Political Alignment of Firms and Employees: the Role of Asset Specificity

Jan Stuckatz*

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Abstract

Do political preferences of employees align with those of their employers? I argue that in firms with more specific assets the economic interests of employers and employees will be more aligned, as the fate of jobs is tied more closely to the firm. Therefore, individuals working in firms with high asset specificity are more likely to share political preferences with their employers. However, simultaneously observing both company and employee preferences is difficult in practice. I match 1,691,790 campaign contribution filings of 85,109 employees to 874 publicly listed firms using US campaign finance data between 2003 and 2016. I accomplish this by employing natural language processing to automatically identify employers and occupations. Holding constant individual occupation, I find that employees in companies with more specific assets are more aligned with their employer, and that most variation in alignment is at the industry-level. The results confirm long-standing expectations from trade theory about firm structure and political alignment and stress the continuing importance of sector-based models for political preference formation, despite a current trend towards occupation-based models.

Key Words: political alignment, employees, firms, asset specificity, campaign finance, natural language processing

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*PhD Student, London School of Economics and Political Science, Government Department. Email: j.stuckatz@lse.ac.uk. I thank In Song Kim for accompanying this project from the start. I also thank Stephanie Rickard, Kenneth Benoit, Alexander Hertel-Fernandez, David Singer, Nikhar Gaikwad, Greg Distelhorst, Adam Dean, Matthew Amengual, Mehmet Efe Akengin, Nicholas Intscher, Nathan Lane, Duanyi Yang, Daniel Limoeiro, Ignacio Puente, Weihuang Wong, James Dunham, Andrew Halterman, Yilang Feng, and Ariel White for feedback and advice on earlier drafts and comment during presentations.

1 Introduction

Do political preferences of employees align with those of their employers? This important question relates to long-standing research on the origins of political preferences and the formation of coalitions. Whereas rational choice accounts hold that economic self-interest dictates political preferences (Meltzer and Richard, 1981), others assert that sociotropic perceptions of the country or society as a whole determine preferences (Kinder and Kiewiet, 1979; Lewis-Beck and Paldam, 2000). Research in the former tradition from Comparative (CPE) and International Political Economy (IPE) states that factor ownership, (Rogowski, 1989) sectors of employment (Hiscox, 2002*b*), or individual occupations (Kitschelt and Rehm, 2014) are an important source of political preferences. Occupation-level factors such as offshorability (Owen and Johnston, 2017), task routineness (Thewissen and Rueda, 2017), or skill specificity of an occupation (Iversen and Soskice, 2001) have been show to shape preferences for redistribution, free trade, or labor market risk.

In this paper, I argue that *political alignment* between firms and employees depends on the asset specificity of an individual's firm. In firms with more specific assets, the economic interests between employers and employees will be more aligned, as the fate of jobs is tied more closely to the firm. Therefore, individuals working in firms with high asset specificity are more likely to share political preferences with their employers. However, observing both individual political preferences and the preferences of individual's employers at the same time is very difficult in practice. [1]

This paper provides *three main contributions*. First, I create a unique dataset of employer-employee political preferences by matching 1,691,790 campaign contribution filings of 85,109 individuals to 874 publicly listed firms and 850 occupations using US campaign finance data between 2003 and 2016.[2] I accomplish this by employing natural language processing techniques to automatically identify unique employer names and individual occupations. The linked employer-employee campaign finance data contains unique identifiers at the firm, industry, and occupation

[1]This is one reason why existing research on trade policy preferences mostly concentrates on the measurement of either firm preferences (Kim et al., 2017; Osgood, 2017; Plouffe, 2013) or individual preferences only (Scheve and Slaughter, 2001; Mayda and Rodrik, 2005; Rho and Tomz, 2017), without comparing employers' and employees' preferences.

[2]The overall number is actually 3,579,530 filings of 466,839 individuals working for 13,991 firms publicly listed firms. Since I look at the alignment between Political Action Committees (PACs) and employees, I only use firms with data on both PAC and employee contributions in this paper.

level which can be easily linked to firm financial databases and data from the Bureau of Labor Statistics, the Census Bureau, or other statistical agencies, opening up avenues for further research. Compared to existing research, this data covers all donating employees for a larger set of firms and occupations and distinguishes more clearly sectors of employment from occupations (Bonica, 2016*a*; Babenko, Fedaseyeu and Zhang, 2016).[3]. Second, holding constant individual occupation, find that employees in companies with more specific assets are more aligned with their employer, controlling for firm-level and geographic characteristics. The results are robust using various empirical specifications, various alternative explanations for alignment, and within-sector labor mobility as an alternative (inverse) measure of specificity. Third, I show that most of the variation in partisan alignment between firms and employees is at the industry level, which goes contrary to new theories emphasizing individual occupation as an important source of political preferences.

The results highlight the continuing importance of sectoral models for the formation of political preferences, contrary to occupation-based models emphasizing tasks and skills as sources of political preferences (Owen and Johnston, 2017; Thewissen and Rueda, 2017; Kitschelt and Rehm, 2014; Walter, 2017). Moreover, the discovered differences in partisan heterogeneity and cohesion across companies have implications for political mobilization of firms (Olson, 1965; March, 1962) and the formation of political coalitions (Sabatier, 1988; Rogowski, 1989; Hiscox, 2002*b*). Finally, the results show possible conditions under which employees might be more susceptible to be politically influenced by employers (Hertel-Fernandez, 2018), and the extent to contribution patterns in the US vary across industries and occupations (Schlozman, Verba and Brady, 2012; Barber, Canes-Wrone and Thrower, 2017; Bonica, 2014).

The rest of the paper proceeds as follows: the first part introduces the argument. The second part describes the process of matching individual campaign contributions to unique firm and occupation codes. The third part shows descriptively the main dimensions of variation in the data and demonstrates that most of the meaningful variation is along industry lines and not across occupations. Then, I empirically analyze the relationship between asset specificity and employer-employee partisan alignment. The final part concludes, discusses implications, and describes avenues for further research based on matched employer-employee donations data.

[3] There is very little research combining campaign contributions data by firms and individuals. Bonica (2016*a*) only compare donations of CEOs to company PACs, and Babenko, Fedaseyeu and Zhang (2016) investigate whether CEO contributions influence donations of individuals working in the same firm.

2 Theory: Asset Specificity and Political Alignment

Where do political preferences come from? Sociotropic approaches state that preferences come from individual concerns about what is good for the country or society as a whole (Kinder and Kiewiet, 1979; Lewis-Beck and Paldam, 2000; Mansfield and Mutz, 2009). Other approaches argue that individual political preference stem from rational expectations about outcomes, based on economic self-interest (Meltzer and Richard, 1981). In Comparative and International Political Economy, economic self-interest has been been the predominant source of political preferences, including preferences about redistribution (Iversen and Soskice, 2001), preferences for or against free trade (Scheve and Slaughter, 2001), or preferences for or against foreign direct investment (Scheve and Slaughter, 2004).[4]

Canonical models in International Political Economy (IPE) state that individual preferences will be aligned along sectoral lines (Grossman and Helpman, 1994; Frieden, 1991) or according to factor endowment (Rogowski, 1989). The extent to which we see coalitions in favor of or in opposition to free trade depends on the degree of factor mobility (Alt and Gilligan, 1994). Factor mobility is the ease with factors of production (usually capital or labor) can move between uses in different sectors. Asset specificity is the opposite of mobility for particular assets and refers to the degree to which an asset can be redeployed to alternative uses without sacrificing its production value. When assets are more specific, they are more 'stuck' in their current use and it becomes more costly to employ said assets in the production of other goods and services. The canonical prediction of this literature is that if asset specificity is high (or factor mobility low) coalitions form along sectoral lines, and when specificity is low (or factor mobility high), we expect broad class-based cleavages (Hiscox, 2002*b*).

Alt et al. (1999) investigate the impact of asset specificity on firm-level lobbying and argue that firms with more specific assets are more likely to engage in lobbying for subsidies. Firms with more specific assets are more vulnerable to external economic shocks or sudden changes in policies affecting their profits because they cannot easily move assets to alternative uses. Given the immobility of their assets, firms will be more likely to invest in corporate political activity to insure against un-wanted policies. One insurance strategy for firms is to use campaign contributions to

[4]This discussion ignores a third option of genetic transmission of political preferences. See (Alford, Funk and Hibbing, 2005).

invest in candidates of parties that minimize the risk of policies that will hurt their economic interest (Sawant, 2012). Since under high asset specificity, the economic interest of employees is tied more closely to the firm they work in, employees will also seek to donate to politicians who reduce the risk of policies hurtful for their company. Therefore, I expect that individuals in firms with more specific assets are more likely to share the partisan preferences of their employers, as expressed in their campaign contributions. By extension, joint political action by both labor (firm employees) and capital (firm leadership) is more likely in firms characterized by high asset specificity. Since under high specificity both labor and and capital are more firm-specific and coalitions form along sectoral lines, both labor and capital benefit more from the rents obtained through corporate political activity, and both realize higher losses in the case of adverse shocks. Hence, the main hypothesis of this paper is simply the following:

> **Hypothesis**: *Individuals in firms with a higher share of specific assets are more aligned with their company in terms of the partisanship of their campaign donations.*

This prediction goes against literature which argues that occupations-specific characteristics of individuals are a main source of preference formation. Based on the idea of asset specificity, Iversen and Soskice (2001) argue that individuals who have invested in skills specific to an occupation will demand more redistribution as an insurance against income losses or longer unemployment in the event of losing their job. More recent research has taken up the findings from labor economics work on skill-biased technological change which disproportionally affects routine tasks occupations (Autor, Levy and Murnane, 2003), or used offshorability of occupations (Blinder, 2009; Blinder and Krueger, 2013) to predict individual preferences about redistribution, labor market risks, and trade policies (Owen and Johnston, 2017; Walter, 2017; Thewissen and Rueda, 2017; Kitschelt and Rehm, 2014). It is important to note that I do not claim that occupation is not an important source of individual preferences. For instance, I would expect CEOs and Presidents of companies to be significantly more aligned with their company, as their compensation most often depends on company profits.[5] However, I argue *for employees with the same occupation* there is variation in alignment across industries and firms of employment, and that part of this variation is characterized by the degree of asset specificity of a given firm. Despite some advantages of the national

[5]This is indeed what my data, presented in the next section, show. Company executives are amongst the most aligned occupations.

surveys used in the occupation-based literature[6] these papers do not investigate within-industry or within-occupation variation, and thus, can only make limited "everything else equal" claims about the impact of industry or occupation level factors on individual preferences.

However, the relationship between asset specificity and partisan alignment might not be the same for both Democratic and Republican partisan alignment. This is because the definition of asset specificity as used in this paper is at its core specificity of capital. In the US, the Democratic party has historically been the political party that was more supportive of the interests of labor, whereas the Republican party has been more representing capital interests. For example, Democrats have a long-standing positive relationship with labor unions (Dark, 2001) while Republicans have historically opposed unions (Ahlquist, 2017). Most recently, Republican states have been quite active in passing right-to-work laws, which have effectively weakened unions across the US (Hertel-Fernandez, 2018). Moreover, even though most US companies split their donations between both parties, most US corporations tend to be conservative (Tripathi, Ansolabehere and Snyder, 2002), on average.[7] Therefore, I expect there to be a stronger relationship between asset specificity and Republican alignment than with Democratic alignment.

One assumption I need to make is that donors understand their own economic interest and the policy consequences of their donations. Indeed, a prominent line of research on campaign contribution argues that donations are too small (Milyo, Primo and Groseclose, 2000) and that there is too little evidence of political returns on donations (Ansolabehere, de Figueiredo and Snyder, 2003) for them to be strategic investments. Similarly, Bartels (2008) finds that individuals routinely vote against their objective economic preferences, and Rho and Tomz (2017) show that individual preferences on free trade and protectionism are less in line with their economic interest if they are not educated about the potential effects of trade on them.

However, there are reasons to believe that (donating) employees can have some understanding of the partisan stance of their company. My focus is on partisanship as expressed by individual donations, and donors are not a random sample of the general US population. On average, they have higher income and are more educated (Francia, 2003). Moreover, there is ample evidence that polit-

[6]For instance, surveys like the European Social Survey or the International Social Survey Program often used in CPE and IPE research are nationally representative.

[7]In the data used for this paper, firms spend on average 60% of donations on Republican candidates, and 40% on Democrats.

ically organized employers communicate their political preferences to their employees, sometimes even coercing them to engage in political action (Hertel-Fernandez, 2018), like contacting legislators or accompanying company lobbyists on visits to Washington DC. Further, recent research on campaign donations shows that donors target legislators who become committee members and those who get procedural powers (Fouirnaies and Hall, 2018), and that donations strategically flow across state borders to competitive districts (Gimpel, Lee and Pearson-merkowitz, 2008). Donors also tend to give to politicians with similar political views or with jurisdiction over their sector of employment (Barber, Canes-Wrone and Thrower, 2017). Considering these findings, it becomes increasingly difficult to support the notion that donations, either from individuals or from corporate Political Action Committees (PACs) are merely another form of political participation, and not an investment in future political favors in line with economic self-interest.

3 Data

For this paper, I collect and match employee to corporate donations using US Campaign Finance data from the US Federal Election Commission (FEC). The FEC data contains information on corporate PAC campaign contributions to political candidates and individual donations to candidates. Moreover, the individual data contains information on donor names, employers, occupation, and ZIP code of residence. However, linking employers in the individual data to firm-level, industry-level, and occupation-level information or PAC donations is challenging for two reasons. First, there are no unique employer names or identifiers, neither in the individual data nor the corporate contributions data. In fact, individuals just manually enter employer names into an online form, resulting vastly different firm names across individuals working for *the same firm*. This problem is shown in Table 1 which depicts political contributions of five `MICROSOFT` employees, each of which provides a slightly different (and sometimes, orthographically incorrect) employer name. The same problem exists for individual occupations. Donors manually enter their occupation, resulting in many un-structured occupation names for essentially the same jobs. Table 2 shows the problematic structure of occupation names in the FEC data for five senior managers of well-known US companies. Second, the sheer amount of the data precludes attempts to manually match individuals to employers or manually categorize individual occupations. Between 1980 and today, the FEC data contains 52,974,196 individual contributions, 4,085,773 unique employer names, and 825,697 unique occupation names. Clearly, one would need lots of resources and time in order to link even only part of this data to external datasets.

Name	**Employer**	**Occupation**	...
Steven Ballmer	`MICROSOFT`	CEO	...
Jeff Teper	`MICROSOFT CORP`	Corporate CEO	...
Lisa Brummel	`MICROSOFT CORPORATION`	Executive Vice President	...
Rae Garret	`MICROSOFT CORPORTATION`	Consultant	...
Dorothy Dwoskin	`MICROSOFT INC.`	Trade Director	...
⋮	⋮	⋮	...

Table 1: Lack of Unique Employer Names for Individual Campaign Donations. The table shows the lack of unique employer names in the FEC individual donations data. In this example, all individuals are employees of Microsoft, but they use different versions of the company name when filing their contribution to the FEC.

Name	**Employer**	**Occupation**	...
John H. Myers	GENERAL ELECTRIC CO	`PRESIDENT/C.E.O.`	...
John H. Chambers	CISCO SYSTEMS INC	`PRESIDENT/CEO`	...
Richard Clark	MERCK & CO	`PRESIDENT, CEO`	...
Christopher M. Crane	EXELON CORP	`PRESIDENT COO`	...
Robert Marcus	TIME WARNER CABLE INC	`PRESIDENT AND COO`	...
⋮	⋮	⋮	...

Table 2: Lack of Unique Occupation Names for Individual Campaign Donations. This table shows examples of different employees of five companies, all of which have a very similar jobs. However, all individuals provide very different occupation names when filing their contributions to the FEC.

Therefore, I need an automated way to match employer names to unique company identifiers and occupation names to unique occupations identifiers. For this purpose, I developed an automated script, written in the programming language `Python`, leveraging python's well-developed and computationally efficient natural language processing capabilities. The process by which the script links un-structured employer and occupation names to unique identifiers is portrayed in Figure 1 below. The script takes as input a list of un-structured employer names (from the FEC)

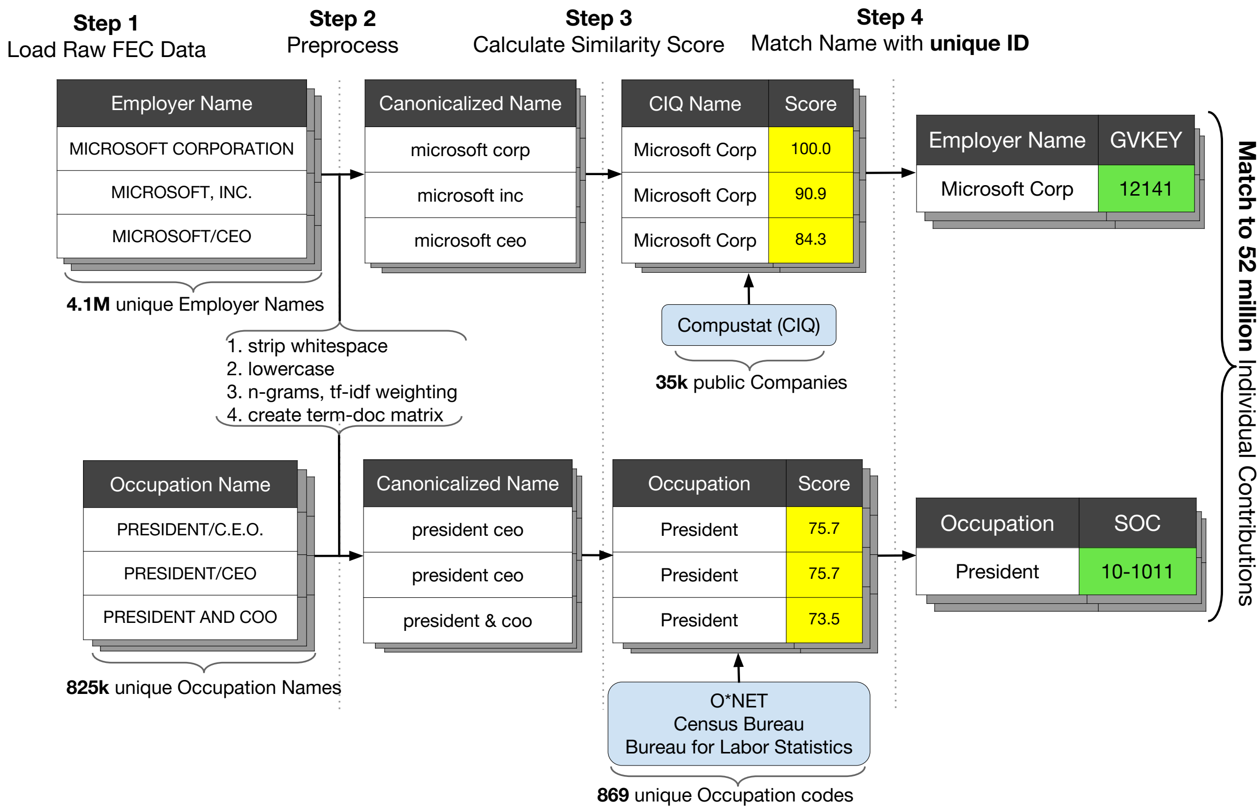


Figure 1: Algorithm matching employees to unique employer IDs and occupation codes. The flow chart shows how employer names and occupations are matched to unique employer IDs (Compustat GVKEY) and occupation codes (Standard Occupational Classification (SOC) Codes) GVKEYs can be linked to firm- and industry level variables from financial databases, and SOC codes can be linked to official employment statistics.

and a list of unique firm (or occupation) names with unique firm IDs (or occupation codes). For company names, I use the full list of 35,672 publicly traded firms in the Compustat Capital IQ North America database, a firm financial data provider. For occupation names, I use the 'direct match files' of occupation titles to occupation codes published by the US Census Bureau and the Bureau for Labor Statistics (89,000 occupation titles relating to 869 unique occupation codes).[8]

First, a number of different employer names is given to the script. Then, the names are cleaned up: they get lower-cased, additional whitespace and punctuation is removed, and company legal forms are canonicalized. Next, a term-document matrix is created from the names and terms are weighted by term frequency-inverse document frequency (tf-idf). Hence, terms that appear in

[8]I also match O∗NET occupation codes to the data (105,000 occupation titles relating 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.

Name	ID	Firm	Firm ID	SOC	Occup. Title	...
Steven Ballmer	I00301999	`MICROSOFT CORP`	12141	11-1011	Chief Executives	...
Jeff Teper	I06497673	`MICROSOFT CORP`	12141	11-1011	Chief Executives	...
Lisa Brummel	I00807330	`MICROSOFT CORP`	12141	11-1011	Chief Executives	...
Rae Garret	I01642142	`MICROSOFT CORP`	12141	13-1199	Consultant	...
Dorothy Dwoskin	I01780528	`MICROSOFT CORP`	12141	19-3011	Economists	...
⋮	⋮	⋮	⋮	⋮	⋮	...

Table 3: Result of Matching Employees to unique Employers and Occupation Codes: This table shows the result of the linkage process shown in Figure 1 above. The individuals shown in Table 1 now have one unique firm name and firm ID (Compustat GVKEY), as well as unique occupation code (SOC) and individual IDs. Individual ID's are assigned by cleaning names, and using exact matching on first name, last name, and state of employee.

many company names (like 'incorporated', 'inc', etc.) receive less weight in the matching step. Second, for each cleaned name, the cosine similarity between a given employer name and each name in the list of 35,672 publicly traded firms in the Compustat is calculated. The similarity between company names d_1, d_2 is calculated as $sim(d_1, d_2) = \frac{d_1 \cdot d_2^T}{||d_1|| \, ||d_2||} = \frac{\sum_{i=1}^n d_{1i} d_{2i}}{\sqrt{\sum_{i=1}^n d_{1i}^2}\sqrt{\sum_{i=1}^n d_{2i}^2}}$, which is simply the angular distance between the two employer name vectors given to the script, normalized by vector length. Finally, the script picks the Compustat firm name with the highest cosine similarity, if above a set threshold, and returns it together with its unique firm ID (GVKEY).[9].

This process is repeated for each of the individual employer names, as well as for 17,215 corporate PAC names between 2003 and 2016. The result can be seen below in Table 3 for `MICROSOFT`. All five employees are now matched to one unique firm name. Moreover, each individual and employer gets assigned a unique ID. In this paper, I use the GVKEY from Compustat in order to add firm financial information. The process for matching occupation titles to unique occupation titles and codes is identical to the procedure for employers - only the inputs to the script differ.

I match 3,537,187 filings of 466,840 individuals, to 13,991 firms and 850 occupations between 2003 and 2016. I also match 274,106 out of 825,697 unique occupation names in the FEC data. Those occupations make up about 85 percent of the individuals contribution records matched to employers, excluding unemployed individuals and students. For this paper, I limit the period of

[9]The similarity measure is between 0 and 1, where 0 means no match at all, and 1 indicates a full match. For employer names, I use a threshold of 0.81, and for occupations 0.72, based on similar record linkage problems in existing research (Raffo and Lhuillery, 2009).

investigation to the years between 2003 and 2016, because occupation data is only available from 2003 onwards. I also only use companies for which I observe both firm and employee donations, which are 1,691,790 campaign contribution filings of 85,109 individuals, working in 874 publicly listed firms and 850 occupations. I also match the zip codes of donors to Federal Information Processing Standard (FIPS) county codes. Individual identifiers were created using exact matching on the cleaned up versions of first name, last name, and state of residence of donors.[10] The Tables 7, 8, and 9 in the appendix show the frequency distribution of the most common firms, industries, and occupations in the data used for this paper.

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, a threshold which has not been changed since 1980 (McGeveran, 2003). While employers can and do report all contributions, even those smaller than USD 200 most candidates report only donations over USD 200.[11] Contribution limits differ by entity donated to, and change each electoral cycle.[12] 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.[13] 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.

These data provide some *significant advantages over existing databases* of US campaign donations like De Paula and Scheinkman (2011) or the Database on Ideology, Money in Politics, and Elections (DIME) (Bonica, 2016*b*). First, the data uses commonly used unique identifiers for firms (Com-

[10]The credit for the individual IDs goes to Mehmet Efe Akengin. The matching strategy is a compromise between having accurate individual IDs and being able to observe individuals changing workplaces or occupations. See below.

[11]Non-federal candidate disclosure rules are even stricter at times, but are not relevant for this paper which only uses federal contributions data.

[12]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.

[13]Some obviously incorrect or non-informative examples include: 'ANTI-ISLAMOFASCISM EXPERT', 'ANTI-ISLAM OF ASCIST CONSULTANT', as well as '"MOBBED" OCCUPATIONAL THERAPIST', 'Mother :)', 'DINOSAUR EXPERT', 'UNEMPLOYED LIKE 22% OF AMERICANS', 'UNEMPLOYED & LOVING IT', or 'VP DICK CHENEY'.

pustat GVKEY), industries (North American Industry Classification - NAICS) and occupations (Standard Occupational Classification - SOC). Those allow researchers to easily link companies and individuals to firm financial databases (e.g. Compustat or Orbis) and add industry and occupation level data from the Census Bureau, the Bureau of Labor Statistics, or other official data sources. In comparison, existing research uses the Open Secrets coding scheme for industry/occupation of donors which cannot easily be linked to any external data. Second, my data is much clearer in terms of analytically separating occupation and industry of employment. Existing data and research in American Politics often confuses occupation with industry and vice versa. For example, Bonica (2014) uses 'Lawyers' as one and 'Mining' as another 'industry/occupation' category, based on the Open Secrets coding scheme. However, 'Lawyers' are not an industry but only one occupation which can be performed in many different industries, and 'Mining' is clearly not an occupation, but an industry comprising different occupations like miners, engineers, managers, and lawyers, among others.[14] Given how central industries and occupations are in Economics and IPE research, they need to be clearly separated, both analytically and empirically. Finally, for future research[15] the data allows me to track individuals when they change firms or occupations.

One downside of the data is 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. Consequently, he loses the ability to follow individuals when they change occupation, address, or workplace. I only use first name, last name and state of residence for determining individual identifiers, to be able to observe changes in occupations and sectors.

4 Empirics

4.1 Description: Alignment across Sectors, Occupations, and Geography

In this section, I present the matched donations data on alignment between firms and their employees. I describe the distribution of alignment across the major dimensions of variation in the

[14]The same problem exists in the paper by Barber, Canes-Wrone and Thrower (2017) who also rely on the Center for Responsive Politics industry/occupation coding scheme. InBonica (2014) or Barber, Canes-Wrone and Thrower (2017) this is not particularly consequential, even though the former provides a misleading description of industry and occupation ideology. Bonica (2014) does not directly test theories on the impact of industry or occupation on donor behavior, and Barber, Canes-Wrone and Thrower (2017) do manually match Open Secrets occupation categories to committees with jurisdiction over said occupations.
[15]See concluding section.

dataset: firm's sectors, individual occupations, and state of residence. This descriptive analysis shows that most of the meaningful variation in the data is at the sectoral level. The main dependent variable for this paper, alignment between employees and their employers, is calculated as:

$$Alignment_{ict} = 1 - \left|\left(\frac{R_{jt}}{(R_{jt} + D_{jt})} - \frac{R_{ijt}}{(R_{ijt} + D_{ijt})}\right)\right|$$

where R_{jt} and D_{jt} are Republican and Democratic donations of firm j in year t, while R_{ijt} and D_{ijt} are Republican and Democratic donations of individual i working for firm j in year t, respectively. This variable ranges from zero to one, where larger values indicate more partisan alignment between and employee and a firm in a given year. Intuitively, some company PACs donate more to one of the two parties while some PACs donate equally to both parties. The measure will be larger if an employee donates to one party and the employer gives a higher proportion of donations to the same party, and less so if they donate to the opposite sides of the isle. Figure 2 below shows the distribution of alignment in the sample of 138,549 employee-employer observations. Alignment is approximately normally distributed, with most observations around the mean of 0.53 (median 0.52). Around 2000 observations show complete non-alignment (corresponding to 1531 individuals) and 4000 observations (corresponding to 2906 individuals) show complete alignment. These are cases when companies donate exclusively to one party in a given year. For example, Blackstone Group LP donated only to Republican candidates from 2011 to 2015. Therefore, 408 employees of Blackstone donating to the Republican party will score 1 (full alignment), and 209 employees will score 0 (no alignment).

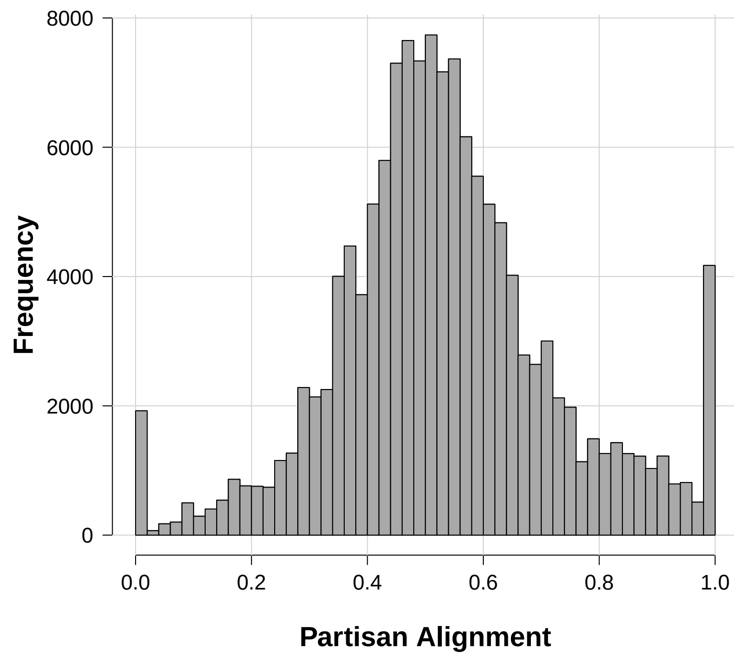
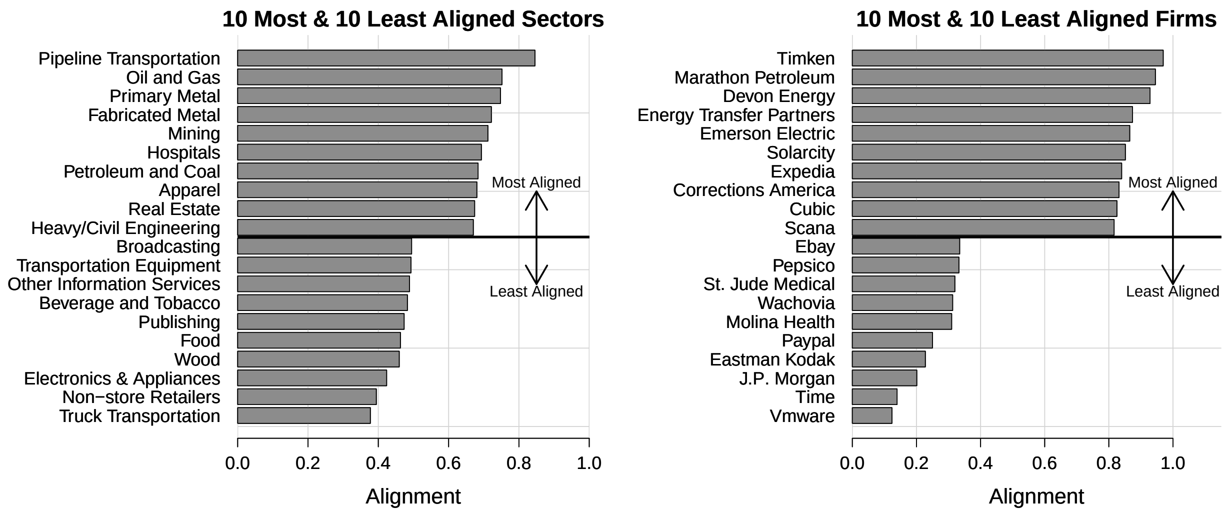


Figure 2: Distribution of Alignment. This histogram depicts the distribution of alignment from complete disalignment (0) to complete alignment (1) in the US campaign finance data. Complete (dis-) alignment happens when companies donate exclusvilely to one party and employees donate to the (other) same party. Data: own calculations.

This means that there can be very high alignment when PACs donate very one-sided, but also very low alignment if most employees of the same company donate to the opposite party. What are the patterns of partisan alignment across sectors, firms and occupations in the matched employer-employee data? Figure 3a shows the ten sectors and firms with the most and least mean alignment at the firm-level. Panel a) shows that the average alignment is highest in extractive industries, primary resources industries like metal and rubber, and real estate and hospitals, while the lowest alignment can be seen in publishing, food, and information services. This translates into specific companies in panel b). Timken, Marathon Petroleoum, and Devon Energy are most alignment between employees and company PAC, and J.P. Morgan, Time Warner, and Vmware are least aligned. It seems quite striking that the companies and sectors with large sunk investment in site-specific structures and physical assets (machinery) are the ones that are most aligned.[16]

[16]The exception is Expedia wich is also very aligned. Both Expedia's PAC and employees donate mostly to Democratic candidates.



(a) Sectoral Alignment **(b) Firm Alignment**

Figure 3: Top 10 Most & Least Aligned Firms and Sectors. This figure shows the ten sectors and firms with most and least alignment. Panel a) shows that extractive industries like oil, gas, and rubber are most aligned, while electronics and transportation manufacturers are least aligned. Panel b) shows that Timken and Marathon Petroleum are most aligned, while Vmware and Time show little alignment. Data: own calculations.

How does alignment between individual and firm contributions look like across all industries? In Figure 4, I plot the distribution of average individual alignment for each 3-digit North American Industry Classification (NAICS) industry in the data. The plot reveals that there is substantive variation in alignment across and within sectors. Heavy industries and extractive industries are much more aligned, with alignment larger than 0.6, on average. Many services industries like information services, merchandise stores, broadcasting, but also some manufacturing industries like food or chemical manufacturing seem to be much more split between the two parties, with alignment scores closer to 0.5.

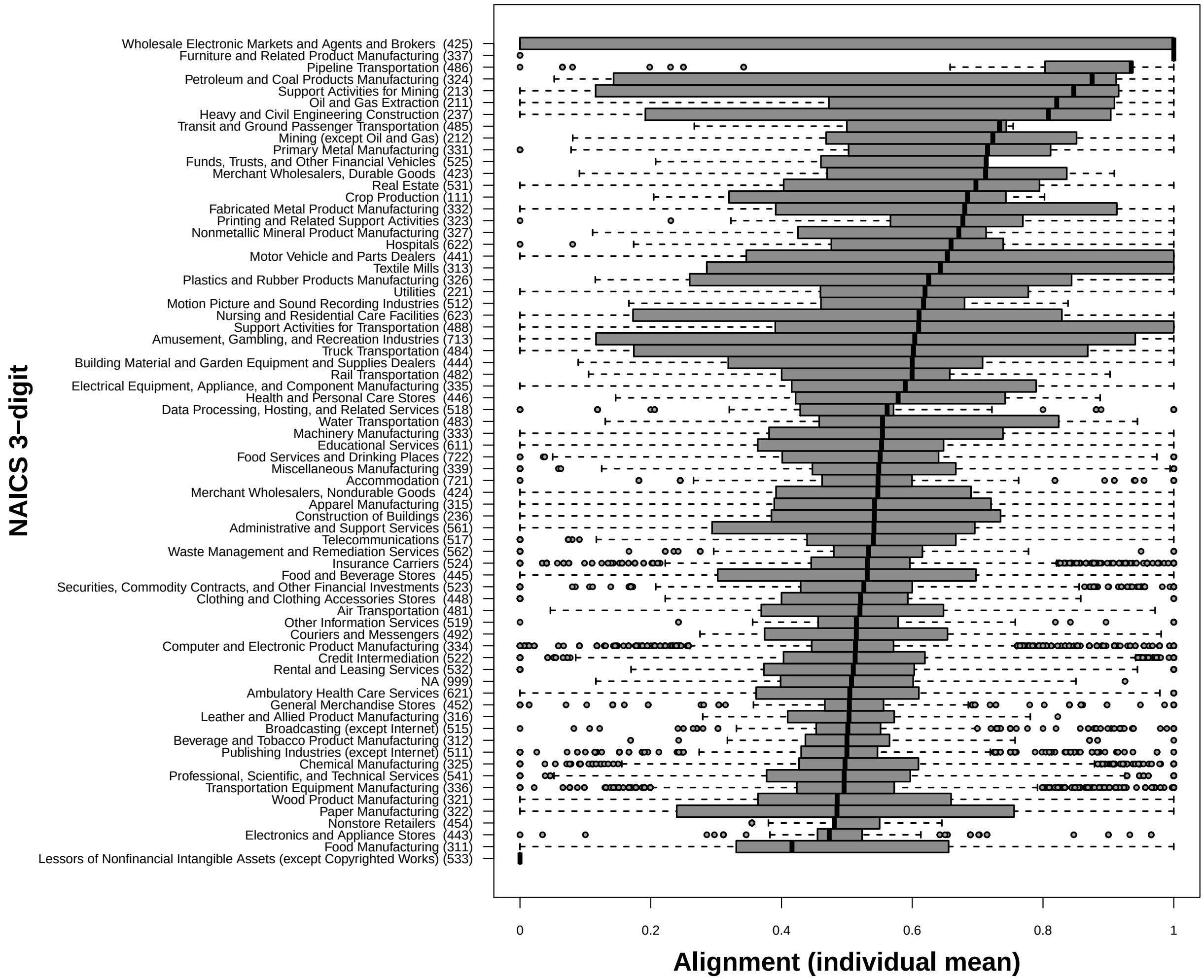


Figure 4: Strong Variation in Alignment across 3-digit NAICS Industries. The boxplot shows that there is strong variation in alignment across 3-digit NAICS industries (3-digit industry codes in parentheses) Heavy and extractive industries are most aligned while most services industries are less aligned. Data: own calculations.

How does the large variation across industries compare to the variation across occupations? Below in Figure 6, I plot the distribution of alignment across 23 two-digit SOC occupations. There is actually little variation in alignment across occupations as different as management, legal services, construction, extraction workers, or personal care.

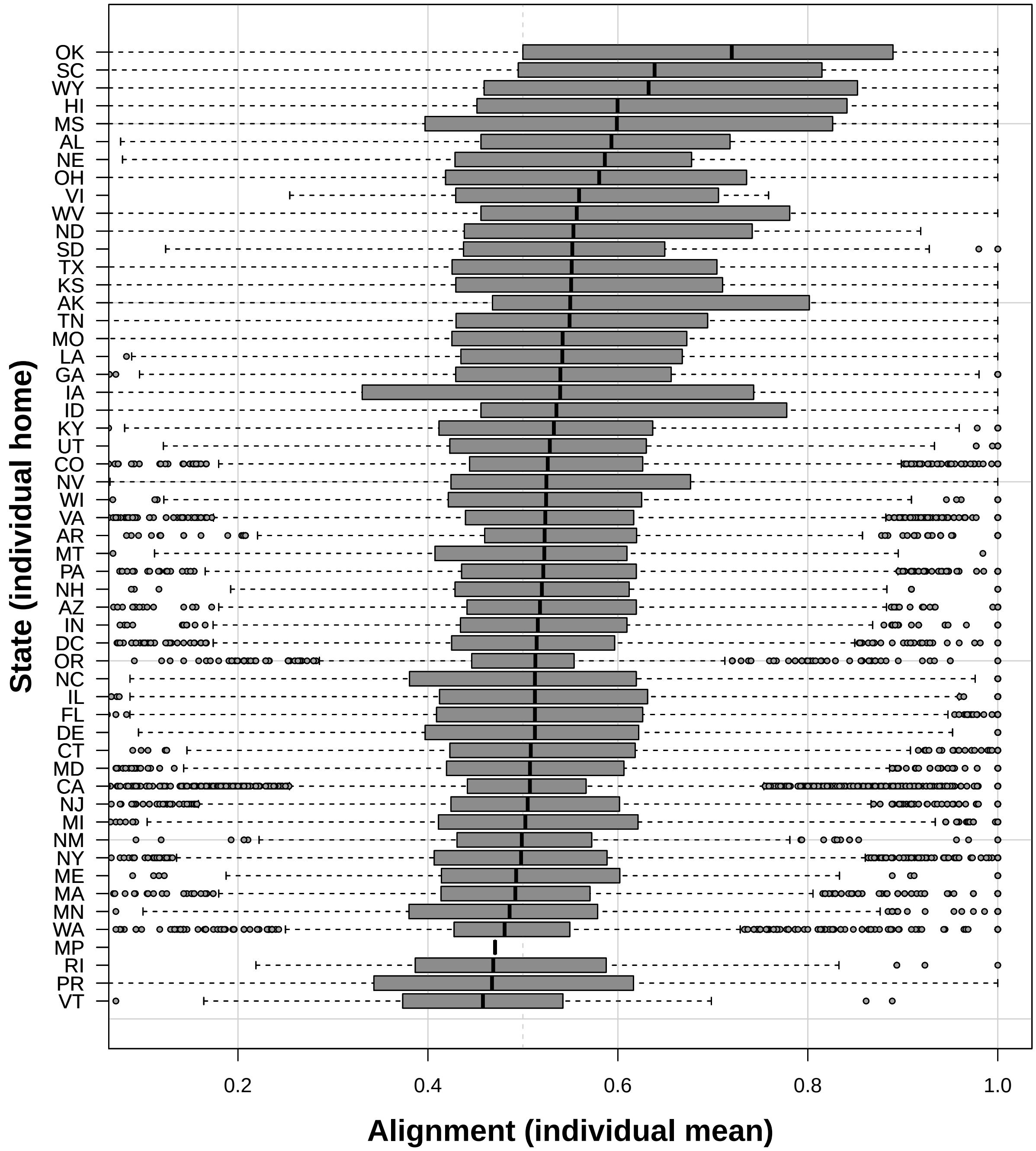


Figure 5: Variation in Alignment across US States. The boxplot shows that there is some variation in alignment across US states, albeit not as much as across industry sectors. Data: own calculations.

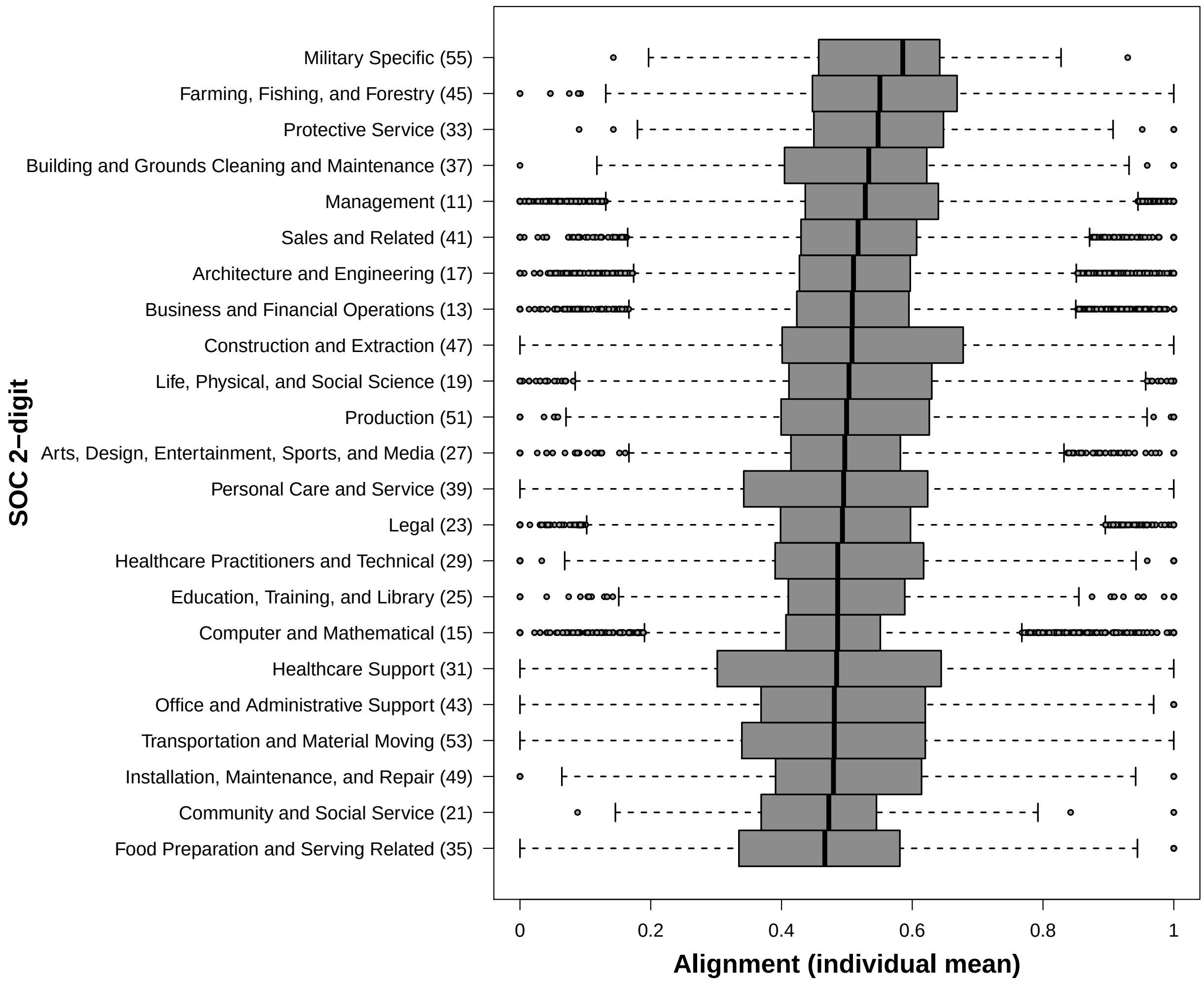


Figure 6: Weak Variation in in Alignment across Occupations. The plot shows that there is very little variation in alignment across (2 digit SOC) occupations of donors. Data: own calculations.

In Figure 13 in the appendix, I show the same pattern of non-variation across 96 more fine-grained three-digit SOC occupations. While there is more variation in Figure , there is still much less divergence in alignment between different occupations than between industries. Some might argue that the differences across industries might simply be driven by geography: certain sectors might be located in red (or blue) states, and these states might happen to have a more politically aligned population of donors. In Figure 5, I show that even though there might be a role for geography in determining alignment, it might not be as large one might think. There is less variation in alignment across the 50 US states than across industries. Despite some states like Oklahoma, South Carolina, and Wyoming showing more alignment between employees and firms than other states, most states are closer to alignment scores of 0.5.

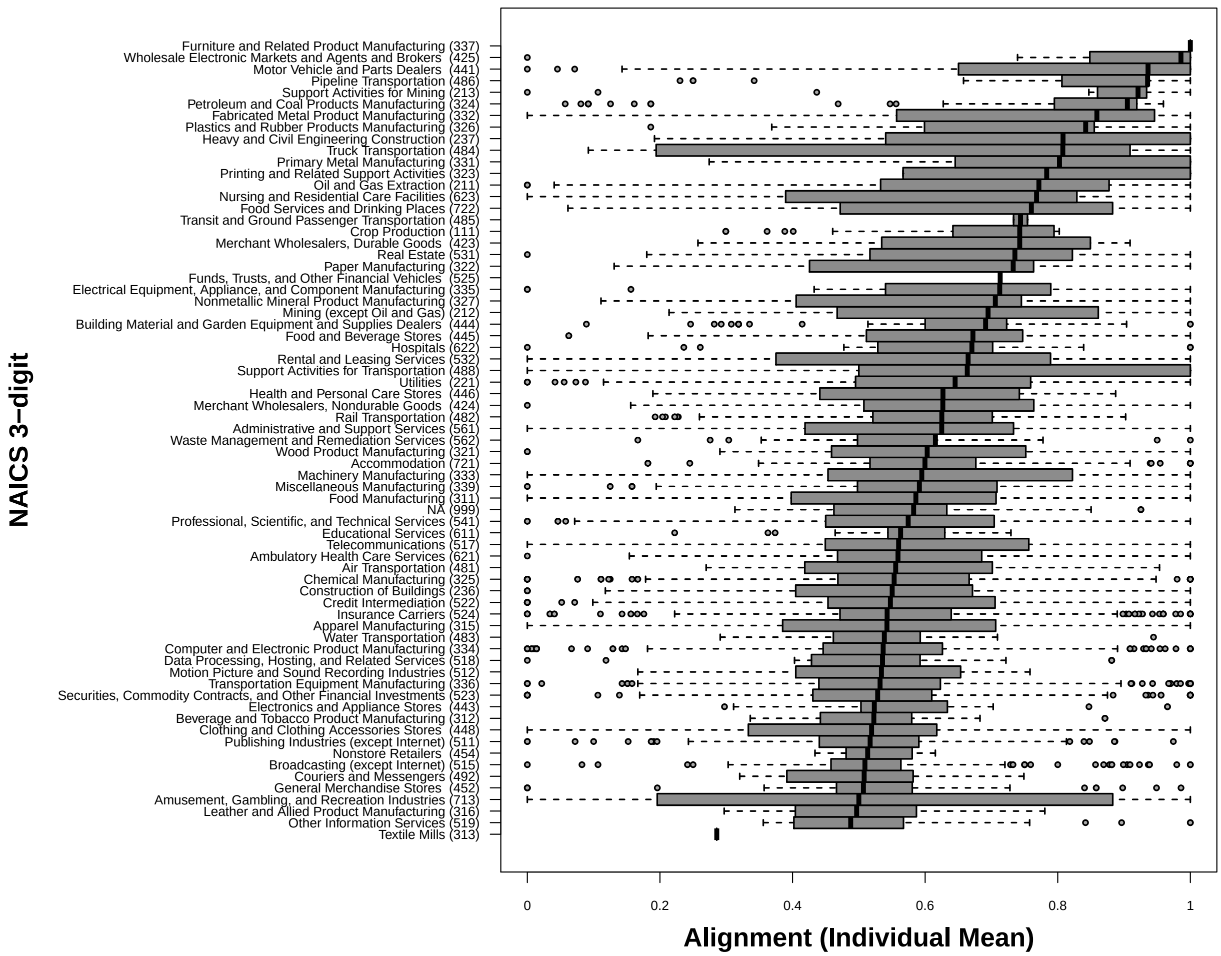


Figure 7: Strong Within-Occupation Variation in Alignment across Industries. The boxplot depicts the strong within-occupation variation in alignment for one specific occupation (chief executives, SOC Code 11-1011) across 3-digit NAICS industries (3-digit industry codes in parentheses). Data: own calculations.

Next, I demonstrate that there is significant variation *within* individual occupations *across* industries. Figure 7 depicts the same three-digit NAICS distribution of alignment as before, but this time for only one very narrow occupation, in this case chief executives and presidents (SOC 11-1011). In fact, the differences in alignment are even starker than pooled across occupations, ranging from approximately equal donations of companies and employees to both sides of the isle in broadcasting and couriers services (median alignment of 0.5) to more than a 0.8 alignment in petroleum, coal, and pipeline transportation. This goes partly against the argument put forward by Bonica (2016*a*) that CEOs are mostly ideological and not strategic in their contributions, if their contributions seem to vary systematically with the industry in which they are employed.[17]

This is a systematic pattern that becomes even clearer if we only look within manufacturing industries (NAICS 31 - 33). Figure 8 below shows that even within manufacturing industries and within the same occupation, there is a trend towards more alignment in industries related to resource extraction and raw materials. Further, in Figure 12 in the appendix I show that very similar patterns can also be observed in other occupations like lawyers, agricultural engineers, and (with some limitations) IT specialists.

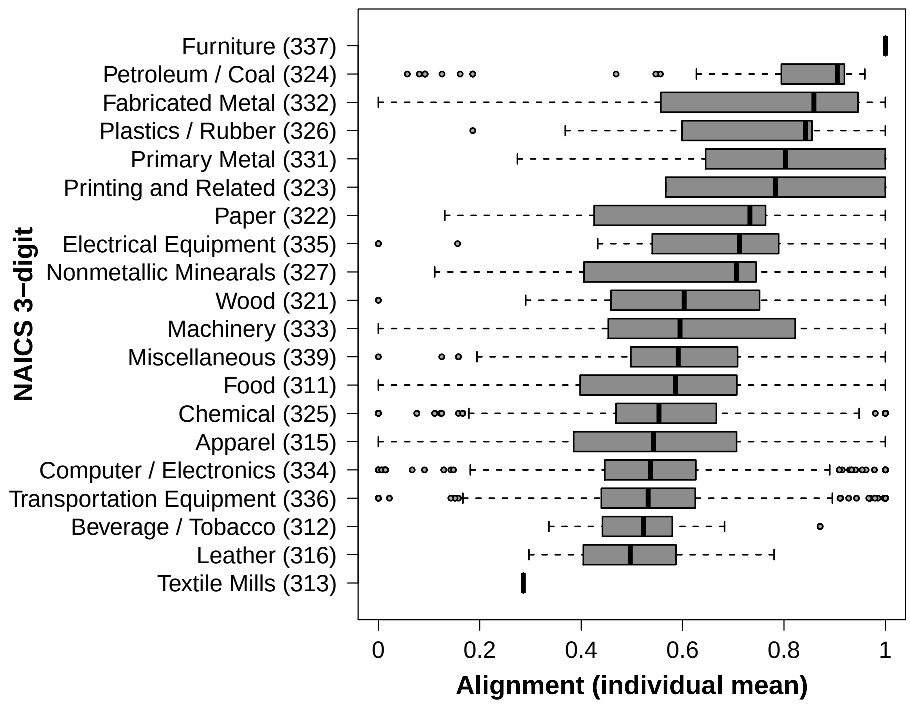


Figure 8: Strong Within-Occupation Variation in Alignment across Manufacturing Industries. The graph shows that within a very narrow occupation (chief executives, SOC Code 11-1011) there is substantive variation in alignment across 3-digit manufacturing industries. CEOs in extractive industries and energy industries tend to be most aligned, and computer and chemical industries less. Data: own calculations.

This initial inspection of the data reveals that there is significantly more variation in alignment across industries (and only a bit more across states) than there is across individual occupations. Hence, *where people work seems to matter more than what people do*, in terms of whether they share the same partisanship with their employer. This is in itself a surprising finding, given that there is a long line of research arguing that occupation characteristics are important sources of political

[17]In fact, it is more coherent with strategic CEO donations as observed by Babenko, Fedaseyeu and Zhang (2016), even though they do not hypothesize about differences in strategies across different industries.

preferences. For instance, Iversen and Soskice (2001) argue that specificity of skills is important for individual demands for redistribution. Recent research by Owen and Johnston (2017), building on Economics research on offshoring (Blinder, 2009; Walter, 2017) and skill-biased technological change (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011), argues that 'offshorability' of occupations or the extent to which they are intensive in 'routine tasks' are major determinants of policy preferences. However, individual skills and occupational characteristics within firms seem not to be as important using partisan alignment based on donations. In sum, the main message of the data seem to be that there is still value in sectoral models of individual preference formation, despite a recent push towards occupation-based models.[18]

4.2 Analysis: Specific Assets and Individual Alignment

In this section, I empirically analyze the impact of asset specificity on partisan alignment between employees and their company in terms of their campaign contributions. In this paper I measure asset specificity as a combination of 'site specificity' and 'physical specificity' (Joskow, 1988, pp.106-107). The former refers to the asset being bound to a specific location in order to minimize inventory and transportation costs, and the latter refers to investment in machinery that is specific to certain design characteristics. I measure asset specificity as firm-level plant, property and equipment expenses as a share of overall firm assets, $100 \times (PPENT/AT)$, both taken from Compustat. I do not use R&D expenditures as a measure of asset specificity, like the paper by Alt et al. (1999). The problem with R&D expenditures is that they are missing for over 60% of the data in Compustat. At the industry level R&D expenditure is often only available at the very rough 2-digit NAICS level or it is missing altogether. Below in Figure 9, I show the distribution of asset specificity in my data. Which companies have high and low specificity, respectively? Companies with a very high share of specific assets in the data include oil and gas extraction companies like Whiting Petroleum (alignment: 0.79, asset specificity: 91.3) and Chesapeake Energy (alignment: 0.69, asset specificity: 87.7), or the pipeline transportation firm Energy Transfer Partners (alignment: 0.84, asset specificity: 68.1). Firms with very low asset specificity include

[18]In separate tests, I did not find a significant relationship between partisan alignment in donations and occupation-level skill specificity from Iversen and Soskice (2001), or different measures of offshorability and job routineness from Acemoglu et al. (2015) or Blinder and Krueger (2013), both used in the study by Owen and Johnston (2017). If there is any relationship in the aggregate, it is driven by CEOs (high specificity and low offshorability in the data) and disappears once I control for this single occupation.

Fannie Mae (alignment: 0.53, asset specificity: 0), the insurance carrier MetLife (alignment: 0.52, asset specificity: 1.2), chemical manufacturer Celegne (alignment: 0.5, asset specificity: 3.7), or the professional services consultancy SRA International (alignment: 0.53, asset specificity: 4.1).

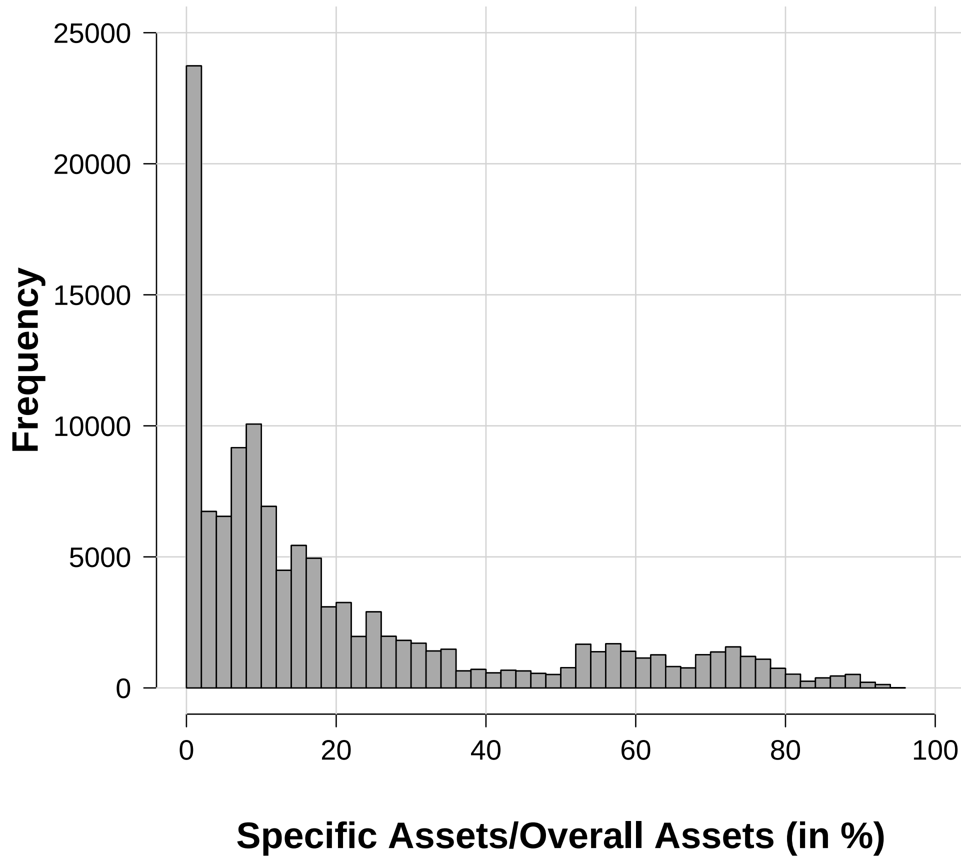


Figure 9: Distribution of Asset Specificity. This histogram depicts the distribution of specific assets as a share of overall assets at the firm level. Data: Compustat Capital IQ North America.

In Figure 10 below, I show the aggregate (mean) alignment between employees and their firms in my data between 2003 and 2016, the time period under investigation. One can see that for most of the time, it is close to 0.5 (firms and employees donate to both parties equally), with occasional up and down swings. The plot also depicts the share of alignment in donations by party, with more Republican alignment except for the time between 2007 and 2009. This seems to be driven by strategic changes in partisan donations by corporations (Fouirnaies and Hall, 2018) during the Obama campaign, as traditionally more conservative companies donated more to Democracts than usual. The graph also includes the mean asset specificity across all firms in my sample. Even though the changes in asset specificity are not large, they seem to tick up in tandem in 2005, 2009, and 2013 with alignment, and decrease in years of lower alignment (correlation of 0.44).

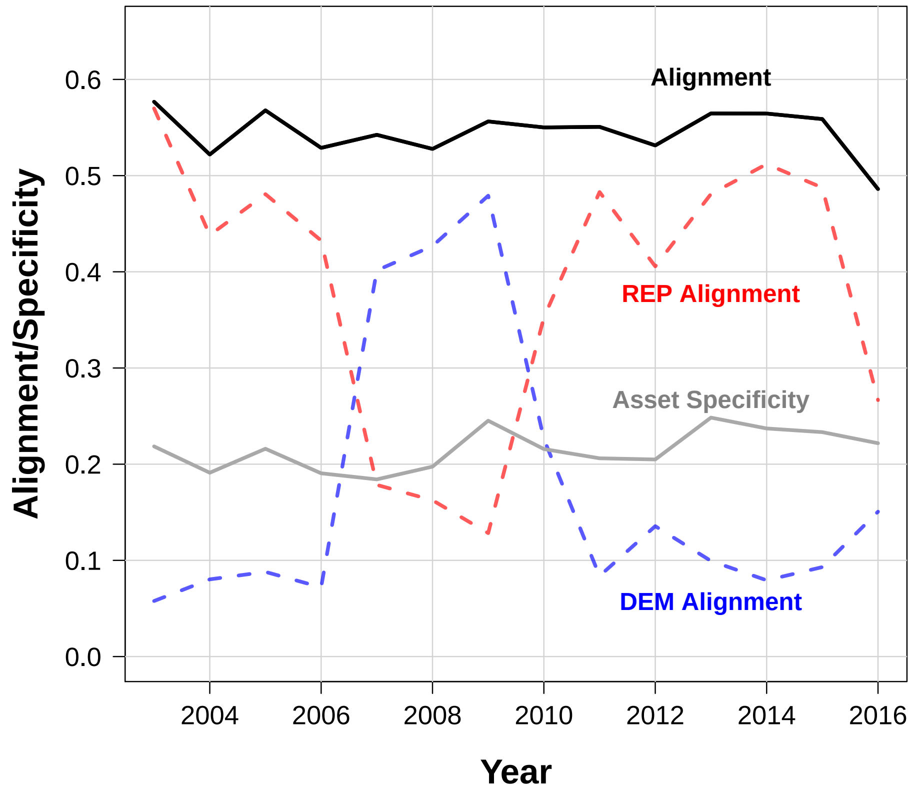


Figure 10: Alignment and Asset Specificity over Time. The graph depicts average alignment across all firms in the sample between 2003 and 2016. It shows that average asset specificity moves in tandem with overall alignment, and that the share of Republican and Democratic Alignment changes with election years. Data: own calculations and Compustat Capital IQ North America.

How does the relationship between asset specificity and alignment look like at the firm level? Figure 11 (left panel) shows that there is indeed a positive association between asset specificity and alignment. However, there is still a large variation in the alignment within firms with high and low asset specificity, respectively. The center and right panel of the same figure depict another interesting pattern in the data. The relationship shown in the left panel seems to be driven by the share of Republican alignment at the firm-level which is more positively related to asset specificity. Democratic alignment, on the other hand, is indeed weakly negatively related to asset specificity. This partly supports my expectation that specificity is more strongly associated with Republican alignment, based on historic relationships between labor- and capital intensive industries and US parties.[19]

[19]I find the same pattern using labor mobility as an alternative (inverse) measure asset specificity, as shown in Figure 14 in the appendix.

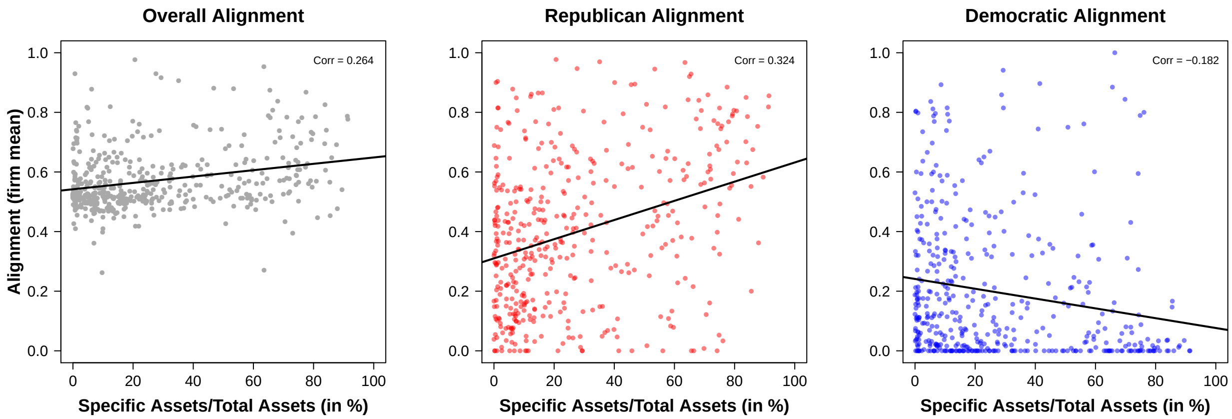


Figure 11: Positive Relationship between Alignment and Specific Assets. These scatter plots show that there is a positive relationship between specific assets and average firm-employee partisan alignment. Moreover, the relationship is negative for Democratic aignment, but strongly positive for Republican alignment. Data: own calculations and Compustat Capital IQ Annual Updates North America.

Table 4: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Year	138,549	2,010.39	4.04	2,003	2,016
Partisan Alignment	138,539	0.53	0.19	0.00	1.00
Democratic Alignment	138,549	0.20	0.40	0	1
Republican Alignment	138,549	0.35	0.48	0	1
(Specific Assets/Overall Assets)*100	122,657	21.12	23.40	0.00	94.39
log(Median Annual Income, Occupation)	111,634	11.39	0.45	9.58	12.24
log(Employees)	121,601	3.77	1.31	0.00	7.74
log(Sales)	126,109	9.90	1.41	−0.28	13.09
log(Capital Expenditure)	124,645	6.41	2.00	−0.06	10.44
log(Cost of Goods Sold)	126,110	9.15	1.52	0.00	12.78
Productivity	120,601	−0.06	0.33	−4.07	3.62
Union Membership (in %)	124,419	8.30	11.19	0.00	72.90
log(# Regulatory Restrictions)	84,068	7.93	1.56	5.27	10.49
Herfindahl-Hirschman (geographic)	120,057	0.16	0.20	0.00	1.00
Red State (Presidential Vote)	137,919	0.31	0.46	0	1
County Unemployment Rate (in %)	123,272	5.82	2.05	1.50	28.80

Table 4 includes descriptives of the main variables used in the following analysis. Motivated by the initial descriptive results shown above, I am interested in the relationship between partisan alignment and firm-level asset specificity and expect that more specific assets will be related to more alignment between employees and employers, regardless of individual occupation. Therefore, for the first empirical specification, I estimate the following linear model, regressing individual alignment on asset specificity with occupation and year fixed effects:

$$Alignment_{ikjst} = \alpha_k + \theta_t + \gamma Specific\_Assets_{jt} + \beta Z_{jt} + \delta I_{kt} + \tau R_{st} + \epsilon_{ikjst}$$

where alignment is measured for employee i in occupation k working in firm j living in county c in state s, with t denoting year. The α_k refers to occupation fixed effects, and θ_t to year fixed effects. My coefficient of interest is γ, the degree of asset specificity. In the initial specification, I control for a host of firm-level factors like log sales, employment, cost of goods sold, capital expenditure, and firm productivity[20], contained in the matrix Z_{jt}. Moreover, I control for the log of the occupation-specific median income from the Bureau of Labor Statistics, I_{ikt}, and for R_{ist}, whether the state an employee lives in is Republican or Democratic, according to the presidential vote share from the respective election.

The main specification in column 1 in Table 5 shows that there is a strong positive relationship between asset specificity of a firm and individual partisan alignment between firms and employees. Holding constant SOC occupation and several controls, a one-unit increase in asset specificity means a 0.001 (or 0.1%) increase in alignment. A one-standard deviation increase in asset specificity (23.4) would therefore be associated with a 0.023 increase in alignment share, which is a significant increase given that most firms are located around the 0.5 alignment score mark.

I also find that firms with more employees are less aligned, on average. This is an interesting result in itself that is in line with the expectation that from collective action theory, that collective political actions is more difficult in larger groups (Olson, 1965; Hansen, Mitchell and Drope, 2005). While larger firms might potentially be more powerful, they are also more likely to have more politically heterogeneous employees which would reduce alignment. In fact, one line of social science research has been on how group size and heterogeneity (or cohesiveness) of preferences inhibit or foster collective action (Ostrom, 2010). Moreover, as the number group members increases, the likelihood of free riding increases, decreasing alignment further. The negative rela-

[20]Productivity is measured by estimating the Solow-residual, i.e. by regressing (logged) sales on employment and expenditures for plant, property and equipment, as well as industry and year fixed effects (Bilir, 2014). The resulting residual is my measure of productivity.

tionship between number of employees and alignment is also consistent with my main hypothesis. Firms with more employees tend to be more labor intensive, and the main claim and finding of this paper is that firms with more specific assets (capital) are more aligned.

Finally, the coefficient on the dummy for red states is positive and significant, indicating that living in a Republican-voting state increases alignment by 0.031, on average. As expected from the theoretical discussion and the descriptives shown in the previous section, this result is driven by firms and employees being aligned on Republican candidates. In sum, being in a firm with more specific assets is almost as predictive of alignment as the state individuals live in. In this context, the magnitude of relationship between asset specificity and alignment found in this paper is quite substantive.

Of course, there are *alternative explanations* for why individuals might donate to the same party as their employer. Hertel-Fernandez (2018) argues that employers are increasingly using their employees as lobbyists or political machines in the US. He notes that when individuals live in a context with higher unemployment, they are more likely to become politically active for the company because they are more fearful of retaliation if they do not follow company demands. Therefore, I control for the annual county-level unemployment rate taken from the Local Area Unemployment Statistics (LAUS), published by the Bureau of Labor Statistics. The mean unemployment rate in the linked firm-employee data is 5.82 percent, which is slightly lower than the US-wide mean unemployment rate of 6.53 between 2003 and 2016. In all specifications in Table 5 the coefficient on the unemployment rate is negative and significant, though. This suggests that the mechanism suggested by Hertel-Fernandez does not hold for donations. In fact, companies report that donations are the least-used tactic when using employees as lobbyists (Hertel-Fernandez, 2016). The results in this paper indicate that those employees who are living in more affluent counties are more aligned with their company, on average.

Moreover, geographic concentration of an industry has been shown to be positively related to political mobilization (Busch and Reinhardt, 2000). In column 2 of Table 5, I control for industry concentration using a local Herfindahl-Hirschmann Index (HHI), measured as $\sum_{k=1}^{K} s_{ik}^2$ where s_{ik}^2 are the squared employment shares of each industry k in county i, which are subsequently summed over all counties. Intuitively, if all employees in an industry are located in one county, this measure is one, indicating full geographic concentration, and approaches zero as the number

Table 5: Regression Results: The Effect of Asset Specificity on Partisan Alignment

	Dependent variable:					
	Partisan Alignment					
	(1)	(2)	(3)	(4)	(5)	(6)
Share Specific Assets	0.068^{***}	0.065^{***}	0.072^{***}	0.079^{***}	0.079^{***}	0.078^{***}
	(0.017)	(0.018)	(0.020)	(0.020)	(0.020)	(0.020)
log(Capital Expenditure)	0.003	0.003	0.003	0.001	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
log(Sales)	-0.005	-0.004	-0.005	-0.003	-0.007	-0.002
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
log(Employees)	-0.016^{***}	-0.017^{***}	-0.016^{***}	-0.018^{***}	-0.016^{***}	-0.017^{***}
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
log(Cost of Goods Sold)	0.003	0.003	0.003	0.004	0.005	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Productivity	-0.0001	-0.0003	0.00005	-0.004	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
log(Median Income)	-0.045	-0.044	-0.045	0.028	-0.046	-0.064^{**}
	(0.031)	(0.031)	(0.031)	(0.034)	(0.031)	(0.030)
Red State (1/0)	0.031^{***}	0.032^{***}	0.030^{***}	0.030^{***}	0.031^{***}	0.027^{***}
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Unemployment Rate		-0.003^{**}				
		(0.001)				
HHI			-0.005			
			(0.015)			
Labor Mobility				-0.029		
				(0.028)		
Union Membership					-0.0004	
					(0.0004)	
# Regulatory Restrictions						0.001
						(0.002)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,220	85,110	90,293	74,575	93,543	62,881
Adjusted R^2	0.085	0.085	0.084	0.069	0.084	0.083

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

of employees is distributed across more and more counties.[21] I do not find that including this control variable changes the result for my main independent variable of interest. While the coefficient on the HHI is negatively signed, opposite to what I would expect from existing research, it is not significantly different from zero.

Related to the argument of this paper, employees in sectors with stronger profit-sharing institutions like unions could be more likely to align politically with their employer, because their own wages are more closely linked to company profits (Dean, 2016). Controlling for union membership as in column 4 of Table 5 does not change the strong positive relationship between asset specificity and alignment. Furthermore, the coefficient on union membership is not significantly different from zero, suggesting no impact of unions as profit sharing institutions on partisan alignment. Finally, Hertel-Fernandez (2018) also finds that companies are more likely to engage politically with their employees in industries with high regulatory exposure, i.e. in sectors where there is a tighter connection between regulation and company profits. In column 5 of Table 5, I control for regulatory exposure using the number of regulatory restrictions from the RegData database as a measure of regulatory exposure, measured at the 6-digit NAICS level (McLaughlin et al., 2017). I do not find any relationship between the extent to which an industry is exposed to regulation and the degree of partisan alignment between firms and employees.

Moreover, Table 6 replicates the main results from above, but splits alignment by partisanship. I also control for more geographic factors by including county-fixed effects, and include broad industry fixed effects. Column 1 and 4 show that the main results of this paper hold using county and broad industry fixed effects, even though the magnitude of the coefficient decreases. In general, the relationship between asset specificity and Republican alignment is stronger, and holds up to different fixed effects specifications. The association between asset specificity and Democratic alignment is negative, albeit not significant in the specification using county fixed effects. In sum, these results point to a positive relationship between asset specificity and partisan alignment. However, both from the descriptive graphs and the below analysis, this relationship seems to hold for Republican alignment, and less so for Democratic alignment.

[21]The geographic HHI has a mean of 0.16 in the sample analyzed which is higher than the US-wide 0.12, on average. This makes sense as I am only looking at companies which are politically organized (i.e. which have a PAC). Industry concentration has been shown to be positively related to the existence of corporate political activity at the firm and industry level, although with mixed results (Hansen, Mitchell and Drope, 2005).

Table 6: Regression Results: The Effect of Asset Specificity on Partisan Alignment - Different Fixed Effects

	Dependent variable:					
	Align	REP	DEM	Align	REP	DEM
	(1)	(2)	(3)	(4)	(5)	(6)
Share Specific Assets	0.070***	0.181**	−0.089	0.036**	0.156***	−0.146**
	(0.026)	(0.073)	(0.100)	(0.015)	(0.051)	(0.057)
log(Capital Expenditure)	0.002	0.004	0.004	0.002	0.008	0.00004
	(0.002)	(0.006)	(0.010)	(0.002)	(0.007)	(0.010)
log(Sales)	−0.005	−0.078***	0.087**	−0.002	−0.034*	0.038
	(0.006)	(0.024)	(0.035)	(0.005)	(0.019)	(0.031)
log(Employees)	−0.015***	0.007	−0.032	−0.014***	−0.018	−0.005
	(0.005)	(0.014)	(0.020)	(0.003)	(0.012)	(0.015)
log(Cost Goods Sold)	0.002	0.064***	−0.079***	−0.001	0.038**	−0.048*
	(0.005)	(0.017)	(0.025)	(0.004)	(0.015)	(0.026)
Productivity	−0.004	−0.014	−0.003	−0.001	−0.003	−0.013
	(0.005)	(0.019)	(0.019)	(0.004)	(0.020)	(0.018)
log(Med. Income)	−0.047	−0.142*	0.047	−0.032	−0.124	0.043
	(0.031)	(0.086)	(0.049)	(0.030)	(0.085)	(0.051)
Red State (1/0)	0.030***	0.139***	−0.071***	0.014**	0.032**	−0.006
	(0.004)	(0.011)	(0.011)	(0.006)	(0.016)	(0.019)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FEs	Yes	Yes	Yes	Yes	Yes	Yes
NAICS 2-digit FEs	No	No	No	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	No	No	No
Observations	95,220	95,230	95,230	85,524	85,533	85,533
Adjusted R^2	0.089	0.200	0.208	0.133	0.243	0.230

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

Finally, in the appendix in Table 11 I show that the results hold using the empirical quartiles of asset specificity, not the continuous measure. Compared to Table 5 above, the result remains essentially unchanged. In Table 10 in the appendix, I also replicate the results from Table 11 above using labor mobility as an inverse measure of asset specificity, as in Alt et al. (1999). If my expectations with regards to the relationship is correct, the coefficient on labor mobility should be negatively signed. When factors of production are more mobile, we would expect more class-based cleavages and less industry- or firm-based cleavages (Hiscox, 2002*a*) and therefore, less employee-employer alignment. My results show that labor mobility is indeed negatively related to partisan alignment, controlling for geographic and firm-level factors, and using different combinations of fixed effects as before. Moreover, as in the case of asset specificity, the relationship differs by partisanship of alignment. Why Republican alignment is negatively associated with more labor mobility, Democratic alignment is positively related to higher mobility. I also show the relationship between partisanship of alignment at the aggregate level in Figure 14, confirming my argument.

5 Conclusions

In this paper, I explore whether political preferences of firms and their employees align with each other. This important question touches upon long-standing work on the sources of individual political preferences, and lies at the heart of political economy research on individual preferences on trade, redistribution, or labor market risk. Unfortunately, simultaneously measuring both employer and employee political preferences is often impossible. I argue that in firms with more asset specificity, the economic interests of employers and employees will be more aligned since the fate of their jobs is tied more closely to the firm, and thus, employees are more likely to share similar political preferences with their employers. For testing this claim, I match big data on 1,691,790 US campaign contribution filings of 85,109 individuals to 874 publicly listed firms and 850 occupations using natural language processing techniques. This new dataset includes widely-used identifiers for firms, industries, and occupations, which can easily be linked to external databases on firm financial data, census data, or data by other government agencies. I find that employees in companies with more specific assets are significantly more aligned with their employer, on average. This relationship is substantive and stronger for Republican alignment than for Democratic alignment. Moreover, the descriptive analysis reveals that most of the variation in alignment is at the level of the industry and not at the occupation-level. Hence, where individuals work seems to matter more for partisan alignment than what they do.

There are several important *implications* of these findings. First, the results go contrary to recent political economy research which emphasizes the importance of individual occupation-based tasks and skills for preference formation (Kitschelt and Rehm, 2014; Owen and Johnston, 2017; Walter, 2017; Thewissen and Rueda, 2017). I do not find the large differences in partisan alignment across occupations predicted by this occupation-focused literature. Given the vast differences in partisan alignment across sectors (but not across geography or occupations), a main conclusion from this paper is that there is still a valuable role for sectoral models of individual political preferences (Grossman and Helpman, 1994). Second, the large differences in partisan heterogeneity or cohesion across companies has implications for political mobilization of firms (Olson, 1965; March, 1962). While homogeneous firms could potentially be more likely to overcome collective political action and mobilize politically (Ostrom, 2010), it needs empirical research to determine whether this business unity within firms and sectors also translates into more political influence (Walker and Rea, 2014). The results also hold potential implications for the formation of policy coalitions (Sabatier, 1988; Rogowski, 1989; Hiscox, 2002*b*; Dean, 2016). For instance, while sectoral coalitions could more likely to form among firms aligning on the same party, coalitions would be more difficult in the presence of more partisan differences between firms in the same sector. Third, if individual economic interests are more aligned in firms with highly specific assets, they might also be more likely to respond to efforts by their employers to influence their political actions (Hertel-Fernandez, 2018). Finally, this paper also adds to American Politics work on the unequal distribution of campaign donations across industries and occupations (Schlozman, Verba and Brady, 2012; Bonica, 2014, 2016*a*). In particular, I differentiate occupations and industries more clearly from each other than existing American Politics research.

This paper also opens up a rich *research agenda* on political alignment between employees and employers. First, it would be important to know whether individuals self-select into companies with similar partisan ideology or whether they actually change the partisanship of their donations when switching into industries with high asset specificity. If the former would be true, this would imply that firm partisanship could be another factor attracting employees to firms as suggested by recent Labor Economics research (Card et al., 2018). Consequently, if individuals systematically self-select into employers amplifying particular policy demands, then firms could be another channel facilitating polarization (Bafumi and Herron, 2010). However, if individuals change partisanship of donations after switching industries, this would challenge established views in American Politics about the stability of partisan ideology (Campbell et al., 1960). Second, it would be interesting to investigate the impact of specific institutional reforms or structural economic changes on partisan alignment, such as the proliferation of laws weakening unions or laws increasing leverage of employers vis-a-vis employees, adding to new work on politics at the workplace (Hertel-Fernandez, 2018). Third, the unique identifiers make it possible to link firm-level donations to lobbying behavior of firms. Thus, researchers can distinguish between these different corporate political strategies and their effects on policies. Finally, this paper only uses a fraction of the linked employer-employee campaign contributions data. The full dataset can be used to show changes in the economic geography and the industrial structure of campaign donations going back until the 1980s, at a much more fine-grained level than current studies relying on OpenSecrets data, thus also shedding light on the evolution of the US political geography.

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References

Acemoglu, Daron and David Autor. 2011. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics*. Vol. 4 Elsevier Inc. pp. 1043–1171.

Acemoglu, Daron, David H. Autor, David Dorn, Gordon H Hanson and Brendan Price. 2015. "Import Competition and the Great US Employment Sag of the 2000s." *Journal of Labor Economics* 34(1):141–198.

Ahlquist, John S. 2017. "Labor Unions, Political Representation, and Economic Inequality." *Annual Review of Political Science* 20:409–432.

Alford, John R., Carolyn L. Funk and John R. Hibbing. 2005. "Are political orientations genetically transmitted?".

Alt, James E., Fredrik Carlsen, Per Heum and Kare Johansen. 1999. "Asset Specificity and the Political Behavior of Firms: Lobbying for Subsidies in Norway." *International Organization* 53(01):99–116.

Alt, James E. and Michael J. Gilligan. 1994. "The Political Economy of Trading States: Factor Specifity, Collective Action Problems and Domestic Political Institutions." *The Journal of Political Philosophy* 2(2):165–192.

Ansolabehere, Stephen, John M. de Figueiredo and James M. Snyder. 2003. "Why Is There So Little Money in U.S. Politics?" *Journal of Economic Perspectives* 17(1):105–130.

Autor, David H., Frank Levy and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118(4):1279–1333.

Babenko, Ilona, Viktar Fedaseyeu and Song Zhang. 2016. "Do CEO's Affect Employees' Political Choices?" *Working Paper* .

Bafumi, Joseph and Michael C. Herron. 2010. "Leapfrog Representation and Extremism: A Study of American Vorters and Their Members in Congress." *American Political Science Review* 104(3):519–542.

Barber, Michael J., Brandice Canes-Wrone and Sharece Thrower. 2017. "Ideologically Sophisticated Donors: Which Candidates Do Individual Contributors Finance?" *American Journal of Political Science* 61(2):271–288.

Bartels, Larry M. 2008. *Unequal Democracy. The Political Economy of the New Gilded Age*. New York: Princeton University Press.

Bilir, L. Kamran. 2014. "Patent Laws, Product Life-Cycle Lengths, and Multinational Activity." *American Economic Review* 104(7):1979–2013.

Blinder, Alan S. 2009. "How Many US Jobs Might be Offshorable?" *World Economics* 10(2):41–78.

Blinder, Alan S. and Alan B. Krueger. 2013. "Alternative Measures of Offshorability: A Survey Approach." *Journal of Labor Economics* 31(2):S97–S128.

Bonica, Adam. 2014. "Mapping the Ideological Marketplace." *American Journal of Political Science* 58(2):367–386.

Bonica, Adam. 2016*a*. "Avenues of influence: On the political expenditures of corporations and their directors and executives." *Business and Politics* 18(4):367–394.

Bonica, Adam. 2016*b*. *Database on Ideology, Money in Politics, and Elections: Public version 2.0 [Computer file]*. Stanford, CA: Stanford University Libraries.
URL: *https://data.stanford.edu/dime*

Busch, Marc L. and Eric Reinhardt. 2000. "Geography, International Trade, and Political Mobilization in U.S. Industries." *American Journal of Political Science* 44(4):703–719.

Campbell, Angus, Converse Philip E., Miller Waren E., Donald E. Stokes, D E Campbell A. Converse P.E. Miller W. E. Stokes, Angus Campbell, Philip E. Converse, Warren E. Miller, Donald E. Stokes and D E Campbell A. Converse P.E. Miller W. E. Stokes. 1960. *The American Voter*. New York: John Wiley and Sons.

Card, David, Ana Rute Cardoso, Joerg Heining and Patrick Kline. 2018. "Firms and Labor Market Inequality: Evidence and Some Theory." *Journal of Labor Economics* 36(S1):S13–S70.

Dark, Taylor E. 2001. *The unions and the Democrats: an enduring alliance*. Ithaca, NY: Cornell University Press.

De Paula, Aureo and Jose A. Scheinkman. 2011. "The informal sector: An equilibrium model and some empirical evidence from Brazil." *The Review of Income and Wealth* 57(May):8–26.
URL: *https://www.opensecrets.org/ http://discovery.ucl.ac.uk/1328282/*

Dean, Adam. 2016. *From Conflict to Coalition: Profit-Sharing Institutions and the Political Economy of Trade*. Cambridge: Cambridge University Press.

Fouirnaies, Alexander and Andrew B. Hall. 2018. "How Do Interest Groups Seek Access to Committees?" *American Journal of Political Science* 62(1):132–147.

Francia, Peter L. 2003. *The financiers of congressional elections investors, ideologues, and intimates*. New York: Columbia University Press.

Frieden, Jeffry A. 1991. "Invested interests: the politics of national economic policies in a world of global finance." *International Organization* 45(4):425–451.

Gimpel, James G, Frances E Lee and Shanna Pearson-merkowitz. 2008. "The Check Is in the Mail: Interdistrict Funding Flows in Congressional Elections." *American Journal of Political Science* 52(2):1–23.

Grier, Kevin B., Michael C. Munger and Brian E. Roberts. 1994. "The Determinants of Industry Political Activity, 1978-1986." *American Political Science Review* 88(04):911–926.

Grossman, Gene M. and Elhanan Helpman. 1994. "Protection for Sale." *The American Economic Review1* 84(4):833–850.

Hansen, Wendy L., Neil J. Mitchell and Jeffrey M. Drope. 2005. "The logic of private and collective action." *American Journal of Political Science* 49(1):150–167.

Hertel-Fernandez, Alexander. 2016. "American Employers as Political Machines." *The Journal of Politics* 79(1):105–117.

Hertel-Fernandez, Alexander. 2018. *Politics at Work: How Companies Turn Their Workers into Lobbyists - And Why Americans Should Care*. New York: Oxford University Press.

Hiscox, Michael J. 2002*a*. "Commerce, Coalitions, and Factor Mobility: Evidence from Congressional Votes on Trade Legislation." *The American Political Science Review* 96(3):593–608.

Hiscox, Michael J. 2002*b*. *International Trade and Political Conflict: Commerce, Coalitions, and Mobility*. Princeton and Oxford: Princeton University Press.

Iversen, Torben and David Soskice. 2001. "An Asset Theory of Social Policy Preferences." *American Political Science Review* 95(4):875–893.

Joskow, Paul L. 1988. "Asset Specificity and the Structure Asset Specificity of Vertical Evidence: Empirical Relationships." *Journal of Law, Economics, & Organization*. 4(1):95–117.

Kim, In Song, Helen V. Milner, Thomas Bernauer, Gabriele Spilker, Iain Osgood and Dustin H. Tingley. 2017. "Firms' Preferences over Multidimensional Trade Policies: Global Production Chains, Investment Protection and Dispute Settlement Mechanisms." *Forthcoming in International Studies Quarterly* .

Kinder, Donald R. and Roderick D. Kiewiet. 1979. "Economic Discontent and Political Behavior: The Role of Personal Grievances and Collective Economic Judgments in Congressional Voting." *American Journal of Political Sciene* 23(3):495–527.

Kitschelt, Herbert and Philipp Rehm. 2014. "Occupations as a Site of Political Preference Formation." *Comparative Political Studies* 47(12):1670–1706.

Lewis-Beck, Michael S. and Martin Paldam. 2000. "Economic voting: an introduction." *Electoral Studies* 19(2-3):113–121.

Mansfield, Edward D. and Diana C. Mutz. 2009. "Support for Free Trade: Self-Interest, Sociotropic Politics, and Out-Group Anxiety." *International Organization* 63(03):425.

March, James G. 1962. "The Business Firm as Political Coalition." *The Journal of Politics* 24(4):662–678.

Mayda, Ana Maria and Dani Rodrik. 2005. "Why are some people (and countries) more protectionist than others?" *European Economic Review* 49(6):1393–1430.

McGeveran, William. 2003. "Mrs. McIntyre's Checkbook: Privacy Costs of Political Contribution Disclosure." *U. Pa. J. Const. L.* 6(1):1–56.

McLaughlin, Patrick A., Oliver Sherouse, Daniel Francis, Michael Gasvoda, Jonathan Nelson, Stephen Strosko and Tyler Richards. 2017. "Regdata 3.0 User's Guide.".

Meltzer, Allan H. and Scott F. Richard. 1981. "A Rational Theory of Government." *Journal of Political Economy* 89(5):914–927.

Milyo, Jeffrey, David Primo and Timothy Groseclose. 2000. "Corporate PAC Campaign Contributions in Perspective." *Business and Politics* 2(1):75–88.

Olson, Mancur. 1965. *The Logic of Collective Action. Public Goods and the Theory of Groups*. Cambridge and London: Harvard University Press.

Osgood, Iain. 2017. "The Breakdown of Industrial Opposition to Trade Firms, Product Variety, and Reciprocal Liberalization." *World Politics* 69(1):184–231.

Ostrom, Elinor. 2010. "Analyzing collective action." *Agricultural Economics* 41(SUPPL. 1):155–166.

Owen, Erica and Noel P. Johnston. 2017. "Occupation and the political economy of trade: Job routineness, offshorability, and protectionist sentiment." *International Organization* 71(4):665–699.

Plouffe, Michael. 2013. "The New Political Economy of Trade: Heterogeneous Firms and Trade Policy." *PhD Dissertation, University of California San Diego, Department of Political Science* .

Raffo, Julio and Stéphane Lhuillery. 2009. "How to play the "Names Game": Patent retrieval comparing different heuristics." *Research Policy* 38(10):1617–1627.

Rho, Sungmin and Michael Tomz. 2017. "Why Don't Trade Preferences Reflect Economic Self-Interest?" *International Organization* 71(1):85–108.

Rogowski, Ronald. 1989. *Commerce and Coalitions: How Trade Affects Domestic Political Alignments*. Princeton and Oxford: Princeton University Press.

Sabatier, Paul A. 1988. "An advocacy coalition framework of policy change and the role of policy-oriented learning therein." *Policy Sciences* 21(2-3):129–168.

Sawant, Rajeev J. 2012. "Asset specificity and corporate political activity in regulated industries." *Academy of Management Review* 37(2):194–210.

Scheve, Kenneth F. and Matthew J. Slaughter. 2001. "What determines individual trade-policy preferences?" *Journal of International Economics* 54(2):267–292.

Scheve, Kenneth F. and Matthew J. Slaughter. 2004. "Economic Insecurity and the Globalisation of Production." *American Journal of Political Science* 48(4):662–674.

Schlozman, Kay, Sidney Verba and Henry E. Brady. 2012. *The unheavenly chorus: Unequal political voice and the broken promise of American democracy*. Princeton: Princeton University Press.

Thewissen, Stefan and David Rueda. 2017. "Automation and the Welfare State: Technological Change as a Determinant of Redistribution Preferences." *Comparative Political Studies* (Online First).

Tripathi, Micky, Stephen Ansolabehere and James M. Snyder. 2002. "Are PAC Contributions and Lobbying Linked? New Evidence from the 1995 Lobby Disclosure Act." *Business and Politics* 4(2):131–156.

Walker, Edward and Christopher M. Rea. 2014. "The Political Mobilization of Firms and Industries." *Annual Review of Sociology* 40:281–304.

Walter, Stefanie. 2017. "Globalization and the Demand-Side of Politics: How Globalization Shapes Labor Market Risk Perceptions and Policy Preferences." *Political Science Research and Methods* 5(01):55–80.

Appendix

5.1 Companies in 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 7: 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.

5.2 Industries in 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 8: 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.

5.3 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 9: Unequal Frequency of Occupations in linked 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 and Financial, and Legal occupations comprise more than half of the individual contributions matched.

5.4 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)

5.5 Within-Occupation Variation in Alignment across 3-digit NAICS Industries

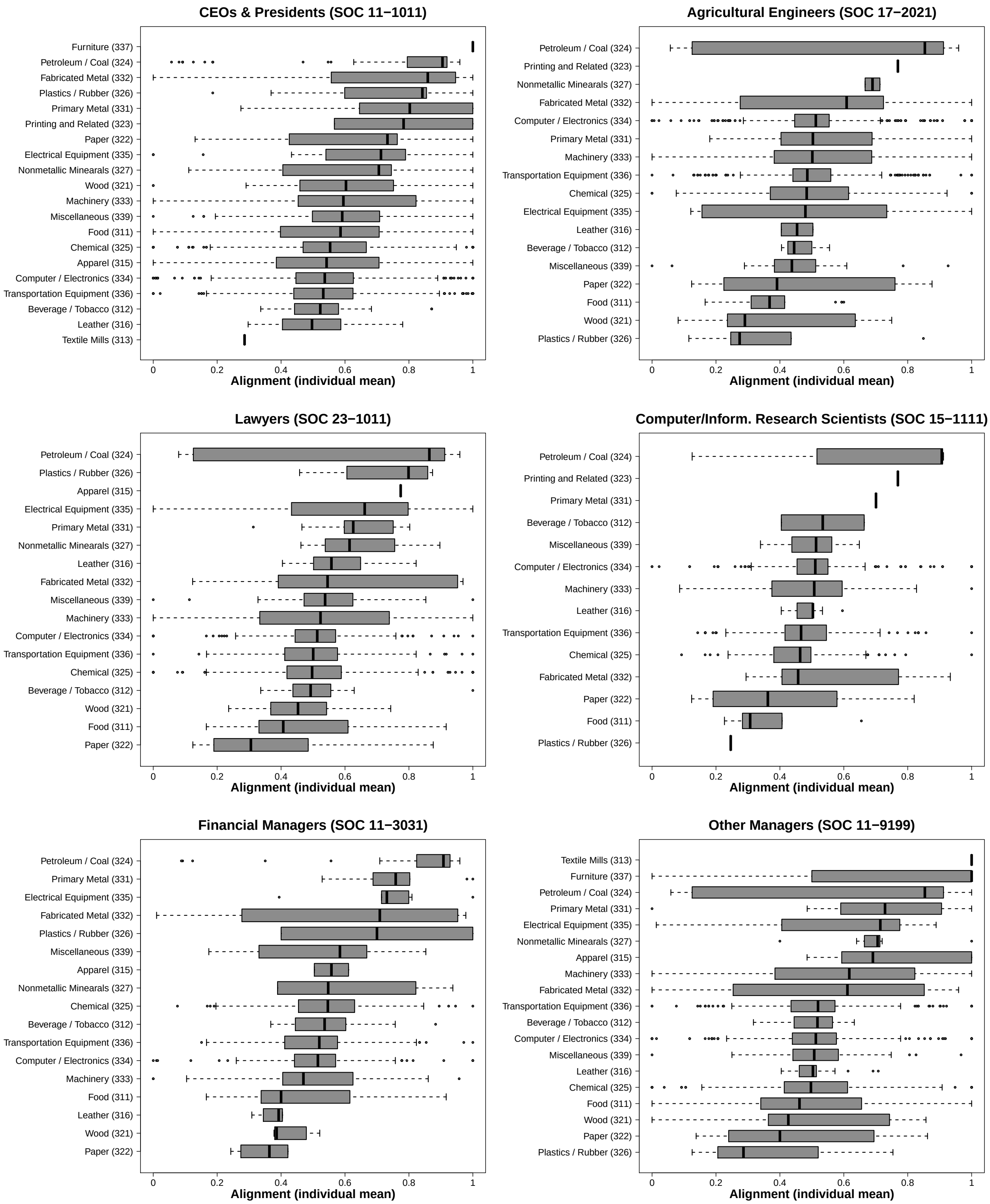

Figure 12: Strong Within-Occupation Variation in Alignment in Manufacturing Industries. These boxplots show that there is strong within-occupation variation in alignment for six very different different six-digit SOC occupations across industries. Data: own calculations.

5.6 Variation in Alignment across 3-digit SOC Occupations

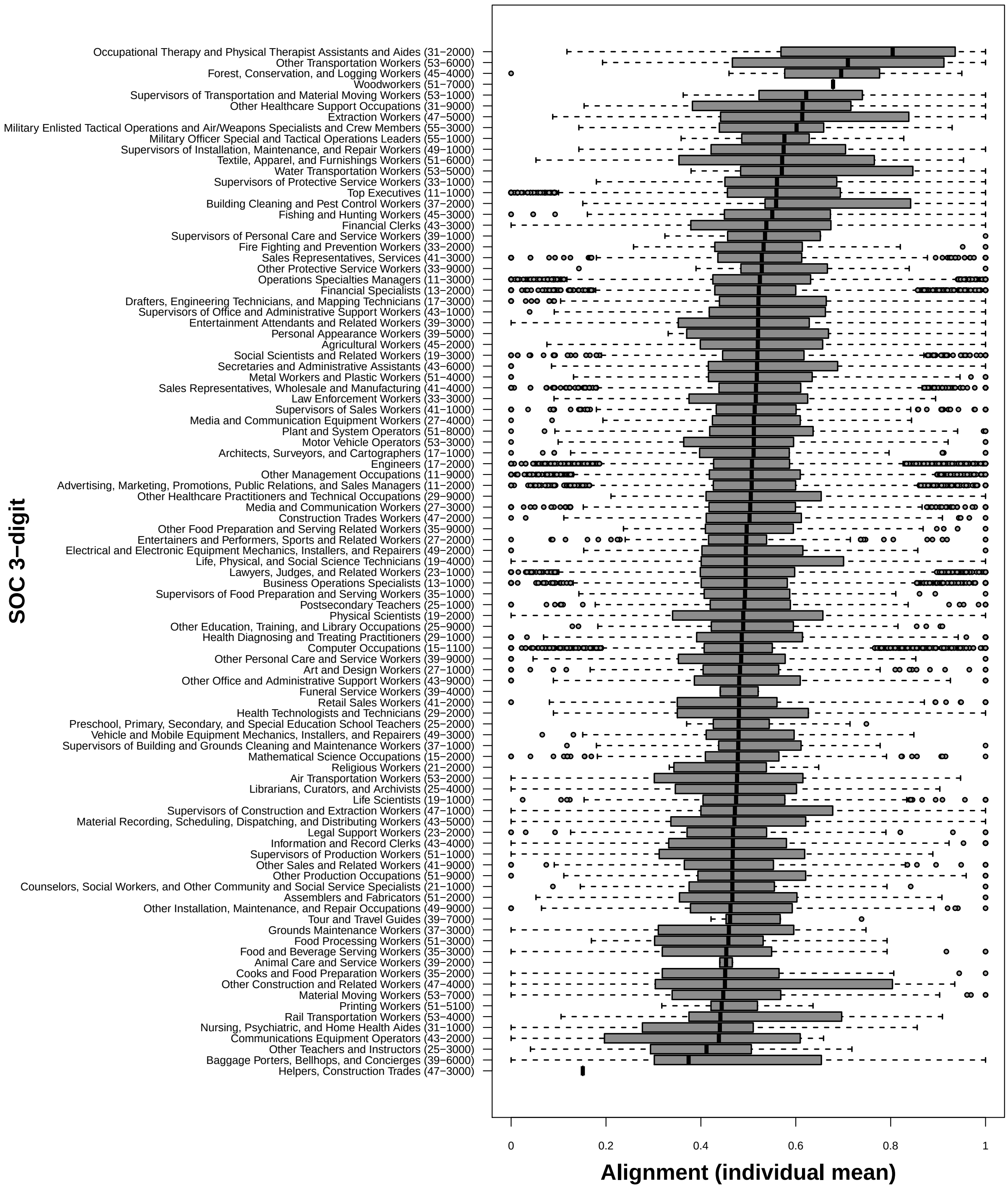

Figure 13: Weak Variation in Alignment across 6-digit Occupations. The graph shows that there are much less differences in alignment across very fine-grained occupations, compared to variation across industries. Data: own calculations.

5.7 Relationship between Labor Mobility and Firm Alignment

An alternative measure of asset specificity as measured in this paper, site specificity, is human capital specificity. I measure human capital specificity as former studies with labor mobility, which is measure as $LM_{kt} = \frac{JG_{kt} - JL_{kt}}{JG_{kt} + JL_{kt}}$, where JG_{kt} are job gains in industry k in year t, and JL_{kt} are job losses, taken from the Statistics of US Businesses (SUSB) tables, published by the US Census Bureau. Hence, LM_{kt} measures the overall movements in a given sector in a given year. One caveat of this measure is that the SUSB tables only become available after some delay, so the measure ends in 2015 at the moment. This measure is 0.28 in the sample, which is slightly higher than the country-wide average of 0.26 between 2003 and 2015.

Figure 14 plots the average alignment in each 4-digit NAICS sector in my data against this labor mobility measure. There is only a weakly negative relationship in terms of overall alignment at the industry level. However, the middle and the rightmost scatter plot show that there seems to be a negative relationship between Republican alignment and labor mobility, while there is a positive relationship between labor mobility and Democratic alignment.

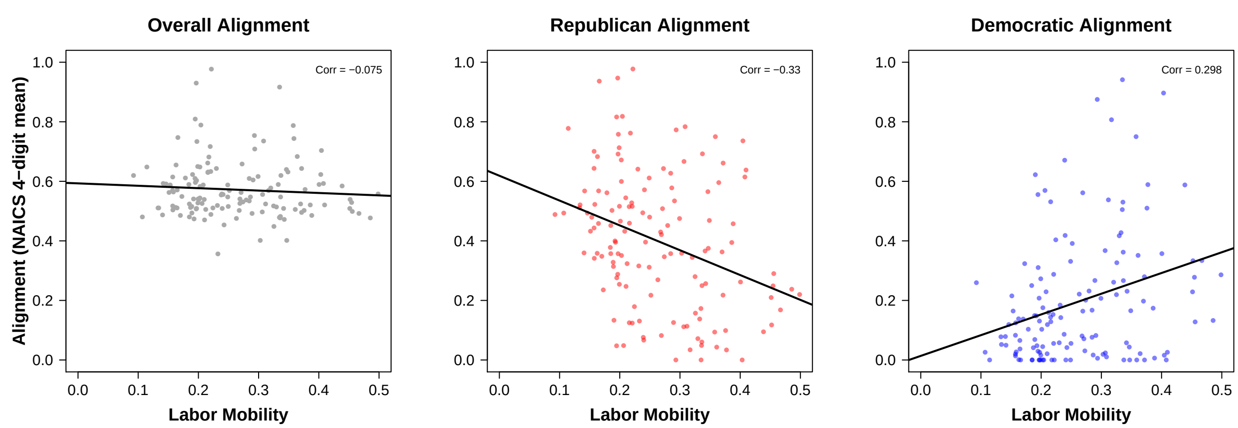

Figure 14: Party-Specific Relationship between Alignment and Labor Mobility. For robustness, these plots show the relationship between labor mobility at the 4-digit NAICS level and mean sectoral alignment. Labor mobility shows a strong negative relationship with Republican alignment, and a strong negative relationship with Democratic alignment. Data: own calculations and Census Bureau Statistics of U.S. Businesses (SUSB).

Controlling for year- and occupation fixed effects, Table 10 replicates the main results from this paper using labor mobility as an inverse measure of firm-level asset specificity. The results show that there is a slight negative relationship between mobility and higher partisan alignment. Moreover, the regressions reflect the asymmetric impact of mobility on Republican and Democratic alignment shown in the scatter plots in Figure 14, using different combinations of fixed effects.

Table 10: Regression Results: The Effect of Labor Mobility on Partisan Alignment

	Dependent variable:								
	Align	REP	DEM	Align	REP	DEM	Align	REP	DEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor Mobility	-0.063^{**}	-0.352^{***}	0.301^{***}	-0.043^{*}	-0.203^{**}	0.200^{**}	-0.098^{***}	-0.277^{**}	0.147
	(0.029)	(0.089)	(0.091)	(0.024)	(0.079)	(0.089)	(0.035)	(0.121)	(0.131)
log(Capital Expenditure)	0.008^{***}	0.025^{***}	-0.015^{**}	0.004^{*}	0.021^{***}	-0.016^{**}	0.002	0.014^{**}	-0.006
	(0.003)	(0.007)	(0.006)	(0.002)	(0.006)	(0.006)	(0.002)	(0.006)	(0.008)
log(Sales)	-0.012^{**}	-0.087^{***}	0.061^{***}	-0.003	-0.051^{***}	0.041^{*}	-0.007	-0.088^{***}	0.075^{***}
	(0.006)	(0.017)	(0.022)	(0.005)	(0.015)	(0.024)	(0.006)	(0.022)	(0.029)
log(Employees)	-0.023^{***}	-0.032^{***}	0.007	-0.019^{***}	-0.032^{***}	0.010	-0.023^{***}	-0.013	-0.016
	(0.005)	(0.012)	(0.013)	(0.004)	(0.011)	(0.013)	(0.006)	(0.014)	(0.017)
log(Cost of Goods Sold)	0.010^{**}	0.080^{***}	-0.058^{***}	0.003	0.051^{***}	-0.040^{*}	0.009	0.075^{***}	-0.062^{***}
	(0.005)	(0.015)	(0.021)	(0.004)	(0.014)	(0.023)	(0.006)	(0.018)	(0.022)
Productivity	-0.007	-0.021	-0.010	-0.007^{**}	-0.018	-0.011	-0.017^{***}	-0.036^{**}	-0.002
	(0.005)	(0.017)	(0.016)	(0.004)	(0.018)	(0.018)	(0.004)	(0.017)	(0.017)
log(Median Income)	0.029	0.049	0.028	0.042	0.056	0.037	0.029	0.037	0.046
	(0.033)	(0.117)	(0.064)	(0.035)	(0.116)	(0.063)	(0.034)	(0.116)	(0.064)
Red State (1/0)	0.037^{***}	0.166^{***}	-0.092^{***}	0.017^{**}	0.026	0.018	0.032^{***}	0.145^{***}	-0.076^{***}
	(0.006)	(0.014)	(0.011)	(0.008)	(0.019)	(0.018)	(0.006)	(0.013)	(0.011)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	No	No	No	Yes	Yes	Yes	No	No	No
NAICS 2-digit FEs	No	No	No	No	No	No	Yes	Yes	Yes
Observations	74,576	74,576	74,576	67,117	67,117	67,117	74,576	74,576	74,576
Adjusted R^2	0.065	0.185	0.203	0.120	0.246	0.239	0.073	0.203	0.219

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Standard errors clustered by firm are in parentheses.

Table 11: Regression Results: The Effect of Asset Specificity on Partisan Alignment

	Dependent variable:					
	Partisan Alignment					
	(1)	(2)	(3)	(4)	(5)	(6)
Specific Assets - Q2	0.014	0.014	0.013	0.013	0.015	0.016*
	(0.009)	(0.010)	(0.010)	(0.011)	(0.010)	(0.009)
Specific Assets - Q3	0.035***	0.033***	0.035***	0.039***	0.037***	0.049***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.012)	(0.016)
Specific Assets - Q4	0.040**	0.037**	0.041**	0.040**	0.045***	0.037**
	(0.016)	(0.017)	(0.020)	(0.018)	(0.016)	(0.016)
log(Capital Expenditure)	0.004**	0.004**	0.004**	0.003	0.004**	0.005**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
log(Sales)	−0.008*	−0.007	−0.008*	−0.007	−0.010*	−0.005
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
log(Employees)	−0.016***	−0.016***	−0.016***	−0.018***	−0.015***	−0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
log(Cost of Goods Sold)	0.004	0.004	0.005	0.006	0.005	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Productivity	0.0001	−0.00005	0.0001	−0.004	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
log(Median Income)	−0.041	−0.040	−0.040	0.032	−0.042	−0.058**
	(0.030)	(0.031)	(0.031)	(0.034)	(0.030)	(0.029)
Red State (1/0)	0.032***	0.033***	0.031***	0.032***	0.032***	0.028***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Unemployment Rate		−0.003**				
		(0.001)				
HHI			−0.006			
			(0.015)			
Labor Mobility				−0.041		
				(0.028)		
Union Membership					−0.0003	
					(0.0003)	
# Regulatory Restrictions						0.002
						(0.002)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,220	85,110	90,293	74,575	93,543	62,881
Adjusted R^2	0.084	0.085	0.083	0.068	0.084	0.083

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Standard errors clustered by firm are in parentheses.