Political Polarization and Investor Disagreement

Yi Hao* Amrita Nain† Haocheng Xu‡

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Abstract

We study the impact of political disagreement on investor disagreement. Using continuous, time-varying measures of ideological leanings of U.S. state legislators on the liberal-conservative scale, we show that greater political polarization in a state leads to greater dispersion in earnings forecasts of analysts located in that state. This effect is stronger for firms in politically sensitive industries and firms that commit significant resources to social issues. We document the importance of our finding for both asset pricing and corporate investments. Looking at the cross-section of returns, we show that stocks covered by more politically polarized analysts earn lower future returns. This finding is consistent with Miller's (1977) idea that in the presence of belief heterogeneity and short-sale constraints, prices reflect more optimistic valuations. In an M&A setting, we show that acquirers covered by more polarized analysts earn significantly lower announcement returns for equity offers but not for all-cash offers. These findings are consistent with models in which greater investor disagreement leads to steeper demand curves for stocks.

Keywords: Politics; polarization; analysts; disagreement; acquisitions

JEL classification: D72, G14, G24, G34, G41, M14

*University of Iowa. Email: yhao16@uiowa.edu

†University of Iowa. Email: amrita-nain@uiowa.edu

‡University of Iowa. Email: haocheng-xu@uiowa.edu

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1. Introduction

Political parties in the United States have become increasingly polarized over the last few decades (Iyengar, Sood, and Lelkes, 2012; Mason, 2013; Lott and Hassett, 2014; Mason, 2015; McCarty, Poole, and Rosenthal, 2008; Boxell, Gentzkow, and Shapiro, 2017). The rise in ideological polarization is not confined to party elites - the share of Democrat and Republican voters who hold highly negative views of the opposing party has more than doubled in recent decades.[1]

Several studies in the finance literature show that political partisanship influences the actions of finance professionals such as sell-side equity analysts, credit analysts, fund managers, and loan officers (Hong and Kostovetsky, 2012; Wintoki and Xi, 2020; Kempf and Tsoutsoura, 2021; Dagostino, Gao, and Ma, 2023; Jiang, Kumar, and Law, 2016). These studies find that political values affect portfolio choice and that financial intermediaries politically misaligned with the party of the U.S. president are more pessimistic. We add to this literature by showing that when the degree of ideological polarization increases, investor opinions about future corporate performance, as measured by the dispersion in analyst earnings forecasts, also diverge. Studying the impact of political polarization on investor disagreement is important because a voluminous body of research shows that differences in investor opinion affect corporate decisions, trading volume, and the cross section of returns.[2]

A rise in ideological polarization can affect the dispersion of analysts' earnings forecasts because Democrats and Republicans disagree on a range of politically sensitive issues to which corporations commit resources such as combating climate change, gender and racial equity, healthcare, defense, etc. Prior evidence shows that individuals with liberal ideologies are more concerned about environmental and social issues than conservatives (Hong and Kostovetsky, 2012; Feinberg and Willer, 2013; Aiken, Ellis, and Kang, 2020; Wintoki and Xi, 2020). For example, Democrats believe climate change poses a serious risk to the U.S. economy and support both public and private sector investments to combat climate change. In contrast, almost 60% of Republican voters think investments aimed at reducing climate change will hurt the US economy.[3] We show that as polarization increases, i.e., as the median Democrat moves further left and the median Republican moves right on the ideology scale, investors disagree more strongly on the economic value of corporate investments on social issues as well as politically sensitive industries such as oil and gas, defense, etc.

[1] See *'Political Polarization in the American Public'*, 2014, Pew Research Center.

[2] For the impact of investor disagreement on asset prices see Miller (1977), Diether, Malloy, and Scherbina (2002), Carlin, Longstaff, and Matoba (2014), Golez and Goyenko (2022) and numerous references therein. For the impact of investor disagreement on corporate investments, see Moeller, Schlingemann, and Stulz (2007); Chatterjee, John, and Yan (2012).

[3] See the *Democratic Party Platform* for a discussion of climate change. For Republican views on climate change, see *this climate survey* by the Pew Research Center.

Following prior literature, we use dispersion in analysts' earnings forecasts to capture differences in investor opinion. To capture the extent of political polarization that analysts are exposed to, we use the distance between the median 'ideal point' of Republican and Democrat legislators located in the analyst's state. State legislator ideal points, provided by Shor and McCarty (2011, 2022), are continuous measures of legislators' ideology on the liberal-conservative scale that vary across states and over time.[4] We use the ideological polarization of a state's political elites as a proxy for ideological polarization between analysts located in that state for the following reasons. First, prior evidence in the political science literature suggests that elite polarization has led to an increase in ideological awareness and polarization among the public (Abramowitz and Saunders, 1998; Abramowitz and Saunders, 2008; Hetherington, 2001; Layman and Carsey, 2002; Jacobson, 2000). Second, previous studies have found the partisan leaning of the area in which an individual resides to be a reasonable proxy for the individual's own party affiliation (Mian, Sufi, and Khoshkhou, 2023; Meeuwis, Parker, Schoar, and Simester, 2022).

An innovative feature of our empirical method is that we compare the dispersion in earnings forecasts of analysts that cover the same stock but are located in different states that experience different levels of political polarization over time. We have location data on almost 6,000 analysts located in 30 states that issue forecasts for about 9,000 unique firms between the years 2000 and 2020. Using analysts' earnings forecasts issued for fiscal year one, we show that the dispersion in earnings forecasts is significantly higher in state-years that experience more political polarization. Our estimates indicate that the impact is economically meaningful - a one standard deviation increase in a state's ideological polarization is associated with a 0.12 standard deviation increase in the dispersion of earnings forecasts of analysts located in that state. We control for several time-varying firm characteristics and state characteristics such as the level of economic policy uncertainty in a state and also include state-, year-, and firm-fixed effects. Our findings are robust if we examine earnings forecasts issued for fiscal year two and three instead. Almost 60% of the analysts in our sample are located in New York and five states account for 80% of the analysts. We confirm that our findings are not driven by analysts located in any one of these states and, more importantly, our findings hold if we exclude analysts located in New York.

We hypothesize that the positive association between ideological polarization and analyst dispersion is a pecuniary-based explanation in which individuals believe that companies inconsistent with their values will be less profitable in the future. The same corporate or government policy may be viewed as positive for a company's future performance by individuals on one end of the ideology spectrum and as negative by individuals on the other end of the ideology spectrum. The

[4]The cross-sectional variation of the Shor-McCorty data offers a significant advantage over national measures of polarization that offer time series variation only. See Poole and Rosenthal (2001); Duca and Saving (2016).

notion that political values shape investors' risk-return models is supported by recent evidence that Republicans and Democrats interpret public information differently and disagree on the economic impact of government and corporate policies (Kempf and Tsoutsoura, 2021; Meeuwis et al., 2022). To test this hypothesis, we follow Hong and Kostovetsky (2012) and classify stocks in industries such as oil and gas industry, guns, defense, etc. as being politically sensitive. We find that as political polarization in a state increases, the dispersion in earnings forecasts of analysts located in that state widens more (relative to analysts in less polarized states) for politically sensitive stocks than for other stocks.

Anecdotal evidence suggests that Democrats tend to support corporate investment in social programs such diversity, equity and inclusion (DEI) while conservatives question the value of spending corporate dollars on DEI efforts as is evidenced by the recent conservative backlash against the DEI efforts of Tractor Supply and Deere.[5] We use ESG scores from Sustainalytics to identify firms that invest resources into environmental, social, and governance issues. Consistent with this anecdotal evidence, our analysis reveals that ideological disagreement is associated with greater analyst disagreement about the value of corporate investment in social causes. Specifically, we find robust evidence that as a state becomes more politically polarized, dispersion in earnings forecasts of analysts located in that state rises significantly more for firms that have a high Social score in the ESG rating.

In robustness tests, we explore an alternative explanation for our results based on prior evidence that analysts politically misaligned with the U.S. presidents party are more pessimistic. As ideological polarization widens in a state, misaligned analysts may issue increasingly pessimistic forecasts, leading to greater forecast dispersion. We identify analysts' party affiliations based on their political contributions and run two tests to assess this explanation. First, we include a dummy variable for misaligned analysts as a control variable and find that our main results still hold. Second, in untabulated results, we look at forecast level data and find that, consistent with prior research, misaligned analysts issue more pessimistic (i.e. lower) earnings forecasts on average. However, the pessimism of misaligned analysts is not higher during periods of higher ideological polarization in their state. Therefore, our findings regarding the positive link between forecast dispersion and polarization is unlikely to be explained just by misalignment of some analysts with the party of the U.S. president.

Next, we address concerns about endogeneity. Unobserved time-varying characteristics of a state may independently affect both political polarization and forecast dispersion of analysts located in

[5]Tractor Supply pulled back on DEI investment after criticism spearheaded by activist blogger called Robbie Starbuck. See the Wall Street Journal article *'How Tractor Supply Decided to End DEI, and Fast'*. For the Deere story in the Wall Street Journal see *'Deere Slashes Diversity Initiatives After Backlash From Conservative Activist'*.

that state, leading to a spurious correlation between the two. We use two strategies to identify the causal role of ideological polarization on investor disagreement. First, we use an instrumental variable (IV) approach in which we instrument ideological polarization of a state on the occurrence of weather-related natural hazards in that state. This choice of instrument is based on survey evidence that shows sharp disagreement between Republicans and Democrats on climate change. In the first stage of the IV analysis, we find that more occurrences of weather-related natural hazards significantly increase political polarization in that state with Republican legislators' ideal points shifting right on the liberal-conservative scale and Democrat legislators' ideal points shifting left. In the second stage, we continue to find that an increase in ideological polarization of a state is associated with a significant increase in forecast dispersion of analysts located in that state, especially for stocks in politically sensitive industries. Our IV analysis requires the exclusion restriction that inclement weather events in a state do not affect the diversity of analyst opinions in that state relative to analysts located in other states for the same stock through channels other than political ideology. While we cannot dismiss all possible violations of the exclusion restriction, we discuss and rule out a few plausible violations.

In our second test to address concerns about endogeneity that might arise from unobserved time-varying state characteristics, we create a measure of ideological polarization at the firm-quarter level. To do this, we first assign ideal points to analysts. If an analyst appears in the Federal Election Commission (FEC) database as having made a political contribution, she is assigned the ideal point of the politician to whom she donated. If an analyst does not make political donations, she is assigned the median (or mean) ideal point of her state's legislators. After assigning ideal points to all analysts in our sample, we calculate the standard deviation of ideal points across all analysts issuing forecasts in each firm-quarter regardless of location and use it as a measure of political disagreement. Since analysts who issue forecasts for a firm vary from one quarter to the next, we have within-firm and between-firm variation in political disagreement. Controlling for several firm-characteristics, and including firm- and time-fixed effects, we find that firm-quarters with higher standard deviation of analyst ideal points have greater earnings forecast dispersion. This result is stronger for stocks in politically sensitive industries than other stocks, which further suggests that our findings are capturing a causal role of political disagreement.

We close by presenting two important implications of our findings for the finance literature, one in the area of asset pricing and one in corporate investments. First, our findings have implications for the literature on the cross-section of returns. Asset pricing theory argues that in the presence of short-sale constraints, greater belief disagreement causes stock prices to be high relative to fundamentals because investors with pessimistic beliefs are kept out of the market (see Miller, 1977; Chen et al., 2002). Diether et al. (2002) find support for this argument using dispersion in analysts forecasts as a proxy for investor disagreement. They show that stocks with higher forecast dispersion earn lower future returns. Using our firm-quarter level measure of analysts' ideological polarization, we add to this literature by documenting that stocks covered by more ideologically polarized analysts earn lower future returns. Specifically, we find that stocks in the highest quintile of ideologically polarized analysts (P5) underperform stocks in the lowest polarization quintile (P1) by 3.5% per year. When stocks are double-sorted on size and political polarization of analysts, we find that the P1-P5 long-short strategy delivers significant returns in the smallest size quintile as well in the two largest size quintiles.

Our findings also have implications for acquirer returns. Models in which diversity of opinion affects the slope of a stock's demand curve predict that diversity of opinion should be negatively related to acquirer returns when equity is issued to pay for an acquisition. Supportive evidence is found in Moeller, Schlingemann, and Stulz (2007) who show that dispersion in analyst forecasts is associated with lower bidder announcement returns for stock acquisitions. We add to this literature by documenting that in politically sensitive industries, greater ideological polarization of analysts is associated with lower acquirer announcement returns when equity is used to pay for the acquisition. In contrast, when acquisitions are paid for with cash only, polarization of analysts is unrelated to acquirer announcement returns.

To our knowledge, our study is the first to show that greater ideological disagreement leads to more diversity in analysts' opinions and has distinct consequences for investors as evidenced by the cross-section returns. The paper closest in spirit to ours is Goldman, Gupta, and Israelsen (2024) who show that polarized news coverage increases trading volume. We complement Goldman et al. (2024) by providing direct evidence that diversity of investor opinion widens in the presence of ideological polarization. Since we measure polarization using politicians' ideal points instead of news coverage, our evidence highlights the consequence of rising *elite polarization* on investors, especially for industries sensitive to government policy. Our study is also related to Atanassov, Julio, and Leng (2024) who find that ideological polarization between state legislators leads to lower corporate investment in the state.

The paper is organized as follows. Section 2 discusses related literature. Section 3 describes our data. Section 4 presents the main results, Section 5 documents the importance of our findings for investors. Section 6 presents robustness tests and Section 7 concludes the paper.

2. Related Literature

The division between the Republican and Democratic parties on policy issues is evident in the analysis of congressional voting (Poole, Rosenthal, and Koford, 1991; McCarty, Poole, and Rosenthal, 2001), interest group ratings of congressmen (Stonecash and Brewer, 2003), analysis of party platforms (Layman, 1999), and surveys of party activists (Aldrich, 1996; Layman, 1999; Layman, Carsey, and Horowitz, 2006)

Several studies in the finance and economics literature find that these partisan beliefs affect the decisions of financial intermediaries as well as households. For example, Hong and Kostovetsky (2012) find that liberal leaning mutual fund managers invest less in companies deemed socially irresponsible. Wintoki and Xi (2020) find that fund managers are more likely to invest in firms managed by executives with whom they are politically aligned. Others show a link between political leaning and corporate investment (Hutton, Jiang, and Kumar, 2014). Partisan decision-making has also been documented for financial regulators (Engelberg, Henriksson, Manela, and Williams, 2023) and judges (Gormley, Kaviani, and Maleki, 2024).

One possible reason why political preference affects financial decisions is that investors derive utility from investing in companies that are aligned with their values. An alternative view is that political values influence investors' risk-return models. Support for the view that investors hold different models of the world is provided by Meeuwis et al. (2022) who use data on household portfolio choice to make the case that partisan views influence how households interpret public information.

Despite mounting evidence that partisanship affects the decisions made by financial intermediaries, there is surprisingly little work on how polarization, i.e., the *gap* between Republican and Democratic ideologies, affects financial decisions. Existing evidence provides compelling reasons to expect that a higher ideological gap leads to a greater dispersion in investor opinion. If Democrats and Republicans interpret public information using different models of the world as suggested by Meeuwis et al. (2022), it is plausible that an increase in the liberal-conservative gap causes investors to disagree more on the value of drilling for more oil, investing in a new defense technology, or allocating significant resources in DEI efforts. It is important to understand whether the growing ideological gap in the United States affects the diversity of investor opinion because investor disagreement plays a central role in understanding the cross-section of returns, trading volume, and corporate investments. This literature is too large to summarize here but some key studies are listed in footnote 2 and footnote 20. Recent work by Goldman et al. (2024) comes closest to our research question. They show that polarized news coverage of a stock is associated with greater trading volume in the stock. The implied channel of the finding is that polarization increases investor disagreement, which then results in higher trading volume. Our paper pins down this channel directly by looking at the dispersion in analyst forecasts.

Several studies find in different settings that political alignment leads to a more optimistic economic outlook. For example, when ideologically misaligned with the party of the U.S. president, credit analysts issue less favorable credit ratings (Kempf and Tsoutsoura, 2021), loan officers charge higher loan spreads (Dagostino et al., 2023), and investors rebalance to safer assets (Meeuwis et al., 2022). Although these studies do not examine earnings forecasts of sell-side analysts, it is plausible that alignment with the party in power affects the dispersion in earnings forecasts by making aligned analysts more optimistic. In Section 6, we show that our results hold even after controlling for political misalignment between the analysts and the US president.

3. Data

Our study requires a measure of ideological polarization between political elites and a measure of investor disagreement. In subsection 3.1 below, we describe our elite polarization measure, and in subsection 3.2, we outline construction of the analyst dispersion measure.

3.1. Measuring political disagreement

Existing studies measure individual's political leaning either through their contributions to political campaigns (e.g., Hong and Kostovetsky, 2012) or voter registration data (e.g., Kempf and Tsoutsoura, 2021). While this type of data has the advantage of being at the individual level, affiliation with the Democratic or Republican party is not sufficient to capture *how much* beliefs diverge. As Shor and McCarty (2011) show, in some states with low levels of polarization, Democrats and Republicans have quite similar ideologies whereas in highly polarized regions, Democrats and Republicans hold starkly different ideological beliefs.

We measure polarization as the distance between the Shor and McCarty (2011) ideal points of the state legislators.[6] Ideal points are continuous, time-varying measures of individuals' ideological leaning on the liberal-conservative scale estimated using spatial models of roll-call voting pioneered by Poole and Rosenthal (1985, 1991, 1997). Ideal points have been applied extensively to the study of the U.S. Congress and other legislative and judicial institutions. The advantage of the Shor-McCarty ideal points is that they are available at the state-year level from 1993 to 2020 and are comparable across states and over time.[7] Prior papers use the partisan leaning of the area in which an individual resides as a proxy for the individual's party affiliation (e.g., Mian, Sufi, and Khoshkhou, 2023). In a similar spirit, we use the polarization of the area in which analysts reside as a proxy for polarization of the analysts.

Panel A of Table 1 provides summary statistics of the following four political polarization

[6] See data at *this link*.

[7] Shor and McCarty (2011) use responses to Project Vote Smart's National Political Awareness Test (NPAT) survey to make the ideal points comparable across states.

measures. The difference in the median ideal points of House Democrats and Republicans (h_diffs); the difference in the median ideal points of Senate Democrats and Republicans (s_diffs); a party-free measure of the average distance between House members (h_distance); and a party-free measure of the average distance between Senate members (s_distance). Figure 1a plots these four measures averaged across all states. All four measures indicate a steady increase in ideological polarization over time. Shor and McCarty recommend h_diffs as the preferred measure of ideological polarization within a state because the House has more members representing smaller geographical areas relative to the Senate. We use h_diffs as our primary measure of a state's polarization but demonstrate that our results hold for the remaining three measures.

Figure 1b plots the 50 states by polarization as measured by the average h_diffs over the period 1993 to 2020. It is evident from this figure that polarization varies significantly across states. California is the most polarized state. In contrast, Rhode Island and Louisiana have low levels of polarization because in the former state, the Republican party leans liberal while in the latter, the Democratic party is relatively conservative. In Figure 2, we plot polarization over time in four states that have the highest concentration of analysts - New York, California, Illinois, and Texas. Polarization has trended upward in all four states over the entire sample period.

In Panel B of Table 1 we list the five most polarized and five least polarized states at five-year intervals. We note that a relatively small set of states appear repeatedly in the most-polarized list. However, the transition matrix in Panel C of Table 1 shows that over time states move between being polarized and not polarized. In this matrix, the indicator variable Polarized is assigned the value 1 if h_diffs is above the sample median and 0 otherwise. The Between column shows that 35 states ever had Polarized equal to 1 and 37 states ever had polarized equal to 0 with a grand total of 72 ever having either. Since there are only 50 states in the sample, this indicates that there are states that are polarized in some years and not polarized in other years. The Within column tells the extent of this transition. Conditional on a state *ever* having Polarized equal to 0, 67% of the state's observations have Polarized equal to 0. Similarly, conditional on a state *ever* having Polarized equal to 1, 69% of its observations have Polarized equal to 1. Thus, while polarization status is somewhat sticky, there is significant transition from one status to the other in our sample period.

We assume that the ideological polarization among a state's political elites influences or is reflective of ideological polarization among analysts in the state. This is not directly testable since we do not observe the ideal points of individual analysts and cannot measure the extent of the analysts' disagreement with each other. However, a large body of literature (previously cited in the introduction) shows that elite polarization influences polarization of the populace.

3.2. Measuring diversity of investor opinion

We use dispersion in earnings forecasts issued by sell-side equity analysts as a proxy for investor disagreement. The literature commonly uses analysts' forecast dispersion to capture diversity of investor opinion (see Diether et al., 2002; Moeller et al., 2007; Chatterjee et al., 2012). It is particularly well-suited for our study because we can identify the geographic location of each analyst and from the analyst's location isolate the ideological polarization the analyst is exposed to.

We begin with the split-adjusted detail history file from Institutional Broker Estimates System (IBES) and retain EPS forecasts issued for fiscal year one. Our empirical method requires us to identify the geographic location of the analyst issuing the EPS forecasts. Since this is a manual, labor-intensive task, we first limit our sample to forecasts issued for companies that have non-missing values for firm-level control variables previously shown to affect analyst dispersion such as firm size, turnover, book-to-market etc.

The detail history file contains the analyst ID but not the analyst's name. We obtain each analyst's last name, initial of first name, as well as the name of the brokerage firm the analyst is affiliated with from the IBES Detail Recommendations file. Using this information we manually search FINRA, LinkedIn, and Google to identify the analysts full name and state of employment.[8] Online profiles and employment histories are sketchy prior to the year 2000. Therefore, we limit our search and our analysis to the period 2000 to 2020. If the analyst's last name, first initial, and brokerage firm do not unambiguously identify an analyst's state of employment, we drop the analyst from the sample. If an analyst relocates, we retain all the different available locations including the time interval at each location. We are able to identify the state of employment of 5,931 unique analysts. Since analysts sometimes change locations, we have 6,571 analyst-state observations. Table 2 shows the distribution of analysts for the states with at least 100 analyst-state observations. Consistent with prior research, about 60% of analysts are located in New York (see Gerken and Painter, 2022; Malloy, 2005). California accounts for 10% of the analysts and Illinois, Texas and Massachusetts together account for another 10%. We confirm that our main findings hold if we drop analysts located in New York (or in any of these states) from our sample.

We restrict the sample of earnings forecasts to analysts for whom we can identify a location. In each quarter, we keep only the last forecast issued by an analyst for a given stock and require that at least two analysts in a state-quarter issue forecasts for a firm. After these constraints,

[8] Implicitly we assume that analysts reside in their state of employment and are exposed to polarization of that state. The possibility that some analysts work remotely introduces noise in our measure. However, since the bulk of our sample is from the period preceding the COVID-19 pandemic, remote work is not likely to be a major concern.

we have more than one million forecasts issued for 9,118 unique firms across 30 states. Next, for each firm-state-quarter, we calculate the dispersion of quarterly earnings forecasts as the standard deviation of forecasts divided by the mean forecast. This results in 261,184 firm-state-quarter observations where state refers to the location of the analyst issuing the forecast. We calculate forecast dispersion at a quarterly frequency because analysts are likely to update forecasts based on firms' quarterly earnings reports as well as quarterly releases of macroeconomic indicators. This dataset permits us to control for time-invariant firm fundamentals by comparing the dispersion in analysts forecasts for the same stock issued by analysts located in different states. [9]

Panel A of Table 3 presents summary statistics of analyst dispersion for the five states with the most analysts as well as the for the full sample. Note that the states relate to the location of the analyst covering a stock and not the location of the company. There is significant variation in the mean dispersion across states. Dispersion is highest for analysts located in Texas and lowest for analysts located in Massachusetts. Our analysis includes state-fixed-effects to control for time-invariant characteristics of the analyst's location. Panel B of Table 3 presents summary statistics of control variables all of which are described in Appendix A.

In Table 4 we present a univariate comparison of analyst dispersion across polarized and unpolarized firm-state-quarters. In the first row, we categorize observations into two groups based on an indicator variable called Polarized which takes the value one if the observation has above-median value of h_diffs and zero otherwise. We see that both the mean dispersion and median dispersion are significantly higher in the subsample that has higher polarization. In the remaining rows of Table 4, we present the same comparison using the other three measures of polarization. All measures show that firm-state-quarters with above median polarization have higher dispersion in analyst forecasts. These univariate differences may exist because of differences in the characteristics of the state in which an analyst is located or because analysts in different states tend to cover different stocks. In the next section, we conduct a multivariate analysis that addresses these concerns.

4. RESULTS

In subsection 4.1, we present our baseline empirical specification. In subsection 4.2, we examine the role of politically sensitive stocks and ESG scores. To tighten the causal link, we use an instrumental variable regression in subsection 4.3 and present a firm-level polarization measure in subsection 4.4.

[9] Due to this unique feature of our study, we do not use the analyst dispersion measure available in the IBES summary file because the summary file is based on all analysts covering a stock and does not separate the statistics by the analysts' location.

4.1. Baseline results

To study the impact of political disagreement on the diversity of investor opinion, we run the following regression

$$Dispersion_{i,s,q} = \beta Polar_{s,y} + X_{i,q} + Z_{s,q} + \psi_s + \delta_i + \theta_y + \epsilon_{i,s,q} \quad (1)$$

where $Dispersion_{i,s,q}$ is the dispersion in stock i's earnings forecasts for fiscal year one issued in quarter q by analysts located in state s. It is summarized in Table 3 and its construction is described in subsection 3.2. The main explanatory variable is $Polar_{s,y}$, the degree polarization in the analyst's state during the year in which the forecast is issued.[10] Our preferred polarization measure is h_diffs, the house difference in party medians. However, we also present our main results for the other three measures of polarization, namely, s_diffs, h_distance, and s_distance.

Control variables are as follows. $X_{i,q}$ are firm characteristics measured quarterly. These include market capitalization, book-to-market, turnover, earnings volatility, number of analysts covering the stock, and geographical concentration of analyst coverage. $Z_{s,q}$ are state characteristics measured quarterly such as GDP and economic policy uncertainty (EPU) (Baker, Davis, and Levy, 2022)[11]. EPU captures monthly economic policy uncertainty through text analysis of local news articles. We average EPU to the state-quarter level. In addition, we include an indicator variable for Republican leaning states. All variables are described in Appendix A. In our primary specifications, we also include year-fixed effects (θ_y) to allow for unobserved variables that are constant across firms or states but vary over time, state-fixed effects (ψ_s) to control for time-invariant characteristics of the state in which analysts are located, and firm-fixed effects (δ_i) to control for time-invariant firm characteristics. The inclusion of firm-fixed effects ensures that we compare opinion dispersion about the same stock from analysts exposed to different levels of ideological polarization due to both cross-state and cross-time variation. Standard errors are clustered at the state-year level.[12]

Table 5 presents estimates using the House difference in party medians (h_diffs) as the measure of polarization. We begin in column 1 by presenting an ordinary least squares regression of analyst dispersion on h_diffs without control variables or fixed effects. In the remaining columns of Table 5 we progressively add control variables and fixed effects. Column 5 presents estimates of the specification shown in Equation 1, which is our primary specification and is employed in

[10] Since polarization of a state is available at an annual frequency only, in alternate specifications shown in Section 6, we measure dispersion at the annual level instead of quarterly and find qualitatively similar results.

[11] Also see data at *this link*.

[12] Results are similar if we use quarter-fixed effects and cluster standard errors at the state by quarter level instead of state by year level.

all subsequent tables. In all columns of Table 5, we see that the coefficient on h_diffs is positive and statistically significant at the 1% level, indicating that the dispersion in analysts' earnings forecasts is higher in state-years with greater ideological disagreement between the Republican and Democratic members of the state house. The effect of political polarization on analyst dispersion is economically meaningful. Based on the coefficient on h_diffs in column 5 of Table 5, a one standard deviation increase in h_diffs is associated with a 0.12 standard deviation increase in the dispersion of earnings forecasts.[13]

We briefly discuss the control variables. In subsequent tables, coefficients on the control variables are not reported. Firms with larger market capitalization have lower analyst dispersion. This finding is in line with notion that larger firms tend to have stable and predictable earnings. Firms with higher book-to-market have higher dispersion, which is consistent with the findings of Diether et al. (2002). Turnover has a positive coefficient which likely indicates that firms with greater diversity of opinion experience greater trading activity. As expected, firms with higher earnings volatility have greater analyst dispersion. Finally, analysts located in states with higher economic policy uncertainty (EPU) have higher forecast dispersion.The coefficient on the ideological polarization remains significant even after controlling for EPU which suggests that ideological polarization matters for reasons other than policy uncertainty.

In Table 6, we present estimates of Equation 1 using the three other measures of political polarization, s_diffs, h_distance, and s_distance. The coefficient on the all the polarization measures are positive and statistically significant at the 1% level. Thus our results hold whether we measure polarization using the distance between the ideologies of the median Democrat and median Republicans in the house or in the senate. The results also hold if we ignore the political party and use the average distance between the ideologies of the senate members or the house members.

Table 2 shows that analyst location is concentrated in a handful of states, with almost 60% of analysts based in New York. This feature of our data raises two concerns. First, our findings could be driven by factors that are unique to the state of New York. To address this concern, we drop analysts located in New York and estimate Equation 1 again using all four polarization measures. Estimates, presented in Panel A of Table 7, show that our results still hold. The coefficients on the four polarization measures are positive and statistically significant.

The second concern is that many states have a small number of analysts. In these states, the dispersion measure for some firm-quarters is based on the forecasts of only two analysts (the minimum requirement for calculating standard deviation), which could make the dispersion measure

[13] 0.12 = 0.133 x .497/0.554 where 0.133 is the coefficient on h_diffs in column 5 of Table 5, 0.497 is the standard deviation of h_diffs (see Table 1), and 0.554 is the standard deviation of analyst dispersion (see Panel A of Table 3.

noisy. We address this issue by retaining only those firm-state-quarter observations for which dispersion is calculated using forecasts of 4 or more analysts. Estimates of Equation 1 for this sub-sample are presented in Panel B of Table 7. The coefficient on polarization is positive and statistically significant at the 1% level in three of the four polarization measures. The fourth measure, h_distance, is weakly significant at the 10% level. In Panel C of the same table, we stress-test our findings even further by dropping *both* the observations relating to New York analysts and observations for which dispersion is based on fewer than 4 analysts. This is a much smaller sample with just under 10,000 firm-state-quarter observations representing 839 unique firms covered by analysts located in 14 states. Even in this smaller set of states and firms, the link between political disagreement and investor disagreement is strongly significant.

4.2. Politically sensitive stocks and ESG scores

In this sub-section and the next, we try to pin down the causal effect of political disagreement on analyst dispersion. Our preferred explanation for the baseline results in subsection 4.1 is that differences in political beliefs cause analysts to hold diverse opinions about the same stock possibly because they disagree about the impact of certain corporate or government policies. If this explanation has merit, the baseline findings should be stronger for stocks that are sensitive to ideological beliefs. In our first set of tests, we use the Hong and Kostovetsky (2012) classification of socially irresponsible stocks as a proxy for politically sensitive stocks. These are tobacco (SIC codes 2100–2199), guns and defense(SIC codes 3760–3769, 3795, 3480–3489), natural resources (SIC codes 0800–0899), mining (SIC codes 1000–1119, 1400–1499), and alcohol (SIC codes 2080, 2082–2085). We also include the healthcare industry (SIC codes 8011-8099) as politically sensitive. In addition, we include firms in the gambling industry which are identified by the appearance of the word 'casino' in the company name. We create an indicator variable called Sensitive that takes the value one for stocks in these industries and zero otherwise.

To test if our results are stronger in more politically sensitive industries, we run the following regression:

$$\begin{aligned} Dispersion_{i,s,q} = {} & \alpha_1 Polar_{s,y} * Sensitive_j + \\ & \alpha_2 Polar_{s,y} + \alpha_3 Sensitive_j + X_{i,q} + Z_{s,q} + \gamma_s + \psi_i + \theta_y + \epsilon_{i,s,q} \quad (2) \end{aligned}$$

In this equation, we interact the ideological polarization analysts are exposed to with the indicator variable for politically sensitive industries. All other features of Equation 2 are the same as in Equation 1. The coefficient of interest, α_1 captures whether the impact of polarization on analyst dispersion is stronger for politically sensitive stocks. Panel A of Table 8 presents estimates of Equation 2. In the interest of space, coefficients on control variables are not reported. Note that the coefficient on the stand-alone indicator variable Sensitive is subsumed by firm-fixed effects because a firm's industry does not change over time. There are four columns in Panel A of Table 8, one for each measure of polarization. In all four columns, the coefficient on the polarization measures remains positive as in the baseline results of subsection 4.1. More importantly, we see that α_1, the coefficient on the interaction term, is positive and statistically significant at either the 1% level or the 5% level. This implies that when ideological differences between a state's political elites widens, the dispersion in forecasts issued by analysts located in that state increases, and it increases more for politically sensitive stocks than for other stocks.

The next set of tests in this sub-section exploits the variation across companies in the resources committed to social and environmental issues. Liberals are more likely than conservatives to support corporate investment in a clean environment, labor protection, and in social causes such as racial and gender equality. Recent anecdotal evidence suggests that conservatives are opposed to investment in DEI programs. The backlash against corporate DEI efforts spearheaded by the activist Robby Starbuck has caused companies like Tractor Supply, Deere, and Harley-Davidson to pull back investment in DEI initiatives (see footnote 5) If our baseline results are attributable to ideological polarization, the positive link between analyst dispersion and elite polarization should be stronger for firms that invest more in environmental and/or social causes. To test this, we obtain ESG scores from Sustainalytics and run the following regression:

$$Dispersion_{i,s,q} = \gamma_1 Polar_{s,y} * Score_{i,y} + \gamma_2 Polar_{s,y} + \gamma_3 Score_{i,y} + X_{i,q} + Z_{s,q} + \psi_s + \delta_i + \theta_y + \epsilon_{i,s,q} \quad (3)$$

In this equation, Polar is one of the four polarization measures for the state-year in which analysts are located. The variable Score can be one of the following: the total ESG score of a firm in a given year, the environmental score alone, the social score, or the governance score. Summary statistics of the total ESG score and its three components is provided in Appendix B. We are primarily interested in the coefficient on the interaction term, γ_1, when the score is either the social score or the environmental score because these two scores relate to issues that liberals and conservatives tend to disagree on. Nevertheless, for comparison and completeness, we estimate Equation 3 using all four scores. Given four polarization measures and four ESG scores, we have 16 possible iterations of Equation 3.

In the interests of space, Panel B of Table 8 presents only the estimate of γ_1 from the sixteen regressions. All regressions include the full set of control variables previously shown in column 5 of Table 5 and include year-, state-, and firm-fixed effects. Column 1 of Panel B presents estimates of γ_1 when the total ESG score is used in Equation 3. γ_1 is positive and statistically significant for only one of the four measures of polarization (h_distance in the third row). Thus, a high total ESG score does not have a robust effect on the relation between political polarization and analyst dispersion. In column 2 of Panel B, we present estimates of γ_1 when a firm's governance score is used in Equation 3. In this column, the interaction term is always insignificant. This is not altogether surprising - good corporate governance should not be an ideologically polarizing issue.

Estimates of γ_1 in column 3 relate to a firm's social score. Here we see that γ_1 is consistently for positive all four measures of polarization in column 3. For two measures of polarization the interaction term is significant at the 5% level and for two measures it is weakly significant at the 10% level. These results indicate that the positive relation between polarization and analyst dispersion tends to be stronger for firms that score high on the social component of the ESG rating. That is, ideologically polarized analysts disagree on the value proposition of investing resources on social causes. Interestingly, in column 4, the interaction of polarization and environmental scores is only weakly significant in one of the four measures of polarization.

Overall, the results in this subsection indicate that our baseline results are stronger for stocks in politically sensitive industries and for firms that invest significant resources on social causes. These findings are supportive of the hypothesis that analyst forecast dispersion rises due to political disagreement. In the next subsection, we use an instrumental variable approach to further address the issue of causality.

4.3. Using weather-related natural hazards as an instrument for polarization

Our baseline results indicate that analysts in state-years with high elite polarization issue more dispersed earnings forecasts for the same stock at the same time as compared with analysts in state-years with low elite polarization. In this section, we consider the possibility that omitted state-level variables cause both elite polarization and dispersion in analyst earnings forecasts to increase. We attempt to tighten the causal link using weather-related natural hazards as an instrument for ideological polarization. Democrats and Republicans hold significantly polarized views on climate change. The growing frequency and severity of hurricanes, tornadoes, and other weather-related disasters in the United States has led Democrats to call for urgent action on climate change. According to a Pew Research Center survey, 78% of Democrats believe climate change should be a top priority of the federal government compared with just 21% of Republicans. Republicans are skeptical about the effectiveness of climate policies, with many believing that climate policies harm the economy.[14]

We obtain the number of natural hazards in each state-year using the Spatial Hazard Events and Losses Database for the United States (SHELDUS) from Arizona State University[15]. This data covers 18 types of natural hazards provided by National Centers for Environmental Information. Of these, we retain only weather-related natural hazards. Specifically, we keep 'drought', 'flooding', 'wildfire', 'heat', 'hurricane/tropical storm', 'severe storm/thunder storm', 'tornado', and 'hail'. Summary statistics of this variable, which we call *Natural hazard*, are provided in Table C1 for the five states with the most number of natural hazards and five states with the least number of natural hazards over our sample period.

We first examine the relevance of weather-related natural hazards for increasing ideological polarization. We regress our main polarization measure, h_diffs, on *Natural hazard* at the state-year level controlling for time-varying state characteristics like GDP and state EPU index and including state- and year-fixed effects. Standard errors are clustered by state. Column 1 in Panel A of Table 10 shows that political polarization is higher in state-years that have more natural hazards. The F-statistic is above 14 indicating that the natural hazard variable does not suffer from a weak instrument problem.[16] Since, on average, Democrats are in favor of addressing climate change through government policy and Republicans opposed, the positive link between weather-related natural hazards and polarization should intuitively be driven by Democrat ideal points shifting left or Republican ideal points shifting right or both. We confirm this by regressing ideal points of House Democrats or House Republicans on the natural hazard variable. In column 2 of Table 10 - Panel A, the dependent variable is the ideal points of House Democrats. The coefficient on the natural hazard variable is negative and significant, indicating that more weather-related natural hazards shift Democrat ideal points to the left on the liberal-conservative scale. In column 3, the dependent variable is the ideal points of House Republicans. The coefficient on natural hazards is positive and significant, indicating that more natural hazards shift Republican ideal points to the right. Overall, the findings of Table 10 - Panel A indicate that weather-related natural hazards are a valid instrument for political polarization.

Next, we merge the natural hazard instrument to the earnings forecasts data used in Equation 1 which is at the firm-state-quarter level, where the state represents the location of the analysts issuing the forecast. We conduct a two-stage least squares analysis of earnings dispersion in which

[14] See the Feb 28, 2020 Pew Research Center survey article *'More Americans see climate change as a priority, but Democrats are much more concerned than Republicans'*. Also see the September 6, 2019 Politico article *'Democrats kick up a storm over climate change and Dorian'*.

[15] ASU Center for Emergency Management and Homeland Security (2024)

[16] In untabulated results, we find that the F-statistics is also greater than 10 if standard errors are clustered by year or double clustered by state and year.

the polarization variable h_diffs is instrumented on *Natural hazard*. Second stage estimates are presented in Panel B of Table 10. Column 1 includes all control variables from Table 5 as well as firm, year, and state-fixed effects. The coefficient on polarization is positive and statistically significant at the 1% level in both columns. Next we present a few sub-sample results for robustness. In column 2, we exclude analysts located in New York. Column 3 excludes observations in which dispersion is based on fewer than 4 analysts. Column 4 imposes both these restrictions by excluding analysts located in New York and observations based on fewer than 4 analysts. In all sub-samples, the coefficient on h_diffs is positive and statistically significant. These findings help address concerns that our baseline findings suffer from an omitted variable bias.

The validity of our IV analysis requires that weather-related natural hazards affect analyst dispersion only through the effect on political ideology. Although we cannot rule out all possible violations of the exclusion restriction, here we briefly discuss two plausible violations. Recall that our method compares forecasts issued for the same stock by analysts located in different states. Moreover, the focal state reflects the location of the analyst and not the location of the firm for which the forecast is being issued. If California experiences more weather-related hazards in a given year as compared with other states, analysts located in California may update their priors about weather-related cash flow uncertainty faced by the focal firm and issue more dispersed earnings forecasts than analysts located in other states.

We run two tests to explore this alternate explanation. First, we show that firms in our sample do not suffer significant cash flow shocks due to localized extreme weather events. We match natural hazards in a state-year to firms' headquarter states and regress cash flow in each firm-year on our natural hazard instrument and several lagged control variables. In Table D1 of the appendix, we find a positive but insignificant coefficient on the natural hazard instrument. This finding is consistent with prior evidence in Brown, Gustafson, and Ivanov (2021) who also find that public firms are unlikely to suffer significant cash flow shocks from local weather events since they operate in multiple states and locations.

Second, if our findings are due to changing views about weather-related uncertainty instead of ideological polarization, our results should be driven by firms whose cash flows are vulnerable to weather-related hazards. We classify firms in the following industries as being exposed to inclement weather: Agriculture, forestry, and fishing (SIC 0100-0999), Construction (SIC 1500-1799), Transportation and public utilities (SIC 4000-4999), Retail (SIC: 5200-5999), and Insurers (SIC: 6300-6499). We then re-run our IV analysis within subsamples of firms in weather-sensitive industries and non-weather-sensitive industries. Second-stage estimates are presented in Table E1 of the appendix. We see that the coefficient on h_diffs is positive and statistically significant in industries that are not weather sensitive, which means that analyst dispersion goes up with political polarization in industries that are not vulnerable to inclement weather. On the other hand, in the weather-sensitive industries, the coefficient on h_diffs is statistically insignificant. In the last column, we interact h_diffs with an indicator variable called *W_sensitive* which takes the value one for weather-sensitive industries and zero for remaining industries. The coefficient on the interaction term is statistically insignificant which indicates that our findings are not stronger in (or driven by) weather-sensitive industries[17]. In contrast, if we interact the polarization measure h_diffs with an indicator variable for politically sensitive industries (defined earlier in subsection 4.2), the interaction term is positive and statistically significant at the 10% level (see column 5 of Table 10-Panel B). To address concerns that industries such as oil & gas, mining, and defense (which are classified as politically sensitive) can also be affected by the inclement weather, we create a subset of politically sensitive industries that excludes oil &gas, mining and defense. These are tobacco (SIC codes 2100–2199), alcohol (SIC codes 2080, 2082–2085) and healthcare industry (SIC codes 8011-8099), captured by the indicator variable *Sensitive_sub*. In column 6, we interact h_diffs with Sensitive_sub and obtain qualitatively similar results. The coefficient on the interaction term is positive and weakly statistically significant at the 10% level. These findings suggest that the increase in analyst dispersion is attributable to increase in political polarization and not due to a change in perceptions about weather uncertainty.

4.4. Firm-level measure of polarization

In our main specification, polarization is measured at the state-year level as the median distance between the house (or senate) legislators or as the average distance between house (or senate) legislators regardless of party. As recognized above, one drawback of using state-level polarization measure to explain forecast dispersion of analysts located in that state is that unobserved state characteristics may independently affect polarization in the state as well as dispersion of earnings forecasts of analysts located in that state. In this subsection, we address this concern by constructing a firm-quarter level measure of ideological polarization. This method uses ideal point data but does not rely on state-level polarization. To construct this measure, we assign an ideal point to *each analyst* in our sample and then calculate the standard deviation of ideal points across all analysts covering a stock in each quarter regardless of where the analyst is located. We call this measure *Firm_polar*. Since analysts issuing forecasts for a firm vary across quarters, Firm_polar varies from one quarter to another within firm. Firm-quarters with higher standard deviation of ideal points are considered to experience more ideological polarization.

Assigning ideal points to analysts is a two-step process. First, we search the Federal Election

[17] In subsample analyses in Table D1, we also show that firms sensitive to climate change do not suffer significant cash flow shocks.

Commission (FEC) website for political contribution by analysts in our sample. Of the 5,931 unique analysts in our sample, we find contributions by 441 analysts, 227 of which donated to candidates in the Democratic party and 164 donated to candidates in the Republican party.[18] If an analyst makes a donation to a politician, we assign the ideal point of the politician to that analyst. The assumption we make here is that the political ideology of the analyst is similar to the ideology of the politician the analyst is donating to. The majority of the donations are made to candidates running for the U.S. Congress while some are made to candidates running in state elections. Ideal points of U.S. Congress members are obtained from Bailey (2013) and Bailey (2021) and ideal points for state legislators are from Shor and McCarty (2011).[19]

For analysts that do not make a political contribution, which is the majority of our sample, we rely on location. We assume that analysts located in conservative (liberal) leaning states are more likely to be conservative (liberal). That is, we assign the analyst the ideal point of the median house member of the state in which the analyst is located. Many firm-quarters receive forecasts from analysts located in the same state. For these firm-quarters standard deviation of analyst ideal points will be zero if none of the analysts were in the FEC database. The reason is that these analysts would all have been assigned the median ideal point of the state's house members. Panel A of Table 11 presents summary statistics of firm_polar. The median value of firm-level ideological polarization is zero, the mean value is 0.19.

Next, we regress dispersion of earnings forecasts for each firm-quarter on the standard deviation of analyst ideal points, Firm_polar. We include all firm-level control variables from the baseline specification shown in Table 5 and also include firm-fixed effects and year-fixed effects. Results are presented in Panel B of Table 11. Standard errors are clustered by firm. In untabulated results, we find that results are qualitatively similar if we cluster by year or double cluster by firm and year. In column 1 of Panel B, we see that the coefficient on Firm_polar is positive and statistically significant indicating that higher standard deviation of analysts' ideal points is associated with higher dispersion of analyst earnings forecasts. In column 2, we interact Firm_polar with the indicator variable called Sensitive which takes the value one for politically sensitive industries and zero otherwise. The stand-alone indicator variable is absorbed by firm-fixed effects. We see that the coefficient on the interaction of Sensitive and Firm_polar is positive and statistically significant, which indicates that the positive relation between analysts' ideological polarization and earnings forecast dispersion is stronger for stocks in politically sensitive industries. This result provides

[18]These numbers are reasonable in light of Hill and Huber (2017) who show that fewer than 10% of registered U.S. voters are federal or state donors.

[19]For example, in 2019, an analyst named Robert Katz working at Bear Sterns donated to Ben McAdams who served as the U.S. representative from Utah's 4th congressional district from 2019 to 2021. In Bailey's data, Ben McAdams ideal point is -0.337. Therefore, we assign an ideal point of -0.337 to Robert Katz.

further reassurance that we are capturing the causal role of political ideology.

In the remaining columns, we present the same analysis with the following variation. In columns 3 and 4, for analysts that do not make political donations, we assign the analyst the mean ideal point (instead of median) of her state's house members and then recalculate standard deviation of ideal points. In columns 5 and 6 (7 and 8), we assign the analyst the median (mean) ideal point of her state's *senate* members instead of house members. In all specifications, we find a positive coefficient on Firm_polar and a positive coefficient on the interaction term.

The results in Table 11 help address concerns that our baseline findings in Table 5 are driven by unobserved time-varying characteristics of a state. However, the method used in this section is not without limitations. We assume that analysts' political ideology can be approximated by the political ideology of the politicians to whom they make political contributions or the median/mean ideology of the legislators in their state. These assumptions introduce noise in our measure of polarization. While neither method is perfect, together the two approaches help build the case that greater political polarization leads to greater investor disagreement.

5. IMPLICATIONS

Our results have important implications for the finance literature because a large body of research shows that investor disagreement matters for asset prices and corporate decisions. Dispersion in analysts' earnings forecasts specifically has been linked to the cross-section of returns (Diether et al., 2002) and also to the cross-section of acquirer returns (Moeller et al., 2007). In this section, we build on both these findings and show that ideological disagreement affects the cross-section of returns in general and also the returns for corporate acquirers when equity is used as a method of payment.[20]

5.1. The cross-section of stock returns

The first implication of our finding for the finance literature is rooted in the idea that prices reflect more optimistic beliefs when differences in opinion are combined with short-sale constraints (Miller, 1977, Chen, Hong, and Stein, 2002). These price-optimism models suggest that the greater the disagreement among investors about a stock's true value, the higher prices will be relative to true value because pessimistic investors sit out of the market due to short-sale constraints. Diether

[20]For related literature on the link between disagreement and stock returns see footnote 2 and also Jarrow (1980); Mayshar (1983); Diamond and Verrecchia (1987); Wang (1994); He and Wang (1995a); Morris (1996); Viswanathan (2000); Diether et al. (2002); Scheinkman and Xiong (2003); Goetzmann and Massa (2005); Yu (2011); Carlin et al. (2014); Golez and Goyenko (2022). The link between differences of opinion and trading volume is addressed in Varian (1989); Harris and Raviv (1993); Kandel and Pearson (1995); Odean (1998).

et al. (2002) find supportive evidence using dispersion in analysts' earnings forecasts as a proxy for differences in opinion among investors. They show that stocks with higher dispersion in earnings forecasts earn significantly lower future returns. In light of this prior literature, our evidence that political polarization exacerbates disagreement between analysts leads to the interesting possibility that polarization contributes to lower future returns. To test this hypothesis, we examine the link between firm-level political disagreement between analysts (described previously in subsection 4.4) and the cross section of returns.

We follow the standard approach in asset pricing which involves reducing the variability in returns by assigning stocks to portfolios based on stock characteristics (Jegadeesh and Titman, 1993). We examine stock returns for a holding period of three months. After dropping penny stocks (price less than \$5) we double-sort stocks based on size and political polarization to form equal-weighted quintile portfolios and then hold the portfolios over the next quarter. Specifically, at the end of each quarter in our sample period, we assign stocks into five size quintiles based on market capitalization. Next we sort stocks within each size quintile into five additional quintiles based on the standard deviation of ideal points of analysts covering the stock in that quarter (see subsection 4.4 for a description on analyst ideal points are assigned)

After assigning stocks to portfolios, stocks are held for the next quarter. We calculate the quarterly portfolio return as the equal-weighted average of the returns of all the stocks in the portfolio. The last column of Table 12 shows that among all stocks, the highest polarization quintile (P5) has lower returns than the lowest polarization quintile (P1). The annual return on the P1-P5 strategy is statistically significant 3.5%. Almost 80% of the P1-P5 spread comes from the short side of the trade, that is, the difference between medium-polarization stocks and high-polarization stocks. This is in line with Miller (1977) because Miller's argument implies that high-disagreement stocks will underperform. The converse, that low-disagreement stocks will outperform, need not be true. We note that the importance of the short side of the trade is also found in the Diether et al. (2002) sorting based on analyst forecast dispersion.

Looking within each of the five size quintiles, we see that returns are consistently lower in the highest polarization quintile as compared with the lowest polarization quintile. The P1-P5 strategy delivers significant returns in the smallest size quintile and also in the two largest size quintiles. In the smallest size quintile, the annual return on a P1-P5 strategy is a statistically significant 5.2%, while in the largest size quintile, the annual return on a P1-P5 strategy is a statistically significant 4%. The results in this section provide new evidence that stocks covered by politically polarized analysts earn lower future returns. This finding is consistent with the arguments in Miller (1977) and the evidence in Diether et al. (2002) that investor disagreement leads to lower future returns.

5.2. Acquirer returns

In existing theory, heterogeneity in opinions about firms' future performance leads to downward-sloping demand curves for stocks and greater diversity of opinion is associated with steeper demand curves (Miller, 1977; Chen, Hong, and Stein, 2002; Hong, Scheinkman, and Xiong, 2006). Therefore, as the float of a stock increases, the additional supply must be absorbed by investors who hold lower valuations. Moeller et al. (2007) extend this intuition to corporate acquisitions. They show that as the diversity of analysts' opinion increases, the returns to acquirers at the announcement of an acquisition decrease for stock-financed acquisitions (which increase float) but not for cash-financed acquisitions.

Our main finding is that higher political polarization leads to an economically meaningful increase in the dispersion of earnings forecasts. Therefore, we expect higher political polarization to be associated with lower returns of acquirers in stock-financed mergers, but not in cash financed mergers. Moreover, we expect this result to be stronger for acquirers in politically sensitive industries. To test this hypothesis, we obtain mergers and acquisitions announced between the years 2000 and 2020 from Refinitiv's SDC database. To be included in our sample, the acquisition must meet the following criteria (i) it is a completed, majority-stake acquisition by a U.S. based acquirer with a deal value greater than $1 million, (ii) the acquirer is a publicly traded firm for which analyst forecasts were issued during the merger year, (iii) the acquirer's cumulative abnormal returns (CAR) is available over the (-1,+1) window around merger announcement, and (iv) the acquirer has forecast dispersion data available from at least one state during merger announcement year. These conditions result in a sample of 18,144 mergers.

We calculate cumulative abnormal returns for the acquirer over a three-day window from one day before merger announcement till one day after ($CAR_{-1,+1}$). To calculate a firm's CAR, we first calculate daily abnormal returns over the three-day window surrounding merger announcement by deducting the return on the CRSP value-weighted index from the firm's return as $AR_{it} = R_{it} - R_{mt}$, where R_{it} is firm i's daily stock return on date t and R_{mt} is the return for the value-weighted CRSP index on date t. $CAR_{-1,+1}$ for each firm is calculated by cumulating the abnormal return, AR, over the three-day window. Summary statistics of acquirer CARs, deal characteristics and firm-level control variables are provided in Table 13. All variables are defined in Appendix A.

Next, we regress acquirer CARs on the ideological polarization of analysts covering the acquirer in the merger announcement year. This polarization variable is simply the average value of the quarterly polarization variable Firm_polar described in subsection 4.4. It captures the standard deviation of analysts' ideal points. Panel B of Table 13 presents results of CAR regressions. All variables summarized in Panel A are included as control variables but not tabulated for brevity.

We also include industry-fixed effects, year-fixed effects, and standard errors clustered by industry. Adjusting for industry is important because prior literature shows that merger activity is driven by industry-level shocks (Harford, 2005; Mitchell and Mulherin, 1996).

In columns 1 and 2, we restrict the sample to acquirers in politically sensitive industries. Politically sensitive industries are described in subsection 4.2. Theory predicts that the negative relation between disagreement and acquirer returns should be driven by acquisitions that increase the supply of shares, i.e., acquisitions that involve the use of equity as a method of payment. To test this hypothesis, in column 1, we use the sample of 'mixed payment' acquisitions, i.e. deals in which at least some stock was issued to pay for the transaction and find that the coefficient on analyst polarization is negative and statistically significant at the 5% confidence level. This finding is consistent with the hypothesis that greater political disagreement reduces acquirer announcement returns in deals that involve an increase in float. In column 2, we limit the sample to acquisitions that are 100% cash financed and find that the coefficient on analyst polarization is statistically indistinguishable from zero. That is, when no equity is issued to finance the acquisition, there is no relation between polarization and acquirer returns.

In columns 3 and 4, we restrict the sample to acquirers that are not in politically sensitive industries. Here we find no relation between acquirer returns and analysts' political polarization regardless of whether equity is issued (column 3) or the deal is 100% cash financed (column 4). Next, we test if the coefficient on analyst polarization for mixed-payment mergers in politically sensitive industries (column 1) is statistically different from the coefficient in mixed-payment mergers in non-politically sensitive industries. To this end, we pool acquirers in all industries together and create an indicator variable equal to one for acquirers in politically sensitive industries and zero otherwise. We repeat the CAR regressions in the subsample of mixed-payment deals, but this time include an interaction of analyst polarization with the indicator for politically sensitive industries. In column 5 of Panel B, we see that the coefficient on the interaction term is negative and statistically significant at the 1% level. That is, the negative effect of ideological polarization on acquirer CARs (when stock is issued as payment) is significantly stronger in politically sensitive industries than in other industries. For completeness, column 6 shows that in 100% cash-financed deals the interaction term is insignificant. These findings are consistent with the hypothesis that greater political disagreement reduces acquirer announcement returns in deals that involve an increase in float.

Overall, these results are consistent with the evidence in Moeller et al. (2007) that acquirer returns are declining in analyst dispersion for equity financed mergers but not for cash financed mergers. The novelty of our study is that our disagreement measure captures ideological polarization between analysts who issue forecasts for the acquirer. To our knowledge, we are the first to provide evidence that, in politically sensitive industries, ideological polarization affects the cross-section of acquirer returns by widening the forecast dispersion of sell-side analysts.

6. ROBUSTNESS

In this section, we run a battery of robustness tests on our main finding that diversity of analyst opinion increases with political polarization.

First, we test robustness to the frequency at which forecast dispersion is measured. Our primary specification calculates forecast dispersion for a firm across analysts located in each state in each quarter. However, polarization, our main explanatory variable is only available at the state-year level. Here, we show that our results are not sensitive to this difference in frequency at which analyst dispersion is measured. We collapse forecast dispersion to the firm-state-year level by averaging across all quarters in a year and run the following regression

$$Dispersion_{i,s,y} = \beta Polar_{s,y} + X_{i,y} + Z_{s,y} + \psi_s + \delta_i + \theta_y + \epsilon_{i,s,y} \tag{4}$$

where $Dispersion_{i,s,y}$ is the dispersion in stock i's earnings forecasts for fiscal year one issued by analysts located in state s in year y. $Polar_{s,y}$ is our preferred polarization measure, h_diffs, in the analyst's state during the year in which the forecast is issued. $X_{i,y}$ are firm characteristics measured yearly and $Z_{s,y}$ are state characteristics measured yearly. Results are presented in column 1 of Table 14 - Panel A. The coefficient is positive and statistically significant at the 1% confidence level

Next, we test robustness to the choice of forecast period. Our main specifications focus on dispersion of earnings forecasts issued for the next fiscal year. In this section we look at the dispersion of earnings forecasts issued for fiscal year two and three using regression specified in Equation 1. Results for dispersion in earnings forecasts for fiscal year 2 are presented in column 2 of Table 14 - Panel A while estimates for dispersion in earnings forecasts for fiscal year 3 are presented in column 3 of Table 14 - Panel A. In both columns, the coefficient on our preferred measure of polarization is positive and statistically significant. Thus, our findings are robust to the fiscal period for which forecasts are issued.

In Panel B of Table 14, we present two additional robustness tests. We try to rule out the alternate explanation that our main results are driven by heightened uncertainty during recession years. In rational expectation models without short-sale constraints, higher information uncertainty drives up differences in opinion (He and Wang, 1995b and Wang, 1994). Uncertainty is also known to be correlated with recession periods (Bloom, 2014). These prior findings open up an alternative explanation in which higher economic uncertainty in recession years drives up both disagreement and political polarization leading to a spurious positive association between disagreement and polarization. In column 1 Table 14 - Panel B , we exclude NBER recession years (2001, 2002, 2007, 2008, 2009, and 2020) and re-run our baseline model from subsection 4.1 and continue to find a positive and statistically significant relation between analyst dispersion and political polarization.

In our last robustness check, we explore whether our results are driven by analysts whose political party affiliation is different from that of the incumbent president. Kempf and Tsoutsoura (2021) show that credit analysts that are politically misaligned with the US president adjust ratings downwards because of a more pessimistic view of the incumbent president's economic policy. In our study, if misaligned analysts revise their earnings forecasts downward relative to aligned analysts, we would observe an increase in forecast dispersion. To control for this possibility, we include an indicator variable that takes the value of 1 if at least one analyst covering the firm from a state belongs to a party is misaligned with the incumbent President's in our baseline model from subsection 4.1. Because of the limited information on analysts' party affiliation, the sample size of this test shrinks to less than 100,000. However, column 2 of Table 14 - Panel B shows that there is still a positive and statistically significant relationship between political polarization and forecast dispersion and an insignificant relationship between misaligned dummy variable and forecast dispersion at the same time. Thus, our findings are not driven by misaligned analysts issuing pessimistic forecasts.

7. CONCLUSION

A sizeable body of literature shows that political preferences affect the choices of finance professionals such as fund managers and analysts as well household finance decisions. However, we know little about how political disagreement affects the diversity of opinions among investors. Democrats and Republicans disagree strongly on how an economy should address challenges relating to climate change, defense, gender and racial equality etc. We show that this ideological disagreement translates to differences in opinion about future corporate earnings.

Using ideal points of state legislators estimated from roll-call voting data we show that an increase in ideological polarization of a state's legislators is associated with an increase in the dispersion of earnings forecasts issued by analysts located in that state. We pin down the causal effect of political polarization on dispersion of analysts forecasts using several strategies. First, we show that the link between ideological polarization in a state and the forecast dispersion of analysts located in that state is stronger for firms in politically sensitive industries such as the oil and gas, defense, tobacco etc. Second, we show that our results hold if we use the number of natural hazards in a state as an instrument for political polarization in the state. Third, we create a firm-quarter level measure of ideological polarization by assigning 'ideal points' to each analyst and then calculate the standard deviation of ideal points of all analysts issuing forecasts in a firm-quarter. We find that higher standard deviation of analyst ideal points is associated with higher forecast dispersion, and that this result is stronger in politically sensitive industries.

Our findings are important because a large body of research shows that differences in investor opinion affect corporate decisions, trading volume, and the cross section of returns. We use two settings to document the relevance of our finding for investors. First, looking at the cross-section of returns, we show that stocks covered by more polarized analysts earn lower future returns. Second, we show that in politically sensitive industries, acquirers covered by more polarized analyst earn significantly lower announcement returns for acquisitions that involve stock offers. To our knowledge, this paper provides the first evidence of the impact of political disagreement on the dispersion of analyst earnings forecasts and the consequences for the cross-section of returns.

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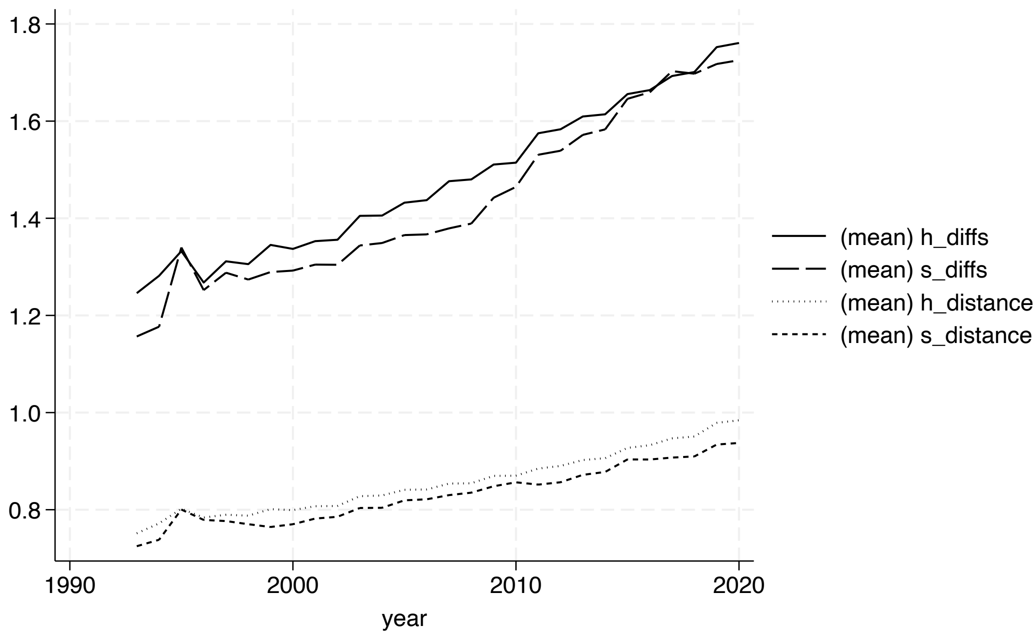
Figure 1: State-Level Political Polarization

Figure 1(a) shows the trend over time of the four state-level polarization measures. The solid line plots the difference in the median ideal points of House Democrats and Republicans (h_diffs); the long-dashed line plots the difference in the median ideal points of Senate Democrats and Republicans (s_diffs); the dotted line plots the party-free average distance between House members (h_distance); and the short-dashed line plots the party-free average distance between Senate members (s_distance). The period depicted is from 1993 to 2020. Figure 1(b) plots the 50 states by polarization as measured by the average h_diffs over the period 1993 to 2020.

(a) Average Polarization Across All States from 1993-2020



(b) Average State Polarization from 1993-2020

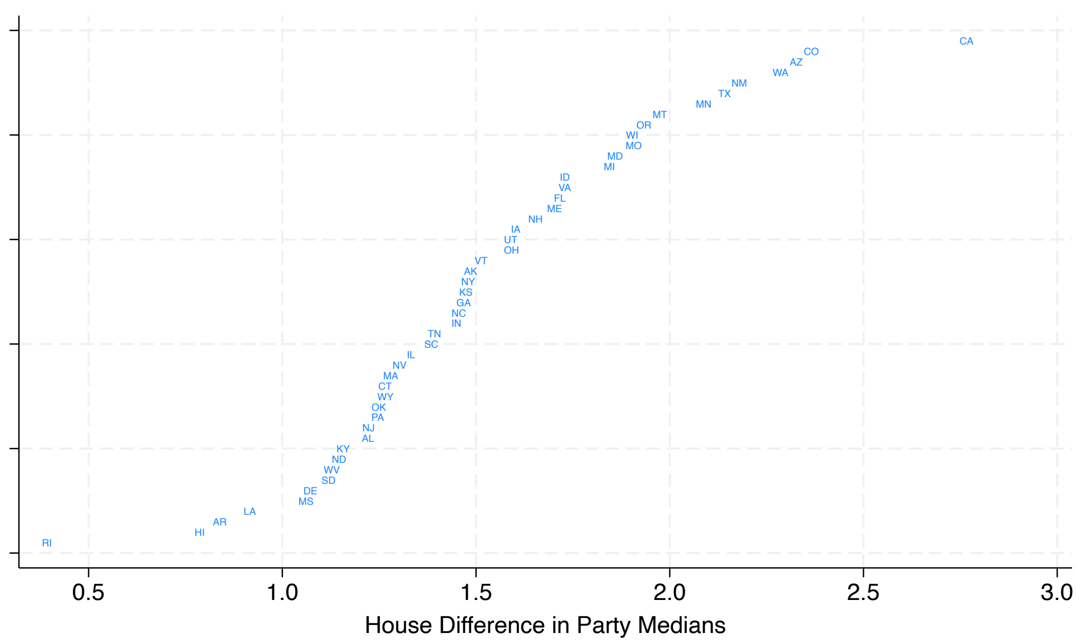


Figure 2: Polarization Level Over Time for Select States

This figure describes the trends in the state legislative polarization across time for four states with the most analysts based on Table 2. We use the preferred measure, the difference in the median ideal points of House Democrats and Republicans (h_diffs). In each plot, the blue line shows the moving trend of h_diffs in each state.

(a) Polarization in States with Most Analysts

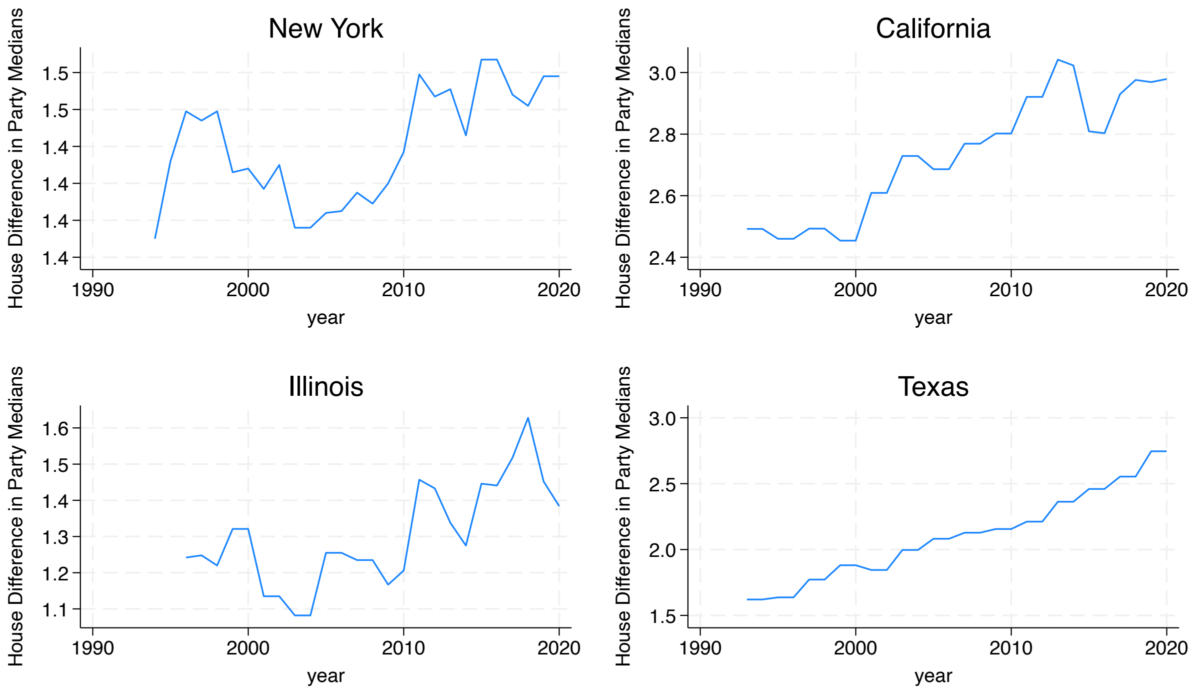


Table 1: Summary Statistics for Polarization Measures

Panel A presents summary statistics for four state-level legislative polarization measures from Shor and McCarty (2011) for the sample period 2000 to 2020. The measures are as follows: the difference in the median ideal points of House Democrats and Republicans (h_diffs); the difference in the median ideal points of Senate Democrats and Republicans (s_diffs); the party-free average distance between House members (h_distance); and the party-free average distance between Senate members (s_distance). Panel B lists the five most polarized and five least polarized states at five-year intervals based on our preferred polarization measure, h_diffs. Panel C reports the transition matrix of states moving between being polarized and not polarized over time. In this panel, the indicator variable, *Polarized*, has the value one if h_diffs is above the sample median and zero otherwise. See Appendix A for detailed variable descriptions.

Panel A: Summary statistics of all four polarization measures

Variable	N	Mean	p25	Median	p75	SD
h_diffs (House difference in party medians)	1256	1.496	1.178	1.429	1.782	0.497
s_diffs (Senate difference in party medians)	1263	1.453	1.125	1.437	1.761	0.492
h_distance (Average distance between House members)	1256	0.864	0.690	0.840	1.028	0.282
s_distance (Average distance between Senate members)	1265	0.838	0.638	0.834	1.004	0.283

Panel B: Most and least polarized states using h_diffs

Year	1995	2000	2005	2010	2015	2020
Five most polarized states	CA	CA	CA	CA	CA	CO
	WA	WA	AZ	AZ	CO	CA
	MN	NM	WA	CO	AZ	TX
	WI	MN	TX	WA	TX	NM
	TX	MI	NM	TX	WA	AZ
Five least polarized states	GA	HI	KY	DE	ND	ND
	SC	AR	MS	AR	LA	NJ
	DE	MS	HI	LA	SD	SD
	HI	LA	AR	HI	HI	HI
	AR	RI	LA	RI	RI	RI

Panel C: Polarization transition matrix using h_diffs

	Overall		Between		Within
	Freq	**Percent**	**Freq**	**Percent**	**Percent**
Polarized=0	628	50	37	75.5	66.8
Polarized=1	628	50	35	71.4	69.3
Total	1256	100	72	146.9	68.06

Table 2: Number of Analysts by State

This table reports the number and the fraction of analyst-state observations for states with at least 100 observations. Since analysts sometimes change locations, the same analyst may be counted twice in the table. The states are arranged from the most to least number of observations. The sample period is from 2000 to 2020.

Analysts by State

State	**Number**	**Fraction**
NY	3892	59.23%
CA	639	9.72%
IL	331	5.04%
TX	222	3.38%
MA	171	2.60%
MN	166	2.53%
OH	118	1.80%
FL	109	1.66%
VA	108	1.64%
MD	101	1.54%
MO	101	1.54%

Table 3: Summary Statistics of Analyst Dispersion and Control Variables

Panel A presents summary statistics of the dispersion in analysts' earnings forecasts over the period 2000 to 2020. Panel B presents statistics for the main firm- and state-level control variables. Following Diether et al. (2002), analyst forecast dispersion is defined as the standard deviation of analyst forecasts scaled by the absolute value of the mean forecasts following. Dispersion is at the firm-state-quarter level,meaning it is calculated using quarterly forecasts issued for a firm by analysts located in a state. We report summary statistics of analyst dispersion for the full sample and also within the five states with the largest number of analyst-state observations. Panel B describes the summary statistics of control variables. *Market cap* is computed by multiplying the quarterly close price (prccq) with the number of common shares outstanding (cshoq). *Book to market* is measured as the ratio of the common/ordinary equity value (ceqq) to market capitalization. *Turnover* is defined as the ratio of the number of common share traded (cshtrq) to the lagged number of common shares outstanding (cshoq). *Number of analysts* is measured as the number of analysts following the firm in each quarter. *HHI of analyst coverage* measures the geographical concentration of analysts covering the firm. *State GDP* measures the quarterly state-level gross domestic product in 2012 dollars. *Republican state* is an indicator variable that takes the value 1 if the state where the analyst is voted for the Republican candidate in the nearest (in time) presidential election. *Firm HQ is in the state* is an indicator variable that takes the value one if the headquarter of the firm is in the same state as the analyst covering it. *State EPU* measures the state-level economic policy uncertainty index. *Earnings volatility* is defined as the time-series standard deviation of firm's earnings following Graham, Leary, and Roberts (2015). *Misaligned dummy* is an indicator variable that takes value of 1 if at least one analyst covering the firm has misaligned party affiliation with the incumbent President's. For more detailed variable description, see Appendix A.

Panel A: Analyst Dispersion

State	N	Mean	p25	Median	p75	SD
NY	163,378	0.216	0.018	0.051	0.152	0.563
CA	27,905	0.194	0.014	0.041	0.127	0.540
IL	14,261	0.102	0.007	0.019	0.062	0.355
TX	10,876	0.394	0.042	0.114	0.334	0.790
MA	5,697	0.099	0.005	0.017	0.060	0.355
ALL	261,184	0.206	0.015	0.045	0.139	0.554

Panel B: Control Variables

Variable	N	Mean	p25	Median	p75	SD
Market cap (billions)	255,480	11.542	0.728	2.237	7.528	43.254
BM	254,714	0.504	0.216	0.399	0.678	0.457
Turnover (millions)	255,369	0.708	0.329	0.533	0.879	0.594
Number of analysts	261,184	11.756	6.000	10.000	16.000	7.547
HHI of analyst coverage	261,184	0.744	0.506	0.722	1.000	0.259
State GDP (trillions)	261,184	1.217	1.106	1.276	1.415	0.513
Republican state	261,184	0.106	0.000	0.000	0.000	0.308
Firm HQ is in the state	261,184	0.148	0.000	0.000	0.000	0.355
State EPU	261,183	92.912	44.000	65.000	93.000	105.133
Earnings volatility	235,438	0.122	0.020	0.041	0.087	1.584
Misaligned dummy	79,492	0.785	1	1	1	0.411

Table 4: Univariate Comparison of Analyst Dispersion

This table reports univariate tests of the mean and median analyst dispersion across polarized and unpolarized firm-state-quarters over the sample period 2000 to 2020. For each polarization measure, we partition the firm-state-quarter observations into two groups based on the indicator variable, Polarized, which takes the value one if the observation is above the median of the polarization measure and zero otherwise. See Appendix A for the detailed description of each variable. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	Group	**N**	**Dispersion**	**Median test**
h_diffs	Polarized=0	134,528	0.188	260.703***
	Polarized=1	126,656	0.224	
	Difference		0.036***	
s_diffs	Polarized=0	136,283	0.185	469.743***
	Polarized=1	124,901	0.228	
	Difference		0.042***	
h_distance	Polarized=0	137,799	0.194	46.242***
	Polarized=1	123,385	0.218	
	Difference		0.024***	
s_distance	Polarized=0	131,191	0.181	870.693***
	Polarized=1	129,993	0.230	
	Difference		0.049***	

Table 5: The Effect of Political Polarization on Analyst Dispersion

This table presents the effect of political polarization on analyst forecast dispersion at firm-state-quarter level over the sample period 2000 to 2020. The dependent variable in all columns is the analyst dispersion defined as the standard deviation of forecasts scaled by the absolute value of mean forecasts following Diether et al. (2002). The key independent variable is the difference in the median ideal points of House Democrats and Republicans (h_diffs). Control variables are defined in Appendix A. In column (1), we present an ordinary least squares regression of analyst dispersion on h_diffs without control variables, fixed effects, or clustering standard errors. Starting in column (2), we progressively add controls and fixed effects. Column (5) presents the estimation results using the specification in Equation 1. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	Forecast dispersion				
	(1)	(2)	(3)	(4)	(5)
h_diffs	0.035***	0.026***	0.231***	0.226***	0.133***
	(15.525)	(10.937)	(5.174)	(4.989)	(3.582)
Market Capitalization		-0.043***	-0.047***	-0.047***	-0.077***
		(-46.495)	(-34.326)	(-34.626)	(-13.838)
BM		0.124***	0.103***	0.103***	0.090***
		(48.394)	(11.892)	(11.941)	(6.695)
log(Turnover)		0.045***	0.036***	0.036***	0.040***
		(28.386)	(11.690)	(11.750)	(8.504)
log(number of analyst)		0.027***	0.032***	0.032***	0.025***
		(9.662)	(5.723)	(5.690)	(5.720)
HHI		0.036***	0.018**	0.019**	-0.017**
		(6.858)	(2.171)	(2.232)	(-2.351)
Earnings Volatility		0.194***	0.149***	0.149***	0.088*
		(22.924)	(4.597)	(4.624)	(1.782)
State GDP				0.026	-0.008
				(0.724)	(-0.286)
Republican state				-0.017	-0.018
				(-0.997)	(-1.595)
Firm HQ is in the state				-0.008	0.004
				(-1.568)	(0.765)
State EPU				0.021***	0.022***
				(6.346)	(6.732)
Constant	0.148***	0.368***	0.069	0.027	0.507***
	(38.331)	(38.367)	(0.943)	(0.273)	(5.900)
Observations	260,813	233,009	233,007	233,006	232,486
R-squared	0.001	0.038	0.054	0.055	0.237
Year FE	No	No	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes
Clustered SE	No	No	State-Year	State-Year	State-Year

Table 6: Using Other Measures of Polarization

This table examines the effect of political polarization on analyst forecast dispersion at firm-state-quarter level over the sample period 2000 to 2020. The dependent variable in all columns is the analyst dispersion defined as the standard deviation of forecasts scaled by the absolute value of mean forecasts following Diether et al. (2002). The key independent variables are the three other polarization measures, s_diffs, h_distance, and s_distance, all of which are defined in Table 1. All columns present the estimation using the specification in Equation 1. Detailed variable description is in Appendix A. The sample period is from 2000 to 2020. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	Forecast dispersion		
	(1)	(2)	(3)
s_diffs	0.098***		
	(3.563)		
h_distance		0.263***	
		(3.711)	
s_distance			0.372***
			(5.048)
Observations	232,483	232,486	232,483
R-squared	0.237	0.237	0.238
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Clustered SE	State-Year	State-Year	State-Year

Table 7: Excluding Analysts in New York and Observations with Few Analysts

This table examines the effect of political polarization on analyst forecast dispersion at firm-state-quarter level over the sample period 2000 to 2020. In Panel A, we drop analysts located in New York. In Panel B, we only retain firm-state-quarter observations whose dispersion is calculated using 4 or more analyst forecasts. Panel C combines the restrictions in Panel A and B. All panels estimate results using the specification in Equation 1. The dependent variable in all passes is the analyst dispersion defined as the standard deviation of forecasts scaled by the absolute value of mean forecasts following Diether et al. (2002). The key independent variables are the polarization measures, h_diffs, s_diffs, h_distance, and s_distance previously defined in Table 1. All columns present the estimates using the specification in Equation 1. Detailed variable description is in Appendix A. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: Excluding NY analysts

	Forecast dispersion			
	(1)	(2)	(3)	(4)
h_diffs	0.284***			
	(5.958)			
s_diffs		0.142***		
		(3.615)		
h_distance			0.385***	
			(4.852)	
s_distance				0.432***
				(5.567)
Observations	88,482	88,479	88,482	88,479
R-squared	0.239	0.238	0.239	0.239
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Clustered SE	State-Year	State-Year	State-Year	State-Year

Panel B: c-s-q analyst count >=4

	Forecast dispersion			
	(1)	(2)	(3)	(4)
h_diffs	0.352**			
	(2.060)			
s_diffs		0.356***		
		(3.517)		
h_distance			0.391*	
			(1.784)	
s_distance				0.676***
				(4.941)
Observations	86,703	86,703	86,703	86,703
R-squared	0.294	0.294	0.294	0.295
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Clustered SE	State-Year	State-Year	State-Year	State-Year

Table 7: (Continued)

Panel C: Excluding NY analysts AND c-s-q analyst count>=4				
	Forecast dispersion			
	(1)	(2)	(3)	(4)
h_diffs	0.694***			
	(3.897)			
s_diffs		0.559***		
		(3.596)		
h_distance			0.422**	
			(2.013)	
s_distance				0.657***
				(4.173)
Observations	9,645	9,645	9,645	9,645
R-squared	0.287	0.287	0.285	0.286
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Clustered SE	State-Year	State-Year	State-Year	State-Year

Table 8: Politically Sensitive Stocks and ESG

Panel A presents the effect of political polarization on analyst forecast dispersion conditional on the sensitivity of a firm's industry to government policy over the sample period 2000 to 2020 using the specification in Equation 2. The dependent variable is analyst dispersion defined as the standard deviation of forecasts scaled by the absolute value of mean forecasts following Diether et al. (2002). *Sensitive* is an indicator variable that takes the value 1 if the stock is in a socially irresponsible industry and 0 otherwise. Details about the classification of socially irresponsible industries is in subsection 4.2. Panel B presents the effect of political polarization on analyst forecast dispersion conditional on a firm's ESG scores using the specification in Equation 3 over the period 2000 to 2020. In Panel B, each cell represents a separate regression but only the coefficient on the interaction term is reported. All cells (regressions) include both firm- and state-level control variables and firm-, state-, and year-fixed effects. Standard errors are clustered at state-by-year level. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: Political sensitive stocks

	Forecast dispersion			
	(1) **h_diffs**	(2) **s_diffs**	(3) **h_distance**	(4) **s_distance**
Polarization	0.109***	0.070***	0.213***	0.291***
	(3.134)	(2.736)	(3.291)	(4.613)
Polarization x Sensitive	0.075**	0.121***	0.129**	0.206***
	(2.497)	(3.952)	(2.492)	(3.579)
Observations	232,486	232,483	232,486	232,483
R-squared	0.237	0.238	0.238	0.238
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Clustered SE	State-year	State-year	State-year	State-year

Panel B: ESG scores

	Forecast dispersion			
	(1) **Total score**	(2) **Governance**	(3) **Social**	(4) **Environmental**
h_diffs x score	0.098	-0.000	0.108*	0.077
	(1.514)	(-0.007)	(1.809)	(1.553)
	N=92,617	N=71,968	N=71,968	N=71,968
	R2=0.277	R2=0.260	R2=0.260	R2=0.261
s_diffs x score	0.089	-0.034	0.133**	0.067
	(1.447)	(-0.534)	(2.384)	(1.457)
	N=92,617	N=71,968	N=71,968	N=71,968
	R2=0.276	R2=0.260	R2=0.260	R2=0.260
h_distance x score	0.280**	0.011	0.244**	0.169*
	(2.152)	(0.092)	(1.992)	(1.943)
	N=92,617	N=71,968	N=71,968	N=71,968
	R2=0.277	R2=0.261	R2=0.261	R2=0.261
s_distance x score	0.144	-0.148	0.209*	0.120
	(1.246)	(-1.211)	(1.887)	(1.472)
	N=92,617	N=71,968	N=71,968	N=71,968
	R2=0.277	R2=0.261	R2=0.261	R2=0.261

Table 9: Instrumental Variable Regression

This table presents an instrumental variable estimation. The independent variable in all columns of Panel A is the total number of natural hazards at state-year level scaled by the state population of that year. Panel A column (1) presents the first stage in which the dependent variable is our preferred measures of polarization in a state, h_diffs. This measure is described in Table 1. We also report the F-statistic of column (1) testing for the relevance condition. Column (2) and (3) of Panel A present a validation test of the first-stage by regressing ideal points of House Democrats and Republicans on our natural hazard instrument. Panel B presents second-stage estimates by regressing analyst dispersion in a firm-state-quarter on fitted values of our preferred polarization measure, h_diffs. Dispersion is defined as the standard deviation of forecasts scaled by the absolute value of mean forecasts following Diether et al. (2002). In column (1), we presents the strictest specification with all fixed effects and all controls. Column (2) restricts the sample by dropping analysts located in New York, and column (3) restricts the sample by only retaining firm-state-quarter observations whose disperison is claulutated using 4 or more analyst forecasts. In column (4), we report results combining the restrictions from column (2) and (3). Column (5) reports the second-stage effect of political polarization on forecast dispersion conditional on the sensitivity of a firm's industry to government policy. *Sensitive* follows definition in subsection 4.2. Column (6) presents the same tests as in column (5) except that we exclude *Oil & Gas, Mining, and Defense* from *Sensitive*, which can also be affected by inclement weather. The sample period is from 2000 to 2020. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: First stage and validation

	(1) **h_diffs**	(2) **House Democrats**	(3) **House Republicans**
Natural hazard	47.977***	-27.376***	19.046**
	(3.831)	(-3.024)	(2.424)
F-statistic	14.68	.	.
Observations	996	996	996
R-squared	0.955	0.962	0.962
State-level controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Clustered SE	State	State	State

Panel B: Second stage

	Forecast dispersion					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{h\_diffs}$	0.494***	0.772**	0.661***	1.237**	0.505***	0.487***
	(2.963)	(2.559)	(3.134)	(2.128)	(2.884)	(2.943)
$\widehat{h\_diffs}$ x Sensitive					0.095*	
					(1.934)	
$\widehat{h\_diffs}$ x Sensitive_sub						0.052*
						(1.723)
Observations	232,485	88,482	86,757	9,697	232,485	232,485
All controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	State-Year	State-Year	State-Year	State-Year	State-Year	State-Year

Table 10: Bartik IV reg

Panel A: First stage and validation			
	(1) h_diffs	(2) House Democrats	(3) House Republicans
Foreign Immigrants x Republican	0.051**	-0.036**	-0.006
	(2.042)	(-2.364)	(-0.403)
F-statistic	36.254	.	.
Observations	996	996	996
R-squared	0.957	0.964	0.964
State-level controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Clustered SE	State	State	State

Panel B: Second stage						
	Forecast dispersion					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Instrument}$	0.133**	0.479***	0.727***	0.927*	0.108**	0.310**
	(2.318)	(3.753)	(3.973)	(1.846)	(2.004)	(2.133)
$\widehat{Instrument}$ x Sensitive					0.118***	
					(2.794)	
$\widehat{Instrument}$ x Social_score						0.002*
						(1.741)
Observations	232,485	88,482	86,757	9,697	232,485	232,485
All controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	State-Year	State-Year	State-Year	State-Year	State-Year	State-Year

Table 11: Using Firm-level Measure of Polarization

This table presents the effect of firm-quarter level political polarization on analyst earnings forecast dispersion. Panel A reports the summary statistics of the independent variable, *firm_polar*. The construction of it is in subsection 4.4. In Panel B, we report regression results of firm_polar on forecast dispersion at firm-quarter level. The dependent variable in all columns is analyst forecast dispersion at firm-quarter level. Analyst ideal points are assigned based on candidates donated to. For analysts making no contributions, we assign the median ideal point of analyst state's house members to them in column (1) to (2). In column (3) to (4), we assign the mean ideal point of analyst state's house members. In column (5), (6) and (7), (8), we assign the median and mean ideal point of analyst state's senate members, respectively. The sample period is from 2000 to 2020. Detailed variable description is in Appendix A. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A

Summary Statistics						
Variable	**N**	**Mean**	**p25**	**Median**	**p75**	**SD**
Firm_polar	182,160	0.195	0	0	0.251	0.340

Panel B

	Analyst forecast dispersion							
	House Median		House Mean		Senate Median		Senate Mean	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm_polar	0.019***	0.006	0.060***	0.033***	0.070***	0.048***	0.084***	0.045***
	(2.663)	(0.823)	(4.778)	(2.600)	(6.124)	(4.118)	(5.434)	(2.917)
Sensitive x Firm_polar		0.108***		0.177***		0.158***		0.242***
		(4.257)		(4.468)		(4.128)		(5.034)
Observations	159,926	159,926	159,926	159,926	159,926	159,927	159,927	159,927
R-squared	0.255	0.255	0.255	0.255	0.255	0.255	0.255	0.255
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Table 12: Mean Portfolio Returns by Size and Firm-level Polarization

In each quarter, stocks are sorted in five groups based on the level of market capitalization of the last month in the previous quarter. Stocks in each size group are then sorted into five additional groups based on *firm_polar* in the previous quarter. Definition of firm_polar is in subsection 4.4 and Appendix A Stocks are held for one quarter, and portfolio returns are equal-weighted. Stocks with a price less than five dollars are excluded. The testing sample period starts from the second quarter of 2000 through the last quarter of 2020. The table reports average quarterly portfolio returns; *t*-statistics in the parenthesis are adjusted for autocorrelation. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Mean Returns

	Size Quintiles					
Polarization	Small				Large	All
Quintiles	S1	S2	S3	S4	S5	Stocks
P1 (low)	4.86	3.52	2.73	3.22	2.65	3.44
P2	3.68	3.28	3.11	2.93	2.47	3.22
P3	5.01	3.62	3.02	3.56	2.45	3.27
P4	4.15	3.50	2.58	2.67	1.83	2.90
P5 (high)	3.57	2.79	1.98	2.18	1.65	2.59
P1-P5	1.29*	0.73	0.76	1.04**	1.00**	0.86**
t-statistic	(1.78)	(1.54)	(1.48)	(2.27)	(2.05)	(2.15)

Mean Polarization

	Size Quintiles					
Polarization	Small				Large	All
Quintiles	S1	S2	S3	S4	S5	Stocks
P1 (low)	0.026	0.043	0.070	0.094	0.188	0.058
P2	0.230	0.360	0.453	0.476	0.512	0.419
P3	0.600	0.677	0.701	0.683	0.653	0.668
P4	0.843	0.839	0.831	0.810	0.763	0.815
P5 (high)	1.108	1.048	1.020	0.988	0.922	1.023

Table 13: Mergers and Acquisitions

Panel A presents summary statistics for 18,144 majority stake acquisitions over 2000 and 2020 obtained from Refinitiv's SDC database. Panel A presents summary statistics of dependent variables($CAR_{-1,+1}$) the main explanatory variable, *Firm_polar*, and several deal-level control variables. $CAR_{-1,+1}$ is the acquirers' market-adjusted cumulative abnormal returns (CARs) calculated over a three-day window surrounding the announcement of the merger. Definition of firm_polar is in subsection 4.4 and Appendix A. Panel B reports the regression results. Column (1) and (2) report subsample of firms in politically sensitive industries, and column (3) and (4) present results of all other industries. Column (5) and (6) presents whole sample with interaction of firm_polar and sensitive indicator variable. Coefficient estimations of control variables are omitted for brevity. Detailed variable description is in Appendix A. The sample period is from 2000 to 2020. t-statistics are reported in parentheses, and *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: Summary Statistics

Variable	N	Mean	p25	Median	p75	SD
$CAR_{-1,+1}$	18,144	0.007	-0.019	0.004	0.030	0.057
Firm_polar	18,671	0.555	0.383	0.612	0.779	0.298
Pct. Stock	18,671	0.153	0.000	0.000	0.000	0.319
Market cap	16,940	7.753	6.536	7.560	8.823	1.727
BM	16,911	0.447	0.245	0.399	0.599	0.274
Tender	18,671	0.028	0.000	0.000	0.000	0.166
Public target	18,671	0.161	0.000	0.000	0.000	0.367
Friendly	18,671	0.992	1.000	1.000	1.000	0.090
Relative size	16,940	0.145	0.013	0.043	0.130	0.357

Panel B

	$(CAR_{-1,+1})$					
	Sensitive Ind.		**Other Ind.**		**All Ind.**	
	(1) Mixed	**(2) All cash**	**(3) Mixed**	**(4) All cash**	**(5) Mixed**	**(6) All cash**
Firm_polar	-0.012**	-0.008	-0.0014	-0.004	-0.000	-0.004
	(-2.233)	(-0.71)	(-0.058)	(-1.541)	(-0.01)	(-1.413)
Firm_polar x Sensitive					-0.014***	-0.007
					(-2.844)	(-0.643)
Observations	971	410	9,618	5,192	10,589	5,604
All controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.140	0.157	0.075	0.110	0.079	0.110
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Industry	Industry	Industry	Industry	Industry	Industry

Table 14: Robustness Checks

This table presents robustness test results of the effect of political polarization on analyst forecast dispersion. The dependent variables in all columns are firm-state-quarter forecast dispersion, except in Panel column (1) where it is firm-state-**year** level forecast dispersion computed as averaging all firm-state-quarter forecast dispersion in a year; in Panel A column (2) and (3), the forecast dispersion is calculated based on estimates issued for fiscal year **two** (FPI=2) and **three** (FPI=3) as in Diether et al. (2002). The key independent variable is our preferred polarization measure, h_diffs. Panel B column (1) reports results excluding NBER recession years and Panel B column (2) reports results including the control variable taking value of 1 if at least one analyst's party misaligns with incumbent President's. Detailed variable description is in Appendix A. The sample period is from 2000 to 2020. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A

	Forecast dispersion		
	(1) **Annual dispersion**	(2) **FPI=2**	(3) **FPI=3**
h_diffs	0.095***	0.134***	0.247***
	(3.091)	(4.111)	(3.006)
Observations	58,262	235,071	98,021
R-squared	0.399	0.306	0.340
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Clustered SE	State-year	State-year	State-year

Panel B

	Forecast dispersion	
	(1) **Excluding Recessions**	(2) **Misaligned party**
h_diffs	0.113***	0.111**
	(3.211)	(2.471)
Misaligned Dummy		0.007
		(1.214)
Observations	175,731	70,844
R-squared	0.262	0.288
Controls	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes
Firm FE	Yes	Yes
Clustered SE	State-year	State-year

A. VARIABLE DESCRIPTION

Variable	Description
Dependent variables	
Analyst earnings forecast dispersion	The standard deviation of analyst forecasts scaled by the absolute value of mean forecasts as in Diether et al. (2002). The variable is winsorized at top and bottom 1% and is at firm-state-quarter level.
House Democrats	Mean of the ideal points of Democratic party members of the state's House. This variable is at state-year level.
House Republicans	Mean of the ideal points of Republican party members of the state's House. This variable is at state-year level.
Senate Democrats	Mean of the ideal points of Democratic party members of the state's Senate. This variable is at state-year level.
Senate Repulicans	Mean of the ideal points of Republican party members of the state's Senate. This variable is at state-year level.
$CAR_{-1,+1}$	Market adjusted cumulative abnormal returns calculated over a three-day window surrounding the announcement of the deal. This variable is at deal level.
Key independent variables	
h_diffs	Our preferred measure of polarization. The difference in the median ideal point of House Democrats and Republicans. This variable is at state-year level.
s_diffs	The difference in the median ideal point of Senate Democrats and Republicans. This variable is at state-year level.

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Variable	Description
h_distance	A party-free measure of the average ideal point distance between any two House members. This variable is at state-year level.
s_distance	A party-free measure of the average ideal point distance between any two Senate members. This variable is at state-year level.
Sensitive	An indicator variable that takes the value of one if the stock is in a socially irresponsible industry and 0 otherwise as in Hong and Kostovetsky (2012). This variable is at firm level.
Natural hazard	The number of weather-related natural hazards in a state. The types of natural hazards include 'drought', 'flooding', 'wildfire', 'heat', 'hurricane/tropical storm', 'severe storm/thunder storm', 'tornado', and 'hail'. Excluded types of natural hazards include 'earthquake', and 'volcanoes', which are arguably not associated with the climate change. The original data source is the Spatial Hazard Events and Losses Database for the United States (SHELDUS) from Arizona State University. This variable is at state-year level.
W_sensitive	An indicator variable that takes the value of one if the stock is in a weather sensitive industry based on direct physical climate change risk and transition climate change risk. This variable is at firm level.

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Variable	Description
Firm_polar	The polarization measure for each firm in each quarter, obtained through computing the standard deviation of analyst ideal points. We assign ideal point of the politician to each analyst making contribution to. For those making no contribution, we assign the ideal point of the politician to that analyst. This variable is at firm-quarter level.
Control variables	
Market capitalization	Quarterly close price (prccq) multiplied by the number of common shares outstanding (cshoq). This variable is at firm-quarter level and in millions.
BM	Book to market ratio as common/ordinary equity value (ceqq) scaled by the market capitalization. This variable is winsorized at top and bottom 1% and is at firm-quarter level.
Turnover	The number of common shares traded (cshtrq) scaled by the one-quarter lagged number of common shares outstanding (cshoq). This variable is at firm-quarter level.
number of analysts	The number of analysts following the firm in each quarter. This variable is at firm-quarter level.
HHI of analyst coverage	A geographical concentration measure of analysts covering the firm as in Gerken and Painter (2022). It takes value from 0 to 1, with a higher value indicating that analysts covering the firm are from the same state. This variable is at firm-quarter level.
Earnings volatility	Time-series standard deviation of firm's earning streams as in Graham et al. (2015). This variable is at firm-year level.

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Variable	Description
State GDP	State-level gross domestic product in 2012 dollars. This variable is at state-quarter level.
Republican state	An indicator variable that takes the value one if the state where the analyst is located is voted for the Republican candidate in the most recent presidential election. This variable is at state-year level.
Firm HQ is in the state	A indicator variable that takes the value of one if the headquarter of the firm is in the same state as the analyst covering it. This variable is at firm-quarter level.
State EPU	Monthly state-level economic policy uncertainty index measured using local daily newspaper as in Baker et al. (2022), averaged to the quarterly level. This variable is at state-quarter level.
Pct. stock	Percentage of equity in payment when paying the target. This variable is at deal level.
Tender	An indicator variable that takes the value one if tender offer solicitation happens in the deal. This variable is at deal level.
Public target	An indicator variable that takes the value one if the target is a public firm. This variable is at deal level.
Friendly	An indicator variable that takes the value one if the deal is not hostile. This variable is at deal level.
Relative size	The ratio between the deal value and the acquirer's market capitalization. This variable is at deal level.

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Variable	Description
Misaligned dummy	An indicator variable that takes value of 1 if at least one analyst covering the stock from the same state whose party affiliation is misaligned with incumbent President's in a given quarter. This variable is at firm-state-quarter level.

B. ESG SCORE SUMMARY STATISTICS

Table B1: ESG Score Summary Statistics

Variable	**N**	**Mean**	**p25**	**p50**	**p75**	**SD**
Total ESG score	96,421	0.534	0.475	0.512	0.583	0.083
Governance score	74,384	0.631	0.576	0.634	0.687	0.084
Social score	74,384	0.540	0.463	0.531	0.605	0.102
Environmental score	74,384	0.512	0.412	0.489	0.592	0.128

This table reports the summary statistics of ESG scores used in Panel B of Table 8. We use the legacy ESG data whose score ranges from 0 to 100, with higher values indicating better performance. We scale the ESG score by 100 when running the regression in Panel B of Table 8. Data is for the period 2000 to 2020.

C. STATE LEVEL NATURAL HAZARDS SUMMARY STATISTICS

Table C1: Top and Bottom Five States with Most Natural Hazards

State	Total Natural hazards	State	Total Natural hazards
KS	167,501	CT	737
TX	127,237	ME	844
IL	98,089	MA	1,174
MN	94,926	NJ	2,648
MO	87,972	OR	4,556

This table presents the top and bottom five states with the most number of natural hazards over the entire sample period. We only include states that have at least one analyst in our sample. We exclude 'earthquake' and 'volcano' hazards which are arguably not associated with the climate change. Types of natural hazards included can be found in Appendix A.

D. EXCLUSION RESTRICTION TEST: IMPACT OF LOCAL NATURAL HAZARD EVENTS ON LOCAL FIRM CASH FLOWS

Table D1: Exclusion test: Natural hazards on corporate cash flows

This table examines the exclusion restriction that local natural hazard events may impact cash flow of firms who headquartered in the same state, and subsequently affect analysts' forecasts. This table reports results at **firm-year** level. Following Brown et al. (2021), we regress firm cash flows on our natural hazard instrument and a rich set of control variables. Variable definitions are in Appendix A and Appendix B of Brown et al. (2021). The dependent variable is firm cash flows whose headquarter is in the same state as the natural hazard events. The sample period is from 2000 to 2020. Column (1) reports in full sample. Column (2) and (3) restrict sample to be firms sensitive and not sensitive to climate change, respectively. Last Column presents the interaction effect estimation. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	$CashFlow_{it}$			
	(1)	(2)	(3)	(4)
Natural hazard	31.314	5.479	72.538	20.822
	(1.203)	(0.924)	(1.563)	(0.804)
W_sensitive X Natural hazard				21.480
				(0.900)
$Log(Assets_{it-1})$	0.088***	0.006	0.091***	0.088***
	(4.146)	(1.527)	(4.874)	(4.153)
$FixedAssets_{it-1}$	0.269**	0.039***	0.294**	0.269**
	(2.024)	(2.674)	(2.000)	(2.024)
$Leverage_{it-1}$	-0.750	-0.070*	-0.761	-0.749
	(-1.478)	(-1.879)	(-1.363)	(-1.482)
$Sales_{it-1}$	0.038	0.021***	0.019	0.038
	(1.460)	(2.673)	(0.448)	(1.464)
$Cash_{it-1}$	0.402	0.019	0.361	0.402
	(1.393)	(0.342)	(1.287)	1.392
$Debt_{it-1}$	0.421	0.117***	0.402	0.421
	(0.859)	(3.244)	(0.693)	(0.864)
$WorkCap_{it-1}$	3.112**	0.161***	3.234**	3.113**
	(2.404)	(2.848)	(2.427)	(2.400)
$Constant$	-0.670***	0.030	-0.700***	-0.669***
	(-2.924)	(0.790)	(-3.087)	(-2.924)
Observations	36,863	8,500	28,362	36,863
R-squared	0.471	0.350	0.488	0.471
Industry x Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Clustered SE	Industry	Industry	Industry	Industry

E. EXCLUSION RESTRICTION TEST: CLIMATE CHANGE SENSITIVE INDUSTRIES

Table E1: Exclusion test: Climate change sensitive industries

This table examines the exclusion restriction of our natural hazard instrument that our second-stage results are driven by the firms in industries that are sensitive to climate change risk. *W_sensitive* is an indicator variable that takes one for weather-sensitive industries. In column (1), we present the subsample test only including weather-sensitive industries. Column (2) reports the subsample test with non weather-sensitive industries. And column (3) presents the results interacting W_sensitive with our main measure of polarization, h_diffs. The dependent variable in all columns is the analyst dispersion defined as the standard deviation of forecasts scaled by the absolute value of mean forecasts following Diether et al. (2002). All columns present the estimates of the second-stage regression. Detailed variable description is in Appendix A. The sample period is from 2000 to 2020. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	(1) Weather-sensitive	(2) Not weather-sensitive	(3) All
$\widehat{h\_diffs}$	0.405	0.478***	0.481***
	(1.184)	(2.907)	(2.937)
$\widehat{h\_diffs}$ x W_sensitive			-0.023
			(-0.993)
Observations	53,171	179,314	232,485
R-squared	.	.	.
All controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Clustered SE	State-year	State-year	State-year