Political Alignment between Firms and Employees inthe United States: Evidence from a new Dataset

Appendix (For Online Publication)

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Appendix (For Online Publication)

A1 Details on Matching Employees, Employers, and Occupations

The similarity score: The similarity between company (occupation) name vectors d_1, d_2 is calculated as $sim(d_1, d_2) = \frac{d_1 \cdot d_2^T}{||d_1|| \, ||d_2||} = \frac{\sum_{i=1}^{n} d_{1i} d_{2i}}{\sqrt{\sum_{i=1}^{n} d_{1i}^2} \sqrt{\sum_{i=1}^{n} d_{2i}^2}}$. The numerator of this fraction is dot product between the two vectors, $d_1 \cdot d_2^T$, where the superscript T indicates the transpose of the of the respective Compustat company name (BLS/Census occupation title) vector. The denominator normalizes the dot product by vector length (the magnitude) of both vectors d_{1i} and d_{2i}. The result is the cosine of the angle between the two employer name vectors in a two-dimensional space, that is between 0 (no similarity, or an angle of 90°between both vectors) and 1 (complete similarity, or an angle of 0°between the vectors). The more similar the two vectors are with respect to the weighted term frequencies present in the company (occupation) names, the smaller the angular distance between the names, and hence, the closer is the match. For implementation, the script uses the 'cosine_similarity' function from the widely used python machine learning package 'skicit-learn'. Finally, the script picks the Compustat firm name (BLS/Census occupation title) with the highest cosine similarity, and returns it with its unique Compustat firm ID (GVKEY), given that the similarity is above a pre-defined threshold. For employer names, I use a threshold of 0.81, based on similar research linking company information to company patent data in the US (Raffo and Lhuillery, 2009). For occupations, I use a lower threshold of 0.72. First, the occupation field in the FEC data contains more unnecessary text than the company name field which adds noise makes finding a matching occupation more difficult. Second, while the 0.81 threshold for employer names is a good compromise between maximizing the number of matches and achieving accurate matches given a match is found, the 0.72 threshold is in practice very stringent, resulting in highly accurate matches. Therefore, conditional on there being a match between employer PAC and employee, the occupations will be very accurate.

Occupation Codes: For the SOC codes, there are 89,000 occupation titles relating to 867 unique occupation codes. For O∗NET occupation codes 105,000 occupation titles are related to 1100 unique occupation codes. The US Census Bureau and US Bureau for Labor Statistics use the Standard Occupational Classification Codes (SOC), while O∗NET uses O∗NET SOC, a more fine-grained system based on but fully compatible to SOC codes. The direct match files of the Census Bureau and the Bureau for Labor Statistics contain a combined number of 89,000 occupation names which include around 1,500 widely used acronyms for many occupations, for example 'CEO' for 'Chief Executive', 'SVP' for 'Senior Vice President', or 'EVP' for 'Executive Vice President'. The occupational matching files are very extensive but do not contain all possible acronyms for all occupations. In the future, I will extend the occupational matching file to include a richer set of occupation acronyms.

Level	Identifer	Categories	CRP Identifier	CRP Categories
Occupation	SOC 2010	840	–	–
	O$\star$NET SOC 2010	1010	–	–
Sector	NAICS 2012	1068	own scheme	400
Firm	GVKEY	13,766 (1980 - 2018)	–	–

Table A1: Unique Identifiers in Linked Employer-Employee Data: This table shows the unique identifiers available in the employer-employee data and the number of categories covered in comparison with the Center for Responsive Politics (CRP) data. Unique occupation and firm codes are missing from the CRP data, and sector codes cannot easily be linked to external datasets.

A2 Firm-Employee Alignment across Offices and Incumbency Status

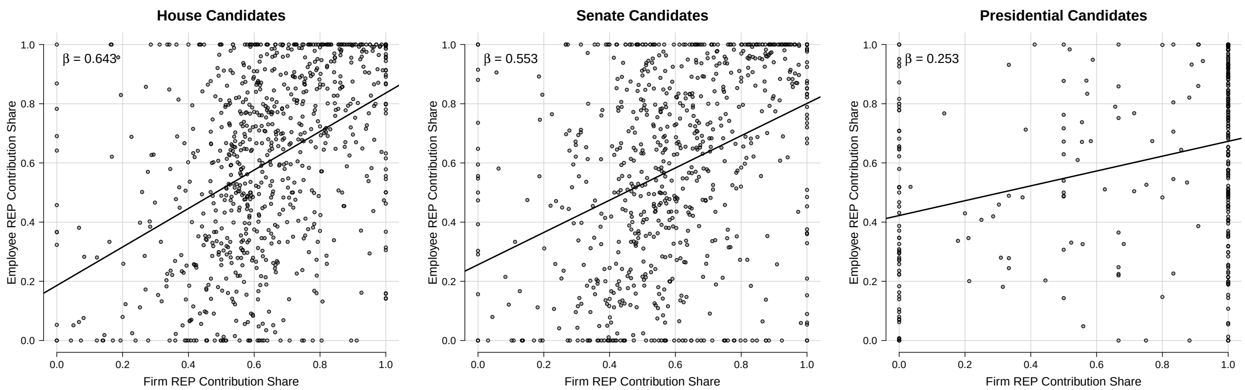


Figure A1: Correlation between Firm- and Employee Donations across Candidate Offices: The plots show the correlation between employee and firm Republican donation share, aggregated at the firm-level between 2003 and 2016, across different offices donated to. It shows that donations of corporations and employees are more correlated for House and Senate candidates than for Presidential candidates. β denotes the slope coefficient of the fitted line from a bivariate linear regression.

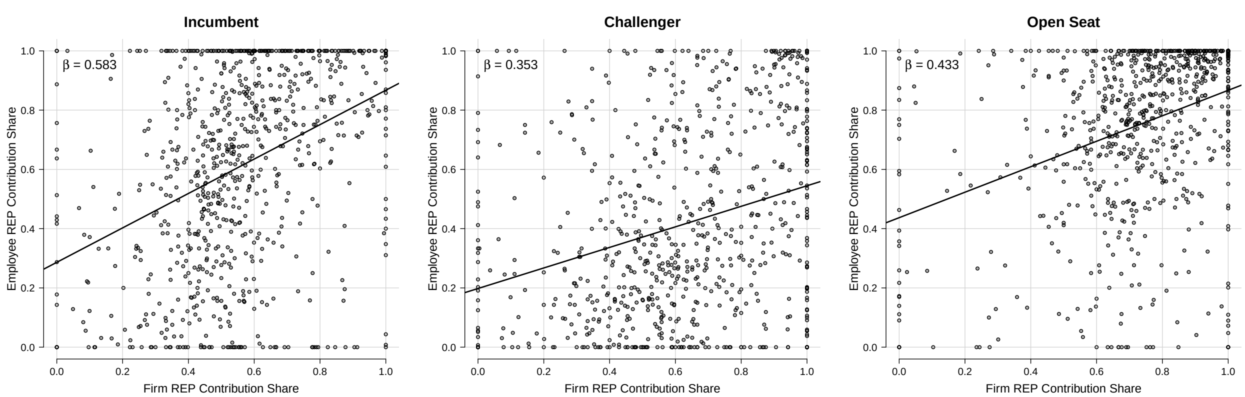


Figure A2: Correlation between Firm- and Employee Donations and Candidate Incumbency Status: The plots show the correlation between employee and firm Republican donation share, aggregated at the firm-level between 2003 and 2016, for different candidate types. It shows that donations of corporations and employees are more correlated for Incumbent and Open Seat candidates than for Challengers. β denotes the slope coefficient of the fitted line from a bivariate linear regression.

A3 Accuracy of Information in FEC Data

How accurate are the FEC data files in terms of individual employers or occupations? Based on the 1974 Federal Election Campaign Act (FECA), disclosure of donations is mandatory for all individual contributions exceeding USD 200, and since 2015, if the sum of individual donations exceeds USD 200 within a reporting period. While employers can and do report all contributions, even those smaller than USD 200 most candidates report only donations over USD 200. Contribution limits differ by entity donated to, and change each electoral cycle.[1] Individuals who give to federal candidate must disclose their occupation and employer. Committees receiving donations must make their best effort to determine employer and occupation of donors before filing contributions to the FEC. Nevertheless, there is some mis-reporting, especially among occupation names. Some obviously incorrect or non-informative examples include:

- `ANTI-ISLAMOFASCISM EXPERT`
- `ANTI-ISLAM OF ASCIST CONSULTANT`
- `''MOBBED'' OCCUPATIONAL THERAPIST`
- `Mother :  )`
- `DINOSAUR EXPERT`
- `UNEMPLOYED LIKE 22% OF AMERICANS`
- `UNEMPLOYED & LOVING IT`
- `VP DICK CHENEY`

That being said, there are few ways to check the accuracy of each individual filing. Hence, I need to assume that committees are checking the accuracy of individual donations thoroughly, on average. One downside of the data are that I have to compromise on the accuracy of individual identifiers. Bonica (2014, p.370) maximizes the precision of his identity-resolution algorithm by utilizing individual names, addresses, occupations, and employer names. I only use first name, last name and state of residence for determining individual identifiers, to be able to observe changes in occupations and employers. The DIME database also allows individuals to be tracked across locations and jobs, but the lack of unique identifiers for occupations and employers makes it more difficult to observe individuals changing the latter, despite considerable standardization of employer and occupation names in DIME.

[1]The 2017/2018 electoral cycle contribution limits within a given per election are: (1) USD 2,700 to individual candidates (2) USD 5,000 to PACs (3) USD 10,000 to non-national party committees (state, local, district), and (4) up to USD 33,900 to national party committees. Those limits are subject to adjustment for inflation every electoral cycle.

A4 Companies in matched Employer-Employee Campaign Finance Data

Company Name	NAICS Code	NAICS Title	Frequency
MICROSOFT CORP	511210	Software Publishers	6294
GOLDMAN SACHS GROUP INC	523110	Investment Banking and Securities Dealing	5139
MORGAN STANLEY	523110	Investment Banking and Securities Dealing	5115
BOEING CO	336411	Aircraft Manufacturing	4360
BANK OF AMERICA CORP	522110	Commercial Banking	3293
MERRILL LYNCH & CO INC	523110	Investment Banking and Securities Dealing	2723
COMCAST CORP	515210	Cable and Other Subscription Programming	2665
RAYTHEON CO	334511	Aeronautical, and Nautical Manufacturing	2134
ORACLE CORP	511210	Software Publishers	2115
NORTHWESTERN MUTUAL LIFE INS	524113	Direct Life Insurance Carriers	1974
AMERICAN AIRLINES INC	481111	Scheduled Passenger Air Transportation	1973
PFIZER INC	325412	Pharmaceutical Preparation Manufacturing	1881
CISCO SYSTEMS INC	334210	Telephone Apparatus Manufacturing	1834
JOHNSON & JOHNSON	325412	Pharmaceutical Preparation Manufacturing	1618
GENERAL ELECTRIC CO	999977	Unknown/Other	1550
ACCENTURE PLC	541611	Management Consulting Services	1508
NEW YORK LIFE INSURANCE	524113	Direct Life Insurance Carriers	1243
INTEL CORP	334413	Semiconductor Manufacturing	1199
AMGEN INC	325414	Biological Product Manufacturing	1146
GENERAL DYNAMICS CORP	336411	Aircraft Manufacturing	1138
FORD MOTOR CO	33611	Automobile Manufacturing	1121
GENERAL MOTORS CO	33611	Automobile Manufacturing	1098
AMERICAN EXPRESS CO	522210	Credit Card Issuing	1082
UNITED AIRLINES INC	48111	Scheduled Air Transportation	997
MERCK & CO	325412	Pharmaceutical Preparation Manufacturing	995
MCDONALD'S CORP	722513	Limited-Service Restaurants	973
AMAZON.COM INC	454111	Electronic Shopping	951
LILLY (ELI) & CO	325412	Pharmaceutical Preparation Manufacturing	945
TARGET CORP	452990	All Other General Merchandise Stores	939
SOUTHWEST AIRLINES	481111	Scheduled Passenger Air Transportation	856
COCA-COLA CO	312111	Soft Drink Manufacturing	819
EXXON MOBIL CORP	324110	Petroleum Refineries	814
BLACKSTONE GROUP LP	523920	Portfolio Management	802
PROCTER & GAMBLE CO	325611	Soap and Other Detergent Manufacturing	783
DISNEY (WALT) CO	515120	Television Broadcasting	772
AMERICAN ELECTRIC POWER CO	2211	Electric Power Generation and Distribution	743
HOME DEPOT INC	444110	Home Centers	743
3M CO	322220	Paper Manufacturing	733
HARRIS CORP	334511	Aeronautical, and Nautical Manufacturing	733
EXPRESS SCRIPTS HOLDING CO	446110	Pharmacies and Drug Stores	724

Table A2: Most frequent Firms in Linked Firm-Employee Campaign Contributions Data: The table shows the distribution of 40 most common firms in the linked employer-employee data, their matched North American Industrial Classification System (NAICS) code, as well as their industry title.

A5 Industries in matched Employer-Employee Campaign Finance Data

NAICS Code	NAICS Title	Frequency
523	Securities, Commodity Contracts, and Other Financial Investments	15660
325	Chemical Manufacturing	11931
334	Computer and Electronic Product Manufacturing	10615
511	Publishing Industries (except Internet)	9826
336	Transportation Equipment Manufacturing	9514
522	Credit Intermediation	8538
524	Insurance Carriers	6229
221	Utilities	5723
515	Broadcasting (except Internet)	4869
541	Professional, Scientific, and Technical Services	4331
481	Air Transportation	4207
333	Machinery Manufacturing	2970
999	Unknown/Other	2167
211	Oil and Gas Extraction	1950
311	Food Manufacturing	1590
517	Telecommunications	1547
452	General Merchandise Stores	1359
722	Food Services and Drinking Places	1235
324	Petroleum and Coal Products Manufacturing	1186
621	Ambulatory Health Care Services	1153
446	Health and Personal Care Stores	1098
482	Rail Transportation	1038
561	Administrative and Support Services	1012
424	Merchant Wholesalers, Nondurable Goods	994
312	Beverage and Tobacco Product Manufacturing	986
454	Nonstore Retailers	951
339	Miscellaneous Manufacturing	935
444	Building Material and Garden Equipment and Supplies Dealers	849
322	Paper Manufacturing	778
721	Accommodation	764
445	Food and Beverage Stores	718
519	Other Information Services	712
236	Construction of Buildings	672
111	Crop Production	583
332	Fabricated Metal Product Manufacturing	571
512	Motion Picture and Sound Recording Industries	532
212	Mining (except Oil and Gas)	496
316	Leather and Allied Product Manufacturing	476
492	Couriers and Messengers	438
532	Rental and Leasing Services	437

Table A3: Most frequent Industries in linked Firm-Employee Campaign Contributions Data:The table shows the distribution of 40 most frequent North American Industrial Classification System (NAICS) 3-digit industries in the linked employer-employee data.

A6 Industries in Data vs. US Economy

NAICS Code	Industry Name	% 2016 US Employment	% FEC Filings	Difference
31–33	Manufacturing	8.8	32.3	23.5
52	Finance and Insurance	4.1	14.0	9.9
22	Utilities	0.4	5.3	4.9
51	Information	2.0	6.7	4.7
48–49	Transportation/Warehousing	4.0	7.0	3.0
21	Mining, Oil & Gas	0.5	2.0	1.5
11	Agriculture, Forestry & Hunting	0.3	0.5	0.2
53	Real Estate, Rental & Leasing	1.5	1.2	-0.3
71	Arts & Entertainment	1.7	0.1	-1.6
42	Wholesale Trade	4.2	1.6	-2.6
81	Other Services	2.9	0.0	-2.9
54	Professional Services	6.2	2.5	-3.7
23	Construction	4.8	0.6	-4.2
56	Administrative & Support	6.5	0.9	-5.6
99	Unknown	6.8	0.3	-6.5
44–45	Retail Trade	11.4	4.0	-7.4
72	Accommodation & Food Services	9.5	0.9	-8.6
61	Educational Services	9.2	0.2	-9.0
62	Health Care & Social Assistance	13.7	1.9	-11.8

Table A4: Differences between US Industry Employment and FEC Industry Filings: The table shows that there are large differences between 2016 US private Employment across 2-digit North American Industry Classification System (NAICS) industries and Filings per Industry in the FEC data. Source: Bureau for Labor Statistics and own calculations.

A7 Occupations in Data

SOC 2010	SOC 2010 Title	Frequency
11-1011	Chief Executives	24291
23-1011	Lawyers	9057
11-3031	Financial Managers	7726
11-9199	Managers, All Other	7375
17-2021	Agricultural Engineers	6079
15-1111	Computer and Information Research Scientists	3727
13-2052	Personal Financial Advisors	3719
11-2021	Marketing Managers	2880
41-3031	Financial Services Sales Agents	2748
41-4011	Sales Representatives, Wholesale and Manufacturing	2726
11-1021	General and Operations Managers	2357
11-9081	Lodging Managers	1636
11-9041	Architectural and Engineering Managers	1571
13-1199	Business Operations Specialists, All Other	1558
45-3011	Fishers and Related Fishing Workers	1486
13-2011	Accountants and Auditors	1335
11-3121	Human Resources Managers	1308
19-3094	Political Scientists	1259
11-2031	Public Relations and Fundraising Managers	1171
11-2022	Sales Managers	1168
29-1069	Physicians and Surgeons, All Other	968
11-9021	Construction Managers	947
15-1132	Software Developers, Applications	914
17-3029	Engineering Technicians, Except Drafters, All Other	890
11-3021	Computer and Information Systems Managers	888
41-3021	Insurance Sales Agents	826
13-1111	Management Analysts	742
15-1199	Computer Occupations, All Other	700
53-2031	Flight Attendants	630
41-1012	First-Line Supervisors of Non-Retail Sales Workers	624
11-9033	Education Administrators, Postsecondary	617
27-3031	Public Relations Specialists	578
15-1121	Computer Systems Analysts	569
13-2031	Budget Analysts	557
11-9111	Medical and Health Services Managers	546
29-1051	Pharmacists	507
15-1152	Computer Network Support Specialists	481
13-1161	Market Research Analysts and Marketing Specialists	419
13-1011	Agents and Managers of Artists, Performers, and Athletes	411
11-3061	Purchasing Managers	394

Table A5: Unequal Frequency of Occupations in Firm-Employee Campaign Contributions Data: The table shows the distribution of 40 most common Standardized Occupation Classification (SCO) codes in the linked firm-employee contributions data. The table shows that Management, Business, Financial, and Legal occupations comprise more than half of the individual contributions.

A8 Occupations in Data vs. US Economy

SOC Code	Occupation Name	% 2016 US Employment	% FEC Filings	Difference
11-0000	Management	5.1	34.0	28.9
23-0000	Legal	0.8	3.9	3.1
17-0000	Architecture & Engineering	1.8	4.1	2.3
13-0000	Business & Financial Operations	5.2	7.3	2.1
15-0000	Computer & Mathematical	3.0	5.1	2.1
19-0000	Life, Physical, & Social Science	0.8	2.0	1.2
45-0000	Farming, Fishing, & Forestry	0.3	0.6	0.3
27-0000	Arts, Design & Entertainment	1.4	1.1	-0.3
21-0000	Community and Social Service	1.4	0.1	-1.3
33-0000	Protective Service	2.4	0.2	-2.2
39-0000	Personal Care & Service	3.2	0.8	-2.4
31-0000	Healthcare Support	2.9	0.0	-2.9
37-0000	Building Cleaning & Maintenance	3.2	0.2	-3.0
49-0000	Installation, Maintenance, & Repair	3.9	0.3	-3.6
47-0000	Construction and Extraction	4.0	0.3	-3.7
29-0000	Healthcare Practitioners and Technical	5.9	1.1	-4.8
53-0000	Transportation and Material Moving	6.9	1.5	-5.4
25-0000	Education, Training, and Library	6.2	0.3	-5.9
51-0000	Production	6.5	0.6	-5.9
41-0000	Sales and Related	10.4	3.3	-7.1
35-0000	Food Preparation and Serving Related	9.2	0.6	-8.6
43-0000	Office and Administrative Support	15.7	1.4	-14.3

Table A6: Differences between US Occupational Employment and FEC Occupation Filings: The table shows that there are large differences between 2016 US private Employment across 2-digit Standard Occupation Classification (SOC) categories and Filings per occupation in the FEC data. Source: Bureau for Labor Statistics and own calculations.

A9 Examples of Firms Donating only for One Party

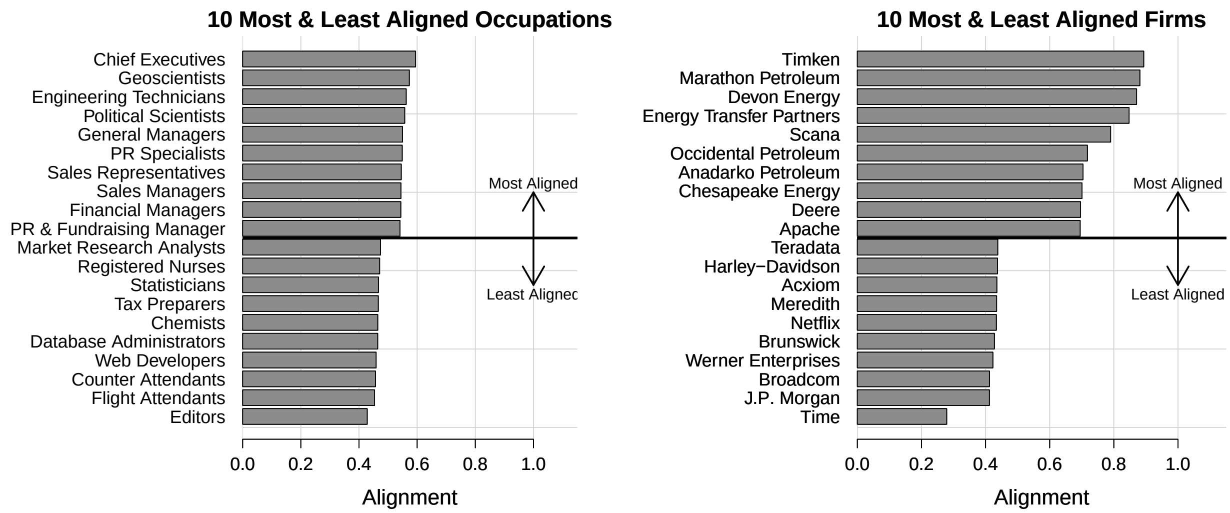
Only 1282 firm-year observations (out of 7844, or 16%) donate one-sided. 83% donate to both parties. There are some firms with consistent Republican-only donations, but not as many donating to the Democratic party only. Below, see examples of **Republican companies** (gvkey in parenthesis):

- XTO ENERGY INC (28256),
- WORTHINGTON INDUSTRIES (11600)
- WERNER ENTERPRISES INC (12266)
- SUN BANCORP INC (19420)
- REMINGTON ARMS COMPANY INC (9043)
- COOPER INDUSTRIES PLC (3497)
- CRYOLIFE INC (27823)
- LEGGETT & PLATT INC (6649)
- COLONIAL BANCGROUP (14201)

Below, see examples of **Democratic companies** (gvkey in parenthesis):

- JERRYS INC (6252)
- HOMESTREET INC (187164)
- MAUI LAND & PINEAPPLE CO (7117)
- PHOENIX COMPANIES INC (142462)
- REEBOK INTERNATIONAL LTD (9004)
- BANK OF HAWAII CORP (16200)
- BROWN & BROWN INC (117500)
- FUELCELL ENERGY INC (25430)

A10 Partisan Alignment of Firms and Occupations



(a) Occupational Alignment **(b)** Firm Alignment

Figure A3: Most & Least Aligned Occupations and Firms: This figure shows the ten occupations and firms with most and least alignment. Panel a) shows that CEOs, Geoscientists, and Engineers are most aligned, while Editors, Attendants, and IT occupations are least aligned. Panel b) shows that Timken and Marathon Petroleum are most aligned, while J.P. Morgan and Time show little alignment. All sectors and occupations with $\geq$ 100 observations.

A11 Cross-Validation for Matching Firm- and Occupation Codes

The script for matching employer and occupation names in the FEC data to unique names and identifiers for publicly traded companies (GVKEY) and occupation categories (SOC) is based on textual distance between FEC employer and occupation names and unique names in the Compustat Capital IQ database, as well as occupation titles published by the Bureau of Labor Statistics and the Census Bureau. The script calculates the cosine similarity between FEC employer (occupation) names and Compustat firm names (BLS/Census occupation titles) and picks the best match, if above a pre-defined threshold. The threshold is 0.81 for the cosine similarity of employer names to compustat company names, and 0.72 for similarity between occupation names and BLS/Census occupation titles. The thresholds were chosen based on recommendations from existing research on similar record-linkage problems for corporate patent data (Raffo and Lhuillery, 2009).

To investigate how the choice of the threshold affects the number and quality of matches, I used cross-validation for both employer names and occupation names, a method employed in computer science to evaluate the quality of predictions. First, I randomly sampled 1000 employer and occupation names between 2003 and 2016. Second, I ran the matching script on these names using different thresholds for both occupations (0.72, 0.60, 0.50) and employers (0.81, 0.70, 0.60), where lower values indicate that matches can be less exact. Third, I compare the actual matches against manual matches done by me. The manual matches serve as the 'ground truth' against which the script matches are compared. Finally, I note whether the matches and non-matches are:

- *True Positive (TP)*: there is a correct matched, and the name was matched correctly.
- *False Positive (FP)*: there is no match, but the script matched a name erroneously.
- *True Negative (TN)*: there is no match, and the script did not match anything.
- *False Negative (FN)*: there is a correct match, but the script did not find it.

In Table A7 I show the results from this exercise. The first column shows the type of match (employer or occupation) and the chosen thresholds. The second column depicts the overall number of correct matches and non-matches, followed by the number of true positive, false positive, and false negative matches (the true negatives are simply the difference between the overall number of names, 1000, and the sum of TP, FP, and FN). The sixth column shows the fraction of overall correct matches and non-matches. Precision is the fraction of correct matches over all names that were matched by the script. Recall is the fraction of correct matches over correct matches plus the

Threshold	Correct Overall	Correctly Matched (TP)	Incorrectly Matched (FP)	Incorrectly Not Matched (FN)	Accuracy (Frac. Correct)	Precision TP/(TP+FP)	Recall TP/(TP+FN)	F1
Employers								
0.81	994	21	2	5	0.99	0.91	0.81	0.86
0.70	953	22	48	4	0.95	0.31	0.85	0.45
0.60	819	23	179	3	0.82	0.11	0.88	0.20
Occupations								
0.72	536	272	22	444	0.54	0.93	0.38	0.54
0.60	615	408	136	252	0.62	0.75	0.62	0.68
0.50	625	490	276	102	0.63	0.64	0.83	0.72

Table A7: Cross-Validation of 1000 Employer and Occupation Names: This Table shows the quality of matched firm and occupation codes to employer and occupation names, using a random sample of 1000 employer names and a random sample of 1000 occupation names. The top row for occupations and employers shows the specification used for this paper. While the chosen threshold for employer names is a good compromise between accuracy, precision, and recall, the threshold for occupations puts more emphasis on precision, i.e. matching only occupation names to codes when it is very likely to be a good match.

names that should have been matched but were not. The former tells us how well the script did if it actually identified a match, and the latter how many potential matches were missed. F1 is the harmonic mean between precision and recall.

There are *two main conclusions from the cross-validation*. First, the chosen threshold for employer names seems to be a good compromise between finding potential matches and producing very accurate matches. While there are few cases of incorrect matches and incorrect non-matches, precision (0.91) and recall (0.81) are high, as is accuracy (0.99). Lowering the matching threshold increases recall slightly, but at the expense of producing too many incorrect matches. Note that the number of possible correct matches is low (26) because I only want to match publicly traded companies, which correspond to a large number of donations, but only few employer names in the FEC data. Second, the threshold for occupations produces highly accurate occupation matches when there is a match (the precision is 0.93), but tends to produce too many false negatives, indicated by the low recall.

This shows the *trade-off between providing accurate matches and matching as many occupations as possible*. For the purpose of this paper, I wanted to provide as accurate as possible occupation codes give that employer PACs were matched to employees, and hence, used a higher threshold. However, this does not mean that many observations get lost: the number of individual donations corresponding to the occupation codes for each of the thresholds do not increase dramatically using a lower threshold: while all matched occupations using the threshold of 0.72 correspond to approximately 74,800 donations between 2003 and 2016, while thresholds of 0.60 and 0.50 only add around 3,000 and 1,300, respectively (77,800 and 79,600). This in turn, does not translate into a lot of additional observations once linked to the matched employee-employer donations, as seen in the replication of the main regression results below. This is ultimately a choice that is up to the researcher, and the occupation-matching will still be improved in future versions of this data.

In addition, I show the *sensitivity of the main results to different thresholds*. Below, I use 0.60 instead of 0.72 as a threshold, providing more potential matches at less precision for matched occupations (a more balanced relationship of precision and recall). The boxplot comparing the distribution of alignment for chief executives and other employees in Figure A4 looks the same as in Figure 4b in the main text. Moreover, the regression results in Table A8 below are almost exactly the same when compared to Table 6 in the main text. The estimates in the main text are slightly lower, but the differences in the coefficients are minimal, as are the differences in observations or R^2.

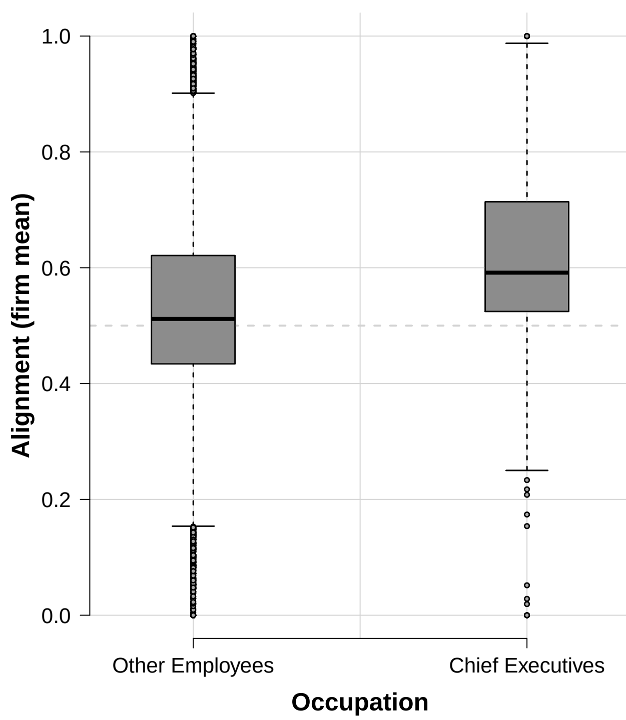


Figure A4: Alignment and Occupation, using lower Threshold to match Occupation Codes: The figure shows that chief executives are more aligned with their firm, compared to all other firm employees, also if one uses a threshold of 0.60 (instead of 0.72) to match occupation codes to occupation names in the FEC data.

Table A8: Regression Results: Chief Executives and Alignment, Matching Threshold of 0.60

	Dependent variable:					
	Align					
	(1)	(2)	(3)	(4)	(5)	(6)
CEO	0.074***	0.059***	0.056***	0.047***	0.047***	0.045***
	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)
Firm Controls		✓	✓	✓	✓	✓
Cycle FEs			✓	✓	✓	✓
Firm FEs				✓	✓	✓
County FEs					✓	✓
SOC 2-digit FEs						✓
Observations	127,458	112,952	112,952	112,952	101,579	101,579
Adjusted R^2	0.023	0.049	0.055	0.166	0.188	0.190

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm.

A12 Excluding Extreme Observations

Readers might be worried that the presence of extreme values scoring zero or one on the partisan alignment measure might bias the empirical validations provided in the main text. Therefore, I first replicate Figure 2 in the main text excluding firms where both PACs and employees donate exclusively to either Democrats or Republicans, i.e. for which the Republican donation share equals zero or one. I show the result Figure A5 below. In fact, the slope coefficient is larger (0.75 vs. 0.61), as is the R^2 (0.27 vs 0.2). Hence, the inclusion of these extreme values results in a slightly weaker relationship between firm and employee partisan donations.

Moreover, in the Tables A9, A10, and A11, I replicate the regression results in the main text without the extreme values visible in Figure 3. As one can see in Table A9, excluding zeros and ones leads to a stronger association between Republican donation shares of corporate PACs and those of their employees. While the coefficients are a bit larger, they are in the same order of magnitude. Table A10 and A11 show very similar results. Excluding extreme values leads to almost identical estimates for the relationship between the logged number of employees and partisan alignment, and for slightly lower (though highy similar) coefficients for the association between being a chief executives and partisan alignment. In sum, while coefficients differ slightly, these robustness checks confirm the results from the main part of this paper in the Tables 2, 5, and 6.

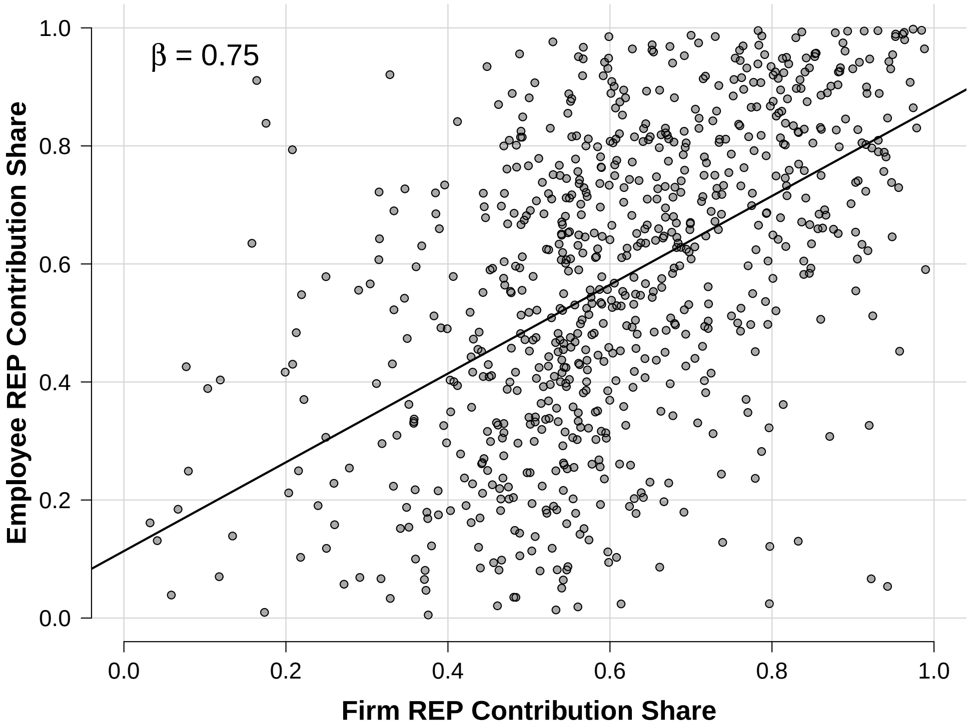


Figure A5: Relationship between Firm and Employee Donations, excluding extreme values: This scatter plot shows that there is a positive association between the share of donations donated to Republicans by firms and their employees even if either PACs or employees donate exclusively to either Republican or Democratic candidates. β denotes the slope coefficient of the bivariate linear regression of employee Republican donation share on the firm Republican donation share. The R^2 of the fitted line is 0.27.

Table A9: Regression Results: Employee and Firm Donations, excluding extreme values

	Dependent variable:			
	Employee REP Donation Share			
	(1)	(2)	(3)	(4)
Firm REP Donation Share	0.525***	0.511***	0.550***	0.266***
	(0.034)	(0.040)	(0.045)	(0.061)
Firm Controls		✓	✓	✓
Cycle FEs			✓	✓
Firm FEs				✓
Observations	2,631	2,154	2,154	2,154
Adjusted R^2	0.128	0.154	0.166	0.456

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm.

Table A10: Regression Results: Firm Size and Alignment, excluding extreme values

	Dependent variable:					
	Align					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Employees)	-0.018^{***}	-0.023^{***}	-0.022^{***}	-0.019^{***}	-0.015^{***}	-0.011^{***}
	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Firm Controls		✓	✓	✓	✓	✓
Cycle FEs			✓	✓	✓	✓
Occupation FEs				✓	✓	✓
County FEs					✓	✓
NAICS 2-digit FEs						✓
Observations	106,915	106,264	106,264	106,264	95,571	95,571
Adjusted R^2	0.020	0.034	0.042	0.068	0.126	0.131

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm.

Table A11: Regression Results: Chief Executives and Alignment, excluding extreme values

	Dependent variable:					
	Align					
	(1)	(2)	(3)	(4)	(5)	(6)
CEO	0.067^{***}	0.054^{***}	0.051^{***}	0.043^{***}	0.043^{***}	0.042^{***}
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Firm Controls		✓	✓	✓	✓	✓
Cycle FEs			✓	✓	✓	✓
Firm FEs				✓	✓	✓
County FEs					✓	✓
SOC 2-digit FEs						✓
Observations	119,578	106,264	106,264	106,264	95,571	95,571
Adjusted R^2	0.022	0.047	0.054	0.152	0.176	0.179

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm.

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