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ENTER THE PARTISAN FIRM: HOW AFFECTIVE POLARIZATION SHAPES CORPORATION AND CAREER

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BY
JOSHUA GARY MAUSOLF

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CHAPTER 4

Party in the Boardroom: The Role of Affective Polarization in Corporate Board Appointments

When pondering office politics, we might at first envision apolitical jockeying to curry favor, the office rumor mill, and less savory careerist machinations. However, given the rising tide of political partisanship in American society, another conception comes to mind. In this study, I ask how the partisan behavior of a corporate board of directors affects the likelihood of appointing a Democrat or a Republican to that board. Indeed, we have witnessed a proverbial inundation of partisanship and polarization across both the scientific press and the news media (Bail et al. 2018; Douthat 2020; Iyengar et al. 2019; Klein 2020; Macy et al. 2019; Pew Research Center 2016), affecting everything from cultural values, romantic entanglements, and economic behavior (DellaPosta et al. 2015; Gift and Gift 2015; Huber and Malhotra 2017; Iyengar and Westwood 2015; McConnell et al. 2018). Although polarization can have many meanings (*c.f.* Baldassarri and Gelman 2008; Fiorina and Abrams 2008; Iyengar et al. 2019; McCarty et al. 2006), I specifically focus on affective polarization, defined as "the tendency of people identifying as Republicans or Democrats to view opposing partisans negatively and copartisans positively" (Iyengar and Westwood 2015:691), although the term more often denotes partisan animus, the "phenomenon of animosity between the parties. . . known as affective polarization" (Iyengar et al. 2019: 130). Adopting this convention, I likewise refer to partisan animus as affective polarization. For clarity, I denote the antipodal process of viewing copartisans favorably as partisan homophily, a term often used in the study of romantic relationships, which more generally refers to the tendency of similar others to cluster or associate (Huber and Malhotra 2017; Iyengar et al. 2019; Lazarsfeld and Merton 1954; McPherson et al. 2001). Yet, to understand how these phenomena might affect corporate board appointments, we must more closely examine the literature on affective polarization and partisan homophily.

4.1 Unpacking the Role of Affective Polarization and Partisan Homophily in Corporate Boards

With this preliminary understanding of affective polarization and partisan homophily, let us inquire how these partisan processes affect organizational behavior, particularly the action of corporate board members to either add a new board member or replace an existing board member, where the latter process is alternatively referred to as board member swaps or board member succession. Although partisanship—especially affective polarization—can affect economic behavior (Carlin and Love 2013; Iyengar and Westwood 2015; McConnell et al. 2018), shape resume evaluation or job applicant callbacks (Gift and Gift 2015; Iyengar and Westwood 2015; Mausolf 2020b), or structure inter-firm business relationships, executive compensation, and corporate social responsibility (Gupta and Briscoe 2019; Gupta and Wowak 2017; Stark and Vedres 2012), we have little understanding of how partisan mechanisms, such as affective polarization or partisan homophily, shape corporate board appointments. In fact, given Bonica's (2016) assertion on the "prevalence of bipartisan boardrooms," and the potential benefits of promoting board member diversity (DiTomaso et al. 2007; Dobbin and Jung 2011; Hambrick et al. 1996), we might indeed question whether partisanship should affect board member appointments. Consider a related trend in the corporate board interlock literature, where political unity in campaign contributions is weakened by the decline of the inner circle (Burris 2005; Chu and Davis 2016; Useem 1984), resulting in greater partisan heterogeneity across interlocked directors (Burris 2005; Chu and Davis 2016), but increased partisan homogeneity within corporate boards, where partisan political contributions are more likely to align (Burris 2005; Chu and Davis 2016). Yet, the puzzle lies at the exact confluence of dichotomous theories and empirical findings suggesting the possibility that boardrooms might exhibit either partisan heterogeneity (bipartisanship or diversity) or conversely embrace partisan homogeneity. My research seeks to address this question and illustrate the power of party in the boardroom, especially the partisan mechanisms of affective polarization and partisan homophily.

4.1.1 Resolving Boardroom Ideology and Partisanship

Fundamentally, a key to answering these empirical questions on affective polarization, partisan homophily, and analyses of boardrooms, rests at a nexus surrounding the conflation of ideology and partisanship. Although ideology and party are correlated (Bonica 2013, 2014, 2016), ideology refers to a set of positions on political issues whereas party refers to identification with a political party (Campbell et al. 1960; McCarty et al. 2006), which many scholars argue shapes ideological beliefs (Barber and Pope 2019; Goren 2005). Despite tightly clustered ideological polarization among party elites (Hetherington 2001; McCarty et al. 2006), ideological beliefs among average citizens are not similarly polarized and in fact remain highly heterogeneous, with overlap existing even across party divisions (Baldassarri and Goldberg 2014; DiMaggio et al. 1996; Fiorina and Abrams 2008). As such, many of the reports of heightened polarization actually reflect increases in party sorting or partisan polarization (Macy et al. 2019; Mausolf 2020a), increased ideological clarity as structured by increasing partisan division (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Barber and Pope 2019; Mason 2015), or animosity between parties as a result of affective polarization (Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Pew Research Center 2016). Furthermore, partisan mechanisms, such as affective polarization, operate irrespective of underlying, unexpressed ideological beliefs (Iyengar and Westwood 2015). That is, animosity toward opposing partisans and preference for copartisans exist implicitly, exceeding the effects of race, and occurs on the sole basis of a partisan signal (Iyengar and Westwood 2015). For these reasons, we must take analyses conflating party and ideology with some incredulity, alongside the understanding that the existence of partisan diversity does not preclude partisan discrimination, a fact familiar to scholars of race.

4.1.2 Disentangling Competing Partisan Mechanisms

Ergo, when we turn our attention to what lessons can be gleaned from scholars, such as Bonica (2016), several insights emerge. Extending his past analyses, which design a novel method for mapping ideological scores for incumbent and challenger candidates, political action committees (PACs), and individual contributors (Bonica 2013, 2014), Bonica next turns to assess the ideological distribution of individual Fortune 500 directors (Bonica 2016). Among other findings, Bonica (2016) reveals that "compared to corporate PACs, corporate elites are more ideological" but have "substantial heterogeneity. . . both across and within firms" (367). Most relevant, however, to this study, Bonica (2016) also demonstrates "the prevalence of bipartisan boardrooms" (367). Digging into the results, however, we can see that not all firms are created equal. For instance, although many boards have some ideological diversity, many other boards, such as Apple or Marathon Petroleum, are comprised of primarily liberals or conservatives (Bonica 2016), and given ideological heterogeneity even among a homogenous group of partisans (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Fiorina and Abrams 2008), suggests that such firms may have high partisan homogeneity, a finding demonstrated in Mausolf (2020a). Even by Bonica's (2016) analysis, however, the plurality of Republican corporate boards gave at least half of their political contributions to Republican political committees (Bonica 2016: 388). In this way, firms could be considered bipartisan, but many firms also seem to have a dominant party. Although Bonica (2016) operates within an ideological framework, his supposition that ideological heterogeneity might result from either non-ideological rationales, or by design to correct ideological imbalances, proves useful (Bonica 2016: 390). As I have elsewhere stated, party rather than ideology proves a far more salient constraining force (Barber and Pope 2019; Goren et al. 2009), and partisan behaviors, such as affective polarization and partisan homophily, seem more likely to shape board decisions than ideology since these biases can operate implicitly (Iyengar and Westwood 2015; Iyengar et al. 2019). Thus, board member selection might be influenced by partisanship, such that a board may be more likely to appoint a new board member whose partisanship aligns with that of the board and similarly less likely to appoint a board member whose partisanship diverges from that of the board.

Both of these latter hypotheses align with the idea of affective polarization and partisan homophily. A preference for copartisans would theoretically result in a situation of board member appointments aligning with the extant board. Yet, we would also generally expect the aversion toward opposing partisans to more often than not result in a lower likelihood of opposing partisans joining the board and a higher likelihood of copartisans joining the board, at least when only considering the appointment of known partisans. We could achieve better adjudication between these parallel but discrete mechanisms through experimental studies (Gift and Gift 2015; Iyengar and Westwood 2015; Mausolf 2020b), or by having better data about the exact selection pool for given board member appointments. For instance, as I describe in the data and methods section below, we can make inferences about corporate board member appointments by examining changes in board composition across two time periods. Such data, however, only show the positive outcome of board member selection. For example, we have no data about who may have been considered for a board appointment but was not ultimately selected.

Adjudicating between affective polarization and partisan homophily would further require data about those without any partisan signaling, and simply having an unknown party identity (from the analyst's perspective) is not equivalent to a board member having truly no ostensible partisan leaning since many partisan and other political attributes can be inferred by cultural preferences (DellaPosta et al. 2015). Outside of experiments or observational data an order of magnitude better than what is currently available, it may be difficult to disentangle the antipodal forces of partisan animus versus partisan homophily. In the end, both theories of affective polarization (in the sense of animus toward opposing partisans) and partisan homophily, or preference for copartisans (Huber and Malhotra 2017; Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Iyengar et al. 2019; Mausolf 2020b), suggest that incoming board members, whether those appointments are an addition or succession, will more likely to be copartisans than opposing partisans.

Although I argue that affective polarization and partisan homophily present one of the most compelling political rationales for selecting board members, we must also consider alternative possibilities. Here, the prospect raised by Bonica (2016), in which corporate boards may intentionally correct partisan imbalance has some merit. Rather than ideology, however, I contend that partisan rebalancing could prove more likely, particularly if considered from the perspective in which corporate board appointments reflect intentional signaling to shareholders (Dobbin and Jung 2011; Khurana 2002; Krawiec and Broome 2008). From this perspective, a strategic partisan rebalancing of a board parallels a similar phenomenon of corporate political action committees (PACs) supporting both parties (Bonica 2016; Hacker and Pierson 2010; Tripathi et al. 2002), or revolving door politics wherein corporate boards appoint former government officials and government leaders appoint former corporate titans (Hacker and Pierson 2010; Kuttner 2010; Luechinger and Moser 2014). To the extent that partisan rebalancing of corporate boards exists, I expect the process would be responsive to transitions in partisan control of U.S. presidential administrations. To account for this possibility in the analysis, I include a control for the U.S. presidential party in the models.

4.2 Folding In Theories of Board Diversity and Board Appointments

Outside of affective polarization, partisan homophily, and alternative partisan perspectives, I augment these theories with the research on organizational diversity, particularly as it relates to board member appointments. Here, two key but interrelated perspectives exist in relation to board appointments. The first is considering how diversity can positively or negatively alter board dynamics, and the second is using board appointments as an outward signal. Both perspectives, while discrete, offer parallel expectations that ground the initial hypotheses on partisan board appointments via affective polarization and partisan homophily.

Regarding the first idea of board diversity, we encounter a raft of studies, including a number of reviews and meta-analyses, which conclude that despite some evidence supporting benefits in innovation or creativity from functional diversity (Ancona and Caldwell 1992; Burt 2000), in most cases of organizational, team, or group diversity, particularly along salient social dimensions, we see substantial negative effects on "social integration, communication, and conflict" (DiTomaso et al. 2007; Jackson, Joshi, and Erhardt 2003; Williams and O'Reilly 1998: 115).[1] However, we can examine how diversity appointments on corporate boards affect firm dynamics and valuation. On this front, although some studies find positive effects of gender, racial, or ethnic diversity appointments to firm performance (Carter, Simkins, and Simpson 2003), these might simply reflect a reverse causality of successful firms appointing female or minority directors, particularly since more robust longitudinal evaluations show negative effects on firm performance and stock valuation (Adams and Ferreira 2009; Dobbin and Jung 2011).[2] Related to Adams and Ferreira (2009), important dimensions of diversity, be they gender, political ideology, or partisanship, can affect not just executive pay, but also the governance styles of directors and what leadership qualities they value (Adams and Ferreira 2009; Cheng and Groysberg 2016; Chin et al. 2013; Gupta and Briscoe 2019; Gupta and Wowak 2017; Gupta et al. 2017). Consistent across this evidence, however, whether considering the demonstrable detriments to performance, firm valuation, and board

[1] Multiple review articles conclude that diversity, especially on key social dimensions, has primarily negative effects. Consider the *Annual Review* article by DiTomaso et al. (2007), or publications in organizational behavior and management literature, such as Williams and O'Reilly (1998), which reviews over 80 studies and 40 years of research or Jackson et al. (2003) which also consults 63 studies on the topic.

[2] See, for example, the extended discussion throughout Dobbin and Jung (2011) and Adams and Ferreira (2009) about reverse causality and spurious results of positive effects, once longitudinal data and robust modeling is implemented, showing in actuality, negative effects for diversity appointments, in this case, gender diversity.

dynamics—or differences in leadership priorities and governance style—all suggest that corporate boards would, on balance, prefer to associate with similar others—in this case copartisans—and be averse to those who deviate from the typical appointee—in this case opposing partisans.

Yet, these arguments lead to an alternative albeit supportive perspective that board appointments serve as salient signals. When thinking about CEO appointments, for instance, Khurana (2002) argues that when a corporate board deliberates on the selection and appointment of a CEO, they consider what external signal that selection will send to external audiences, including institutional investors, Wall Street analysts, business media, and firm competitors. Translating the executive perspective to board members, Krawiec and Broome (2008) argue that the appointment of a board member serves as a valuable signal to shareholders, among other external audiences, a perspective adopted and expanded upon by Dobbin and Jung (2011). Integral to this argument, although boards might seek to signal a commitment to diversity and equality by appointing women or minorities to the board and thereby appease certain contingents (Dobbin and Jung 2011; Krawiec and Broome 2008),[3] such actions can also backfire if institutional investors interpret this signal as one indicating a prioritization of diversity over profits (Dobbin and Jung 2011).

Although most research articulates the downsides of diversity (Jackson et al. 2003; Williams and O'Reilly 1998), or even that corporate board diversity might negatively affect performance or firm profitability (Adams and Ferreira 2009), some studies instead suggest that a board's diversity appointments do not alter board dynamics, such as "efficacy or monitoring capabilities," or directly alter firm profitability and by consequence, stock prices

[3] For example, in their interviews with corporate boards of directors, Krawiec and Broome (2008) find that directors believed the "presence of women and minorities on the board sent an important, positive signal to labor" and other corporate constituents (453). See also Dobbin and Jung (2011). These ideas also have a connection to the social movements literature, wherein firms and directors can respond to mobilization objectives (Davis et al. 2008; McDonnell, King, and Soule 2015), although such studies often assess mobilization and corporate diversity (Olzak and Ryo 2007), or mobilization and firm shareholder value (King and Soule 2007), versus the interplay between corporate board diversity, firm performance, and shareholder value as argued in Dobbin and Jung (2011).

(Dobbin and Jung 2011: 837). Rather, the appointment of diversity candidates to the board of directors activates institutional investor bias, which directly and negatively affects stock valuation (Dobbin and Jung 2011).

Given the widespread and significant salience of partisan discrimination, particularly animus against imposing partisans via affective polarization (Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Iyengar et al. 2019), we might also expect that a corporate board appointment of a known partisan, particularly a partisan minority, might induce institutional investors to sell, or otherwise devalue the stock, not because such an appointment would necessarily affect the firm performance, but rather because investors are biased against those in the opposing political party. Although this study does not speak to how partisan board member appointments affect stock valuation, and indeed such studies are lacking,[4] the confluence of affective polarization (Iyengar et al. 2019), with the idea of institutional investor bias against board members' sociodemographic features (Dobbin and Jung 2011), and the idea that board member appointments can directly impact stock value (Dobbin and Jung 2011; Luechinger and Moser 2014), reify the idea that board appointments act as important signals (Dobbin and Jung 2011; Khurana 2002; Krawiec and Broome 2008). In this way, beyond board members' own partisan bias via affective polarization or partisan homophily, board members might additionally consider the signal that would be sent by and the consequences that could follow the appointment of an opposing partisan to the board.

Beyond affective polarization—or alternative perspectives of partisan homophily, diversity, and organizational culture—a host of additional possibilities exist that might explain the partisan selection of board members. For instance, the industry or sector in which a firm operates might map to specific policy positions and accordingly reflect a partisan

[4]As mentioned, studies have examined how gender diversity impacts stock value (Dobbin and Jung 2011), how firm value under Democratic versus Republican presidencies is higher (Camyar and Ulupinar 2013), or how corporate appointments of former government officials leads to an increase in stock value (Luechinger and Moser 2014). Less, however, is known about the general impact of in-partisan and out-partisan board appointees and stock valuation.

predilection. To account for this possibility, therefore, a subset of models includes controls for firm sector. We might expect, for instance, that technology firms might on balance be more Democratic, and energy sector firms, especially oil and gas companies, might lean Republican—a supposition which aligns with current empirical findings with some notable exceptions (Bonica 2014, 2016; Mausolf 2020a).[5]

Similarly, extant corporate board features might also shape the likelihood of appointing a Republican versus Democratic board member. For instance, corporate board diversity features, such as the proportion of the corporate board that is female, black, Hispanic, or non-white minority could potentially alter partisan behavior. As shown in Mausolf (2020a), Republican firms are significantly associated with having boards of directors that do not have any minorities or women. Although polarized Democratic firms did not necessarily have a converse association, it is possible that an increased number of women and minorities on the board of directors could decrease the likelihood of appointing Republican board members. We might also expect having a higher number of board members with an international background to have a similar effect. Moreover, having a board whose members are more advanced in age may negatively affect the likelihood of appointing Democrats. Conversely, the overall size of the board might have positive effects for Democratic appointment. With a larger board, there is a lower risk of partisan rebalancing from appointing an opposing partisan than in a comparatively smaller board. Lastly, the type of board appointment would logically affect the admission of partisan members. Chiefly, for cases of board member succession, the likelihood of appointing a copartisan or opposing partisan might depend on

[5]Consider the energy sector, for instance. Bonica (2014) shows that employees in the oil, gas, coal industry tend to have conservative CFscores, and that board members in these firms, such as Marathon Petroleum, are highly conservative (Bonica 2016), a finding aligning with those in Mausolf (2020a), that likewise shows that oil and gas companies like Marathon Petroleum or ConocoPhillips are polarized Republican firms, that is, are highly homogenous in consisting almost exclusively of Republicans, not just in executives but also in managers and all other employees. Yet, not all energy companies are Republican, and in fact, some companies, especially those in alternative energies, such as solar or wind, gravitate toward the Democratic Party (Mausolf 2020a). Likewise, not all technology firms are overwhelmingly Democratic and may, in fact, reflect an amphibious mixture of Democrats and Republicans (Mausolf 2020a). If caveats such as this exist for stereotypically partisan industries, other categories might prove even less prognostic. For these reasons, firm sector might not be the best predictor of board partisanship appointments.

whether the swap in question is equal—that is, a replacement of an outgoing board member with someone matching that member's partisanship—or unequal, where the incoming board member's party opposes the outgoing board member's partisanship.

4.3 Data and Methods

Data for this project comes from several data sources. The corporate board membership data comes from the Institutional Shareholder Services (ISS) - Directors Dataset (2007-2018), which has a variety of information on corporate boards of directors. Both the ISS and a related dataset, known as BoardEx, largely draw upon U.S. Securities and Exchange Commission filings and have been used in a number of studies looking at boards of directors and their activity (Chu and Davis 2016; Gupta and Wowak 2017).[6] While the BoardEx dataset has benefits when examining complex network dynamics and corporate interlocks, for my purpose of examining how the immediate board's partisanship affects board appointments, the ISS more than suffices and has added benefits, such as containing race and ethnicity data.

To execute this project also requires data on the political partisanship of board members. For this, I draw upon two primary data sources, namely the FEC - Corporate Politics data (Mausolf 2020a) and the DIME - Avenues of Influence data (Bonica 2016), which I detail below. Although these datasets vary in their construction and data coverage, both evolve from the same base data provided from the Federal Election Commission (FEC), which provides details on individual contributions to political committees as well as committees' itemized expenditures to other committees and candidates. Studies using some derivation of the FEC data to examine corporate elites (executives or board members) have emerged in multiple studies (Bonica 2016; Briscoe et al. 2014; Chin et al. 2013; Gupta and Briscoe 2019; Gupta and Wowak 2017; Gupta et al. 2017; Mausolf 2020a).

[6]Other commonly used datasets for researching corporate leadership include ExecuComp, particularly for studying executive compensation (Bertrand and Hallock 2001; DiPrete et al. 2010). Chin et al. (2013) also utilize both ExecuComp and RiskMetrics (now known as ISS) in a limited capacity.

4.3.1 ISS Directors Data Subset

For this study, I analyze a subset of the Institutional Shareholder Services (ISS) - Directors Dataset (2007-2018). In particular, I restrict my initial dataset to companies for which I have corresponding FEC campaign finance data, as described in (Mausolf 2020a), which contains firm-level data for a subset of 378 of the Fortune 400 companies as well as individual-level and contribution-level data for individuals within these companies. The final dataset analyzed in this paper reflects a smaller subset of companies, since I only include companies passing a certain board member missingness threshold. Substantively, this means that I am able to match the board member identity to a named individual in one of the partisanship datasets. For the majority of individuals therein, I am able to determine their partisanship using one of the two partisan data sources, the FEC - Corporate Politics data and the DIME - Avenues of Influence data from Mausolf (2020a) and Bonica (2016), respectively.

4.3.2 FEC - Corporate Politics (CP) Data

In this paper, I utilize data from Mausolf (2020a), which employs a method of determining the political partisanship, as well as the strength of that partisanship (partisan polarization), for firms and their subunits using Federal Election Commission (FEC) data. For brevity, I refer to this dataset as FEC-CP. This data comes into play at several points in the data preparation pipeline. First, as described above, I restrict the ISS directors dataset to include only the 378 companies found in the FEC-CP data. Second, I incorporate available firm-level metrics on partisan polarization from Mausolf (2020a). Third, beyond firm-level metrics, I also utilize information on individual partisanship by election cycle and overall individual partisanship, which is joined with the ISS data (described below). Lastly, I utilize political committee partisanship information in the FEC-CP data to supplement the DIME-AOI data, whose original partisanship measures are limited.

4.3.3 DIME - Avenues of Influence (AOI) Data

Like the FEC-CP data, the DIME-AOI data used in Bonica (2016) contains a variety of political data on individual contributors, particularly corporate board members, originally derived from the FEC. Although Bonica (2016) emphasizes board member ideology, the data also contains data on contributor partisanship, such as total individual contributions to the Democratic and Republican Party or the recipient's party if available. Likewise, there is data on contributor ideology, and in some cases linking data on the political committee, which I use to determine the partisanship of a given contribution using the FEC-CP data from Mausolf (2020a). Critically, we also have the full names of individual contributors and the company for which they work, which in the case of Bonica (2016) are all members of Fortune 500 boards of directors. When examining the DIME-AOI data, provided online for replication, Bonica (2016) includes two primary datasets, "bod_fortune_500" and "bod_fortune_500_cont_records," which I hereafter refer to as DM1 and DM2, respectively. Whereas DM1 contains summary-level metrics for board members at Fortune 500 companies, DM2 contains contribution-level records for board members. DM2 is, therefore, a preferable dataset since information derived thereof can contain board member partisanship measures by election cycle (as well as summary partisanship measures). DM1 can only signal the overall partisanship of a board member across all election cycles and cannot be supplemented by the FEC-CP data.

4.3.4 Deriving Individual Partisanship

As previously mentioned, to understand the role of partisanship in board member events, such as additions, swaps, or drops, we must first know the partisanship of board members. Although we might not be able to determine the partisanship of every board member (Gupta and Wowak 2017), we can certainly determine the partisanship for most board members, which I achieve using both the FEC-CP data as well as the DM1 and DM2 datasets from the

DIME-AOI data (Bonica 2016; Mausolf 2020a). Below, I describe the methods for obtaining standardized partisanship measures across these datasets.

DIME-AOI-DM1. Since the DM1 only provides summary-level data for individual partisans, deriving partisanship relies on the data columns therein, chiefly *dime.cfscore*, *total.dem*, *total.rep*, *total*, and *pct.to.dems*. From these variables, I generate three discrete measures of partisanship. First, I derive a *majority party* measure using *total.dem*, *total.rep*, and *total*,[7] such that the individual's party is determined by the party to which they have given the most contributions if the total is greater than zero. Similarly, I created a measure, *percentage Democrat party*, which relies on *pct.to.dems*,[8] such that the individual is a Democrat if ≥ 0.500 of contributions are to Democrats; otherwise, they are presumed to be Republican. Lastly, I derive the measure *CFscore party* from *dime.cfscore*, which is the "Contributor common-space CFscore" per the DIME-AOI codebook (Bonica 2016). As shown in (Bonica 2014: Appendix Figures 1-2), the contributor CFscore cut-point of 0 approximately divides the contributor CFscore scale $[-2, 2]$ between Democrats $[-2, 0)$ and $[0, 2]$ Republicans. I use this cut-point to create a partisanship measure using the *contributor CFscore*. I create an overall partisanship measure utilizing if-else logic to rank-order the three DM1 partisanship measures (*majority party*, *percentage Democrat party*, and *CFscore party*) to fill non-null values.[9] The resulting binary *party* measure [DEM, REP] excludes null values.

DIME-AOI-DM2. Since DM2 has contribution-level data, we may glean additional partisanship detail with supplementation from the FEC-CP data. Supplementation occurs through a series of joins using the DM2 dataset's *recipient.party* column, which contains the names of the FEC committees (or candidates). This identifying data links to the FEC-CP and comes directly from the FEC (Federal Election Commission 2018a). From the FEC-CP

[7] The measure *majority party* is denoted in code using *pct_party*.

[8] The measure *percentage Democrat party* is denoted in code using *pct_dem_party*.

[9] In other words, where the *majority party* is not null, the new variable *party* equals the *majority party* else, where *percentage Democrat party* is not null, party equals percentage Democrat party, else party equals *CFscore party* (excluding null values).

data, I can derive two datasets: (1) containing the committee name, election cycle, and party and (2) containing the candidate name, election cycle, and party. Using a series of left-joins, anti-joins, and unions, I first join DM2 with the FEC-CP by committee name and cycle, followed by another join using candidate name and cycle. In this way, for matching cases, I have a *party_ID* column, which is used throughout the FEC-CP data (Mausolf 2020a). This *party_ID* column is the first generated partisanship measure for DM2.[10] Next, I use the DM2 column *recipient.party*, recoded into "DEM", "REP", and "IND/OTH" results. As was the case in DM1, in DM2, I create a third measure of partisanship *CFscore party* using the aforementioned DEM/REP cut-point of 0. As before, I create an overall partisanship measure that utilizes if-else logic to rank-order the three DM2 partisanship measures (*party_ID*, *recipient party*, and *CFscore party*) to fill non-null values, respectively. This party variable is subsequently recoded into three district values [DEM, IND/OTH, and REP] with corresponding [-1, 0, 1] values.

To mirror the output of DM1, I summarize these character and numeric party variables in two ways. Recall, the original DM2 data is at the contribution level. This data is transformed to provide each individual with two collective partisanship measures: (1) *cycle_party*, the overall partisanship [DEM, REP] for a given election cycle, and (2) *party*, a given individual's dominant partisanship across all election cycles. Following prior cut-points, partisanship in both cases follows the convention such that Democrats have a party mean < 0 and Republicans have a party mean ≥ 0.

FEC-CP. The manipulation needed to derive concordant party measures in the FEC-CP is minimal. In its original state, each unique individual per firm has the possibility of a *party_ID* and *partisan_score* for each election cycle (Mausolf 2020a). Those variables generally have low missingness. After converting *partisan_score* to a second party measure,

[10]The measure *party_ID* as described in Mausolf (2020a) primarily consists of DEM or REP values, but may have other parties, unresolvable party concatenations, such as UNK_DEM_REP or other unknown values.

the two measures were combined into a singular *party_cycle* measure, which I subsequently recoded into three district values [DEM, IND/OTH, and REP] with corresponding [-1, 0, 1] values. Prior to calculating final party metrics, the individual's name underwent additional cleaning to facilitate matching to the names in the ISS data.

4.3.5 Matching Measures of Partisanship to Board Members

Having described the datasets and preparation, I now turn to the method of matching board member identities in the ISS with measures of individual partisanship in the FEC-CP and DIME-AOI. Some similar studies, such as Gupta and Wowak (2017), utilize methods such as fuzzy matching to align names in board member and FEC data. Although fuzzy matching can probabilistically join both full and partial matches of names, there is no guarantee that the names matched would pass a qualitative evaluation.[11] Rather than accidentally create these mismatch errors, I instead chose to perform a series of successive joins between the ISS and either the FEC-CP or one of the two DIME-AOI datasets using discrete join methods (Appendix D, Table D.1 and Table D.2).[12] This procedure has the added benefit of explicitly matching individuals. In most cases, the join includes the full name and firm.

To perform joins by name, I first worked to clean and standardize name formatting across the three partisanship datasets (FEC-CP, DM1, DM2) as well as the board member dataset (ISS). Although the exact changes for each dataset varied, each received some common treatments, such as switching the name to lowercase and stripping whitespace padding. Although the original FEC-CP data had previously been cleaned such that there were unique individuals (by full name) per firm and election cycle (Mausolf 2020a), the original name cleaning, while efficient for its purpose, was not optimized for joining datasets by name. In

[11] For example in testing fuzzy matching in Python in earlier versions of this analysis as well as in Mausolf (2020a), a number of errors were found in qualitatively reviewing fuzzy match results. See also the post-fuzzy-matching qualitative evaluation needed in Gupta and Wowak (2017).

[12] As I describe below, I include two tables in Appendix D, Table D.1 and Table D.2, which detail the exact join methods used and how many matched observations come from the FEC-CP, DM1, and DM2.

particular, I extracted suffixes from the FEC-CP data full names, which were additionally split into first and last name columns. Where any newly cleaned full name duplicates occurred, I retained the version of the individual with the most contributions.[13] Both of the DIME-AOI datasets (DM1, DM2) had already highly processed names and needed minimal cleaning to optimize matching with the ISS. For the ISS, a substantial amount of cleaning was needed. For example, I utilized regular expressions to extract titles, degrees, and suffixes from the full names of board members. Similarly, I also extracted nicknames from full names. For the first name column, I removed nicknames and middle initials, among other changes. Last name columns also had any lingering titles or suffixes removed. Beyond the original cleaned full name, I also generated supplemental full name columns using variations of the cleaned name elements, for example, (A) first name + last name or (B) nickname + last name. In this way, I had several permutations of full names as well as discrete first and last name columns for which I could attempt explicit joins with the partisanship datasets.

In total, I utilize twenty discrete join methods, and I perform these joins following two approaches regarding the fluidity or constancy of partisanship, namely (1) allowing an individual's partisanship to vary by election cycle and (2) assuming an individual's partisanship is fixed and reflective of their dominant party identity. For the primary analysis, I use the first approach, although I also perform analyses assuming the latter fixed partisanship, which appear in Appendix D. For both approaches (1) and (2), I perform the aforementioned sequence of joins, where the exact join method and number of cases resulting from each method are detailed in Appendix D, Table D.1 and Table D.2. For quality control purposes, I set a board-missingness threshold of 0.30. In other words, I only kept companies for subsequent analysis if I could match at least 70% of the board member identities to an

[13]The original FEC-CP data that had been reduced to unique individuals by cleaned full name, firm, and cycle collapsed all individual contributions for that person, averaging the *party_ID* and *partisan_score* for each contribution. For this reason, simply recalculating the mean of any new duplicate names would prove ill-advised and could inaccurately distort the overall partisanship. Since recalculating means with the original data was not readily available, the safer practice was dropping the result with fewer contributions. For example, if an individual made 25 contributions with one version of their name, but only two contributions with another name variation, I kept the version with the most contributions.

identity in one of the partisanship datasets. Because not every identity in the partisanship datasets (FEC-CP, DM1, DM2) was known, this translates to only analyzing boards where approximately 70% or more of the board has known partisanship.

4.3.6 Outlining (1) Variable Partisanship and (2) Fixed Partisanship Determination and Imputation

At first, the distinction between (1) variable partisanship and (2) fixed partisanship may seem obvious. Yet, to fully understand the distinction requires a better understanding of the determination of partisanship for these methods and how the datasets impact this determination. Recall, for example, the three partisanship datasets, FEC-CP: 1980-2018, DM1: 2002-2012, and DM2: 1980-2014. Although we could perform joins by election cycle using the FEC-CP data and DM2 data, for any join methods involving DM1, joining by cycle is impossible since that dataset summarizes activity across multiple election cycles. In this case, any joins for variable partisanship are the same as those performed for fixed partisanship. Furthermore, the FEC-CP covers the greatest time period compared to either DIME-AOI datasets. Thus, I first attempt to determine partisanship using the FEC-CP before falling back to the DM1 or DM2. Ignoring differences in each dataset's election cycle coverage, substantial gaps for individuals also exist within each dataset. For instance, some individuals might not have any discernible partisanship. In other cases, we might only have information about an individual in a single election cycle. Using the (2) fixed partisanship approach, the determination of partisanship reflects the binary (REP/DEM) conversion of either (A) the mean partisanship across all available election cycles (for FEC-CP and DM2) or (B) the expressed partisanship for an individual in DM1.

Of course, the approach differs in determining (1) variable partisanship. For instance, to determine an individual's partisanship for missing election cycles, I adopt a two-phase imputation approach: (1) first using forward fill imputation, and (2) second using backward fill imputation. All imputation of values occurs by company and individual. In other words, only known values of partisanship for an individual are used in determining their partisan expression in other cycles. If an individual has no known party identity, the value remains unknown. When data is forward filled, a given value is carried forward to fill missing values until another known value is encountered or no future values exist for that individual. Forward filling values makes logical sense. We would assume an individual retains their expressed partisan value into the future unless presented with evidence to the contrary. For example, if an individual were a Republican in 2016, we would assume they were also a Republican in 2018. Yet, taken alone, forward filling values is not enough. If we only have one observation for an individual, in this example, that they were a Republican in 2016, only future values, would be filled using forward fill, as described above. Because we have no information to the contrary, we might presume they were also a Republican in 2008-2014. This is an example of backward filling.

Formally, when data is backward filled, a given value is carried backward to fill missing values until another known value is encountered or no prior values exist for that individual. In the case of a single value, the order does not matter. Yet, in the case of two or more values where at least one party switch occurs, the order greatly matters. Consider the example in Table 4.1. Compared to the original method of determining overall partisanship, the forward fill, backward fill method differs primarily in the scenario where an individual makes one or more partisan transitions across cycles. If an individual is consistently the same partisan in one or more election cycles, there is no difference.

4.3.7 Determining Board Change Events

After determining parties, we must calculate board events. But first, we must define a board change event. Simply put, a board change event reflects an ostensible difference in the composition of the board as determined by its members. A board change transpires when

Table 4.1: Examining How Forward Fill (FFILL), Backfill (BFILL) Order Matters

Firm	Individual	Cycle	Party	Party (FFILL, BFILL)	Party (BFILL, FFILL)
C01	E01	2004	nan	REP	REP
C01	E01	2006	REP	REP	REP
C01	E01	2008	nan	REP	DEM
C01	E01	2010	nan	REP	DEM
C01	E01	2012	DEM	DEM	DEM
C01	E01	2014	nan	DEM	DEM
C01	E01	2016	nan	DEM	DEM
C01	E01	2018	nan	DEM	DEM

Notes: Example of how the two-phase imputation method occurs, grouped by company and individual. The utilized two-phase approach occurs in the order (1) forward fill (FFILL), (2) backward fill (BFILL) as represented in the column 'Party (FFILL, BFILL).' The other column 'Party (BFILL, FFILL)' illustrates why the order the steps are executed matter.

one or more changes occur in the set of board members between two time periods. If a set of board members is constant, no change exists. Thus, determining a board change event evolves from comparing the sets of all given board members within a firm at two points in time. As previously mentioned, this data comes from the ISS, which delimits the individual board members for a firm annually. Thus, we might minimally determine board change events by examining the set of board members each year with the set of board members in the prior year. We might alternatively express this comparison as a yearly comparison of board change events using a one-year lag. Below, I expand upon the prospect of relaxing the one-year lag to incorporate alternative lag possibilities.

Now that we understand that board events are changes in the set composition of a corporate board between two times, however, I must explain how practically this change is calculated. All changes are calculated using a self-designed code repository developed in *Python*, which for every firm, creates two lists of (a) current board members and (b) prior board members (for a given year-lag) for each available year of comparison, dependent on the number of lag-years included (Mausolf 2020g). The comparison of the two lists is not dependent on the order of the board members and uses a cleaned, lowercase version of the full name to prevent registering false change events from board-member name variations. When comparing two board sets, two elemental types of board change are possible. New board members may be added or dropped, and these events are not mutually exclusive. For example, two new board members may be added and only one old member is dropped. In most cases, the comparison of two board member sets reveals a large intersection of persistent board members. Where no new members are added and no old members are dropped, no board change occurs, and the intersection of persistent members is equal to the board set at either time period.

Thus, the set comparison of boards at two time periods results in the following possibilities from the combination of No Change (NC), Addition (A), or Drop (D) events: $[NC] \oplus [A \vee D]$, where $A \cup D \neq \varnothing$, $A = \varnothing \vee A = [A_1, \ldots, A_n]$, $D = \varnothing \vee D = [D_1, \ldots, D_n]$. In other words, we can have either no change or some non-empty combination of additions and drops. Where we have an equal number of additions and drops, this would be recoded as a swap. To give a few examples, suppose we have the following supersets of board change events: $\Big($[ADD, ADD, ADD], [DROP, DROP]$\Big)$, $\Big($[ADD], $\varnothing_{\text{DROP}}\Big)$, $\Big(\varnothing_{\text{ADD}}$, [DROP, DROP]$\Big)$. These supersets of events would be resolved as follows: [SWAP, SWAP, ADD], [ADD], [DROP, DROP]. Of course, a host of other possibilities exist, especially as the period between comparison boards increases. Nonetheless, the resolution of this process results in a dataset of board events.

The astute observer will note that the above process of codifying board change events relies upon the names of board members. The names of added, dropped, swapped, and persistent board members, while perhaps interesting, lacks generalizable utility in that names do not confer partisanship. To extract this information, I utilized a solution of creating two columns, one for the current board and one for the prior board, which contained a dictionary using board member names as keys, and board member parties as the values. Combined with discrete columns articulating added and dropped board member names, I could thus generate columns specifying the party of the added and dropped board members, which I utilize in the subsequent analysis. Recalling that not all board members have a known party identity, we have occurrences where the party of the added board member or the dropped board member has an unknown party identity. Although missing board partisanship could perhaps be either crudely imputed using the board mean or with a more advanced multiple imputation with chained equations approach, such approaches would to a great extent simply reify the hypothesized outcome (that added board members are more likely to match the board party). Therefore, the statistically conservative approach is to simply perform the analysis of board member appointments for only known partisans.

4.3.8 Board Change Event Lag Periods

As previously indicated, although board change events rely upon the comparison of a current board and a prior board occurring in the past, referred to as the lag, l, the period of lag varies. Practically, what sort of phenomena could be reflected by a multiyear lag? For instance, if a board simply adds and drops one member over a one-year lag, we would classify this event as a swap. Yet, a board likely makes changes outside of an annual calendar, and may, in fact, go through multiyear transition periods. Consider a board that adds and drops one member in 2013, adds two members in 2014, and drops two members in 2015. A one-year lag would show the following events: {2013: [SWAP], 2014: [ADD, ADD], 2015: [DROP, DROP]}; whereas a two-year lag would reveal: {2014: [SWAP, ADD, ADD], 2015: [SWAP, SWAP]}; and a three-year lag would show: {2015: [SWAP, SWAP, SWAP]}. In point of fact, depending on the lag set, we see discrete sets of board events.

Analytically, we could simply select a given lag-year and do analysis for that lag-year set of data only. For instance, we could analyze the data only for lag year, $l = 1$, $l = 2$, or $l = 4$. Since the ISS data is annual data, with included years of 2007-2018, if a given company has a board for each of these years, the range of possible lag years, $l = [1 \ldots 11]$. Examining a single year lag may capture a certain phenomenon but overlook others if board member compositional changes could theoretically evolve over several years. So I may best analyze the scenarios, I designed code to calculate board change events for every range of lag years available to a firm, $l = [1 \dots N]$, where N equals the number of included years for a firm less one. As I elaborate below, there are several approaches to analyzing the number of possible lag years, and I include both approaches, including full lag-year ranges $[1, 11]$, as well as single-year lags, among other possibilities, reserving most of the additional analyses for the appendix.

4.3.9 Cross-Classified Random Effects Logistic Regression Models

In this analysis, I ask how the partisanship of a firm's board influences the decision to admit either a new Democratic or Republican board member, and whether that likelihood varies by whether the board member is simply an additional member or succeeding an outgoing member of the board. Although the primary analysis utilizes multivariate, multi-level modeling, I also provide a number of descriptive statistics of the study variables as well as some bivariate graphs to illustrate the underlying phenomena. Before turning to the formal models, consider the descriptive statistics that result from the above data pipeline (Table 4.2).

To formally model how the partisanship of a firm's board influences the addition or succession of new board members of a given party, I conduct a type of longitudinal modeling known as cross-classified random effects (CCRE) logistic regression models (Raudenbush and Bryk 2002), used in educational studies, age-period-cohort analyses, and electoral studies (Park and Jensen 2007; Yang and Land 2006, 2006). Given the binary outcome variables, I utilize logistic regression, a type of hierarchical generalized linear model, which can be extended with cross-classified random effects (Caren, Ghoshal, and Ribas 2011; Raudenbush and Bryk 2002).

This type of hierarchical generalized linear model includes both level-1 fixed effects for primarily board-level features as well as level-2 cross-classified random effects for intersecting

Table 4.2: Descriptive Statistics, Board Member Events, 2007-2018: Party-Cycle

	1-Year Lag	2-Year Lag	2-4-Year Lags	All-Year Lags
Board Events				
Add	1,105 (24.07%)	1,298 (20.78%)	3,842 (17.70%)	10,031 (14.98%)
Drop	1,075 (23.42%)	1,267 (20.28%)	3,747 (17.26%)	9,628 (14.38%)
Swap	1,760 (38.34%)	3,484 (55.78%)	13,855 (63.83%)	46,371 (69.27%)
Equal Swap	644 (14.03%)	1,192 (19.08%)	4,768 (21.97%)	16,531 (24.69%)
Unequal Swap	1,116 (24.31%)	2,292 (36.70%)	9,087 (41.87%)	29,840 (44.58%)
No Change	650 (14.16%)	197 (3.15%)	261 (1.20%)	913 (1.36%)
New Board Members				
Republicans	1,055 (36.82%)	1,807 (37.79%)	6,924 (39.13%)	22,484 (39.86%)
Democrats	583 (20.35%)	961 (20.10%)	3,366 (19.02%)	10,049 (17.82%)
Unknown	1,227 (42.83%)	2,014 (42.12%)	7,407 (41.85%)	23,869 (42.32%)
Dropped Board Members				
Republicans	1,142 (40.28%)	1,947 (40.98%)	7,253 (41.21%)	22,657 (40.46%)
Democrats	667 (23.53%)	1,127 (23.72%)	4,309 (24.48%)	14,220 (25.39%)
Unknown	1,026 (36.19%)	1,677 (35.30%)	6,040 (34.31%)	19,122 (34.15%)
Event Match				
Match	1,780 (45.18%)	2,742 (45.33%)	9,740 (45.42%)	30,148 (45.66%)
Unmatched	2,160 (54.82%)	3,307 (54.67%)	11,704 (54.58%)	35,882 (54.34%)
Missing	650 (14.16%)	197 (3.15%)	261 (1.20%)	913 (1.36%)
Board-Level Metrics (Mean)				
Median Age	62.97 ± 3.49	63.01 ± 3.41	63.05 ± 3.37	63.03 ± 3.32
Female Proportion	0.20 ± 0.09	0.20 ± 0.09	0.21 ± 0.09	0.22 ± 0.09
Black / Hispanic Proportion	0.11 ± 0.09	0.12 ± 0.09	0.12 ± 0.09	0.13 ± 0.09
Minority Proportion	0.20 ± 0.17	0.19 ± 0.15	0.17 ± 0.13	0.17 ± 0.12
Non-USA Proportion	0.03 ± 0.06	0.04 ± 0.06	0.03 ± 0.06	0.03 ± 0.06
Board Size	11.38 ± 2.12	11.40 ± 2.05	11.40 ± 2.00	11.38 ± 1.97
Median Outside Board Ties	0.99 ± 0.56	0.99 ± 0.55	0.99 ± 0.55	0.98 ± 0.54
Board Party X Events				
Democratic Board	1,092 (23.79%)	1,411 (22.59%)	4,593 (21.16%)	13,203 (19.72%)
Republican Board	3,498 (76.21%)	4,835 (77.41%)	17,112 (78.84%)	53,740 (80.28%)
Firm Party X Events				
Polarized Democratic	444 (13.39%)	556 (12.19%)	1,926 (12.06%)	5,917 (12.01%)
Amphibious Firm	2,143 (64.63%)	3,001 (65.78%)	10,485 (65.63%)	32,338 (65.62%)
Polarized Republican	729 (21.98%)	1,005 (22.03%)	3,565 (22.31%)	11,029 (22.38%)
U.S. Presidential Party				
Democrat	3,286 (71.59%)	4,840 (77.49%)	16,193 (74.60%)	39,258 (58.64%)
Republican	1,304 (28.41%)	1,406 (22.51%)	5,512 (25.40%)	27,685 (41.36%)
Observations				
N	4590	6246	21705	66943
Firms	274	273	273	274
Sectors	14	14	14	14
Years	11	10	10	11
Lag Years	1	1	3	11
Time Period and Lags				
Year Range	2008, 2018	2009, 2018	2009, 2018	2008, 2018
Years Included (w/lag)	2007, 2018	2007, 2018	2007, 2018	2007, 2018
Lag Range	1, 1	2, 2	2, 4	1, 11

Notes: Descriptive statistics calculated for discrete lag years. That is, each column uses a discrete set of year lag(s) as follows: 1-year lag, 2-year lag, 2-4-year lags, and 1-11 (all) year lags. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.

random variation of the fixed effects, namely how the modeled effects might vary by both firm and election cycle. Each model takes the following general form:

Level 1 - within-cell model:

$$\eta_{ijk} = \beta_{0jk} + \sum_{p=1}^{P} \beta_p X_p \tag{4.1}$$

Level 2 - between-cell model:

$$\beta_{0jk} = \gamma_0 + u_{0j} + v_{0k},\ u_{0j} \sim N(0, \tau_{u0}), v_{0k} \sim N(0, \tau_{v0}) \tag{4.2}$$

Combined model:

$$\eta_{ijk} = \gamma_0 + \sum_{p=1}^{P} \beta_p X_p + u_{0j} + v_{0k},\ u_{0j} \sim N(0, \tau_{u0}), v_{0k} \sim N(0, \tau_{v0}) \tag{4.3}$$

for $i = 1, \ldots, n_{jk}$ board events within firms j and years k;
$j = 1, \ldots, 274$ firms;
$k = 1, \ldots, 11$ years;

where $\eta_{ijk} = log\Big[\frac{\pi_{ijk}}{(1-\pi_{ijk})}\Big]$ and $\pi_{ijk} = Prob\Big\{\text{New REP|DEM Board Member}_{ijk}\Big\}$ for a given board event i in firm j for year k; β_p reflects level-1 fixed-effect coefficients β_p for the vector X_p of board-event variables, such as the board's political party, the type of board event (addition or succession), as well as other company variables; for $p, \ldots, P$ variables, where P is the maximum number of level-1 variables for a given model; γ_0 is the intercept; and $u_{0j} \sim N(0, \tau_{u0})$, $v_{0k} \sim N(0, \tau_{v0})$ are the random intercepts, which have variances τ_{u0} and τ_{v0}.

In other words, our outcome, η_{ijk} can be thought of as the log odds of successfully adding a new Republican or Democratic board member. Since a number of outcomes are possible, I examine discrete models for the $Prob\Big\{\text{New REP Board Member}_{ijk}\Big\}$ and $Prob\Big\{\text{New DEM Board Member}_{ijk}\Big\}$. It should further be noted that in the above model, the exact number of board events i, firms j, and years k vary by the included number of covariates P as well as the fixed number of lag-years l included in the underlying board-level data pipeline. The astute observer will note that l is not included in equation 4.3, chiefly because it is fixed for the entire subset of data modeled. We can extend the primary model 4.3 by adding an additional random effect for the number of lag-years utilized in the board-level data-generation pipeline. That is, rather than restrict the number of lag-years, I decided to analyze every lag-year subset at once with an additional cross-classified random-intercept for the lag years, l:

$$\text{Combined model:}$$
$$\begin{aligned}\eta_{ijkl} = &\gamma_0 + \sum_{p=1}^{P} \beta_p X_p + u_{0j} + v_{0k} + w_{0l}, \\ &u_{0j} \sim N(0, \tau_{u0}), v_{0k} \sim N(0, \tau_{v0}), w_{0l} \sim N(0, \tau_{w0})\end{aligned} \tag{4.4}$$

for $i = 1, \ldots, n_{jkl}$ board events within firms j, years k, and lag years l;
$j = 1, \ldots, 274$ firms;
$k = 1, \ldots, 11$ years;
$l = 1, \ldots, 11$ lag-years;

where the specifications for equation 4.3 also apply to equation 4.4 for a given board event i in firm j for year k and lag-year l, with the additional caveat that the number of possible years k is inversely related to lag-years l. All modeling for equations 4.3 and 4.4 was calculated using the *glmer* function from the *lme4* package with the BOBYQA optimizer set in the glmerControl (Bates et al. 2015; Douglas Bates, Bolker, and Walker 2015). To reiterate a point made earlier, in all the models, as well as the bivariate analyses, I only evaluate data where the incoming or added board member has a known party identity.[14] Descriptive

[14] To clarify this point, all the models—for example, Table 4.3 and Table 4.4—as well as Figure 4.2, only perform analysis where the incoming or added board member has a known party identity. The two primary categories of board member appointments include board member additions and board member successions (alternatively referred to as a swap or replacement). Because swaps involve not only an incoming board member but also an outgoing board member, I only require that the incoming board member have a known party identity. The departing board member may have either a known or unknown party identity. Descriptive statistics for this specific subset of observations can be found in Appendix D, Table D.4. For simplicity, the bivariate graph, Figure 4.1, only contains cases where the incoming and outgoing board members have known

statistics for the entire analysis dataset, including persistent boards (no change over the lag period) and board drops is provided in Table 4.2), and a more selective subset reflecting data for only known incoming partisan board members is found in Appendix D, Table D.4. Collectively, the analysis will help illustrate the extent to which affective polarization and partisan homophily affect the appointment of new members to a firm's corporate board.

4.4 Analysis

When considering whether affective polarization and partisan homophily can affect the appointment of corporate board members, let us first consider the bivariate pattern witnessed in board member events. Here, I specifically focus on the incoming board members in two types of board appointment events, additions and successions, which I alternatively refer to as swaps. Additionally, I consider the party of outgoing board member drops (excluding swaps).[15] In Figure 4.1, we can see the partisan pattern of incoming and outgoing board members demonstrated in both Democratic and Republican corporate boards.

Examining the results, we can see that Democratic boards are significantly more likely to appoint copartisan board members. We see these results for both board member successions and additions. Although we see significant differences for all Democratic board appointments, in the case of swaps, the incoming board member is a Democrat in 66.5% of cases compared to 58.4% of the cases for additions. Turning to the results for Republican boards, we see a similar pattern. For both board member swaps and additions, Republican boards have a significantly higher incidence of appointing incoming Republican board members. For

partisanship. Descriptive statistics for this alternative subset of observations can be found in Appendix D, Table D.3.

[15]Note that in this example, I only evaluate board member events that are specifically encoded as a drop. Thus, these are outgoing board members only from drops, not all outgoing board members from swaps and drops. A preliminary analysis considering all outgoing members shows similar results to only considering drops in isolation.

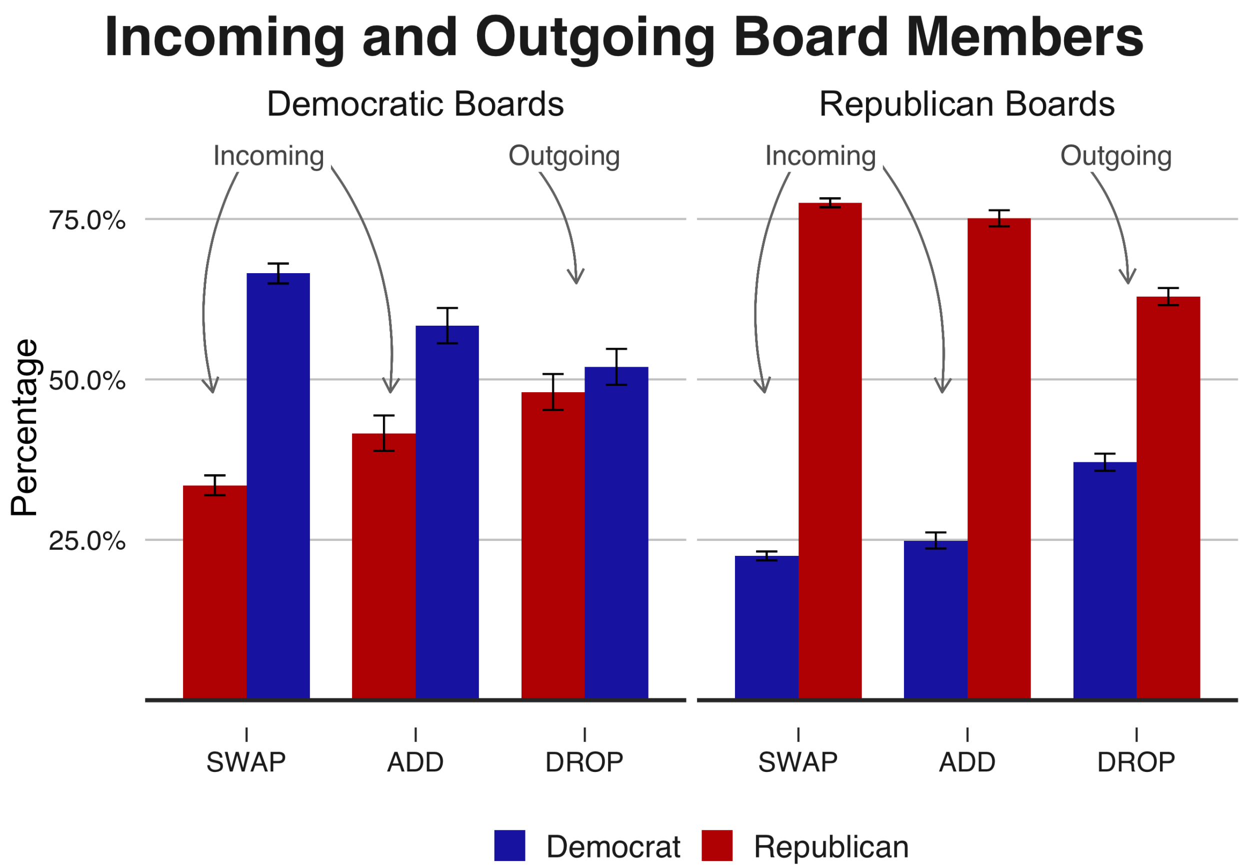

Figure 4.1: Incoming and Outgoing Board Members by Board Member and Board Party

Notes: Figure generated using all lags (1-year, 11-year) included. Error bars indicate a 95% CI. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. For swaps or adds, the incoming board member is represented in the figure. For drops, the outgoing board member is represented. Collectively, we can see to what extent the party of the incoming or outgoing board member matches with the party of the firm's board. Only known partisans used. Specifically, all events with an unknown board member party in either the incoming or outgoing board member were dropped. N = 29,340 events. Republican board swaps, adds, drops: 13,799, 4,543, 5,016. Democratic board swaps, adds, drops: 3,534, 1,226, 1,222.

Republican boards, 77.5% of incoming board member swaps and 75.1% of board member additions were Republicans.

Synthesizing these patterns, we see that both Democratic and Republican boards favored copartisan appointments. These patterns exist for both board additions and swaps. The higher frequency of copartisan board appointments parallels the significantly less frequent occurrence of appointing opposing partisans. These patterns of affective polarization and partisan homophily, while evident in both Republican and Democratic boards, are more salient in Republican boards. In contrast to board appointments, we do not see evidence that boards are more likely to drop opposing partisans. In fact, Republican boards are significantly more likely to drop Republican board members. Democratic boards also have slightly higher rates of dropping copartisans but the results are not significant. Since copartisans are most frequently added, such results most likely reflect the need to drop copartisans in order to maintain a consistent board size. Although these drops are not part of an identified swap, they may be part of swaps using an alternative lag-year or instead precede future board additions. Nonetheless, we see patent partisan patterns in board member appointments in this bivariate analysis.

If we turn our attention to how these patterns might vary by year, we can glean additional insight. Consider how the level of partisanship has changed in recent years, starting with Democratic boards. Although Democratic boards are more likely to select a board member who matches the partisanship of the board (Figure 4.1)—that is appoint a Democratic board member in at least 50% of cases—this fact varies by year and whether the appointment is a swap or addition. Mirroring the trend seen in Figure 4.1, we can see that in Democratic firms, board member swaps more frequently exemplify partisan matching than board member additions (Figure 4.2). From 2008 to 2018, partisan matching in board member succession increased for Democratic firms and remained fairly stable year over year.

In contrast, we have seen a downward trend in partisan matching for board member additions in Democratic firms. In part, this trend may be related to the lesser frequency of Democratic board additions, compared to the increasing frequency of board member swaps in Democratic boards.[16] Although it proves difficult to disentangle, a possible explanation is that Democratic boards might elect to utilize board member succession more commonly than additions to bolster their Democratic ranks, relative to Republican boards. For Republican boards, the magnitude of partisan matching, both for board member succession and board member additions, has tended to increase over the years. When considering all boards, we

[16]To elaborate, whereas Democratic board member addition events increase from 31 to 205 between 2008 and 2018, Democratic board member swap events increase from 27 to 1079 over the same period. I visualize these trends in Appendix D, Figure D.1. To an extent, swaps would be expected to increase more than additions since multiple lag-years compound in successive years.

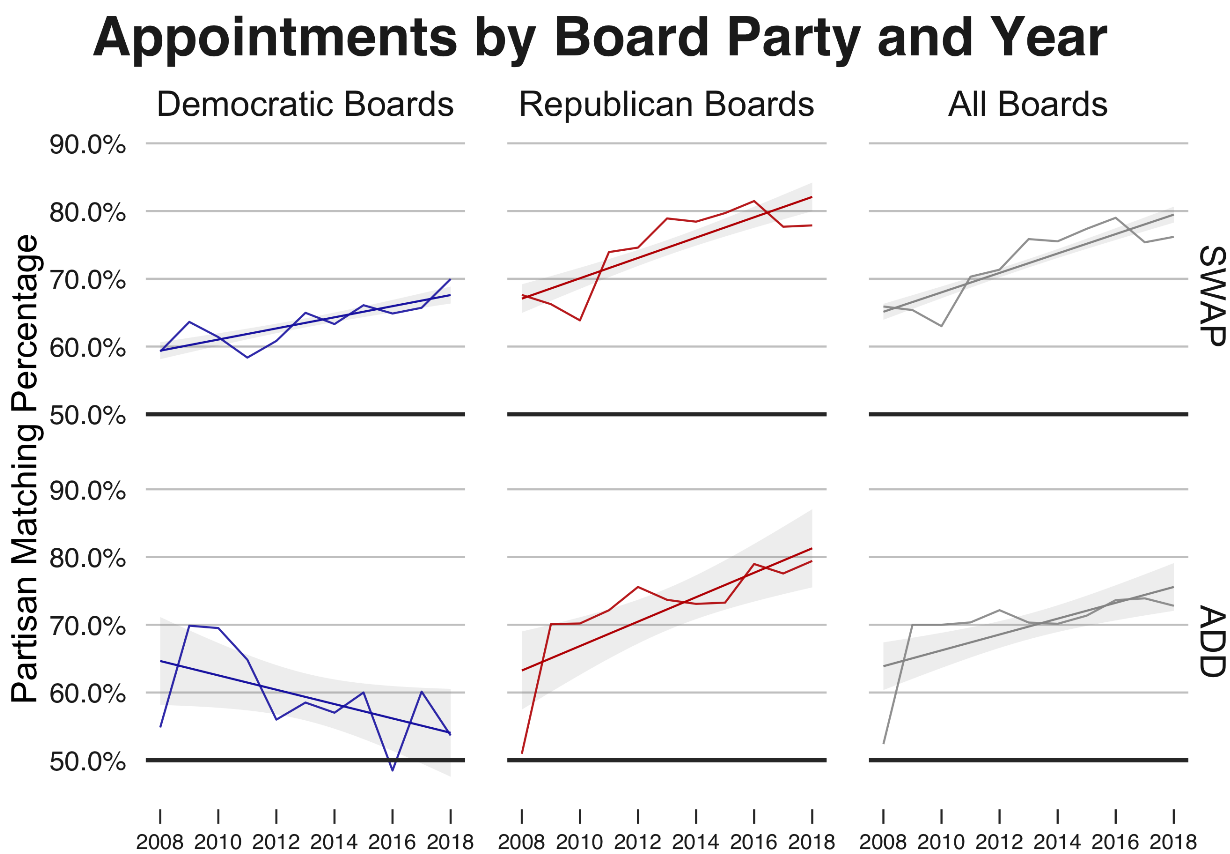

Figure 4.2: Partisan Matching for Board Appointments by Party and Year

Notes: Figure generated using all lags (1-year, 11-year) included. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. Collectively, we can see to what extent the party of the incoming board member matches with the party of the firm's board. All events with an unknown board member party in the incoming board member were dropped, but unknown outgoing board party members were retained, which is the same approach adopted in the formal models. In the subplots, the yearly figure is plotted along with a GLM trend line and confidence interval calculated in R.

witness similar tends of intensified partisan matching from 2008 to 2018. Of course, a number of potential factors might be unaccounted for in these bivariate plots. To garner greater confidence in the results and their robustness, let us turn to the multivariate models.

Turning to the CCRE logit models, let us first consider the likelihood that a given board appoints a Republican board member (Table 4.3). Examining the models, we can see that not only is there a significantly higher likelihood that a Republican board will appoint a Republican board member, but the effect size is also fairly large ($OR = 3.85 - 4.18$) and highly significant $p < 0.001$ in each of the four models. In fact, besides stability across various model parameterizations (Table 4.3), these effects seem robust to multiple lag-year permutations as well as fixed versus variable partisanship, as displayed in Appendix D. If anything, we see even stronger effect sizes in the appendix models versus Table 4.3, which utilizes all available lag years. Models using only the one-year lag demonstrate a similar effect, ($OR = 3.58 - 4.24$), $p < 0.001$ (Table D.5), and those with a two-year lag are even stronger, ($OR = 4.86 - 5.25$), $p < 0.001$ (Table D.7). Models using fixed partisanship (versus the party-cycle measure) likewise, have stronger effects still. Keep in mind that for all these models, a Republican board has the reference group of a Democratic board. We can alternatively interpret these results as stating that Democratic boards have a significantly lower likelihood of appointing a Republican board member (Appendix D, Table D.9). Before diving into the results for the additional covariates, let us continue the discussion of primary partisan effects. Consider the results in Table 4.4, which shows the likelihood that a Democratic board member will be appointed. Examining the Republican board coefficient, we can see that a Republican board is significantly less likely to appoint a Democrat to the board ($OR = 0.24 - 0.26$), $p < 0.001$, compared to the reference group of a Democratic board. As before, we can alternatively interpret this to say that a Democratic board is significantly more likely to appoint a Democratic board member ($OR = 3.85 - 4.18$), $p < 0.001$, compared to a Republican board member (Appendix D, Table D.10).

Synthesizing the results seen across these models, board members are significantly more likely to be appointed when their partisanship matches the partisanship of the board. That is, copartisans are most likely to be appointed to the board. Democratic boards are more likely to appoint Democrats, while Republican boards are more likely to appoint Republicans. The opposite is also true. Opposing partisans remain significantly less likely to be appointed to a corporate board. Democrats have much lower odds of appointment to a Republican board, while Republicans similarly have low odds of appointment to a Democratic board. Although we might conclude that these results support a theory of partisan homophily, the results do not conversely exclude the affective polarization argument. In fact, as highlighted above, partisan homophily simply reflects a condition of association among like others, in this

Table 4.3: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-11-Year Lags, Odds Ratios Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.264***	1.269***	1.349***	1.352***
Board Member Equal Swap	1.713***	1.716***	1.696***	1.678***
Republican Board	4.180***	4.071***	3.967***	3.848***
Democratic Firm			0.851	0.869
Republican Firm			1.678	1.383
Board Features				
Board Size (Log)		0.857	0.706*	0.680*
Median Age (Log)		0.441*	1.023	1.185
Proportion Female		0.481*	0.478*	0.444*
Proportion Black or Hispanic		0.150***		0.357*
Proportion Minority			0.338***	0.429***
Proportion Non-US				1.301
Median Outside Board Ties		0.883**	0.916	0.932
Firm Sectors				
Capital Goods				3.359
Conglomerates				0.267
Consumer Cyclical				0.487
Consumer Goods				0.869
Consumer/Non-Cyclical				0.656
Energy				0.472
Financial				0.473
Healthcare				0.673
Services				0.613
Technology				0.578
Transportation				0.533
Utilities				0.929
Other Features				
U.S. President (Democrat)		1.051	0.959	0.924
Constant	0.736*	50.261*	2.247	2.506
Level-2 Random Intercepts				
Firm Variance	3.132	3.198	2.735	2.471
Year Variance	0.06	0.082	0.052	0.058
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-15,382.530	-15,355.190	-11,838.270	-11,674.410
AIC	30,779.060	30,736.370	23,706.540	23,406.810
BIC	30,837.790	30,845.440	23,828.380	23,642.040

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

case, copartisans. We certainly see the more likely association of copartisans in corporate boards. Affective polarization commonly references partisan animus or aversion to those in the opposing party, which likewise finds support in the models.

Although I will elaborate on these findings in the discussion, at the moment, however, let us return to the additional conclusions that can be gleaned from the models beyond partisan homophily and affective polarization (Tables 4.3, 4.4). Consider how the type of appointment affects the likelihood of appointment for Republican versus Democratic board members. Recall that these models consider not only additions but also board member successions or swaps, namely equal swaps and unequal swaps. Checking Table 4.3, we can see that a Republican board member is significantly more likely to be appointed if the event is an addition, ($OR = 1.26 - 1.35$), $p < 0.001$, or an equal swap (an equal partisan exchange), ($OR = 1.68 - 1.71$), $p < 0.001$, which in this case would be an incoming Republican replacing an outgoing Republican board member. By extension, Republicans are less likely to be appointed in the event of an unequal swap, which in this case would be a Republican replacing a Democrat.

When considering the results for appointing a Democrat, a parallel albeit reverse set of findings exists. Democratic board members are less likely to be appointed following an addition event, ($OR = 0.74 - 0.79$), $p < 0.001$, or an equal swap (Democrat replacing a Democrat), ($OR = 0.58 - 0.60$), $p < 0.001$, compared to the reference group, wherein a Democrat succeeds a Republican board member. In part, these results shed additional light on Figure 4.2. We know from the models that Democratic boards are more likely to appoint Democratic board members and that Democrats are more often appointed when they succeed outgoing Republican members. The declining incidence of partisan matching for additions versus the increased partisan matching in swaps follows this interpretation from the multivariate models. Overall, while the type of event impacts a board member's odds of appointment, and these results are significant, they represent a considerably smaller effect than the partisanship of the firm's board.

Next, let us evaluate the results of other board features. Here, I focus on the results using other predictors of board diversity, particularly the proportion of the board that is

Table 4.4: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-11-Year Lags, Odds Ratios Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.791***	0.788***	0.742***	0.740***
Board Member Equal Swap	0.584***	0.583***	0.590***	0.596***
Republican Board	0.239***	0.246***	0.252***	0.260***
Democratic Firm			1.176	1.151
Republican Firm			0.596	0.723
Board Features				
Board Size (Log)		1.167	1.416*	1.470*
Median Age (Log)		2.268	0.977	0.844
Proportion Female		2.078*	2.093*	2.251*
Proportion Black or Hispanic		6.663***		2.798*
Proportion Minority			2.959***	2.333***
Proportion Non-US				0.769
Median Outside Board Ties		1.132**	1.092	1.073
Firm Sectors				
Capital Goods				0.298
Conglomerates				3.734
Consumer Cyclical				2.052
Consumer Goods				1.151
Consumer/Non-Cyclical				1.524
Energy				2.116
Financial				2.113
Healthcare				1.486
Services				1.630
Technology				1.729
Transportation				1.875
Utilities				1.076
Other Features				
U.S. President (Democrat)		0.951	1.042	1.083
Constant	1.358*	0.020	0.447	0.399
Level-2 Random Intercepts				
Firm Variance	3.132	3.198	2.735	2.471
Year Variance	0.06	0.082	0.052	0.058
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-15,382.530	-15,355.190	-11,838.270	-11,674.410
AIC	30,779.060	30,736.370	23,706.540	23,406.810
BIC	30,837.790	30,845.440	23,828.380	23,642.040

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

female, black or Hispanic, or minority. First, consider the proportion of the board that is female. Here, we can see that as the board includes a greater proportion of women, we see a lower likelihood of appointing a Republican to the board, $(OR = 0.44 - 0.48)$, $p < 0.05$

(Table 4.3), and a higher likelihood of appointing a Democrat ($OR = 2.08 - 2.25$), $p < 0.05$ (Table 4.4). Similarly, as the proportion of black or Hispanic or alternatively minority board members increases, we see a lower likelihood of appointing a Republican board member, ($OR = 0.15 - 0.36$), $p < 0.05 - 0.001$ and ($OR = 0.34 - 0.43$), $p < 0.001$, respectively. Conversely, we see opposite effects for the likelihood of appointing a Democrat. Of these effects, however, those for the proportion of minority board members appear most robust since they remain significant in at least one of the two possible models, $p < 0.05$ for the 1-year and 2-year lag models (Appendix D, Tables D.5-D.8).

Although we see effects for proportion female or proportion black or Hispanic in the main 1-11-year lag models, we see no significant effects for gender or black or Hispanic corporate board proportions in the more simplistic single 1-year or 2-year lag models (Appendix D, Tables D.5-D.8). In this way, although we see an effect under certain modeling constraints, because these effects only emerge in the scenario of increased event observations and do not appear in the more simplistic models using a single lag year, they should be considered somewhat tenuous as compared to the findings for board partisanship and event type which consistently appear across all modeled contexts.[17]

Apart from diversity features, we should also note several additional findings. Given the power of board partisanship, we do not seem to find any consistent effects for the magnitude of partisanship of the firm. For example, it seems to matter not whether the firm is a polarized Republican, polarized Democratic, or Amphibious firm, as described

[17] To provide additional context about the comparative significance vis-à-vis the number of observations, although the effect for both a Republican board and proportion minority are both $p < 0.001$, this fact would seem to equate their significance. For instance, a p-value of 0.000015 and 0.04 are both $p < 0.05$. In the same way, although both effects, have a probability $p < 0.001$ (Table 4.3), a Republican board has a z value $= 24.49 - 20.20, p < 2e - 16$, that is $p < 0.00000000000000022$, compared to the effects for a higher proportion minority board, which has a z value $= |3.65 - 5.20|$, $p < 0.00026 - 1.98e - 07$. By contrast, in the single-year lag model (Table D.5), the proportion minority has a z value $= |2.43|$, $p < 0.015$ in one model, while a Republican board still has a z value $= 8.06 - 11.01$, $p < 0.00000000000000022 - 0.00000000000000075$. In this way, not only is a Republican board several orders of magnitude more significant, but this significance remains stable across models using $N = 1,638 - 32,533$ events, whereas those for the strongest diversity predictor (minority proportion) largely erode.

in Mausolf (2020a), at least when using variable board partisanship. Truly, many of the so-called Amphibious firms (the reference group in the models), had overall Republican boards with occasionally Democratic-leaning employees (Mausolf 2020a). Generally, the power of the board's partisanship dominated, and in only a handful of the models with a simpler parameterization did we see any effects. Here, a polarized Republican firm predicted a higher likelihood of appointing a Republican board member, ($OR = 1.57 - 1.87$), $p < 0.05$, and a significantly lower likelihood of appointing a Democratic board member, ($OR = 0.64 - 0.54$), $p < 0.05$ (Appendix D, Tables D.11, D.12).

Models using fixed partisanship, however, reveal stronger effects, ($OR = 1.59 - 5.17$), $p < 0.01 - 0.001$ and ($OR = 0.63 - 0.19$), $p < 0.05 - 0.001$ for a Republican board's likelihood of appointing a Republican versus Democrat, respectively (Appendix D, Tables D.14-D.21). For the fixed partisan models, although the significance level and effect size varies, we witness the effects not simply in the simpler model parameterizations, but also a number of the more complex models (Models 3 or 4), often with a significance of $p < 0.001$ under different lag-periods. That the results chiefly exist for fixed partisan models is most likely associated with the fact that the clustering measure of firm partisanship employed from Mausolf (2020a) does not vary by election cycle, but rather is a summary measure after evaluating all election cycles for which data exists. Although the degree of partisan homogeneity in a firm has demonstrable, albeit weaker and less consistent effects, at least for variable partisanship, it nonetheless suggests that firms that are polarized Republican firms might have even more patent partisanship in their board member appointments. As opposed to firm partisanship, however, the models do not show much evidence to support that presidential election cycle, that is, the party of the U.S. president matters since we see only weakly significant effects, $p < 0.05$, in only two models among dozens. Similarly, no persistent, reliable effects exist for firm sector. These latter null findings underscore that in the matter of appointing known partisans to the corporate board of directors, the factors that matter most seem to be those characterizing the partisanship of the board, the firm, and the incoming board member.

4.5 Discussion

In this study, I evaluate the role of political partisanship, chiefly affective polarization and partisan homophily, in corporate board appointments. As we have seen across a series of bivariate and multivariate analyses, the results prove consistent with both affective polarization and partisan homophily hypotheses. Specifically, we see consistent robust effects suggesting that Republican corporate boards are more likely to appoint incoming Republican board members and are less likely to appoint Democratic board members. Likewise, Democratic board members are more likely to be appointed by Democratic corporate boards and less likely to be appointed by Republican boards. Collectively, these patterns support the generalized pattern that corporate boards are significantly more likely to appoint copartisan board members, which supports the partisan homophily hypothesis, and are significantly less likely to appoint opposing partisans, which supports the affective polarization hypothesis, in the sense of partisan animus.

From one perspective, these results extend the canon on partisan homophily (Huber and Malhotra 2017; Iyengar et al. 2018, 2019; Mausolf 2020b), or more generally the types of status homophily for which we see effects (Lazarsfeld and Merton 1954; McPherson et al. 2001). For example, Huber and Malhotra (2017) previously demonstrated political and partisan homophily on both the basis of political, ideological identity and partisan identity using the case of online dating, and Iyengar et al. (2018) shows political alignment in marital partnership to be "choice homophily" or "the individual-level propensity to choose similar others" versus "induced homophily," to use the terminology of (McPherson and Smith-Lovin 1987: 371). Although this study cannot possibly adjudicate whether the partisan homophily demonstrated by corporate boards is purely by choice or preference for copartisans or conversely avoidance of opposing partisans, among other possibilities, the results do augment the growing literature on the effects of partisan homophily in the workplace. For example, although Gift and Gift (2015) does not find partisan homophily in resume evaluation, rather finding affective polarization, we see in Mausolf (2020b), evidence of partisan homophily in resume callbacks. Copartisan applicants were more likely to receive a callback, that is, when the partisanship of the applicant matched the partisanship of the firm, compared to apolitical neutral applicants. Although we cannot make the same comparison to neutral applicants in this study, the results are nonetheless consistent with partisan homophily, except that rather than transpire for entry-level positions, we also see evidence of partisan homophily among corporate leadership.

At the same time, the results of this analysis are also consistent with affective polarization in the sense of partisan animus or aversion toward opposing partisans (Iyengar and Westwood 2015; Iyengar et al. 2019). In point of fact, although research on partisan homophily is limited, occurring in limited contexts, such as romance or resume evaluation (Huber and Malhotra 2017; Mausolf 2020b), manifest effects exist for affective polarization, which has previously appeared on a number of fronts, including denigrating trust, discounting economic rewards, or lowering wage-floor preferences (Carlin and Love 2013; Iyengar and Westwood 2015; McConnell et al. 2018), altering purchase behavior or market decisions (McConnell et al. 2018; Panagopoulos et al. 2016), creating an aversion to cross-party romantic entanglements (Iyengar et al. 2012; Kiefer 2017), or lowering the likelihood of scholarships or gaining first-round interviews while searching for employment (Gift and Gift 2015; Iyengar and Westwood 2015; Mausolf 2020b). Extending these results, we can now state that forces of affective polarization also appear to lower the likelihood that a potential board member will be appointed to a corporate board of directors.

The general trend of witnessing stronger effects of affective polarization than partisan homophily can, in part, be explained by the salience of partisan animus or partisan hostility toward opposing partisans over positive affect for copartisans (Iyengar and Krupenkin 2018). Yet, the difficulty also exists in the common use of affective polarization as synonymous with opposing party animus (Iyengar and Westwood 2015; Iyengar et al. 2019). To wit, affective polarization also captures the difference spanning attitudes toward copartisans versus opposing partisans (Iyengar and Westwood 2015; Iyengar et al. 2019). In fact, many of the aforementioned studies on affective polarization demonstrate this fact without being able to disentangle animus versus positive affect through, for example, a neutral partisan category. In fact, the effects are more often shown by contrasting the behavior experienced by opposing partisans versus copartisans, such as rewards or benefits for copartisans contra deficits for opposing partisans. From this perspective, although we cannot disentangle forces of attraction and aversion, the overarching pattern of preference for copartisans and aversion to opposing partisans in corporate board appointments remains consistent with the affective polarization canon (Iyengar et al. 2019), and thus extends its legacy to an important dimension of organizational behavior.

Shifting the focus to dimensions of organizational behavior and diversity, my results likewise make important contributions. Considering first the role of political diversity in organizations, these results present a foil to the quintessential ideological analysis by (Bonica 2013, 2014, 2016). In particular, although Bonica (2016) demonstrates ideological diversity, even among highly partisan firms, such as Marathon Petroleum (Bonica 2016; Mausolf 2020a), such results are not necessarily heterodox given the considerable ideological heterogeneity evident among homogenous partisans (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Fiorina and Abrams 2008). Similarly, the results do not necessarily countervail Bonica's (2016) assertion of bipartisan boardrooms, at least in one sense. Certainly, some types of firms are more bipartisan than others (Mausolf 2020a), and indeed both among overall Democratic or Republican boards, we see evidence that these boards on occasion appoint members of the opposing political party. Yet, in the sense that the term *bipartisan* connotes some echelon of magnanimous collaboration that transcends the frictions of partisanship, this is certainly not the case. Rather, despite having some degree of bipartisanship, in the sense that not all boards are in totality comprised of a single party, we see salient partisan behavior within these largely homogenous groups of partisans, such that the prospects of appointing someone from the opposing political party remains considerably less probable than appointing someone matching the party in the boardroom.

Reflecting how these findings relate to theories of diversity within firms, and especially corporate board membership, a number of points are worth discussion. Consistent with the general body of diversity literature, I likewise find that partisan diversity, like diversity on so many other key social dimensions, such as race, ethnicity, or gender, likewise presents a detrimental scenario for minorities in organizations (DiTomaso et al. 2007; Jackson et al. 2003; Williams and O'Reilly 1998). Of course, an important distinction here is that while many of the studies reviewed in organizational research consider performance outcomes, value, or dynamics (DiTomaso et al. 2007; Jackson et al. 2003; Williams and O'Reilly 1998), I simply evaluate the likelihood of appointment on the basis of partisanship. Since the perceived downfalls of diversity extend from denigrated communication, integration, and conflict associated with diversity on categorical dimensions, on which trust remains an integral part (Brewer 1981; Meyerson et al. 1996), and cross-party relationships instill diminished trust and increased hostility (Carlin and Love 2013; Iyengar and Westwood 2015), we would expect boards to more often discriminate against opposing partisans over copartisans, and to this end, my work is consistent with the general standing of diversity in organizational research. Of course, more research is needed to better understand how the existence of partisan minorities contributes to intra-firm dynamics and performance.

Considering board appointments specifically, prevailing evidence suggests the appointment of minorities, such as gender or minority members to the board, negatively impact firm performance and stock valuation (Adams and Ferreira 2009; Dobbin and Jung 2011). Likewise, boards might also consider what signal would be sent by the appointment of a board or other executive position to institutional investors or business media (Dobbin and Jung 2011; Khurana 2002; Krawiec and Broome 2008), which could directly, negatively impact stock price as a result of investor bias against the social identity of minority board appointees (Dobbin and Jung 2011). Since these prior findings suggest boards would preference non-diversity partisan appointees versus diversity partisan appointees, my findings are consistent with the supposition that can be derived from these studies on organizational diversity. Since corporate boards are indeed less likely to appoint partisan minorities, further research should be conducted to first consider to what extent the appointment of partisan minorities positively or negatively affects stock valuation, investor bias, or discourse from business media and analysts (*c.f.* Dobbin and Jung 2011; Khurana 2002). Research should also unpack board members' rationales in appointing copartisans versus opposing partisans along the lines of Krawiec and Broome (2008). Furthermore, although we have seen burgeoning research on how political ideology or partisanship affect corporate social responsibility or executive compensation (Briscoe et al. 2014; Chin et al. 2013; Gupta and Briscoe 2019; Gupta and Wowak 2017; Gupta et al. 2017), since as I have demonstrated, partisanship, chiefly affective polarization and partisan homophily, shape corporate board appointments and the partisan balance of boards, we need a better understanding of how the appointment of copartisan and opposing partisan members can shift dimensions of organizational behavior like corporate social responsibility or responsiveness to mobilization compared to prior firm behavior under prior instantiations of partisan diversity or homogeneity on corporate boards.

Beyond the diverse literature to which this study speaks, certain caveats, some of which have been previously highlighted, deserve mention. As perhaps evident in the data, methods, and analysis segments, performing this type of research using quantitative public records data proves challenging, just in determining the partisan leanings of firms, their employees, and boards of directors (Bonica 2016; Mausolf 2020a). As we have seen, a number of challenges persist, such as the ability to adequately capture repeated measures of individual partisanship for individuals spanning several election cycles. Although I have captured variable partisanship to an extent, the temporal partisan challenge, combined with the difficulties of linking external proprietary datasets on directors to this partisan data, creates a high bar to entry, a fact familiar to scholars in this space (Bonica 2016; Chu and

Davis 2016; Gupta and Wowak 2017; Gupta et al. 2017). This not only presents a barrier to future scholarship but also makes temporal analyses, such as those performed here, somewhat limited, given the caveats of variable partisanship. Nonetheless, since the models show that most variation exists across firms rather than time, combined with the consistent main effects using both fixed and variable partisanship, to an extent assuages concerns about the robustness of primary partisan effects. Similarly, the partisan effects prevail across multiple model permutations and do not seem to be adversely affected by the number of lag-years considered. As previously discussed, the same cannot be said for alternative effects like gender diversity. Lastly, an additional caveat exists in that the analysis can only consider the results for successful board appointments. We have no knowledge, for example, of the exact pool of all potential applicants (or their partisanship), which may have been considered for a board appointment prior to that event occurring. Such a scenario, while optimal, however, seems unlikely, at least at scale from a quantitative records perspective and implausible experimentally at this level of corporate leadership.

Collectively, although various caveats exist in any such study and disentangling positive affect versus partisan animus proves arduous, I demonstrate consistent effects of political partisanship, especially affective polarization, in corporate board appointments. These effects remain consistent both with affective polarization and partisan homophily hypotheses, and if we consider the vantage wherein we emphasize the differential experience faced by copartisans versus opposing partisans, I have demonstrated that political partisanship not only exists at the highest levels of corporate leadership, but indeed helps shape the likelihood of which board members are appointed, and thus not only who wields power in corporate America, but which party retains power for a given firm. The results of increasing affective polarization in firms suggest that corporate boards, if anything, will become more partisan in the future, not less. Given the power of corporations, and especially corporate boards, over both politics and the economy, such results underscore that we must better attune to the role of party in the boardroom.

APPENDIX D

Appendix Chapter 4: Additional Tables and Figures

D.1 Expanding on the Matching Measures of Partisanship to Board Members

To elaborate on the method described in the main paper, I iteratively perform a series of successive joins between the ISS and either the FEC-CP or one of the two DIME-AOI datasets using discrete join methods. This method has the added benefit of explicitly matching individuals. In the majority of cases, the join includes the full name and firm. In total, I utilize twenty discrete join methods.

In brief, this method works as follows. First I attempt an inner join between the ISS and given dataset (FEC-CP, DM1, DM2) on a specified set of left and right join columns and drop all rows not joined on the right side. Once the first join is performed, I perform an anti-join between the original dataset and the latest join. That is, I isolate all rows in the ISS that were not found in the most recent join. Subsequently, the process repeats using a different join method. In total, 20 discrete merge methods are performed. The majority of these joins occur using a company id and some version of the full name, including variations of a full name as a single column or combinations of the full name from first and last name columns. Similarly, most joins first try to find the individual using the primary company id in the ISS data. However, a handful of individuals have a second company at which they are employed. Methods 1-9 rely on the primary company id. Methods 10-18 rely upon the alternative id. These joins mirror joins 1-9 but use the alternative company id instead. The last two joins capitalize on a general search using the DIME-AOI datasets.

According to Bonica (2016), DIME-AOI data only contains board members at Fortune

Table D.1: Summary Matched Partisans by Source and Join: Measure, Fixed-Party

Merge Type	Partisan Data	Left Columns	Right Columns	Count
1A	FEC-CPD	'cid__master', 'fullname__clean__pure'	'cid__master', 'fullname__fec'	7,977
1B	FEC-CPD	'cid__master', 'fullname__clean__simple'	'cid__master', 'fullname__fec'	0
1C	FEC-CPD	'cid__master', 'fullname__clean__nickname'	'cid__master', 'fullname__fec'	1
1D	FEC-CPD	'cid__master', 'fullname__clean'	'cid__master', 'fullname__fec'	0
1E	FEC-CPD	'cid__master', 'first__name__clean', 'last__name__clean'	'cid__master', 'full__first', 'last'	0
2A	DM2	'ticker', 'last__name__clean', 'first__name__clean'	'ticker', 'contributor.lname__clean', 'contributor.fname__clean'	11,242
2B	DM2	'ticker', 'last__name__clean'	'ticker', 'contributor.lname__clean'	594
3A	DM1	'ticker', 'last__name__clean', 'first__name__clean'	'ticker', 'last.name__clean', 'first.name__clean'	6,462
3B	DM1	'ticker', 'last__name__clean'	'ticker', 'last.name__clean'	736
1A (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean__pure'	'cid__master', 'fullname__fec'	463
1B (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean__simple'	'cid__master', 'fullname__fec'	0
1C (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean__nickname'	'cid__master', 'fullname__fec'	1
1D (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean'	'cid__master', 'fullname__fec'	0
1E (Alt)	FEC-CPD	'alt__cid__master', 'first__name__clean', 'last__name__clean'	'cid__master', 'full__first', 'last'	0
2A (Alt)	DM2	'alt__ticker', 'last__name__clean', 'first__name__clean'	'ticker', 'contributor.lname__clean', 'contributor.fname__clean'	11
2B (Alt)	DM2	'alt__ticker', 'last__name__clean'	'ticker', 'contributor.lname__clean'	0
3A (Alt)	DM1	'alt__ticker', 'last__name__clean', 'first__name__clean'	'ticker', 'last.name__clean', 'first.name__clean'	8
3B (Alt)	DM1	'alt__ticker', 'last__name__clean'	'ticker', 'last.name__clean'	0
2A (Gen)	DM2	'last__name__clean', 'first__name__clean'	'contributor.lname__clean', 'contributor.fname__clean'	1,667
3A (Gen)	DM1	'last__name__clean', 'first__name__clean'	'last.name__clean', 'first.name__clean'	197

Notes: All joins are inner joins between the left-side ISS dataset and a right-side partisan dataset denoted in the table. For each join left and right columns are indicated. Joins performed for analyses using the *party* measure.

500 companies, and based on our knowledge of board networks (Chu and Davis 2011, 2016), board members often serve on the boards of multiple firms. Following this premise, board members in the ISS not yet found in the prior 18 joins, were generally searched for among the DM1, and DM2 datasets using the full name (first and last name) without regard for the given company limitation. Table D.1 further describes the joins that occur for the party measure. In first creating the joins for the *party measure*, the FEC-CP, DM1, and DM2 were (1) loaded for the set of possible join columns, as well as the party measure, (2) deduplicated, and (3) had NA values dropped in all columns except the party measure.

This process resulted in a certain allocation of joins from each method and dataset in an optimized order. To best replicate this method when performing the joins by cycle, a special series of prior joins was performed on the FEC, DM1, and DM2 data, such that each deduplicated identity X firm X cycle observation inherited additional rows for each election cycle in the ISS data (2008-2018). In this way, the FEC, DM1, and DM2 datasets each had not only all years natively found in those datasets but also every year in the ISS, where those cycles may or may not intersect. Ostensibly, this method initially results in a number of missing party-cycle observations, which are then imputed (grouped by individual and firm) using the aforementioned two-phase forward-fill, back-fill method. When this data is then joined with the ISS, we have a full range of cycles for each identity. In this way, applying the same series of merge methods (but additionally joining on election cycle) results in a similar allocation of observations from each dataset for the various methods (Table D.2).

Table D.2: Summary Matched Partisans by Source and Join: Measure, Party-Cycle

Merge Type	Partisan Data	Left Columns	Right Columns	Count
1A	FEC-CPD	'cid__master', 'fullname__clean__pure', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	7,949
1B	FEC-CPD	'cid__master', 'fullname__clean__simple', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	0
1C	FEC-CPD	'cid__master', 'fullname__clean__nickname', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	1
1D	FEC-CPD	'cid__master', 'fullname__clean', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	0
1E	FEC-CPD	'cid__master', 'first__name__clean', 'last__name__clean', 'cycle'	'cid__master', 'full__first', 'last', 'cycle'	0
2A	DM2	'ticker', 'last__name__clean', 'first__name__clean', 'cycle'	'ticker', 'contributor.lname__clean', 'contributor.fname__clean', 'cycle'	11,235
2B	DM2	'ticker', 'last__name__clean', 'cycle'	'ticker', 'contributor.lname__clean', 'cycle'	594
3A	DM1	'ticker', 'last__name__clean', 'first__name__clean'	'ticker', 'last.name__clean', 'first.name__clean'	6,490
3B	DM1	'ticker', 'last__name__clean'	'ticker', 'last.name__clean'	743
1A (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean__pure', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	462
1B (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean__simple', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	0
1C (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean__nickname', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	1
1D (Alt)	FEC-CPD	'alt__cid__master', 'fullname__clean', 'cycle'	'cid__master', 'fullname__fec', 'cycle'	0
1E (Alt)	FEC-CPD	'alt__cid__master', 'first__name__clean', 'last__name__clean', 'cycle'	'cid__master', 'full__first', 'last', 'cycle'	0
2A (Alt)	DM2	'alt__ticker', 'last__name__clean', 'first__name__clean', 'cycle'	'ticker', 'contributor.lname__clean', 'contributor.fname__clean', 'cycle'	11
2B (Alt)	DM2	'alt__ticker', 'last__name__clean', 'cycle'	'ticker', 'contributor.lname__clean', 'cycle'	0
3A (Alt)	DM1	'alt__ticker', 'last__name__clean', 'first__name__clean'	'ticker', 'last.name__clean', 'first.name__clean'	8
3B (Alt)	DM1	'alt__ticker', 'last__name__clean'	'ticker', 'last.name__clean'	0
2A (Gen)	DM2	'last__name__clean', 'first__name__clean'	'contributor.lname__clean', 'contributor.fname__clean'	1,667
3A (Gen)	DM1	'last__name__clean', 'first__name__clean'	'last.name__clean', 'first.name__clean'	197

Notes: All joins are inner joins between the left-side ISS dataset and a right-side partisan dataset denoted in the table. For each join left and right columns are indicated. Joins performed for analyses using the *party__cycle* measure.

Table D.3: Descriptive Statistics, Board Member Events, 2007-2018: Party-Cycle, Only Known Partisans Subset

	1-Year Lag	2-Year Lag	2-4-Year Lags	All-Year Lags
Board Events				
Add	644 (33.11%)	754 (26.79%)	2,238 (22.92%)	5,769 (19.66%)
Drop	689 (35.42%)	802 (28.50%)	2,404 (24.62%)	6,238 (21.26%)
Swap	612 (31.47%)	1,258 (44.71%)	5,123 (52.46%)	17,333 (59.08%)
Equal Swap	386 (19.85%)	736 (26.15%)	3,000 (30.72%)	10,230 (34.87%)
Unequal Swap	226 (11.62%)	522 (18.55%)	2,123 (21.74%)	7,103 (24.21%)
New Board Members				
Republicans	810 (64.49%)	1,317 (65.46%)	4,941 (67.12%)	15,804 (68.41%)
Democrats	446 (35.51%)	695 (34.54%)	2,420 (32.88%)	7,298 (31.59%)
Dropped Board Members				
Republicans	820 (63.03%)	1,289 (62.57%)	4,623 (61.42%)	14,251 (60.46%)
Democrats	481 (36.97%)	771 (37.43%)	2,904 (38.58%)	9,320 (39.54%)
Event Match				
Match	1,127 (57.94%)	1,744 (61.98%)	6,285 (64.36%)	19,625 (66.89%)
Unmatched	818 (42.06%)	1,070 (38.02%)	3,480 (35.64%)	9,715 (33.11%)
Board-Level Metrics (Mean)				
Median Age	62.99 ± 3.45	63.11 ± 3.39	63.19 ± 3.37	63.11 ± 3.36
Female Proportion	0.20 ± 0.09	0.20 ± 0.09	0.21 ± 0.09	0.22 ± 0.09
Black / Hispanic Proportion	0.12 ± 0.09	0.12 ± 0.09	0.12 ± 0.09	0.13 ± 0.09
Minority Proportion	0.20 ± 0.17	0.19 ± 0.16	0.17 ± 0.13	0.17 ± 0.12
Non-USA Proportion	0.04 ± 0.06	0.03 ± 0.06	0.03 ± 0.06	0.03 ± 0.05
Board Size	11.48 ± 2.15	11.40 ± 2.04	11.37 ± 1.99	11.36 ± 1.98
Median Outside Board Ties	1.01 ± 0.55	1.00 ± 0.54	1.01 ± 0.54	0.99 ± 0.53
Board Party X Events				
Democratic Board	470 (24.16%)	655 (23.28%)	2,122 (21.73%)	5,982 (20.39%)
Republican Board	1,475 (75.84%)	2,159 (76.72%)	7,643 (78.27%)	23,358 (79.61%)
Firm Party X Events				
Polarized Democratic	185 (12.46%)	240 (11.24%)	850 (11.34%)	2,568 (11.29%)
Amphibious Firm	966 (65.05%)	1,407 (65.90%)	4,922 (65.67%)	14,975 (65.86%)
Polarized Republican	334 (22.49%)	488 (22.86%)	1,723 (22.99%)	5,193 (22.84%)
U.S. Presidential Party				
Democrat	1,440 (74.04%)	2,234 (79.39%)	7,444 (76.23%)	17,698 (60.32%)
Republican	505 (25.96%)	580 (20.61%)	2,321 (23.77%)	11,642 (39.68%)
Observations				
N	1945	2814	9765	29340
Firms	271	269	270	271
Sectors	14	14	14	14
Years	11	10	10	11
Lag Years	1	1	3	11
Time Period and Lags				
Year Range	2008, 2018	2009, 2018	2009, 2018	2008, 2018
Years Included (w/lag)	2007, 2018	2007, 2018	2007, 2018	2007, 2018
Lag Range	1, 1	2, 2	2, 4	1, 11

Notes: Descriptive statistics calculated for discrete lag years. That is, each column uses a discrete set of year lag(s) as follows: 1-year lag, 2-year lag, 2-4-year lags, and 1-11 (all) year lags. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. All events with an unknown board member party in either the incoming or outgoing board member were dropped. This is the same approach taken in Figure 4.1.

Table D.4: Descriptive Statistics, Board Member Events, 2007-2018: Party-Cycle, Formal Models Subset

	1-Year Lag	2-Year Lag	2-4-Year Lags	All-Year Lags
Board Events				
Add	644 (39.32%)	754 (27.24%)	2,238 (21.75%)	5,769 (17.73%)
Swap	994 (60.68%)	2,014 (72.76%)	8,052 (78.25%)	26,764 (82.27%)
Equal Swap	386 (23.57%)	736 (26.59%)	3,000 (29.15%)	10,230 (31.44%)
Unequal Swap	608 (37.12%)	1,278 (46.17%)	5,052 (49.10%)	16,534 (50.82%)
New Board Members				
Republicans	1,055 (64.41%)	1,807 (65.28%)	6,924 (67.29%)	22,484 (69.11%)
Democrats	583 (35.59%)	961 (34.72%)	3,366 (32.71%)	10,049 (30.89%)
Dropped Board Members				
Republicans	380 (38.23%)	789 (39.18%)	3,141 (39.01%)	10,508 (39.26%)
Democrats	232 (23.34%)	469 (23.29%)	1,982 (24.62%)	6,825 (25.50%)
Unknown	382 (38.43%)	756 (37.54%)	2,929 (36.38%)	9,431 (35.24%)
Event Match				
Match	1,149 (70.15%)	1,990 (71.89%)	7,519 (73.07%)	24,311 (74.73%)
Unmatched	489 (29.85%)	778 (28.11%)	2,771 (26.93%)	8,222 (25.27%)
Board-Level Metrics (Mean)				
Median Age	62.77 ± 3.38	62.89 ± 3.32	63.01 ± 3.30	63.07 ± 3.29
Female Proportion	0.19 ± 0.09	0.20 ± 0.09	0.20 ± 0.09	0.22 ± 0.09
Black / Hispanic Proportion	0.11 ± 0.08	0.12 ± 0.08	0.12 ± 0.09	0.13 ± 0.09
Minority Proportion	0.21 ± 0.18	0.19 ± 0.16	0.17 ± 0.13	0.17 ± 0.12
Non-USA Proportion	0.04 ± 0.07	0.04 ± 0.06	0.03 ± 0.06	0.03 ± 0.05
Board Size	11.82 ± 2.13	11.70 ± 2.01	11.60 ± 1.96	11.55 ± 1.92
Median Outside Board Ties	1.01 ± 0.56	0.99 ± 0.54	1.00 ± 0.55	0.99 ± 0.54
Board Party X Events				
Democratic Board	416 (25.40%)	671 (24.24%)	2,297 (22.32%)	6,573 (20.20%)
Republican Board	1,222 (74.60%)	2,097 (75.76%)	7,993 (77.68%)	25,960 (79.80%)
Firm Party X Events				
Polarized Democratic	141 (11.30%)	218 (10.39%)	796 (10.18%)	2,584 (10.38%)
Amphibious Firm	818 (65.54%)	1,406 (67.02%)	5,222 (66.79%)	16,536 (66.41%)
Polarized Republican	289 (23.16%)	474 (22.59%)	1,801 (23.03%)	5,779 (23.21%)
U.S. Presidential Party				
Democrat	1,236 (75.46%)	2,350 (84.90%)	8,457 (82.19%)	20,932 (64.34%)
Republican	402 (24.54%)	418 (15.10%)	1,833 (17.81%)	11,601 (35.66%)
Observations				
N	1638	2768	10290	32533
Firms	269	269	269	269
Sectors	14	14	14	14
Years	11	10	10	11
Lag Years	1	1	3	11
Time Period and Lags				
Year Range	2008, 2018	2009, 2018	2009, 2018	2008, 2018
Years Included (w/lag)	2007, 2018	2007, 2018	2007, 2018	2007, 2018
Lag Range	1, 1	2, 2	2, 4	1, 11

Notes: Descriptive statistics calculated for discrete lag years. That is, each column uses a discrete set of year lag(s) as follows: 1-year lag, 2-year lag, 2-4-year lags, and 1-11 (all) year lags. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. All events with an unknown board member party in the incoming board member were dropped, but unknown outgoing board party members were retained, which is the same approach adopted in the formal models as well as Figure 4.2.

D.2 Supplemental Figures

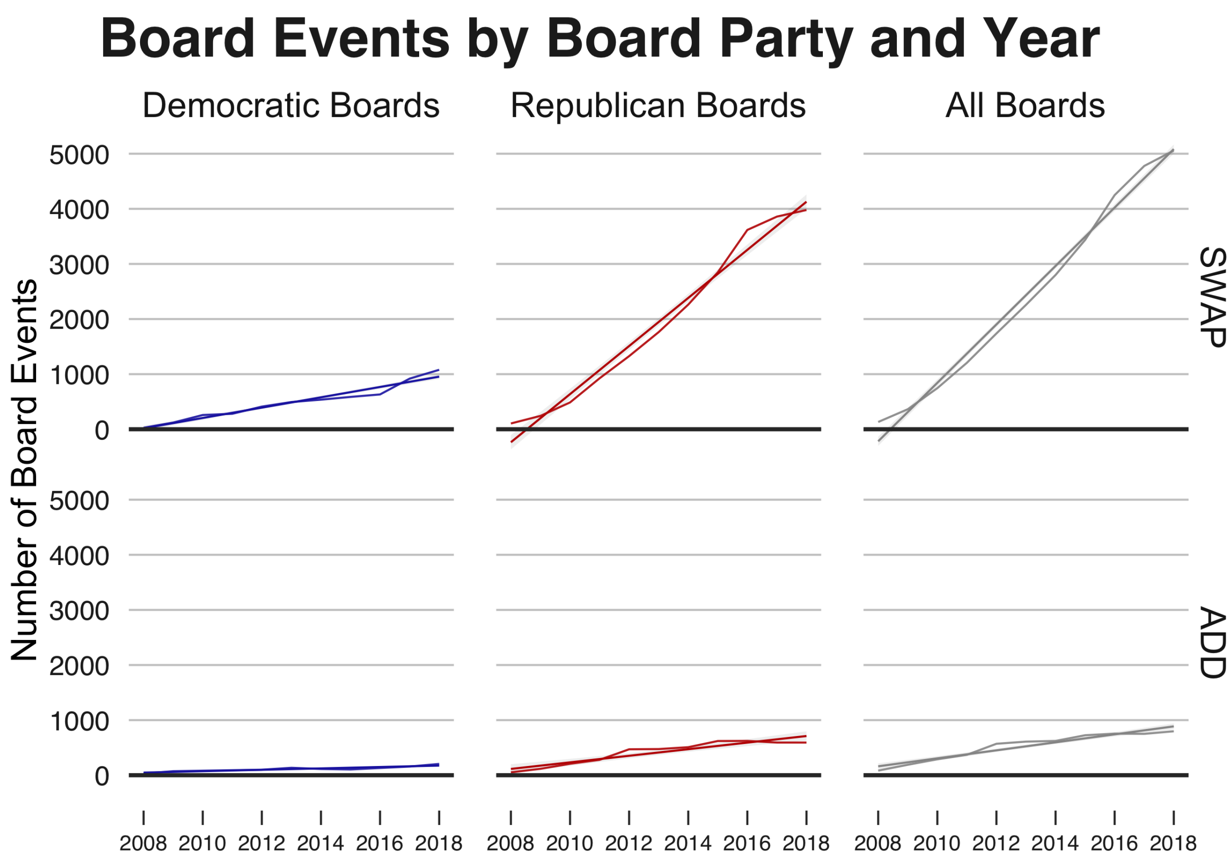

Figure D.1: Yearly Board Member Events by Event Type and Board Party

Notes: Figure generated using all lags (1-year, 11-year) included. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles. In the plot, we can see to the number of board events for swaps and additions. All events with an unknown board member party in the incoming board member were dropped, but unknown outgoing board party members were retained, which is the same approach adopted in the formal models. In the subplots, the yearly figure is plotted along with a GLM trend line and confidence interval calculated in R.

D.3 Additional CCRE Logistic Regression Models Using both the Time-Varying Party-Cycle Measure and the Fixed-Party Measure

Similar to the analysis in the main paper, the following models similarly utilize the *party-cycle* measure, which has the opportunity to change over time for individual board members, at least for those matched using either the FEC-CPD or DM2 datasets, as shown in Table D.2. Importantly, these tables exemplify that the effects found in the primary paper are not simply artifacts of including multiple lag-years, but instead similarly emerge when looking at a single lag-year definition in isolation. In this case, I include both a 1-year lag and a 2-year lag for comparison. To reiterate an earlier point, a 1-year lag means that board-event calculations capture change over a two-year period where those years are consecutive, for example, the changes between a firm's board in 2007 and a firm's board in 2008. By contrast, although a two-year lag also measures changes using two board-years, a two-year gap (versus a one-year gap) exists in calculating board events. To continue the example, a two-year lag would capture differences between a firm's board in 2007 and that firm's board in 2009. Beyond additional models showing the one-year or two-year lag, I also include additional models utilizing an alternative reference group for the partisanship of the board, that is, a reference group of a Republican board instead of a Democratic board. Otherwise, these models mirror those in the main analysis. I also include a simpler set of models with the same covariate parameterization but discrete lag-year periods. Lastly, I include a parallel set of models, which instead use the *fixed-party* measure instead of the variable *party-cycle* measure.

Table D.5: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-Year Lag, Odds Ratios (OR) Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.110	1.115	1.012	0.969
Board Member Equal Swap	1.512**	1.531**	1.373	1.356
Republican Board	4.238***	4.333***	3.642***	3.583***
Democratic Firm			0.984	1.027
Republican Firm			1.698**	1.529*
Board Features				
Board Size (Log)		0.988	1.397	1.543
Median Age (Log)		3.806	3.557	2.985
Proportion Female		1.244	1.131	1.392
Proportion Black or Hispanic		1.130		1.314
Proportion Minority			0.402*	0.490
Proportion Non-US				0.352
Median Outside Board Ties		0.982	0.916	0.889
Firm Sectors				
Capital Goods				1.039
Conglomerates				0.266
Consumer Cyclical				0.348*
Consumer Goods				0.795
Consumer/Non-Cyclical				0.712
Energy				0.578
Financial				0.490
Healthcare				0.597
Services				0.477
Technology				0.412*
Transportation				0.495
Utilities				0.605
Other Features				
U.S. President (Democrat)		1.329*	1.233	1.201
Constant	0.576***	0.002	0.002	0.005
Level-2 Random Intercepts				
Firm Variance	0.126	0.113	0.106	0.04
Year Variance	0.021	0.003	0	0
N	1,638	1,638	1,248	1,222
Firms	269	269	204	197
Years	11	11	11	11
Log Likelihood	-981.837	-979.260	-739.202	-713.009
AIC	1,975.674	1,982.520	1,506.404	1,482.018
BIC	2,008.082	2,047.335	1,578.214	1,625.048

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 1-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.6: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-Year Lag, Odds Ratios (OR) Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.901	0.897	0.988	1.032
Board Member Equal Swap	0.661**	0.653**	0.728	0.737
Republican Board	0.236***	0.231***	0.275***	0.279***
Democratic Firm			1.016	0.974
Republican Firm			0.589**	0.654*
Board Features				
Board Size (Log)		1.012	0.716	0.648
Median Age (Log)		0.263	0.281	0.333
Proportion Female		0.804	0.884	0.718
Proportion Black or Hispanic		0.885		0.761
Proportion Minority			2.489*	2.042
Proportion Non-US				2.837
Median Outside Board Ties		1.018	1.091	1.125
Firm Sectors				
Capital Goods				0.962
Conglomerates				3.765
Consumer Cyclical				2.873*
Consumer Goods				1.258
Consumer/Non-Cyclical				1.404
Energy				1.730
Financial				2.039
Healthcare				1.674
Services				2.098
Technology				2.429*
Transportation				2.020
Utilities				1.652
Other Features				
U.S. President (Democrat)		0.753*	0.811	0.833
Constant	1.735***	563.757	639.359	212.550
Level-2 Random Intercepts				
Firm Variance	0.126	0.113	0.106	0.04
Year Variance	0.021	0.003	0	0
N	1,638	1,638	1,248	1,222
Firms	269	269	204	197
Years	11	11	11	11
Log Likelihood	-981.837	-979.260	-739.202	-713.009
AIC	1,975.674	1,982.520	1,506.404	1,482.018
BIC	2,008.082	2,047.335	1,578.214	1,625.048

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 1-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.7: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 2-Year Lag, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.359**	1.382**	1.419**	1.426**
Board Member Equal Swap	1.901***	1.904***	1.879***	1.853***
Republican Board	5.253***	5.307***	4.915***	4.856***
Democratic Firm			1.013	1.047
Republican Firm			1.423	1.295
Board Features				
Board Size (Log)		0.817	0.916	0.861
Median Age (Log)		1.365	2.278	2.483
Proportion Female		1.533	1.696	1.969
Proportion Black or Hispanic		0.846		2.036
Proportion Minority			0.401*	0.408*
Proportion Non-US				0.288
Median Outside Board Ties		1.026	0.965	0.934
Firm Sectors				
Capital Goods				1.772
Conglomerates				0.667
Consumer Cyclical				0.566
Consumer Goods				0.852
Consumer/Non-Cyclical				0.806
Energy				0.613
Financial				0.588
Healthcare				0.746
Services				0.645
Technology				0.571
Transportation				0.605
Utilities				0.942
Other Features				
U.S. President (Democrat)		1.087	1.030	0.995
Constant	0.470***	0.179	0.020	0.024
Level-2 Random Intercepts				
Firm Variance	0.539	0.534	0.521	0.449
Year Variance	0.024	0.022	0.007	0
N	2,768	2,768	2,098	2,057
Firms	269	269	205	198
Years	10	10	10	10
Log Likelihood	-1,577.552	-1,577.046	-1,187.561	-1,152.853
AIC	3,167.103	3,178.092	2,403.122	2,361.706
BIC	3,202.659	3,249.202	2,482.204	2,519.319

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 2-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.8: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 2-Year Lag, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.736**	0.724**	0.705**	0.701**
Board Member Equal Swap	0.526***	0.525***	0.532***	0.540***
Republican Board	0.190***	0.188***	0.203***	0.206***
Democratic Firm			0.987	0.955
Republican Firm			0.703	0.772
Board Features				
Board Size (Log)		1.225	1.091	1.161
Median Age (Log)		0.733	0.439	0.400
Proportion Female		0.652	0.590	0.508
Proportion Black or Hispanic		1.182		0.491
Proportion Minority			2.497*	2.452*
Proportion Non-US				3.468
Median Outside Board Ties		0.975	1.036	1.071
Firm Sectors				
Capital Goods				0.565
Conglomerates				1.500
Consumer Cyclical				1.766
Consumer Goods				1.173
Consumer/Non-Cyclical				1.240
Energy				1.632
Financial				1.700
Healthcare				1.341
Services				1.551
Technology				1.752
Transportation				1.654
Utilities				1.062
Other Features				
U.S. President (Democrat)		0.920	0.971	1.005
Constant	2.127***	5.597	49.199	41.977
Level-2 Random Intercepts				
Firm Variance	0.539	0.534	0.521	0.449
Year Variance	0.024	0.022	0.007	0
N	2,768	2,768	2,098	2,057
Firms	269	269	205	198
Years	10	10	10	10
Log Likelihood	-1,577.552	-1,577.046	-1,187.561	-1,152.853
AIC	3,167.103	3,178.092	2,403.122	2,361.706
BIC	3,202.659	3,249.202	2,482.204	2,519.318

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 2-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.9: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-11-Year Lags, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.264***	1.269***	1.349***	1.352***
Board Member Equal Swap	1.713***	1.716***	1.696***	1.678***
Democratic Board	0.239***	0.246***	0.252***	0.260***
Democratic Firm			0.851	0.869
Republican Firm			1.678	1.383
Board Features				
Board Size (Log)		0.857	0.706*	0.680*
Median Age (Log)		0.441	1.023	1.186
Proportion Female		0.481*	0.478*	0.444*
Proportion Black or Hispanic		0.150***		0.357*
Proportion Minority			0.338***	0.429***
Proportion Non-US				1.301
Median Outside Board Ties		0.883**	0.916	0.932
Firm Sectors				
Capital Goods				3.360
Conglomerates				0.268
Consumer Cyclical				0.487
Consumer Goods				0.868
Consumer/Non-Cyclical				0.656
Energy				0.473
Financial				0.473
Healthcare				0.673
Services				0.614
Technology				0.578
Transportation				0.533
Utilities				0.929
Other Features				
U.S. President (Democrat)		1.052	0.959	0.924
Constant	3.077***	204.676**	8.915	9.631
Level-2 Random Intercepts				
Firm Variance	3.132	3.198	2.735	2.471
Year Variance	0.06	0.082	0.052	0.058
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-15,382.530	-15,355.190	-11,838.270	-11,674.410
AIC	30,779.060	30,736.370	23,706.540	23,406.810
BIC	30,837.790	30,845.440	23,828.380	23,642.040

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.10: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-11-Year Lags, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.791***	0.788***	0.742***	0.740***
Board Member Equal Swap	0.584***	0.583***	0.590***	0.596***
Democratic Board	4.180***	4.071***	3.967***	3.848***
Democratic Firm			1.176	1.151
Republican Firm			0.596	0.723
Board Features				
Board Size (Log)		1.167	1.416*	1.470*
Median Age (Log)		2.267	0.977	0.843
Proportion Female		2.078*	2.094*	2.251*
Proportion Black or Hispanic		6.664***		2.798*
Proportion Minority			2.960***	2.333***
Proportion Non-US				0.769
Median Outside Board Ties		1.132**	1.092	1.073
Firm Sectors				
Capital Goods				0.298
Conglomerates				3.733
Consumer Cyclical				2.052
Consumer Goods				1.151
Consumer/Non-Cyclical				1.524
Energy				2.116
Financial				2.113
Healthcare				1.486
Services				1.630
Technology				1.729
Transportation				1.876
Utilities				1.076
Other Features				
U.S. President (Democrat)		0.951	1.042	1.083
Constant	0.325***	0.005**	0.112	0.104
Level-2 Random Intercepts				
Firm Variance	3.132	3.198	2.735	2.471
Year Variance	0.06	0.082	0.052	0.058
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-15,382.530	-15,355.190	-11,838.270	-11,674.410
AIC	30,779.060	30,736.370	23,706.540	23,406.810
BIC	30,837.790	30,845.440	23,828.380	23,642.040

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.11: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, Lag Year Sets, OR Displayed

	Pr{New Board Member: Republican}			
	1-2 Year Lags	1-4 Year Lags	1-6 Year Lags	1-8 Year Lags
	(1)	(2)	(3)	(4)
Board Member Added	1.238*	1.261***	1.244***	1.295***
Board Member Equal Swap	1.704***	1.713***	1.749***	1.740***
Republican Board	4.315***	4.280***	4.198***	4.084***
Democratic Firm	0.998	0.959	0.861	0.875
Republican Firm	1.571*	1.714*	1.800*	1.867*
Constant	0.548***	0.584**	0.605**	0.624**
Level-2 Random Intercepts				
Firm Variance	0.946	1.897	2.378	2.656
Year Variance	0.056	0.083	0.08	0.074
Lag Year Variance	0	0	0	0
N	3,346	9,067	15,373	20,852
Firms	206	208	209	209
Years	11	11	11	11
Lag Years	$[1, 2]$	$[1, 4]$	$[1, 6]$	$[1, 8]$
Log Likelihood	-1,870.259	-4,659.973	-7,534.939	-9,994.861
AIC	3,758.519	9,337.945	15,087.880	20,007.720
BIC	3,813.559	9,401.957	15,156.640	20,079.230

Notes: Cross-classified random effects (CCRE) logistic regression model with discrete multiyear lags. That is, each model uses a discrete set of year lags as follows: 1-2 year lags, 1-4 year lags, 1-6 year lags, and 1-8 year lags. Cross-classified random intercepts include firm, year, and lag years. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.12: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, Lag Year Sets, OR Displayed

	Pr{New Board Member: Democrat}			
	1-2 Year Lags	1-4 Year Lags	1-6 Year Lags	1-8 Year Lags
	(1)	(2)	(3)	(4)
Board Member Added	0.808*	0.793***	0.804***	0.772***
Board Member Equal Swap	0.587***	0.584***	0.572***	0.575***
Republican Board	0.232***	0.234***	0.238***	0.245***
Democratic Firm	1.002	1.042	1.162	1.143
Republican Firm	0.637*	0.584*	0.556*	0.536*
Constant	1.826***	1.713**	1.652**	1.601**
Level-2 Random Intercepts				
Firm Variance	0.946	1.897	2.378	2.656
Year Variance	0.056	0.083	0.08	0.074
Lag Year Variance	0	0	0	0
N	3,346	9,067	15,373	20,852
Firms	206	208	209	209
Years	11	11	11	11
Lag Years	[1, 2]	[1, 4]	[1, 6]	[1, 8]
Log Likelihood	-1,870.259	-4,659.973	-7,534.939	-9,994.861
AIC	3,758.519	9,337.945	15,087.880	20,007.720
BIC	3,813.559	9,401.957	15,156.640	20,079.230

Notes: Cross-classified random effects (CCRE) logistic regression model with discrete multiyear lags. That is, each model uses a discrete set of year lags as follows: 1-2 year lags, 1-4 year lags, 1-6 year lags, and 1-8 year lags. Cross-classified random intercepts include firm, year, and lag years. Measure of board-member partisanship: *party-cycle*, which may vary across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.13: Descriptive Statistics of Analysis Data, Board Member Events, 2007-2018: Fixed-Party

	1-Year Lag	2-Year Lag	2-4-Year Lags	All-Year Lags
Board Events				
Add	1,105 (24.07%)	1,298 (20.78%)	3,842 (17.70%)	10,031 (14.98%)
Drop	1,075 (23.42%)	1,267 (20.28%)	3,747 (17.26%)	9,628 (14.38%)
Swap	1,760 (38.34%)	3,484 (55.78%)	13,855 (63.83%)	46,371 (69.27%)
Equal Swap	667 (14.53%)	1,242 (19.88%)	4,989 (22.99%)	17,294 (25.83%)
Unequal Swap	1,093 (23.81%)	2,242 (35.89%)	8,866 (40.85%)	29,077 (43.44%)
No Change	650 (14.16%)	197 (3.15%)	261 (1.20%)	913 (1.36%)
New Board Members				
Republicans	1,168 (40.77%)	1,989 (41.59%)	7,465 (42.18%)	23,909 (42.39%)
Democrats	470 (16.40%)	779 (16.29%)	2,825 (15.96%)	8,624 (15.29%)
Unknown	1,227 (42.83%)	2,014 (42.12%)	7,407 (41.85%)	23,869 (42.32%)
Dropped Board Members				
Republicans	1,217 (42.93%)	2,072 (43.61%)	7,788 (44.24%)	24,867 (44.41%)
Democrats	591 (20.85%)	1,000 (21.05%)	3,770 (21.42%)	12,002 (21.43%)
Unknown	1,027 (36.23%)	1,679 (35.34%)	6,044 (34.34%)	19,130 (34.16%)
Event Match				
Match	1,842 (46.75%)	2,816 (46.55%)	9,924 (46.28%)	30,247 (45.81%)
Unmatched	2,098 (53.25%)	3,233 (53.45%)	11,520 (53.72%)	35,783 (54.19%)
Missing	650 (14.16%)	197 (3.15%)	261 (1.20%)	913 (1.36%)
Board-Level Metrics (Mean)				
Median Age	62.97 ± 3.49	63.01 ± 3.41	63.05 ± 3.37	63.03 ± 3.32
Female Proportion	0.20 ± 0.09	0.20 ± 0.09	0.21 ± 0.09	0.22 ± 0.09
Black / Hispanic Proportion	0.11 ± 0.09	0.12 ± 0.09	0.12 ± 0.09	0.13 ± 0.09
Minority Proportion	0.20 ± 0.17	0.19 ± 0.15	0.17 ± 0.13	0.17 ± 0.12
Non-USA Proportion	0.03 ± 0.06	0.04 ± 0.06	0.03 ± 0.06	0.03 ± 0.06
Board Size	11.38 ± 2.12	11.40 ± 2.05	11.40 ± 2.00	11.38 ± 1.97
Median Outside Board Ties	0.99 ± 0.56	0.99 ± 0.55	0.99 ± 0.55	0.98 ± 0.54
Board Party X Events				
Democratic Board	837 (18.24%)	1,131 (18.11%)	3,844 (17.71%)	10,953 (16.36%)
Republican Board	3,753 (81.76%)	5,115 (81.89%)	17,861 (82.29%)	55,990 (83.64%)
Firm Party X Events				
Polarized Democratic	444 (13.39%)	556 (12.19%)	1,926 (12.06%)	5,917 (12.01%)
Amphibious Firm	2,143 (64.63%)	3,001 (65.78%)	10,485 (65.63%)	32,338 (65.62%)
Polarized Republican	729 (21.98%)	1,005 (22.03%)	3,565 (22.31%)	11,029 (22.38%)
U.S. Presidential Party				
Democrat	3,286 (71.59%)	4,840 (77.49%)	16,193 (74.60%)	39,258 (58.64%)
Republican	1,304 (28.41%)	1,406 (22.51%)	5,512 (25.40%)	27,685 (41.36%)
Observations				
N	4590	6246	21705	66943
Firms	274	273	273	274
Sectors	14	14	14	14
Years	11	10	10	11
Lag Years	1	1	3	11
Time Period and Lags				
Year Range	2008, 2018	2009, 2018	2009, 2018	2008, 2018
Years Included (w/lag)	2007, 2018	2007, 2018	2007, 2018	2007, 2018
Lag Range	1, 1	2, 2	2, 4	1, 11

Notes: Descriptive statistics calculated for discrete lag years. That is, each column uses a discrete set of year lag(s) as follows: 1-year lag, 2-year lag, 2-4-year lags, and 1-11 (all) year lags. Measure of board-member partisanship: *party*, which is fixed across election cycles.

Table D.14: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-Year Lag, Fixed-Party, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.420**	1.417*	1.299	1.279
Board Member Equal Swap	1.881***	1.885***	1.744**	1.853***
Republican Board	5.644***	5.691***	4.279***	4.462***
Democratic Firm			0.748	0.740
Republican Firm			1.866**	1.587*
Board Features				
Board Size (Log)		1.011	1.162	1.233
Median Age (Log)		1.074	5.760	6.602
Proportion Female		1.179	1.286	1.799
Proportion Black or Hispanic		0.420		0.650
Proportion Minority			0.661	0.749
Proportion Non-US				1.705
Median Outside Board Ties		1.011	0.919	0.874
Firm Sectors				
Capital Goods				1.007
Conglomerates				0.169
Consumer Cyclical				0.309*
Consumer Goods				0.605
Consumer/Non-Cyclical				0.621
Energy				0.606
Financial				0.527
Healthcare				0.571
Services				0.589
Technology				0.498
Transportation				0.350*
Utilities				0.635
Other Features				
U.S. President (Democrat)		1.265	1.171	1.127
Constant	0.496***	0.318	0.0003	0.0003
Level-2 Random Intercepts				
Firm Variance	0.065	0.075	0.014	0
Year Variance	0.002	0	0	0
N	1,638	1,638	1,248	1,222
Firms	269	269	204	197
Years	11	11	11	11
Log Likelihood	-890.108	-887.894	-678.226	-651.393
AIC	1,792.216	1,799.788	1,384.453	1,358.786
BIC	1,824.624	1,864.603	1,456.263	1,501.817

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 1-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.15: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-Year Lag, Fixed-Party, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.704**	0.706*	0.770	0.782
Board Member Equal Swap	0.532***	0.531***	0.573**	0.540***
Republican Board	0.177***	0.176***	0.234***	0.224***
Democratic Firm			1.336	1.351
Republican Firm			0.536**	0.630*
Board Features				
Board Size (Log)		0.989	0.861	0.811
Median Age (Log)		0.932	0.174	0.151
Proportion Female		0.848	0.778	0.556
Proportion Black or Hispanic		2.382		1.539
Proportion Minority			1.512	1.335
Proportion Non-US				0.587
Median Outside Board Ties		0.989	1.088	1.144
Firm Sectors				
Capital Goods				0.993
Conglomerates				5.911
Consumer Cyclical				3.236*
Consumer Goods				1.653
Consumer/Non-Cyclical				1.609
Energy				1.651
Financial				1.897
Healthcare				1.751
Services				1.698
Technology				2.007
Transportation				2.859*
Utilities				1.576
Other Features				
U.S. President (Democrat)		0.791	0.854	0.887
Constant	2.016***	3.145	3,419.748	3,799.836
Level-2 Random Intercepts				
Firm Variance	0.065	0.075	0.014	0
Year Variance	0.002	0	0	0
N	1,638	1,638	1,248	1,222
Firms	269	269	204	197
Years	11	11	11	11
Log Likelihood	-890.108	-887.894	-678.226	-651.393
AIC	1,792.216	1,799.788	1,384.453	1,358.786
BIC	1,824.624	1,864.603	1,456.263	1,501.817

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 1-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.16: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 2-Year Lag, Fixed-Party, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.486***	1.522***	1.443**	1.483**
Board Member Equal Swap	2.284***	2.303***	2.217***	2.302***
Republican Board	6.241***	6.274***	4.643***	4.615***
Democratic Firm			0.657	0.634
Republican Firm			1.953**	1.558
Board Features				
Board Size (Log)		0.767	0.855	0.791
Median Age (Log)		0.791	14.500*	18.971*
Proportion Female		1.978	2.372	2.718
Proportion Black or Hispanic		0.393		0.657
Proportion Minority			0.687	0.769
Proportion Non-US				0.908
Median Outside Board Ties		0.992	0.925	0.904
Firm Sectors				
Capital Goods				1.358
Conglomerates				0.432
Consumer Cyclical				0.445
Consumer Goods				0.618
Consumer/Non-Cyclical				0.889
Energy				0.602
Financial				0.522
Healthcare				0.507
Services				0.665
Technology				0.538
Transportation				0.378*
Utilities				0.911
Other Features				
U.S. President (Democrat)		1.117	0.989	0.920
Constant	0.489***	2.179	0.00001*	0.00001*
Level-2 Random Intercepts				
Firm Variance	0.681	0.703	0.528	0.478
Year Variance	0.002	0.002	0.004	0.002
N	2,768	2,768	2,098	2,057
Firms	269	269	205	198
Years	10	10	10	10
Log Likelihood	-1,439.578	-1,437.894	-1,100.955	-1,062.734
AIC	2,891.157	2,899.789	2,229.910	2,181.468
BIC	2,926.712	2,970.900	2,308.993	2,339.080

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 2-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.17: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 2-Year Lag, Fixed-Party, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.673***	0.657***	0.693**	0.674**
Board Member Equal Swap	0.438***	0.434***	0.451***	0.434***
Republican Board	0.160***	0.159***	0.215***	0.217***
Democratic Firm			1.523	1.577
Republican Firm			0.512**	0.642
Board Features				
Board Size (Log)		1.304	1.168	1.264
Median Age (Log)		1.264	0.069*	0.052*
Proportion Female		0.506	0.416	0.368
Proportion Black or Hispanic		2.545		1.520
Proportion Minority			1.456	1.301
Proportion Non-US				1.102
Median Outside Board Ties		1.008	1.082	1.106
Firm Sectors				
Capital Goods				0.736
Conglomerates				2.316
Consumer Cyclical				2.247
Consumer Goods				1.618
Consumer/Non-Cyclical				1.124
Energy				1.660
Financial				1.915
Healthcare				1.972
Services				1.504
Technology				1.856
Transportation				2.643*
Utilities				1.098
Other Features				
U.S. President (Democrat)		0.895		1.087
Constant	2.046***	0.459	76,523.470*	108,935.000*
Level-2 Random Intercepts				
Firm Variance	0.681	0.703	0.528	0.478
Year Variance	0.002	0.002	0.005	0.002
N	2,768	2,768	2,098	2,057
Firms	269	269	205	198
Years	10	10	10	10
Log Likelihood	-1,439.578	-1,437.894	-1,100.957	-1,062.734
AIC	2,891.157	2,899.789	2,227.914	2,181.468
BIC	2,926.712	2,970.900	2,301.348	2,339.080

Notes: Cross-classified random effects (CCRE) logistic regression model with fixed 2-year lag. Cross-classified random intercepts include firm and year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.18: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, 1-11-Year Lags, Fixed-Party, OR Displayed

	Pr{New Board Member: Republican}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	1.338***	1.313***	1.403***	1.406***
Board Member Equal Swap	2.090***	2.092***	2.162***	2.177***
Republican Board	2.979***	2.864***	2.676***	2.636***
Democratic Firm			0.690	0.693
Republican Firm			5.168***	3.556**
Board Features				
Board Size (Log)		1.132	0.972	0.934
Median Age (Log)		0.330*	1.859	1.844
Proportion Female		0.553	0.707	0.668
Proportion Black or Hispanic		0.086***		0.147***
Proportion Minority			0.459***	0.730
Proportion Non-US				2.791*
Median Outside Board Ties		0.959	0.995	1.035
Firm Sectors				
Capital Goods				3.797
Conglomerates				0.246
Consumer Cyclical				0.263
Consumer Goods				0.563
Consumer/Non-Cyclical				1.989
Energy				0.419
Financial				0.394
Healthcare				0.486
Services				0.606
Technology				0.476
Transportation				0.348
Utilities				1.125
Other Features				
U.S. President (Democrat)		0.973	0.890	0.861
Constant	1.742**	210.047**	0.147	0.346
Level-2 Random Intercepts				
Firm Variance	6.148	6.224	4.79	4.319
Year Variance	0.009	0.018	0.008	0.018
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-13,851.910	-13,822.500	-10,887.620	-10,698.570
AIC	27,717.830	27,670.990	21,805.240	21,455.130
BIC	27,776.560	27,780.060	21,927.080	21,690.370

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.19: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, 1-11-Year Lags, Fixed-Party, OR Displayed

	Pr{New Board Member: Democrat}			
	(1)	(2)	(3)	(4)
Boards and Firm Politics				
Board Member Added	0.747***	0.762***	0.712***	0.711***
Board Member Equal Swap	0.479***	0.478***	0.462***	0.459***
Republican Board	0.336***	0.349***	0.373***	0.379***
Democratic Firm			1.449	1.444
Republican Firm			0.194***	0.281**
Board Features				
Board Size (Log)		0.883	1.031	1.070
Median Age (Log)		3.032*	0.571	0.542
Proportion Female		1.809	1.376	1.498
Proportion Black or Hispanic		11.592***		6.786***
Proportion Minority			2.096***	1.369
Proportion Non-US				0.358*
Median Outside Board Ties		1.042	1.007	0.966
Firm Sectors				
Capital Goods				0.263
Conglomerates				4.061
Consumer Cyclical				3.809
Consumer Goods				1.777
Consumer/Non-Cyclical				0.503
Energy				2.390
Financial				2.540
Healthcare				2.059
Services				1.651
Technology				2.101
Transportation				2.875
Utilities				0.889
Other Features				
U.S. President (Democrat)		1.028		1.162
Constant	0.574**	0.005**	5.858	2.890
Level-2 Random Intercepts				
Firm Variance	6.148	6.224	4.788	4.319
Year Variance	0.009	0.018	0.013	0.018
Lag-Year Variance	0	0	0	0
N	32,533	32,533	24,899	24,624
Firms	269	269	209	202
Years	11	11	11	11
Lag-Years	11	11	11	11
Log Likelihood	-13,851.910	-13,822.500	-10,888.460	-10,698.570
AIC	27,717.830	27,670.990	21,804.920	21,455.130
BIC	27,776.560	27,780.060	21,918.640	21,690.370

Notes: Cross-classified random effects (CCRE) logistic regression model, all lags (1-year, 11-year) included. Cross-classified random intercepts include firm, year, and lag-year. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.20: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Republican, Lag Year Sets, Fixed-Party, OR Displayed

	Pr{New Board Member: Republican}			
	1-2 Year Lags	1-4 Year Lags	1-6 Year Lags	1-8 Year Lags
	(1)	(2)	(3)	(4)
Board Member Added	1.385**	1.314***	1.302***	1.366***
Board Member Equal Swap	2.049***	2.070***	2.162***	2.208***
Republican Board	4.902***	4.021***	3.363***	2.945***
Democratic Firm	0.706	0.735	0.666	0.685
Republican Firm	2.034**	3.076***	4.142***	4.891***
Constant	0.597**	0.829	1.034	1.172
Level-2 Random Intercepts				
Firm Variance	1.013	2.762	3.949	4.454
Year Variance	0.027	0.031	0.025	0.022
Lag Year Variance	0	0	0	0
N	3,346	9,067	15,373	20,852
Firms	206	208	209	209
Years	11	11	11	11
Lag Years	[1, 2]	[1, 4]	[1, 6]	[1, 8]
Log Likelihood	-1,724.902	-4,273.586	-6,905.128	-9,165.326
AIC	3,467.804	8,565.173	13,828.250	18,348.650
BIC	3,522.843	8,629.184	13,897.020	18,420.160

Notes: Cross-classified random effects (CCRE) logistic regression model with discrete multiyear lags. That is, each model uses a discrete set of year lags as follows: 1-2 year lags, 1-4 year lags, 1-6 year lags, and 1-8 year lags. Cross-classified random intercepts include firm, year, and lag years. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

Table D.21: Cross-Classified Random Effects Logit Models of the Likelihood that the New Board Member is a Democrat, Lag Year Sets, Fixed-Party, OR Displayed

	Pr{New Board Member: Democrat}			
	1-2 Year Lags	1-4 Year Lags	1-6 Year Lags	1-8 Year Lags
	(1)	(2)	(3)	(4)
Board Member Added	0.722**	0.761***	0.768***	0.732***
Board Member Equal Swap	0.488***	0.483***	0.463***	0.453***
Republican Board	0.204***	0.249***	0.297***	0.340***
Democratic Firm	1.416	1.361	1.501	1.461
Republican Firm	0.492**	0.325***	0.241***	0.204***
Constant	1.674**	1.206	0.967	0.854
Level-2 Random Intercepts				
Firm Variance	1.013	2.762	3.949	4.454
Year Variance	0.027	0.031	0.025	0.022
Lag Year Variance	0	0	0	0
N	3,346	9,067	15,373	20,852
Firms	206	208	209	209
Years	11	11	11	11
Lag Years	[1, 2]	[1, 4]	[1, 6]	[1, 8]
Log Likelihood	-1,724.902	-4,273.586	-6,905.128	-9,165.326
AIC	3,467.804	8,565.173	13,828.250	18,348.650
BIC	3,522.843	8,629.184	13,897.020	18,420.160

Notes: Cross-classified random effects (CCRE) logistic regression model with discrete multiyear lags. That is, each model uses a discrete set of year lags as follows: 1-2 year lags, 1-4 year lags, 1-6 year lags, and 1-8 year lags. Cross-classified random intercepts include firm, year, and lag years. Measure of board-member partisanship: *party*, which is fixed across election cycles.
*p < .05; **p < .01; ***p < .001

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