Supplementary Appendix: Conglomerates at the Court: The Political Consequences of Mergers & Acquisitions

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Contents

A Additional Theoretical Motivation

A.1 Does Politics Influence M&As?

While we are aware of few other works that have conducted a broad empirical exploration of the political *consequences* of M&As, it is important to note that the flipside of our question has received more attention; i.e., the political *factors* of M&As. Many works, even dating back considerably, have found a role for politics in constraining M&As (e.g., Blumberg 1975; Yantek and Gartrell 1988; Croci et al. 2017; Ferris, Houston, and Javakhadze 2016). In addition, a different vein of scholarship focuses on the internal changes and integration process of firms post-merger (e.g., Safavi 2021; Haspeslagh and Jemison 1991; Graebner et al. 2017; Monin et al. 2013; Birkinshaw, Bresman, and Håkanson 2000).

Relatedly, and as we note in the manuscript's Data Section, evaluating the effects of M&As poses methodological hurdles that may have lead to a dearth of research on this subject. We require knowledge and timing of the company's restructuring, as well as those for their political activities and outcomes. Combining such financial and political data is nontrivial and rarely engaged across long periods of time or a variety of issues and industries. We move towards a longer and broader scope study by looking at the entire history of M&As among Fortune 500 companies. In terms of political activities, we focus solely on their history of lobbying the Supreme Court. In particular, we analyze firms' submissions of amicus curiae briefs—how they cosign, on which kinds of issues, and on their success before the Court.

A.2 The Effects of Amicus Curiae

There is a long history of attention to the influence of interest groups on judicial behavior, much of which has focused on their submission of amicus curiae briefs (e.g., Krislov 1962).[1] In these briefs, nonjudicial actors convey their political preferences on cases to judges (and their clerks) and frequently collaborate to do so (Box-Steffensmeier, Christenson, and Leavitt 2016). While signers of the briefs are not party to it, they seek to provide invaluable information and persuade the Justices. Indeed, they are considered the most cost-effective methods of legal advocacy Krislov (1962), with recent empirical work uncovering effects on judicial decision-making (e.g., Collins 2007; Box-Steffensmeier, Christenson, and Hitt 2013).

B Additional Data Description

B.1 Generating Our List of Corporations

The U.S. Bureau of Labor Statistics estimates that approximately 10.75 million companies operate within the United States; however, detailed economic and political data on all companies is elusive. Companies often change names, merge into larger corporations, or quietly dissolve, making tracking them over long periods difficult. Simply identifying whether a company is a parent or subsidiary of another company can become complicated due to a complex system of holding companies and cryptic naming conventions. These hurdles make constructing a longitudinal dataset of a company's corporate and political histories challenging. As one of the first attempts at overcoming these problems, we gathered the names and identifying information for all companies that made the

1. Of course, other avenues of influence have been considered as well, e.g., public opinion (Epstein and Martin 2010; Stimson, Mackuen, and Erikson 1995; Casillas, Enns, and Wohlfarth 2011).

Fortune 500 list over the last five years.[2] This process gives us a list of 751 unique companies spanning 14 industries, each with an average annual revenue of $62 billion. As discussed in the manuscript, focusing on these large companies provides at least three key benefits. First, given their size, these companies are almost guaranteed to be affected by government policies and, by extension, Supreme Court rulings.[3] Second, these companies are more likely to have better-kept records of their corporate histories and political behavior. Finally, this strategy allows us to construct a universe of companies independent of existing records of corporate political behavior.

We recognize, however, that this solution is imperfect. While examining companies throughout their lifetime, we are ultimately selecting companies that eventually become incredibly successful. Our sample does not include smaller companies that may not be near the same level of financial success or companies which themselves are merged into larger businesses. We acknowledge these problems limit the generalizability of our findings but believe this sacrifice is worth the normative contributions of our paper and novel dataset. Moreover, we are primarily interested in the most influential corporate actors before the Supreme Court. The majority of corporations—especially those which are smaller or more regional—do not engage in lobbying the courts. Even within our dataset, only 18% of these large companies submit a brief. Our dataset, while limited in scope, captures the corporations that are both most likely to lobby the courts at the highest level and continue to do so as they grow in corporate power.

B.2 Corporate History Data Sample

To gather the corporate histories for our, we rely on MarketLine data, which was designed for investors rather than for social scientists. Thus the data often records rumors of M&As, incomplete M&As, and acquisitions of materials or properties mixed in with completed M&As. For our primary analysis, we follow the current U.S. Security Exchange Commission's minimal reporting requirements and only count acquisitions of at least 5% of another company's stock. This definition is imperfect, as it counts complete company-wide mergers the same as a partial acquisition of a company's stock. But for the sake of our research interests, both represent a substantial investment and potential influx of resources for companies. Within Table D5 of the Appendix, we take an alternative approach by hand coding each M&A as either a merger, acquisition, or partial acquisition and find substantively similar results. For each M&A, we also record its year of completion and use it to calculate annual totals for each company. Our final dataset contains a yearly record of M&As for each company from its founding until 2012. Notably, our database of corporate history covers a far more expansive timeline from 1900 until 2022, but we truncate it due to the coverage of the amicus dataset. We hope that this larger dataset proves helpful for future work studying the influence of corporate consolidation and growth.

B.3 Judicial Data Sample

To capture corporate activity at the Court, we rely on amicus curiae brief signing behavior data from Box-Steffensmeier and Christenson (2012). We first identify all briefs signed under the company's current name to match the corporate dataset to the judicial one. We match company names using fuzzy string matching to produce our initial matched pairs and then validate matches through human coders. If the company underwent a name change—e.g., Facebook to Meta—we identify all

2. The Fortune 500 list historically goes back to 1955, but we opt only to examine the past five years to keep our universe of companies to a reasonable size. At the time of writing, 49 companies have been on the Fortune 500 list every year since 1955.

3. While not one-for-one, Ansolabehere, Figueiredo, and Snyder (2003) make a similar assumption in their study of campaign finance

briefs signed under their previous name. We do not count briefs signed by a company's subsidiaries or their originating companies in the case of a merger. This restriction is intended to reduce the universe of company names we must match and limit our examination to companies as they exist today. Even our relatively small sample of 731 companies controls over 10,000 subsidiaries, many of which share names and other identifying information. For large mergers, we do not include originating companies to avoid complex situations in which both original companies submit separate briefs before they merge. An example of this is ExxonMobil, where both Exxon and Mobil signed different briefs on different cases prior to their merger in 1998.[4] This procedure likely biases our results, but should do so in the opposite direction of our theorized results as we are systematically undercounting corporations total brief signing behavior. Using this process, we successfully identified 318 unique briefs signed by 136 of our original 751 companies. These briefs cover 216 cases from 1940 to 2012. While 136 out of 751 companies may seem small, it is important to remember we are not counting briefs submitted by subsidiaries and that, much like campaign donations, amicus curiae briefs are likely relatively rare for companies to submit (Ansolabehere, Figueiredo, and Snyder 2003).

Evolution of Fortune 500 Egocentric Networks

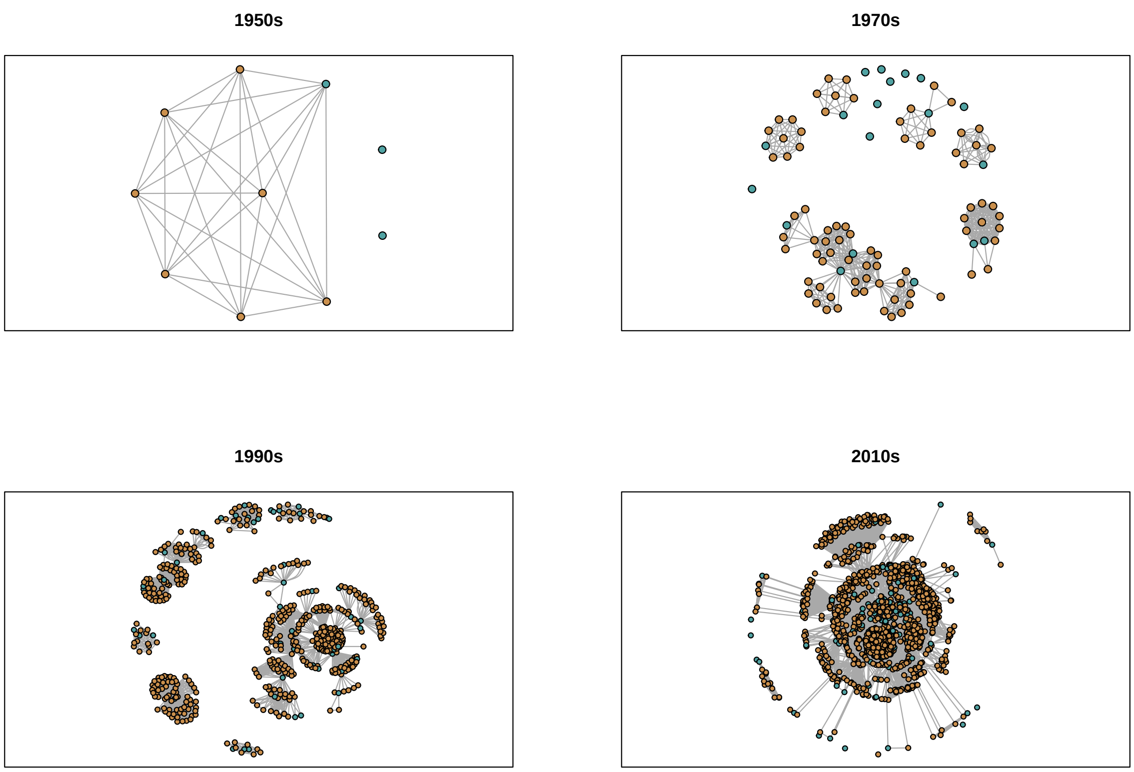

Figure B1: Blue nodes represent Fortune 500 companies within our dataset. Yellow nodes represent other interest groups within each Fortune 500 company's egocentric networks.

4. ExxonMobil is a particularly interesting example as in addition to submitting briefs as separate companies, they submitted briefs as Standard Oil of New Jersey before it broke apart following the decision in Standard Oil Co. of New Jersey v. United States

To provide insights into the collaborative and centrality hypotheses, we use these data to construct a network based on cosigner status. Each company that submits a brief represents a unique node. When two companies cosign a brief, we draw an edge between their nodes—and maintain all nodes that are cosigned with at leat one of our 136 Fortune 500 companies. Given the focus of our paper, we only include the 136 companies that submitted a brief and their immediate cosigners within our network. Using the date of the brief, we can then model our network of cosigners over time. Figure B1 illustrates the evolution of the network from the 1950s until the 2010s. The network remained relatively sparse from the 1950s until the 1990s, with each company having its own clique. However, by the 2010s, the network's overall density increased as bridges formed between previously isolated clusters of cosigners.

C Additional Modeling Details

C.1 Descriptive Statistics of Key Measures

In Table C1 we provide a list of the dependent variables, their measurement and both the central tendency and variance.

Table C1: Variables of Interest

Variable	Description	Mean	Stan. Dev.
Num. Briefs	The number of briefs a company submits in time period t. (H1)	0.47	0.98
Num. Issues	The number of issue areas for which a company submits a brief since time period t. Issue coding provided by the Spaeth data set. (H2)	2.55	2.41
Win Rate	The proportion of briefs a company submits to the winning side of a case since time period t. Case outcome data provided by the Spaeth database. (H5)	0.59	0.38
Eigenvector Centraility	The value of the first eigenvector of the network with respect to the sum of all connected companies. Provides a measure of a company's influence within the network (Bonacich 1987). (H4)	0.06	0.20
Betweenness*	The number of shortess paths between any two companies within the nework which pass through the company. Provides a measure of how much information passes through a company (Freeman 1977). (H4)	2.23	1
Degree	The number of connections a company has within the network. (H3)	38.22	52.53
Harmonic Centraility	The mean inverse distance to all other companies within the newtork. Provides a measure of how central a company is within the network (Marchiori and Latora 2000). (H4)	224.14	198.88

*Some variables have been Z-score normalized to aid in interpretability.

C.2 Model Specification

To estimate the effect M&A's have on a company's brief and network behavior, we estimate the following equation:

$$Y_{it} = \beta_1 NumMA_{it} + \beta_2 NumMA_{it-1} + \gamma_i + \delta_t + \epsilon_{it} \tag{1}$$

where Y_{it} represents our outcome of interest for a particular company i at time period t. Our main explanatory variable $NumMA_{it}$ indicates the number of M&As a company reported at time period t. To account for the post-merger integration process, we also include a lagged term of $NumMA_{it-1}$ which captures the number of M&A a company made at time period $t-1$. The company (γ_i), and year (δ_t) fixed effects control for the time-invariant characteristics within and surrounding companies that may affect their propensity to submit an amicus curiae brief. Finally, since some of our variables represent counts and others continuous outcomes, we model the equation above using either Negative Binomial or Ordinary Least Squares regression depending on the dependent variable in question.

C.3 Binning Years

For our analyses we bin the data into five-year periods of time from 1940 until 2012. We choose to bin our estimates for two key reasons. First, the act of undergoing an M&A and submitting an amicus curiae brief within a particular year is relatively rare for companies within our dataset and often occurs in waves. On average, companies only submit a brief once every 11.1 years. Thus our dataset would likely become inflated by years of no measurable change and make adequately modeling our desired relation difficult given our relatively small sample size. Second, M&As are often time-consuming processes that can take anywhere from 1 to 10 years to complete (Safavi 2021). On average, companies only undergo an M&A once every 3.3 years. Thus, binning our variables of interest allow us to emulate better the process of undergoing a merger or acquisition and more effectively model its relation to a company's brief signing behavior. One possible concern in binning our variables is that our results become sensitive to our selection bin sizes. To address this concern, we replicate our primary results with five-year, ten-year, and fifthteen-year bins and present the results in the tables below. While we notice new significant effects surrounding *Win rates* and *Eigenvector Centrality*, our core results remain unchanged.

Table C2: Alternative Specification: 5-Year Bins

	Num. Briefs	Win Rate	Num. Issues	Eigenvector Cent.	Betweenness	Degree	Harmonic Cent.
Num. M&As	0.031	−0.0004	0.026*	−0.004	0.071*	0.027*	2.771
	(0.019)	(0.003)	(0.011)	(0.004)	(0.019)	(0.012)	(1.699)
1 Period Lag M&As	0.032	0.026	0.040	−0.016	−0.004	−0.029	−4.825
	(0.141)	(0.020)	(0.079)	(0.021)	(0.111)	(0.075)	(9.989)
Constant	−3.440*	0.006	−1.485	0.858*	−1.496	0.849	5.800
	(1.093)	(0.134)	(0.761)	(0.179)	(0.956)	(0.674)	(85.893)
Year FE	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓
Court FE	✓	✓	✓	✓	✓	✓	✓
Model Type	NB	OLS	NB	OLS	OLS	NB	OLS
N	938	558	558	548	548	548	548
Adj. R-squared		0.823		0.253	0.329		0.853
AIC	1551.983		1837.953			4181.493	

*p<0.05

Table C3: Alternative Specification: 10-Year Bins

	Num. Briefs	Win Rate	Num. Issues	Eigenvector Cent.	Betweenness	Degree	Harmonic Cent.
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Num. M&As	0.041*	0.001	0.024*	−0.008*	0.049*	0.022*	1.896
	(0.014)	(0.004)	(0.010)	(0.004)	(0.019)	(0.010)	(1.824)
1 Lag M&As	−0.220	−0.025	−0.064	0.037	0.507*	−0.060	20.342
	(0.169)	(0.038)	(0.129)	(0.037)	(0.198)	(0.110)	(19.023)
Constant	−1.031*	0.445*	−0.375	0.035	−0.799	1.056*	105.812
	(0.516)	(0.118)	(0.418)	(0.116)	(0.624)	(0.355)	(59.843)
Year FE	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓
Model Type	NB	OLS	NB	OLS	OLS	NB	OLS
N	415	290	290	285	285	285	285
Adj. R-squared		0.764		0.022	0.274		0.823
AIC	1072.635		1081.563			2265.442	

*p<0.05

Table C4: Alternative Specification: 15-Year Bins

	Num. Briefs	Win Rate	Num. Issues	Eigenvector Cent.	Betweenness	Degree	Harmonic Cent.
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Num. M&As	0.038*	0.001	0.025*	−0.00000	0.056*	0.021*	0.594
	(0.013)	(0.004)	(0.011)	(0.001)	(0.026)	(0.010)	(2.209)
1 Period Lag M&As	0.164	0.005	0.047	0.003	0.432	0.158	12.327
	(0.175)	(0.042)	(0.146)	(0.012)	(0.286)	(0.117)	(24.489)
Constant	0.200	0.289*	0.459	−0.027	−0.654	2.389*	101.925
	(0.464)	(0.131)	(0.436)	(0.036)	(0.874)	(0.324)	(74.710)
Year FE	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓
Model Type	NB	OLS	NB	OLS	OLS	NB	OLS
N	246	189	189	187	187	187	187
Adj. R-squared		0.761		0.866	−0.017		0.773
AIC	784.143		762.092			1529.028	

*p<0.05

D Supplemental Analyses

D.1 Alternative Lag Specification

As an additional robustness check, we replicate our core findings using both two-period and three-period lags for M&As. We do this to address concerns that M&A are often lengthy processes whose effects may not be fully captured within a single lagged period. Table D1 and Table D2 show that our results appear robust to both alternative lag specifications. Notably, the coefficient surrounding *Degree* does seem to lose significance in the 3-period lag specification. While this difference may be substantively important, it may also be a product of the demanding model specification on our relatively small sample of corporate M&As.

Table D1: Alternative Specification: 2-Period Lag Specification

	Num. Briefs	Win Rate	Num. Issues	Eigenvector Cent.	Betweenness	Degree	Harmonic Cent.
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Num. M&As	0.030	0.001	0.026*	−0.006	0.075*	0.027*	2.108
	(0.020)	(0.004)	(0.011)	(0.004)	(0.021)	(0.012)	(1.866)
1 Period Lag M&As	0.056	0.028	0.036	−0.012	−0.026	−0.037	−7.651
	(0.156)	(0.022)	(0.082)	(0.021)	(0.118)	(0.076)	(10.764)
2 Period Lag M&As	−0.109	0.006	0.001	0.033	0.203	0.073	8.019
	(0.154)	(0.021)	(0.084)	(0.021)	(0.117)	(0.075)	(10.635)
Constant	−2.776*	0.047	−1.287*	0.271*	−1.102	0.045	27.747
	(0.835)	(0.106)	(0.572)	(0.111)	(0.630)	(0.538)	(57.314)
Year FE	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓
Model Type	NB	OLS	NB	OLS	OLS	NB	OLS
N	801	497	497	489	489	489	489
Adj. R-squared		0.821		0.244	0.386		0.850
AIC	1361.252		1676.713			3739.011	

*p<0.05

Table D2: Alternative Specification: 3-Period Lag Specification

	Num. Briefs	Win Rate	Num. Issues	Eigenvector Cent.	Betweenness	Degree	Harmonic Cent.
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Num. M&As	0.031	0.001	0.027*	−0.004	0.065*	0.023	0.572
	(0.022)	(0.004)	(0.012)	(0.004)	(0.021)	(0.013)	(2.006)
1 Period Lag M&As	0.037	0.041	0.050	−0.014	0.025	−0.032	−7.237
	(0.164)	(0.024)	(0.086)	(0.021)	(0.126)	(0.080)	(11.757)
2 Period Lag M&As	−0.148	0.007	−0.019	0.019	0.167	0.029	0.641
	(0.171)	(0.024)	(0.090)	(0.021)	(0.128)	(0.082)	(11.971)
3 Period Lag M&As	−0.228	0.006	−0.079	−0.011	0.185	−0.009	2.620
	(0.164)	(0.024)	(0.092)	(0.022)	(0.129)	(0.083)	(12.087)
Constant	−2.799*	0.210*	−1.012*	0.204*	−0.954	0.106	31.916
	(0.836)	(0.100)	(0.493)	(0.094)	(0.561)	(0.489)	(52.374)
Year FE	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓
Model Type	NB	OLS	NB	OLS	OLS	NB	OLS
N	667	424	424	418	418	418	418
Adj. R-squared		0.814		0.280	0.487		0.847
AIC	1174.800		1451.198			3197.559	

*p<0.05

D.2 Alternative Model Controls

Beyond the company and time fixed effects included within our original model specification, we also examine two alternative factors that may influence a company's M&A behavior and judicial behavior. First, following Box-Steffensmeier, Christenson, and Hitt 2013, we control for the first three-digit NAICS industry codes for each company within our dataset and present the results in Table D3. Second, to account for any effect each Court's composition may have on judicial and business practices, we then control for each particular court era and present the results in Table D4. In both cases, these additional controls disappear into our time and company-based fixed effects, and our results remain unchanged.

Table D3: Alternative Specification: Court Fixed Effects

	Num. Briefs	Win Rate	Num. Issues	Eigenvector Cent.	Betweenness	Degree	Harmonic Cent.
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Num. M&As	0.031	−0.0004	0.026*	−0.004	0.071*	0.027*	2.771
	(0.019)	(0.003)	(0.011)	(0.004)	(0.019)	(0.012)	(1.699)
Lag M&As	0.032	0.026	0.040	−0.016	−0.004	−0.029	−4.825
	(0.141)	(0.020)	(0.079)	(0.021)	(0.111)	(0.075)	(9.989)
Constant	−3.440*	0.006	−1.485	0.858*	−1.496	0.849	5.800
	(1.093)	(0.134)	(0.761)	(0.179)	(0.956)	(0.674)	(85.893)
Year FE	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓
Court FE	✓	✓	✓	✓	✓	✓	✓
Model Type	NB	OLS	NB	OLS	OLS	NB	OLS
N	938	558	558	548	548	548	548
Adj. R-squared		0.823		0.253	0.329		0.853
AIC	1551.983		1837.953			4181.493	

*p<0.05

Table D4: Alternative Specification: Industry Fixed Effects

	Num. Briefs	Win Rate	Num. Issues	Eigenvector Cent.	Betweenness	Degree	Harmonic Cent.
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Num. M&As	0.031	−0.0004	0.026*	−0.004	0.071*	0.027*	2.771
	(0.019)	(0.003)	(0.011)	(0.004)	(0.019)	(0.012)	(1.699)
Lag M&As	0.032	0.026	0.040	−0.016	−0.004	−0.029	−4.825
	(0.141)	(0.020)	(0.079)	(0.021)	(0.111)	(0.075)	(9.989)
Constant	−3.440*	0.006	−1.485	0.858*	−1.496	0.849	5.800
	(1.093)	(0.134)	(0.761)	(0.179)	(0.956)	(0.674)	(85.893)
Year FE	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
Model Type	NB	OLS	NB	OLS	OLS	NB	OLS
N	938	558	558	548	548	548	548
Adj. R-squared		0.823		0.253	0.329		0.853
AIC	1551.983		1837.953			4181.493	

*p<0.05

D.3 Alternative M&A Codings

As an additional analysis, we classify each M&A as either a merger, acquisition, or partial acquisition. We code a M&A as a partial acquisition if a company acquires less than complete control of another company. Companies can often make several partial acquisitions of another company over many years before they entirely acquire it. We then control for each of these forms of M&As and their respective lagged terms and present them in the table below. Doing so, we corroborate the results in the body of the paper, with one exception: harmonic centrality is significant. That is, as companies complete acquisitions, their influence within their network of cosigners appears to increase significantly. Interestingly, these results suggest that full acquisitions rather than mergers or partial acquisitions are what primarily drive changes within a companies judicial behavior.

Table D5: Alternative Specification: Mergers, Acquisitions, and Partial Acquisitions

	Num. Briefs	Win Rate	Num. Issues	Eigenvector Cent.	Betweenness	Degree	Harmonic Cent.
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Num. Acquisitions	0.022	−0.0003	0.029*	−0.003	0.101*	0.041*	4.659*
	(0.024)	(0.004)	(0.014)	(0.004)	(0.023)	(0.015)	(2.089)
Num. Mergers	0.086	−0.030	−0.017	−0.010	−0.044	−0.148	−7.366
	(0.185)	(0.024)	(0.096)	(0.025)	(0.130)	(0.087)	(11.786)
Num. Part. Acquistions	−0.073	0.010	−0.019	−0.004	−0.049	−0.001	−7.022
	(0.081)	(0.009)	(0.037)	(0.009)	(0.048)	(0.034)	(4.382)
Lagged Acquistions	0.064	−0.011	0.018	−0.003	0.054	−0.002	3.150
	(0.048)	(0.007)	(0.028)	(0.008)	(0.039)	(0.026)	(3.577)
Lagged Mergers	−0.114	−0.014	−0.015	0.013	0.068	−0.091	−5.331
	(0.215)	(0.028)	(0.111)	(0.029)	(0.149)	(0.100)	(13.581)
Lagged Part. Acquistions	−0.044	0.018	−0.034	−0.005	−0.132	−0.063	−0.986
	(0.138)	(0.015)	(0.061)	(0.016)	(0.081)	(0.055)	(7.379)
Constant	−3.467*	0.001	−1.511*	0.858*	−1.587	0.807	1.284
	(1.093)	(0.134)	(0.761)	(0.180)	(0.941)	(0.669)	(85.527)
Year FE	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓
Model Type	NB	OLS	NB	OLS	OLS	NB	OLS
N	938	558	558	548	548	548	548
Adj. R-squared		0.824		0.245	0.349		0.854
AIC	1556.205		1843.445			4181.849	

*p<0.05

D.4 The Net Effect of M&As on Judicial Outcomes

In addition to the analysis presented in the body of the paper, we investigate whether the total number of M&As a company undergoes has an effect on our variables of interest. We begin our analysis by examining how a company's total number of M&As relates to its brief signing behavior and the outcomes of the associated cases at the aggregate level. Figure D1 depicts the bivariate relationship between a company's total number of M&As from 1940 until 2012 and our outcomes of interest. To better visualize each relationship, we plot a curve fitted from a loess nonparametric regression along with its 95% confidence intervals. While loess likely oversimplifies the relationship between our variables of interest, it is an effective strategy to suggest which variables should be related and, often, the direction of the relationship (Jacoby 2000). This estimation process provides early correlational evidence as to whether our hypotheses are supported or not.

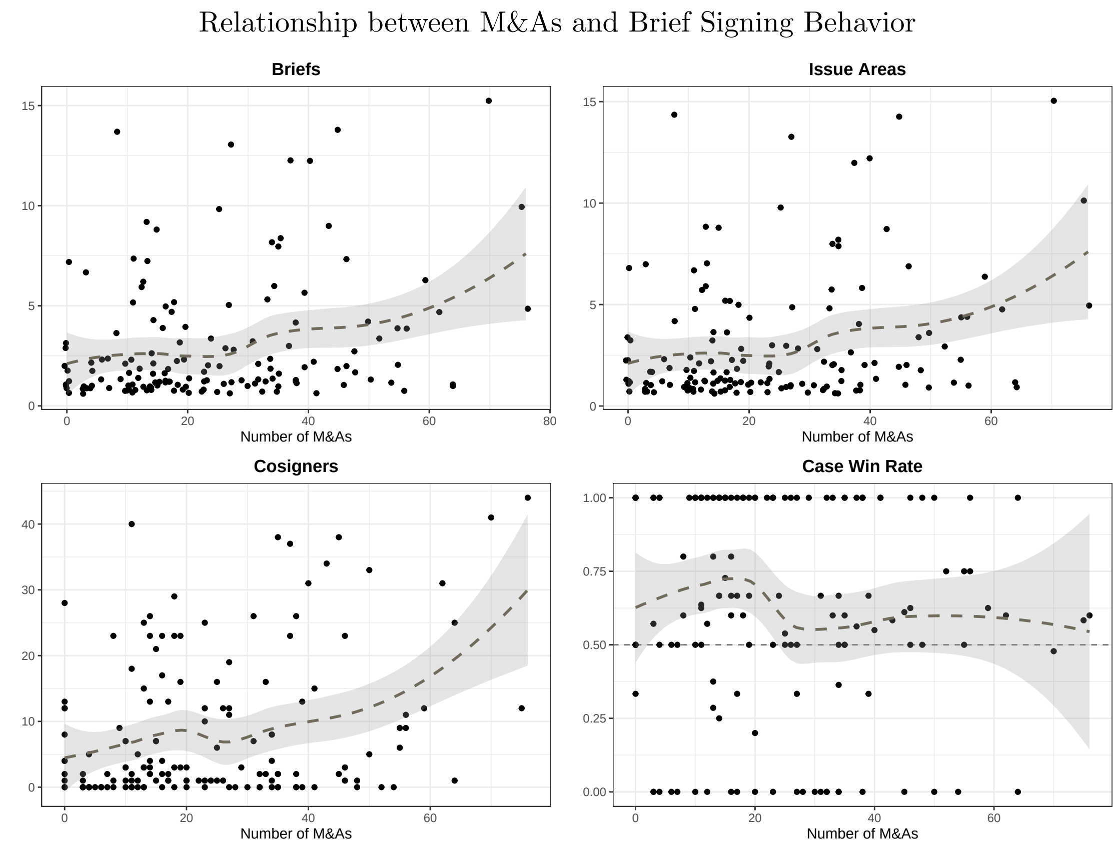

Figure D1: Data covers 136 companies from 1940 until 2012. Dotted line represents a nonparametric loess curve with shaded 95% confidence intervals.

The first plot within Figure D1 provides mixed support for our first hypothesis. The number of M&As and the total number of briefs appear weakly correlated with a coefficient of 0.14 ($p<0.1$), but the relationship is not significant. In fact, most of the relationship appears driven by outlier companies with above-average M&As and briefs. If we examine these companies more closely, we can see that while some share industry sectors such as Royal Dutch Shell and Exxon Mobil, which both operate in the oil and gas industries, other companies such as Intel, an electronics manufacture, and Gannett, a mass media company, also share similarly large volumes of both M&As and submitted briefs.

Unlike our first hypothesis, we find some initial support for both our second and third hypotheses. As illustrated in Figure D1's second and third figures, companies with more M&As tend to submit briefs to a wider variety of issue areas and sign briefs with a broader network of cosigners. Both variables are significantly and positively correlated with a coefficient of 0.25 ($p<0.05$) and

0.30 (p<0.05), respectively. These results may suggest that as companies expand into potentially new industries, they expand their political influence to follow suit.

Finally, we examine the association of M&As with their case win rates. As a reminder, we consider a company as "winning" if the case is decided in the same direction as their brief. Contrary to our expectations, a company's total number of M&As is uncorrelated with their case win rate. Despite the theoretical increase in economic and political resources provided by a merger or acquisition, they appear no more likely to win a case.

While this finding contradicts our final hypothesis, it reveals an interesting feature of the data. Fortune 500 companies appear to win the majority of cases for which they submit briefs. These companies submit briefs to the winning side of a case 64% of the time. This high win rate is likely a result of these companies' ability to both fund and submit detailed briefs (Lynch 2004) and their heightened reputation within a case's particular issue area (Box-Steffensmeier, Christenson, and Hitt 2013; Collins 2007). Thus companies may not experience noticeable gains as they have effectively reached the ceiling of potential influence. Overall our correlational results suggest that M&As do not relate to the total number of briefs a company submits nor their case win rate, though they are associated with additional issue areas and a greater network of cosigners.

D.5 Industry Specific Influence

While the body of our letter focuses on the effects of M&As, our novel dataset also allows us to investigate industry-specific influences before the Court and within our cosigner network. For this analysis, we use the same industry coding presented in Section D.2 of the Appendix. First, in Figure D2, we present the total number of briefs signed by each industry. Surprisingly, brief submission rates appear broadly consistent across industries and thus largely resemble our distribution of companies by industry.[5] Second, in Figure D3, we present the average win rate for each industry covered in our dataset. While most industries appear successful before the Court, some, such as professional industries, find significantly greater success, and others, such as utilities, real estate, and food, significantly less.

5. See Figure 1 within the main text.

Brief Signing Behavior By Industry

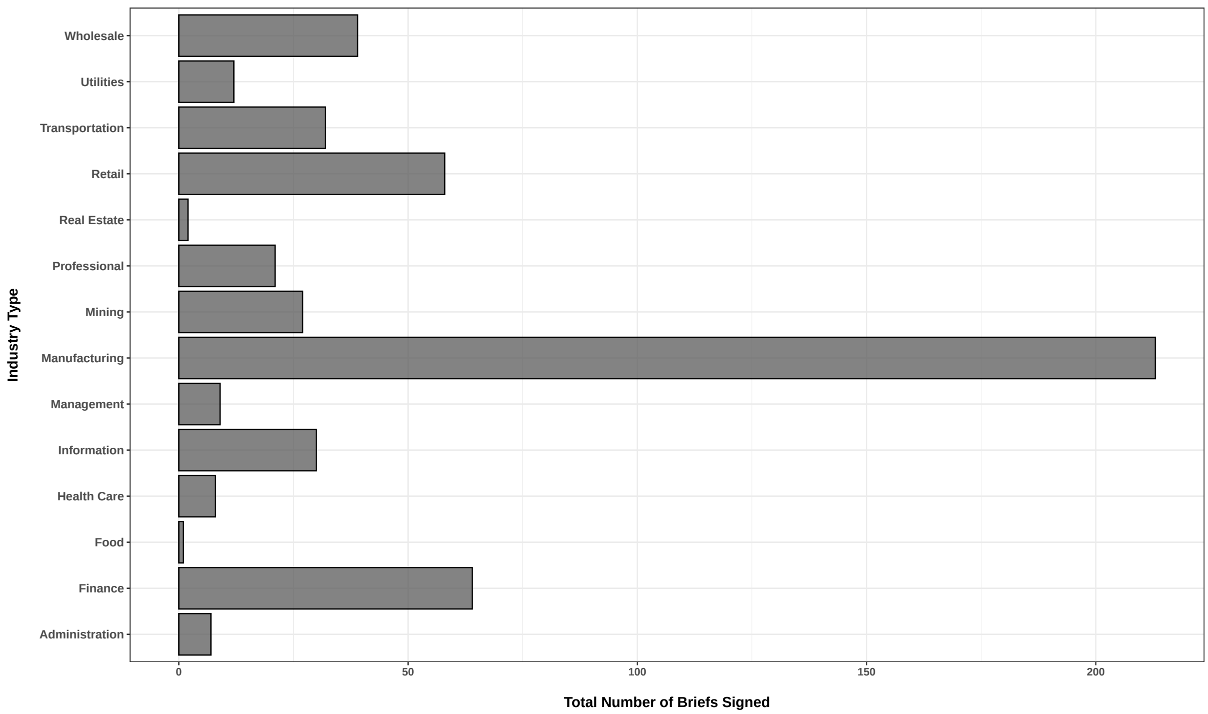

Figure D2: We assign industries based on each company's three-digit NAICS industry code.

Win-Rate By Industry

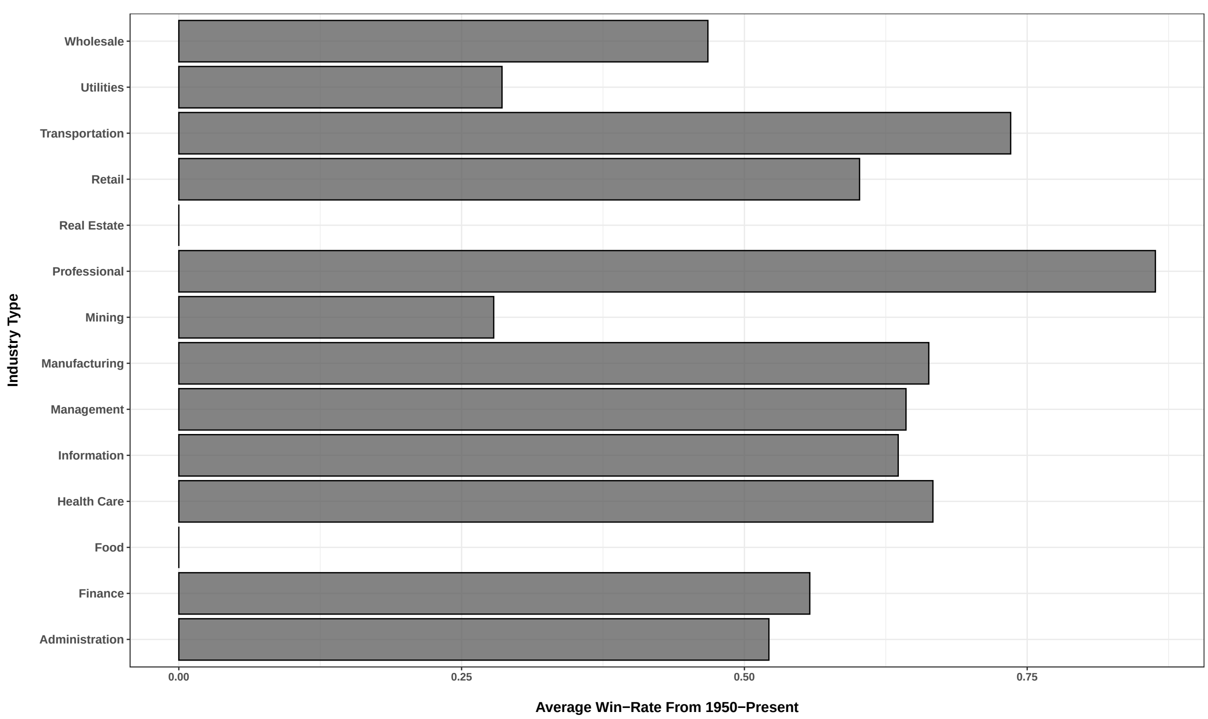

Figure D3: Win Rates refers to proportion of cases decided in a company's favor.

Finally, we find which industries are most influential by examining company fixed effects. Figure D4 presents the number of companies from each industry with a significant and normatively important fixed effect within our primary models.[6] Importantly, the bars in the figure do not display the magnitude of the fixed effects but rather the total number of companies. While this process does not provide the aggregate influence of each industry, it allows us to visualize which industries have the most influential companies. Figure D4 reveals that three industries are particularly influential: manufacturing, transportation, and retail. These industries include companies such as the 3M Corporation, General Motors, and American Airlines, each appearing active before the Court and key in network formation and influence. Additonally, industries surrounding finance and information appear influential, but primarily before the Court.

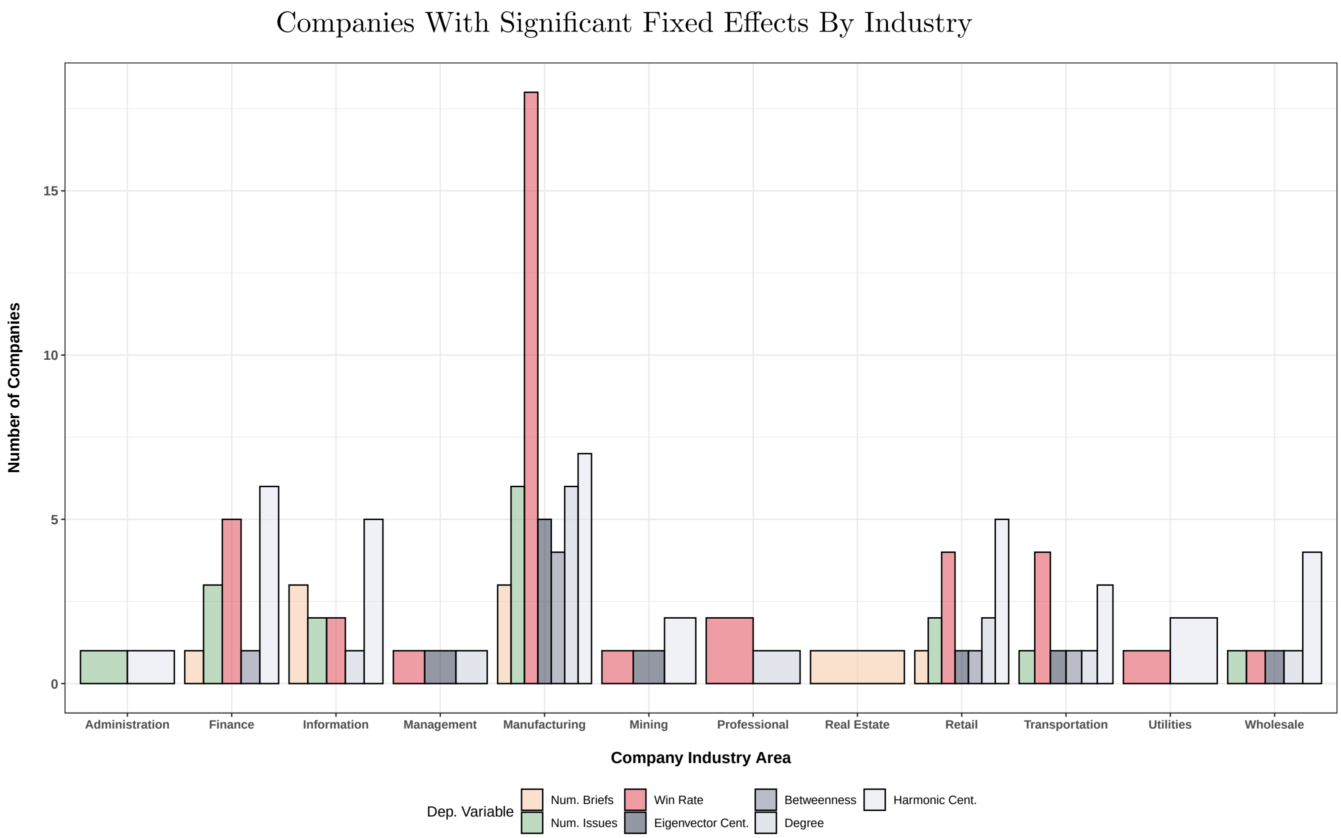

Figure D4: The figure displays the number of companies with signficant fixed effects by industry. In the case of both Win Rate and Degree we subset to companies with signficant effects in a positive direction and of a substantial magnitude.

6. For example, we only include companies with large, positive, and significant fixed effects in the case of win rates.