The Economic Effects of Political Polarization: Evidence from the Real Asset Market*

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Abstract

The rise of political polarization affected the landscape of the U.S. real asset market. Mergers between politically divergent firms became less common over time, and those between firms from politically divergent states have virtually disappeared in recent years. We analyze deal-level data to consider confounding factors and explore the mechanisms underlying these dramatic trends. We find that the likelihood of merger announcement or completion, announcement returns, and post-merger operating performance are lower for politically divergent firms. The effects are stronger when political polarization is greater, when firms plan to integrate operations, and during economic expansions. These findings hold after controlling for geographical distance, product similarity, and existing measures of corporate culture.

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1. Introduction

A defining feature of 21st-century American politics is the rise of political polarization, whose levels reached record highs in recent years. In 2019, 82 percentage points separated Republicans' (89%) and Democrats' (7%) average job approval ratings of President Trump – the largest degree of political polarization measured by Gallup until then.[1] By 2021, a new record of 84 percentage points separated Republicans' (8%) and Democrats' (92%) average job approval ratings of President Biden. This trend has not escaped the notice of political scientists, who documented a similar increase in the gap between Democrats and Republicans based on roll-call votes (McCarty, Poole, and Rosenthal 2016), the political orientation of campaign contributors (Bonica 2013), and the content of political speech and media coverage (Gentzkow, Shapiro, and Taddy 2019; DellaVigna and Kaplan 2007; Levendusky 2013; Martin and Yurukoglu 2017).

Economic research attempts to understand the economic causes of political polarization. Mian, Sufi, and Trebbi (2014) document a transient increase in the polarization of congressional votes following financial crises. Voorheis, McCarty, and Shor (2016) investigate the link between rising inequality and political polarization. Autor, Dorn, Hanson, and Majlesi (2020) study the impact of import competition on polarization. Contrary to these studies, which explore the economic *determinants* of political polarization, this paper investigates its economic *consequences*. We focus on the real asset market, and explore the role of political divergence between acquirers and targets in mergers and acquisitions. We hypothesize that the rise in political polarization has made it more difficult for politically divergent firms to merge and integrate. This hypothesis is rooted in political science research showing that the rise of political polarization has led to a new type of division in the mass public coined "affective polarization," whereby Americans increasingly dislike and distrust those from the other party (e.g., Iyengar, Sood, and Lelkes 2012; Iyengar et al. 2019).

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[1] See Jeffrey M. Jones "Trump Third Year Sets New Standard for Party Polarization," *Gallup*, January 21, 2020. https://news.gallup.com/poll/283910/trump-third-year-sets-new-standard-party-polarization.aspx

To test this hypothesis, we hand-collect detailed data on the personal contributions of corporate employees to political campaigns from 1978-2019. These data include 1,803,816 contributions from 405,510 employees of 9,590 firms. Using these data, we measure a firm's political attitude as the ratio of the number of employee contributions to Democratic campaigns to the total number of contributions to both Democratic and Republican campaigns over a rolling window of two presidential elections. Using this measure of firms' political attitudes, we construct a pairwise measure of the political divergence between any two firms, labeled *Political Divergence*, which equals the absolute value of the difference between their political attitudes.

Our main findings are that the rise in political polarization has had considerable consequences for the landscape of mergers and acquisitions in the U.S. In particular, the percentage of mergers and acquisitions between politically divergent companies significantly declined over time: before 2010, mergers between extremely divergent firms (top decile) comprised more than 11% of all deals. After 2010, they comprised 6% of all deals. By 2019, they comprised less than 3% of all deals. A similar trend emerges for the average *Political Divergence* between acquirers and targets: It declined by 20% between 1985 and 2019, with about 50% of the decline concentrated in the years 2010-2019. This trend is also reflected in the geographical landscape of mergers and acquisitions in the U.S. Before 2010, roughly 30% of all mergers occurred between firms from politically different states. After 2010, this number dropped to 15% of all deals, and by 2019 it dropped to virtually zero.

We analyze deal-level data to consider confounding factors and explore the mechanisms underlying these dramatic trends. We begin by investigating the effect of *Political Divergence* 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 2,325 mergers from 1985-2019. 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 Divergence* corresponds to a lower likelihood of a future merger announcement. The estimates are economically meaningful and imply that an increase of one standard deviation in *Political Divergence* reduces the likelihood of a merger by 0.6 to 1.3 percentage points (or 6.4% to 14.6% relative to the sample-mean pseudo-likelihood of 9.2%). These estimates are statistically significant in all specifications. They hold after controlling for the geographic distance between the firms, product similarity (Hoberg and Phillips 2010, 2016), acquirer- and target-specific characteristics, and industry-by-year and deal fixed effects. They also hold after controlling for differences across other dimensions of corporate culture – Innovation, Integrity, Quality, Respect, and Teamwork – adopted from Li, Mai, Shen, and Yan (2020).[2] *Political Divergence* appears unrelated to other corporate culture differences, and the relation between *Political Divergence* and the likelihood of merger announcements remains equally important, both economically and statistically, after controlling for corporate cultural differences.

We conjecture that the role of *Political Divergence* should be stronger when aggregate affective polarization is more pronounced. We use a measure of affective polarization – the Partisan Conflict Index constructed by Azzimonti (2018) – to estimate the role of *Political Divergence* separately during periods of low and high polarization. We find that the relation between *Political Divergence* and merger likelihood is more pronounced when affective polarization is higher. During periods of low polarization, we estimate that a one standard deviation increase in *Political Divergence* decreases merger likelihood by only 0.4 percentage points. However, when polarization is high, the estimate more than triples to 1.3 percentage points (or 14.3% of the sample mean). The difference in these two coefficients is statistically significant. Taken together, the estimates suggest that affective polarization strengthens the role of *Political Divergence* in merger formation.

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

In the next set of analyses, we explore the mechanisms underlying the relation between mergers and *Political Divergence*. First, we hypothesize that political differences and affective polarization can create considerable post-merger integration costs. These differences, however, are only relevant if the acquirer and target are 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 analyses separately for firms that emphasize integration in their post-merger filings and those that do not. An increase of one standard deviation in *Political Divergence* corresponds to a decrease of 2.17% in merger likelihood (23.63% of the mean pseudo-likelihood) for firms that emphasize integration, compared to a decrease of 1.10% (11.96% of the mean) for firms that do not, and this relation is only statistically significant (at the 1% level) for firms emphasizing integration. Moreover, for the subset of firms emphasizing post-merger integration, the role of *Political Divergence* is only significant when polarization is high.

Second, we hypothesize that political divergence 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 acquirer and the target are more politically divergent. An increase of one standard deviation in *Political Divergence* increases the likelihood of deal failure by 2.03 to 2.33 percentage points, or 12.4% to 14.3% relative to the sample-mean likelihood of 16.3%. We also find that the likelihood of a hostile or unsolicited bid is significantly higher when the acquirer and the target are more politically divergent. An increase of one standard deviation in *Political Divergence* increases the likelihood of hostility by 1.25 to 1.77 percentage points, or 10.2% to 14.3% relative to the sample mean of 12.4%.

Together, these findings are consistent with the hypothesis that affective polarization, that is, the dislike/distrust towards those from the other party (e.g., Iyengar, Sood, and Lelkes 2012; Iyengar et al. 2019), increases post-merger integration costs and the likelihood of failed merger negotiations or hostile takeovers.

We also investigate the effects of *Political Divergence* on merger performance. We find that announcement returns and post-merger performance are lower when *Political Divergence* is higher. An increase of one standard deviation in *Political Divergence* corresponds to a decline of 35 to 43 basis points in cumulative abnormal announcement returns. We also find that an increase of one standard deviation in *Political Divergence* corresponds to a reduction of three-year average *ROA* by 0.56% to 0.67%. Further, an increase of one standard deviation in *Political Divergence* corresponds to a drop of 9.5% to 12.8% in the 3-year CAPM buy-and-hold abnormal return. Collectively, these findings indicate that political divergence between acquirers and targets has negative consequences for merger performance and value. These costs provide an ex-ante incentive for politically divergent firms to avoid merging with each other. An important caveat 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.

Lastly, we investigate which factors can moderate the role of *Political Divergence* in merger formation. We propose that *Political Divergence* may play a weaker role during economic recessions for two reasons. First, political polarization tends to be lower during recessions (e.g., Stanig (2013)). Indeed, we find that the Partisan Conflict Index is lower during NBER recessions. Second, recession mergers are often "necessity" mergers aimed to allow the merging firms to restructure, downsize, and continue operating (e.g., Dutz (1989), Jensen (1993), Mitchell and Mulherin (1996)). As such, firms might put aside their political and ideological differences. Consistent with this hypothesis, we find that the relation between *Political Divergence* and merger likelihood is only economically and statistically significant outside NBER recessions.

Overall, our paper contributes to a growing body of research that studies the implications of political partisanship for economic behavior, including that of households (e.g., Makridis (2022); McGrath (2017); Mian, Sufi, and Khoshkhou (2018); Coibion, Gorodnichenko, and Weber (2020); Meeuwis, Parker, Schoar, and Simester (2022)), judges (e.g., Posner (2008), McKenzie (2012), and Chen (2020)), and credit analysts (Kempf and Tsoutsoura (2021)). While these studies explore unilateral political views and economic decisions, we study bilateral corporate decisions in a setting where political partisanship is measured directly across the two interested counterparties (the acquirer and the target).

Our paper also contributes to a large body of research that studies the determinants and consequences of mergers. Some researchers focus on the value-maximizing attributes of mergers (e.g., Matsusaka (2001); Jovanovic and Braguinsky (2004)), while others study inefficiencies, possibly driven by agency conflicts (e.g., Baumol (1959); Jensen (1986, 1993); Stulz (1990)) or hubris (Roll (1986)). We add to this literature by showing that the political fit between acquirers and targets is an important predictor of merger success, performance, and value.

This study also broadly relates to prior studies of the interaction between mergers and politics or regulation. 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 Röller (2007) study the stock market response to regulatory decisions or legislative actions. Contrary to prior work, which focuses on the role of governments and regulators in mergers, we study the role of political partisanship and polarization across the acquirer and the target themselves.

Lastly, our paper also contributes to understanding the role of culture and trust in mergers. 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 et al. (2018) show that similarity in firms' corporate social responsibility is positively correlated with merger incidence and performance. Graham, Grennan, Harvey, and Rajgopal (2022) provide survey evidence that 46% of executives would walk away from a culturally misaligned target. More broadly, 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. Our results establish that, even within a country, trust of those with politically different views is a significant factor, whose importance has risen in parallel with polarization.

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.[3]

For each transaction, the FEC records the transaction amount, date, and 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 where the donor resides, and the donor's employer name. We utilize the self-reported employer names to match individuals with firms.

We start by removing donations from individuals who are not employed or self-employed. There are 38 million donations reporting one of the following employer strings: "Not Employed", "Retired", "None", "Self", and "Self Employed." We then 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 82,000 string matches that we manually check. Altogether, we match 6.9 million donations out of 57 million donations with relevant employer names from 1979 to 2019. The low match rate is explained by the fact that we only attempt to match employees with publicly traded firms. Consequently, employees of private corporations, small businesses, non-profit organizations, and the public sector will not be matched. More details on the matching process are available in Appendix B.

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

Next, we classify donations into Republican or Democratic based on the affiliated party declared by the Political Action Committee (PAC) receiving each donation. PACs registered with the FEC, however, often do not declare a party affiliation. In fact, only 51% of PAC-election cycle observations correspond to PACs that declare a party affiliation.[4] To overcome this issue and retain as many observations as possible, we first identify PACs with no declared party affiliation that are connected to a specific candidate who does declare a party affiliation. We assign these PACs the party affiliation of their connected candidate. This procedure populates an additional 13% of the PAC-election cycle observations in our sample with party affiliations.[5] We then classify the remaining PACs based on their donations. Specifically, we assign a Democratic (Republican) affiliation to committees in a given election cycle when at least 80% of their donations go to committees declared Democratic (Republican). This procedure populates an additional 8% of the PAC-election cycle observations with party affiliations.[6]

The final sample comprises 1,803,816 donations corresponding to 9,590 unique firms, with an average of \$6,957 in donations per firm each year, of which \$3,433 is contributed to Democrat-affiliated committees and \$3,524 to Republican-affiliated committees. Figure 1 shows the natural log of the aggregate number of donations to each party by year. It suggests that the number of donations has been increasing over time and that there is time-variation in the aggregate number of employee donations to the Democratic and Republican parties.

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[4] An election cycle corresponds to the two-year House of Representatives election cycle. The FEC reports connected candidates for PACs every two years, and we use the same time frame to assign party affiliations.

[5] For example, in 2016, the committee "Secure Our Senate 2016" declared no party affiliation and was connected to Kamala Harris. We thus assign a party affiliation of "Democratic" to "Secure Our Senate 2016". From 2016 to 2018, 95% of the committee's donations went to committees declared Democratic, 5% went to committees with no declared party affiliation, and 0% went to committees declared Republican.

[6] To validate our method, we compare the donations of committees with declared party affiliations to donations of committees whose party affiliations we assigned. We find that our affiliation assignments are more highly correlated with partisan political donations than those of declared party affiliations.

Using these data, we construct a *Democratic Affiliation* score for each firm-year, defined as the fraction of donations to Democrat-affiliated committees out of the total number of donations in the past 8 years.[7] 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 256 for acquirers and 53 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.[8] Since EDGAR started in 1995, this alternative measure is available from 1995 to 2019. The average number of donations using the zip-code political measure is considerably higher: 667 for acquirers and 586 for targets.

To construct the sample of mergers, we obtain information on all U.S. domestic mergers announced between 1985 and 2019 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the

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[7] 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.

[8] We thank Bill McDonald for making the 10K/Q header data available online (https://sraf.nd.edu/).

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 2,262 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. Appendix A provides all variable definitions. Panels A and B show that the average acquirer is larger and has higher *Sales Growth*, *Return on Assets,* and *Return on Equity* and lower *Book-to-Market* compared to the average target. The average acquirer and average target have similar estimates of *Book Leverage* and *Cash Ratio*. Based on the measure of *Democratic Affiliation*, both acquirers and targets lean slightly more towards the Republican party.

Panel C of Table 1 presents summary statistics for the announced mergers included in the sample. The sample includes 2,262 announced deals, of which 16.5% are withdrawn, 12.6% are hostile, and 43.0% occur between parties with differing 2-digit SIC codes. The average physical distance between the headquarters of acquirers and targets is 826 miles. The average deal value is \$3.9 billion. The main variable of interest, *Political Divergence,* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation,* based on the number of donations. As such, *Political Divergence* lies between 0 and 1, and measures the difference between the political affiliations of the acquirer and the target. The average *Political Divergence* across all the deals in the sample equals 0.327.

3. Aggregate Trends in the Real Asset Market

We begin the empirical analyses by exploring the changing landscape of the real asset market in the United States. We find a considerable decline in political divergence between acquirers and targets over time. By the end of the sample period in 2019, the average political divergence between acquirers and targets has declined by more than 30% compared to its peak in the early 1990's, with roughly 50% of the decline concentrated in the period 2010-2019. Figure 2 plots ten-year moving averages of the political divergence between acquirers and targets, illustrating the downward time-trend in political differences. This pattern suggests that firms have increasingly opted to merge with politically similar firms over time.

A possible concern with the evidence in Figure 2 is that all firms in the United States have become less politically divergent over time, and not just acquirers and targets. According to this scenario, the average divergence between acquirers and targets has not declined because firms opt to merge with more politically similar firms. Rather, the average divergence declines because firms in general become more politically similar. We address this concern by sorting mergers into political divergence deciles based on the entire sample period and tracing the prevalence of the sample-wide merger deciles over time.

In Figure 3, we consider mergers across the most politically divergent firms by focusing on the top decile of politically divergent mergers. Panel A provides the relative prevalence of top-decile mergers each year during the sample period. The estimates suggest that the occurrence of mergers between highly politically divergent firms has been declining throughout the sample period. In Panel B, we compare between earlier sample years and more recent years. Before 2010, mergers in the top political divergence decile accounted for close to 12% of all mergers. After 2010, they only accounted for about 6% of all mergers. By 2019, mergers in the highest decile of political divergence accounted for merely 2% of all mergers.

In Table 2, we present the frequency distribution of merger announcements by political divergence quintiles and presidential election cycles. The main takeaways from Table 2 are twofold. First, looking across the rows, the number of mergers declines as the political divergence of the merging parties 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 presidential 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 99% confidence level, we reject the null hypothesis that the number of mergers is random with respect to political divergence in each election cycle. Second, we find that the percentage of mergers in the highest political divergence quintile has declined considerably over time. From its peak of 12.5% (22/176) over the 1989-1992 cycle, it has declined to only 4.4% (10/226 or 9/203) for the 2012-2016 and 2017-2019 cycles.

In Figure 4, we investigate the implications of this trend for the geographical landscape of mergers and acquisitions in the United States. Specifically, we explore whether the decline in the prevalence of merger announcements between politically divergent firms has led to a decline in mergers across firms from politically divergent states. To measure the political alignment of states across the United States, we aggregate all individual donations to Democrats and Republicans in each state each year. We define two states as politically similar (divergent) in a given year if the majority of their donations goes to the same (opposite) party. We then classify all mergers each year into three categories: same-state mergers, politically-similar-state mergers, and politically-divergent-state mergers.

Panel A of Figure 4 plots the annual percentage of mergers that fall into each of the three categories. The main finding in Panel A is that the prevalence of mergers between firms headquartered in politically divergent states has fallen sharply in the last five years, with the vast majority of mergers occurring between firms from politically similar states or from the same state. In Panel B, we divide the sample period around 2010. Before 2010, roughly 30% of all mergers occurred between firms from politically different states. After 2010, this number dropped to 15% of all deals.

Collectively, these findings uncover a fundamental structural change in the real asset market in the United States. Over time, politically divergent firms, or firms from politically divergent states, have become considerably less likely to merge with each other. We conjecture that the above structural change can be attributed to the rise in affective polarization in the United States over time. This hypothesis is consistent with prior research, which shows that affective polarization exacerbates the impact of partisanship on behavior (e.g., Iyengar and Westwood (2015); McConnell, Margalit, Malhotra, and Levendusky (2018)), and with the recent findings of Fos, Kempf, Tsoutsoura (2022), who find that executive teams in U.S. firms have also become more partisan in recent years.

To explore this hypothesis, we use the Partisan Conflict Index constructed by Azzimonti (2018) to measure affective polarization. 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. We calculate the annual average of the Partisan Conflict Index and standardize its values by subtracting its sample mean and dividing by its standard deviation to generate the variable *Partisan Conflict Index*.

We plot the variable *Partisan Conflict Index* in Figure 5. The figure shows that the values of the *Partisan Conflict Index* are considerably higher in the second half of the sample period. This pattern is consistent with numerous studies showing that polarization and hostility across party lines have increased in the U.S. in 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)).

In Table 3, we explore the correlation between political polarization and the role of political divergence in mergers over time. In column 1, we provide estimates from regressing the average annual political divergence between acquirers and targets in announced mergers on the *Partisan Conflict Index*. The estimates suggest that higher political polarization corresponds to lower average political divergence between acquires and targets. A one standard deviation increase in the *Partisan Conflict Index* corresponds to a decrease of 0.014 in the average political divergence of announced mergers, or a 5.3% decrease relative to the average aggregate annual divergence of 0.26. In column 2, we focus on the highest levels of political divergence. Specifically, column 2 provides estimates from regressions explaining the likelihood of mergers between firms in the top decile of political divergence. The results indicate that higher political polarization is particularly correlated with a lower incidence of the most politically divergent mergers. The estimates imply that a one standard deviation increase in the *Partisan Conflict Index* corresponds to a decrease of 1.8 percentage points in the proportion of high divergence deals, a decline of 18% relative to the sample mean of 10%.

In column 3 of Table 3, we show results from regressing the annual proportion of mergers between firms headquartered in politically divergent states on the *Partisan Conflict Index*. The results suggest that mergers between firms headquartered in politically divergent states are less common when political polarization is high. Specifically, a one standard deviation increase in the *Partisan Conflict Index* corresponds to a decrease of 6.3 percentage points in the proportion of mergers between firms headquartered in politically divergent states, a decline of 23% relative to the sample mean of 27%.

Taken together, the results in this section provide evidence of a declining trend in mergers between politically different firms over time, which coincides with the rise of political and affective polarization in the United States. In the remainder of the analyses, we provide deal-level estimates that allow us to control for confounding effects by saturating the empirical models with different combinations of control variables and fixed effects, and to investigate the mechanisms underlying the aggregate time-series shifts documented in this section.

4. Deal-Level Evidence

4.1. The Likelihood of Mergers

In this section, we investigate the relation between firms' *Political Divergence* and the likelihood of merger announcements. We conjecture that politically divergent 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.

To illustrate this behavior at the deal-level, Figure 6 plots acquirers' and targets' political affiliations for the largest merger announcements in our sample by transaction value. Each point corresponds to a merger and reflects the combination of the acquirer's and target's *Democratic Affiliation*. Deals between politically similar acquirers and targets would appear on or near the 45-degree line, while deals with politically divergent firms would appear elsewhere.

To capture the role of affective polarization in deal-level political divergence, Figure 6 provides separate plots of the 25 largest deals before 2010, when affective polarization levels are lower, and after 2010, when polarization levels are considerably higher. The main finding in Figure 6 is the clustering around the 45-degree line in the post-2010 period, when affective polarization is greatest. This evidence suggests that as affective polarization levels rise, even the largest mergers announced in the United States occur between politically close firms.

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 and targets with several pseudo-targets and 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.

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 as well as 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 industry definitions are based on 2-digit SIC codes—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 4, 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 measure *Political Divergence* using donations originating from the zip-code where the firm is headquartered instead of using employee donations. The regressions in each panel differ with respect to the inclusion of control variables, Industry-by-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 Divergence* 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 Divergence* on announced merger pairings to strengthen in the subset of negotiated deals.

Across 14 of 16 regression specifications in Panels A, B, C, and D of Table 4, the coefficient on the main variable of interest, *Political Divergence*, is negative and statistically significant at the 1% level (in the remaining two cases it is significant at the 5% level). These findings hold robustly across the three different matched control samples and after including all the control variables, Industry-by-Year fixed effects, or Deal fixed effects. They also hold when we measure firms' political attitudes based on donations originating from the zip-code where the firm is headquartered.

The economic magnitude of the effect of *Political Divergence* on the likelihood of merger announcements is nontrivial. We estimate the marginal effect of *Political Divergence* using linear probability models since the inclusion of fixed effects can confound the interpretation of marginal effects in conditional logit models. Based on linear probability models, a one standard deviation increase in *Political Divergence* reduces the likelihood of mergers by 0.56 to 1.81 percentage points, which implies a reduction of 6.1% to 19.7% relative to the sample-mean pseudo-likelihood of 9.18%.

Furthermore, we find that the coefficient estimate on *Political Divergence* is 11-24% larger in magnitude when we exclude hostile bids and only focus on announced merger agreements. This finding holds across all three matched samples in Panels A, B, and C, and is consistent with our conjecture that hostile bids result from disagreements between acquirers and targets that are likely exacerbated by, or reflective of, differences in political attitudes. We will formally test the prediction that the likelihood of deal hostility increases with *Political Divergence* in Table 8 and restrict our attention in the remaining tests of merger formation to the subsample of merger agreements that exclude hostile bids.

Taken together, the findings in this subsection suggest that political similarity across firms positively predicts merger announcements. Stated differently, the evidence suggests that greater political divergence between firms decreases the likelihood that the two firms will choose to merge. In the next set of analyses, we compare the effects of differences in political attitudes to differences in other dimensions of corporate culture across firms.

4.2. Corporate Culture

Existing studies have shown that corporate culture plays an important role in merger formation and merger success (e.g., Ahern, Daminelli, and Fracassi (2015); Bereskin et al. (2018)). Do the political leanings of rank-and-file employees proxy for other dimensions of corporate culture? 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 2002 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 correlation estimates are: 0.21 with *Innovation*, 0.06 with *Integrity*, 0.11 with *Quality,* 0.07 with *Respect,* and 0.17 with *Teamwork*. These correlations suggest that political party affiliation is distinct from existing measures of corporate culture.

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 the *Political Divergence* and *Cultural Distance* measures by subtracting their respective sample means and dividing by their respective sample standard deviations. The correlation estimates between *Political Divergence* and each of the five *Cultural Distance* measures are: 0.00 with *Innovation Distance*, -0.02 with *Integrity Distance*, 0.03 with *Quality Distance*, -0.01 with *Respect Distance*, -0.01 with *Teamwork Distance*, and 0.00 with *Aggregate Distance*. These correlations suggest that political differences are distinguishable from cultural differences, and quell concerns about collinearity.

Next, we include the *Cultural Distance* between the target and the acquirer alongside the *Political Divergence* between them 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 4 because the corporate culture data is available only for a subset of firm-years. To mitigate this issue, we linearly interpolate years where corporate culture measures are missing and we linearly extrapolate the sample period to the end of the 2019.[9]

Panel A of Table 5 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 Divergence* remain negative and statistically significant at the 5% level across all the specifications. The coefficient estimates vary from -0.135 to -0.137 across the specifications, suggesting that they are effectively unchanged (compared to the baseline specification in column 1) after controlling for various dimensions of *Cultural Distance*. Moreover, the coefficient estimates on the measures of *Cultural Distance* are negative in four out of the five specifications, consistent with the prior findings that culturally distant firms are less likely to merge.

In Panel B of Table 5, we consider the *Aggregate Cultural Distance* (column 2) as well as all the individual *Cultural Distance* measures simultaneously (column 3). As before, the coefficient estimate on *Political Divergence* is negative and statistically significant at the 5% level across all columns. The coefficient estimate on *Aggregate Cultural Distance* in column 2 is negative and statistically significant. The individual corporate *Culture Distance* measures are also negative (with the exception of *Teamwork*). This evidence is consistent with the hypothesis that culturally different firms are less likely to merge, but that prior measures of culture are distinct from *Political Divergence*.

[9] Specifically, we interpolate and extrapolate culture measures for firms with at least three data points throughout the sample period. If a firm has less than three data-points, we carryforward values to populate the data.

While politics and culture might be intertwined, overall, the results in this section provide evidence that *Political Divergence* affects merger formation distinctly from prior measures of cultural dissimilarities. These findings may also highlight the distinction between other cultural differences and affective polarization. Past research shows that social norms can temper disapproval of culturally dissimilar groups, but do not temper disapproval of politically dissimilar groups (e.g., Himmelfarb and Lickteig (1982); Iyengar and Westwood (2015); Maccoby and Maccoby (1954); Sigall and Page (1971)). Given the rising trend in affective polarization in the United States, which appears unmitigated by social norms, we predict that the role of *Political Divergence* in merger formation will strengthen over time. In the next subsection, we evaluate how changes in national affective polarization impact the relation between *Political Divergence* and the likelihood of mergers.

4.3. Affective Polarization

In this section, we test whether affective polarization influences the relation between political attitudes and the likelihood of mergers. Recall that we use Azzimonti (2018)'s Partisan Conflict Index to measure affective polarization. We calculate the annual average of the monthly Partisan Conflict Index to generate the variable *Partisan Conflict Index*, and standardize it by subtracting its sample mean and dividing by its standard deviation. As Figure 5 shows, affective polarization is greater in the second half of the sample period. 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 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 observation when we study the mediating role of recessions.

To investigate the influence of affective polarization on merger formation, we separately estimate the effects of political divergence between the acquirer and the target from 1985 to 2019 in subsamples of low vs. high affective polarization. We divide the sample around the indicator variable *High PCI*, which is equal to one when the value of *Partisan Conflict Index* is above median, and zero otherwise.

Table 6 reports the coefficient estimates from tests using the most stringent, industry, size, and book-to-market, matched sample. In columns (1) and (2), we separately estimate the effect of political divergence when *High PCI* is equal to zero and one, respectively. The coefficient estimate on *Political Divergence* in column (2), where polarization is higher, is more than quadruple the value of the estimate in column (1), where polarization is lower, and the difference between the estimated coefficients is statistically significant at the 5% level (t-statistic = -2.10). The estimates suggest a one standard deviation increase in *Political Divergence* reduces the probability of a merger announcement by 1.31 percentage points (14.3% of the mean probability) during periods of high polarization. By contrast, during periods of low polarization, the estimates suggest a marginal effect of only 0.40 percentage points (4% of the mean) for each standard deviation change in *Political Divergence*.

Overall, these results show that there are significant differences in the relevance of political divergence to merger formation between periods of lower and higher 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.

4.4. Mechanisms

In this section, we seek to provide evidence on the mechanisms underlying the relation between political attitudes and 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. These channels are also illustrated through anecdotal evidence provided in Appendix C.

4.4.1 Integration

In this subsection, we study post-merger integration costs. We conjecture that the political divergence between acquirers and targets will be more important for merger formation when the acquirer and target are integrating their business operations. Moreover, the costs of integrating politically divergent firms will be particularly high during periods of elevated affective polarization that hampers trust and consequently coordination efforts and teamwork. 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.

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, and count the number of times the words “integrate” or “integration” appear in the documents.[10,11] We set the variable *Integration* equal to zero for deals in which integration is mentioned less frequently than the median frequency, and equal to one when integration is mentioned more frequently than the median.

In Panel A of Table 7, we separately estimate the relation between *Political Divergence* and the likelihood of merger formation in subsamples formed based on whether integration is mentioned in the acquirer’s SEC filings more or less frequently than the median. As before, we only present coefficient estimates of conditional logit regressions using the industry, size, and book-to-market matched sample. Column (1) corresponds to the subsample where acquirers in the realized deals mention integration in their SEC filings less frequently than the median acquirer (i.e., *Integration* = 0). The coefficient estimate on *Political Divergence* is negative but not statistically significant. In column (2), we repeat the test where the acquiring firms’ SEC filings include above median references to integration. The coefficient estimate on *Political Divergence* 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 combine operations. The difference between the two coefficients (-0.718) is not statistically significant at conventional levels, but the coefficient estimate in column (2) is more than double the coefficient estimate in column (1).

In Panel B of Table 7, we focus on firms that emphasize post-merger integration, and compare the role of political divergence on merger formation between periods of low vs. high levels of political polarization (i.e., *High PCI=0* vs. *High PCI=1*). The coefficient estimate on

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[10] 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.”

[11] 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. We also exclude deals where “Maxim Integrated Products Inc” is the acquirer.

Political Divergence in column (2), where polarization is higher, is 4.6 times the value of the estimate in column (1), where polarization is lower, and the difference between the coefficients is statistically significant (t-statistic = -1.68). These findings indicate that political divergence plays an especially important role in post-merger integration when affective polarization is high. Combined, the results in Table 7 suggest that post-merger integration is an important channel through which differences in political ideology operate in merger formation, particularly when affective polarization, which increases the costs of combining politically divergent firms, is high.

4.4.2 Negotiations and Deal Hostility

Another channel through which political differences might matter for merger formation is the negotiation process itself. 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 Divergence* 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 and completing the merger. We therefore hypothesize that announced mergers between more politically divergent firms will have a lower likelihood of completion.

To test these hypotheses, we focus on the sample of announced deals, and create two outcome variables, *Hostile* and *Withdrawn*. The variable *Hostile* is an indicator variable equal to one if there is a hostile or unsolicited bid, and zero otherwise. The variable *Withdrawn* is an indicator variable equal to one if a deal is withdrawn after its announcement and zero otherwise. We then estimate conditional logit regressions explaining these two variables.

We present the coefficient estimates of these tests in Table 8. In columns (1) and (2), the outcome variable is *Hostile*, and the coefficient estimate on *Political Divergence* is positive and statistically significant at the 10% and 5% levels, respectively. The coefficient estimates imply that, conditional on announcement, a one standard deviation increase in *Political Divergence* is associated with a 1.7-1.8 percentage point increase in the likelihood of it being a hostile bid, representing a 13.5-14.2% increase compared to the sample mean of 12.4%.

In columns (3) and (4) of Table 8, we test how *Political Divergence* influences post-announcement negotiations leading to merger withdrawal. The coefficient estimate on *Political Divergence* is positive and statistically significant at the 5% level and 10% level in columns (3) and (4), respectively. The coefficient estimates imply that a one standard deviation increase in political divergence between the target and acquirer is associated with a 2.0-2.1 percentage point higher probability that the merger will fail to complete. Relative to the sample mean withdrawal rate of 16.3%, this represents a 12.1-12.7% increase in failure to complete. Interestingly, the estimates in Table 8 suggest that product similarity is an additional significant predictor of merger hostility and withdrawals. These findings are consistent with prior evidence on the role of competition and antitrust, which are particularly relevant for firms with similar products, in deal hostility and withdrawals (e.g., Andrade, Mitchell, and Stafford (2001), Gerasimenko (2020)).

Overall, the results in this subsection show that not only does political divergence play a role in the likelihood of deal announcement, but it also corresponds to the hostility of the deal and the likelihood of its completion.

4.5. Merger Announcement Returns and Post-Merger Performance

In this section, we investigate the relation between *Political Divergence* and announcement returns or post-merger performance. We propose that politically divergent acquirers and targets would experience more difficulties in post-merger integration, leading to lower expected merger value and performance.

We begin by considering the relation between *Political Divergence* and combined merger announcement returns. We calculate the value-weighted average of the acquirer's and target's cumulative abnormal returns over a three-day event window corresponding to the interval [-1, 1] around the merger announcement date. We calculate abnormal returns using the CAPM and the Fama and French (1993) 3-Factor plus Momentum (Carhart (1997)) Model (FF3M).

Table 9 presents estimates from ordinary least squares regressions of combined cumulative abnormal returns on *Political Divergence*. In columns (1) and (2), abnormal returns are the excess returns from the CAPM. In columns (3) and (4), we use excess returns from the FF3M model. The coefficient estimates are negative in all columns and statistically significant at the 10% level in three of the four specifications, indicating that the political divergence between the acquirer and the target is negatively associated with merger announcement returns. 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 Divergence* corresponds to a decrease in announcement returns between 29.7 and 32.4 basis points.

We also investigate the relation between *Political Divergence* and post-merger performance. To this end, we employ two measures of the combined firm's performance for the three years following the merger: (1) industry-adjusted return on assets (*3-year Industry-adjusted ROA*); and (2) buy-and-hold abnormal returns (*3-year BHAR*) using the Capital Asset Pricing Model (CAPM).

We present coefficient estimates from OLS regressions explaining post-merger performance in Table 10. In columns (1) and (2), the dependent variable is *3-year Industry-adjusted ROA*. The coefficient estimate on *Political Divergence* is negative and statistically significant at the 5% level in both columns. An increase of one standard deviation in *Political Divergence* is associated with a decrease of 0.54-0.59% in *3-year Industry-adjusted ROA.* Relative to the mean of 2.99% among merging firms, this corresponds to an 18.1 – 19.7% decrease in *3-year Industry-adjusted ROA*. In columns (3) and (4), the outcome variables are three-year BHARs using the CAPM. In both columns, the coefficient estimate for *Political Divergence* is negative and statistically significant at conventional levels. The estimates imply that an increase of one standard deviation in *Political Divergence* corresponds to 9.3-12.7% lower 3-year CAPM buy-and-hold abnormal returns.

Combined, the findings in this section imply 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.

4.6. The Mediating Role of Economic Recessions

In the last set of analyses, we investigate how macroeconomic conditions mediate the role that political divergence plays in mergers and acquisitions. We argue that economic recessions may attenuate the negative relation between *Political Divergence* and the likelihood of merger formation for two reasons. First, as shown in Fig. 5, 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, consistent with prior evidence (e.g., Stanig (2013)). Second, during recessions, firms' incentives for entering a merger agreement can change. In particular, mergers during recessions might be necessity mergers that allow the merging firms to restructure, downsize, and continue to operate (e.g., Dutz (1989), Jensen (1993), Mitchell and Mulherin (1996)). As such, firms might put aside their political and ideological differences.

To test the role of recessions in the relation between *Political Divergence* and the likelihood of merger formation, we create an indicator variable, *Recession*, equal to one for mergers announced during NBER recessions and zero otherwise. We then estimate conditional logit regressions explaining the likelihood of merger formation separately during NBER recessions and outside NBER recessions.

Table 11 reports the results. In column (1), which corresponds to non-recessionary periods, the coefficient estimate on *Political Divergence* is negative and statistically significant at the 1% level. In contrast, the estimate for recessionary periods in column (2) is positive and not statistically significant. The difference between the coefficients in columns (1) and (2) is economically large but not statistically significant (difference = 0.636; *t*-statistic = 1.34). Overall, these findings are consistent with the hypothesis that economic recessions moderate the role of political differences in mergers and acquisitions.

5. Conclusion

This study provides novel evidence that political polarization and partisanship matter for the combination and management of real assets in the economy. Our main findings are that the political landscape of mergers and acquisitions in the United States has changed considerably in recent years. Firms that merge are substantially more likely to be politically aligned, and the percentage of mergers between politically divergent companies has significantly declined over time. This trend is also reflected in the geographical landscape of mergers and acquisitions in the U.S. The percentage of mergers between firms from politically different states has continuously shrunk over time, and such mergers have all but disappeared in the most recent sample years.

We provide deal-level analyses to investigate the mechanisms underlying these time trends. We find that differences in political attitudes between firms play an important role in merger decisions and outcomes, and that the nature of these decisions has changed with the rise of political and affective polarization.

Specifically, we find that firms are more likely to announce and complete mergers when they have similar political attitudes. These effects strengthen during periods of elevated political polarization, and when the target and the acquirer seek to integrate their business operations. We also find that mergers generate higher announcement returns and stronger post-merger performance when the target and the acquirer are less politically divergent.

Collectively, our findings provide some of the first evidence on the real economic effects of the rise in political polarization. We document a structural shift in the real asset market for mergers and acquisitions in the U.S., with implications for the allocation of real assets in the economy. Our findings are consistent with numerous studies in political science showing that polarization and hostility across party lines have increased in the U.S. in 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)), and with a growing body of evidence that political polarization exerts powerful effects on nonpolitical behavior (e.g., McConnell, Margalit, Malhotra, and Levendusky (2018) and Iyengar and Westwood (2015)).

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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 two presidential election cycles
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 two presidential election cycles
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 Divergence	The absolute value of the difference between acquirer's and target's Democratic Affiliation
Political Divergence (V)	The absolute value of the difference between acquirer's and target's Democratic Affiliation (V)
HQ Political Divergence	The absolute value of the difference between acquirer's and target's HQ Democratic Affiliation
National Polarization	
Partisan Conflict Index	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 and standardize it by substracting the sample mean and dividing by the sample standard deviation to generate the variable *Partisan Conflict Index*.
Financial Variables	
Book Assets	Total Assets, the natural logarithm of total assets
Book to Market	Book equity divided by market equity. Market equity is the equity market capitalization defined as PRCC_C*CSHO, winsorized at the 1^{st} and 99^{th} percentiles
Leverage	Book liabilities divided by book assets (LT/AT)
Cash Ratio	Cash and cash equivalents divided by book assets (CHE/AT)
ROA	Net income divided by total book assets (NI/AT)

Industry-adjusted ROA	ROA minus the median ROA from the sample of firms in the same 2-digit SIC code in the same year
3-year Industry-adjusted ROA	The arithmetic average of Industry-adjusted ROA reported in the three fiscal years following merger completion.
Sales Growth	Percentage growth in sales
Deal-Level Variables	
Deal Value	The proposed deal value at announcement, in $millions
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, winsorized at the 1st and 99th percentiles
HQ Distance	The distance, in hundreds of miles, between the zip-code of the acquiror's headquarters and the zip-code of the target's headquarters
Similar Products	An indicator variable equal to one if the acquirer and target have similar products from Hoberg and Phillips (2010, 2016)
Integration	Indicator variable equal to one for mergers where the DEF14A or post-merger 10K/Q filing mentions the words "integrate" or "integration" more frequently than the median deal and zero otherwise
Cash Only	Indicator variable equal to one if the consideration structure at announcement is all cash and zero otherwise
Diversifying	Indicator variable equal to one if the acquiror and target are classified under different 2-digit Standard Industrial Classification (SIC) codes and zero otherwise
Hostile	Indicator variable equal to one if the announced bid is hostile or unsolicited and zero otherwise
Withdrawn	Indicator variable equal to one if the announced deal is withdrawn 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.

We start from the FEC individual donations bulk data, available from 1979. We drop any employer string that appears fewer than 5 times throughout the sample and 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 compute the bigram score between each employer string in the FEC files and each company name available in the CRSP names files after 1978. 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, 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 (91st 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 (90th 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
Employees' Individual Political Donations by Party and Year

This figure plots the natural logarithm of the annual number of employees' individual political donations to each party for the period 1979-2019. The sample includes all the individual political donations from the Federal Election Commission (FEC) database that could be matched to CRSP/Compustat firms.

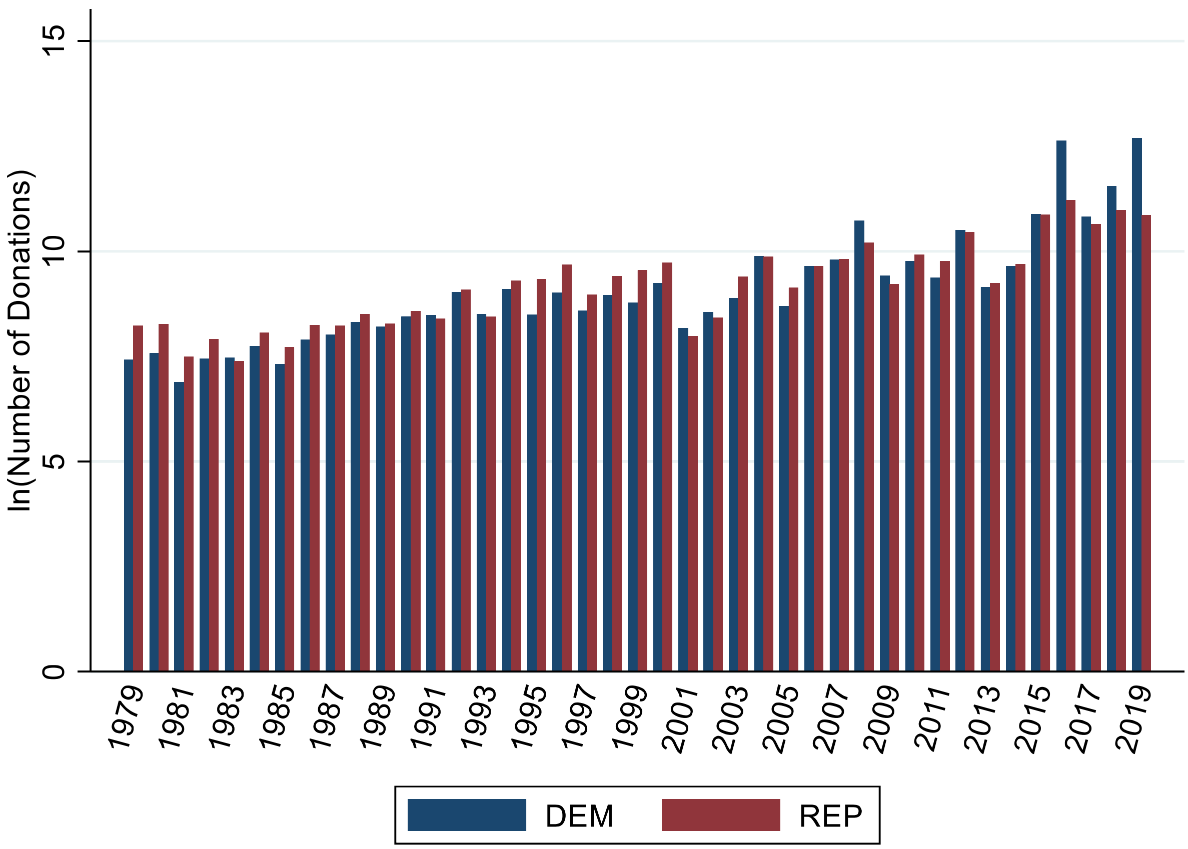


Figure 2
Average Political Divergence in Announced Deals through Time

This figure plots the ten-year moving average of the *Political Divergence* between the acquirer and target in merger announcements through time. We calculate *Political Divergence* as the absolute value of the difference between the acquirer's and target's *Democratic Affiliation*. We calculate *Democratic Affiliation* as the number of employees' donations made to Democrat-affiliated committees over the number of donations made to Democrat- and Republican-affiliated committees. The sample comprises 2,262 merger announcements from 1985 to 2019.

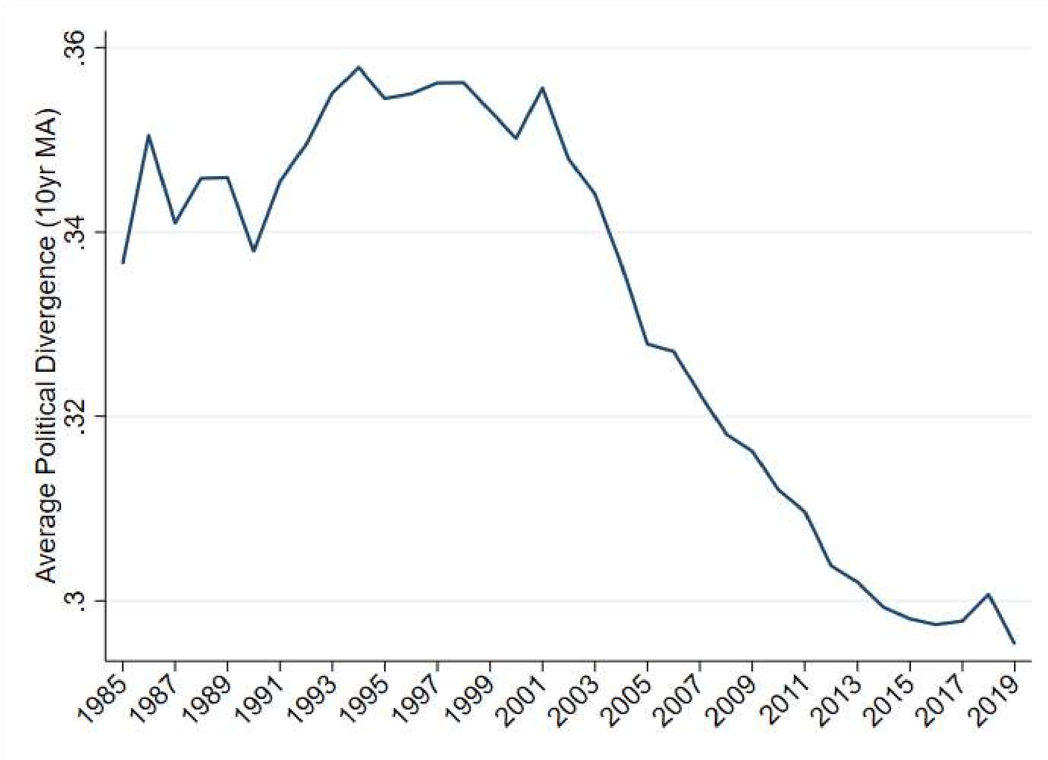
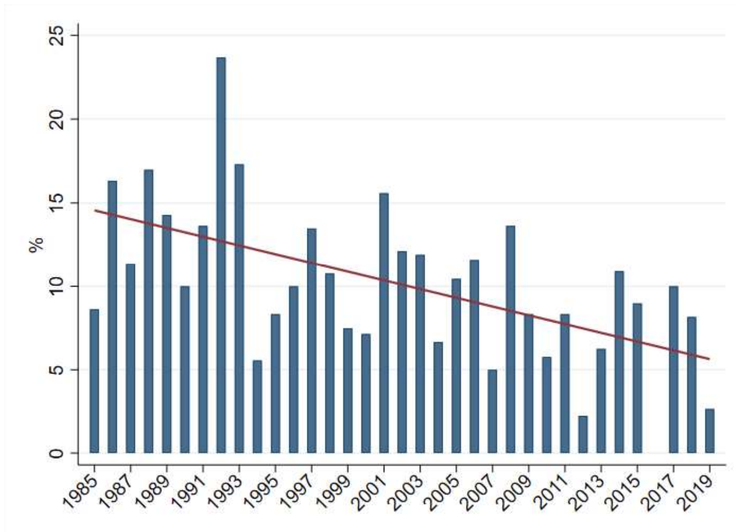


Figure 3
The Top Decile of Politically Divergent Mergers

This figure sorts all sample mergers into deciles based on the Political Divergence between the acquirer and the target. Panel A reports the annual percentage prevalence of top decile mergers. Panel B calculates the average prevalence of top decile mergers before vs. after 2010. We calculate Political Divergence as the absolute value of the difference between the acquirer's and target's *Democratic Affiliation*. We calculate Democratic Affiliation as the number of employees' donations made to Democrat-affiliated committees over the number of donations made to Democrat- and Republican-affiliated committees. The sample includes 2,262 merger announcements from 1985 to 2019.

Panel A: Annual Likelihood of Top-Decile Mergers



Panel B: The Likelihood of Top-Decile Mergers Before vs. After 2010

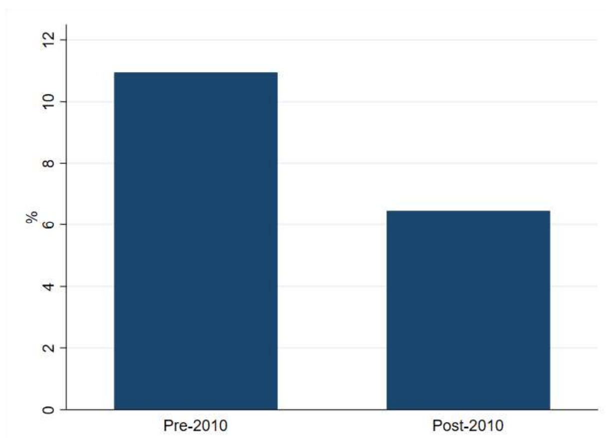
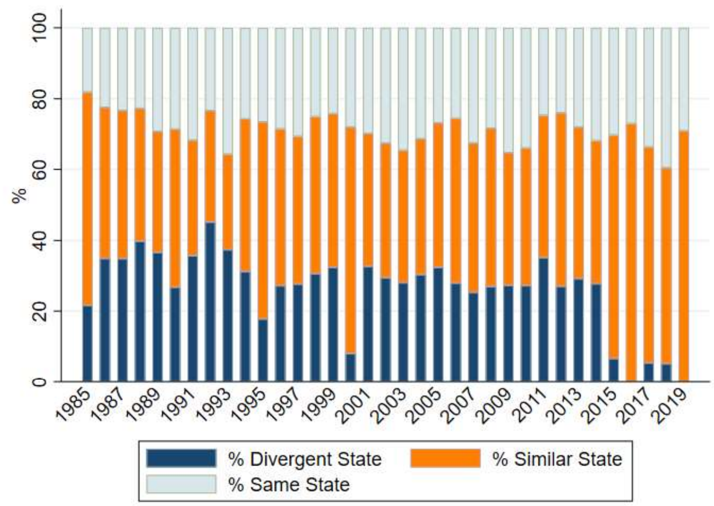


Figure 4
Mergers Across Politically Divergent States

This figure explores the prevalence of mergers between firms from politically divergent states over time. To measure the political alignment of states across the United States, we aggregate all individual donations to Democrats and Republicans in each state each year. We define two states as politically similar (divergent) in a given year if the majority of their donations goes to the same (opposite) party. We then classify all mergers each year into three categories: same-state mergers, mergers across politically similar states, and mergers across politically divergent states. Panel A reports the annual likelihood of mergers across the three categories. Panel B calculates their likelihood before vs. after 2010. The sample includes 2,262 merger announcements from 1985 to 2019.

Panel A: Annual Merger Likelihood Across States



Panel B: Merger Likelihood Across States Before vs. After 2010

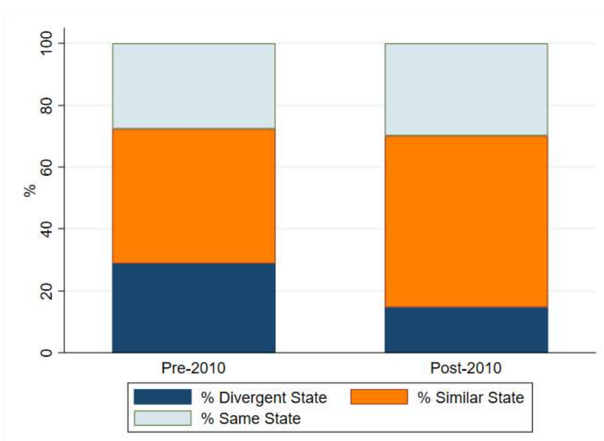


Figure 5
Political Polarization from 1995 - 2021

This figure describes the evolution of political polarization from 1985 to 2019 using standardized values of the Partisan Conflict Index from Azzimonti (2018). We standardize the Partisan Conflict Index by subtracting the sample mean and dividing by the sample standard deviation. All variable definitions are given in Appendix A. Shaded areas are NBER recession periods.

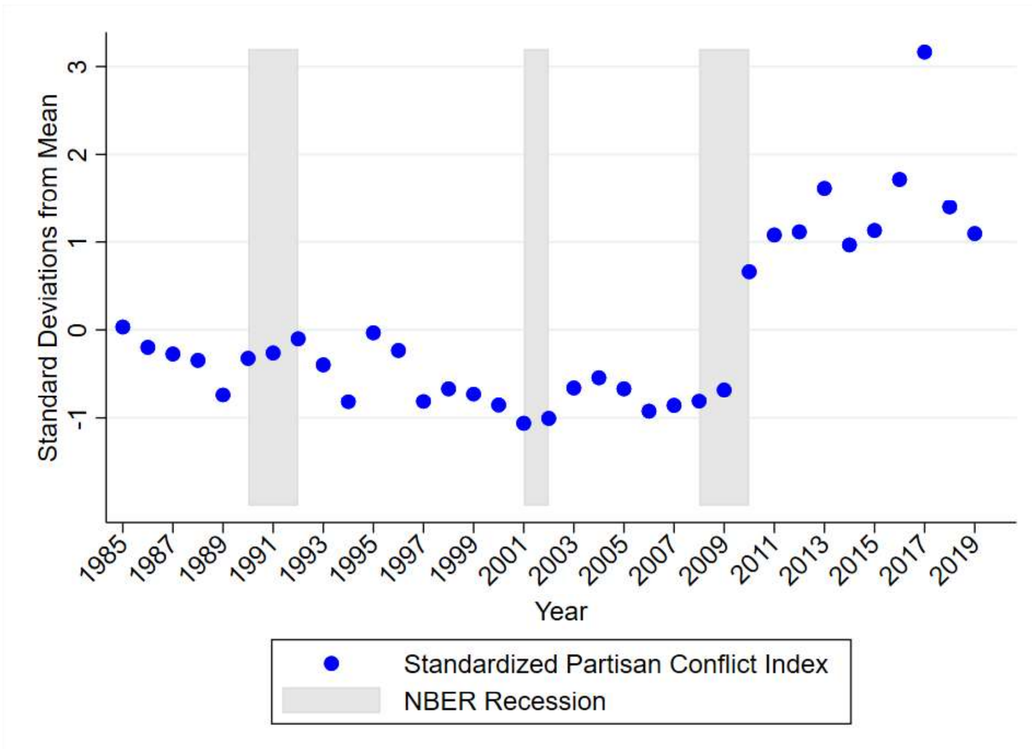
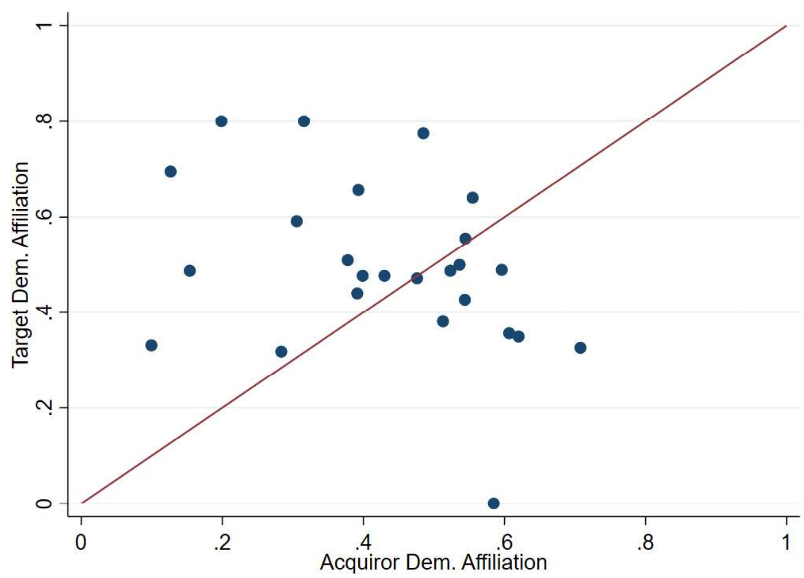


Figure 6
Deal Incidence by Acquirer and Target Party Affiliation

This figure plots acquirers' and targets' Democratic Affiliation for the 25 largest announced deals (by transaction value) in the pre-2010 sample period (Panel A) and the post-2010 sample period (Panel B). Democratic Affiliation is the number of employees' individual 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 divergence is measured as zero (i.e. political similarity is maximized).

Panel A: Pre-2010 Mergers



Panel B: Post-2010 Mergers

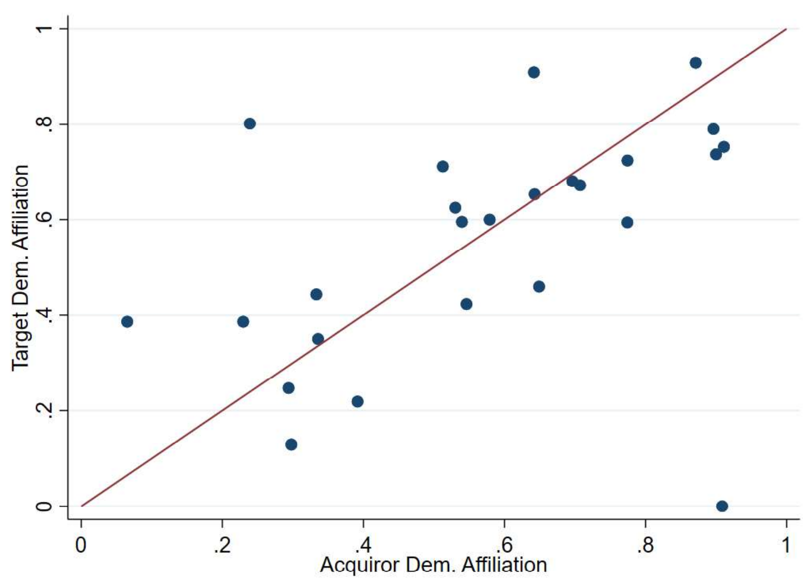


Table 1
Acquirer, Target, and Deal Descriptive Statistics

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 2,262 U.S. domestic mergers announced between 1985 and 2019 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 political donation data 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	0.440	0.302	0.188	0.429	0.667	2262
Democratic Affiliation (V)	0.422	0.310	0.150	0.400	0.667	2262
Book Assets ($mil)	34315	121233	1671	6007	22617	2232
Book to Market	0.747	9.780	0.265	0.451	0.683	2232
Sales Growth	0.220	0.678	0.024	0.105	0.247	2193
Book Leverage	0.621	0.219	0.476	0.613	0.785	2232
Cash Ratio	0.125	0.158	0.022	0.065	0.155	2232
Return on Assets	0.040	0.171	0.012	0.039	0.075	2231
Return on Equity	0.091	2.767	0.073	0.128	0.188	2231

Panel B: Target Summary Statistics

Variable	Mean	St.Dev	p25	Median	p75	N
Democratic Affiliation	0.438	0.359	0.083	0.400	0.750	2262
Democratic Affiliation (V)	0.424	0.367	0.053	0.357	0.770	2262
Book Assets ($mil)	9644	67806	294	1092	4050	2020
Book to Market	1.751	51.505	0.307	0.512	0.787	2020
Sales Growth	0.158	0.555	-0.012	0.080	0.213	1952
Book Leverage	0.615	0.272	0.426	0.613	0.811	2020
Cash Ratio	0.148	0.191	0.021	0.066	0.193	2017
Return on Assets	-0.004	0.173	-0.003	0.023	0.060	2019
Return on Equity	0.015	2.021	-0.006	0.090	0.151	2019

Panel C: Announced Deal Summary Statistics

Variable	Mean	St.Dev	p25	Median	p75	N
Political Divergence	0.327	0.269	0.109	0.260	0.500	2262
Political Divergence (V)	0.345	0.278	0.113	0.279	0.519	2262
Deal Value ($mil)	3913	11176	206	794	2583	2262
PostDealOwnership	0.882	0.295	1.000	1.000	1.000	1865
Relative Size (Acq/Tar)	66.728	816.445	1.577	4.167	16.158	1995
HQ Distance (100s of miles)	8.264	8.158	1.639	5.856	12.525	2220
Cash Only	0.365	0.482	0.000	0.000	1.000	2262
Diversifying	0.430	0.495	0.000	0.000	1.000	2262
Similar Products	0.288	0.453	0.000	0.000	1.000	2262
Hostile	0.126	0.332	0.000	0.000	0.000	2262
Withdrawn	0.165	0.371	0.000	0.000	0.000	2262

Table 2
The Frequency of Mergers by Political Divergence Over Time

This table shows the percentage of M&A deal announcements across ranges of Political Divergence over time periods corresponding to U.S. Presidential election cycles. Each row represents a 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 2,262 U.S. domestic mergers announced between 1985 and 2019 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 political donation data be available for both the acquirer and the target. All variable definitions are given in Appendix A.

	Political Divergence							
Election Cycle	[0,0.2]	(0.2,0.4]	(0.4,0.6]	(0.6,0.8]	(0.8,1]	Total	χ^2	p-value
1985- 1988	45.0%	15.9%	17.9%	9.9%	11.3%	151	14.71	0.54%
1989 -1992	38.6%	25.6%	13.1%	10.2%	12.5%	176	10.79	2.90%
1993 -1996	35.4%	24.8%	17.9%	13.4%	8.5%	246	15.82	0.33%
1997 -2000	35.9%	28.6%	17.6%	9.7%	8.3%	518	52.25	0.00%
2001-2004	43.6%	20.8%	17.4%	10.2%	8.0%	264	27.94	0.00%
2005-2008	41.7%	28.6%	17.4%	6.5%	5.8%	276	49.95	0.00%
2009-2012	45.5%	25.2%	14.9%	7.4%	6.9%	202	33.79	0.00%
2013-2016	43.8%	28.8%	14.6%	8.4%	4.4%	226	46.11	0.00%
2017-2019*	42.4%	26.1%	19.7%	7.4%	4.4%	203	37.14	0.00%
Total	40.5%	25.7%	16.9%	9.3%	7.6%	2262	246.30	0.00%

*The sample ends in 2019.

Table 3
Political Polarization and the Role of Political Divergence in Mergers and Acquisitions

This table presents estimates from aggregate time series regressions. In column 1, the dependent variable is the average annual political divergence between acquirers and targets in announced mergers. In column 2, the dependent variable is the annual likelihood of mergers in the top decile of political divergence between acquirers and targets. In column 3, the dependent variable is the annual likelihood of mergers between firms headquartered in politically divergent states. *Political Divergence* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation. Democratic Affiliation* is calculated using the number of employee donations. The sample includes 2,262 U.S. domestic mergers announced between 1985 and 2019 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 political donation data be available for both the acquirer and the target. All variables are defined in Appendix A. We report t-statistics in parentheses. Significance: * p <10%, ** p < 5%, *** p < 1%.

Variables	Average Political Divergence	Percentage High Divergence Deals	Percentage Divergent State Deals
	(1)	(2)	(3)
Partisan Conflict Index	-0.014**	-0.018**	-0.063***
	(-2.59)	(-2.40)	(-3.89)
Constant	0.325***	0.101***	0.260***
	(60.40)	(13.47)	(16.20)
Observations	35	35	35
R-squared	0.169	0.148	0.314

Table 4
The Likelihood of Merger Formation

This table presents estimates from 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. Panel D uses the Industry, Size, B/M Match sample. The Random sample uses five randomly paired pseudo-targets (acquirers) for each acquirer (target) within a 2-digit SIC industry group. For the Industry, Size sample, we match to the five candidates with the smallest difference in book assets within a 2-digit SIC industry group. For the Industry, Size, B/M, sample, we match to the five candidates with the smallest standardized difference in size and book-to-market, weighed by industry standard deviation of those variables. *Political Divergence* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation.* In Panels A, B, and C, *Democratic Affiliation* is calculated using the number of employee donations. In Panel D, we measure political affiliations using donations originating from the zip-code where the firm is headquartered (*HQ Political Divergence*). The dependent variable is an indicator variable equal to one for the acquirer-target firm pair and zero for the control firm-pairs. The control variables include *Book Assets*, *Book to Market*, *Sales Growth, Book Leverage,* and *Cash Ratio* for each of the target and acquirer, as well as the deal-level variables *Relative Size*, *HQ Distance*, *Cash Only*, *Diversifying* and *Similar Products*. The sample in Panels A-C includes 2,262 U.S. domestic mergers announced between 1985 and 2019 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 3,655 mergers. We require that both the acquirer and the target be publicly listed firms and that political donation data be available for both the acquirer and the target, except in Panel D where we require available data on political donations from the firm's headquarter zip-code. All variables are defined 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 Divergence	-0.657***	-0.388***	-0.415***	-0.464***
	(-7.03)	(-3.74)	(-3.78)	(-3.97)
Acquirer Democratic Affiliation	0.085	-0.059	-0.014	0.002
	(1.08)	(-0.76)	(-0.17)	(0.02)
Target Democratic Affiliation	0.099	0.180***	0.184**	0.218***
	(1.37)	(2.70)	(2.54)	(2.85)
HQ Distance		-0.040***	-0.041***	-0.041***
		(-9.21)	(-9.67)	(-9.14)
Similar Products		0.596***	0.636***	0.481***
		(6.43)	(7.69)	(5.43)
Additional 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	19,067	17,307	16,928	14,841
Pseudo R^2	0.004	0.105	0.158	0.150

Panel B: Industry, Size Match sample

Model	(1)	(2)	(3)	(4)
Political Divergence	-0.396***	-0.250**	-0.232**	-0.287***
	(-4.15)	(-2.48)	(-2.23)	(-2.58)
Acquirer Democratic Affiliation	0.063	-0.014	-0.014	-0.035
	(0.76)	(-0.19)	(-0.18)	(-0.42)
Target Democratic Affiliation	0.070	0.143**	0.188***	0.219***
	(0.96)	(2.37)	(2.63)	(2.91)
HQ Distance		-0.042***	-0.043***	-0.042***
		(-9.95)	(-10.20)	(-9.41)
Similar Products		0.658***	0.666***	0.489***
		(7.64)	(8.16)	(5.62)
Additional 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	19,067	17,534	17,154	15,008
Pseudo R^2	0.002	0.0423	0.145	0.133

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

Model	(1)	(2)	(3)	(4)
Political Divergence	-0.630***	-0.327***	-0.307***	-0.343***
	(-6.73)	(-3.16)	(-2.83)	(-2.94)
Acquirer Democratic Affiliation	0.097	-0.012	-0.068	-0.051
	(1.23)	(-0.15)	(-0.83)	(-0.58)
Target Democratic Affiliation	0.088	0.175***	0.182**	0.210***
	(1.21)	(2.66)	(2.55)	(2.77)
HQ Distance		-0.039***	-0.041***	-0.039***
		(-9.09)	(-9.52)	(-8.72)
Similar Products		0.527***	0.566***	0.399***
		(5.61)	(6.75)	(4.45)
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	19,067	17,290	16,917	14,832
Pseudo R^2	0.004	0.0949	0.148	0.141

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

Model	(1)	(2)	(3)	(4)
HQ Political Divergence	-0.847***	-0.716***	-0.756***	-0.748***
	(-7.98)	(-5.86)	(-6.19)	(-5.79)
Acquirer HQ Democratic Affiliation	0.054	-0.046	-0.144	-0.155
	(0.66)	(-0.67)	(-1.58)	(-1.59)
Target HQ Democratic Affiliation	0.016	0.087	0.105	0.091
	(0.20)	(1.13)	(1.18)	(0.97)
HQ Distance		-0.049***	-0.052***	-0.052***
		(-12.67)	(-16.52)	(-15.69)
Similar Products		0.423***	0.444***	0.283***
		(5.31)	(7.18)	(4.31)
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	38,653	32,500	31,120	27,858
Pseudo R^2	0.003	0.102	0.177	0.170

Table 5
Corporate Culture

This table presents estimates from conditional logit models predicting merger likelihood that include the five measures of culture from Li, Mai, Shen, and Yan (2020): *Innovation*, *Integrity*, *Quality*, *Respect*, and *Teamwork*. For each culture measure, we calculate the cultural distance as the absolute value of the difference between the acquirer and target's value of that measure. We also calculate an overall cultural distance measure, *Aggregate Cultural Distance*, that is the sum of the cultural distances calculated under each measure. *Political Divergence* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation* calculated using the number of employee donations. We standardize *Political Divergence* and each cultural distance measure by subtracting their respective means and dividing by their respective standard deviations. To construct the sample, we 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 present results for the Industry, Size, B/M sample. The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. The control variables include *Book Assets*, *Book to Market*, *Sales Growth, Book Leverage,* and *Cash Ratio* for each of the target and acquirer, and the deal-level variables *Relative Size*, *HQ Distance*, *Cash Only*, *Diversifying* and *Similar Products*. The sample includes 418 U.S. domestic merger agreements announced between 2002 and 2019 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We exclude hostile bids. We require that both the acquirer and the target be publicly listed firms and that political donation and corporate culture data 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 Divergence	-0.136**	-0.135**	-0.135**	-0.136**	-0.134**	-0.137**
	(-2.18)	(-2.15)	(-2.16)	(-2.17)	(-2.16)	(-2.20)
Innovation Distance		-0.076				
		(-1.15)				
Integrity Distance			-0.079			
			(-1.46)			
Quality Distance				-0.158**		
				(-2.08)		
Respect Distance					-0.083	
					(-1.34)	
Teamwork Distance						0.083
						(1.39)
Acquirer Democratic Affiliation	-0.124	-0.114	-0.110	-0.120	-0.132	-0.132
	(-0.64)	(-0.59)	(-0.57)	(-0.61)	(-0.68)	(-0.68)
Target Democratic Affiliation	0.139	0.141	0.141	0.140	0.137	0.133
	(0.86)	(0.87)	(0.87)	(0.86)	(0.84)	(0.82)
HQ Distance	-0.042***	-0.042***	-0.042***	-0.041***	-0.042***	-0.042***
	(-5.06)	(-5.04)	(-5.08)	(-5.01)	(-5.08)	(-5.06)
Similar Products	0.926***	0.925***	0.926***	0.904***	0.915***	0.929***
	(5.51)	(5.51)	(5.48)	(5.40)	(5.45)	(5.51)
Additional Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FEs?	Yes	Yes	Yes	Yes	Yes	Yes
Deal FEs?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,256	4,256	4,256	4,256	4,256	4,256
Pseudo R-squared	0.167	0.168	0.168	0.169	0.168	0.168

Panel B: Combined Cultural Distance Measures

Model	(1)	(2)	(3)
Political Divergence	-0.136**	-0.133**	-0.134**
	(-2.18)	(-2.12)	(-2.14)
Innovation Distance			-0.067
			(-1.04)
Integrity Distance			-0.071
			(-1.23)
Quality Distance			-0.161**
			(-2.08)
Respect Distance			-0.050
			(-0.76)
Teamwork Distance			0.113*
			(1.85)
Aggregate Cultural Distance		-0.142*	
		(-1.76)	
Acquirer Democratic Affiliation	-0.124	-0.111	-0.113
	(-0.64)	(-0.57)	(-0.57)
Target Democratic Affiliation	0.139	0.142	0.134
	(0.86)	-0.111	-0.113
HQ Distance	-0.042***	-0.042***	-0.042***
	(-5.06)	(-5.05)	(-5.02)
Similar Products	0.926***	0.910***	0.898***
	(5.51)	(5.44)	(5.33)
Additional Controls?	Yes	Yes	Yes
Industry×Year FEs?	Yes	Yes	Yes
Deal FEs?	Yes	Yes	Yes
Observations	4,256	4,256	4,256
Pseudo R-squared	0.167	0.169	0.172

Table 6
Political Polarization

This table presents estimates from conditional logit models predicting merger likelihood across subsamples with high vs. low levels of political polarization. *High PCI* is an indicator variable equal to one if the value of *Partisan Conflict Index,* the annual average of the monthly Partisan Conflict Index from Azzimonti (2018), is greater than its sample median and zero otherwise. *Political Divergence* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation* calculated using the number of employee donations. 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. The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. The control variables include *Book Assets*, *Book to Market*, *Sales Growth, Book Leverage,* and *Cash Ratio* for each of the target and acquirer, and the deal-level variables *Relative Size*, *HQ Distance*, *Cash Only*, *Diversifying* and *Similar Products*. The sample includes 2,262 U.S. domestic mergers announced between 1995 and 2019 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We exclude hostile bids. 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
Model	(1)	(2)	(2)-(1)
Political Divergence	-0.153	-0.662***	-0.509**
	(-1.03)	(-3.45)	(-2.10)
	0.068	-0.215	
Acquirer Democratic Affiliation	(0.58)	(-1.53)	
	0.134	0.316***	
Target Democratic Affiliation	(1.33)	(2.58)	
HQ Distance	-0.041***	-0.038***	
	(-7.22)	(-5.14)	
Similar Products	0.509***	0.233	
	(4.43)	(1.63)	
Additional Controls?	Yes	Yes	
Industry×Year FEs?	Yes	Yes	
Deal FEs?	Yes	Yes	
Observations	8,997	5,835	
Pseudo R-squared	0.170	0.113	

Table 7
Integration

This table presents estimates from conditional logit models predicting merger likelihood. Panel A provides estimates from regressions estimated separately across deals involving high vs. low levels of post-merger integration. Panel B provides estimates from regressions estimated separately across years with high vs. low levels of polarization for deals involving high levels of post-merger integration. *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" more frequently than the median deal and zero otherwise. *High PCI* is an indicator variable equal to one if the value of *Partisan Conflict Index,* the annual average of the monthly Partisan Conflict Index from Azzimonti (2018), is greater than its sample median and zero otherwise. *Political Divergence* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation* calculated using the number of employee donations. 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. The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. The control variables include *Book Assets*, *Book to Market*, *Sales Growth, Book Leverage,* and *Cash Ratio* for each of the target and acquirer, and the deal-level variables *Relative Size*, *HQ Distance*, *Cash Only*, *Diversifying* and *Similar Products*. The sample includes 426 U.S. domestic merger agreements announced between 1993 and 2019 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We exclude hostile bids. 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: High vs. Low Levels of Post-Merger Integration

	Integration = 0	Integration = 1	Difference
Model	(1)	(2)	(2)-(1)
Political Divergence	-0.485	-1.203***	-0.718
	(-1.45)	(-2.95)	(-1.36)
Acquirer Democratic Affiliation	-0.039	0.034	
	(-0.15)	(0.10)	
Target Democratic Affiliation	0.240	0.088	
	(1.05)	(0.34)	
HQ Distance	-0.048***	-0.033***	
	(-3.56)	(-2.86)	
Similar Products	0.125	0.347	
	(0.49)	(1.45)	
Controls?	Yes	Yes	
Industry×Year Fes?	Yes	Yes	
Deal Fes?	Yes	Yes	
Observations	2,044	2,163	
Pseudo R-squared	0.234	0.241	

Panel B: Post-Merger Integration and High vs. Low Levels of Polarization

	Integration = 1	Integration = 1	
	High PCI = 0	High PCI = 1	Difference
Model	(1)	(2)	(2)-(1)
Political Divergence	-0.381	-1.764***	-1.383*
	(-0.62)	(-3.23)	(-1.68)
Acquirer Democratic Affiliation	0.817	-0.363	
	(1.39)	(-0.76)	
Target Democratic Affiliation	-0.240	0.354	
	(-0.54)	(1.07)	
HQ Distance	-0.042**	-0.026*	
	(-2.32)	(-1.74)	
Similar Products	0.737**	0.153	
	(1.99)	(0.48)	
Controls?	Yes	Yes	
Deal Fes?	Yes	Yes	
Observations	901	1,262	
Pseudo R-squared	0.376	0.201	

Table 8
Merger Completion and Hostile Takeovers

This table presents estimates from conditional logit regressions predicting the likelihood of a hostile takeover (Columns 1 and 2) and the likelihood of merger completion (Columns 3 and 4). *Hostile* is an indicator variable equal to one if the announced merger is a hostile takeover and zero otherwise. *Withdrawn* is an indicator variable equal to one if the merger is withdrawn and zero otherwise. *Political Divergence* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation* calculated using the number of employee donations. The control variables include *Book Assets*, *Book to Market*, and *Cash Ratio* for each of the target and acquirer, and the deal-level variables *Relative Size*, *HQ Distance*, *Cash Only*, *Diversifying* and *Similar Products*. The sample includes 1,956 U.S. domestic merger agreements announced from 1985 to 2019 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%.

Variables	Hostile		Withdrawn	
	(1)	(2)	(3)	(4)
Political Divergence	0.504*	0.529**	0.485**	0.447*
	(1.92)	(2.00)	(2.11)	(1.91)
Acquirer Democratic Affiliation	0.134	0.133	0.402*	0.331
	(0.58)	(0.55)	(1.96)	(1.57)
Target Democratic Affiliation	-0.571***	-0.504**	-0.273	-0.204
	(-2.70)	(-2.30)	(-1.47)	(-1.06)
HQ Distance	-0.001	0.004	0.005	0.005
	(-0.08)	(0.40)	(0.59)	(0.60)
Similar Products	0.487***	0.681***	0.996***	1.098***
	(3.21)	(4.22)	(7.60)	(7.96)
Additional Controls?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	Yes	No	Yes
Observations	1,956	1,956	1,956	1,956
Pseudo R^2	0.121	0.117	0.113	0.119

Table 9
Merger Announcement Returns

This table presents estimates from OLS regressions explaining merger announcement returns. The dependent variable is the value-weighted total cumulative abnormal return (CAR) over the event interval [-1, 1], i.e., the three days surrounding the merger announcement date. *Political Divergence* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation* calculated using the number of employee donations. We calculate CARs using the Capital Asset Pricing Model in columns (1) and (2),and the Fama-French Three Factor Model with Momentum in columns (3) and (4). The control variables include *Book Assets*, *Book to Market*, *Sales Growth, Book Leverage,* and *Cash Ratio* for each of the target and acquirer, as well as the deal-level variables *Relative Size*, *HQ Distance*, *Cash Only*, *Diversifying*, and *Similar Products*. The sample includes 2,262 U.S. domestic merger agreements announced from 1985 to 2019 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%.

Event Window	Capital Asset Pricing Model		Fama-French Three Factor Model with Momentum	
Model	(1)	(2)	(3)	(4)
Political Divergence	-0.012*	-0.011	-0.012*	-0.011*
	(-1.72)	(-1.64)	(-1.75)	(-1.69)
Acquirer Democratic Affiliation	0.010	0.010	0.010*	0.010*
	(1.61)	(1.61)	(1.69)	(1.68)
Target Democratic Affiliation	0.007	0.004	0.007	0.004
	(1.30)	(0.74)	(1.35)	(0.75)
HQ Distance	-0.000	-0.000	-0.000	-0.000*
	(-1.25)	(-1.54)	(-1.39)	(-1.65)
Similar Products	-0.009**	-0.011***	-0.009**	-0.011***
	(-2.28)	(-2.58)	(-2.26)	(-2.58)
Controls?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	Yes	No	Yes
Observations	1,540	1,540	1,540	1,540
Adjusted R^2	0.096	0.117	0.095	0.116

Table 10
Post-Merger Performance

This table presents estimates from OLS regressions explaining firms' industry-adjusted return on assets and buy and hold abnormal returns. In columns 1 and 2, the dependent variable is the combined company's average *Industry-adjusted ROA* in the three years following merger completion (*3-year Industry-adjusted ROA*). In columns 3 and 4, the dependent variable is the 3-year Buy-and-Hold Abnormal Returns (*3-year BHAR*) following the merger announcement. We calculate BHARs using returns in excess of those predicted by the Capital Asset Pricing Model (CAPM), winsorized at the 1st and 99th percentiles. Control variables are the acquirer's *Industry-Adjusted ROA* in the year before the merger announcement, *Relative Size*, *HQ Distance*, *Cash Only*, *Diversifying*, and *Similar Products*. The sample includes 2,262 U.S. domestic merger agreements announced between 1985 and 2019 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%.

Variable	3-year Industry-adjusted ROA		3-year BHAR	
Model	(1)	(2)	(3)	(4)
Political Divergence	-0.022**	-0.020**	-0.469**	-0.344*
	(-2.23)	(-1.99)	(-2.31)	(-1.70)
Acquirer Democratic Affiliation	0.006	0.009	0.017	-0.020
	(0.62)	(0.92)	(0.09)	(-0.10)
Target Democratic Affiliation	-0.003	-0.002	-0.067	-0.161
	(-0.36)	(-0.28)	(-0.44)	(-1.03)
HQ Distance	0.001*	0.000	-0.013*	-0.010
	(1.77)	(1.36)	(-1.92)	(-1.52)
Similar Products	-0.024***	-0.024***	-0.060	-0.014
	(-3.92)	(-3.90)	(-0.48)	(-0.11)
Controls?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	Yes	No	Yes
Observations	1,661	1,661	1,579	1,578
Adjusted R^2	0.240	0.257	0.021	0.050

Table 11
Economic Recessions

This table presents estimates from conditional logit models predicting merger likelihood across NBER recessions and non-recession periods. *Political Divergence* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation* calculated using the number of employee donations. 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. The control variables include *Book Assets*, *Book to Market*, *Sales Growth, Book Leverage,* and *Cash Ratio* for each of the target and acquirer, and the deal-level variables *Relative Size*, *HQ Distance*, *Cash Only*, *Diversifying* and *Similar Products*. The sample includes 2,262 U.S. domestic mergers announced between 1985 and 2019 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We exclude hostile bids. 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 Divergence	-0.397***	0.239	0.636
	(-3.29)	(0.52)	(1.34)
Acquirer Democratic Affiliation	-0.050	-0.097	
	(-0.55)	(-0.23)	
Target Democratic Affiliation	0.216***	0.206	
	(2.75)	(0.67)	
HQ Distance	-0.040***	-0.037***	
	(-8.31)	(-2.67)	
Similar Products	0.399***	0.493	
	(4.29)	(1.45)	
Controls	Yes	Yes	
Industry×Year FEs?	Yes	Yes	
Deal FEs?	Yes	Yes	
Observations	13,716	1,116	
Pseudo R-squared	0.137	0.227	