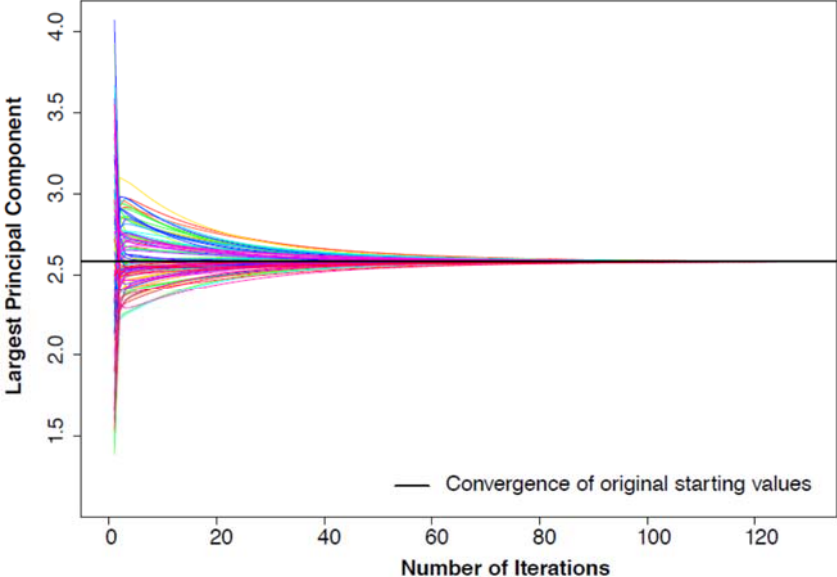


Figure A.4. Paths of the Expectation-Management Chains for Yearly Data



For both yearly and quarterly panels, we imputed 100 datasets. The random-effects quarterly panel model and the yearly difference-in-differences estimates¹¹ both relied on imputed data. For each of these, the models were applied to all 100 imputed datasets the estimates and standard errors were combined using Rubin's (1987) rules for combining results.

References for Appendix A

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¹¹ Imputed data were used as part of the kernel-weighting procedure for the difference-in-differences estimates, described in Appendix C.

Appendix B. Robustness Analysis

Table B.1. Robustness Analysis: Variations on Specifying Model 1

<i>Variable</i>	Model 4 <i>Revenue per Lobbyist</i>	Model 5 <i>Revenue per Lobbyist</i>	Model 6 <i>Revenue per Lobbyist</i>
	Coefficient (Standard Error)		
<i>Firm Aligned with House Leadership</i>	6129* (2221)		6585* (2325)
<i>Firm Aligned with Senate Leadership</i>		2563 (1921)	1479 (1880)
<i>Number of Clients</i>	1820* (253)	1833* (251)	
<i>Client Diversity</i>	1135* (331)	1120* (329)	
N	33,243	33,243	33,243
Firms	1,603	1,603	1,603
T	2 to 35	2 to 35	2 to 35
F-statistic	942*	921*	43*
F degrees of Freedom	3, 31603	3, 31603	2, 31604
Method	Panel Linear Model with two-way fixed effects	Panel Linear Model with two-way fixed effects	Panel Linear Model with two-way fixed effects

Note: * $p \leq 0.05$.

Table B.2. Robustness Analysis: Variations on Specifying Model 3

<i>Variable</i>	Model 7 <i>Change in Revenue per Lobbyist⁺</i>	Model 8 <i>Change in Revenue per Lobbyist⁺</i>	Model 9 <i>Change in Revenue per Lobbyist⁺</i>
	Coefficient (Standard Error)		
<i>Firm Aligned with House Leadership</i>	4090* (2021)		5274* (2127)
<i>Firm Aligned with Senate Leadership</i>		1123 (1598)	1059 (1602)
<i>Number of Clients</i>	3118* (316)	3121* (316)	
<i>Client Diversity</i>	-658 (395)	-658 (395)	
<i>Constant</i>	-181* (70)	-180* (70)	-318* (75)
N	31,640	31,640	31,640
Firms	1,603	1,603	1,603
T	2 to 35	2 to 35	2 to 35
F-statistic	508*	506*	5*
F degrees of Freedom	3, 31636	3, 31636	2, 31637
Method	Panel Linear Model with first differences, i.e., ΔY on ΔX	Panel Linear Model with first differences, i.e., ΔY on ΔX	Panel Linear Model with first differences, i.e., ΔY on ΔX

Note: * $p \leq 0.05$.

⁺ Independent variables in Model 3 are first differences, ΔX .

Appendix C. Difference-in-Differences Analysis

Identification with a difference-in-differences estimator relies on a parallel trends assumption. That is, the identification assumes that the average change in the potential outcomes between the treatment and control units between two time periods would be the same, and the difference in the change across the two groups can be attributable to the intervention on the treatment units. Mathematically, this assumption is as follows:

$$E[Y_{i1}(0) - Y_{i0}(0)|D_i = 1] = E[Y_{i1}(0) - Y_{i0}(0)|D_i = 0]$$

where Y_{it} is the observed outcome Y for unit i in time t and D_i is the treatment indicator.

In this article, we estimate the causal effect of a party gaining control over a chamber of Congress for lobbying firms that are aligned with that party. In this case, a firm is “treated” when the party it aligns with gains control of a chamber. These firms are compared to the newly out-party firms. Lobbying firms do not appear to exhibit parallel trends clearly, however, as their fortunes are tied to numerous other factors, such as issue and industry portfolios, and how these factors interact with the legislative agenda.

To address this situation, we use a weighting procedure to allow for the control group to more closely compare to the treatment group. This procedure is similar to a matching or synthetic-control approach. However, the usual calculations of standard errors that account for sampling variation when used on matching estimators do not incorporate the uncertainty from the matching process. Researchers have often used bootstrapped standard errors but, as Abadie and Imbens (2008) note, the extreme lumpiness of the matching process violates the smoothness condition necessary for bootstrapping. As a result, bootstrapped variance and actual variance

diverge, making bootstrapped standard errors inappropriate for matching estimators.

Instead, we use a weighting procedure developed by Hazlett (2016), in which none of the unit weights are set to 0. As a result, the estimator satisfies the conditions for the bootstrap to work. Rather than trying to achieve balance on all covariates – such that the treatment and control groups appear identical to each other – Hazlett’s (2016) approach targets the need for the non-treatment potential outcomes for treated and control groups to be equal to each other. It achieves this goal directly by using a kernel-balancing procedure to derive weights that are “equivalent to a form of stabilized inverse propensity score weighting, though it does not require assuming any model of the treatment assignment mechanism” (Hazlett 2016, 1). This procedure allows for unbiased estimation of the Average Treatment Effect on the Treated with bootstrapped standard errors that appropriately account for the uncertainty introduced by the weighting process. We estimate our kernel-balanced difference-in-differences estimator using Hazlett’s (2016) procedure in the R package “KBAL.”

We estimate a difference-in-differences estimator between Republican and Democratic firms for four year-pairs: 2009-2010, 2010-2011, 2013-2014, and 2014-2015. In each case the Republican firms are considered the “treated” units and the Democratic firms are weighted using the *Revenue per Lobbyist* (in 2015 dollars), *Client Diversity*, *Law Firm*, *International Office*, *Number of Domestic Offices*, *Number of Lobbyists*, *Number of Clients*, *Total Campaign Finance Contributions*, *Firm Age*, and a dichotomous variable for whether we found a website for the firm as covariates (*Has a Website*). For each pair of years for which the difference-in-differences estimator was calculated (noted as $t=0$ and $t=1$), kernel balancing was used on the units from $t=0$, and then applied to both $t=0$ and $t=1$. Units that were present in $t=0$ but not $t=1$ were assigned a *Revenue per Lobbyist* value of 0, as a firm that closes earns no revenue. The

weights from the balancing were then used to calculate a weighted difference-in-means test on the difference in *Revenue per Lobbyist* for each firm between t=0 and t=1 across the treatment and control groups. This test was performed with the R package “weights” (Pasek 2016). Because the kernel balancing used variables that were imputed in the yearly panel, the balancing and weighted difference-of-means test was performed on 100 imputed datasets. The results were combined using Rubin’s (1987) rules for combining estimates from multiple imputed datasets.

Hazlett (2016, 28) introduces a measure of imbalance based on the L1 norm of the imbalance terms, which he shows “naturally interpretable as an average of the pointwise gaps between the density of the treated and control at every observation.” In Table C1, we report this measure of imbalance before and after the weighting for each estimate. In every case the post-weighting norm is roughly an order of magnitude smaller than the pre-weighting norm.

Table C1. Pre- and Post-Weight Imbalance L1 Norm

Year	2009	2010	2013	2014
Pre-Weight L1	0.00775	0.00701	0.00618	0.00409
Post-Weight L1	0.00069	0.00076	0.00051	0.00034

For every difference-in-differences estimate, we produce a weighted parallel-trend plot shown below. We use apply the weights derived from year t=0 (i.e., 2010 for the 2010-2011 difference-in-differences, 2014 for the 2014-2015 difference-in-difference), and report the weighted-mean *Revenue per Lobbyist*. Figures C1, C2, C3, and C4 reflect this analysis. In each case, we see some deviations from the parallel trends in years where we note institutional change: 2010-2011 when Republicans gain control of the House and, to a lesser extent, 2014-2015 when Republicans gain control of the Senate. However, by and large, the trends track each other, excepting these substantively meaningful deviations. This finding lends credence to the validity of the parallel-trends assumption necessary for identification in difference-in-

differences. In particular, it is of note that the parallel trends plot for the 2010-2011 difference-in-differences estimate, identification of which is most critical to testing our hypotheses, is quite good.

Figure C1. Parallel-Trends Analysis for 2009.

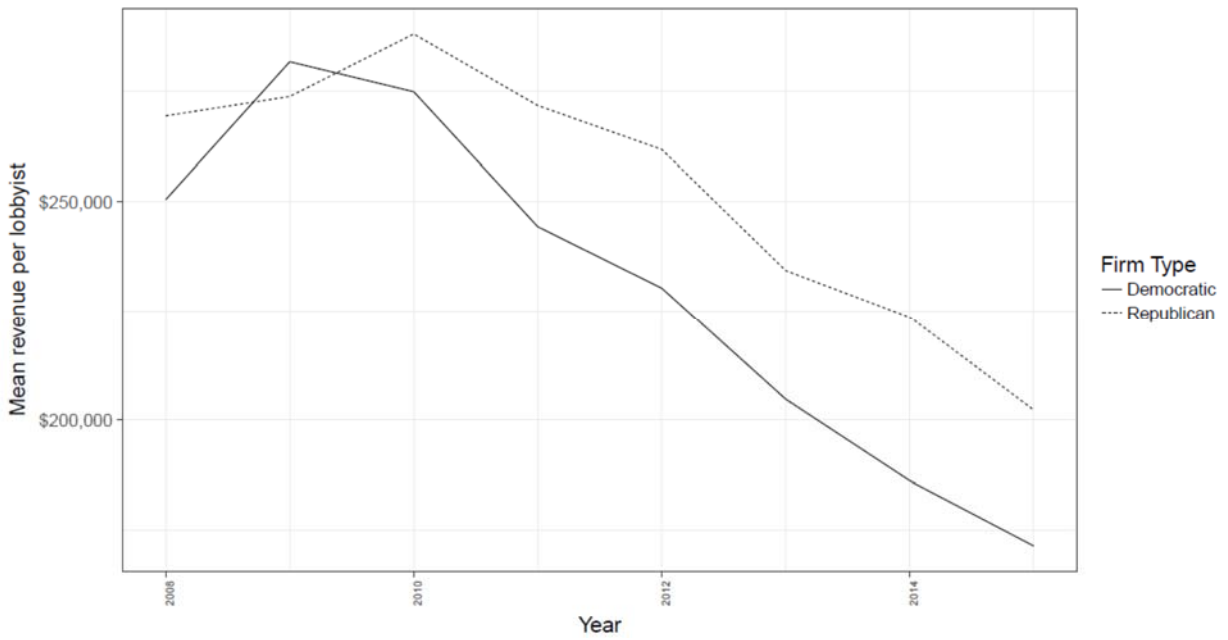


Figure C2. Parallel-Trends Analysis for 2010

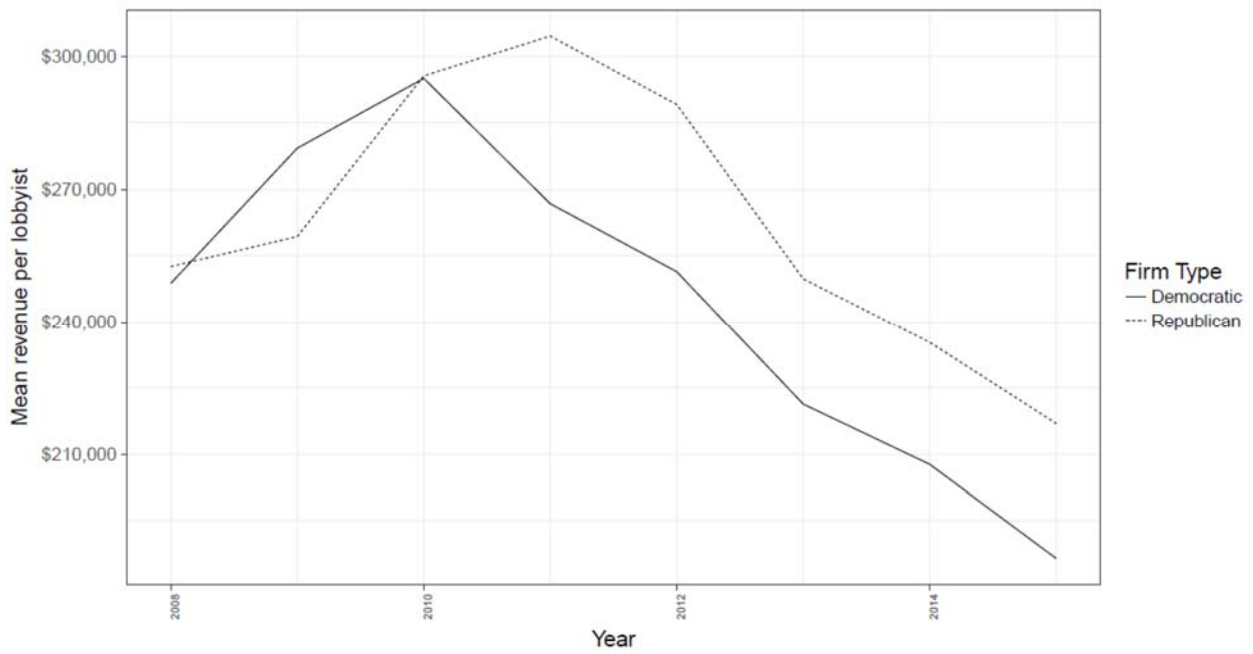


Figure C3. Parallel-Trends Analysis for 2013

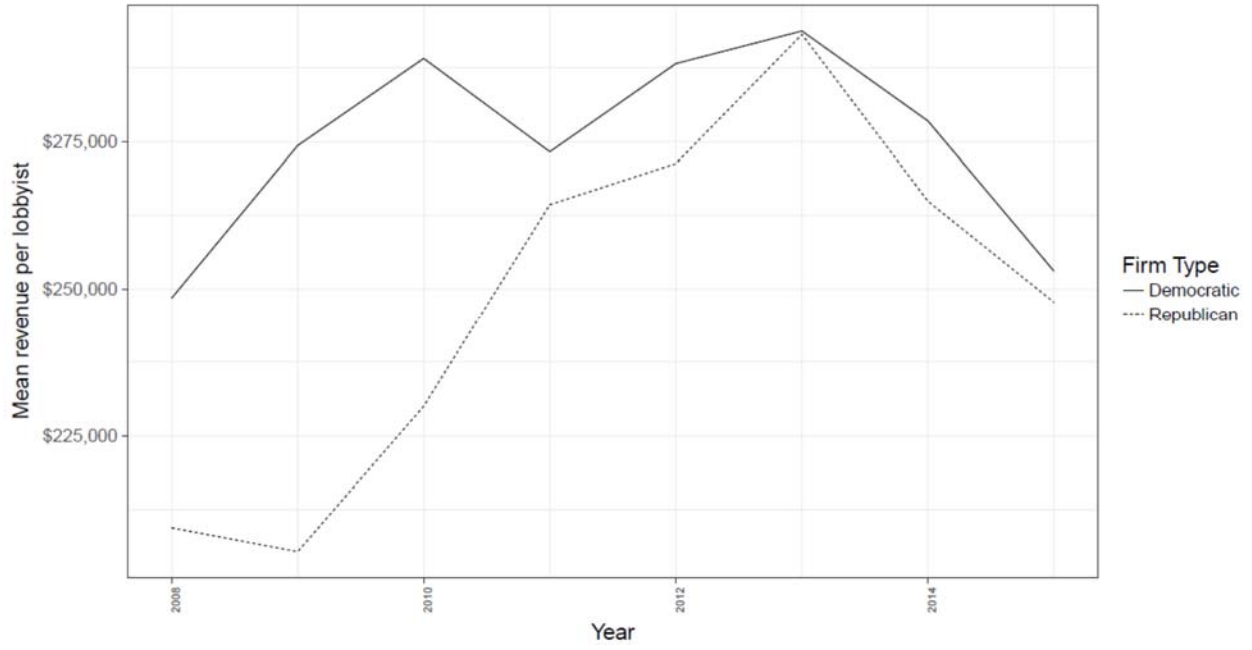
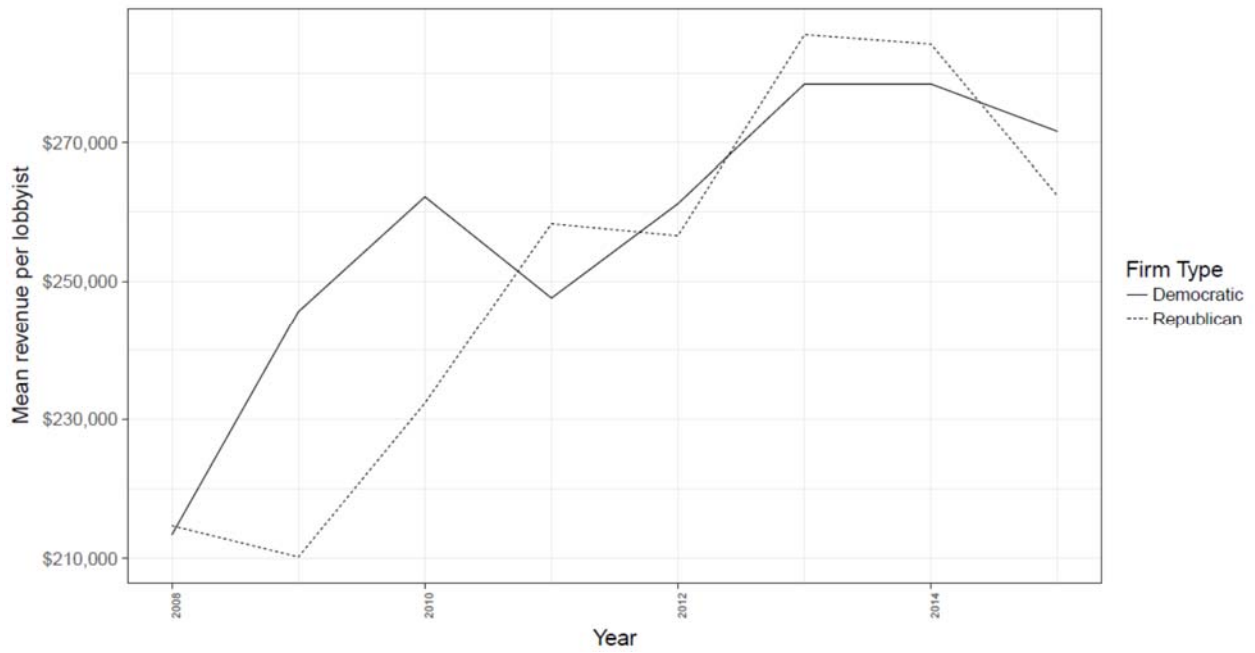


Figure C4. Parallel-Trends Analysis for 2014



References for Appendix C

- Abadie, Alberto, and Guido W. Imbens. 2008. “On the failure of the bootstrap for matching estimators.” *Econometrica* 76 (6): 1537-1557.
- Pasek, Josh. 2016. “Package ‘weights’.” <https://cran.r-project.org/web/packages/weights/weights.pdf> (accessed July 26, 2017).
- Hazlett, Chad. 2016. “Kernel Balancing: A flexible non-parametric weighting procedure for estimating causal effects.” Unpublished manuscript. <https://arxiv.org/pdf/1605.00155.pdf> (accessed July 21, 2017).

Appendix D. Computer Code (R Script)

```
rm(list=ls())

library(readr)
library(dplyr)

#load yearly data
firm_data_year <- read_csv("final_nonimputed_yearly.csv")
firm_data_year$website.dum[is.na(firm_data_year$website.dum)] <- 0

col_nums <- c(7,8,9,10,11,12, 18)
lowers <- c(0,0,0,0,0,0,0)
uppers <- c(1,1,1,1022987, 1022987, 1,180)

constraint_mat <-matrix(c(col_nums,lowers, uppers),nrow=length(col_nums))
library(Amelia)
firm_data_year$year <- as.numeric(firm_data_year$year)
a.out_y <- amelia(as.data.frame(firm_data_year), m=100, ts="year",
cs="registrant", p2s = 2, logs = c("num.lobbyists", "num.clients",
"client.div.index", "num.domestic.offices", "total_contrib", "Rcontribs"),
bounds = constraint_mat)
plot(a.out_y, which.vars = c(7,8,9,10,11, 18))
summary(a.out_y)
dev.off()
disperse(a.out_y, dims = 1, m = 100)

#conduct the diff and diff for 2010 - 2011
library(KBAL)
a.out_2010 <- lapply(a.out_y$imputations, function(i) filter(i, year == 2010,
Rfirm == 1 | Dfirm == 1))
a.out_2011 <- lapply(a.out_y$imputations, function(i) filter(i, year == 2011,
Rfirm == 1 | Dfirm == 1))
```

```

a.out_2010_X <- lapply(a.out_2010, function(i)
apply(as.matrix(i)[,c("rev.perlobbyist.2015", "client.div.index"
,"law.firm.dum" , "international.offices.dum", "num.domestic.offices",
"num.lobbyists", "num.clients", "total_contrib", "age", "website.dum")], 2,
as.numeric))

out_2010_D <- as.numeric(a.out_2010$simpl$Rfirm)
a.kdbal_2010 <- lapply(a.out_2010_X, function(i) kbal(i, out_2010_D))

a.out_diff <- vector("list", 100)
a.L1_orig2010 <- vector("list", 100)
a.L1_kbal2010 <- vector("list", 100)

for (i in 1:100){
  a.L1_orig2010[i] <- a.kdbal_2010[[i]]$L1_orig
  a.L1_kbal2010[i] <- a.kdbal_2010[[i]]$L1_kbal

  w <- a.kdbal_2010[[i]]$w
  partisan_10 <- a.out_2010[[i]] %>%
    cbind(w)

  partisan_11 <- a.out_2010[[i]] %>%
    dplyr::select(registrant) %>%
    left_join(a.out_2011[[i]])

  partisan_11$year[is.na(partisan_11$year)] <- 2011
  partisan_11$rev.perlobbyist.2015[is.na(partisan_11$rev.perlobbyist.2015)]
<- 0

  dat_diff <- partisan_10 %>%
    left_join(dplyr::select(partisan_11, registrant, rev.perlobbyist.2015),
by = "registrant") %>%
    mutate(rev.perlobbyist.y = replace(rev.perlobbyist.2015.y,
is.na(rev.perlobbyist.2015.y), 0), rpl.diff = rev.perlobbyist.2015.y -

```

```

rev.perlobbyist.2015.x)
  a.out_diff[[i]] <- dat_diff

}
(L1_orig2010 <- mean(unlist(a.L1_orig2010)))
(L1_kbal2010 <- mean(unlist(a.L1_kbal2010)))

library(weights)

a.wtt <- lapply(a.out_diff, function(i) wtd.t.test(filter(i,
Rfirm==1)$rpl.diff, filter(i, Rfirm==0)$rpl.diff, weight=filter(i,
Rfirm==1)$w, weighty=filter(i, Rfirm==0)$w, samedata=FALSE, bootse = TRUE,
bootn=1000))

a.wtt.diff <- do.call(rbind, lapply(a.wtt, function(i) i$additional[1]))
a.wtt.meanR <- do.call(rbind, lapply(a.wtt, function(i) i$additional[2]))
a.wtt.meanD <- do.call(rbind, lapply(a.wtt, function(i) i$additional[3]))
a.wtt.se <- do.call(rbind, lapply(a.wtt, function(i) i$additional[4]))

diff_mi <- mi.meld(a.wtt.diff, a.wtt.se)

meanR_mi <- mi.meld(a.wtt.meanR, a.wtt.se)
meanD_mi <- mi.meld(a.wtt.meanD, a.wtt.se)

means_mi <- c(meanR_mi[[1]], meanD_mi[[1]])
uppers_mi <- unname(c(meanR_mi[[1]] + meanR_mi[[2]], meanD_mi[[1]] +
meanD_mi[[2]]))
lowers_mi <- unname(c(meanR_mi[[1]] - meanR_mi[[2]], meanD_mi[[1]] -
meanD_mi[[2]]))

dm_dat10 <- data.frame(vars = c("Republican", "Democratic"), means_mi,
lowers_mi, uppers_mi)

g10 <- ggplot(dm_dat10, aes(x=vars, y=means_mi)) +
geom_errorbar(aes(ymin=lowers_mi, ymax=uppers_mi), colour="black", width=.1)+
geom_point(size=4) + theme_bw(base_size = 14) + xlab("") + ylab("Change
between 2010 and 2011") + ggtitle("Revenue per lobbyist difference in

```

```

differences for 2010 to 2011") + scale_y_continuous(labels = scales::dollar)
ggsave("DiffnDiff2010_2011.pdf", g10, device="pdf")

a.out_dat <- vector("list", 100)
for(i in 1:100){
  w <- a.kdbal_2010[[i]]$w
  partisan_10 <-a.out_2010[[i]]%>%
    select(registrant, Dfirm, Rfirm) %>%
    cbind(w)

  out_dat <- expand.grid(registrant = partisan_10$registrant, year =
c(2008,2009,2010,2011,2012,2013,2014,2015)) %>%
    left_join(partisan_10) %>%
    left_join(a.out_y$imputations[[i]])
  out_dat$rev.perlobbyist.2015[is.na(out_dat$rev.perlobbyist.2015)]<- 0
  a.out_dat[[i]] <- out_dat
}

wmean <- do.call(rbind, lapply(a.out_dat, function(i) i %>% group_by(Rfirm,
year) %>% summarise(wmean = weighted.mean(rev.perlobbyist.2015, w))))
wmean <- wmean %>% group_by(Rfirm, year) %>% summarise(mean_rpl =
mean(wmean))

wmean$Rfirm[wmean$Rfirm==1] <- "Republican"
wmean$Rfirm[wmean$Rfirm==0] <- "Democratic"

pt10 <- ggplot(wmean, aes(x=year, y=mean_rpl, group=as.factor(Rfirm),
linetype=as.factor(Rfirm))) +geom_line() +theme_bw(base_size=16) +
theme(axis.text.x = element_text(angle = 90, hjust = 1, size=8))
+scale_y_continuous(labels = scales::dollar) + xlab("Year") + ylab("Mean
revenue per lobbyist") + labs(linetype='Firm Type') +ggtitle("Parallel trends
for 2010-2011 diff-in-diff")

ggsave("parallell_trends10.pdf", pt10, device="pdf")

#difference in differences for 2013-2014

```

```

library(KBAL)

a.out_2013 <- lapply(a.out_y$imputations, function(i) filter(i, year == 2013,
Rfirm == 1 | Dfirm == 1))

a.out_2014 <- lapply(a.out_y$imputations, function(i) filter(i, year == 2014,
Rfirm == 1 | Dfirm == 1))

a.out_2013_X <- lapply(a.out_2013, function(i)
apply(as.matrix(i)[,c("rev.perlobbyist.2015", "client.div.index"
,"law.firm.dum" , "international.offices.dum", "num.domestic.offices",
"num.lobbyists", "num.clients", "total_contrib", "age", "website.dum")], 2,
as.numeric))

out_2013_D <- as.numeric(a.out_2013$impl$Rfirm)

a.kdbal_2013 <- lapply(a.out_2013_X, function(i) kbal(i, out_2013_D))

a.out_diff13 <- vector("list", 100)
a.L1_orig2013 <- vector("list", 100)
a.L1_kbal2013 <- vector("list", 100)

for (i in 1:100){
  a.L1_orig2013[i] <- a.kdbal_2013[[i]]$L1_orig
  a.L1_kbal2013[i] <- a.kdbal_2013[[i]]$L1_kbal

  w <- a.kdbal_2013[[i]]$w
  partisan_13 <-a.out_2013[[i]]%>%
    cbind(w)

  partisan_14 <- a.out_2013[[i]]%>%
    dplyr::select(registrant) %>%
    left_join(a.out_2014[[i]])

  partisan_14$year[is.na(partisan_14$year)] <- 2014
  partisan_14$rev.perlobbyist.2015[is.na(partisan_12$rev.perlobbyist.2015)]
<- 0

```



```

dat_diff <- partisan_13 %>%

  left_join(dplyr::select(partisan_14, registrant, rev.perlobbyist.2015),
by = "registrant") %>%

  mutate(rev.perlobbyist.y = replace(rev.perlobbyist.2015.y,
is.na(rev.perlobbyist.2015.y), 0), rpl.diff = rev.perlobbyist.2015.y -
rev.perlobbyist.2015.x)

  a.out_diff13[[i]] <- dat_diff

}

(L1_orig2013 <- mean(unlist(a.L1_orig2013)))
(L1_kbal2013 <- mean(unlist(a.L1_kbal2013)))

library(weights)

a.wtt13 <- lapply(a.out_diff13, function(i) wtd.t.test(filter(i,
Rfirm==1)$rpl.diff, filter(i, Rfirm==0)$rpl.diff, weight=filter(i,
Rfirm==1)$w, weighty=filter(i, Rfirm==0)$w, samedata=FALSE, bootse = TRUE,
bootn=1000))

a.wtt.diff13 <- do.call(rbind, lapply(a.wtt13, function(i) i$additional[1]))
a.wtt.meanR13 <- do.call(rbind, lapply(a.wtt13, function(i)
i$additional[2]))
a.wtt.meanD13 <- do.call(rbind, lapply(a.wtt13, function(i)
i$additional[3]))
a.wtt.se13 <- do.call(rbind, lapply(a.wtt13, function(i) i$additional[4]))

diff_mi13 <- mi.meld(a.wtt.diff13, a.wtt.se13)

meanR_mi13 <- mi.meld(a.wtt.meanR13, a.wtt.se13)
meanD_mi13 <- mi.meld(a.wtt.meanD13, a.wtt.se13)

means_mi <- c(meanR_mi13[[1]], meanD_mi13[[1]])
uppers_mi <- unname(c(meanR_mi13[[1]] + meanR_mi13[[2]], meanD_mi13[[1]] +
meanD_mi13[[2]]))

```

```

lowers_mi <- unname(c(meanR_mi13[[1]] - meanR_mi13[[2]], meanD_mi13[[1]] -
meanD_mi13[[2]]))

dm_dat13 <- data.frame(vars = c("Republican", "Democratic"), means_mi,
lowers_mi, uppers_mi)

g13 <- ggplot(dm_dat13, aes(x=vars, y=means_mi)) +
geom_errorbar(aes(ymin=lowers_mi, ymax=uppers_mi), colour="black", width=.1)+
geom_point(size=4) + theme_bw(base_size = 14) + xlab("") + ylab("Change
between 2013 and 2014") + ggtitle("Revenue per lobbyist difference in
differences for 2013 to 2014") + scale_y_continuous(labels = scales::dollar)

ggsave("DiffnDiff2013_2014.pdf", g13, device="pdf")

a.out_dat13 <- vector("list", 100)
for(i in 1:100){
  w <- a.kdbal_2013[[i]]$w
  partisan_13 <- a.out_2013[[i]] %>%
    select(registrant, Dfirm, Rfirm) %>%
    cbind(w)

  out_dat <- expand.grid(registrant = partisan_13$registrant, year =
c(2008,2009,2010,2011,2012,2013,2014,2015)) %>%
    left_join(partisan_13) %>%
    left_join(a.out_y$imputations[[i]])
  out_dat$rev.perlobbyist.2015[is.na(out_dat$rev.perlobbyist.2015)] <- 0
  a.out_dat13[[i]] <- out_dat
}

wmean <- do.call(rbind, lapply(a.out_dat13, function(i) i %>% group_by(Rfirm,
year) %>% summarise(wmean = weighted.mean(rev.perlobbyist.2015, w))))

wmean <- wmean %>% group_by(Rfirm, year) %>% summarise(mean_rpl =
mean(wmean))

wmean$Rfirm[wmean$Rfirm==1] <- "Republican"
wmean$Rfirm[wmean$Rfirm==0] <- "Democratic"

pt13 <- ggplot(wmean, aes(x=year, y=mean_rpl, group=as.factor(Rfirm),
linetype=as.factor(Rfirm))) + geom_line() + theme_bw(base_size=16) +
theme(axis.text.x = element_text(angle = 90, hjust = 1, size=8))

```

```
+scale_y_continuous(labels = scales::dollar) + xlab("Year") + ylab("Mean
revenue per lobbyist") + labs(linetype='Firm Type') +ggtitle("Parallel trends
for 2013-2014 diff-in-diff")
```

```
ggsave("parallell_trends13.pdf", pt13, device="pdf")
```

```
#conduct the diff and diff for 2014 - 2015
```

```
a.out_2014 <- lapply(a.out_y$imputations, function(i) filter(i, year == 2014,
Rfirm == 1 | Dfirm == 1))
```

```
a.out_2015 <- lapply(a.out_y$imputations, function(i) filter(i, year == 2015,
Rfirm == 1 | Dfirm == 1))
```

```
a.out_2014_X <- lapply(a.out_2014, function(i)
apply(as.matrix(i)[,c("rev.perlobbyist.2015", "client.div.index"
,"law.firm.dum" , "international.offices.dum", "num.domestic.offices",
"num.lobbyists", "num.clients", "total_contrib", "age", "website.dum")], 2,
as.numeric))
```

```
out_2014_D <- as.numeric(a.out_2014$imp1$Rfirm)
```

```
a.kdbal_2014 <- lapply(a.out_2014_X, function(i) kbal(i, out_2014_D))
```

```
a.out_diff14 <- vector("list", 100)
```

```
a.L1_orig2014 <- vector("list", 100)
```

```
a.L1_kbal2014 <- vector("list", 100)
```

```
for (i in 1:100){
```

```
  a.L1_orig2014[i] <- a.kdbal_2014[[i]]$L1_orig
```

```
  a.L1_kbal2014[i] <- a.kdbal_2014[[i]]$L1_kbal
```

```
  w <- a.kdbal_2014[[i]]$w
```

```
  partisan_14 <-a.out_2014[[i]]%>%
```

```
    cbind(w)
```

```

partisan_15 <- a.out_2014[[i]]%>%
  dplyr::select(registrant) %>%
  left_join(a.out_2015[[i]])

partisan_15$year[is.na(partisan_15$year)] <- 2015
partisan_15$rev.perlobbyist.2015[is.na(partisan_15$rev.perlobbyist.2015)]
<- 0

dat_diff <- partisan_14 %>%
  left_join(dplyr::select(partisan_15, registrant, rev.perlobbyist.2015),
by = "registrant") %>%
  mutate(rev.perlobbyist.y = replace(rev.perlobbyist.2015.y,
is.na(rev.perlobbyist.2015.y), 0), rpl.diff = rev.perlobbyist.2015.y -
rev.perlobbyist.2015.x)
  a.out_diff14[[i]] <- dat_diff
}

(L1_orig2014 <- mean(unlist(a.L1_orig2014)))
(L1_kbal2014 <- mean(unlist(a.L1_kbal2014)))

library(weights)

a.wtt14 <- lapply(a.out_diff14, function(i) wtd.t.test(filter(i,
Rfirm==1)$rpl.diff, filter(i, Rfirm==0)$rpl.diff, weight=filter(i,
Rfirm==1)$w, weighty=filter(i, Rfirm==0)$w, samedata=FALSE, bootse = TRUE,
bootn=1000))

a.wtt14.diff <- do.call(rbind, lapply(a.wtt14, function(i) i$additional[1]))
a.wtt14.meanR <- do.call(rbind, lapply(a.wtt14, function(i)
i$additional[2]))
a.wtt14.meanD <- do.call(rbind, lapply(a.wtt14, function(i)
i$additional[3]))
a.wtt14.se <- do.call(rbind, lapply(a.wtt14, function(i) i$additional[4]))

```

```

diff_mi14 <- mi.meld(a.wtt14.diff, a.wtt14.se)

meanR_mi14 <- mi.meld(a.wtt14.meanR, a.wtt14.se)
meanD_mi14 <- mi.meld(a.wtt14.meanD, a.wtt14.se)

means_mi <- c(meanR_mi14[[1]], meanD_mi14[[1]])

uppers_mi <- unname(c(meanR_mi14[[1]] + meanR_mi14[[2]], meanD_mi14[[1]] +
meanD_mi14[[2]]))

lowers_mi <- unname(c(meanR_mi14[[1]] - meanR_mi14[[2]], meanD_mi14[[1]] -
meanD_mi14[[2]]))

dm_dat14 <- data.frame(vars = c("Republican", "Democratic"), means_mi,
lowers_mi, uppers_mi)

g14 <- ggplot(dm_dat14, aes(x=vars, y=means_mi)) +
geom_errorbar(aes(ymin=lowers_mi, ymax=uppers_mi), colour="black", width=.1)+
geom_point(size=4) + theme_bw(base_size = 14) + xlab("") + ylab("Change
between 2014 and 2015") + ggtitle("Revenue per lobbyist difference in
differences for 2014 to 2015") + scale_y_continuous(labels = scales::dollar)

ggsave("DiffnDiff2014_2015.pdf", g14, device="pdf")

a.out_dat14 <- vector("list", 100)
for(i in 1:100){
  w <- a.kdbal_2014[[i]]$w
  partisan_14 <- a.out_2014[[i]] %>%
  select(registrant, Dfirm, Rfirm) %>%
  cbind(w)

  out_dat <- expand.grid(registrant = partisan_14$registrant, year =
c(2008,2009,2010,2011,2012,2013,2014,2015)) %>%
  left_join(partisan_14) %>%
  left_join(a.out_y$imputations[[i]])
  out_dat$rev.perlobbyist.2015[is.na(out_dat$rev.perlobbyist.2015)] <- 0
  a.out_dat14[[i]] <- out_dat
}

```

```

wmean <- do.call(rbind, lapply(a.out_dat14, function(i) i %>% group_by(Rfirm,
year) %>% summarise(wmean = weighted.mean(rev.perlobbyist.2015, w))))

wmean <- wmean %>% group_by(Rfirm, year) %>% summarise(mean_rpl =
mean(wmean))

wmean$Rfirm[wmean$Rfirm==1] <- "Republican"

wmean$Rfirm[wmean$Rfirm==0] <- "Democratic"

pt14 <- ggplot(wmean, aes(x=year, y=mean_rpl, group=as.factor(Rfirm),
linetype=as.factor(Rfirm))) +geom_line() +theme_bw(base_size=16) +
theme(axis.text.x = element_text(angle = 90, hjust = 1, size=8))
+scale_y_continuous(labels = scales::dollar) + xlab("Year") + ylab("Mean
revenue per lobbyist") + labs(linetype='Firm Type') +ggtitle("Parallel trends
for 2014-2015 diff-in-diff")

ggsave("parallell_trends14.pdf", pt14, device="pdf")

# conduct diff and diff for 2009 - 2010 as a placebo

a.out_2009 <- lapply(a.out_y$imputations, function(i) filter(i, year == 2009,
Rfirm == 1 | Dfirm == 1))

a.out_2010 <- lapply(a.out_y$imputations, function(i) filter(i, year == 2010,
Rfirm == 1 | Dfirm == 1))

a.out_2009_X <- lapply(a.out_2009, function(i)
apply(as.matrix(i)[,c("rev.perlobbyist.2015", "client.div.index"
,"law.firm.dum" , "international.offices.dum", "num.domestic.offices",
"num.lobbyists", "num.clients", "total_contrib", "age", "website.dum")], 2,
as.numeric))

out_2009_D <- as.numeric(a.out_2009$simpl$Rfirm)

a.kdbal_2009 <- lapply(a.out_2009_X, function(i) kbal(i, out_2009_D))

a.out_diff09 <- vector("list", 100)
a.L1_orig2009 <- vector("list", 100)
a.L1_kbal2009 <- vector("list", 100)

for (i in 1:100){

```

```

a.L1_orig2009[i] <- a.kdbal_2009[[i]]$L1_orig
a.L1_kbal2009[i] <- a.kdbal_2009[[i]]$L1_kbal

w <- a.kdbal_2009[[i]]$w
partisan_09 <-a.out_2009[[i]]%>%
  cbind(w)

partisan_10 <- a.out_2009[[i]]%>%
  dplyr::select(registrant) %>%
  left_join(a.out_2010[[i]])

partisan_10$year[is.na(partisan_10$year)] <- 2010
partisan_10$rev.perlobbyist.2015[is.na(partisan_10$rev.perlobbyist.2015)]
<- 0

dat_diff <- partisan_09 %>%
  left_join(dplyr::select(partisan_10, registrant, rev.perlobbyist.2015),
by = "registrant") %>%
  mutate(rev.perlobbyist.y = replace(rev.perlobbyist.2015.y,
is.na(rev.perlobbyist.2015.y), 0), rpl.diff = rev.perlobbyist.2015.y -
rev.perlobbyist.2015.x)

a.out_diff09[[i]] <- dat_diff

}

(L1_orig2009 <- mean(unlist(a.L1_orig2009)))
(L1_kbal2009 <- mean(unlist(a.L1_kbal2009)))

a.wtt09 <- lapply(a.out_diff09, function(i) wtd.t.test(filter(i,
Rfirm==1)$rpl.diff, filter(i, Rfirm==0)$rpl.diff, weight=filter(i,
Rfirm==1)$w, weighty=filter(i, Rfirm==0)$w, samedata=FALSE, bootse = TRUE,
bootn=1000))

a.wtt09.diff <- do.call(rbind, lapply(a.wtt09, function(i) i$additional[1]))
a.wtt09.meanR <- do.call(rbind, lapply(a.wtt09, function(i)

```

```

i$additional[2]))

a.wtt09.meanD <- do.call(rbind, lapply(a.wtt09, function(i)
i$additional[3]))

a.wtt09.se <- do.call(rbind, lapply(a.wtt09, function(i) i$additional[4]))

diff_mi09 <- mi.meld(a.wtt09.diff, a.wtt09.se)

meanR_mi09 <- mi.meld(a.wtt09.meanR, a.wtt09.se)
meanD_mi09 <- mi.meld(a.wtt09.meanD, a.wtt09.se)

means_mi <- c(meanR_mi09[[1]], meanD_mi09[[1]])

uppers_mi <- unname(c(meanR_mi09[[1]] + meanR_mi09[[2]], meanD_mi09[[1]] +
meanD_mi09[[2]]))

lowers_mi <- unname(c(meanR_mi09[[1]] - meanR_mi09[[2]], meanD_mi09[[1]] -
meanD_mi09[[2]]))

dm_dat09 <- data.frame(vars = c("Republican", "Democratic"), means_mi,
lowers_mi, uppers_mi)

g09 <- ggplot(dm_dat09, aes(x=vars, y=means_mi)) +
geom_errorbar(aes(ymin=lowers_mi, ymax=uppers_mi), colour="black", width=.1)+
geom_point(size=4) + theme_bw(base_size = 14) + xlab("") + ylab("Change
between 2009 and 2010") + ggtitle("Revenue per lobbyist difference in
differences for 2009 to 2010") + scale_y_continuous(labels = scales::dollar)

ggsave("DiffnDiff2009_2010.pdf", g09, device="pdf")

a.out_dat09 <- vector("list", 100)

for(i in 1:100){
  w <- a.kdbal_2009[[i]]$w
  partisan_09 <-a.out_2009[[i]]%>%
  select(registrant, Dfirm, Rfirm) %>%
  cbind(w)

  out_dat <- expand.grid(registrant = partisan_09$registrant, year = c(2008,
2009,2010,2011,2012,2013,2014,2015)) %>%
  left_join(partisan_09) %>%
  left_join(a.out_y$imputations[[i]])

```



```

out_dat$rev.perlobbyist.2015[is.na(out_dat$rev.perlobbyist.2015)]<- 0

a.out_dat09[[i]] <- out_dat

}

wmean <- do.call(rbind, lapply(a.out_dat09, function(i) i %>% group_by(Rfirm,
year) %>% summarise(wmean = weighted.mean(rev.perlobbyist.2015, w))))

wmean <- wmean %>% group_by(Rfirm, year) %>% summarise(mean_rpl =
mean(wmean))

wmean$Rfirm[wmean$Rfirm==1] <- "Republican"
wmean$Rfirm[wmean$Rfirm==0] <- "Democratic"

pt09 <- ggplot(wmean, aes(x=year, y=mean_rpl, group=as.factor(Rfirm),
linetype=as.factor(Rfirm))) +geom_line() +theme_bw(base_size=16) +
theme(axis.text.x = element_text(angle = 90, hjust = 1, size=8))
+scale_y_continuous(labels = scales::dollar) + xlab("Year") + ylab("Mean
revenue per lobbyist") + labs(linetype='Firm Type') +ggtitle("Parallel trends
for 2009-2010 diff-in-diff")

ggsave("parallell_trends09.pdf", pt09, device="pdf")

balance <- cbind( c(L1_orig2009, L1_kbal2009), c(L1_orig2010,
L1_kbal2010),c(L1_orig2013, L1_kbal2013), c(L1_orig2014, L1_kbal2014))

rownames(balance) <- c("preweight L1", "postweight L1")
colnames(balance) <- c( "2009", "2010", "2013","2014")

difftable <- cbind(c(diff_mi09$q.mi, diff_mi09$se.mi), c(diff_mi13$q.mi,
diff_mi13$se.mi), c(diff_mi14$q.mi,
diff_mi14$se.mi))

rownames(difftable) <- c("Difference in mean revenue per lobbyist", "Standard
error")
colnames(difftable) <- c( "2009-2010", "2010-2011","2013-2014", "2014-2015")

#Quarterly Panel Regressions

#load in the data

```

```

firm_dat <- read_csv("final_nonimputed_quarterly.csv")
firm_dat$year_q <- as.character(firm_dat$year_q)
firm_dat$tot_rev <- firm_dat$rev.perlobbyist.2015*firm_dat$num.lobbyists

#Generate summary statistics about firms for figure 1a and 1b
firms <- firm_dat %>% select(registrant, Rfirm, Bfirm, Dfirm) %>% unique()
firms$firm_type <- "Other"
firms$firm_type[firms$Bfirm == 1] <- "Bipartisan"
firms$firm_type[firms$Rfirm == 1] <- "Republican"
firms$firm_type[firms$Dfirm == 1] <- "Democratic"

#figure 1a
firm_plot <- ggplot(filter(firms, firm_type != "Other"), aes(x=firm_type))
+geom_bar() +theme_bw(base_size=18) +xlab("Firm type") +ylab("Number of
firms")
ggsave("firm_plot.pdf",plot=firm_plot, device = "pdf")

firms <- firm_dat %>% select(registrant,year_q, Rfirm, Bfirm, Dfirm,
rev.perlobbyist.2015) %>% unique()
firms$firm_type <- "Other"
firms$firm_type[firms$Bfirm == 1] <- "Bipartisan"
firms$firm_type[firms$Rfirm == 1] <- "Republican"
firms$firm_type[firms$Dfirm == 1] <- "Democratic"

firms <- firms %>% group_by(firm_type, year_q) %>% summarise(med_rev =
median(rev.perlobbyist.2015))

#figure 1b
firm_timeseries <- ggplot(filter(firms, firm_type != "Other"),
aes(x=year_q,y=med_rev, group=firm_type, linetype = as.factor(firm_type)))
+geom_line() +theme_bw(base_size=16) + theme(axis.text.x = element_text(angle
= 90, hjust = 1, size=8)) +scale_y_continuous(labels = scales::dollar, limits
= c(0, 130000)) + xlab("Year/Quarter") + ylab("Median revenue per lobbyist")
+ labs(linetype='Firm Type')
ggsave("firm_timeseries.pdf",plot=firm_timeseries, device = "pdf")

```

```

library(plm)
library(lmtest)

#create data panel

firm_panel <- pdata.frame(firm_dat, index = c("registrant", "year_q"))

#fixed effects model

femodel <- plm(rev.perlobbyist.2015 ~ h.aligned + s.aligned +num.clients +
client.div.index , data = firm_panel, model="within", effect="twoways")

coeffe <- coeftest(femodel, vcovHC(femodel, type="HC3",method="arellano",
cluster="group"))

coeffe

gc()

#first differences model

fdmodel <- plm(rev.perlobbyist.2015 ~ h.aligned + s.aligned +num.clients +
client.div.index , data = firm_panel, model="fd")

coefffd <- coeftest(fdmodel, vcovHC(fdmodel, type="HC3",method="arellano",
cluster="group"))

coefffd

gc()

#multiple imputation for additional variables for random effects model

col_nums <- c(9,10,11,12, 13, 20)

lowers <- c(0,0,0,0,0,0)

uppers <- c(1,1,1,397000,397000, 180)

constraint_mat <-matrix(c(col_nums,lowers, uppers),nrow=length(col_nums))

library(Amelia)

a.out_q <- amelia(as.data.frame(firm_dat), m=100,ts="year_q_int",
cs="registrant", p2s = 2, idvars = c("year_q"), logs = c("num.lobbyists",
"num.clients", "client.div.index", "num.domestic.offices", "total_contrib",
"Rcontribs", "age"), bounds = constraint_mat)

```

```

plot(a.out_q, which.vars = c(9,10,11,12, 13, 20))

disperse(a.out_q, dims = 1, m = 100)

summary(a.out_q)

#estimate random effects models

rm.amelia.out <- lapply(a.out_q$imputations, function(i)
plm(rev.perlobbyist.2015 ~ client.div.index + num.clients + s.aligned
+h.aligned +law.firm.dum + international.offices.dum + num.domestic.offices
+ age + as.factor(year_q_int), data = pdata.frame(i,index = c("registrant",
"year_q")), model="random"))

gc()

coeftests.amelia <- lapply(rm.amelia.out, function(i) coeftest(i, vcovHC(i,
type="HC3", method = "arellano", cluster="group"))))

coefnames <- rownames(coeftests.amelia[[1]])

coefs.amelia <- do.call(rbind, lapply(coeftests.amelia, function(i) i[,1]))
ses.amelia <- do.call(rbind, lapply(coeftests.amelia, function(i) i[, 2]))
random_effects<- mi.meld(coefs.amelia, ses.amelia)

#results of random effects models

results.mi.re <- cbind(coefnames, as.vector(random_effects$q.mi),
as.vector(random_effects$se.mi))

adjrsq.amelia <- do.call(rbind, lapply(rm.amelia.out, function(i)
summary(i)$r.squared[2]))

mean(adjrsq.amelia)

fstat.amelia <- do.call(rbind, lapply(rm.amelia.out, function(i)
summary(i)$fstatistic$statistic))

mean(fstat.amelia)

#Appendix Models

gc()

femodel.h <- plm(rev.perlobbyist.2015 ~ h.aligned +num.clients +
client.div.index , data = firm_panel, model="within", effect="twoways")

```

```

coeffe.h <- coeftest(femodel.h, vcovHC(femodel.h,
type="HC3",method="arellano", cluster="group"))

gc()

femodel.s <- plm(rev.perlobbyist.2015 ~ s.aligned +num.clients +
client.div.index , data = firm_panel, model="within", effect="twoways")

coeffe.s <- coeftest(femodel.s, vcovHC(femodel.s,
type="HC3",method="arellano", cluster="group"))

gc()

femodel.o <- plm(rev.perlobbyist.2015 ~ s.aligned +h.aligned, data =
firm_panel, model="within", effect="twoways")

coeffe.o <- coeftest(femodel.o, vcovHC(femodel.o,
type="HC3",method="arellano", cluster="group"))

#First Differences Robustness Models

gc()

fdmodel.h <- plm(rev.perlobbyist.2015 ~ h.aligned +num.clients +
client.div.index , data = firm_panel, model="fd")

gc()

coeffd.h <- coeftest(fdmodel.h, vcovHC(fdmodel.h,
type="HC3",method="arellano", cluster="group"))

gc()

fdmodel.s <- plm(rev.perlobbyist.2015 ~ s.aligned +num.clients +
client.div.index , data = firm_panel, model="fd")

gc()

coeffd.s <- coeftest(fdmodel.s, vcovHC(fdmodel.s,
type="HC3",method="arellano", cluster="group"))

gc()

fdmodel.o <- plm(rev.perlobbyist.2015 ~ s.aligned +h.aligned, data =
firm_panel, model="fd")

gc()

coeffd.o <- coeftest(fdmodel.o, vcovHC(fdmodel.o,
type="HC3",method="arellano", cluster="group"))

library(stargazer)

stargazer(coeffe, coeffd, style = "ajps")

```

```
xtable(results.mi.re)
stargazer(coeffe.h,coeffe.s,coeffe.o, style="ajps")
stargazer(coeffd.h,coeffd.s,coeffd.o, style="ajps")

library(xtable)
xtable(difftable, digits=3)
xtable(balance, digits=5)

plot(a.out_q, which.vars = c(7,8,9,12, 18))

dev.off()
disperse(a.out_q, dims = 1, m = 100)

summary(femodel.h)
summary(femodel.s)
summary(femodel.o)
```