Political Attitudes, Partisanship, and Merger Activity[*]

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Abstract

We demonstrate that similarity in employees' political attitudes plays an important role in mergers and acquisitions. Using detailed data on employees' campaign contributions to Democrats and Republicans, we find that firms are considerably more likely to announce and complete a merger when their political attitudes are closer. Furthermore, acquisition announcement returns and post-merger performance are higher when employees have more similar political attitudes. The effects are stronger when political polarization is greater, and when the target and acquirer plan to integrate operations. Overall, we provide new estimates that political attitudes and polarization affect the allocation of real assets.

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1. Introduction

This paper studies a new channel, unexplored by previous studies, through which corporate political attitudes and political partisanship affect one of the firm's most important investment decisions – mergers and acquisitions. Rather than focusing on firms' direct dealings with politicians and government officials, we explore the role of the political divergence or similarity between potential acquirers and targets, as reflected by their employees' personal contributions to political campaigns of Democrats and Republicans. The resulting estimates provide novel evidence on the real effects of political attitudes and partisanship on the allocation of assets in the economy and its efficiency.

A growing body of research studies the increase in political partisanship and polarization in the U.S. (e.g., McCarty, Poole, and Rosenthal (2006); Iyengar, Sood, and Lelkes (2012); Mason (2013, 2015); Lott and Hassett (2014); Gentzkow (2016); Boxell, Gentzkow, and Shapiro (2017); Autor, Dorn, Hanson, and Majlesi (2020)) and its implications for the behavior of households (e.g., Makridis (2020); McGrath (2017); Mian, Sufi, and Khoshkhou (2018); Meeuwis, Parker, Schoar, and Simester (2018)), judges (e.g., Posner (2008), McKenzie (2012), and Chen (2020)), and credit analysts (Kempf and Tsoutsoura (2021)). These studies explore the effects of political partisanship using the variation in unilateral decisions of individual agents whose perceptions and economic outlook are influenced by the dichotomy of whether the President is from the party they support.

In contrast, this paper investigates the role of political partisanship in bilateral corporate decisions – mergers and acquisitions – a setting where political partisanship is measured directly across the two interested counterparties (the acquirer and the target) and can influence both ex-ante deal formation and ex-post integration and outcomes. An additional benefit of this setting is that the distance between the political attitudes of the acquirer and the target offers continuous variation in political partisanship rather than the discrete variation of the President's party used in many prior studies.

We aim to answer four main questions: (1) How does the political distance between firms affect the likelihood of mergers and acquisitions? (2) How does variation in political polarization and economic conditions over time affect the role of political attitudes in mergers and acquisitions? (3) What are the implications of political attitudes for merger negotiations, announcement returns, and post-merger integration and performance? (4) How does the role of political distance differ from that of corporate culture?

To answer these questions, we hand-collect detailed data on the personal contributions of corporate employees to political campaigns from 1980-2018. These data include a total of 965,379 contributions from 316,757 employees of 9,136 firms, which average \$8,921 per firm each year (inflation-adjusted to 2015), of which \$3,924 is contributed to Democrats and \$4,997 to Republicans. Using these data, we measure a firm's political attitude as the ratio of the total number of employee contributions to Democratic campaigns to the total number of contributions to both Democratic and Republican campaigns over an 8-year-rolling window. By focusing on the personal contributions of a firm's entire labor force, which is dominated by rank-and-file employees who are uninvolved in merger decisions, and purging the estimates 8 years back, we generate estimates that are largely free from concerns that contributions are contemporaneously or endogenously related to a merger through channels different from political partisanship. Using this measure of firms' political attitudes, we construct a pairwise measure of the political distance between any two firms, labeled *Political Distance*, which equals the absolute value of the difference between their political attitudes.

In the first set of analyses, we investigate the effect of the political distance between firms on the likelihood of a merger. Following the method of Bena and Li (2014), we estimate the likelihood of mergers and acquisitions by generating synthetic (or pseudo) acquirers and targets for each merger in our sample of 2,103 mergers from 1980-2018. We implement this procedure using three different matching rules. First, we match each acquirer and target with random firms.

Second, we match each acquirer and target with industry- and size-matched firms. Third, we match each acquirer and target with industry-, size-, and book-to-market-matched firms.

Across all matched samples, we find that greater political distance between firms reduces the likelihood of a future merger announcement. The estimates are economically meaningful and imply that an increase of one standard deviation in the political distance between firms reduces the likelihood of a merger by 0.89 to 2.94 percentage points (or 5.9% to 19.5% relative to the sample-mean pseudo-likelihood of 15.1%). These estimates are statistically significant in all specifications, and they hold robustly after controlling for geographic proximity, acquirer/target characteristics, and after including industry, industry-year, and deal fixed effects.

A natural question that arises is how political differences between acquirers and targets differ from other corporate cultural differences. It is increasingly clear that people supporting different political parties often have fundamentally different views about policies on taxation, labor, markets, fair compensation, and even whether firms should seek contracts with the government, in particular the defense department.[5] Existing research shows that unlike cultural or other social divides, where group-related attitudes are constrained by social norms, there are no corresponding pressures to temper disapproval of political opponents (e.g., Himmelfarb and Lickteig (1982); Iyengar and Westwood (2015); Maccoby and Maccoby (1954); Sigall and Page (1971)). Hence, we posit that the effects of political partisanship likely are distinct from, and add to, those of other cultural differences.

To test this hypothesis, we re-estimate the analyses in a subsample that includes measures of cultural distances across five aspects of corporate culture -- Innovation, Integrity, Quality, Respect, and Teamwork – adopted from Li, Mai, Shen, and Yan (2020).[6] The estimates suggest

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[5] See, for example, "Google Wants to Do Business With the Military—Many of Its Employees Don't," by Joshua Brustein and Mark Bergen, https://www.bloomberg.com/features/2019-google-military-contract-dilemma/.

[6] We thank Kai Li, Feng Mai, Rui Shen, and Xinyan Yan for sharing their corporate culture data with us.

that political distance has little correlation with any of the cultural distance measures. Further, the effect of political distance on the likelihood of merger announcements remains equally important, both economically and statistically, after controlling for corporate cultural differences.

Taken together, these findings suggest that political differences across firms are a strong predictor of future mergers. Moreover, the effects of political differences are separate from those of traditional measures of corporate culture.

In the second set of analyses, we explore the role of the variation in political polarization and economic conditions in the United States over time. We conjecture that the effects of the political distance between acquirers and targets are stronger when the political divide is more pronounced. To test this conjecture, we use two measures of political polarization. The first measure, *PCI,* is based on the Political Conflict Index constructed by Azzimonti (2018). The second measure, the *House Partisanship Index* (*HPI*), is based on voting data from the U.S. House of Representatives. Using both measures, the estimates indicate that the effects of political partisanship on merger likelihood are more pronounced when political polarization is higher, suggesting that polarization exacerbates the effect of political attitudes.

We also explore the effects of the variation in economic conditions over time. We conjecture that political distance plays a weaker role in merger formation during recessions for two reasons. First, political polarization tends to be lower during recessions. Second, recession mergers are often "necessity" mergers aimed to allow the merging firms to continue operating. As such, firms might put aside their political and ideological differences. Consistent with this hypothesis, we find that the effect of political distance on merger likelihood is only economically and statistically significant outside recessions.

In the third set of analyses, we attempt to provide evidence on the mechanisms through which political partisanship affects the likelihood of mergers and acquisitions. First, we hypothesize that differences in political alignment can create costs in post-merger integration. These differences, however, are less relevant if the acquirer and target are not planning to integrate their businesses. To test this hypothesis, we search the merging firms' SEC filings for words related to integration. We then re-estimate the effects of political distance on merger likelihood for firms that mention integration and those that do not. The estimates suggest that political differences more negatively affect merger likelihood when the companies plan to integrate their operations.

Second, we hypothesize that political distance can affect the success of the merger negotiations themselves. We find that the likelihood of deal completion in announced mergers is significantly lower when the political distance between the acquirer and the target is greater. An increase of one standard deviation in the political distance between the acquirer and the target increases the likelihood of deal failure by 2.54 percentage points, or 13.3% relative to the sample-mean likelihood of 19.1%. We also find that the likelihood of a hostile or unsolicited bid is significantly greater when the political distance between the acquirer and target is higher. An increase of one standard deviation in political distance increases the likelihood of a hostile bid by 1.76 percentage points, or 20.0% relative to the sample-mean of 8.8%. Together, these results imply that the greater the political distance between acquirers and targets is, the more likely merger negotiations are to break down, resulting in incomplete deals or hostile takeovers.

In the last set of analyses, we investigate the effects of the political distance between acquirers and targets on merger performance. We start by studying acquisition announcement returns. The estimates suggest that the combined announcement returns are lower when the political distance is higher. The effects are economically nontrivial and statistically significant. An increase of one standard deviation in political distance reduces cumulative abnormal returns at merger announcement by 40.4 to 70.8 basis points. We also investigate the effects of political distance on post-merger performance in completed deals. We find that in the years following a merger completion, ROA is lower when the political distance is greater. An increase of one standard deviation in political distance reduces ROA by 0.67%, and the estimate is statistically significant at the 5% level. We also find that an increase of one standard deviation in political distance reduces the 3-year buy-and-hold abnormal cumulative returns by 36.4 to 66.9 basis points, estimates that are statistically significant at the 5% level.

Collectively, these findings indicate that political divergence between the acquirer and target has negative consequences for merger performance and value. An important caveat, however, is that these estimates likely underestimate the true effect of political partisanship on integration because, as we have shown, politically misaligned firms are less likely to merge in the first place.

Overall, our paper contributes to a large body of research that studies the determinants and consequences of mergers and acquisitions. Some researchers suggest that mergers are value-maximizing (e.g., Matsusaka (2001); Jovanovic and Braguinsky (2004)), while others suggest they are inefficient, potentially driven by agency conflicts (e.g., Baumol (1959); Jensen (1986, 1993); Stulz (1990)) or hubris (Roll (1986)). Our paper adds to this literature by showing that the political fit between acquirers and targets is an important predictor of merger success, performance, and value.

Our paper is also broadly related to prior studies of the relation between politics and mergers and acquisitions. Holburn and Bergh (2014) show that mergers in regulated industries are preceded by increases in election campaign contributions to influence regulatory merger approvals. Dinc and Erel (2013) provide evidence on the involvement of European governments in acquisitions to keep target companies domestically owned. Aktas, de Bodt, and Roll (2004), Carletti, Hartmann, and Ongena (2015), and Duso, Neven, and Roller (2007) study the stock market response to regulatory decisions or legislative actions. Contrary to prior work, which focuses on the role of outsiders – governments and regulators – in mergers, this paper studies the role of the political attitudes and partisanship across the acquirer and the target themselves.

Lastly, our paper is also related to prior research on the role of the cultural fit and of trust in mergers and acquisitions. To the extent that political similarity fosters trust, our paper is related to the studies by Guiso, Sapienza, and Zingales (2009) and Bottazzi, Da Rin, and Hellmann (2008), who demonstrate the importance of trust in cross-border financial investments by using macroeconomic and venture capital investment data, respectively. Further, several studies investigate the link between mergers and corporate culture. Ahern, Daminelli, and Fracassi (2015) find that the volume of cross-border mergers is smaller when countries are more culturally distant. Li, Mai, Shen, and Yan (2020) generate machine-learning-based measures of corporate culture and show that it plays an important role in merger incidence. Bereskin, Byun, Officer, and Oh (2018) show that similarity in firms' corporate social responsibility is positively correlated with the likelihood of a merger and with greater synergies, superior long-run operating performance, and fewer write-offs of goodwill. Lastly, based on survey evidence, Graham, Grennan, Harvey, and Rajgopal (2018) find that 46% of executives would walk away from a culturally misaligned target. Our estimates show that partisanship and political polarization play an increasingly important role in mergers and acquisitions, which is distinct from the role of corporate culture.

2. Data and Variables

To measure employees' political attitudes, we obtain information on individual contributions to political campaigns. The Federal Election Commission (FEC) maintains transaction-level records of individual donations organized by election cycle. Donations must be above a minimum value to be recorded in the file, and the minimum has changed over time: $500 and above from 1975 to 1988, $200 and above from 1989 to 2014, and above $200 from 2015 onwards.[7]

For each transaction, the FEC records the transaction amount, date, ID of the committee receiving the donation, as well as information about the donor. The donor information includes, among other details, self-reported information on the name of the donor, state, zip-code, and city

[7] More information is available on the FEC's website: https://www.fec.gov/campaign-finance-data/contributions-individuals-file-description/.

where the donor resides, and the donor's employer name. We utilize the self-reported employer names to match individuals with firms.

We match each FEC employer name with its closest CRSP name using bigram scores. We delete all matches with a bigram score less than 0.75, and manually check all matches with a score of 0.75 or higher. This yields 78,000 string matches that we manually check. Ultimately, we match 5.5 million donations out of 545 million donations with non-missing employer names from 1979 to 2018. The low match rate is explained by two observations. First, we only attempt to match employees with publicly traded firms. Consequently, employees of small businesses, non-profit organizations, and the public sector will not be matched. Second, we do not match donations from individuals who are not employed or self-employed. For example, there are 18 million donations reporting one of the following employer strings: "Not Employed", "Retired", "None", "Self", and "Self Employed." More details on the matching process are available in Appendix B.

Next, we classify donations into Republican or Democratic based on the affiliated party declared by the committee receiving the donation. Individuals are not allowed to make contributions directly to politicians; instead, they donate to Political Action Committees (PACs) that, in turn, expend money on political campaigns. We drop donations made to committees with no declared party affiliation or with a declared party affiliation that is not Democratic or Republican.[8,9] We end up with 973,537 donations corresponding to 9,136 unique firms. Fig. 1 shows the log of the aggregate number of donations to each party by year. It suggests that the

[8] 85% of committees with a declared affiliation are affiliated with the Republican or the Democratic party.
[9] This process drops donations made to firms' PACs since they rarely declare a partisan affiliation. Out of 2,690 committees where the connected organization is a corporation, only 196 declare such an affiliation.

number of donations has been increasing over time and that there is variation in the aggregate number of employee donations to the Democratic and Republican parties over time.

Using the employee-firm matched donation data, we construct a *Democratic Affiliation* score for each firm-year, defined as the fraction of the number of donations to Democrats over the total number of donations in the past 8 years.[10] By purging the estimates 8 years back, we generate estimates that are largely free from concerns that the most recent contributions are endogenously related to firms' merger decisions or outcomes through channels different from political partisanship. We ignore donations further in the past because they are less likely to reflect the current political affiliation of the firm's employees.

In our sample, the average number of donations used to calculate *Democratic Affiliation* is 132 for acquirers and 33 for targets. To address concerns about potential data scarcity, we provide estimates from robustness tests that use an alternative *Democratic Affiliation* score based on all the individual donations originating from the zip-code where the firm is headquartered. To construct the zip-code political measures, we obtain historical headquarter zip-code data from 10Ks/Qs (and all variants) filed on the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR), and then match each firm with donations originating from its headquarter zip-code using information reported to the FEC.[11] Since EDGAR started in 1995, this alternative measure is available from 1995 till 2018. The average number of donations using the zip-code political measure is considerably higher: 865 for acquirers and 751 for targets.

Fig. 2 assigns a *Democratic Affiliation* score to each state-decade based on our matched data. The figure maps the proportion of donations made to Democratic committees in each state relative to total donations to both Democratic and Republican committees over the past four

[10] We construct similar measures based on the dollar value of donations instead of the number of donations and obtain virtually identical results. We therefore only report those based on the number of donations throughout the paper.
[11] We thank Bill McDonald for making the 10K/Q header data available online (https://sraf.nd.edu/).

decades. The resulting maps summarize the evolution of the geographical landscape of employee political contributions over the past 40 years. Most notably, West Coast- and New York-based firms increasingly lean towards the Democrats, whereas in most other states, firms lean more towards the Republicans.

To construct the sample of mergers, we obtain information on all U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least \$10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms. We match the acquirer and target of each deal with the political contributions data and end up with 2,103 deals in which *Democratic Affiliation* is available for both the acquirer and the target. In a final step, we match the acquirers and the targets with information from the Center of Research in Security Prices (CRSP) and Compustat databases on firms' stock returns and accounting data.

Table 1 presents summary statistics for the acquirers (Panel A), targets (Panel B), and deals (Panel C) used in the analyses. The statistics in Panels A and B show that the average acquirer has higher Return on Assets and Return on Equity compared to the average target. The average acquirer also has a higher Tobin's Q, lower Z-score, and higher book leverage than the average target. Based on the measure of *Democratic Affiliation*, on average, acquirers lean slightly more towards the Democratic party than do targets.

Panel C of Table 1 presents summary statistics for the announced mergers included in the sample. The sample includes 2,103 announced deals, of which 81% are completed, 8.8% are hostile, 25.2% are stock-only, 36% are cash-only, 49.3% occur between parties that share the same 2-digit SIC code, and 22.3% occur between parties headquartered in the same state. At the median, the acquirer is 4.5 times larger than the target. The average deal value is \$3.5 billion. The main variable of interest, *Political Distance,* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation,* based on the number of donations. The average *Political Distance* for deals in the sample equals 0.337.

3. The Likelihood of Mergers

In this section, we investigate the effect of the political distance between firms on the likelihood of merger announcements. We conjecture that politically distant firms will be less likely to announce mergers for two main reasons. First, differences in political attitudes might negatively affect the success of merger negotiations. Second, such differences could adversely affect the prospects of post-merger integration, synergies, and outcomes. These conjectures are founded in extensive research showing that party affiliation is an important form of social identity (e.g., Huddy, Mason, and Aarøe (2015); Iyengar, Sood, and Lelkes (2012)), which inculcates hostility towards members of the outgroup.

We begin the analyses with descriptive evidence. Fig. 3 provides illustrative evidence on firms' political affiliations for the 50 largest mergers in our sample by transaction value. Each point corresponds to one of the 50 mergers and reflects the combination of the acquirer's and target's *Democratic Affiliation*. The main finding in Fig. 3 is the apparent clustering around the 45-degree line, suggesting mergers are more common between politically close firms.

In Table 2, we present the frequency distribution of merger announcements by political distance and presidential election cycle. The estimates in Table 2 suggest that the number of mergers declines as political distance increases. To test whether the pattern differs from a hypothetical distribution with randomized pairing between firms, we form all hypothetical merger pairs within a given election cycle using the population of Compustat firms for which we have measures of political attitudes. Then, we utilize a χ^2 goodness-of-fit test between the realized and hypothetical distributions. At the 95% confidence level, we reject the null hypothesis that the number of mergers is random with respect to political distance in 8 out of the 10 election cycles, and in all of the cycles since 1992. This test provides initial suggestive evidence that differences in political attitudes negatively affect the likelihood of merger announcements, particularly in more recent years when political polarization has been increasing in the U.S.

Next, we provide estimates from selection models of firms becoming acquirers or targets that follow the method used by Bena and Li (2014). For each merger announcement, we match acquirers (targets) with several pseudo-targets (pseudo-acquirers) in the year preceding the merger announcement. In the resulting sample, we create an indicator variable equal to one for the actual merger and zero for the pseudo-mergers.

In particular, we use three different control samples of potential acquirers and targets, all of which exclude firms that have been acquirers or targets in the three years preceding the merger and firms with missing measurements of political attitudes. First, we form a random control sample that matches each acquirer/target of a deal announced in year t with five paired firms drawn randomly from Compustat/CRSP in year t-1. This pool of potential merger participants captures merger clustering in time (Mitchell and Mulherin (1996), Maksimovic, Phillips, and Yang (2013)).

Second, we form an industry- and size-matched control sample that matches each acquirer/target of a deal announced in year t with up to five paired firms by industry—where the industry definitions are based on the narrowest SIC grouping that includes at least five firms—and by size from Compustat/CRSP in year t-1. This pool of potential merger participants captures merger clustering both in time and industry (Andrade, Mitchell, and Stafford (2001), Harford (2005)).

Third, we form an industry, size, and book-to-market matched control sample that matches each acquirer/target of a deal announced in year *t* with up to five paired firms—first matched by industry and then matched on propensity scores estimated using size and book-to-market ratios—from Compustat/CRSP in year *t*-1. We add the book-to-market ratio to the matching characteristics because prior studies show that it captures important drivers of mergers, such as growth opportunities (Andrade, Mitchell, and Stafford (2001)), overvaluation (Shleifer and Vishny (2003), Rhodes-Kropf and Viswanathan (2004)), and asset complementarity (Rhodes-Kropf and Robinson (2008)).

In Table 3, we present coefficient estimates from conditional logit models predicting mergers. Panels A, B, and C correspond to the randomly-matched sample; the industry- and size-matched sample; and the industry-, size-, and book-to-market matched sample, respectively. In Panel D, we instead measure political distance using donations originating from the zip-code where the firm is headquartered. The regressions in each panel alternate with respect to the inclusion of control variables (Target and acquirer Size, Return on Assets (ROA), Return on Equity (ROE), Leverage, Tobin's Q, Altman's Z score, Geographic proximity), Industry + Year fixed effects, and Deal fixed effects (each deal participant has one actual deal partner and up to 5 pseudo deal partners from the matched pairings).

The last column of each panel excludes hostile offers to focus on the announcement of negotiated deals. While political distance likely decreases the odds of announcing negotiated deals because it adversely affects the success of merger negotiations and post-merger integration, it might increase the odds of announcing hostile deals, which are noncooperative and result from disagreement by definition. Hence, we expect the negative effect of political distance to strengthen in the subset of negotiated deals, and will return to the prediction that deal hostility increases with political distance in subsequent analyses.

Across all 16 regression specifications in Panels A, B, C and D of Table 3, the coefficient on the main variable of interest, *Political Distance*, is negative and statistically significant at the 5% level or 1% level. These findings hold robustly across the three different control samples and after including all the control variables, Industry + Year fixed effects, or Deal fixed effects. They also hold when we measure firms' political based on donations originating from the zip-code where the firm is headquartered.

The economic magnitude of the effect of political distance on the likelihood of merger announcements is nontrivial. We estimate the marginal effect of political distance at the mean values of each predictor under a conditional logit model. Based on these predictive models, a one standard deviation increase in *Political Distance* reduces the likelihood of mergers by 0.89 to 2.94 percentage points (or 5.9% to 19.5% relative to the sample-mean pseudo-likelihood of 15.1%).[12]

Moreover, focusing on announced merger agreements (i.e., excluding hostile bids), where we expect political distance to play a more pronounced negative role, the coefficient estimate on *Political Distance* is 12-20% larger in magnitude compared to the same coefficient estimate in the sample that includes hostile takeovers. In samples using only announced merger agreements, the coefficient estimate on *Political Distance* is statistically significant at the 1% level in all three samples.

[12] The inclusion of fixed effects can confound the interpretation of marginal effects in conditional logit models. We obtain estimates using linear probability models to address this concern. Based on linear probability models, a one standard deviation increase in political distance reduces the likelihood of merger announcement by 0.89 to 2.04 percentage points (or 5.9% to 13.5% relative to the sample-mean pseudo-likelihood of 15.1%).

Taken together, these findings suggest that political similarity across firms positively predicts merger announcements. Stated differently, the evidence suggests that greater political distance between firms decreases the likelihood that the two firms will choose to merge. In the next set of analyses, we test whether changes in national political polarization and economic conditions impact the relation between political distance and merger likelihood.

4. Corporate Culture

Existing studies have shown that corporate culture plays an important role in merger formation and merger success (e.g., Ahern et al. (2015); Bereskin et al. (2018)). Are the political leanings of rank-and-file employees another proxy for corporate culture or does political distance affect merger likelihood beyond the effects of cultural distance? In this section, we use measures of firm culture from Li, Mai, Shen, and Yan (2020) to empirically study the distinction between politics and culture.

The five measures of corporate culture from Li, Mai, Shen, and Yan (2020) are *Innovation*, *Integrity*, *Quality*, *Respect*, and *Teamwork*. Those measures are constructed from the question-and-answer section of earnings call transcripts using a machine learning technique – the word embedding model. The data are available from 2003 to 2018 for the subset of firm-years that have electronically available transcripts. We start by examining the correlations between our political affiliation measure, *Democratic Affiliation*, and each of the five measures of culture. The correlations are: 0.24 with *Innovation*, 0.05 with *Integrity*, 0.07 with *Respect*, 0.13 with *Quality,* and 0.21 with *Teamwork*. These correlations suggest that political partisanship is distinct from measures of corporate culture, and do not raise concerns about collinearity in the regression model.

Next, we calculate cultural distance separately for each measure as the absolute value of the difference between the acquirer's and target's value for that measure. We also calculate an overall measure of cultural distance, *Aggregate Cultural Distance,* which is the sum of all five cultural distance measures. To facilitate a meaningful comparison, we standardize *Political Distance* and the cultural distance measures by subtracting their respective sample means and dividing by their respective sample standard deviations. Then, we include cultural distance between the target and the acquirer alongside *Political Distance* in the tests of merger formation likelihood. We note that the sample size of our tests is significantly reduced compared to our baseline specification in Table 3 because the corporate culture data is available only for the subset of firm-years where electronic earnings call transcripts are available.

Panel A of Table 4 reports coefficient estimates of conditional logit regressions predicting merger formation using the industry, size, and book-to-market matched sample with each cultural distance measure added individually. The coefficient estimates on *Political Distance* are negative and statistically significant at the 1% level in all specifications (except for column (2), where it is significant at the 5% level). The coefficient estimate varies from -0.182 to -0.186 across the specifications, suggesting that it is effectively unchanged when controlling for various dimensions of cultural distance. The coefficient estimates on cultural distances are negative in all specifications and statistically significant in three out of the five specifications. These results are consistent with findings of other studies showing that culturally distant firms are less likely to merge.

In Panel B of Table 4, we present coefficient estimates of merger formation likelihood tests including *Aggregate Cultural Distance* (Column 2) and all the individual cultural distance measures (Column 3). The coefficient estimate on *Political Distance* is negative and statistically significant at the 1% level in Column 1 and the 5% level in Column 2. The coefficient estimate on *Aggregate Cultural Distance* is negative and statistically significant at the 1% level, again conforming to the literature finding that cultural dissimilarity impedes merger formation. In our sample, we estimate that *Innovation Distance* has the greatest negative effect on merger formation out of the five culture variables studied.

Overall, the results in this section provide evidence that political dissimilarities affect merger formation above and beyond the impact of cultural dissimilarities. The findings draw a distinction between cultural dissimilarity and political dissimilarity consistent with past research (e.g., Himmelfarb and Lickteig (1982); Iyengar and Westwood (2015); Maccoby and Maccoby (1954); Sigall and Page (1971)). These studies have shown that social norms temper disapproval of culturally dissimilar groups but not politically dissimilar ones; political disapproval is likely increasing in the level of national political polarization and decreasing in tough times when togetherness and bipartisanship tend to dominate the national political narrative. In the following sections, we explore this variation to further highlight the importance of political attitudes and their interaction with national-level economic and political conditions on the allocation of assets in the economy.

5. Political Polarization and Economic Conditions

We open this section by testing whether political polarization influences the interaction between political attitudes and the likelihood of mergers. Since political distance plays an important role in merger announcements, we conjecture that when the U.S. is more politically polarized, the political distance between the acquirer and the target will have a stronger negative effect on the probability of mergers. This hypothesis is consistent with prior research, which shows that political polarization exacerbates the impact of partisanship on behavior (e.g., Iyengar and Westwood (2015); McConnell, Margalit, Malhotra, and Levendusky (2018)).

We use two variables to study political polarization. The first variable is based on the Partisan Conflict Index constructed by Azzimonti (2018). The Partisan Conflict Index is computed monthly and measures the frequency of newspaper articles reporting political disagreement about government policy, scaled by the total number of news articles in the same newspapers over the same month. The Partisan Conflict Index is normalized to average 100 in 1990. We take the annual average of the Partisan Conflict Index to generate the variable *PCI*.

The second variable is *HPI*, that is, the House Partisanship Index, which we construct using outcomes on yea-or-nay voting in the United States House of Representatives. For each vote in the House of Representatives, we define Partisan Disagreement as follows:

$$Partisan\ Disagreement_{v,t} = |RepYes_{v,t} - DemYes_{v,t}| \tag{1}$$

where $RepYes_{v,t}$ is the proportion of "yea" votes cast by Republican representatives as a proportion of all Republican votes cast on vote v in year t, and $DemYes_{v,t}$ is the proportion of "yea" votes cast by Democratic representatives as a proportion of all Democratic votes. We exclude all independent votes, absent votes, and abstain votes. The variable *Partisan Disagreement* increases (decreases) when political parties cast votes in the opposite (same) direction. Then, we define *HPI* as the average *Partisan Disagreement* for all votes in the U.S. House of Representatives in calendar year t.

We standardize both variables by subtracting their respective sample means and dividing by their respective standard deviations. We plot these standardized values in Fig. 4. In general, values for both measures of political polarization are greater in the second half of the sample. This pattern is consistent with numerous studies in political science showing that polarization and hostility across party lines have increased in the U.S. in more recent years (e.g., McCarty, Poole, and Rosenthal (2006); Haidt and Hetherington (2012); Iyengar, Sood, and Lelkes (2012); Lott and Hassett (2014); Iyengar and Westwood (2015); Gentzkow (2016); Boxell, Gentzkow, and Shapiro (2017); Autor, Dorn, Hanson, and Majlesi (2020)). We also note that political polarization appears lower during NBER recessions. We will revisit this issue when we study the effects of economic conditions.

To investigate the influence of political polarization on merger formation, we separately estimate the effects of political distance between the acquirer and the target from 1996 to 2018 in subsamples of low vs. high political polarization. We divide the sample around two indicator variables, *High PCI* and *High HPI*, which are equal to one when the values of *PCI* and *HPI*, respectively, are above average, and zero otherwise.

Table 5 reports the coefficient estimates from tests using the most stringent, industry, size, and book-to-market, matched samples. In columns (1) and (2), we separately estimate the effect of political distance when *High PCI* is equal to zero and one, respectively. The coefficient estimate on *Political Distance* in column (2), where polarization is higher, is more than triple the value of the estimate in column (1), where polarization is lower, and the difference between the coefficients is statistically significant at the 10% level (t-statistic = 1.80). This finding implies that differences in firms' political alignment are more important to merger formation when political polarization is higher. In columns (3) and (4), we repeat the analysis measuring political polarization using *High HPI* and obtain a similar result.

Overall, these results show that there are significant differences in the relevance of political similarity to merger formation between periods of lower and higher political polarization. The covariation of the effect's magnitude with political polarization is intuitive and supports our interpretation that the results reflect the effects of political attitudes rather than a correlated omitted variable unrelated to firms' political attitudes.

We now return to the role of economic conditions and study the effect of recessions on the relation between political attitudes and mergers and acquisitions. We conjecture that economic recessions attenuate the negative impact of political distance on the likelihood of merger formation for two reasons. First, as shown in Fig. 4, political polarization is lower during recessions (NBER recessions are represented by shaded areas). This finding might be driven by the tendency of Democrats and Republicans to cooperate more during economic downturns – for example, the *HPI* suggests that House representatives are more likely to vote together during recessions despite party differences. Second, during recessions, firms' incentives for entering a merger agreement can change. In particular, mergers during recessions might be necessity/emergency mergers that allow the merging firms to continue to operate. As such, firms might put aside their political and ideological differences.

To test the role of recessions in the relation between political distance and the likelihood of merger formation, we create an indicator variable, *Recession*, equal to one for mergers announced during NBER recessions and zero otherwise. Table 6 reports coefficient estimates of conditional logit regressions testing the effects of political distance on merger formation. In column (1), which corresponds to non-recessionary periods, the coefficient estimate on *Political Distance* is negative and statistically significant at the 1% level. In contrast, the estimate for recessionary periods in column (2) is negative and not statistically significant. The difference between the coefficients in columns (1) and (2) is economically large but not statistically significant (coefficient = 0.533; *t*-statistic = 1.22). Overall, this result indicates that recessions moderate the role of political differences in merger formation.

6. Mechanisms

In this section, we seek to provide evidence on the mechanisms through which political attitudes affect merger formation. We first provide evidence on post-merger integration using textual analysis of firms' financial reports. We then provide evidence on merger negotiations by studying the likelihood of merger completion and hostile takeovers.

6.1 Integration

In this subsection, we explore post-merger integration as a channel through which political attitudes can influence merger formation. We conjecture that the political distance between acquirers and targets will be more important for merger formation when the acquirer and target are integrating their businesses.

We measure the importance of integration for each announced deal by searching for keywords in the acquirer's Securities and Exchange Commission (SEC) filings following merger announcement. Specifically, we read the closest form 10K/Q filed post-announcement, and the closest form DEF 14A filed within a year after announcement. The variable *Integration* is equal to one if the words "integrate" or "integration" appear in the documents and zero otherwise.[13,14] After constructing the indicator variable *Integrate* for realized deals, we re-estimate the likelihood regressions for each group keeping the same pseudo deals for each realized deal.

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[13] A representative example where mentioning these terms is informative about the cost of integration is the acquisition of Asterias Biotherapeutics Inc by BioTime Inc. BioTime's 10-Q following the acquisition states: "If the merger is completed, BioTime expects to incur significant costs in connection with consummating the merger and integrating the operations of Asterias. BioTime may incur additional costs to maintain employee morale and to retain key employees."
[14] We exclude the acquisition of Rotech Medical Corp by Integrated Health Services Inc because the word "integrate" is mentioned 352 times in the acquirer's 10Q following announcement.

In Table 7, we separately estimate the effects of political distance on the likelihood of merger formation in subsamples formed based on whether integration is mentioned in SEC filings or not. As before, we only present coefficient estimates of conditional logit regressions using the industry, size, and book-to-market matched samples. Column (1) corresponds to the subsample where acquirers in the realized deals make no mention of integration in their SEC filings (i.e., *Integration* = 0). The coefficient estimate on *Political Distance* is positive but not statistically significant, suggesting that politically dissimilarity does not affect merger likelihood when integration of the merging firms' operations is not a priority. In column (2), we repeat the test where the acquiring firms' SEC filings have references to integration. The coefficient estimate on *Political Distance* is negative and statistically significant at the 1% level, indicating that greater political differences negatively influence the formation of deals where the merging firms plan to intermingle operations. The difference between the two coefficients (-1.104) is statistically significant at the 5% level (*t*-statistic = -2.23).

Altogether, the results in Table 7 show that differences in political ideology negatively affect merger formation when the merging firms plan to integrate operations. We note that since 88% of the mergers in the sample make some reference to integration, political distance is more often than not an economically meaningful predictor of merger formation.

6.2 Negotiations and Hostility

Another channel through which the effects of political differences can materialize is in the tone of negotiations between acquirers and targets. Negotiations between the acquirer and target could collapse before announcement, possibly leading the acquirer to initiate a hostile takeover bid. As Schwert (2002) points out, a hostile takeover is simply the announcement of an unnegotiated offer.

We hypothesize that greater political distance increases the chance of a breakdown in negotiations preceding the merger announcement, resulting in a greater chance of a hostile bid.

Furthermore, after the merger announcement, managers at either firm will learn more about their merger partner as integration discussions continue. Similarity in political attitudes can play a role in successfully reaching an agreement on integration issues and completing the merger. We therefore hypothesize that announced mergers between more politically distant firms will have a lower likelihood of completion.

These hypotheses are motivated by ample evidence that political differences are barriers to cooperation. For example, McConnell, Margalit, Malhotra, and Levendusky (2018) show experimentally that partisanship hurts cooperation in everyday economic behavior of workers and consumers. Iyengar and Westwood (2015) show that political polarization exerts powerful effects on nonpolitical judgments and behaviors and leads to confrontation rather than cooperation.

To test these hypotheses, we focus on the sample of announced deals, and create two outcome variables, *Hostile* and *Completed*. The variable *Hostile* is an indicator variable equal to one if there is a hostile or unsolicited bid, and zero otherwise. The variable *Completed* is an indicator variable equal to one if the deal is eventually completed. We then estimate conditional logit regressions using these two variables as outcomes.

We present the coefficient estimates of these tests in Table 8. In column (1), the outcome variable is *Hostile*, and the coefficient estimate on *Political Distance* is positive and statistically significant at the 10% level. The coefficient estimate implies that, conditional on announcement, a one standard deviation increase in political distance is associated with a 1.76 percentage point increase in the likelihood of a hostile bid, representing a 20.0% increase compared to the sample mean of 8.8%.

In column (2) of Table 8, we test how political distance influences post-announcement negotiations leading to merger completion. The coefficient estimate on *Political Distance* is negative and statistically significant at the 5% level. The coefficient estimate implies that a one standard deviation increase in political distance between the target and acquirer is associated with a 2.54 percentage point higher probability that the merger will fail to complete. Relative to the sample mean failure rate of 19.1%, this represents a 13.3% increase in failure to complete.

Overall, the results in this subsection show that not only does political distance influence the likelihood of deal announcement, it also affects the hostility of the deal and the likelihood of its completion.

7. Merger Announcement Returns and Post-Merger Announcement Outcomes

In the last set of analyses, we investigate the effects of political distance on post-merger announcement outcomes. We propose that more politically distant acquirers and targets would experience more difficulties in post-merger integration, leading to lower merger value and performance.

We begin by considering the effects of political distance on combined merger announcement returns. Table 9 presents estimates from ordinary least squares regressions explaining cumulative combined abnormal returns. In Panel A, abnormal returns are those in excess of the market return. In Panels B and C, abnormal returns are the excess of returns predicted by the CAPM (Sharpe (1964); Lintner (1965)) and the Fama and French (1993) 3-Factor plus Momentum (Carhart (1997)) Model (FF3M), respectively. Columns (1) and (2) of each panel correspond to the use of a three-day window (-1,1) and a six-day window (-1, 5), respectively.

In all the regression specifications, the coefficient estimates indicate the political distance between the acquirer and the target has a negative effect on merger announcement returns. In five out of six of the estimation models, the estimates are statistically significant at conventional levels. Furthermore, the coefficient estimates suggest that the effects are economically meaningful across all regression specifications. We estimate that a one standard deviation increase in *Political Distance* corresponds to a decrease in announcement returns of between 40.4 to 70.8 basis points. Collectively, the results in Table 9 suggest that political differences between firms are negatively associated with merger announcement returns.

We also investigate whether political distance affects post-merger performance. To this end, we employ two measures of the combined firm's performance following the merger: (1) return on assets (*ROA*); and (2) buy-and-hold abnormal returns (BHAR) using both the Capital Asset Pricing Model (CAPM) and the Fama-French 3-Factor Model plus Momentum.

We present coefficient estimates from OLS regressions explaining post-merger performance in Table 10. In column (1), which tests the effect of political distance on *ROA*, the coefficient estimate on *Political Distance* is negative and statistically significant at the 5% level. An increase of one standard deviation in *Political Distance* is associated with a decrease of 0.67% in *ROA*. In columns (2) and (3), the outcome variables are three-year BHARs using the CAPM and the FF3M. In both columns, the coefficient estimate for *Political Distance* is negative and statistically significant at the 5% level. The estimates imply an increase of one standard deviation in *Political Distance* corresponds to a decline of 36 to 67 basis points in buy-and-hold abnormal returns.

Overall, the findings in this section indicate that political divergence between the acquirer and the target is an obstacle to post-merger integration, with negative consequences for post-merger performance and value. An important caveat, however, is that these estimates likely underestimate the true effect of political partisanship on performance because, as we have shown, politically misaligned firms are less likely to merge in the first place.

8. Conclusion

This paper provides novel evidence that differences in political attitudes between firms play an important role in merger decisions and outcomes. We proxy for corporate political attitudes using detailed data on employees' individual political contributions to the campaigns of the two primary political parties in the U.S over the prior 8 years. By focusing on the personal contributions of a firm's entire labor force, which is dominated by rank-and-file employees who are uninvolved in merger decisions, we generate estimates that are largely free from concerns that political contributions are endogenously related to firms' merger decisions or outcomes through channels different from political partisanship.

The estimates show that firms are more likely to announce and complete mergers when they have similar political attitudes. Political polarization acts as a moderator; the role of political partisanship is more pronounced when political polarization is greater. Furthermore, political differences are important when firms seek to integrate their business operations. Finally, merger announcement returns and post-merger performance are stronger for more politically similar companies.

Collectively, the findings presented in this paper suggest that political attitudes and polarization affect the allocation of real assets in the economy. As such, this paper contributes to the vast literature studying the causes and consequences of mergers and acquisitions by showing that political similarity is a strong predictor of merger formation and merger success, and that the effects of political similarity vary over time with variations in the level of political polarization.

This paper also contributes to prior research on the relation between politics and mergers by showing that corporate political attitudes influence mergers by affecting firms' interactions with other firms, which might be politically close or distant, and not just through their interactions with the government and with regulators. Finally, this paper is also related to prior work on the relation between mergers and cultural fit, highlighting the importance of the similarity in political attitudes, which have been shown to play a more important role in everyday or economic behavior compared to other cultural traits.

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Appendix A: Variable Definitions

Variable	Definition
Firm-Level Political Measures	
Democratic Affiliation	The fraction of the number of donations to Democrats over the total number of donations to both Democrats and Republicans in the past 8 years.
Democratic Affiliation (V)	The fraction of the value of donations to Democrats over the value of total donations to both Democrats and Republicans in the past 8 years.
HQ Democratic Affiliation	The fraction of the number of donations to Democrats over the total number of donations to both Democrats and Republicans in the past 8 years, calculated using all individual donations originating from the zip-code where the firm is headquartered.
Pair-Level Political Measures	
Political Distance	The absolute value of the difference between acquirer's and target's Democratic Affiliation.
Political Distance (V)	The absolute value of the difference between acquirer's and target's Democratic Affiliation (V).
HQ Political Distance	The absolute value of the difference between acquirer's and target's HQ Democratic Affiliation.
Polarization Measures	
PCI	The Partisan Conflict Index was constructed by Azzimonti (2018). It is computed monthly and measures the frequency of newspaper articles reporting political disagreement about government policy scaled by the total number of news articles in the same newspapers over the same month. The Partisan Conflict Index is normalized to average 100 in 1990. We take the annual average of the Partisan Conflict Index to generate the variable *PCI*.
HPI	The House Partisanship Index is constructed using outcomes on yea-or-nay voting in the United States House of Representatives. For each vote in the House of Representative, we define Partisan Disagreement as follows: $Partisan\ Disagreement_{v,t} = \lvert RepYes_{y,t} - DemYes_{y,t} \rvert$ where $RepYes_{v,t}$ is the proportion of "yea" votes cast by Republican representatives as a proportion of all Republican votes cast on vote v in year t. $DemYes_{v,t}$ is, in turn, the proportion of "yea" votes cast by Democratic representatives as a proportion of all Democratic votes. We exclude all independent votes, absent votes, and abstain votes. The variable *Partisan Disagreement* increases (decreases) when political parties cast votes in the opposite (same) direction. Then, we define *HPI* as the average *Partisan Disagreement* for all votes in the U.S. House of Representatives in calendar year *t*.
Financial Variables	
Altman's Z-score	3.3*(EBIT/AT) + 0.99*(SALE/AT) + 0.6*(ME/LT) + 1.2*(ACT/AT) + 1.4*(RE/AT)

	EBIT is earnings before interest and taxes, AT is total assets, Sale is sales, ME is the market value of equity, LT is liabilities, ACT is current assets, and RE is retained earnings.
AT, Ln(AT)	Total Assets, the natural logarithm of total assets.
ME, Ln(ME)	Equity Market Capitalization (PRCC_C*CSHO), the natural logarithm of equity market capitalization.
Book Leverage	Book liabilities divided by book assets.
ROA	Net income divided by total book assets.
ROE	Net income divided by total book equity.
Tobin's Q	(AT + ME – BE)/AT BE is the book value of equity, AT and ME are as before.
Deal-Level Variables	
Deal Value	The proposed deal value at announcement, in $million
PostDealOwnership	The proportion of the target firm the acquirer will own if the deal completes as stated on the announcement day
Relative Size	Acquirer book assets divided by target book assets
Same HQ State	Indicator variable equal to one if the acquiror and target are headquartered in the same state, and 0 otherwise. Headquarter states are from SEC filings beginning in 1993.
Same 2-Digit SIC	Indicator variable equal to one if the acquiror and target are classified under the same 2-digit Standard Industrial Classification (SIC) code and zero otherwise.
Hostile	Indicator variable equal to one if the announced bid is hostile or unsolicited and zero otherwise.
Stock Only	Indicator variable equal to one if the announced bid is stock only and zero otherwise.
Cash Only	Indicator variable equal to one if the announced bid is cash only and zero otherwise.
Completed	Indicator variable equal to one if the announced deal is completed and zero otherwise.

Appendix B: Matching FEC Data

The FEC does not maintain a standardized method to record employer names. For example, the telecommunications company Verizon appears as “Verizon Communications Inc” in the Center of Research in Security Prices (CRSP) names file. However, it is reported in approximately 500 different ways in the FEC files. Examples include: “Verizon”, “Verizon Comm”, “Verizon Communications”, “Verizon Communications Inc”, “Verizon Communications, Inc”, etc. Therefore, we cannot use direct matching on names, and develop our own matching procedure to match employer strings in the FEC individual donation files to company historical names in CRSP.

We start from the FEC individual donations bulk data, available from 1979 to 2018. We drop any employer string that appears fewer than 5 times throughout the sample. We then apply a series of edits to standardize the data. The edits include dropping all symbols such as hyphens, underscores, and question marks. To minimize false matches, we overwrite common terms such as “communications”, “development”, “real estate”, “enterprise”, and “limited” with their respective abbreviations. These terms are common to many company names and can inflate the matching score, especially when the rest of the name is short. Finally, we replace numbers with their full spelling to increase the weight of numbers in the matching score. We apply the same set of edits to company historical names in CRSP.

After standardizing the data, we calculate the bigram score between each employer string in the FEC files and each company name available in the CRSP names files after 1979. Bigram score decomposes each string into elements of two characters on a moving-window basis, and then calculates a similarity score as follows:

$$similscore = \frac{number\ of\ common\ bigrams}{\sqrt{number\ of\ bigrams\ in\ string\ 1 * number\ of\ bigrams\ in\ string\ 2}}.$$

similscore thus ranges from 0 to 1. For example, consider the two strings: “Verizon Inc” and “Verzon Inc”. Bigram decomposes each string into elements of two characters as follows:

“Verizon Inc”: “Ve”, “er”, “ri”, “iz”, “zo”, “on”, “n ”, “ I”, “In”, “nc”

“Verzon Inc”: “Ve”, “er”, “rz”, “zo”, “on”, “n ”, “ I”, “In”, “nc”

Hence, the similarity score between the above two strings is:

$$similscore = \frac{8}{\sqrt{10 * 9}} = 0.84.$$

We keep the best matched CRSP name for each FEC employer string. We delete all matches with a bigram score less than 0.75, and manually check all matches with a score of 0.75 or higher.

Appendix C: Anecdotal evidence

Phycor Inc. and MedPartners Inc.

Political distance: 0.833 (91^{st} percentile of announced deals in our sample)

[i]t became apparent that the differences [between] the two companies were significant," said Larry House, MedPartners' chairman and chief executive. In discussions over several months, he said, it became obvious that the firms' "business philosophies and practices" were incompatible. -- Los Angeles Times (January 8, 1998)

In 1998, two physician management companies, Phycor Inc. and MedPartners Inc. announced an $8 billion merger. The market reacted negatively to the merger announcement. The combined market-adjusted returns were only 0.18% on the announcement day and -5.80% over the subsequent five trading days. Phycor, the acquirer, had returns of -23% on the first day after the announcement. Ultimately, the two companies did not merge, citing differences in strategies and higher-than-expected costs of integration.

LSI Logic Corp and Agere Systems

Political distance: 0.772 (90^{th} percentile of announced deals in our sample)

In addition, key employees may depart because of issues relating to the uncertainty and difficulty of integration or a desire not to remain with us following the proposed merger. The loss of services of any key personnel or the inability to hire new personnel with the requisite skills could restrict our ability to develop new products or enhance existing products in a timely matter, to sell products to customers or to manage our business effectively. -- LSI Logic Corp's post-announcement 10-K

In 2006, semiconductor and software designer LSI Logic Corp announced agreement to acquire rival and chipmaker Agere Systems. The market reacted negatively with the combined announcement returns being -0.0287. The acquisition was completed, however, LSI Logic Corp ended up discontinuing several development projects citing difficulties integrating Agere Systems and retaining key employees. The three-year buy and hold return of the deal is -0.0820

Figure 1: The Number of Donations by Party and Year

This figure plots the number of donations matched to Compustat/CRSP firms separated by party and year for the period 1979-2018.

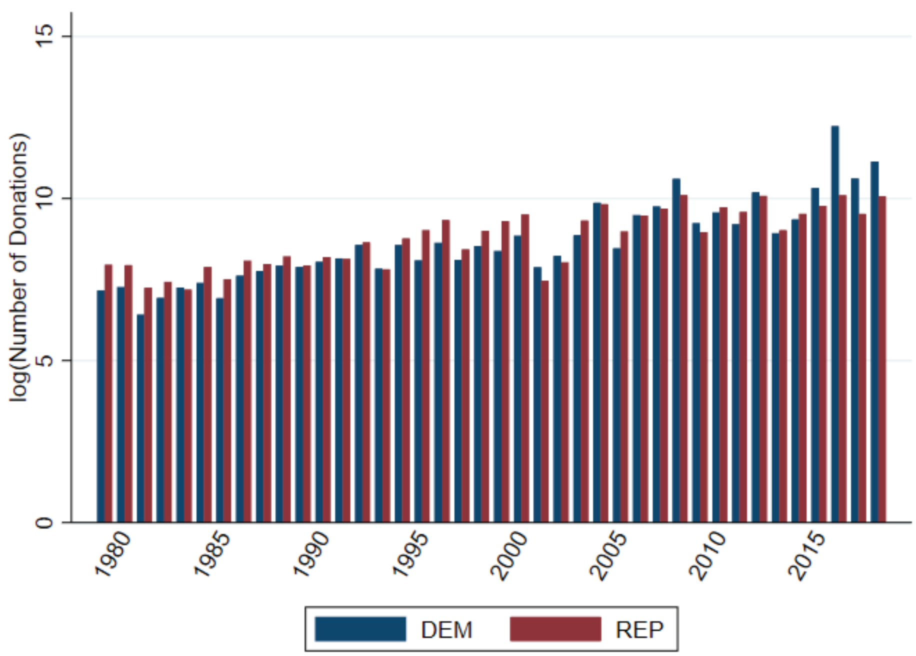
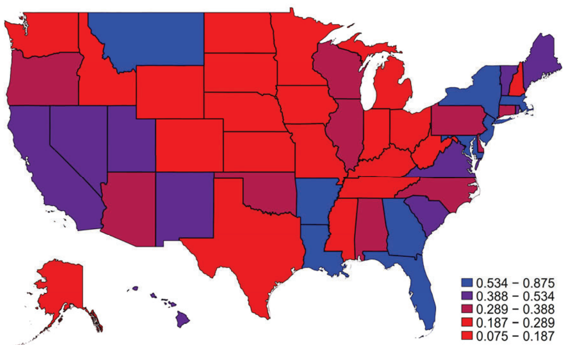


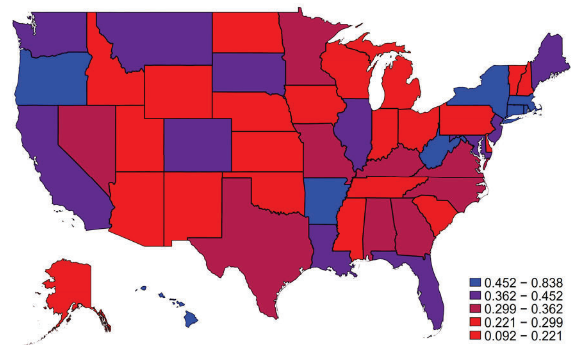
Figure 2: Political Donations by Decade and State

This figure maps the proportion of employees' individual donations made to Democratic committees as a percentage of donations to both Democratic and Republican committees in each state. Each map represents a decade of donations.

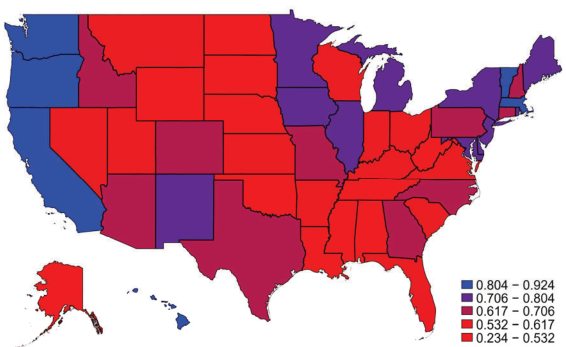
(i) 1980 - 1989



(ii) 1990 - 1999



(iii) 2000 - 2009



(iv) 2010 - 2019

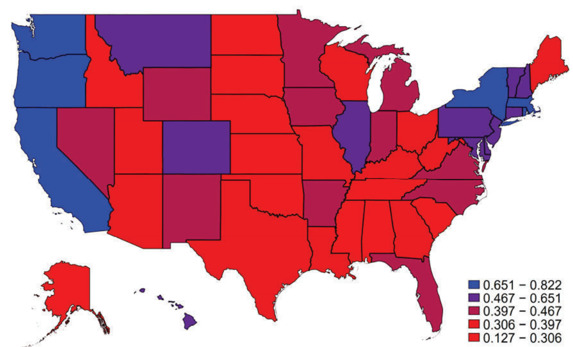


Figure 3: Deal Incidence by Acquirer and Target Party Affiliation

This figure plots acquirers' and targets' Democratic Affiliation for the 50 largest announced deals (by transaction value) in the sample. Democratic Affiliation is the number of employees' donations to Democrat committees divided by the number of donations to both Democrat and Republican committees. Additionally, we present a 45-degree line, representing where political distance is measured as zero (i.e. political similarity is maximized).

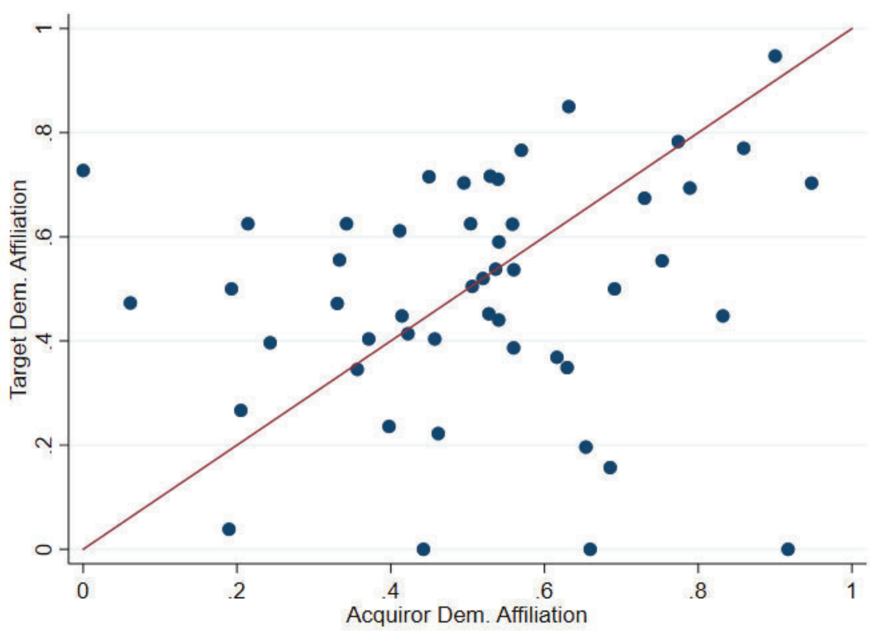


Figure 4: Political Polarization from 1996 - 2018

This figure plots Political Polarization from 1996 to 2018 using two measures that have been standardized by subtracting the sample mean and dividing by the sample standard deviation. The first is the standardized value of the annual average of the Partisan Conflict Index from Azzimonti (2018). The second is the standardized value of the annual House Partisanship Index, which measures the tendency of U.S. House of Representatives members to vote on opposite sides along party lines. All variable definitions are given in Appendix A. Shaded areas are NBER recession periods.

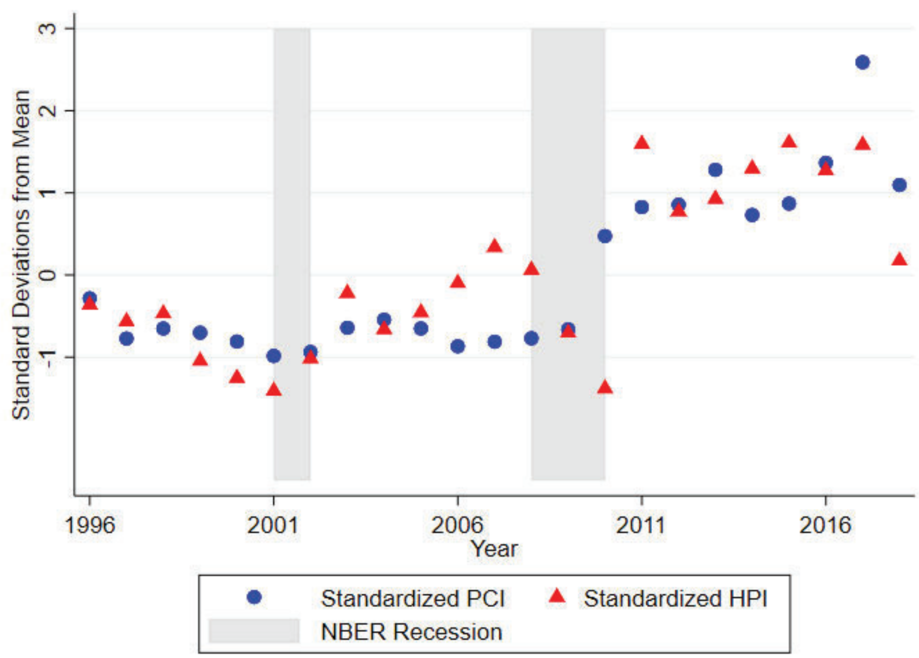


Table 1: Acquirer, Target, and Deal Descriptive Statistics

This table presents summary statistics for the acquirers and targets in the sample. Panel A describes acquirers and Panel B describes targets. Panel C describes the characteristics of announced deals. The sample includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A.

Panel A: Acquirer Summary Statistics

Variable	Mean	St.Dev	p25	Median	p75	N
Democratic Affiliation	0.433	0.314	0.163	0.425	0.667	2103
Democratic Affiliation (V)	0.405	0.324	0.117	0.369	0.648	2103
Book Assets ($mil)	26933	61230	1495	5491	21561	2103
Return on Assets	0.048	0.063	0.013	0.043	0.079	2103
Return on Equity	0.127	0.185	0.077	0.133	0.19	2097
Book Leverage	0.245	0.167	0.12	0.226	0.339	2086
Tobin's Q	1.871	1.374	1.083	1.399	2.052	2101
Altman Z Score	3.820	4.096	1.525	2.959	4.506	2019

Panel B: Target Summary Statistics

Variable	Mean	St.Dev	p25	Median	p75	N
Democratic Affiliation	0.425	0.37	0	0.367	0.757	2103
Democratic Affiliation (V)	0.408	0.381	0	0.301	0.795	2103
Book Assets ($mil)	5573	15849	254	851	3279	2103
Return on Assets	0.001	0.14	-0.002	0.026	0.062	2103
Return on Equity	-0.030	0.549	-0.006	0.091	0.151	2095
Book Leverage	0.238	0.191	0.077	0.217	0.358	2084
Tobin's Q	1.767	1.276	1.041	1.315	1.952	2099
Altman Z Score	3.951	4.835	1.553	2.936	4.682	1944

Panel C: Announced Deal Summary Statistics

Variable	Mean	St.Dev	p25	Median	p75	N
Political Distance	0.337	0.281	0.102	0.265	0.5	2103
Political Distance (V)	0.356	0.294	0.106	0.292	0.553	2103
Deal Value ($mil)	3548	9840	198	750	2533	2103
PostDealOwnership	0.902	0.272	1	1	1	2103
Relative Size (Acq/Tar)	33.357	96.815	1.616	4.460	18.495	2103
Same 2-Digit SIC	0.493	0.5	0	0	1	2103
Same HQ State	0.223	0.416	0	0	0	2103
Hostile	0.088	0.283	0	0	0	2103
Stock Only	0.252	0.434	0	0	1	2103
Cash Only	0.360	0.48	0	0	1	2103
Completed	0.809	0.393	1	1	1	2103

Table 2: Frequency of Mergers and Acquisitions by Political Distance

This table shows the frequency of M&A deal announcements based on political distance and U.S. Presidential election cycle. We present merger announcement counts by presidential election cycle, defined as the four years leading up to a U.S. Presidential Election. For each cycle, we present χ^2 tests against a hypothetical distribution of all possible firm combinations for which we have data in that cycle. The sample includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A.

Election	Political Distance							
Cycle	[0,0.2]	(0.2,0.4]	(0.4,0.6]	(0.6,0.8]	(0.8,1]	Total	χ^2	p-value
1984	51	25	15	9	17	117	8.59	7.23%
1988	65	37	33	21	25	181	5.51	23.91%
1992	62	27	28	21	16	154	10.21	3.70%
1996	99	67	41	39	34	280	16.10	0.29%
2000	166	111	78	41	45	441	41.62	0.00%
2004	71	56	25	18	18	188	28.35	0.00%
2008	121	62	43	19	18	263	45.26	0.00%
2012	79	41	31	11	7	169	39.23	0.00%
2016	76	69	28	21	10	204	54.92	0.00%
2020	49	28	14	12	3	106	25.59	0.00%
Total	839	523	336	212	193	2103	217.52	0.0000%

Table 3: Political Distance and Merger Likelihood

This table presents coefficient estimates of conditional logit models predicting merger likelihood. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. We exclude firms that have been acquirers or targets in the three years preceding the merger announcement. Panels A, B, and C correspond to the Random Match; Industry, Size Match; and Industry, Size, B/M Match samples; respectively. The Random sample uses five randomly paired pseudo-targets (acquirers) for each acquirer (target). For the Industry, Size and Industry, Size, B/M samples, we match the highest number of SIC digits that offers at least five candidate matches per firm. In Panel D, we measure political affiliations using donations originating from the zip-code where the firm is headquartered (*HQ Political Distance*), while still employing an Industry, Size, B/M Match. The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. All non-indicator variables are winsorized at the 1st and 99th percentiles. Control variables include Leverage, natural log of Book Assets, and Tobin's Q for each of the target and acquiror, Same HQ State, and Same 2-Digit SIC. The sample in Panels A-C includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. In Panel D, the sample includes 2,753 mergers. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target, except in Panel D where we instead require available data on political donations from the firm's headquarter zip-code. All variable definitions are given in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

Panel A: Random Match sample

Model	(1)	(2)	(3)	(4)
Political Distance	-0.937***	-0.560***	-0.611***	-0.718***
	(-8.43)	(-3.92)	(-3.93)	(-4.47)
Acquirer Democratic Affiliation	0.133	-0.087	-0.018	0.037
	(1.42)	(-0.72)	(-0.15)	(0.30)
Target Democratic Affiliation	0.130	-0.002	0.125	0.201*
	(1.53)	(-0.02)	(1.17)	(1.83)
Controls?	No	Yes	Yes	Yes
Industry+Year FEs?	No	Yes	Yes	Yes
Deal FEs?	No	No	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes	No
Observations	13,985	13,743	13,670	12,593
Pseudo R^2	0.009	0.317	0.448	0.440

Panel B: Industry, Size Match sample

Model	(1)	(2)	(3)	(4)
Political Distance	-0.580***	-0.376***	-0.380**	-0.458***
	(-5.93)	(-3.10)	(-2.55)	(-2.95)
Acquirer Democratic Affiliation	0.027	-0.117	-0.165	-0.096
	(0.32)	(-1.02)	(-1.25)	(-0.69)
Target Democratic Affiliation	0.009	-0.021	0.082	0.114
	(0.12)	(-0.23)	(0.73)	(0.99)
Controls?	No	Yes	Yes	Yes
Industry+Year FEs?	No	Yes	Yes	Yes
Deal FEs?	No	No	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes	No
Observations	11,761	11,509	11,506	10,689
Pseudo R^2	0.004	0.062	0.198	0.195

Panel C: Industry, Size, B/M Match sample

Model	(1)	(2)	(3)	(4)
Political Distance	-0.725***	-0.398***	-0.391**	-0.440***
	(-7.60)	(-3.00)	(-2.46)	(-2.65)
Acquirer Democratic Affiliation	0.112	-0.110	-0.106	-0.066
	(1.39)	(-0.88)	(-0.72)	(-0.42)
Target Democratic Affiliation	0.046	0.075	0.221*	0.265**
	(0.62)	(0.99)	(1.85)	(2.13)
Controls?	No	Yes	Yes	Yes
Industry+Year FEs?	No	Yes	Yes	Yes
Deal FEs?	No	No	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes	No
Observations	11,727	11,491	11,489	10,685
Pseudo R^2	0.006	0.108	0.258	0.258

Panel D: Zip-code Donations and Industry, Size, B/M Match sample

Model	(1)	(2)	(3)	(4)
HQ Political Distance	-0.748***	-0.373***	-0.435***	-0.412**
	(-7.16)	(-2.59)	(-2.62)	(-2.40)
Acquirer HQ Democratic	-0.143*	-0.359***	-0.409***	-0.426***
Affiliation	(-1.71)	(-2.83)	(-2.87)	(-2.87)
Target HQ Democratic	0.022	-0.089	-0.014	-0.013
Affiliation	(0.26)	(-0.74)	(-0.10)	(-0.09)
Controls?	No	Yes	Yes	Yes
Industry+Year FEs?	No	Yes	Yes	Yes
Deal FEs?	No	No	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes	No
Observations	28,316	27,905	27,848	26,177
Pseudo R^2	0.002	0.132	0.290	0.292

Table 4: Corporate Culture

This table presents coefficient estimates of conditional logit models that include the measures of firm culture from Li, Mai, Shen, and Yan (2020). The five measures of culture are *Innovation*, *Integrity*, *Quality*, *Respect*, and *Teamwork*, and are constructed from electronic earnings call transcripts. For each measure, we estimate distance as the absolute value of the difference between the acquirer and target's value of that culture measure, respectively. We also calculate an overall cultural distance measure, *Aggregate Cultural Distance*, which is the sum of the cultural distances calculated under each measure. We then standardize *Political Distance* and each cultural distance measure by subtracting their respective means and dividing by their respective standard deviations. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. We exclude firms that have been acquirers or targets in the three years preceding the merger announcement. We also exclude firm-years for which *Democratic Affiliation* measures are unavailable. We present results for the Industry, Size, B/M sample for which we match the highest number of SIC digits that offers at least five candidate matches per firm. We then choose the five closest pseudo-targets (acquirers) to the actual target (acquirer). The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. All non-indicator variables are winsorized at the 1st and 99th percentiles. Control variables include Leverage, natural log of Book Assets, and Tobin's Q for each of the target and acquiror, Same HQ State, and Same 2-Digit SIC. The sample includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least \$10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

Panel A: Individual Cultural Distance Measures

Model	(1)	(2)	(3)	(4)	(5)	(6)
Political Distance	-0.185***	-0.182**	-0.185***	-0.183***	-0.186***	-0.185***
	(-2.63)	(-2.57)	(-2.63)	(-2.60)	(-2.64)	(-2.63)
Innovation Distance		-0.406***				
		(-4.94)				
Integrity Distance			-0.076			
			(-1.10)			
Quality Distance				-0.135*		
				(-1.82)		
Respect Distance					-0.191**	
					(-2.35)	
Teamwork Distance						-0.010
						(-0.14)
Acquirer Democratic Affiliation	0.126	0.181	0.121	0.111	0.100	0.125
	(0.43)	(0.62)	(0.41)	(0.38)	(0.34)	(0.43)
Target Democratic Affiliation	0.365	0.410*	0.378	0.378	0.386*	0.365
	(1.58)	(1.77)	(1.63)	(1.63)	(1.67)	(1.58)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs?	Yes	Yes	Yes	Yes	Yes	Yes
Deal FEs?	Yes	Yes	Yes	Yes	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,884	2,884	2,884	2,884	2,884	2,884
Pseudo R-squared	0.280	0.296	0.281	0.282	0.284	0.280

Panel B: Combined Cultural Distance Measures

Model	(1)	(2)	(3)
Political Distance	-0.185***	-0.185***	-0.181**
	(-2.63)	(-2.60)	(-2.54)
Innovation Distance			-0.390***
			(-4.67)
Integrity Distance			-0.060
			(-0.85)
Quality Distance			-0.080
			(-1.05)
Respect Distance			-0.153*
			(-1.91)
Teamwork Distance			0.048
			(0.63)
Aggregate Cultural Distance		-0.418***	
		(-4.78)	
Acquirer Democratic Affiliation	0.126	0.107	0.151
	(0.43)	(0.36)	(0.51)
Target Democratic Affiliation	0.365	0.435*	0.442*
	(1.58)	(1.87)	(1.90)
Controls?	Yes	Yes	Yes
Industry FEs?	Yes	Yes	Yes
Deal FEs?	Yes	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes
Observations	2,884	2,884	2,884
Pseudo R-squared	0.280	0.295	0.300

Table 5: Political Polarization

This table presents coefficient estimates of conditional logit models based on levels of partisanship. The variable *High PCI* is an indicator variable equal to one if the value of *PCI,* constructed as the annual average of the Partisan Conflict Index from Azzimonti (2018), is greater than its mean and zero otherwise. The variable *High HPI* is an indicator variable equal to one if the value of *HPI,* the house partisanship index, is greater than its mean and zero otherwise. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. We exclude firms that have been acquirers or targets in the three years preceding the merger announcement. We also exclude firm-years for which *Democratic Affiliation* measures are unavailable. We present results for the Industry, Size, B/M sample for which we match the highest number of SIC digits that offers at least five candidate matches per firm. We then choose the five closest pseudo-targets (acquirers) to the actual target (acquirer). The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. All non-indicator variables are winsorized at the 1st and 99th percentiles. Control variables include Leverage, natural log of Book Assets, and Tobin's Q for each of the target and acquiror, Same HQ State, and Same 2-Digit SIC. The sample includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

	High PCI = 0	High PCI = 1	Difference	High HPI = 0	High HPI = 1	Difference
Model	(1)	(2)	(2)-(1)	(3)	(4)	(4)-(3)
Political Distance	-0.264*	-0.793***	-0.529*	-0.133	-0.721***	-0.588**
	(-1.81)	(-3.10)	(-1.80)	(-0.65)	(-2.63)	(-2.22)
Acquirer Democratic Affiliation	-0.302*	0.252		-0.431**	0.248	
	(-1.88)	(0.94)		(-2.20)	(1.00)	
Target Democratic Affiliation	0.219	0.150		0.132	0.264	
	(1.60)	(0.61)		(0.83)	(1.33)	
Controls	Yes	Yes		Yes	Yes	
Industry FEs?	Yes	Yes		Yes	Yes	
Deal FEs?	Yes	Yes		Yes	Yes	
Includes Hostile Bids?	Yes	Yes		Yes	Yes	
Observations	8,220	3,269		6,810	4,679	
Pseudo R-squared	0.274	0.247		0.268	0.258	

Table 6: Economic Recessions

This table presents coefficient estimates of conditional logit models based on NBER recessions versus non-recession periods. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. All non-indicator variables are winsorized at the 1st and 99th percentiles. Control variables include Leverage, natural log of Book Assets, and Tobin's Q for each of the target and acquiror, Same HQ State, and Same 2-Digit SIC. The sample includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

	Recession = 0	Recession = 1	Difference
Model	(1)	(2)	(2)-(1)
Political Distance	-0.433***	0.100	0.533
	(-3.32)	(0.24)	(1.22)
Acquirer Democratic Affiliation	-0.133	0.225	
	(-0.95)	(0.45)	
Target Democratic Affiliation	0.221*	0.337	
	(1.78)	(0.89)	
Controls	Yes	Yes	
Industry FEs?	Yes	Yes	
Deal FEs?	Yes	Yes	
Includes Hostile Bids?	Yes	Yes	
Observations	10,387	931	
Pseudo R-squared	0.255	0.291	

Table 7: Integration

This table presents coefficient estimates of conditional logit models based on the presence of keywords in SEC filings. The variable *Integration* is an indicator variable equal to one for mergers where the DEF14A or post-merger 10K/Q filing mentions the words "integrate" or "integration" and zero otherwise. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. We exclude firms that have been acquirers or targets in the three years preceding the merger announcement. We also exclude firm-years for which Democratic Affiliation measures are unavailable. We present results for the Industry, Size, B/M samples, for which we match the highest number of SIC digits that offers at least five candidate matches per firm. We then choose the five closest pseudo-targets (acquirers) to the actual target (acquirer). The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. All non-indicator variables are winsorized at the 1st and 99th percentiles. Control variables include Leverage, natural log of Book Assets, and Tobin's Q for each of the target and acquiror, Same HQ State, and Same 2-Digit SIC. The sample includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

	Integration = 0	Integration = 1	Difference
Model	(1)	(2)	(2)-(1)
Political Distance	0.593	-0.511***	-1.104**
	(1.28)	(-2.98)	(-2.23)
Acquirer Democratic Affiliation	-0.876*	0.082	
	(-1.85)	(0.44)	
Target Democratic Affiliation	-0.121	0.211	
	(-0.26)	(1.26)	
Controls	Yes	Yes	
Industry FEs?	Yes	Yes	
Deal FEs?	Yes	Yes	
Includes Hostile Bids?	Yes	Yes	
Observations	725	6,104	
Pseudo R-squared	0.238	0.271	

Table 8: Merger Completion and Hostile Takeovers

This table presents coefficient estimates of conditional logit regressions testing the effect of political distance on the likelihood of a hostile takeover and the likelihood of merger completion. *Hostile* is an indicator variable equal to one if the announced merger is a hostile takeover and zero otherwise. *Completed* is an indicator variable equal to one if the merger eventually occurs and zero otherwise. All non-indicator variables are winsorized at the 1st and 99th percentiles. Control variables include Altman's Z-Score, Leverage, natural log of Book Assets, ROA, ROE, and Tobin's Q as of the fiscal year prior to the merger for each of the target and acquirer, natural log of Market Capitalization on the day preceding merger announcement for each of the target and acquirer, Relative Size, Same HQ State, and Same 2-Digit SIC. The sample includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Significance: * p <10%, ** p < 5%, *** p < 1%.

Dependent Variable	Hostile	Completed
Model	(1)	(2)
Political Distance	0.652*	-0.489**
	(1.82)	(-1.99)
Acquirer Democratic Affiliation	-0.310	-0.011
	(-0.93)	(-0.05)
Target Democratic Affiliation	-1.023***	0.381*
	(-3.31)	(1.90)
Controls?	Yes	Yes
Industry FEs?	Yes	Yes
Year FEs?	Yes	Yes
Observations	1,577	1,739
Pseudo R^2	0.227	0.140

Table 9: Announcement Returns

This table presents coefficient estimates testing the relation between political distance and merger announcement returns. The dependent variable is value-weighted total cumulative abnormal returns (CARs) in the days surrounding the merger announcement date. The variable, *Political Distance,* is the absolute value of the difference between acquirer and target *Democratic Affiliation* calculated using the number of employee donations. In Panel A, we calculate CARs using returns in excess of the market, in Panel B, we calculate CARs using the Capital Asset Pricing Model, and in Panel C, we calculate CARs using the Fama-French Three Factor Model with Momentum. All non-indicator variables are winsorized at the 1st and 99th percentiles. Control variables include Altman's Z-Score, Leverage, natural log of Book Assets, ROA, ROE, and Tobin's Q as of the fiscal year prior to the merger for each of the target and acquirer, natural log of Market Capitalization on the day preceding merger announcement for each of the target and acquirer, Relative Size, Same HQ State, and Same 2-Digit SIC. The sample includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report *t*-statistics in parentheses. Significance: * p <10%, ** p < 5%, *** p < 1%.

Panel A: Excess Returns

Event Window	[-1, 1]	[-1, 5]
Model	(1)	(2)
Political Distance	-0.015**	-0.021**
	(-2.03)	(-2.33)
Acquirer Democratic Affiliation	0.025***	0.022**
	(3.23)	(2.34)
Target Democratic Affiliation	-0.009	-0.005
	(-1.42)	(-0.70)
Controls?	Yes	Yes
Industry×Year FEs?	Yes	Yes
Observations	1,374	1,374
Adjusted R^2	0.165	0.130

Panel B: CAPM

Event Window	[-1, 1]	[-1, 5]
Model	(1)	(2)
Political Distance	-0.014*	-0.018**
	(-1.86)	(-2.12)
Acquirer Democratic Affiliation	0.025***	0.028***
	(3.26)	(3.15)
Target Democratic Affiliation	-0.008	-0.004
	(-1.28)	(-0.51)
Controls?	Yes	Yes
Industry×Year FEs?	Yes	Yes
Observations	1,374	1,374
Adjusted R^2	0.158	0.130

Panel C: Fama French Three Factor with Momentum

Event Window	[-1, 1]	[-1, 5]
Model	(1)	(2)
Political Distance	-0.012	-0.016*
	(-1.63)	(-1.83)
Acquirer Democratic Affiliation	0.026***	0.030***
	(3.43)	(3.40)
Target Democratic Affiliation	-0.009	-0.007
	(-1.55)	(-1.07)
Controls?	Yes	Yes
Industry×Year FEs?	Yes	Yes
Observations	1,374	1,374
Adjusted R^2	0.157	0.141

Table 10: Post-Merger Performance

This table presents coefficient estimates for OLS regressions of political distance on accounting performance and 3-year buy and hold abnormal returns. The dependent variables are the combined company's Return on Assets (*ROA*) in the year following merger completion and 3-year Buy-and-Hold Average Returns (*3-year BHAR*) following the merger announcement. The variable *ROA* is calculated as Net Income over Total Book Assets. We calculate BHARs in two ways, using returns in excess of those predicted by the Capital Asset Pricing Model (CAPM), and using returns in excess of those predicted by the Fama-French Three Factor Model with Momentum (FF3M). All non-indicator variables are winsorized at the 1st and 99th percentiles. The sample includes 2,103 U.S. domestic mergers announced between 1980 and 2018 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report *t*-statistics in parentheses. Significance: * p <10%, ** p < 5%, *** p < 1%.

Dependent Variable	ROA	3-year BHARs	
		CAPM	FF3M
Model	(1)	(2)	(3)
Political Distance	-0.020**	-1.081**	-1.986**
	(-2.14)	(-2.11)	(-2.43)
Acquirer Democratic Affiliation	0.000	0.588	1.131
	(0.05)	(1.25)	(1.51)
Target Democratic Affiliation	-0.024***	-0.317	-1.028
	(-3.28)	(-0.80)	(-1.62)
Observations	2,011	1,950	1,950
Adjusted R^2	0.007	0.002	0.004