Online Appendix to "The Political Power of Firms"

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For the North Holland Handbook of Political Economy

The final dataset is called data_politicalpower_final.dta and is in the main folder. All calculated values are in millions of current US$. Relevant variables are prefixed v0x_, with x corresponding to the section numbers in this document.

1. Sample

As sample, we take the list of S&P 500 firms from Compustat/CapitalIQ. Since this is a time-varying firm-year panel, we restrict the dataset to firms that were active until at least 2015. The dataset ranges from 2000 to 2024. The cleaning and preparation of the S&P 500 dataset are in Code/01_00_SP500.do

2. Data

We generate the political footprint of a firm, our summary measure, as the sum of monetized value of political power across five dimensions: campaign contributions, politically motivated charitable giving, lobbying expenditure, value of employee voting bloc and value of political connections. The creation of each of these is explained below.

2.1 Campaign Contributions

Campaign contributions are the sum of PAC giving (PAC to PAC giving, PAC to candidate giving), the political giving of employees, and direct contributions of firms.

2.1.1 PAC Giving

To match PACs to firms, we used Dane Christensen's FEC/OpenSecrets to Compustat link table to link PAC IDs to Compustat GVKEYs (Webpage, Christensen et al. 2022, Christensen et al. 2023). This dataset is available for the period 1991-2020. To avoid double counting, we employ the following algorithm: The OpenSecrets data has PAC-to-PAC, PAC-to-Candidate, and Individual-to-anyone) contributions in separate files. Under PAC giving, we track for firm PACs, PAC-to-PAC and PAC-to-Candidate contributions. If an individual contribution to a firm PAC is recorded in the Individual contribution dataset, we drop it since further contributions by that firm PAC should be covered in either PAC-to-PAC or PAC-to-Candidate datasets.

PAC to PAC giving

This comes from OpenSecrets' *pac_other* table. It contains contributions from PACs to PACs, such as party committees, leadership PACs, etc. We do not pose any restrictions based on the type of recipient PACs, however, we restrict the data to where the donor PAC was a firm PAC. The main data processing steps are:

1. Merge OpenSecrets' PAC-PAC data with Christensen's PAC-GVKEY table. Keep only the matched observations, thus keeping only those observations where the donor was a firm PAC. Also drop transfers.

2. After some basic cleaning of the amount variable and dropping any observations with missing GVKEYs, collapse data on the firm PACs' contributions to the firm-year level, getting a firm-year panel of PAC-PAC contributions for years 2000-2020.

3. Merge this panel with the SP500 panel and keep only the observations pertaining to firms that had ever been in the SP500 index between 2000-2020.

Code: 01_01_2_PAC2PACImportExport.ipynb, 01_01_3_PAC2PACContributions.do

Dataset created: 01_PACContributions/PAC2PAC_SP500Panel.dta

PAC to candidate giving

This comes from OpenSecrets' *pacs* table. It contains contributions from PACs to candidates. As recommended in OpenSecrets' user guide, we restrict the data to direct contributions to candidates and drop transfers/joint fundraising committees. The main data processing steps are:

1. Merge OpenSecrets' PAC-Candidates data with Christensen's PAC-GVKEY table. Keep only matched observations (where the donor was a firm PAC). Keep only direct contributions to candidates and drop transfers (as recommended in OpenSecrets' user guide).

2. After some basic cleaning of the amount variable and dropping any observations with missing GVKEYs, collapse data on the firm PACs' contributions to the firm-year level, getting a firm-year panel of PAC-to-candidate contributions for years 2000-2020.

3. Merge this panel with the SP500 panel and keep only the observations pertaining to firms that had ever been in the SP500 index between 2000-2020.

Code: 01_01_1_PAC2CandContributions.do

Dataset created: 01_PACContributions/PAC2Cand_SP500Panel.dta

2.1.2 Political Giving of Employees

To track political giving of employees, we used OpenSecrets data on contributions by individuals. The variable "contribid" identifies individual contributors. For direct contributions of individuals (not firms)n, we only keep records that are non-empty for contribid. This data records all individual contributions, including contributions to candidates, candidate PACs, firm PACs, etc. However, we already count firm PAC contributions in PAC-candidate and PAC-PAC data. Thus, we need to exclude the contributions made by individuals to firm PACs. Thus, political giving of employees data will be focused on employees' political contributions to non-company PACs and to candidates directly. The main data processing steps are:

1. Drop transfers. Drop any contributions from an individual to a firm PAC: merge with Christensen's PAC-GVKEY link table and keep only those that are unmatched from the individual contributions data.

2. Collapse to level of self-reported employer name-by-year. Thus, we get an (self-reported) employer-year panel of individual contributions for years 2000-2020.

3. Match employer names with the self-created link table that will return the GVKEY for that employer if it is a firm and was matched with a firm in the compustat data. (see below for the matching process)

4. After all the matching is finished, collapse the data to sum up the contributions at gvkey-year level, i.e., firm-year level. Thus, we get a firm-year panel of individual contributions for years 2000-2020.

5. Then we merged this panel with the SP500 panel and kept only the observations pertaining to firms that had ever been in the SP500 index between 2000-2020.

Matching OpenSecrets' employer names with Compustat's firm names: The OpenSecrets data contains the self-reported company/organization name. It also contains a cleaned, standardized name of the company. OpenSecrets' standardized company names are especially useful in case of mergers and acquisitions (and subsidiaries) because they help match observations that would have no chance of being matched based on a fuzzy merge of reported company names. However, the standardized name is often missing. Hence, we first fuzzy-match the self-reported company names to the company names in Compustat and then do the same for OpenSecrets' standardized company names:

1. We keep all fuzzy matches with a similarity score of 0.6 or higher.

2. Then we manually go over this list of potential matches and marked as 1 the correct matches

3. Thus, we were left with a list of matches

4. We repeated the above steps using OpenSecrets' standardized company names (but only for the observations that were unmatched at the end of step 3)

Issue[1]: The matching between self-reported employer names and firm names in Compustat suffers from two issues:

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[1] This issue is likely much less severe for the PAC contributions. Dane Christensen's webpage notes: "Although many PACs are sponsored by parent companies, they are often sponsored by subsidiaries of public companies. When PACs are sponsored by parent companies, we have manually verified the links here based on historical CRSP

1. Compustat contains only the latest name. But the employer name in contributions data relates to the firm's name in that particular year. This poses no issue if the name change was small enough. But for bigger changes in names arising from, for example, mergers/acquisitions, fuzzy matching will be insufficient, potentially missing out on matching such observations in the OpenSecrets data with the Compustat data.

2. If a firm's subsidiaries have very different names (which can happen, example: Instagram is a subsidiary of Meta), then our fuzzy matching of employer names will miss them.

OpenSecrets' standardized company names are especially useful in the above cases because they account for changes in firm names and subsidiary-parent relationships. However, not all observations have standardized company names. Thus, it is likely that that there is some undercounting of individual contributions coming from employees of the SP500 firms.

Code: 01_02_1_EmployeeContributionsImportExport.ipynb, 01_02_2_EmployeeContributions.do

Dataset created: 02_EmployeeContributions/EmployeeDirectContribution_SP500Panel.dta

2.1.3 Direct contributions of firms

To measure direct contributions of firms to candidates, we rely on the same data and method as for Political Giving of Employees. The variable "contribid" identifies individual contributors. For direct contributions of firms, we only keep records that are empty for contribid (i.e., contributions by firms).

Code: 01_07_FirmDirectContributions.do

Dataset created: 07_FirmDirectContributions/FirmDirectContribution_SP500Panel.dta

2.2 Politically motivated charitable giving of Firms via 501(c)(3)

Reference paper: Bertrand, Bombardini, Fisman and Trebbi (2020). Code: Code/01_03_foundation_sp500.do.

The goal of the do-file is to find, for every firm on the list of S&P500 firms, the set of charitable 510(c)(3) foundations, and then to use their tax returns to estimate politically motivated charitable giving. This is done in multiple steps:

1. We first merge companies to foundations using the "client_foundation_gvkeyx.csv" file from Bertrand et al. (2020) (307 firm-foundation pairs, 288 unique firms, 281 unique foundations). The data is slightly outdated, and so we update it in the following steps.

company names. When PACs are sponsored by subsidiaries, we have verified the links using internet searches (e.g., reading news articles, press releases, company websites)."

2. For companies that were not merged, we then did a string match in Stata with the foundation names from "AllGrants_eins_new.dta" file from Bertrand et al. (2020), manually verifying the matched firm-foundation pairs (62 firm-foundation pairs)

3. For companies that still had no match, we then manually searched (using ProPublica, GuideStar, and Google Search) foundations for the companies. (224 matches. Out of 490 remaining firms, 217 have at least one foundation. 219 unique foundations). We use multiple criteria to verify matches: Foundation mentioned on firm's website, overlap of names (e.g., "Alaska Airlines Foundation" for Alaska Air Group Inc.), foundation of founder or majority shareholder of firm, firm is main contributor in tax return of foundation, match of city and state of foundation with headquarters of firm alongside a partial match of other criteria.[2]

Within the Stata script, we call the Python script "Code/01_03_scrape_propublica.py" to scrape the tax returns for all foundations from ProPublica, including the contributor information that can be used to verify whether the money is indeed coming from the associated firm.[3]

Several research decisions have been taken in the script:

1. Foundations with multiple companies: very rare, but in that case, we took the ratio of total income (foreign + domestic) of the companies and split foundation values across companies.

2. Companies with multiple foundations: We sum up the values across all foundations belonging to a company.

Finally, the extracted tax returns are used to estimate the value of politically motivated charitable giving. For this, we use the value of disbursed funds from foundations.[4] We then multiply these charitable disbursements with 14.3%. This is the sum of two components: First, the share of charitable giving that is politically motivated, which is estimated to be 6.3%, from Bertrand, Bombardini, Fisman and Trebbi (2020). Second, the share firm foundations' total grants to non-profits that comment on the same rule as they do, which is estimated to be 8%, from Bertrand, Bombardini, Hackinen, Fisman and Trebbi (2021). This variable is saved as v03_ch_disb_pol_med. We also create variables that capture the average amount of charitable giving over the last three years (v03_avg_3y_ch_disb_pol_med, v03_avg_3y_ch_disb_pol_high).

The average value of charitable disbursements by foundations is US$ 1.61 million (note, however, that this is conditional on having a foundation, and the foundation having completed a tax return, and the tax return having been digitized), with a standard deviation of US$ 8.7 million. The largest influence is wielded by the foundations of Pfizer and Goldman Sachs (both

[2] The generated dataset is in /03_Charitable Donations/list_unmatched_sp500_firms_with_foundations.xlsx. We added notes for some special cases, e.g. mergers, uncertainties, multiple foundations, etc.

[3] In many cases, the contributor information is restricted.

[4] Disbursements may be different from total expenditures because foundations may pay executives. Disbursements are a better measure of charitable giving.

exceeding US$100 million for at least two years), followed by MasterCard, Hilton Worldwide, PayPal, WK Kellogg Co, and Meta (all above US$20 million).

2.3 Lobbying Expenditure

For lobbying expenditure by firms, we relied wholly on LobbyView (Kim 2018). LobbyView provides compustat GVKEYs for the firm names reported in lobbying expenditure reports. The main steps for data processing are:

1. We merge Lobbyview's two datasets: dataset_client_level.csv and dataset_report_level.csv. The first one contains matches between GVKEY and client ID, and the second one contains data on lobbying reports (with the client ID).
2. After some basic cleaning of the amount variable and dropping any observations with missing GVKEYs, collapse expenditures to the firm-year. Thus, we get a firm-year panel of lobbying expenditures for years 2000-2023 (2023 is the most recent year in LobbyView's dataset).
3. Then we merge this panel with the SP500 panel and kept only the observations pertaining to firms that had ever been in the SP500 index between 2000-2024.

Code: 01_04_Lobby.do

Dataset created: 04_Lobby/LobbyView/LobbyView_SP500Panel.dta

2.4 Value of Employee Voting Bloc

Reference paper: Bombardini and Trebbi (2011). Code: Code/01_05_Employees.do.

There are two central challenges in estimating the value of votes that a firm controls via its employees. The first is data on (domestic) employees, the second is to estimate the value of a vote.

For the first, Compustat/CapitalIQ supplies an estimate for the number of employees of a firm. However, not all employees are domestic. To get around this, we take the ratio of domestic (pidom) to total (domestic+foreign, pidom+pifo) income, and multiply this with the number of employees (emp) to get a proxy for domestic employees. For firms that do not have data on domestic or foreign income available, we adjust by the mean ratio in the data, which is 0.6.

For the second challenge, we rely on Bombardini and Trebbi (2011). They estimate (in table 5 of the paper) the value of a vote in a district to a politician (in the terms of their model, $1/\alpha$). The mean estimate for value of a vote is US$145.6, the median US$117.0, and the sd US$131.2. We multiply these amounts with the number of domestic employees estimated in step one.

In the final dataset, we include the mean (v05_bloc_mean), median (v05_bloc_median), mean+sd (v05_bloc_mean_plus_sd) and mean-sd (v05_bloc_mean_minus_sd) to have a range of plausible values.

On average, the value of employee votes in our data is US$3.5 million, with a standard deviation of US$11.5. The firms with the largest values in the data are, by construction, the largest employers: Walmart, Amazon, Target, Ford, Home Depot, Kroger, UPS all have values above US$50 million (Walmart and Amazon above US$100 million).

2.5 Value of Political Connections

Reference paper: Emery and Faccio (2025). Code: Code/01_06_Connections.do.

For this part, we rely on Emery and Faccio (2025), who collect a large panel data set on the number of transitions between executive branch agencies and firms. They combine this with data on procurement contracts to estimate how political connections affect procurement decisions.

First, to get the number of political connections, we follow their methodology and re-create a panel dataset for all S&P500 firms from 2000 until 2023, containing the number and value of political connections at the firm-year level. For this, we use the BoardEx dataset containing biographies of top corporate managers (CEOs, board members, etc.) together with data on federal agencies. The panel dataset contains, for every firm-year, the number of individuals who are working in a top corporate position in a firm in that year that have joined from an executive agency with a gap not exceeding two years.[5]

Second, we estimate the value of political connections using on the event study estimates from Emery and Faccio (2025). One challenge is that the paper calculates a *flow* variable (the number of new political connections), while we are interested in a *stock* variable: The value of the political connections of a firm. We get around this by exploiting the dynamics of the estimates and note that the calculated values are intensive-margin values.

Emery and Faccio (2025) estimate the following event study regression model:

$$\mathrm{Y_{i,a,t}} = \sum_{e=-2}^{e=+2} \alpha_{\mathrm{e}} \cdot \mathbf{1}\{\mathrm{E} = \mathrm{e}\} + \alpha_3 \cdot \mathbf{1}\{\mathrm{E} \geq 3\} + \eta_{\mathrm{i,a}} + \xi_{\mathrm{a,ind,t}} + \lambda_{\mathrm{i,t}} + \varepsilon_{\mathrm{i,a,t}}$$

Where $Y_{i,a,t}$ is an outcome of interest, e.g. the value of procurement contracts obtained by firm i, tendered by agency a, in year t, and the event (indicated by the indicator function) is whether there was an agency-to-firm transition in a given event-year. The time frame is -2 to +2 years, with 3 or more years explicitly included, and fewer than -2 years being the reference category. Therefore, all estimates are in relation to this reference category. We assume no anticipation and therefore do not use the coefficients for “negative” event-years.

We use the estimated coefficients α_e and multiply them with (1) the (dynamic) number of agency-to-firm transitions relative to every firm-year in the data and then (2) the average value

[5] For example, an individual working for the Federal Reserve until December 31, 2018, and joining firm A on June 30, 2019 and remaining in that firm until September 30, 2021, will be recorded as one political connection in the years 2019, 2020, and 2021.

of procurement contracts in the data (US$373k). Estimates are taken from table 5 of Emery and Faccio (2025). We use the specification on the (log) value of procurement contracts.

On average, the value of political connections is US$460k, with a standard deviation of US$1.25 million. The values range up to 22.5 million (Northrop Grumman Corp in 2011), and several firms have values above 10 million US$ (Boeing, Citigroup, GE, Northrop, Raytheon, Microsoft).

3. Creation of final data

Finally, we merge all datasets by firm identifier (GVKEY) and year. We create total political expenditure as the sum across all five dimensions (campaign contributions, politically motivated charitable giving, lobbying expenditure, value of employee voting bloc, value of political connections). The different input datasets we use have different time coverage. Therefore, we keep data for 2015 and 2016 and generate the final variables as the unweighted sum of the values for 2015 and 2016.

References

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