Political Polarization and Analyst Disagreement

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Abstract

We show that greater political polarization leads to greater dispersion in analysts' earnings forecasts. This effect is stronger in politically contentious industries and for firms with high social and environmental scores. We develop a continuous, firm-level measure of analysts' ideological disagreement and 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. In an M&A setting, acquirers covered by more polarized analysts earn lower announcement returns for equity offers but not for all-cash offers.

Keywords: Politics; polarization; analysts; disagreement; acquisitions

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

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Political polarization in the United States has increased substantially over the last few decades.[1] Democrats and Republicans disagree on the economic rationale for investing resources in combating climate change, gender and racial equity, defense, etc.[2] This rise in ideological disagreement can have an adverse effect on the production of financial information if financial analysts holding different models of the world interpret the same data differently (Kempf and Tsoutsoura, 2021; Meeuwis, Parker, Schoar, and Simester, 2022) or if they obtain different information from partisan media outlets (Goldman, Gupta, and Israelsen, 2024).

The equity research industry is a key source of information for market participants and, therefore, objective and unbiased analysts are critical for market efficiency.[3] However, prior research shows that personal characteristics such as political ideology affect analyst behavior. For example, we know that Republican-leaning equity analysts adopt a more conservative forecasting style than Democratic-leaning analysts (Jiang, Kumar, and Law, 2016), and that credit analysts aligned with the party of the U.S. president are more optimistic relative to misaligned analysts (Kempf and Tsoutsoura, 2021). These findings point to the possibility that greater divergence in ideological beliefs causes greater dispersion in analysts' earnings forecasts.

In this paper, we study the effect of growing ideological polarization on earnings forecast dispersion of sell-side analysts. This is an important topic to study because greater dispersion in analysts earnings forecasts is known to be associated with lower future returns (Diether, Malloy, and Scherbina, 2002), lower returns to stock acquisitions (Moeller, Schlingemann, and Stulz, 2007), and higher trading costs (Sadka and Scherbina, 2007). In existing studies, dispersion in analyst forecasts is commonly linked to firm-specific factors such as information uncertainty and disclosure practices as well as macroeconomic factors such as economic policy uncertainty.[4] The possibility that an extraneous factor such as analysts ideological disagreement affects forecast dispersion has

[1]See Boxell, Gentzkow, and Shapiro (2017), McCarty, Poole, and Rosenthal (2008). Also see *'Political Polarization in the American Public'*, 2014, Pew Research Center.

[2]See Aiken, Ellis, and Kang (2020); Wintoki and Xi (2020); Feinberg and Willer (2013); Hong and Kostovetsky (2012).

[3]See Womack (1996), Asquith, Mikhail, and Au (2005). Also see the SEC Staff Report on the importance of investment research here.

[4]Zhang (2006); Johnson (2004); Lang and Lundholm (1996); Avramov et al. (2009); Chourou et al. (2021).

not previously been explored.

Identifying the effect of ideological polarization on forecast dispersion is difficult because continuous, time-varying measures of political polarization are scarce. Moreover, since the location of analysts and their political beliefs are not easily observable, measuring ideological disagreement between analysts poses a challenge. Several recent finance studies use an individual's misalignment with the party of the U.S. president to show that partisanship affects optimism.[5] However, this misalignment indicator variable has some limitations because it does not capture the degree of ideological disagreement between individuals, and it does not vary within a presidential term.

We overcome the data challenge by combining state-level data on legislators' ideal points provided by Shor and McCarty (2011) with hand-collected data on the location of almost 6,000 equity analysts across 30 states, and (for a subset) their party affiliations from voter registries. The Shor-McCarty ideal points are continuous measures of state legislators' ideology on the liberal-conservative scale that vary across states and over time.[6] To identify the impact of polarization on forecast dispersion, we exploit this variation in several different identification strategies including one in which we develop a novel, continuous firm-level measure of analysts' ideological polarization.

In our first set of tests, we use the ideological polarization between a state's legislators as a proxy for the ideological polarization between analysts located in that state.[7] We compare the dispersion in earnings forecasts issued for the same stock by analysts located in different states, thereby accounting for unobserved time-invariant firm characteristics. We also control for several time-varying firm and state characteristics such as a state's economic policy uncertainty and include state-, year-, and firm-fixed effects.

We find that the dispersion in earnings forecasts for a stock is significantly higher for analysts in state-years that experience more political polarization. Our estimates indicate that the impact is

[5]See Kempf and Tsoutsoura (2021); Dagostino, Gao, and Ma (2023); Engelberg, Guzman, Lu, and Mullins (2023a); Engelberg, Lu, Mullins, and Townsend (2024); Stuart, Wang, and Willis (2025).

[6]The cross-sectional variation of the Shor-McCarty data offers a significant advantage over national measures of polarization that have time series variation only (Hetherington, 2001; Poole and Rosenthal, 2001).

[7]Prior research also uses partisan leaning of an individual's location as a proxy for that individual's ideological beliefs (Mian et al., 2023; Meeuwis et al., 2022).

economically meaningful - a one standard deviation increase in a state's ideological polarization is associated with a 0.13 standard deviation increase in the dispersion of earnings forecasts of analysts located in that state. This result holds if we exclude analysts located in New York and also if we look within the state of New York only. Our findings are robust to different forecast periods, alternate measures of polarization, controlling for analysts' geographical advantage (Gerken and Painter, 2022), and for the fraction of analysts misaligned with the party of the U.S. president. We confirm that our findings are not driven by analysts located in any one state and our findings hold if we exclude stocks covered by fewer than four analysts. In additional robustness tests, we address the possibility that the information available in Republican- and Democratic-leaning states is different due to the prevalence of different partisan media outlets. We find that our results are qualitatively similar within subsets of Democratic- or Republican-leaning states only.

Unobserved time-varying state characteristics may be correlated with both ideological polarization of a state and forecast dispersion of analysts located in the state. We use four strategies to address this endogeneity and identify the role of political disagreement. First, we document cross-sectional heterogeneity of our results that is consistent with the role of political polarization by leaning on well-known disagreements between Democrats and Republicans on issues such as combating climate change, gender and racial equity, defense, etc.[8]

We classify stocks in industries such as oil and gas, guns, defense, etc., as being politically contentious. 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 contentious stocks than for other stocks. We also use ESG scores from Sustainalytics to identify firms that invest resources into environmental, social, and governance issues. 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 (relative to analysts in less polarized states)

[8]See footnote 2 for academic evidence. Also 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. For examples of disagreement on social issues like Diversity, Equity, and Inclusion (DEI) see Tractor Supply's and John Deere's pull back on DEI investment after criticism from activist Robby Starbuck covered by the Wall Street Journal articles *'How Tractor Supply Decided to End DEI, and Fast'* and *'Deere Slashes Diversity Initiatives After Backlash From Conservative Activist'*.

for firms that have a higher overall ESG score, a higher Social (S) score, and higher Environmental (E) score. This heterogeneity does not exist in the governance (G) score, which is not surprising since good corporate governance is not a politically controversial issue.

Our second strategy to defend against alternative explanations is to look at forecast revisions. If our findings are indeed due to ideological differences between analysts, we should find that as political polarization in a state increases, forecasts of Republican and Democrat analysts move in different directions depending on whether the stock aligns with their political views. We find that as polarization in a state increases, Democratic-leaning analysts issue more negative forecast revisions for stocks in industries like oil & gas, defense, and other stocks classified as 'socially irresponsible' by Hong and Kostovetsky (2012), while Republicans issue more positive forecasts for these stocks. Further, as polarization increases, Republican analysts issue more negative forecast revisions for stocks that have higher overall ESG scores, and higher E scores, while Democratic analysts' views of these stocks remain unchanged. These results provide further confirmation that our findings are capturing the impact of ideological disagreement on analyst dispersion.

In our third strategy to address endogeneity, we use immigration as an instrument for a state's ideological polarization. This choice of instrument is based on survey evidence that shows sharp disagreement between Republicans and Democrats on immigration policies. Since unobservable state characteristics can affect where immigrants choose to settle, we construct a shift-share measure of immigrant flow using a state's pre-existing share of immigrants from a source country and national shifts in total immigration from the source country. We find that an increase in the instrumented polarization of a state is associated with a significant increase in forecast dispersion of analysts located in that state, especially for firms in politically contentious industries and for firms with a higher overall ESG score, higher E score, and higher S score.

Our fourth and final strategy to address endogeneity due to unobserved time-varying state characteristics is to develop a new measure of ideological polarization at the firm-quarter level by assigning legislators' ideal points to analysts. We assign legislators' ideal points to individual analysts based on the analysts' political contributions (if any), their party affiliation, or simply based on the political leanings of the legislators in the analyst's state. After assigning an ideal point to each analyst in our sample, we calculate the standard deviation of ideal points across all analysts issuing forecasts in each firm-quarter regardless of the analysts' 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, this measure of political disagreement has both within-firm and between-firm variation.

Controlling for several firm characteristics, and including firm-fixed and time-fixed effects, we find that firm-quarters with higher standard deviation of analysts' ideal points have greater earnings forecast dispersion. This result is stronger for stocks in politically contentious industries and for stocks with higher overall ESG scores and higher E scores. The heterogeneity indicates that our findings are likely attributable to political disagreement and not other unobserved factors that might be correlated with ideological disagreement. A remaining concern is that if analysts are non-randomly matched to firms, unobserved time-varying firm characteristics may be correlated with the ideological polarization of analysts that are assigned to the firm. Since firm fundamentals are unlikely to change significantly within a calendar year, we address this concern by including firm-year fixed effects and find that our main results still hold.

We use our firm-level measure of ideological polarization to illustrate two important implications of our findings for the finance literature, one in the area of asset pricing and one in corporate investments. First, Fama-MacBeth regressions show that, controlling for various firm characteristics, a one-standard deviation increase in ideological polarization of analysts leads to a 29-basis point lower stock return in the following quarter. In multi-factor time series tests, we find that this negative relation between polarization and future returns cannot be explained by the standard risk factors - the difference in alphas between the lowest and highest (P1-P5) polarization quintiles is positive and significant across all factor models.

This negative relation between political polarization and future returns is consistent with prior evidence on the link between forecast dispersion and future returns and can be understood through similar arguments (Diether et al., 2002).[9] We show that higher polarization makes partisan an-

[9]Different explanations have been put forth for this finding such as short sale constraints (Chen et al., 2002; Miller, 1977), unpriced information risk (Johnson, 2004), and credit risk (Avramov et al., 2009).

alysts revise forecasts downwards for stocks with which they are ideologically misaligned. These pessimistic views may not be impounded in stock prices due to short sale constraints, thereby leading to temporary overvaluations (Miller, 1977). Another potential explanation for temporary overvaluations arises from prior evidence that the most pessimistic analysts have an incentive to keep quiet (Lim, 2001; Jackson, 2005), leading to a higher mean of the observed distribution. In our setting, as dispersion rises due to political polarization, the difference between the observed and the true mean forecast can increase because the missing opinions would be those of the most pessimistic partisan analysts (Scherbina, 2008; Sadka and Scherbina, 2007).

Finally, we show that 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 investor disagreement 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 contentious industries, greater ideological polarization between analysts covering a bidder 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.

The paper is organized as follows. Section I discusses our contribution to existing literature. Section II describes our data. Section III presents the main results. Section IV documents the importance of our findings for investors. Section V presents robustness tests and Section VI concludes the paper.

I. Contribution and Related Literature

Our paper makes several contributions to the literature. We present new evidence that ideological polarization between analysts increases analyst forecast dispersion. Earnings forecast dispersion is an important indicator of information uncertainty (see Zhang, 2006 and references therein) and of differences in opinion among investors (Diether et al., 2002). In existing research, forecast dispersion is commonly attributed to firm fundamentals such as unpriced information risk (Johnson, 2004), corporate disclosure policy (Lang and Lundholm, 1996), complexity of financial statements (Loughran and Mcdonald, 2014, Lehavy, Li, and Merkley, 2011) or financial distress (Avramov et al., 2009). We add to this literature by showing that ideological disagreement between analysts - a factor unrelated to firm fundamentals - causes higher earnings forecast dispersion.

Our second contribution is to show that higher dispersion in analysts ideological beliefs predicts lower future returns. This finding is consistent with prior evidence in Diether et al. (2002) who show that stocks with higher dispersion in analysts' earnings forecast earn significantly lower returns. Earnings forecast dispersion has also been show to have a negative relation with future market returns (Park, 2005) and future portfolio returns (Yu, 2011). We add to this literature by identifying ideological differences as a significant source of earnings forecast dispersion with non-negligible pricing consequences.

In related research, the dispersion in analysts' earnings forecasts has also been linked to cross-sectional variation in acquirer returns. Moeller et al. (2007) show that bidder abnormal returns are lower when forecast dispersion is higher for acquisitions of public firms paid for with equity but not for those paid for in cash. We add to the findings of Moeller et al. (2007) by showing that dispersion in analysts' ideological beliefs is similarly associated with lower returns for bidders in stock acquisitions but not cash acquisitions. These results are consistent with models in which diversity of opinion about a firm's value leads to downward-sloping demand curves for its stock (Miller, 1977; Chen et al., 2002; Hong et al., 2006).

Our third contribution is to develop a firm-level, continuous measure of analyst ideological disagreement. This measure has both within- and between-firm variation and allows us to examine the link between ideological disagreement and returns at the firm-level. Our strategy of mapping ideal points to analysts can be applied to other financial market participants. Since belief disagreement is a fundamental tenet in asset pricing (Miller, 1977, Harris and Raviv, 1993, Chen et al., 2002, Hong et al., 2006) and corporate finance (Huang and Thakor, 2013, Bayar et al., 2015, Thakor and Whited, 2011), we hope our measure will encourage further empirical research on the impact of politics-induced belief disagreement on financial markets and corporate actions.

While numerous papers have studied the economic and financial implications of partisanship (i.e., identifying strongly with your own political party), our paper is one of the first to explore the consequences of growing polarization (i.e., growing divergence of political beliefs or policy positions across parties) on financial markets. One recent paper to study polarization is Goldman et al. (2024), which shows that polarized news coverage of a stock is associated with greater trading volume in the stock. The implied channel of their finding is that polarization increases investor disagreement, which then results in higher trading volume. Insofar as analyst disagreement proxies for investor disagreement, our study pins down this channel directly by documenting an increase in dispersion of analyst forecasts in the presence of greater polarization. Our findings are adjacent to another study on polarization by Leng, Atanassov, and Julio (2024) who find that ideological polarization between state legislators leads to lower corporate investment in the state.

Our paper is related to studies that focus on the effects of partisanship on entrepreneurship (Engelberg et al., 2023a), inventor productivity (Engelberg et al., 2024), home sales (McCartney, Orellana-li, and Zhang, 2024), and loan officers (Dagostino et al., 2023). Others show a link between political leaning and corporate investment (Hutton, Jiang, and Kumar, 2014), corporate social responsibility (Di Giuli and Kostovetsky, 2014), decision-making by financial regulators (Engelberg, Henriksson, Manela, and Williams, 2023b), judges (Gormley, Kaviani, and Maleki, 2024), and fund managers (Hong and Kostovetsky, 2012, Wintoki and Xi, 2020).

More broadly, our paper contributes to the literature on personal biases affecting analysts' forecast behavior such as cultural bias (Pursiainen, 2022), in-group favoritism (Jannati, Kumar, Niessen-Ruenzi, and Wolfers, 2025), social connections (Jia, Wang, and Xiong, 2017), and surname favorability (Jung, Kumar, Lim, and Yoo, 2019).

II. Data

The following subsections describe the polarization data and outline the construction of the analyst dispersion measure.

A. Measuring Political Disagreement

Both our state-level and firm-level polarization measures use the Shor-McCarty individual state legislator ideal point data.[10] 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 (1997), with higher values indicating more conservative ideologies. Ideal points have been applied extensively in studies of the U.S. Congress and other legislative and judicial institutions. The advantage of the Shor-McCarty ideal points is their availability at the state-year level from 1993 to 2020 and comparability across states and over time.[11]

Prior studies use the partisan leaning of an individual's area of residence as a proxy for the individual's party affiliation (e.g., Mian, Sufi, and Khoshkhou, 2023). In a similar spirit, our first approach uses the ideological distance between state legislators as a proxy for polarization among analysts located in that state. We believe this is a plausible assumption because prior evidence in the political science literature suggests that polarization among political elites has led to an increase in ideological awareness and polarization among the public (Abramowitz and Saunders, 2008).

The Shor-McCarty data offer four measures of distance between ideal points of state legislators: the difference in the median ideal points of House (Senate) Democrats and Republicans referred to as h_diffs (s_diffs); a party-free measure of the average distance among House (Senate) members called h_distance (s_distance). 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 summarize h_diffs in Panel A of Table I and use it as our primary measure of a state's polarization. The other three measures are summarized in Table IA.I of the internet appendix (all tables in the internet appendix have the prefix IA). In additional tests shown in the internet appendix, we demonstrate that our main results are robust to these three alternate measures.

[10]The data are available in the Harvard Dataverse at *https://doi.org/10.7910/DVN/WI8ERB.*

[11]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.

Figure 1 presents heat maps of h_diffs across U.S. states in the years 2001 and 2020. There is no h_diffs data for Nebraska because Nebraska has a unicameral legislature consisting of 49 senators. We see that in most states, polarization has increased. In Panel B of Table I we list the five most polarized and five least polarized states over time. 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 I 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 33 states ever had Polarized equal to 1 and 32 states ever had polarized equal to 0 with a grand total of 65 ever having either. Since h_diffs is available for only 49 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, 75% of the state's observations have Polarized equal to 0. Similarly, conditional on a state *ever* having Polarized equal to 1, 76% 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.

B. Measuring Diversity of Analysts' Opinions

As in prior studies, we use dispersion in analysts' earnings forecasts as a proxy for disagreement between analysts (see Chatterjee et al., 2012; Moeller et al., 2007; Diether et al., 2002). We begin with the split-adjusted detail history file from Institutional Brokers' Estimate System (IBES) and retain Earnings per Share (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 restrict the sample to forecasts issued for companies with 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 names and states of employment.[12] Online profiles and employment histories are sketchy prior to the early 2000s. Therefore, we limit our search and our analysis to the period 2001 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 available locations along with the corresponding time periods. We are able to identify the state of employment of 5,831 unique analysts. Since analysts may change locations over time, we have 6,703 analyst-state observations. Panel A of Table II shows the distribution of analysts for 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 11%. We verify that our main results are robust to excluding 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 most recent 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, the final sample contains more than one million forecasts issued for 7,189 unique firms across 29 states. Next, in each firm-state-quarter, we calculate forecast dispersion as the standard deviation of forecasts for firm i issued in quarter q by analysts located in state s, divided by the mean forecast. This results in 256,371 firm-state-quarter observations where state refers to the location of the analysts. We measure forecast dispersion at a quarterly frequency because analysts are likely to update forecasts in response to firms' quarterly earnings announcements as well as quarterly releases of macroeconomic indicators. This structure allows us to control for time-invariant firm fundamentals by comparing the dispersion in forecasts for the same stock issued by analysts located in different states.[13]

[12] 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 most our sample predates the COVID-19 pandemic, remote work is not likely to be a major concern.

[13] We do not use the analyst dispersion measure available in the IBES summary file because it calculates statistics across all analysts covering a stock and does not distinguish analysts by location.

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

III. Results

In subsection A below, we present our baseline specification in which polarization is measured at the state-year level. In subsection B, we examine cross-sectional variation based on politically contentious stocks and ESG scores. In subsection C, we provide additional support for the role of polarization using forecast revisions. In subsection D, we present an instrumental variable regression. Finally, in subsection E we further strengthen the causal link by constructing a firm-level polarization measure.

A. Baseline Results

To study the impact of political disagreement on the dispersion in analysts' earnings forecasts, we estimate the following regression:

$$Forecast\ Dispersion_{i,s,q} = \beta Polarization_{s,y} + X_{i,q} + Z_{s,q} + \psi_s + \delta_i + \theta_y + \epsilon_{i,s,q} \tag{1}$$

where $Forecast\ Dispersion_{i,s,q}$ denotes the dispersion in stock i's earnings forecasts for fiscal year one issued in quarter q by analysts located in state s.[14] It is summarized in Table II and its construction is described in subsection B of Section II. The main explanatory variable, $Polarization_{s,y}$,

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

is measured as h_diffs, the difference between the median ideal points of house Democrats and Republicans in the analyst's state during the year in which the forecast is issued. Since approximately 60% of analysts are located in the state of New York, we estimate Equation 1 using the full sample, as well as a subsample that excludes analysts based in New York and a subsample focused on New York-based analysts only.

Control variables are defined as follows. $X_{i,q}$ denotes firm characteristics measured quarterly. These variables include market capitalization (ME) (in logs), turnover (in logs), number of analysts covering the stock (in logs), book-to-market (BM), earnings volatility, and the geographical concentration of analyst coverage (HHI). To control for the information advantage held by analysts located in the same state as the firm (Gerken and Painter, 2022), we include an indicator variable called *Firm HQ is in the state* which takes the value of 1 if the firm's headquarters are in the same state as the analyst issuing the forecast.[15] $Z_{s,q}$ represents state characteristics measured quarterly, such as GDP growth, and economic policy uncertainty. Monthly data on economic policy uncertainty are obtained from Baker, Davis, and Levy (2022) and averaged to the state-quarter level (EPU).[16] In addition, we include an indicator variable for Republican-leaning states (Republican). All variables are described in Appendix I. In our primary specifications, we also include year-fixed effects (θ_y) and firm-fixed effects (δ_i). The inclusion of firm-fixed effects ensures that we compare opinion dispersion about the same stock among analysts located in different states (and therefore, exposed to different levels of ideological polarization). To control for time-invariant characteristics of the state in which the analyst is located, we include state-fixed effects (ψ_s). In Panel B of Table IA.VI, we also control for complexity of financial statements and find that our results hold (Lehavy, Li, and Merkley, 2011; Loughran and McDonald, 2024). In the main specifications, standard errors are double clustered by state and year.

Table III presents the results. Column 1 presents univariate estimates without control variables or fixed effects. Column 2 adds the control variables, and column 3 further includes firm- and state-fixed effects with standard errors double clustered by state and year. Across all three specifications,

[15]In alternative specifications, we use the state in which the firm's main operations are located from García and Norli (2012) and find that the results are unchanged.

[16]The EPU data are available at *this link*.

the coefficient on Polarization is positive and statistically significant at the 1% level. Column 4 further adds year fixed effects (our main specification described above in Equation 1). The coefficient on polarization remains positive but is only marginally significant at the 10% level. The next set of test shows that this weakening of statistical significance when year fixed effects are included is due to pooling New York with the rest of the states.

When we examine New York and other states separately, we find that the coefficient on polarization is strongly significant. Specifically, in column 5, we exclude all analysts based in New York and find that the coefficient on polarization is positive and significant at the 1% level with all fixed effects and double clustering. In states other than New York, the forecast dispersion measure may be based on a very small number of analysts, leading to a noisy measure. To address this concern, column 6 excludes analysts located in New York and retains only observations for which four or more analysts from the same state issued forecasts for a firm-quarter. This restriction yields a much smaller sample with under 10,000 observations relating to 766 unique firms covered by analysts in 14 states. The coefficient on Polarization remains positive and significant at the 1% level. Finally, in column 7, we restrict the sample to analysts located in New York only. Since this subsample contains only one state, polarization varies by year only. Accordingly, we include firm fixed effects only, with standard errors clustered by year. The estimated coefficient on *Polarization* is again positive and statistically significant.

The significant coefficients on polarization in columns 5 to 7 indicate that the link between polarization and forecast dispersion is robust and not driven solely by New York or only by states other than New York. The weaker statistical significance in the full sample with year-fixed effects (column 4) is possibly due to the over-representation of New York. Since New York accounts for approximately 60% of the sample, the variation in polarization in the state of New York heavily influences the national time trend. Year fixed effects absorb this dominant time-series variation, removing some of the identifying information contributed by New York, thereby decreasing the precision of the estimate and inflating standard errors. In the remainder of the paper, we use the full sample by default and employ our main regression specification but when results are weak in the full sample, we also present results separately for New York and other states.

The effect of political polarization on analyst dispersion is economically meaningful. Based on the coefficient on h_diffs in column 4 (column 5) of Table III, a one standard deviation increase in h_diffs is associated with a 0.13 (0.35) standard deviation increase in the dispersion of earnings forecasts.[17] In Table IA.II and Table IA.III of the Internet Appendix, we present estimates of Equation 1 for the full sample and subsamples using the three alternative measures of political polarization, s_diffs, h_distance, and s_distance. The coefficients on these polarization measures are positive and statistically significant at the 1% level in majority of the specifications.

We briefly discuss the coefficients on the control variables in Table III. 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 the notion that larger firms tend to have more stable and predictable earnings. Firms with higher book-to-market display 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. Finally, analysts located in states with higher economic policy uncertainty (EPU) issue higher forecast dispersion.

B. Politically Contentious Stocks and ESG Scores

Our explanation for the preceding results is that differences in political beliefs cause analysts to hold diverse opinions about the same stock potentially reflecting disagreement over the effects of corporate or government policies on firm value. If this explanation has merit, our results should be more pronounced for stocks that are vulnerable to political ideology.

We use various strategies to identify stocks with greater exposure to political ideology. First, we

[17]Using column 4: $0.13 = 0.142 \times .50/0.56$ where 0.142 is the coefficient on h_diffs in column 4 of Table III, 0.5 is the standard deviation of h_diffs (see Table I), and 0.56 is the standard deviation of analyst dispersion (see Panel B of Table II. Using column 5: $0.35 = 0.286 \times 0.65/0.53$ where 0.286 is the coefficient in column 5, 0.65 is the standard deviation of polarization in this subsample, 0.53 is the standard deviation of the forecast dispersion in this sample. When calculating the economic significance, we follow the suggestions of Mitton (2024) and use the standard deviation of the dependent variable as the scale instead of the mean. This recommendation is based on the concern that using the mean as the scale can sometimes overstate the economic significance.

create a classification of politically contentious stocks similar to the 'socially irresponsible' stocks of Hong and Kostovetsky (2012). Firms operating in 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) are classified as politically contentious. In addition, we consider firms in the gambling industry, identified by the appearance of the word 'casino' in the company's name. We depart from Hong and Kostovetsky (2012) by classifying the healthcare industry (SIC codes 8011-8099) as politically contentious. We create an indicator variable called *Contentious* that takes the value one for stocks in these industries and zero otherwise.

We also employ ESG scores from Sustainalytics to capture cross-sectional variation in firms' commitments to social and environmental issues. Liberals are more likely than conservatives to support corporate investment in environmental sustainability, labor protection, and in social causes, such as racial and gender equality. If the results in Table III reflect ideological polarization, the positive link between analyst forecast dispersion and political polarization should be stronger for firms in politically contentious industries and for firms that have higher ESG scores, driven specifically by higher environmental (E) and social (S) scores. To examine this hypothesis, we estimate the following regression:

$$Forecast\ Dispersion_{i,s,q} = \alpha_1 Polarization_{s,y} * V + \alpha_2 Polarization_{s,y} + \alpha_3 V + X_{i,q} + Z_{s,q} + \psi_s + \delta_i + \theta_y + \epsilon_{i,s,q} \quad (2)$$

In this equation, $Forecast\ Dispersion_{i,s,q}$ and $Polarization_{s,y}$ are the same as in Equation 1. V denotes one of the following variables: (i) an indicator variable called Contentious that takes the value 1 if firm i belongs to a politically contentious industry as defined above, (ii) firm i's overall ESG score, or (iii) firm i's E score or S score. If the observed relations are driven by political ideology, the coefficient of interest, α_1 is expected to be positive. For comparison and completeness, we also interact polarization with the governance (G) score. However, we note that the hallmarks of good governance such as board independence, transparency, and shareholder engagement are not inherently politically controversial. Therefore, we do not expect α_1 to be positive when V is defined as the firm's governance score.[18] All other features of Equation 2 are identical to those in Equation 1.

Table IV presents estimates of Equation 2. All columns use the full sample of analysts across all states and include state-, firm-, and year-fixed effects with standard errors double clustered by state and year. In column 1, V is set equal to the indicator variable Contentious. We see that the coefficient on the interaction term is positive and statistically significant at the 1% level. This implies that when ideological differences between a state's political elites widen, the dispersion in forecasts issued by analysts located in that state increases, with a larger effect for politically contentious stocks relative to other stocks. We note that in column 1, the coefficient on the stand-alone indicator variable Contentious is subsumed by firm-fixed effects because a firm's industry classification is time invariant.

In column 2, we interact polarization with a firm's total ESG score and find that the coefficient on the interaction term is positive and statistically significant at the 5% level. Columns 3 through 5 divide the ESG score into its three components. In column 3 (column 4), the interaction between polarization with the S score (E score) is positive and statistically significant at the 1% (5%) level. In contrast, the interaction between Polarization and the governance score in column 5 is statistically insignificant. Taken together, these results suggest that increases in polarization amplify analysts forecast dispersion (relative to dispersion in less polarized states) for firms that earn high social and environmental scores but not for firms with strong governance profiles. In Table IA.V, we re-estimate Equation 2 using the three alternative measures of polarization from Shor and McCarty (2011) and find qualitatively similar results. Overall, these findings support the hypothesis that political disagreement contributes to higher analyst forecast dispersion.

[18] Summary statistics of the total ESG score and its three components are provided in Table IA.IV of the Internet Appendix.

C. Forecast Revisions

State-level political polarization may be correlated with unobserved time-varying state characteristics that specifically affect firms in oil & gas, defense, or green energy–related industries. To defend against alternate explanations for the subsample results in the previous subsection, we examine analyst forecast revisions. If the positive relation between a state's political polarization and forecast dispersion of analysts located in that state is due to ideological differences between analysts, then earnings forecasts issued by Republican and Democrat analysts should respond differentially depending on whether a firm aligns with the analysts' political views. To test this, we collect data on analysts' party affiliations from voter registration records obtained from different state and county jurisdictions. Given the time-consuming nature of this task, we focus on a subset of states and counties listed in Appendix IA.VI. These locations account for more than 80% of the analysts in our sample. We follow the matching procedure in Kempf and Tsoutsoura (2021) to link analysts to voter registries based on name. This process yields a match rate of 39%, resulting in 1,858 analysts for whom party affiliation can be identified, of whom 1,121 are registered Democrats and 737 are registered Republicans.[19]

Studies cited earlier in the paper show that Democrats hold views that align with causes such as environment and labor protection and oppose 'socially irresponsible' companies such as guns, defense, oil & gas etc. Motivated by this evidence, we estimate the following regression separately for subsamples of Republican and Democratic analysts:

$$
\begin{aligned}
Forecast\ Revision_{a,i,s,q} = \alpha_1 Polarization_{s,y} * V + \\
\alpha_2 Polarization_{s,y} + \alpha_3 V + X_{i,q} + Z_{s,q} + \gamma_{a,i} + \psi_s + \theta_y + \epsilon_{a,i,s,q} \quad (3)
\end{aligned}
$$

where $Forecast\ Revision_{a,i,s,q}$ denotes the forecast revision for firm i issued in quarter q by analyst a located in state s following Hirshleifer, Levi, Lourie, and Teoh (2019). As in the previous

[19] Our matching rates are comparable to but slightly lower than Kempf and Tsoutsoura (2021). For example, we match 41% of analysts in the New York area to voter registries, compared with a 46% match rate in their study

subsection, V is one of the following: (i) Contentious, an indicator variable equals to one if firm i belongs to a politically contentious industry;[20] (ii) a firm i's ESG score; (iii) a firm's E score or S score. We include the same firm-level and state-level control variables, $X_{i,q}$ and $Z_{s,q}$ as before. We also include analyst-by-firm fixed effects ($\gamma_{a,i}$) to remove any unobserved time-invariant analyst forecasting habits (e.g., persistent optimism due to brokerage-firm relationship or personal bias) in each analyst-firm pair. As before, state-fixed effects (ψ_s) and year-fixed effects (θ_y) are included. Since the regression is estimated separately for Republican and Democratic analysts, inclusion of year-fixed effects controls for misalignment with the party of the U.S. president and addresses the concern that when analyst's party differs from that of the incumbent President, she tends to be pessimistic about the current economic conditions (Kempf and Tsoutsoura, 2021). Standard errors are clustered by state.[21]

Panel A of Table V reports summary statistics for the dependent variable, *Forecast Revision* (winsorized at 1% and 99% level) for three samples - all forecast revisions for which analysts' party affiliation is observed, revisions issued by Republican analysts, and revisions issued by Democratic analysts. On average, Republican analysts revise forecasts downward relative to Democratic analysts but the distributions of revisions in the two subsamples are fairly similar.

In Panel B of Table V we present the estimation of Equation 3. Columns 1 to 4 present results for the subsample of Democratic analysts, while columns 5 to 8 present estimates for Republican analysts. We see that the coefficient on the interaction of Polarization and the indicator variable Contentious is significantly negative in the subsample of Democratic analysts (column 1) and insignificant in the subsample of Republican analysts (column 5). That is, as polarization in a state increases, Democratic analysts' opinions about industries such as oil & gas, mining, defense, etc become more negative while the opinions of Republican analysts remain unchanged.

Moving on to ESG scores, the coefficient on the interaction of polarization and a firm's ESG

[20] In this test, the direction of the forecast revision matters. In unreported tests, we focus only on stocks that Democrats consider 'socially irresponsible' by excluding the healthcare industry from the definition of Contentious. Results are qualitatively similar.

[21] Here we cluster standard errors by state only because the inclusion of high-dimensional analyst-firm fixed effects renders the variance-covariance matrix non-invertible if we double cluster by state and year.

score is negative and statistically significant for Republican analysts (column 6). This negative relation is driven by the E score - the interaction between polarization and the E score is negative and statistically significant in column 8, which indicates that as polarization in a state increases, Republican analysts in that state revise their earnings forecasts downwards for firms that invest more resources into environmental issues. In contrast, the interaction of polarization with the ESG score, S score, or E score is insignificant for the subsample of Democratic analysts (columns 2-4).

Together the results in Table V support our claim that the positive link between analyst dispersion and political polarization documented in Table III is due to ideological differences between left-leaning and right-leaning analysts.

D. Using Immigration as An Instrument for Polarization

This section addresses the concern that unobserved time-varying state-level variables may simultaneously increase elite polarization and dispersion of analysts' earnings forecasts. We attempt to tighten the causal link by using immigration as an instrument for ideological polarization. Voter attitudes toward immigration policy have become increasingly polarized over time. According to a 2008 Gallup survey (which does not distinguish between legal and illegal immigration), 46% of Republicans and 39% of Democrats favored a reduction in immigration, implying a seven–percentage-point partisan gap. By 2022, this gap had widened substantially to 52 percentage points, with 69% of Republicans supporting reduced immigration compared with only 17% of Democrats.[22] Not surprisingly, immigration tends to be a salient political issue in GOP-led states, as reflected in recent efforts by these states to align their immigration enforcement policies with those of the Trump administration.[23]

Since the flow of immigrants to a state can be correlated with unobserved state characteristics, our identification strategy leverages a shift-share instrument.[24] Given the tendency of new

[22]See the Aug 8, 2022 Gallup survey article *U.S. Immigration Views Remain Mixed and Highly Partisan*

[23]See the NBC News article *GOP-led states rush to align with Trump's agenda with DOGE committees and immigration bills*.

[24]See Borusyak, Hull, and Jaravel (2022) and Goldsmith-Pinkham, Sorkin, and Swift (2020) for a general discussion and validity assessment of shift-share instruments.

immigrants to move to enclaves established by earlier immigrants from the same source country (Bartel, 1989), we estimate the exogenous supply-push component of immigration from a given source country into a specific state by multiplying the total national inflows from the source country with the fraction of earlier immigrants from that country who live in the state (Card, 2001; Peri, Shih, and Sparber, 2015). We use a state's share of immigrants from a source country in 2000 to predict immigration flow from that source country for the subsequent ten years, that is, from 2001 to 2010. Similarly, a state's share of immigrants from the source country in 2010 is used to predict immigration flow from 2011 to 2020.

We use immigration data from the American Community Survey (ACS) over the sample period 2000–2020, obtained from IPUMS (Ruggles et al., 2025). To compute a state's pre-existing share of the foreign-born population from source country j in state s (in 2000 or 2010), we restrict the sample to respondents whose birthplace is outside the U.S., and divide the number of respondents born in country j by the state's total population. To compute the national shifts in immigration, we restrict the sample to non-U.S. citizens whose birthplace is outside the U.S. and whose year of immigration is the same as the survey year.

The immigration measure is calculated as follows:

$$State\_Immigration_{s,y} = \sum_{j} Immigration_{j,y} \times Foreign\_Born\_Share_{j,s} \quad (4)$$

where $State\_Immigration_{s,y}$ denotes the predicted number of immigrants in state s in year y, constructed as the sum across all source countries j. $Immigration_{j,y}$ is the national inflow of immigrants from country j in year y recorded in the ACS 5-year survey. $Foreign\_Born\_Share_{j,s}$ is the share (% of the state population) of foreign born population from country j in state s. For years y between 2001 and 2010 (between 2011 and 2020), Foreign_Born_Share is calculated in the year 2000 (2010). States with the highest and lowest values of $State\_Immigration_{s,y}$ are reported in Table IA.VIII of the Internet Appendix.[25] In Table IA.VIII, we also document a strong positive correlation between the predicted immigration variable $State\_Immigration_{s,y}$ and actual

[25]IV regression results are similar when using the raw $State\_Immigration_{s,y}$ or its natural logarithm. Results are also similar when using the one-period lagged version of both variables.

immigration to a state.

Next, we use $State\_Immigration_{s,y}$ as an instrument for ideological polarization. The second stage equation of our two-stage least squares (2SLS) specification is,

$$Forecast\ Dispersion_{i,s,q} = \beta_1 \widehat{Polarization}_{s,y} + X_{i,q} + Z_{s,q} + \delta_i + \psi_s + \theta_y + \epsilon_{i,s,q} \quad (5)$$

In Equation 5, all control variables and fixed effects are the same as in Equation 1. $\widehat{Polarization}_{s,y}$ is instrumented on $State\_Immigration_{s,y}$. Motivated by the previously cited surveys and anecdotal evidence that immigration is a more polarizing issue in Republican-leaning states than in Democratic-leaning states, we allow for this heterogeneity to strengthen the first-stage relationship. Specifically, we follow Nunn and Qian (2014) by constructing an interactive instrument, where our shift-share predicted immigration is interacted with an indicator for Republican-leaning states, which equals one if a state is Republican-leaning and zero otherwise. Conceptually, instrumenting for polarization with the interaction term is analogous to a difference-in-differences estimation strategy, where the first-stage estimates compare polarization in Republican-leaning states with that in Democratic-leaning states during periods of high immigration.

The first stage of 2SLS regression is,

$$\begin{aligned} Polarization_{s,y} = \alpha_1 State\_Immigration_{s,y} \times Republican_{s,y} + \alpha_2 State\_Immigration_{s,y} + \\ \alpha_3 Republican_{s,y} + X_{i,q} + Z_{s,q} + \delta_i + \psi_s + \theta_y + \epsilon_{s,y} \quad (6) \end{aligned}$$

In Equation 6, $Republican_{s,y}$ is an indicator variable that equals to 1 if state s voted Republican in the most recent presidential election. The specification includes year, state, and firm fixed effects, along with the same firm characteristics $X_{i,y}$ and state characteristics $Z_{s,y}$ as in the baseline specification. To address concerns that immigration may be correlated with state characteristics that have a differential effect on forecast dispersion in Republican- and Democratic-leaning states, we interact state-level controls with the Republican-leaning state indicator in both stages.

The first-stage results are reported in column 1 of Table VI Panel A. The coefficient on the interaction between $State\_Immigration$ and the Republican-leaning state indicator is positive and statistically significant, indicating that immigration increases polarization in Republican-leaning state-years relative to Democratic-leaning state-years. The Kleibergen-Paap heteroskedasticity and clustering robust F-statistic (KP F-statistic hereafter) is 53 (Kleibergen and Paap, 2006), well above the standard threshold of 10, suggesting that the weak instrument problem is unlikely to be a major concern.

The second-stage results for the full sample are presented in column 2 of Table VI Panel A. The coefficient on $\widehat{Polarization}$ is statistically insignificant. This lack of significance likely arises due to the inclusion of year-fixed effects and over-representation of New York in the sample (see the discussion on page 14). As in the baseline findings in Table III, partitioning the sample into states excluding New York (column 3) and New York alone (in column 4) yields a positive and significant coefficient on $\widehat{Polarization}$ at the 1% level in both subsamples.

In Panel B, we present analysis similar to Section III subsection B and explore heterogeneity for stocks about which political disagreement is more likely to exist. We interact the instrumented polarization with ESG scores or with an indicator variable for politically contentious stocks. These specifications involve two first-stage regressions, one for polarization and another for the interaction between polarization and Contentious, ESG score, S score, or E score. Column 1 of Table VI Panel B shows that the interaction with Contentious is positive. We further find the interactions with the ESG score (column 2), S score (column 3) and the E score (column 4) are positive and statistically significant.[26] Overall, the effects are stronger for stocks where political disagreement is more likely to exist. These findings help address concerns that our baseline findings are driven by omitted variable bias.

The validity of our instrumental variable analysis requires that the instrument affect analyst dispersion only through its impact on political ideology. By construction, the shift-share instrument is exogenous to time-varying state-level confounders as it relies on the pre-existing distribution of immigrants. The exclusion restriction would be violated if the pre-existing distribution of immigrants

[26] In column 3 of Panel B, standard errors are clustered by state only because double clustering by state and year yields a non-invertible variance-covariance matrix.

predicted the state's economic characteristics in a manner that affects analyst forecast dispersion. To address this concern, we regress state-level EPU and GDP on Foreign_Born_Share. Results in Table IA.IX show that the pre-existing share of foreign-born population has no significant predictive power for the state economic characteristics.

E. Firm-level Measure of Polarization

As recognized above, one potential limitation of using state-level polarization measure to explain forecast dispersion of analysts located in that state is that unobserved state characteristics may independently affect both polarization and analysts' earnings forecast dispersion. A related concern is that media outlets vary across states, potentially leading analysts in different locations to be exposed to different information environments.

In this subsection, we address this concern by constructing a firm-quarter level measure of ideological polarization. This method uses the ideal point data but does not rely on state-level polarization. We assign an ideal point to each analyst in our sample and then calculate the standard deviation of ideal points of all analysts covering a stock in each quarter, irrespective of analysts' geographic location. A higher standard deviation of analyst ideal points indicates greater ideological polarization among analysts within a given firm-quarter.

To develop this measure, we assign ideal points to analysts in a three-step process. First, we search the Federal Election Commission (FEC) website for political contributions 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 Democratic candidates and 164 donated to Republican candidates.[27] If an analyst issuing a forecast in year y makes a political donation in that year, we assign the ideal point of the recipient politician to the corresponding analyst–year observation. The assumption we make here is that the political ideology of the analyst is similar to the ideology of the politician the analyst donates to. The majority of the donations are made to candidates running for the U.S. Congress, with the remainder made to candidates in state-level elections. Ideal points of U.S.

[27] 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.

Congress members are obtained from Bailey (2013) and Bailey (2021), and ideal points for state legislators are drawn from Shor and McCarty (2011).[28]

For analyst-years in which a political contribution is not observed, which is the majority of our sample, we infer ideology based on the analyst's location and party affiliation (if available). An analyst affiliated with the Democratic (Republican) party who issued a forecast in year y is assigned the median ideal point of Democratic (Republican) U.S. House members in the analyst's state in year y. Effectively, we assume that the ideology of a Democratic (Republican) analyst is similar to that of the median Democratic (Republican) U.S. house member in the analyst's state. For the remaining analysts without observed party affiliation, we follow prior work in using the partisan leaning of an individual's location as a proxy for ideological beliefs (Meeuwis et al., 2022). That is, an analyst is assigned the median ideal point across all House members in the analyst's state regardless of the House member's party affiliation.[29]

After assigning ideal points to analysts using this method, we calculate the standard deviation of ideal points across all analysts covering a firm in each quarter. We refer to this variable as *Firm_polar*. Since the analysts issuing forecasts for a firm change from one quarter to the next, Firm_polar exhibits both within-firm and between-firm variation. Panel A of Table VII presents summary statistics of *Firm_polar* and other firm-level variables. Using this firm-level measure of polarization, we estimate the following regression:

$$Forecast\ Dispersion_{i,q} = \beta_1 Firm\_polar_{i,q} + X_{i,q} + \delta_i + \theta_q + \epsilon_{i,q} \tag{7}$$

Here, the dependent variable, *Forecast_Dispersion*, is the dispersion in stock i's earnings forecasts for fiscal year one issued in quarter q. $X_{i,q}$ includes the same firm-level control variables as in prior

[28]For example, in 2019, an analyst 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 this analyst.

[29]In an alternate simulation-based strategy, each analyst-year is randomly assigned (with replacement) an ideal point of an incumbent legislator from the analyst's state (house or senate) in that year. Next, for each firm-quarter, we calculate the standard deviation of ideal points assigned to analysts covering the firm in that quarter. We then repeat this process 1,000 times and compute the average standard deviation of ideal points across the 1,000 simulations. Results using this measure are presented in Table IA.X.

specifications. δ_i and θ_q are firm-fixed effects and calendar quarter-fixed effects, respectively.

Results are presented in Panel B of Table VII. Column 1 presents a univariate specification without control variables or fixed effects. In column 2, we add control variables. Column 3 presents the specification described in Equation 7 including firm-fixed effects and calendar quarter-fixed effects, with standard errors clustered by firm. In all three columns, the coefficient on Firm_polar is positive and statistically significant at the 1% level, indicating that firm-quarters with higher ideological dispersion among analysts have higher earnings forecast dispersion.

The possibility that analysts are non-randomly matched to firms leads to an endogeneity concern. Unobserved time-varying firm fundamentals that affect forecast dispersion may change the ideological composition of analysts matched to the firm. To address this concern, column 4 replaces firm fixed effects and calendar-quarter fixed effects with firm-by-year fixed effects. Since firms' fundamentals are unlikely to vary substantially within a calendar year, this specification effectively controls for unobserved time-varying firm fundamentals. The coefficient on Firm_polar remains positive and statistically significant at the 1% level. Note that in this specification, the control variable earnings volatility, which is calculated at the firm-year level, is subsumed by the firm-by-year fixed effects.

To further mitigate concerns about omitted variables that might be correlated with both dispersion of ideal points and earnings forecast dispersion, we explore heterogeneity based on whether a firm operates in a politically contentious industry and whether it has high social and environmental scores in its ESG rating. The regression specification we use is as follows:

$$Forecast\ Dispersion_{i,q} = \beta_1 Firm\_Polar_{i,q} * V + \alpha_2 Firm\_Polar_{i,q} + \alpha_3 V + X_{i,q} + \delta_i + \theta_q + \epsilon_{i,q} \quad (8)$$

where V denotes one of the following: (i) an indicator variable, Contentious that takes the value 1 if firm i belongs to a politically contentious industry as defined in subsection B of Section III, (ii) firm i's overall ESG score, and (iii) its E score or S score. Results are presented in Table VIII. In column 1, the interaction of Contentious and Firm_Polar is positive and statistically significant indicating that increases in ideological polarization among analysts are associated with larger increases in forecast dispersion for firms in politically contentious industries relative to other firms. The main effect of Contentious is absorbed by firm-fixed effects because a firm's industry classification does not change over the sample period

In column 2, we see that the interaction of Firm_polar with the firm's ESG score is also positive but only weakly significant. Examining on the individual components of the ESG score, column 4 shows that the interaction of Firm_polar with the E score is significantly positive at the 5% level while the S score interaction is not significant in column 3. These results imply that as ideological differences between analysts covering a firm increase, forecast dispersion increases more for firms that emphasize investment in environmental issues. The positive coefficients on the interaction with Contentious and with the E score indicate that the increase in forecast dispersion is due to the increase in ideological differences. Overall, the firm-level tests in this section help address concerns that our baseline findings in Table III are driven by unobserved time-varying characteristics of a state.

IV. Implications

Our results have important implications for the finance literature because a large body of research documents that investor disagreement matters for asset prices and corporate decisions. Dispersion in analysts' earnings forecasts specifically has been shown to predict the cross-section of returns (Diether et al., 2002) and to be related to the cross-section of acquirer returns (Moeller et al., 2007). In this section, we build on both these findings by showing that ideological disagreement affects the cross-section of returns, as well as acquirer returns in transactions financed with equity.[30]

[30]For related literature on the link between disagreement and stock returns see Miller (1977); Yu (2011); Scheinkman and Xiong (2003); He and Wang (1995); Wang (1994).

A. The Cross-Section of Stock Returns

Diether et al. (2002) show that stocks with greater dispersion in earnings forecasts earn significantly lower future returns. Their interpretation is rooted in the idea that prices reflect more optimistic beliefs because short-sale constraints force pessimistic analysts to sit out the market (Chen, Hong, and Stein, 2002, Miller, 1977). The findings of Sadka and Scherbina (2007) suggest that analysts' incentives may also contribute to the dispersion anomaly. A number of studies document a missing left tail of analysts forecasts arising from optimism bias (Lim, 2001; Jackson, 2005; Scherbina, 2008). When analyst disagreement is high, the omitted forecasts are likely to be those that are the most pessimistic, leading to temporary overvaluation.[31]

Our evidence that ideological polarization among analysts exacerbates forecast dispersion raises the possibility that analysts' political polarization contributes to lower subsequent stock returns. To evaluate this hypothesis, we examine the relation between firm-level political disagreement among analysts and the cross-section of returns. In subsection A.1 below, we present Fama-Macbeth regressions of future stock returns on ideological disagreement and subsection A.2 reports the results from multi-factor time-series regressions.

A.1. Fama-MacBeth Regressions

We follow the standard Fama-MacBeth two-step procedure. In each quarter, we estimate a cross-sectional regression of next quarter's return on analysts' ideological disagreement in the current quarter as well as a set of firm characteristics. The cross-sectional regression is given by:

$$R_i = a_1 Firm\_Polar_i + \mathbf{X}_i + \epsilon_i \tag{9}$$

R_i denotes next-quarter's stock return and *Firm_polar* measures analysts' ideological polarization in the current quarter. X_i includes a set of firm characteristics measured in the current quarter: earnings forecast dispersion, firm's beta measured using the market model, market capitalization, book-to-market ratio, investment, and profitability (Fama and French, 2015). In addition, we

[31] Other explanations offered are that analyst forecast dispersion captures unpriced information risk (Johnson (2004)) or credit risk (Avramov et al. (2009)).

present specifications that progressively control for prior return, standardized unexpected earnings (SUE) and leverage. All variables are described in the Appendix. Following standard practice, we exclude stocks with price less than $1 as well as firms in the financial and utilities sectors.

The time series averages of the quarterly cross-sectional regression coefficients and their Newey-West t-statistics are reported in Table IX. In column 1, the coefficient on Firm_polar is negative and statistically significant at the 5% confidence level. The coefficient in column 1 indicates that a one-standard-deviation increase in ideological polarization leads to a 29-basis-point lower stock return in the following quarter.[32] We include analyst forecast dispersion as a control variable and, consistent with Diether et al. (2002) the coefficient on forecast dispersion is negative. The fact that the coefficient on Firm_Polar remains statistically significant after controlling for analyst forecast disagreement indicates that ideological polarization predicts lower future returns beyond its effect on forecast dispersion. In column 2, we include prior return (PrRet) calculated over the past 3 to 12 months and find that the results on Firm_Polar still hold. Columns 3 and 4 further add controls for standardized unexpected earnings (SUE) and leverage, respectively. Across these specifications, the coefficient on Firm_Polar continues to be negative and statistically significant while the coefficient on analyst forecast dispersion becomes insignificant once SUE is included.

A.2. Multifactor Time-series Tests

In this section, we test whether the return differential associated with polarization can be explained by standard asset pricing models. Specifically, we estimate the Fama–French three-factor model (Fama and French, 1996) and the Fama–French five-factor model (Fama and French, 2015), each estimated both with and without the momentum factor (Carhart, 1997). As in prior analyses, we drop stocks with price below $1, and firms in the financial and utilities sectors. We sort stocks into five quintiles based on Firm_polar with the quintile breakpoints based on the subset of NYSE firms. We calculate the quarterly portfolio return as the value-weighted average of the returns of all the stocks in the portfolio. Employing NYSE breakpoints combined with value-weighted returns helps mitigate the concern that findings are driven by small cap stocks (Hou, Xue, and Zhang,

[32] The coefficient -0.009 on Firm_polar in column 1 of Table IX multiplied by 0.327, which is the standard deviation of Firm_polar in the sample used in Table IX.

2020).

Table X reports alphas from multi-factor time-series regressions estimated on portfolios sorted by polarization. Column 1 (Column 3) presents alphas from the Fama-French three-factor (five-factor) model. Column 2 (Column 4) augments the corresponding specification with the momentum factor. Across all four specifications, alphas are negative and statistically significant in the two highest polarization quintiles. In the lower polarization quintiles, alphas are either statistically indistinguishable from zero (P1) or significantly positive (P2). The difference in alphas between the lowest and highest polarization portfolios (P1–P5) is positive and statistically significant across all models. Taken together, these results indicate that differences in factor exposures alone cannot account for the negative relation between polarization and future stock returns.

B. Acquirer Returns

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

Given our finding that higher political polarization leads to an economically meaningful increase in the dispersion of earnings forecasts, we expect higher 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 more pronounced for acquirers in politically contentious industries. To test this hypothesis, we obtain mergers and acquisitions announced between the years 2001 and 2020 from Refinitiv SDC database. To be included in our sample, the acquisition must satisfy the following criteria, (i) it is a completed, majority-stake transaction by a U.S.-based acquirer with a deal value exceeding $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, (iv) ideal points of analysts covering the acquirer during the merger announcement year are available, and (v) all control variables listed in Panel A of Table XI are available. Applying these filters yields a sample of 15,309 mergers.

We measure cumulative abnormal returns for the acquirer over a three-day window from one day prior to one day after the announcement ($CAR_{-1,+1}$). First, abnormal return (AR) is calculated by subtracting the return on the CRSP value-weighted market index from the firm's daily return over the event window: $AR_{it} = R_{it} - R_{mt}$, 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. Then, $CAR_{-1,+1}$ for each firm is calculated by cumulating the abnormal return, AR_{it}, over the three-day window. Summary statistics of acquirer CARs, deal characteristics and firm-level control variables are provided in Table XI. Firm-level control variables are measured one quarter prior to the announcement quarter. All variables are defined in Appendix I.

Next, we regress acquirer CARs on the ideological polarization of analysts covering the acquirer in the merger announcement year, *Firm_polar_ann*. It is calculated as the standard deviation of ideal points of analysts covering the acquirer during the merger announcement year. See Section III subsection E for a description of how ideal points are assigned to analysts. Panel B of Table XI 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 influenced by industry-level shocks (Harford, 2005; Mitchell and Mulherin, 1996).

In columns 1 and 2, we restrict the sample to acquirers in politically contentious industries, as described in Section III subsection B. 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, column 1 focuses on 'mixed payment' acquisitions, i.e., deals in which at least some stock was issued to pay for the transaction. The coefficient on analysts' ideological polarization is negative and statistically significant at the 5% confidence level. In terms of the economic magnitude, a one standard deviation increase in Firm_polar_ann leads to a 42 basis point reduction in the three-day CAR.[33] This finding is consistent with the hypothesis that greater political disagreement reduces acquirer announcement returns in deals that involve an increase in float. Column 2 restricts the sample to acquisitions that are 100% cash financed. In this subsample, the coefficient on analyst polarization is statistically indistinguishable from zero, suggesting no relation between polarization and acquirer announcement returns when equity is not used as a means of payment.

In columns 3 and 4, we restrict the sample to acquirers that are not in politically contentious industries. Here we find no relation between acquirer returns and analysts' political polarization when equity is issued (column 3) or when the deal is 100% cash financed (column 4). Next, we test if the coefficient on analyst polarization for mixed-payment mergers in politically contentious industries (column 1) is statistically different from the coefficient in mixed-payment mergers in non-contentious industries (column 3). To implement this test, we pool mixed-payment deals across all industries and create an indicator variable equal to one for acquirers in politically contentious industries and zero otherwise. We then re-estimate the CAR regression, but this time include an interaction of analysts' polarization with the indicator for politically contentious industries. Column 5 of Panel B shows that the coefficient on this 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 contentious industries than in other industries. For completeness, column 6 shows that the interaction term is statistically insignificant for fully cash-financed transactions.

Overall, these results are consistent with prior evidence in Moeller et al. (2007) that acquirer returns decline with analyst disagreement for equity financed mergers but not for cash financed mergers. The novelty of our study is that our disagreement measure captures ideological polarization among analysts covering the acquirer. To our knowledge, we are the first to provide evidence

[33] Calculated as the coefficient on Firm_polar_ann (-0.016) in column 1 of panel B in Table XI times the standard deviation of Firm_polar_ann (0.26) in the subsample used in column 1.

that, in politically contentious industries, ideological polarization affects the cross-section of acquirer returns by amplifying dispersion in sell-side analysts' earnings forecasts.

V. ROBUSTNESS

In this section, we briefly mention several additional tests, which are discussed in more detail in Appendix IA.III. First, we check whether our results are driven by across-party differences in ideologies or within-party differences. We recompute forecast dispersion for each firm-state-quarter using Republican analysts only and re-run Equation 1. Results are shown in the first column of Panel A in Table IA.VI. Similarly we recalculate forecast dispersion using Democratic analysts only and re-estimate Equation 1, with results presented in column 2 of Panel A. The coefficient on polarization is insignificant in both subsamples, which suggests that our findings are driven by across-party differences in ideologies.

In Panel B of Table IA.VI, we explore whether our results are driven by analysts whose political party affiliation is different from that of the incumbent president. We include a continuous measure of the fraction of analysts who are politically misaligned with the incumbent president at firm-state-quarter level in our baseline model from Section III subsection A and find that our results still hold. Panel B of Table IA.VI also shows that our main results hold if we include the complexity of financial statements as a control variable. This robustness test is motivated by prior evidence that firms with harder-to-read annual reports have higher forecast dispersion (Loughran and Mcdonald, 2014; Lehavy et al., 2011; Loughran and McDonald, 2024).

Panel C of Table IA.VI checks whether the link between polarization and forecast dispersion is driven by heightened uncertainty during election years. We include an interaction of polarization with an indicator variable that takes the value of 1 for presidential election years in our sample (i.e., 2004, 2008, 2012, 2016, 2020). The interaction term is statistically insignificant. In Panel D of Table IA.VI, we address the possibility that residents of Republican states receive different information than residents of Democratic states due to the prevalence of different media outlets. We look separately within subsamples of Republican-leaning states and Democratic-leaning states, and find that our results still hold.

In Table IA.VII, we present a few more robustness tests. Specifically, we show that our baseline results in Section III subsection A are not sensitive to the frequency at which dispersion is calculated. Our findings hold if we calculate dispersion at the firm-state-year level instead of at the firm-state-quarter level. Table IA.VII further provides evidence that our results hold for different forecasting periods like fiscal year 2 and 3. Finally, to address concerns that uncertainty is greater during recession years, we drop recessionary periods from our sample and find that our results remain unchanged.

VI. CONCLUSION

A sizeable body of literature shows that political preferences affect the choices of finance professionals such as fund managers and analysts as well as household finance decisions. However, we know little about how political disagreement affects the diversity of opinions among analysts. This is an important issue to explore because analysts' earnings forecasts are an important source of information for market participants and dispersion in earnings' forecasts have implications for the efficiency of financial markets.

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 with higher social or environment scores and for firms in politically contentious industries such as the oil and gas, gambling, defense, tobacco etc. Second, we examine forecast revisions issued by Republican and Democratic analysts and show that when political polarization in a state is high, Democratic analysts in that state revise forecasts downward (relative to analysts in less polarized states) for stocks in 'socially irresponsible' industries such as oil & gas mining, defense etc, while Republican analysts in that state revise forecasts downwards for stocks that have high environmental and social scores in their ESG rating. We further strengthen the causal link with an instrumental variable approach using immigration as an instrument for polarization.

Finally, we construct a novel firm-level measure of ideological polarization by assigning 'ideal points' to each analyst and then calculating the standard deviation of ideal points of all analysts issuing forecasts in a firm-quarter. We find that greater standard deviation of analyst ideal points is associated with higher forecast dispersion, and that this result is stronger in politically contentious industries and in firms that have higher social or environmental scores.

Our findings are important because a large body of research shows that differences in analysts opinions affect corporate decisions, trading volume, and the cross-section of returns. We use two settings to document the relevance of our findings 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 contentious industries, acquirers covered by more polarized analysts 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: Political Polarization across States: 2001 vs. 2020

This figure shows a heat map of Polarization (*h_diffs*) for the year 2001 and 2020. This measure captures the difference in the median ideal points of House Democrats and Republicans.

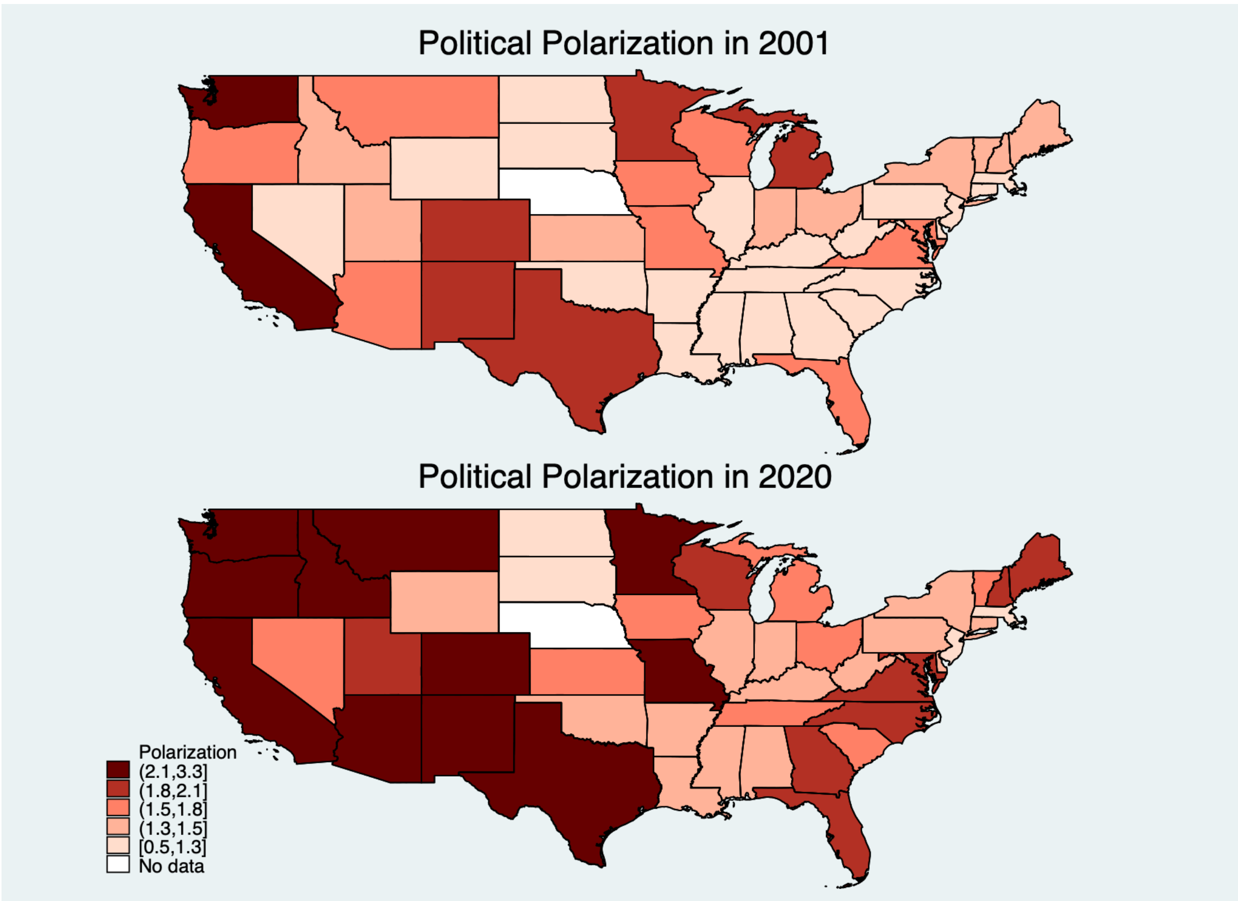

Table I: Summary Statistics of Polarization

Panel A presents summary statistics of Polarization (h_diffs) for the sample period 2001 to 2020. This measure captures the difference in the median ideal points of House Democrats and Republicans. Panel B lists the five most polarized and five least polarized states over time based on h_diffs. Panel C reports the transition matrix of states moving between being polarized and not polarized over time. In Panel C, *Polarized* takes the value one if h_diffs is above the sample median and zero otherwise. See Appendix I for detailed variable descriptions.

Panel A: Summary Statistics of Polarization (h_diffs)

Variable	**N**	**Mean**	**p25**	**Median**	**p75**	**SD**
Polarization (h_diffs)	976	1.549	1.207	1.483	1.851	0.498

Panel B: Most and Least Polarized States Using h_diffs

Year	**2001**	**2005**	**2010**	**2015**	**2020**
States with highest polarization	CA	CA	CA	CA	CO
	WA	AZ	AZ	CO	CA
	NM	WA	CO	AZ	TX
	MN	TX	WA	TX	NM
	CO	NM	TX	WA	AZ
States with lowest polarization	HI	KY	DE	ND	ND
	AR	MS	AR	LA	NJ
	MS	HI	LA	SD	SD
	LA	AR	HI	HI	HI
	RI	LA	RI	RI	RI

Panel C: Polarization Transition Matrix Using h_diffs

	Overall		**Between**		**Within**
	Freq	**Percent**	**Freq**	**Percent**	**Percent**
Polarized=0	488	50	33	67.35	74.55
Polarized=1	488	50	32	65.31	76.25
Total	927	100	65	132.65	75.38

Table II: Summary Statistics of Analyst Dispersion and Control Variables

Panel A reports the number of analysts 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. Panel B presents summary statistics of the dispersion in analysts' earnings forecasts for fiscal year one over the period 2001–2020. Analyst forecast dispersion is the standard deviation of analyst forecasts scaled by the absolute value of the mean forecasts and measured at the firm-state-quarter level, where state relates to the location of the analyst issuing the forecast. We report summary statistics for the full sample and within the five states with the largest number of analyst-state observations. Panel C presents statistics for the main firm- and state-level control variables also summarized at the firm-state-quarter level. Definitions for all variables are in Appendix I.

Panel A: Number of Analysts by State

	NY	CA	IL	TX	MA	MN	OH	FL	VA
Number	3,806	614	327	217	170	164	117	106	103
Fraction	59.45%	9.59%	5.11%	3.39%	2.66%	2.56%	1.83%	1.66%	1.61%

Panel B: Forecast Dispersion (Firm-St-Qtr)

State	**N**	**Mean**	**p25**	**Median**	**p75**	**SD**
NY	159,502	0.218	0.018	0.052	0.153	0.567
CA	27,423	0.195	0.014	0.041	0.127	0.542
IL	14,191	0.101	0.007	0.019	0.062	0.353
TX	10,732	0.397	0.042	0.115	0.337	0.793
MA	5,686	0.099	0.005	0.017	0.060	0.355
Total	256,211	0.207	0.015	0.045	0.141	0.556

Panel C: Control Variables

Variable	**N**	**Mean**	**p25**	**Median**	**p75**	**SD**
ME (log)	250,654	7.774	6.587	7.710	8.925	1.730
BM	249,928	0.505	0.217	0.400	0.679	0.457
Turnover (log)	250,547	-0.636	-1.104	-0.626	-0.128	0.802
Number of analysts (log)	256,209	2.261	1.792	2.303	2.773	0.659
HHI	256,211	0.741	0.505	0.722	1.000	0.259
GDP Growth	255,840	0.015	0.004	0.019	0.030	0.022
Republican	255,840	0.107	0.000	0.000	0.000	0.309
Firm HQ is in the state	256,211	0.148	0.000	0.000	0.000	0.355
EPU	256,211	0.937	0.44	0.65	0.94	1.064
Earnings volatility	231,459	0.123	0.020	0.041	0.087	1.598

Table III: The Effect of Polarization on Analyst Forecast Dispersion

This table presents the effect of polarization on analyst forecast dispersion over the 2001 to 2020 sample period. The dependent variable in all columns is analyst forecast dispersion measured at the firm-state-quarter level, where state represents location of the analysts. The independent variable is polarization as measured by h_diffs. All variables are defined in Appendix I. The columns progressively add control variables and fixed effects. Columns 4 to 7 report results based on the specification in Equation 1. Column 5 excludes analysts based in New York. Column 6 excludes analysts in New York *and* observations with fewer than 4 analysts. Column 7 restricts the sample only to analysts in New York. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	Forecast dispersion (Firm-St-Qtr)						
	(1)	(2)	(3)	(4)	(5) No NY	(6) No NY & N >= 4	(7) NY Only
Polarization(h_diffs)	0.034***	0.019***	0.255***	0.142*	0.286***	0.738***	0.821***
	(15.043)	(7.371)	(3.056)	(1.765)	(3.109)	(3.483)	(4.558)
ME (log)		-0.038***	-0.064***	-0.077***	-0.069***	-0.078*	-0.068***
		(-39.091)	(-8.621)	(-9.309)	(-5.188)	(-2.140)	(-8.647)
BM		0.132***	0.104***	0.091***	0.058**	0.018	0.121***
		(49.639)	(4.457)	(4.318)	(2.205)	(0.412)	(6.635)
Turnover (log)		0.037***	0.041***	0.039***	0.039***	0.070*	0.042***
		(22.846)	(6.611)	(6.192)	(4.424)	(2.144)	(6.015)
Number of analysts (log)		0.028***	0.028***	0.026***	0.038*	0.002	0.023***
		(9.734)	(4.694)	(4.089)	(1.960)	(0.047)	(4.535)
HHI		0.046***	-0.026***	-0.018***	-0.002	0.095*	-0.026***
		(8.495)	(-3.131)	(-3.751)	(-0.135)	(1.826)	(-3.505)
Earnings volatility		0.187***	0.044	0.081	0.110	0.046	0.032
		(21.889)	(0.656)	(1.250)	(0.841)	(0.146)	(0.441)
GDP Growth		-0.024	-0.038	-0.175	-0.491	-1.523	0.555
		(-0.371)	(-0.128)	(-1.052)	(-1.505)	(-1.436)	(1.273)
Republican		0.045***	-0.012	-0.016	-0.025	0.013	
		(11.938)	(-0.925)	(-1.356)	(-1.251)	(0.207)	
Firm HQ is in the state		-0.011***	0.004	0.003	0.004	-0.087*	-0.036
		(-3.299)	(0.656)	(0.556)	(0.813)	(-2.076)	(-1.552)
EPU		0.029***	0.031***	0.024***	0.019***	0.016	0.039***
		(21.908)	(9.014)	(8.368)	(5.191)	(1.572)	(6.526)
Constant	0.151***	0.280***	0.175	0.475***	0.036	-0.866	-0.549*
	(38.586)	(27.423)	(1.298)	(3.657)	(0.169)	(-1.296)	(-2.066)
Observations	255,840	229,149	228,693	228,693	87,695	9,682	140,570
R-squared	0.001	0.044	0.235	0.238	0.239	0.286	0.261
Firm FE	No	No	Yes	Yes	Yes	Yes	Yes
State (St) FE	No	No	Yes	Yes	Yes	Yes	No
Year (Yr) FE	No	No	No	Yes	Yes	Yes	No
Clustered SE	No	No	St&Yr	St&Yr	St&Yr	St&Yr	Yr

Table IV: Politically Contentious Stocks and ESG Scores

This table presents the effect of polarization on forecast dispersion conditional on a firm belongings to a politically contentious industry and its ESG characteristics. The dependent variable is analyst forecast dispersion measured at the firm-state-quarter level, where state represents location of the analysts. Column 1 reports the estimation results of Equation 2 over the sample period 2001 to 2020 with politically contentious industries identified using the indicator variable *Contentious*. Columns 2 to 5 report regression results for Equation 2 using ESG data from Sustainalytics over the period 2009 to 2019. ESG scores are divided by 100 for better display of coefficients. All variables are defined in Appendix I. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	Forecast Dispersion (Firm-St-Qtr)				
	(1)	(2)	(3)	(4)	(5)
Polarization (h_diffs)	0.118	0.108	0.117	0.148	0.214*
	(1.637)	(1.269)	(1.366)	(1.642)	(1.957)
Contentious x Polarization	0.070***				
	(6.625)				
ESG Score x Polarization		0.138**			
		(2.821)			
S Score x Polarization			0.147***		
			(4.007)		
E Score x Polarization				0.094**	
				(2.652)	
G Score x Polarization					-0.009
					(-0.210)
Observations	228,693	69,284	63,756	63,756	63,756
R-squared	0.238	0.294	0.264	0.264	0.263
Firm FE	Yes	Yes	Yes	Yes	Yes
State (St) FE	Yes	Yes	Yes	Yes	Yes
Year (Yr) FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	St&Yr	St&Yr	St&Yr	St&Yr	St&Yr

Table V: Polarization and Forecast Revisions

This table presents the effect of polarization on forecast revisions conditional on a firm belongings to a politically contentious industry and its ESG characteristics. Panel A reports summary statistics of all forecast revisions, and revisions of Republican and Democratic analysts separately over the sample period 2001 to 2020. Panel B presents estimation of Equation 3. The dependent variable in all columns is *Forecast Revision*. The sample period for columns 1 and 5 is 2001 to 2020. For columns 2 to 4 and 6 to 8, which use ESG data from Sustainalytics, the sample period is 2009 to 2019. For variable description see Table IV and Appendix I. 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**
Polarization	579,989	1.535	1.420	1.467	1.479	0.325
Forecast Revision	581,312	-0.012	-0.920	0	0.911	1.879
Forecast Revision (Republican only)	237,226	-0.041	-0.942	-0.034	0.871	1.885
Forecast Revision (Democratic only)	344,086	0.007	-0.904	0	0.938	1.874

Panel B: Forecast Revision

	Democratic Analysts				Republican Analysts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Polarization	0.042	0.244	0.227	0.247*	-0.326	0.707	0.146	0.590
	(0.419)	(1.252)	(1.552)	(1.858)	(-1.402)	(1.456)	(0.382)	(1.186)
Contentious x	-0.389***				0.238			
Polarization	(-5.063)				(0.988)			
ESG Score x		-0.120				-1.617**		
Polarization		(-0.330)				(-2.781)		
S Score x			-0.048				-0.642	
Polarization			(-0.189)				(-1.657)	
E Score x				-0.091				-1.348***
Polarization				(-0.422)				(-2.939)
Observations	307,507	127,710	122,687	122,687	210,979	81,370	77,784	77,784
R-squared	0.145	0.152	0.138	0.138	0.144	0.147	0.131	0.131
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	State	State	State	State	State	State	State	State

Table VI: Instrumental Variable Analysis

This table presents the effect of polarization on analyst forecast dispersion using immigration as an instrument for polarization. Column 1 of Panel A reports first stage results from Equation 6. Column 2 reports second stage estimates of Equation 5 for the full sample. Columns 3 (Column 4) reports second stage estimates excluding analysts in New York (including only analysts in New York). Panel B reports second-stage results (in the full sample) conditional on the the firm's industry being politically contentious and its ESG score, S, and E score. The sample period is 2001 to 2020, except for regressions involving ESG scores, where the sample period is 2009 to 2019. *Republican* (or *Rep.*) is an indicator variable for Republican states. For variable description see Appendix I. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A

	First Stage: Polarization	**Second Stage: Forecast Disp. (Firm-St-Qtr)**		
	(1)	(2) Full sample	(3) No NY	(4) NY only
State immigration x Rep.	0.052***			
	(5.262)			
$\widehat{Polarization}$		0.112	0.555***	0.896***
		(0.975)	(2.279)	(4.434)
State immigration	-0.285***			
	(-8.290)			
Republican	0.252***			
	(3.847)			
F-statistic	53.21			
Observations	224,330	224,330	86,742	137,176
Firm FE	Yes	Yes	Yes	Yes
State(St) FE	Yes	Yes	Yes	No
Year(Yr) FE	Yes	Yes	Yes	No
Clustered SE	St&Yr	St&Yr	St&Yr	Yr

Panel B: Forecast Dispersion (Firm-St-Qtr) in the Full Sample

	(1)	(2)	(3)	(4)
$\widehat{Polarization}$	0.066	0.310	0.318	0.387
	(0.616)	(1.344)	(1.656)	(1.642)
Contentious x $\widehat{Polarization}$	0.111***			
	(4.347)			
ESG Score x $\widehat{Polarization}$		0.265***		
		(3.437)		
S Score x $\widehat{Polarization}$			0.228***	
			(3.144)	
E Score x $\widehat{Polarization}$				0.159**
				(2.239)
Observations	224,330	63,759	63,759	63,759
Firm, State (St), Year (Yr) FE	Yes	Yes	Yes	Yes
Clustered SE	State	St&Yr	State	St&Yr

Table VII: Using a Firm-Level Measure of Polarization

This table presents a firm-level analysis of the effect of political polarization on analyst forecast dispersion. Panel A reports the summary statistics of the dependent variable, *Forecast Dispersion*, the main independent variable, *Firm_polar*, and several control variables over the sample period 2001 to 2020. All variables are summarized at the firm-quarter level. See Section III subsection E for a description of how *Firm_polar* is constructed. Panel B reports estimates of Equation 7, where analyst forecast dispersion is regressed on Firm_polar. Detailed variable description is in Appendix I. 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
Forecast Dispersion (Firm)	177,728	0.228	0.019	0.054	0.157	0.602
Firm_polar	177,828	0.407	0.081	0.400	0.667	0.354
Market cap (billions)	173,505	9.407	0.583	1.789	5.877	34.133
BM	172,988	0.514	0.228	0.417	0.692	0.457
Turnover (millions)	173,426	0.669	0.305	0.494	0.810	0.630
Number of analysts	177,826	9.901	5	8	13	6.566
Earnings volatility	158,721	0.091	0.019	0.039	0.086	0.171

Panel B: Forecast Dispersion (Firm-Qtr)

	(1)	(2)	(3)	(4)
Firm_polar	0.013***	0.022***	0.020***	0.022***
	(3.269)	(5.139)	(2.880)	(2.636)
ME (log)		-0.043***	-0.084***	-0.023**
		(-35.307)	(-12.758)	(-2.087)
BM		0.145***	0.118***	0.087***
		(41.689)	(10.217)	(4.527)
Turnover (log)		0.042***	0.041***	0.038***
		(21.060)	(8.324)	(6.630)
Number of analysts (log)		0.028***	0.037***	0.023***
		(8.608)	(5.050)	(3.151)
Earnings volatility		0.109***	0.052	
		(11.518)	(0.945)	
Observations	177,728	157,126	156,651	152,636
R-squared	0.000	0.037	0.259	0.567
Calendar-Quarter FE	No	No	Yes	No
Firm FE	No	No	Yes	No
Firm-by-Year FE	No	No	No	Yes
Clustered SE	No	No	Firm	Firm

Table VIII: Using Firm-level Measures of Polarization: Politically Contentious Stocks and ESG Scores

This table presents a firm-level analysis of the effect of polarization on forecast dispersion conditional on a firm belonging to a politically contentious industry and its ESG characteristics. The dependent variable, *Forecast Dispersion*, is the dispersion in analysts' earnings forecasts in a firm-quarter. The main independent variable, *Firm_polar*, is the standard deviation of analysts' ideal points in a firm-quarter. Both variables are measured at the firm-quarter level and summarized in Table VII. See Section III subsection E for a description of how *Firm_polar* is constructed. Column 1 reports the results of Equation 8 from interacting Firm_polar with the indicator variable *Contentious* over the sample period 2001 to 2020. Column 2 to 4 report regression results for Equation 8 interacting Firm_polar with ESG data from Sustainalytics over the period 2009 to 2019. For variable description see Table IV and Appendix I. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	Forecast Dispersion (Firm-Qtr)			
	(1)	(2)	(3)	(4)
Firm_polar	0.009	-0.174*	-0.107	-0.121*
	(1.271)	(-1.749)	(-1.271)	(-1.908)
Contentious x Firm_polar	0.123***			
	(4.221)			
ESG Score x Firm_polar		0.337*		
		(1.868)		
S Score x Firm_polar			0.209	
			(1.365)	
E Score x Firm_polar				0.252**
				(2.079)
ME (log)	-0.084***	-0.124***	-0.129***	-0.128***
	(-12.790)	(-7.675)	(-7.632)	(-7.584)
BM	0.117***	0.102***	0.105***	0.106***
	(10.139)	(3.334)	(3.285)	(3.344)
Turnover (log)	0.041***	0.085***	0.084***	0.086***
	(8.227)	(6.516)	(6.024)	(6.178)
Number of analysts (log)	0.037***	0.026	0.027	0.025
	(4.964)	(1.621)	(1.552)	(1.478)
Earnings volatility	0.050	0.335	0.350	0.346
	(0.913)	(1.364)	(1.413)	(1.386)
Observations	156,652	40,063	36,148	36,148
R-squared	0.259	0.351	0.314	0.315
Calendar-Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm

Table IX: Future Return Predictability

This table reports two-step Fama-MacBeth regression of future stock return on firm-level polarization. In each quarter, we perform cross-sectional regressions of next-quarter stock returns on current quarter firm polarization (*Firm_polar*) and the following control variables: analyst forecast dispersion as in Diether et al. (2002), the firm's market beta, market capitalization, book-to-market ratio, investment, profitability, prior returns (PrRet), standardized unexpected earnings (SUE), and leverage ratio. The sample period is from the first quarter of 2001 to the last quarter of 2020. Stocks with price less than $1 and those belonging to the financial or utilities sectors are dropped. Detailed variable description is in Appendix I. Newey-West t-statistics based on four lags are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	Future Returns			
	(1)	(2)	(3)	(4)
Firm_polar	-0.009**	-0.008**	-0.007**	-0.007**
	(-2.423)	(-2.388)	(-2.120)	(-2.025)
Forecast dispersion	-0.005**	-0.005**	-0.003	-0.003
	(-2.069)	(-2.170)	(-1.420)	(-1.554)
Mkt_beta	0.006	0.004	0.005	0.004
	(0.888)	(0.644)	(0.910)	(0.778)
ME (log)	-0.004**	-0.004**	-0.005***	-0.005***
	(-2.191)	(-2.273)	(-3.069)	(-3.055)
BM	0.001	0.002	0.002	0.002
	(0.248)	(0.339)	(0.402)	(0.436)
Investment	-0.000	0.001	-0.004	-0.004
	(-0.064)	(0.157)	(-0.584)	(-0.568)
Profitability	0.023***	0.023***	0.020***	0.020***
	(4.736)	(4.714)	(4.023)	(3.934)
PrRet		-0.004	-0.012	-0.013
		(-0.394)	(-1.147)	(-1.172)
SUE			0.007***	0.007***
			(8.546)	(8.890)
Leverage				0.003
				(0.517)
Constant	0.056***	0.056***	0.059***	0.059***
	(3.535)	(3.448)	(3.744)	(3.825)
Adj. R^2	0.071	0.078	0.089	0.094

Table X: Value-Weighted Polarization Portfolios and Factor Models

This table reports alphas from multi-factor time series models on value-weighted polarization quintiles formed using NYSE breakpoints of the firm-level polarization variable *Firm_polar* described in Section III subsection E. Value-weighted portfolio returns are calculated using one-quarter lagged market capitalization. Column 1 uses the Fama-French three-factor model $R_{it} - R_{Ft} = \alpha_i + b_{iM}(R_{Mt} - R_{Ft}) + s_i SML_t + h_i HML_t + e_{it}$. The market premium, $(R_M - R_F)$ uses the NYSE/AMEX/Nasdaq value-weighted index from CRSP. The size and value premiums SMB and HML are constructed following Fama and French (1996). Column 2 augments the three-factor model with the momentum factor. The momentum premium UMD, obtained from Kenneth French's website, is constructed as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. Column 3 uses the Fama-French 5-factor model $R_{it} - R_{Ft} = \alpha_i + b_{iM}(R_{Mt} - R_{Ft}) + s_i SML_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}$. The investment and profitability premiums CMA and RMW are constructed following Fama and French (2015). Column 4 augments the five-factor model with the momentum factor. The sample period is the second quarter of 2001 through the last quarter of 2020. Stocks with a price of less than $1 and in the financial or utilities sectors are dropped. Detailed variable description is in Appendix I. The Newey-West t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	Alpha (%)			
	FF3F	FF3F+MOM	FF5F	FF5F+MOM
	(1)	(2)	(3)	(4)
P1	0.132	0.177	0.124	0.131
	(0.598)	(0.886)	(0.558)	(0.594)
P2	0.422**	0.475**	0.322*	0.334**
	(2.286)	(2.595)	(1.978)	(2.214)
P3	-0.164	-0.047	-0.027	-0.012
	(-0.932)	(-0.250)	(-0.113)	(-0.056)
P4	-1.059**	-1.032***	-0.992***	-0.990***
	(-2.567)	(-2.764)	(-2.642)	(-2.654)
P5	-0.917*	-1.040**	-0.926*	-0.947*
	(-1.753)	(-2.198)	(-1.866)	(-1.938)
P1-P5	1.049**	1.218***	1.050**	1.078**
	(2.082)	(2.634)	(2.031)	(2.120)

Table XI: Acquirer Cumulative Abnormal Returns

This table examines the impact of political polarization on acquirer cumulative abnormal returns over the sample period 2001 and 2020. Panel A presents summary statistics of the dependent variable, $CAR_{-1,+1}$, the main explanatory variable, *Firm_polar*, and several deal-level control variables. $CAR_{-1,+1}$ is the acquirers' market-adjusted cumulative abnormal return calculated over a three-day window surrounding the announcement of the merger. *Firm_polar_ann* is the standard deviation of ideal points of analysts covering a firm during the merger announcement year. Panel B reports the regression results. Columns 1 and 2 focus on the subsample of firms in politically contentious industries, and columns 3 and 4 present results of all other industries. Columns 5 and 6 include the full sample with an interaction of Firm_polar_ann with an indicator variable that captures politically contentious industries. Coefficient estimations of control variables are omitted for brevity. Firm-level control variables are measured one quarter prior to the deal announcement quarter. Detailed variable description is in Appendix I. 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
$CAR_{-1,+1}$	15,309	0.007	-0.018	0.004	0.029	0.053
Firm_polar_ann	15,309	0.632	0.505	0.672	0.808	0.256
Pct. Stock	15,309	12.768	0.000	0.000	0.000	28.996
ME (log)	15,309	7.697	6.491	7.515	8.743	1.706
BM	15,309	0.455	0.255	0.407	0.607	0.272
Tender	15,309	0.028	0.000	0.000	0.000	0.164
Public target	15,309	0.157	0.000	0.000	0.000	0.364
Friendly	15,309	0.992	1.000	1.000	1.000	0.091
Relative size	15,309	0.143	0.014	0.044	0.131	0.331

Panel B

	$(CAR_{-1,+1})$					
	Contentious Ind.		**Other Ind.**		**All Ind.**	
	(1) Mixed	**(2) All cash**	**(3) Mixed**	**(4) All cash**	**(5) Mixed**	**(6) All cash**
Firm_polar_ann	-0.016**	0.002	-0.000	-0.003	-0.000	-0.002
	(-2.756)	(0.134)	(-0.087)	(-0.850)	(-0.043)	(-0.717)
Firm_polar_ann x Contentious					-0.018***	0.001
					(-3.378)	(0.083)
Observations	905	387	8,837	4,953	9,742	5,342
All controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.147	0.169	0.079	0.109	0.083	0.109
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Industry	Industry	Industry	Industry	Industry	Industry

Appendix

I. VARIABLE DESCRIPTION

Forecast dispersion (Firm-St-Qtr): The standard deviation of forecasts issued by analysts located in each state in each quarter scaled by the absolute value of the mean of forecasts by analysts located in each state in each quarter. The variable is winsorized at the 1% and 99% level and is at firm-state-quarter level.

Forecast dispersion (Firm-Qtr): The standard deviation of forecasts issued by analysts located in all states in each quarter scaled by the absolute value of the mean of forecasts by analysts located in all states in each quarter. The variable is winsorized at the 1% and 99% level and is at firm-quarter level.

BM: Common/ordinary equity value (ceqq) scaled by the market capitalization. This variable is winsorized at the 1% and 99% level and at is firm-quarter level.

$\mathbf{CAR_{-1,+1}}$: Market adjusted cumulative abnormal returns calculated over a three-day window surrounding the announcement of a merger. This variable is winsorized at the 5% and 95% level and is at deal level.

Complexity: A text-based measured defined as the percentage of a company's 10-K filing that consists of specific 'complexity words' as in Loughran and McDonald (2024). This variable is at firm-year level.

Contentious: An indicator variable taking value of 1 if the stock is the following industries: 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), Alcohol (SIC codes 2080, 2082-2085), and Healthcare (SIC codes 8011-8099). We also classify Gambling industry if the company name contains word *'casino'*. This variable is at firm level.

Earnings volatility: Ratio of EBIT to total assets over a trailing ten-year window at firm-year level. We require firms to have at least 4 years of data (Graham et al., 2015). This variable is winsorized at the 1% and 99% level and is at firm-year level.

E Score: The environmental component of a firm's ESG score. This variable is divided by 100 for better display of coefficients and the data source is Sustainlytics.

Election: An indicator variable taking value 1 if the sample period is a U.S. Presidential Election year, namely 2004, 2008, 2012, 2016, 2020.

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 divided by 100 for better display of coefficients and is at state-quarter level.

ESG: An overall numeric score measuring an organization's performance on environmental, social, and governance issues. This variable is divided by 100 for better display of coefficients and the data source is Sustainlytics.

Firm HQ is in the state: An indicator variable taking value of 1 if the headquarter of the firm is in the same state as the analyst covering it. This variable is at firm-quarter level.

Firm_polar: The standard deviation of ideal points assigned to analysts. See Section III subsection E for a description of how ideal points are assigned to analysts. This variable is winsorized at the 1% and 99% level and is at firm-quarter level.

Firm_polar_ann: The standard deviation of ideal points of analysts covering an acquirer during the merger announcement year. See Section III subsection E for a description of how ideal points are assigned to analysts. This variable is at the deal level.

Forecast revision: A measure of the difference between the current annual forecast issued by analyst i covering firm j in quarter q and the annual forecast issued immediately before the current one, scaled by the standard deviation of forecasts of all analyst forecasts covering firm j in quarter q, as in Hirshleifer et al. (2019). This variable is at analyst-firm-quarter level and winsorized at the 1% and 99% level.

Fraction of misaligned: The fraction of analysts covering a firm who do not belong to the same party as the US President. This variable is at firm-state-quarter level.

Friendly: An indicator variable taking value 1 if the deal is not hostile. This variable is at deal level.

G Score: The governance component of a firm's ESG score. This variable is divided by 100 for better display of coefficients and the data source is Sustainlytics.

GDP Growth: Year-on-year percentage change of the state's gross domestic product. This variable is at state-year level.

HHI: A geographical concentration measure of analysts covering the firm as in Gerken and Painter (2022). It lies between 0 and 1, with a higher value indicating that analysts from fewer different states cover the firm. This variable is at firm-quarter level.

h_diffs (same as *Polarization*): The difference in the median ideal point of House Democrats and Republicans. This variable is at the state-year level.

h_distance: A party-free measure of the average ideal point distance between any two House members. This variable is at the state-year level.

Investment: The difference between t-2 quarter's total assets (atq) and t-1 quarter's total assets scaled by t-2 quarter's total assets. This variable is at firm-quarter level.

Leverage: The ratio of book debt (Compustat Quarter item dlttq plus dlcq) over the sum of book debt and book equity. This variable is winsorized at the 1% and 99% level and at firm-quarter level.

ME: Quarterly close price (prccq) multiplied by the number of common shares outstanding (cshoq) measured at the end of each fiscal quarter. This variable is at the firm-quarter level and in logarithm form.

Number of analysts: The number of analysts following the firm in each quarter. This variable is at the firm-quarter level and in logarithm form.

Pct_stock: Percentage of merger consideration paid in stock. This variable is at the deal level.

Polarization (same as *h_diffs*): The difference in the median ideal point of House Democrats and Republicans. This variable is at the state-year level.

Profitability: Ratio of last quarter's revenue (revtq) minus last quarter's cost of goods sold (cogsq) minus last quarter's selling, general, and administrative expenses (xsgaq) minus last quarter's interest expense (xintq) to last quarter's book equity. This variable is at firm-quarter level.

PrRet: The cumulative return between months t-12 and t-3. This variable is adjusted for delistings and at the firm-quarter level.

Public target: An indicator variable taking the value 1 if the target is a public firm. This variable is at the deal level.

Recessions: An indicator variable taking the value 1 if the sample period is one of the NBER recessionary years, namely 2001, 2002, 2007 to 2009, and 2020.

Relative size: The ratio between the deal value and the acquirer's market capitalization. This variable is at the deal level.

Republican: An indicator variable taking the value 1 if the state where the analyst is located voted for the Republican candidate in the most recent presidential election. 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.

s_distance: A party-free measure of the average ideal point distance between any two Senate members. This variable is at state-year level.

Simulated firm_polar: Alternative firm-level polarization measure. Constructed using a bootstrapping approach. In each iteration, we assign each analyst an ideal point randomly (with replacement) drawn from legislators in the analyst's state and compute the standard deviation of these assigned ideal points for each firm-quarter. We repeat this process 1,000 times and calculate the mean of the 1,000 standard deviations. This variable is winsorized at the 1% and 99% level and at firm-quarter level.

S Score: The social component of a firm's ESG score. This variable is divided by 100 for better display of coefficients and the data source is Sustainlytics.

State immigration: The shift-share predicted number of immigrants for each state in each year, constructed as the product of the actual national-level number of immigrants from each source country and the pre-existing share (% of the state population) of foreign born populations from each source country in each state, summed up across all source countries. This variable is at state-year level.

SUE: Standardized unexpected earnings defined as quarterly unexpected earnings (UE) divided by the standard deviation of UE. UE is the reported quarterly earnings per share (EPS) in excess of EPS four quarters ago. The standard deviation of UE is calculated over the past eight quarters or a minimum of four quarters. This variable is at firm-quarter level.

Tender: An indicator variable taking value 1 if the merger involves a tender offer. This variable is at the deal 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 and in logarithm form.

Unemployment rate: Annual measure of the percentage of unemployed labor force in a state obtained from the U.S. Bureau of Labor Statistics (BLS). This variable is at state-year level.

Internet Appendix

IA.I. Additional Information on the Polarization Measure

Table IA.I: Summary Statistics for Polarization Measures

This table presents summary statistics for the three remaining state-level legislative polarization measures from Shor and McCarty (2011) for the sample period 2001 to 2020. The measures are as follows: 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). See Appendix I for detailed variable descriptions.

Summary Statistics of Polarization Measures

Variable	N	Mean	p25	Median	p75	SD
s_diffs (Senate difference in party medians)	983	1.503	1.158	1.496	1.795	0.491
h_distance (Average distance between House members)	976	0.885	0.704	0.859	1.045	0.286
s_distance (Average distance between Senate members)	985	0.857	0.653	0.855	1.023	0.284

IA.II. Additional Tests Using the Firm-State-Quarter Level Sample

This section presents several robustness tests relating to Equation 1 and Equation 2 where forecast dispersion is measured at the firm-state-quarter level and polarization is measured at the state-year level. Table IA.II presents results using three alternative polarization measures with double clustering in full sample and subsamples. Table IA.III mitigates the concern that main results (from using the remaining polarization measures) are driven by forecast dispersion issued by few number of analysts in the same state. Table IA.IV presents summary statistics of ESG scores used in the subsample tests from 2009 to 2019. Table IA.V reports subsample testing results using remaining polarization measures with double clustering in the full sample.

Table IA.II: Using Other Measures of Polarization

This table presents the effect of polarization on analyst forecast dispersion over the sample period 2001 to 2020. The dependent variable in all columns is analyst forecast dispersion measured at the firm-state-quarter level, where state represents location of the analysts. The independent variable is three alternative polarization measures, s_diffs, h_distance, s_distance. All variables are defined in Appendix I. Column 1 to 3 report full sample results. Column 4 to 6 report results excluding analysts based in New York. Column 7 to 9 are restricted only to analysts in New York. t-statistics, based on standard errors that allow for double-clustering at the state and year levels, are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	Forecast Dispersion (Firm-St-Qtr)								
	Full sample			No NY			NY only		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
s_diffs	0.095			0.143			0.117**		
	(1.491)			(1.405)			(2.100)		
h_distance		0.241***			0.321***			0.573**	
		(2.277)			(3.062)			(2.670)	
s_distance			0.362***			0.427***			0.883***
			(3.033)			(5.517)			(6.710)
Observations	228,690	228,693	228,690	87,692	87,695	87,692	140,570	140,570	140,570
R-squared	0.238	0.238	0.238	0.238	0.239	0.239	0.260	0.260	0.261
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Double	Double	Double	Double	Double	Double	Double	Double	Double

Table IA.III: Excluding New York Analysts and Observations with Few Analysts

This table reports results using specification Equation 1 and the same polarization measures as in Table IA.II. Panel A only retains firm-state-quarter observations whose dispersion is calculated using 4 or more analyst forecasts. Panel B combines the restrictions from Panel A and excludes analysts based in New York. The dependent variable in all panels is analyst forecast dispersion measured at the firm-state-quarter level, where state represents location of the analysts. The independent variable is three alternative polarization measures, respectively. t-statistics, based on standard errors that allow for double-clustering at the state and year levels, are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: Excluding Analyst Count < 4

	Forecast Dispersion (Firm-St-Qtr)		
	(1)	(2)	(3)
s_diffs	0.371*		
	(2.121)		
h_distance		0.414***	
		(6.140)	
s_distance			0.427***
			(5.517)
Observations	85,653	85,653	85,653
R-squared	0.295	0.295	0.295
Controls, Full FE, Double Clustering	Yes	Yes	Yes

Panel B: Excluding NY and Analyst Count < 4

	Forecast Dispersion (Firm-St-Qtr)		
	(1)	(2)	(3)
s_diffs	0.621***		
	(2.374)		
h_distance		0.525***	
		(3.290)	
s_distance			0.427***
			(5.517)
Observations	9,682	9,682	9,682
R-squared	0.285	0.284	0.284
Controls, Full FE, Double Clustering	Yes	Yes	Yes

Table IA.IV: ESG Score Summary Statistics

This table reports the summary statistics of ESG scores. We use the legacy ESG data with scores ranging from 0 to 100, with higher values indicating better performance. Data is for the period 2009 to 2019. Summary statistics values are based on scores divided by 100 for better display of coefficients.

Variable	**N**	**Mean**	**p25**	**p50**	**p75**	**SD**
Total score	72,123	0.546	0.482	0.528	0.600	0.084
S score	65,890	0.541	0.464	0.532	0.607	0.101
E score	65,890	0.511	0.412	0.488	0.591	0.127
G score	65,890	0.633	0.578	0.636	0.690	0.084

Table IA.V: Politically Contentious Stocks and ESG Scores

This table runs the same regression as in Table IV, with three alternative measures of polarization: s_diffs, h_distance, and s_distance. The dependent variable in all regressions presented in this table is analyst forecast dispersion. Panel A reports estimates of Equation 2 with politically contentious industries identified using the indicator variable *Contentious*. In column 1 of Panel A, polarization is measured as s_diffs. In columns 2 and 3, polarization is measured as h_distance and s_distance, respectively. Panel B reports estimates of Equation 2 with polarization measures interacted with ESG scores. In Panel B, each cell represents a separate regression but only the coefficient on the interaction of polarization and ESG score is presented. The row label indicate the polarization measure used, while the column titles indicate the ESG score being used. All cells (regressions) include both firm- and state-level control variables and firm-, state-, and year-fixed effects. t-statistics, based on standard errors that allow for double-clustering at the state and year levels, are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: Interaction With Politically Contentious Stocks

	Forecast Dispersion (Firm-St-Qtr)		
Polarization measure used is:	(1) **s_diffs**	(2) **h_distance**	(3) **s_distance**
Polarization	0.067	0.198**	0.282***
	(1.202)	(2.198)	(3.249)
Polarization x Contentious	0.119***	0.128***	0.198***
	(3.614)	(8.250)	(5.871)
Observations	228,690	228,693	228,690
R-squared	0.238	0.238	0.238
Controls	Yes	Yes	Yes
Firm, State, Year FE, Double clustering	Yes	Yes	Yes

Panel B: Interaction With ESG Scores

	Forecast Dispersion (Firm-St-Qtr)			
Score measure used is:	(1) **Total score**	(2) **Governance**	(3) **Social**	(4) **Environmental**
s_diffs x score	0.141**	-0.023	0.154***	0.088**
	(2.460)	(-0.449)	(2.991)	(2.658)
	N=69,284	N=63,756	N=63,756	N=63,756
	R2=0.294	R2=0.263	R2=0.263	R2=0.264
h_distance x score	0.319***	-0.035	0.313***	0.211**
	(3.365)	(-0.374)	(4.408)	(3.154)
	N=69,284	N=63,756	N=63,756	N=63,756
	R2=0.294	R2=0.264	R2=0.264	R2=0.265
s_distance x score	0.243**	-0.101	0.252**	0.145**
	(2.254)	(-0.835)	(2.922)	(2.418)
	N=69,284	N=63,756	N=63,756	N=63,756
	R2=0.295	R2=0.265	R2=0.265	R2=0.265

IA.III. Robustness Tests

In this section, we present a number of additional tests. Unless otherwise indicated, the tests follow the specification of Equation 1 and control variables are the same as in the baseline results shown in Table III.

First, we check whether our results are driven by across-party differences in ideologies or within-party differences. We identify Republican and Democratic analysts in our sample using party affiliation information from voter registries. We then calculate forecast dispersion for each firm-state-quarter using Republican (Democratic) analysts only and re-run Equation 1. Results are shown in column 1 (column 2) of Panel A Table IA.VI. The sample size in these regressions is noticeably smaller because party affiliation is available for only a subset of analysts. The coefficient on polarization is insignificant in both sub-samples, which suggests that our findings are driven by across-party differences in ideologies.

Next, we show that our main results are not driven just by analysts whose political party affiliation is different from that of the incumbent president. Kempf and Tsoutsoura (2021) show that credit analysts who are politically misaligned with the U.S. president adjust ratings downwards because of a more pessimistic view of the incumbent president's economic policy. In our context, if sell-side analysts who are misaligned with the party of the U.S. president revise their earnings forecasts downward relative to aligned analysts, we would observe an increase in forecast dispersion. To control for this possibility, we create a variable, *Fraction of misaligned*, to measure the fraction of analysts whose party is different from that of the incumbent president. We control for this variable in Equation 1 and present results column 1 to 3 of Table IA.VI - Panel B . Column 1 uses the full sample, column 2 excludes analysts in the state of New York, and column 3 focuses on NY only.[i] The sample size of this test shrinks significantly because party affiliation is available for only a subset of analysts. However, in all columns, we still observe a significantly positive coefficient on political polarization. The coefficient on the variable capturing misalignment is insignificant. Thus, our findings are not driven by misaligned analysts.

Past literature (e.g., Loughran and Mcdonald (2014), Lehavy et al. (2011), Loughran and McDonald (2024)) shows that firms with complicated, hard-to-read 10-K filings are related with an increased forecast dispersion by analysts. Using Equation 1, we include a control variable that measures the complexity of firm's 10-K filings (Loughran and McDonald, 2024). Column 4 to column 6 of Panel B in Table IA.VI show that our results are not driven by 10-K complexity.

[i] The covariance-variance matrix is singular when year-level clustering is introduced, possibly because NY accounts for 90% of total observations in this test. Thus, we only cluster at state-level.

We find that, after controlling for firm complexity, polarization remains significantly positively associated with forecast dispersion.

In Panel C in Table IA.VI we check whether our results are driven by heightened polarization or uncertainty during presidential election years. We create an indicator variable, *Election*, which takes value of 1 for the election years in our sample, namely 2004, 2008, 2012, 2016, and 2020. We interact this indicator variable with our polarization measure. The coefficient for the interaction term is insignificantly different from zero, suggesting that our findings are not stronger during election years. More importantly, the coefficient on our polarization measure remains positive and significant.

Residents of Republican states may be exposed to different information than residents of Democratic states due to the prevalence of different media outlets. We attempt to control for differences in the information environment analysts are exposed to by estimating Equation 1 within Republican-leaning states and Democratic-leaning states separately. Results are presented in Panel D of Table IA.VI, with Republican-leaning states only in column 1, Democratic-leaning states only in column 2, Democratic-leaning states excluding New York in column 3, and the state of New York only in column 4. We find that the coefficient on polarization is positive and significant within Republican-leaning states (column 1), Democratic-leaning states excluding New York (column 3), and within the state of New York alone (column 4). The lack of significance in column 2 appears to be due to the large weight of New York in the subsample of Democratic-leaning states combined with the inclusion of year-fixed effects (see the discussion on page 14 of the paper).

Table IA.VII shows additional robustness tests. 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 collapse forecast dispersion to the firm-state-year level by averaging across all quarters in a year and run the following regression

$$Forecast\ Dispersion_{i,s,y} = \beta Polar_{s,y} + X_{i,y} + Z_{s,y} + \psi_s + \delta_i + \theta_y + \epsilon_{i,s,y} \tag{10}$$

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 Table IA.VII - Panel A. Column 1 uses the full sample, column 2 excludes analysts in the state of New York, and column 3 focuses on NY only. In the full sample, the coefficient is positive and weakly significant at the 10% confidence level. However, in the subsamples in column 2 and 3, the relation between forecast disperstion and polarization is strongly significant at the 1% 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 (FPI=1). In this test, we look at the dispersion of earnings forecasts issued for fiscal year two (FPI=2) and fiscal year three (FPI=3) using the regression specified in Equation 1. Results for fiscal year 2 (fiscal year 3) are presented in columns 1 to 3 (columns 4 to 6) in Panel B of Table IA.VII. In column 1, the coefficient on polarization is not significant. However, when we split the sample into the disjoint subsamples of all states excluding New York (column 2), and the state of New York alone (column 3), we see the coefficient on polarization is significant at the 1% level in both subsamples. Moving on to forecast dispersion for fiscal year 3, we see that the coefficient on polarization is positive and significant in all three columns - i.e., in the full sample, the subsample excluding New York, and within New York only. Thus, our findings are robust to the fiscal period for which forecasts are issued.

In column 7 to 9 of Panel B, we examine whether our main results are driven by heightened uncertainty during recessionary years. In rational expectation models without short-sale constraints, higher information uncertainty drives up differences in opinion (He and Wang, 1995 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. To control for this concern, we exclude NBER recession years (2001 to 2002, 2007 to 2009, and 2020) and re-run Equation 1. In the full sample (column 7), the coefficient on polarization becomes insignificant. However, as before this lack of significance arises from pooling New York together with other states while also including year fixed effects. In columns 8 and 9 respectively, we present the same analysis for the subsample of all states excluding New York and the subsample focused on the state of New York alone. We find that the coefficient on polarization is significant at the 1% level in both sub-samples.

Table IA.VI: Additional Robustness Checks

The dependent variable in all panels is forecast dispersion in a firm-state-quarter , where state represents the analyst's location. The main independent variable in all panels is polarization as measured by h_diffs. Column 1 (Column 2) in Panel A limits the sample to Republican (Democratic) analysts only. In Panel B, columns 1 to 3 (columns 4 to 6) report regressions controlling for the fraction of misaligned analysts (complexity of 10-Ks) for the full sample, the subsample excluding New York, and the subsample of New York only. Panel C reports results from interacting polarization with presidential election years. Panel D presents the results of the subsample divided up based on political leanings of states. Detailed variable description is in Appendix I. The sample period is from 2001 to 2020. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: Subsamples by Analysts' Party

	Forecast Dispersion (Firm-St-Qtr)	
	(1) **R Analysts**	(2) **D Analysts**
Polarization	0.455	0.031
	(0.720)	(0.72)
Observations	36,736	53,603
R-squared	0.290	0.317
Controls	Yes	Yes
Firm,State,Year FE	Yes	Yes
Clustered SE	St&Yr	St&Yr

Panel B: Misalignment with US President and Complexity of 10-Ks

	Forecast Dispersion (Firm-St-Qtr)					
	(1) Full Sample	(2) No NY	(3) NY only	(4) Full Sample	(5) No NY	(6) NY only
Polarization	0.174**	0.319**	0.576***	0.141*	0.264***	0.702***
	(3.590)	(3.700)	(3.150)	(1.790)	(2.930)	(4.000)
Fraction of misaligned	-0.016	0.034	-0.027			
	(-0.810)	(0.700)	(-1.070)			
Complexity				0.016	0.018	0.024*
				(1.110)	(0.530)	(1.970)
Observations	25,278	2,472	22,745	199,616	77,808	121,442
R-squared	0.372	0.476	0.402	0.234	0.236	0.257
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No
State FE	Yes	Yes	No	Yes	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	St	St&Yr	Yr	St&Yr	St&Yr	Yr

Panel C: Election Years

	Forecast Dispersion (Firm-St-Qtr)		
	(1) Full Sample	(2) No NY	(3) NY only
Polarization	0.139*	0.283***	0.785***
	(1.790)	(3.150)	(4.290)
Election x Polarization	0.014	0.017	0.148
	(1.060)	(1.130)	(0.530)
Observations	228,693	87,695	140,570
R-squared	0.238	0.239	0.260
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	No
State FE	Yes	Yes	No
Firm FE	Yes	Yes	Yes
Clustered SE	St&Yr	St&Yr	Yr

Panel D: Subsamples by Republican and Analyst States

	Forecast Dispersion (Firm-St-Qtr)			
	(1) **R states**	(2) **D states**	(3) **D states No NY**	(4) **NY only**
Polarization	0.560***	0.043	0.129**	0.821***
	(3.350)	(0.990)	(2.690)	(4.560)
Observations	24,649	203,794	62,859	140,570
R-squared	0.256	0.243	0.243	0.261
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No
State FE	Yes	Yes	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Clustered SE	St&Yr	St&Yr	St&Yr	Yr

Table IA.VII: Annualized Dispersion, Different Forecasting Periods, Recessions

The dependent variable in Panel A is dispersion in earnings forecasts for fiscal year one, i.e. FPI=1, averaged to the firm-state-year level. In columns 1 to 3 (columns 4 to 6) of Panel B, the dependent variable is dispersion in earnings forecasts for fiscal year 2, i.e. FPI=2 (fiscal year 3, FPI=3) measured at the firm-state-quarter level. In columns 7 to 9 of Panel B, the dependent variable is the same as in our main regressions (i.e., dispersion in earnings forecasts for fiscal year 1 measured at the firm-state-quarter level) but the sample excludes recession years. The main explanatory variable in all regressions is Polarization measured by h_diffs. See detailed variable description in Appendix I. t-statistics, based on standard errors that allow for different levels of clustering, are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: Annual Forecast Dispersion (Firm-St-Qtr)

	(1) **Full Sample**	(2) **No NY**	(3) **NY only**
Polarization	0.107*	0.218***	0.881***
	(1.746)	(3.843)	(4.049)
Observations	57,000	23,928	32,204
R-squared	0.402	0.411	0.426
Controls	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes
Clustered SE	St&Yr	St&Yr	Yr

Panel B: Quarterly Forecast Dispersion (Firm-St-Qtr)

	FPI=2			**FPI=3**			**Excl. Rec.**		
	(1) Full	(2) No NY	(3) NY only	(4) Full	(5) No NY	(6) NY only	(7) Full	(8) No NY	(9) NY only
Polarization	0.141	0.310***	0.957***	0.258**	0.443***	1.053***	0.126	0.258***	0.717***
	(1.633)	(3.056)	(5.050)	(2.261)	(4.412)	(2.991)	(1.750)	(3.290)	(4.530)
Observations	230,632	89,622	140,572	97,708	17,341	79,802	171,964	68,926	102,641
R-squared	0.300	0.300	0.340	0.340	0.336	0.335	0.264	0.259	0.293
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	St&Yr	St&Yr	Yr	St&Yr	St&Yr	Yr	St&Yr	St&Yr	Yr

IA.IV. Additional Tests Relating to the IV Analysis

This section presents supplemental tests related to the instrumental variable analysis in subsection D of Section III.

Table IA.VIII: Actual Versus Predicted Immigrants

Panel A of this table presents the top and bottom five states in terms of the number of predicted immigrants following the shift-share methodology. Details on how this variable is estimated is in Section III subsection D. The numbers presented are calculated over the entire sample period, 2001 to 2020 for states with at least one analyst. Panel B reports a regression of the log transformed actual immigrants on the log transformed *State_immigration*, the shift-share predicted immigrants calculated in Equation 4. The sample period is from 2001 to 2020. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: States with the most and least predicted immigrants

State	**State**
States with the most immigrants	States with the least immigrants
CA	WV
TX	MT
NV	ND
AZ	ME
NM	SD

Panel B

	Actual immigration (logs)
State immigration (logs)	0.498***
	(59.07)
Observations	103,282
R-squared	0.765
Clustered SE	State & Year

Table IA.IX: Exclusion Tests

This table examines the exclusion restriction as discussed at the end of Section III subsection D. The dependent variables in columns 1 to 2 are state-level economic policy uncertainty, and average firm earnings volatility at state level, respectively. The independent variable in all passes include state-level variables and foreign-born share. All columns present the estimation using the second-stage sample. Detailed variable description is in Appendix I. The sample period is from 2001 to 2020. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	(1) State EPU	(2) Earnings Volatility
Foreign-born immigrants	-840.549	-3.213
	(-1.430)	(-0.310)
State EPU		-0.000
		(-0.040)
GDP growth	-76.821	0.015
	(-0.550)	(0.231)
Unemployment	8.286**	0.001
	(2.210)	(0.230)
Observations	250,549	250,549
R-squared	0.646	0.819
State controls	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes
Clustered SE	State&Year	State&Year

IA.V. Additional Tests Using the Firm-Level Sample

Table IA.X: Using the Simulation-Based Firm-Level Measure of Polarization

This table presents the effect of political polarization measured at the firm-quarter level on analyst earnings forecast dispersion. Panel A reports the summary statistics of an alternative measure of firm-quarter level polarization, namely *Simulated firm_polar*, defined in Section III footnote 29 as well as its correlation with the variable Firm_polar described in subsection E. In Panel B, we report results of regressing forecast dispersion on *Simulated firm_polar*. The dependent variable in all columns is analyst forecast dispersion at firm-quarter level. The regressions specifications are similar to those in Table VIII. The sample period is from 2001 to 2020 for columns 1 and 2 and 2009 to 2019 for remaining columns. Detailed variable description is in Appendix I. 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**
Simulated firm_polar	182,915	0.768	0.625	0.738	0.891	0.199
Correlation with *Firm_Polar*	0.5235					

Panel B: Forecast Dispersion (Firm-Qtr)

	(1)	(2)	(3)	(4)	(5)	(6)
Simulated firm_polar	0.064***	0.035**	-0.668***	-0.346*	-0.423***	-0.185
	(4.250)	(2.240)	(-2.770)	(-1.660)	(-2.620)	(-0.750)
Simulated firm_polar x Contentious		0.332***				
		(5.520)				
Polarization x ESG Score			1.366***			
			(3.070)			
Polarization x S Score				0.772**		
				(2.010)		
Polarization x E Score					0.990***	
					(3.060)	
Polarization x G Score						0.395
						(1.090)
Observations	160,381	160,381	40,107	36,172	36,172	36,172
R-squared	0.254	0.255	0.349	0.311	0.312	0.311
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm

IA.VI. INFORMATION ON POLITICAL AFFILIATION

A. Voter Registration Files

A.1. New York State

We obtain registered voter files from the New York State Board of Elections. The dataset includes each voter's full name, address, gender, date of birth, registration date, voter status, party affiliation, and voting history. Party affiliation is recorded as Democrat, Republican, or other (e.g., Conservative, Liberal, Green, etc.), or may be left blank. The data covers elections from 2002 to 2024, including General, Primary, Run-off, and Special Elections. Before merging with New York analyst data, we apply the following data cleaning steps:

- We retain only voters whose party affiliation is Democrat or Republican.
- We remove duplicate records based on first name, middle name, last name, and date of birth, ensuring that each observation is uniquely identified by full name and date of birth. There are 14,170 duplicates out of 9,481,044 total observations.

These steps result in a clean New York State voter file with static party affiliation and complete voter information.

A.2. New Jersey

We obtain the statewide registered voter list from the New Jersey Open Public Records Act (OPRA). The information in the New Jersey voter file is similar to that in New York but covers a different time period, spanning from 2007 to 2020. Party affiliation can be Democrat, Republican, other (e.g., Conservative, Green), or unaffiliated. We also remove duplicates based on first name, middle name, last name, and date of birth, resulting in 498 duplicates out of 4,197,451 observations.

A.3. California

Because California statewide voter data does not keep a historical voter list, we obtain registered voter file data from each county.

San Francisco County

We obtain the latest voter registration records from the City and County of San Francisco Department of Elections. This dataset includes a unique voter ID, the voter's full name, address, date of birth, and party affiliation. Party affiliation may be Democrat, Republican, another party (e.g., Conservative, Green), or blank. We drop records whose party affiliation is neither Democrat nor Republican, resulting in a file of 371,774 unique voters.

Orange County

We obtain the latest voter registration records from the Orange County Registrar of Voters. This file is similar in structure to that of San Francisco County, with unique voter ID, voter information, and party affiliation (Democrat, Republican, other, or blank). We retain only voters affiliated with either the Democratic or Republican parties, resulting in 1,337,492 unique observations.

Los Angeles County

We obtain the latest voter registration file from the Los Angeles County Department of RegistrarRecords/County Clerk. This file is also similar in structure to that of San Francisco County, with unique voter ID, voter information, and party affiliation (Democrat, Republican, other, or blank). We keep only voters whose party affiliation is either Democrat or Republican. The dataset contains 4,083,886 unique observations.

A.4. Florida

Pinellas County

We obtain registered voter data from the Pinellas County Supervisor of Elections. Pinellas County, which includes St. Petersburg, covers most of the Florida analysts in our sample. The data spans elections from 2006 to 2020 and contains 423,581 unique voter records with party affiliation recorded as either Democrat or Republican.

A.5. Illinois

City of Chicago

As all Illinois analysts in our sample are located in Cook County, which encloses the Greater Chicago area, we obtain City of Chicago voter registration data from the Illinois State Board of Elections. The data covers elections from 2018 to 2024. We keep only voters affiliated with either the Democratic or Republican parties, resulting in 657,281 unique records.

A.6. Ohio

Cuyahoga County

Because all Ohio analysts in our sample are located in Cuyahoga County, we obtain registered voter data from the Cuyahoga County Supervisor of Elections. The data covers the years 2006 to 2020. Party affiliation is listed as Democrat, Republican, or missing. We retain only records for voters affiliated with either the Democratic or Republican parties. The resulting file contains 895,977 unique voter observations.

B. Merging Analysts Data with Voter Registration Files

We merge the analyst dataset with the voter registration files from each relevant state or county. Analysts' state of employment and city of office are hand-collected, as described in subsection B. We match analysts to voter records in their corresponding state or county using the following procedure:

We match analysts and voters by first name, middle initial, and last name. In cases of multiple matches, we take further steps to identify the correct record. First, we search online for the analyst's age. If this information is unavailable, we infer age from the analyst's self-reported undergraduate graduation year on LinkedIn, assuming graduation occurs at age 22. If that is not available, we use the year of the analyst's first job to estimate age. If the analyst's middle name is missing or unavailable, we match using first and last name only and follow the same age estimation steps. We retain matches where the analyst and voter ages differ by three years or less. If no exact match can be found within this age window, we record the analyst's party affiliation as missing.

Using this approach, we obtain party affiliation for 1,858 analysts out of 4,797 from the states and counties described above.[ii]

[ii] This corresponds to a 39% match rate, which is consistent with previous literature (see Kempf and Tsoutsoura (2021)), given that Cook County, San Francisco County, and Cuyahoga County files contain a significant number of blank or missing party affiliations.