Partisan (Mis)Alignment and Earnings Forecast: Evidence from Sell-Side Analysts

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Abstract

How do partisan beliefs impact how analysts price securities? We use voter registration data of analysts to show that analysts whose party is not affiliated with the president have significantly lower earnings forecasts than other analysts. This effect is neutralized when competition increases in the sector. We examine heightened competition geographically by controlling for battleground states during election cycles. Additionally, we test national effects by controlling for greater partisan disagreement as measured in news feeds. We provide evidence that the impact of partisan bias is lessened during periods of heightened competition. Our results are robust to various fixed effects and clustering. They suggest that partisan beliefs manipulate asset prices.

Keywords: partisan bias, partisan conflict, partisan beliefs, earnings forecasts, competition, political division, asset pricing, analysts forecasts
JEL Codes:

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1 Introduction

1.1 Editorial

The polarization of political parties in the last decade has reached new heights. Discussions between parties, both on and off the platform, have often ended with heated disagreements and contentious resolutions. Between Republican and Democratic pundits, the projected outlooks differ greatly and take extreme swings in various directions over time, leading to brawling debates in government, the media, the workplace, and the family room. Each party wants to take credit for policies that benefit their base regardless of the consequences. The greater good seems to get lost in the scuffle. The optimal implementation of government policy may be blocked or stonewalled simply because of the political source of a policy. In the most extreme case, political division has led to a government shutdown. In the last decade, the government shut down for 54 days: 16 days in 2013, 3 days in 2018, and 35 days from 2018-2019. Prior to 2013, the government shut down for a total of 32 days in total. In light of shutdowns, the most extreme version of political disagreement, the U.S. political landscape appears more antagonistic than ever.

Maybe the shutdowns are simply a political stunt and don't impact the day-to-day workings of government. The following evidence demonstrates that political conflicts are not momentary diversions but continual prevailing sentiments in the political paradigm. The Federal Reserve Bank of Philadelphia has maintained the Partisan Conflict Index (PCI) since 1981 to measure the degree of political disagreement among U.S. politicians at the federal level. The PCI utilizes a search-based algorithm to measure the frequency of news reports on lawmakers' debate about policy. Figure 3 models a 12-month rolling average from 1981 to the present. From 1981 to mid-2010, we observe 12-month rolling averages from 75 to 114, with an overall average of 93.6 and a median of 91.9. Since mid-2010, those averages range from 98 to 213, with an overall average of 146.4 and a median of 146.2. The only time of relative peace since 2010 was during covid from May 2020 to March 2021, when the PCI ranged from 98 to 109. We observe a secular trend with a 50% jump in political conflict since 2010. The conflict appears to have weakened since Covid-19 but is still significantly higher than historical levels. We are interested in how political division impacts an individual's beliefs. We are interested in those beliefs that influence decision-making in the financial sector.

[Insert Figure 1 here]

The disagreement between parties isn't unexpected. From the earliest days, government leaders accepted political division as a necessary evil. The feud between Thomas Jefferson and Alexander Hamilton is a core part of American History, identity, and lore. Doesn't argumentation lead to better outcomes? Isn't political polarization a healthy part of a functioning government? Thomas Jefferson noted that "Men by their constitutions are naturally divided into two parties" in his letter to Henry Lee on August 10th, 1824. The two-party conflict is not only part of the modern political landscape but has been expected since the United States inception. His adversary, Alexander Hamilton, referred to political parties as "the most fatal disease." Although necessary, political parties were known to behave poorly, selfishly seeking personal gain at the expense of the greater good. When should we be concerned if the political division is natural and infectious?

Some might argue that the political division may help governments push ideas to their natural extremes, ultimately creating better policies, at least in theory. It is also important to note that the political division frustrates government policies' predictable timing, scope, and composition. In the most extreme cases, the latter trumps the former. Theory suggests that an increase in political and economic uncertainty and an increase in the volatility of fiscal shocks negatively impact economic activity [citation]. Intuitively, businesses and households will delay decisions that have high costs to undue, slowing economic decision-making and growth. The political division may even slow the response to adverse shocks, delaying government alleviation of citizens' unmet needs during crises. Our concern is that partisan conflict is not isolated to government policy-making, but partisan conflict biases individuals' beliefs, recommendations, and outlooks in the financial sector and specifically in asset pricing.

1.2 Empirical Challenges in Partisan Conflict in Asset Pricing

The heightened partisan conflict undoubtedly impacts partisan beliefs. Partisan beliefs bias economic expectations of market trends, whereby aligned individuals who agree with the party in power are more optimistic than those who are misaligned. Partisan alignment and misalignment influence social, political, and economic choices. We explore the partisan bias channel, which may distort pricing mechanics in financial markets. If partisan beliefs differ in their levels of optimism, those holding those beliefs will maintain different opinions of asset prices. For instance, an aligned (misaligned) individual will require a lower (higher) expected return on securities because they are more optimistic (pessimistic) expectations about the issuer's future market conditions. These biases affect share price, firms' cost of capital, and investment decisions. Due to the difficulty in determining partisan beliefs and the measuring the intensity of those beliefs, only recently has research been uncovering systematic distortion of asset pricing through the channel of partisan bias.

Research on the impact of partisan beliefs encounters empirical challenges. Asset pricing involves numerous participants with various agendas and investor speculation. Assets frequently change hands in liquid markets, frustrating attempts at identifying definitive assignment of pricing effects. We examine earnings forecast errors of analysts covering firms in the S&P500 to address this challenge. These firms provide the highest number of analyst reports in the U.S. market on average. These firms represent 80% of the available market capitalization [1]. Many investors depend on earnings performance to make investment decisions. Investors use earnings forecasts to build valuation models before quarterly earnings are reported. If a firm misses forecast expectations, it may lower the price. If the forecasts are already low, and the market has already priced in expectations, the security price may remain unchanged when the firm doesn't meet its stated goals. Earnings forecast has a meaningful impact on asset pricing. Earnings forecast errors increase market pricing volatility as the market reacts to unmet expectations.

Our key agents are security analysts who are responsible for estimating future earnings. Security analysts evaluate securities and identify trends to reveal investment opportunities for clients and investment firms. Analysts examine historical trends, sector reports, bond performances, daily asset prices, economic forecasts, and news coverage to forecast their assigned securities' earnings. Most analysts start with the firm's projections and market expectations in the previous quarter. They look for changes in expectations such as macroeconomic health, sector changes, new entries into the market, competitor innovation, the sentiment of stakeholders, and many other market factors. New information must be vetted and may be incomplete, requiring a gut response from the analysts to assign value to each piece of information. Analysts have some discretion over their forecasts of project earnings. If partisan beliefs impact an analyst's optimism, it will affect their perception of the anticipated earnings of the firm.

[1] https://www.spglobal.com/spdji/en/indices/equity/sp-500/overview

1.3 The Role of Partisan Conflict in Corporate Finance

In recent years, academic research has shown that partisanship and bias profoundly impact decision-making in the financial sector. Evidence suggests that professionals incorporate certain information which favors their political preferences. Professionals both use political tools to improve and diminish shareholder wealth. Shareholders benefit when political preference maximizes shareholder wealth through strategic political alliances. Shareholders suffer when unconscious biases lead to irrational decision-making motivated by partisan membership and loyalty. Political bias has influenced firm composition, optimism/pessimism towards secular trends, economic outlooks, investment decisions, and even SEC regulations, all impacting asset pricing. We will start with assessing the overall impact to show a broad effect, and then we will hone in on asset pricing effects.

Political bias impacts firm behavior from employment composition to optimism concerning the outlook of their firm. Babenko, Fedaseyeu, and Zhang (2020) examined political implications in firm dynamics. They found that employees donated three times more money to CEO-supported candidates. Misaligned employees were more likely to leave, increasing firm-level political homogeneity. Additionally, firms saw higher returns when CEO-supported candidates were elected, suggesting CEOs prefer candidates who increase shareholder value. Peer pressure to support CEO candidates impacts the composition of the firm, minimizing firm diversity. Arikan, Kara, Masli, and Xi (2022) found that partisan-aligned CEOs demonstrated less accounting conservatism and more optimism in their corporate disclosures. Fos, Kempf, and Tsoutsoura (2022) found increasing political homogeneity in firm composition. They also found that executives politically aligned with the president are less likely to sell shares due to a favorable economic outlook. Political alignment measurably impacts firm decision-making and employee preferences.

Political bias impacts existing firms and encourages (discourages) new business creation. Engelberg, Guzman, Lu, and Mullins (2022) found that, on average, 6% of Republicans and 4% of Democrats become entrepreneurs. The phenomenon is time-varying and administration dependent, with politically aligned entrepreneurs becoming more active and politically misaligned entrepreneurs becoming less active. The optimism effect of the partisanship channel influences the earliest stages of firm development.

The SEC is a U.S. government oversight agency responsible for protecting investors by regulating the securities market. They ensure fair, orderly, and efficient markets and facilitate capital formation. Their oversight enforces financial transparency and integrity for U.S. firms. If the SEC is subject to bias, that bias may interfere with its mission. The SEC is not immune to political bias and its effects. Engelberg, Henriksson, Manela, and Williams (2023) found that although the Fed has historically remained non-partisan, partisanship among SEC commissioners significantly increased since 2010. They linked an increase in partisanship to a decrease in enforcement and rulemaking activity. Although the direct effect of bias is uncertain, lethargic rulemaking and enforcement may marginally influence firm behavior and asset pricing.

1.4 The Role of Partisan Conflict in Asset Pricing

Our paper focuses on economic optimism (pessimism) in economic forecasts. The effect is documented in several financial sectors, such as asset allocation, market predictions, credit lending, and credit ratings. First, we will begin with asset allocation. Cassidy and Blair (2021) found that the political affiliation of a mutual fund has a first-order effect on the fund's portfolio choice. A partisan-aligned fund will invest in high-beta industries after a favorable presidential outcome, displaying heightened optimism. They found that the effect has increased in magnitude from 2012 to 2020. Because of the fund investment size, their asset choices may significantly impact security prices. Addoum and Kumar (2016) proposed a demand-based predictability pattern in stock prices. When the party in power changes, they found systematic differences in the industry-level composition of portfolios, weakening arbitrage forces. Their trading strategy produced a risk-adjusted 6% return from 1939 to 2011. **?** found that funds are more likely to allocate assets to firms with executives and directors with similar partisan affiliations. Stronger partisan bias results in higher idiosyncratic volatility. This bias is more substantial with less experienced managers in more opaque firms during periods when the fund managers align with the presidential party. Partisan bias impacts the flow of funds and, thus, the firms' access to capital, altering the economic landscape via the partisan channel.

The bias is not just political but functions at the gender level. Jannati, Kumar, Niessen-Ruenzi, and Wolfers (2021) found that analysts are more optimistic toward firms with CEOs of the same gender. On average, analysts have a downward bias and exhibit stronger responses to earning surprises towards firms with CEOs of the other gender. Specifically, they found that this effect was more substantial with male analysts. In our analysis, we control for gender. Our research offers similar results, with gender playing a role in analysts' forecasts. We found that female analysts, on average, will more negatively bias earnings estimates than their male counterparts. Our results show that females exhibit more austere opinions for differentiation in the male-dominated security analysis industry. We have reservations concerning our results. Our sample contains 2,106 (11%) reports by 23 females (13%) and 17,182 (89%) reports by males (87%). We may not have a large enough sample of females to account for gender characteristics. Our results contribute to the role of gender in financial markets.

To our knowledge, no research has explored the impact of age and tenure on political bias. We found that misaligned analysts in the 80th age percentile have significantly lower forecasts than aligned analysts of the same age, significant at the 5% level. We expected younger analysts to be more prone to political optimism and idealism. However, younger analysts may be subject to higher levels of feedback and criticism. Older analysts may not be challenged as frequently by peers. Their age affords them stronger stances on issues. Tenure also offered a surprising result. Analysts with longer tenures are more biased than those with shorter tenures. We expect that the same argument for age applies to tenure. Senior analyst forecasts are less prone to outside criticism. It may result in fewer challenges to assumptions and greater autonomy in the workplace.

Researchers have found that party affiliation attracts members with particular traits. Jiang, Kumar, and Law (2016) used political donations to determine analysts' political preferences. They found that Republican contributors are generally more conservative and more accurate. They seldom deviate from other analysts' forecasts nor make bold predictions. We control for party affiliation. We found that Republicans have stronger reactions to misalignment than Democrats. Although our results seem to differ from Jiang, Kumar, and Law (2016), our results add to a more holistic interpretation of party affiliation. Republicans may be more conservative. Their conservatism may minimize optimism and maximize pessimism in earnings forecasts.

1.5 Key Results

Our research examines how security analysts' partisanship affects the earnings forecast errors of the firms they cover. We accomplish this goal by comparing the earnings forecasts with the actual earnings report to derive the analysts' forecast error. Misaligned analysts are defined as those from a different party than the party in power. Aligned analysts are defined as those affiliated with the party in power. We examine alignment (misalignment) with the executive and legislative branches of government. We also looked at key events in the judicial branch but did not find statistically significant results. Our key result looks at alignment with the executive branch. U.S. Presidents set the agenda and often determine policy salience. We found that misaligned analysts have significantly lower forecasts than other analysts. This result is robust to a plethora of fixed effects and clustering. Our results align with Dagostino, Gao, and Ma (2020), who examined partisan conflict in the credit market. They found that politically misaligned bankers charged 7% higher loan spreads. We also align with Kempf and Tsoutsoura (2021), who examined partisan conflict in the credit rating market. They found that misaligned analysts downward adjust credit ratings more than those who are aligned with the presidential party.

We further our discovery by examining the role of partisan bias during heightened partisan conflict periods and geographies. Differences in partisanship may increase conflict in brokerage house dynamics and between competing analysts, negatively impacting communications and information assimilation in asset pricing. Dagostino, Gao, and Ma (2020) found that the partisan bias effect increased during higher levels of political conflict, resulting in higher loan spreads on average in the credit market. The intuition of the result carries, as increased tension may make partisanship more salient. Evans, Porras Prado, Rizzo, and Zambrana (2019) found that the benefits of diversity on mutual fund teams disappeared during heightened partisan conflict periods. They stated that they were unclear on why the benefits of diversity would disappear when political identities are primed. Their results are inconsistent with theories on unobserved variables correlating with team performance and political diversity.

Based on our results, we believe Evans, Porras Prado, Rizzo, and Zambrana (2019) may have overlooked the relationship between competition and bias. Becker (1971) challenges the assumption that heightened competition increases political bias, arguing that increased competition would lead to reduced (labor) market discrimination. Extrapolating his research results suggests that heightened political conflict might remove bias. It is possible that diversity benefits on mutual fund teams didn't disappear, but the costs of political bias on homogenous groups did disappear. If competition decreases bias, maybe competition removes the negative bias impact from groups without diversity; maybe competition removes the competitive advantage of diverse groups. We explored this theory by testing tension on four fronts.

When we test the role of the Political Conflict Index (PCI) in our model, we expected to have similar results and conclusions as Dagostino, Gao, and Ma (2020) and Evans, Porras Prado, Rizzo, and Zambrana (2019). Although insignificant, our results for the PCI tests had the wrong sign. This result led to internal debate to this surprise. We have explored various model specifications without clearly determining the impact of heightened political conflict measured by PCI. We followed up our analysis with a second test on battleground states. We defined battleground states as states whose electoral results for presidential elections were won by less than 5%. When controlling for battleground states, our results indicate that the bias is minimized in contentious election environments, significant at the 1% level. This result confirms Becker's theory that increased competition removes bias. Unconvinced of our results, we are modeling a third test, examining firms covered by analysts of the same party versus those of multiple parties. We expect that forecasts error for misaligned analysts will be lessened when analysts on the same firm are aligned. Finally, our fourth theory is that large firms are more likely to see more competition between analysts during high PCI periods due to the public interest in large firms and the larger number of shareholders including larger stakes by investment funds who employ inhouse analysts. If we interact market cap with PCI we expect to see bias dissipate. The last two analyses are not completed at this time.

Our results suggest a competition channel on asset pricing working in tandem with the political bias channel. In a homogenous group, bias may propagate, while in a heterogenous group, bias is diminished. Our work doesn't necessarily contradict Dagostino, Gao, and Ma (2020) result. They studied the credit market with individuals privately seeking loans. Loan officers are unlikely to be aware of other loan officers' spreads. An individual seeking a loan may go to one source, reducing the impact of the competition channel. Our sample has different characteristics and contextual implications. The analyst's work is subject to public scrutiny in the earnings forecast market. Analysts compete for the most accurate forecasts. Those forecasts are evaluated when the firm releases its actual earnings. Earnings news competition during heightened political conflict may encourage analysts to consider other points of view to determine more accurate financial models. Thus, the competition channel may diminish the impact of the political bias channel.

1.6 Contribution

We contribute to the political bias literature on several facets. Previous researchers have looked at the credit lending and rating spaces. We explore the security forecast space. Dagostino, Gao, and Ma (2020) looked at loan spreads from a single officer, but the data didn't support looking at the same loan applications by different loan officers. Our data covers multiple analysts covering the same firm at the same time. Our enriched variation affords us more robust results and interpretation through increased observations.

Additionally, we contribute to the conversation on gender and innate characteristics of party members. We are the first to document age and tenure effects on political bias. We are the first to evaluate the interaction between the competition and political bias channels. We are also the first to look at battleground states and the impact of politically homogenous and heterogenous analytics on security analysis.

The rest of the paper is organized as follows. Section 2 describes the data and sample construction process, Section 3 provides the main empirical results, and Section 4 concludes.

2 Data and Summary Statistics

2.1 Sample Selection

We collect data from several sources. We start our sample with the S&P 500 firms between 1992 and 2020. For each quarterly earning of each firm, we obtain earnings forecasts from the Thomson Reuters Eikon database. For each forecast, we obtain the first name, last name, and middle initial of the analyst who issued the forecast. We also collect the office phone numbers from analyst reports. Once we have the names of the analysts, we search for their voter registration information in the LexisNexis Public Records database, which serves as a proxy for their political affiliation. For each analyst earnings forecast, our sample contains information about the political affiliation of the analyst who issued the forecast, the firm and fiscal period that the earning belongs to, and the actual earning. Our final sample contains 23,793 earnings forecasts issued by 224 unique sell-side analysts employed at 109 unique brokerage houses on 669 unique firms.

2.2 Variable Construction

2.2.1 Analysts Political Affiliation

We obtain demographic information of the analysts from LexisNexis Public Records. LexisNexis Public Records combines information from various public record sources. Our primary interest is the voter registration record information, which covers 23 states and the District of Columbia.[2] We manually search for each demographic information for each analyst from LexisNexis Public Records.

[2]These states are (Alaska, Arkansas, Colorado, Connecticut, Delaware, Georgia, Illinois, Kansas, Louisiana, Michigan, Minnesota, Missouri, New Jersey, New York, North Carolina, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, Texas, Utah, and Washington.

We search for each analyst by their first name, last name, middle initial, and city in LexisNexis.[3] To qualify our LexisNexis matches, we expanded the data on each analyst. Some names, such as Yun Kim and Michael Lewis, had 500 and 663 name matches in New York, respectively. The additional information was critical to provide credible matches. We gathered additional data on LinkedIn, broker websites, financial websites, WayBackMachine, and Google. We aim to collect key data points: education, job history, and age. LexisNexis provides age as a search function, proving to be the most valuable data point not listed in the analyst reports. We derived an estimated age by subtracting the first year of college from the current year and adding 18. For instance, if an analyst started college in 1990, we modified the search to include ages from 48-52 ($2022 - 1990 + 18 = 50$). The analyst's age reduced potential matches significantly. Once we obtained a reasonable number of matches, we created a system to verify credibility.

Qualifying each analyst in LexisNexis required creative validation metrics. We created dummy variables for key indicators. We provided an estimated chance of accuracy with 99% under *Certainty* with those with clear connections aligning the addresses, work emails, online data, age, SEC qualifications, and employment. If the LinkedIn (website profile) and the LexisNexis record had strong similarities, the applicant scored a 1 for *LinkedinMatch*. If the LexisNexis profile had an email from the firm on the earnings announcement, another firm listed as a former employer, or college education, the applicant scored a 1 for *Email*. If LexisNexis listed a home address within 50 miles of the firm, former employer, or education; the applicant was given a 1 for *Address*. If multiple addresses in different parts of the country matched, we generally scored 99% on *Certainty*. If LexisNexis had any firm from the analyst's history listed, they scored a 1 for *Employment Match*. The analysts scored a

[3] We use the location of the analyst's office, which we obtain from the office phone numbers manually collected from the analyst reports.

1 for *SEC License* if a broker's license was listed. If we found an address near the school or the school was listed on their profile, the analysts scored a 1 in *Education*. Our method provides evidence that we have the same person in the earnings report and the LexisNexis platform.

For some analysts, their record was sparse at best. At times more than one LexisNexis profile was possible. We use each prospective analyst's LexisNexis data to create a new profile for an online inquiry. The reverse search helped eliminate alternative options. LexisNexis sometimes lists the same person under multiple LexisNexis IDs. We recorded the ID with the voting record under *LexID* and the alternative under *LexID˙02*. If LexisNexis listed more than two IDs of the same person, we recorded additional IDs in the *notes*. We kept detailed notes under *Re-CheckNotes* for more difficult determinations, documenting the reasons for the *Certainty* metric. For instance, some analysts used a nickname; some had a former occupation verified in the LexisNexis database; and some had multiple address matches. If we were uncertain, we noted details on why it could be a match and why we were uncertain. Certainty ranged from 10% to 99%. The number was subjective based on the experience of the data researcher and their gut-level confidence. Once we determined a LexisNexis ID for the analysts, we downloaded the webpage to scrape all relevant details.

The LexisNexis Public Records database provides individuals' historical voter registration data and is widely used in various studies (e.g., Dagostino, Gao, and Ma, 2020).[4] We collect the analyst's most recent party registration for each earnings forecast. Following Dagostino, Gao, and Ma (2020), we determine the analyst's political affiliation for each U.S. presidential general election. If the analysts switch parties during a presidential term, we update the political affiliation accordingly.

[4]Dagostino, Gao, and Ma (2020) also verify the quality of the voter registration data in LexisNexis Public Records, by via FOIA requests with the New York State Board of Election. They find a complete overlap of party affiliation between LexisNexis Public Records and the information provided by New York State.

Using the party affiliation information, we denote the analyst's political alignment as the analyst's affiliation with the party the U.S. President represents. Specifically, we define *Misalign* as a dummy variable that equals one if the analyst's party affiliation does not match the president's party. For analysts who reside in states that are not covered by the LexisNexis Public Records database, we exclude them from our sample. Following Dagostino, Gao, and Ma (2020) and Kempf and Tsoutsoura (2021), we assign a zero value to *Misalign* for analysts who are unaffiliated with any political parties. Our results are robust to excluding analysts unaffiliated with any political parties.

2.2.2 Other Variables

Our main dependent variable is *Forecast Error*, a scaled signed forecast error. Specifically, for each earnings forecast, we calculate the forecast error as the difference between the forecast earnings and the actual earnings, scaled by the price of the stock as of the previous month-end, multiplied by 100 (*Forecast Error*). Intuitively, a more positive (negative) *Forecast Error* indicates a more optimistic (pessimistic) earnings forecast.

For each earnings forecast, we construct a list of analyst and forecast characteristics as of the forecast issuance date, including the natural logarithm of the age of the analyst (*Age*), the natural logarithm of one plus the number of quarters since the analyst's first earnings forecast for a given broker (*Tenure*), the natural logarithm of the number of firms covered by the analyst in a given quarter (*Num Covered*), and the natural logarithm of the number of days between the forecast issue date and the fiscal period end date (*Distance*).

2.3 Summary Statistics

We report the summary statistics of the variables used in the paper in Table 1,

[Insert Table 1 here]

3 Main Results

3.1 Analysts' Partisan Misalignment and Earnings Forecast

We study the effect of analyst partisan misalignment on earnings forecasts. Specifically, we estimate the following specification,

$$Forecast\ Error_{i,j,q,t} = \beta Misalign_{i,t} + \Gamma Z_{i,j,q,t} + \alpha_{j,q} + \eta_i + \theta_b + \tau_t + \varepsilon_{i,j,q,t}, \tag{1}$$

where $Forecast\ Error_{i,j,q,t}$ is the forecast error associated with analyst i's forecast of firm j's earnings for fiscal quarter q, issued at time t. The key independent variable is $Misalign_{i,t}$, a dummy variable that equals one if the analyst i's party affiliation does not match that of the president at time t. $Z_{i,j,q,t}$ is a vector of control variables, including *Tenure*, *Num Covered*, and *Distance*. We include a battery of fixed effects, including firm × fiscal quarter fixed effects ($\alpha_{j,q}$). The aforementioned interactive fixed effect controls for both underlying observable and unobservable systematic differences between observed time units for each firm, facilitating the capture of the variation in each analyst. Effectively, we compare forecasts from misaligned analysts to forecasts from aligned analysts who forecast the same quarterly earning. Our approach is consistent with the literature on analyst forecast accuracy (e.g., Clement, Koonce, and Lopez, 2007; Green, Jame, Markov, and Subasi, 2014; Bradley, Gokkaya, and Liu, 2017). We control for unobserved time-invariant differences across analysts and brokers by including analyst and broker fixed effects (γ_i and θ_b). Finally, we include year-quarter fixed effects (τ_t) to account for macroeconomic events. Following Dagostino, Gao, and Ma (2020) and Kempf and Tsoutsoura (2021), we double-cluster our standard errors by analyst and firm.

We present the results in Table 3. We start our analysis using a minimalist approach of firm × fiscal quarter and broker fixed effects and report the results in column (1). We find that misaligned analysts issue significantly lower forecasts than analysts whose party affiliations match that of the president. Next, we add year-quarter and analyst fixed effects and find similar results, shown in columns (2) and (3), respectively. Comparing the results in columns (2) and (3), the magnitude of the coefficient estimate nearly doubled in size, highlighting the importance of controlling for time-invariant analyst characteristics. Finally, we include all of the aforementioned fixed effects and report the results in column (4). We continue to find that misaligned analysts issue lower earnings forecasts. Regarding economic magnitudes, the coefficient estimates on *Misalign* range from -0.05 to -0.108. This effect is roughly equivalent to moving from the 50$^{\text{th}}$ (-0.026) to the 33$^{\text{th}}$ (-0.073) and the 23$^{\text{th}}$ (-0.129) percentile of the sample *Forecast Error* distribution, respectively. Taken together, we find that misaligned analysts whose party affiliation does not match that of the president issue more pessimistic earnings forecasts than analyst whose party affiliation align with the president.

[Insert Table 3 here]

3.2 Event Study around Presidential Elections

To provide further evidence, we conduct an event study around the presidential elections. Following Kempf and Tsoutsoura (2021), we focus on presidential elections around which the president's party changed, namely the 2000, 2008, and 2016 presidential elections. We do so to better isolate the effect of a change in political alignment on analyst earnings forecast errors. We estimate the following specification,

$$Forecast\ Error_{i,j,q,t} = \sum_{s=-5}^{s=+6} \beta_n Misalign_{i,e} \times D^n_{e,t} + \lambda_n D^n_{e,t} + \Gamma Z_{i,j,q,t} + \alpha_{j,q} + \eta_p + \theta_b + \tau_t + \varepsilon_{i,j,q,t}, \tag{2}$$

where $Forecast\ Error_{i,j,q,t}$ is the forecast error associated with analyst i's forecast of firm j's earnings for fiscal quarter q, issued at time t. For a given presidential election e, we keep forecasts issued within 540 days before and after the presidential election. The key independent variable is $Misalign_{i,e}$, which is a dummy variable that equals one if the analyst i switched from aligned to misaligned around the presidential election e. D_e^s, are dummy variables that equal one if time t is n 90-day periods before/after election e, for $n \in [-5, 6]$.[5] $Z_{i,j,q,t}$ is the same vector of control variables as Eq. (1). Since the same analyst can either be misaligned or aligned during the same presidential election, we use party fixed effects (η_p) instead of analyst fixed effects (η_i). $\alpha_{j,q}$, θ_b, τ_t are firm × fiscal-quarter, broker, and year-quarter fixed effects, respectively. We double-cluster our standard errors by analyst and firm.

We plot the estimates of β_n in Figure 2. We find insignificant differences between forecasts issued by misaligned and aligned analysts during the five 90-day periods before the election (i.e., $n \in [-5, -1]$). After the election, misaligned analysts become more pessimistic than aligned analysts and issue statistically lower forecasts. This effect is temporary and is only present during the 90-day period immediately after the election (i.e., $n = 0$).

[Insert Figure 2 here]

Next, we zoom in on the 2016 election due to its unexpected outcome. In addition, the candidates' opposing views on economic issues provide a cleaner setting to examine the effect of analyst partisan misalignment on earnings forecasts. Specifically, we estimate the following specification:

$$Forecast\ Error_{i,j,q,t} = \sum_{s=-5}^{s=+6} \beta_n Dem_i \times D_t^n + \lambda_n D_t^n + \Gamma Z_{i,j,q,t} + \alpha_{j,q} + \theta_b + \tau_t + \varepsilon_{i,j,q,t}, \quad (3)$$

[5] D_e^n are not absorbed by the fixed effect since they are defined relative to the election date rather than calendar time.

where $Forecast\ Error_{i,j,q,t}$ is the forecast error associated with analyst i's forecast of firm j's earnings for fiscal quarter q, issued at time t. We keep forecasts issued within 540 days before and after the 2016 presidential election. The key independent variable is Dem_i, which is a dummy variable that equals one if the analyst i affiliates with the Democratic party before and after the 2016 presidential election. All other empirical specifications are the same as in Eq. (2). Similar to the previous section, we plot the estimates of β_n in Figure 3. We find that analysts affiliated with the Democratic party issued significantly more pessimistic earnings forecasts immediately after the 2016 presidential election. Taken together, the event studies around the presidential elections show evidence consistent with analysts reacting to unfavorable election outcomes by downward adjusting their earnings forecasts Such partisan misalignment effect is temporary.

[Insert Figure 3 here]

3.3 Heterogeneity across Analysts

We next examine whether the effect of partisan misalignment on analyst earnings forecasts varies with different analyst characteristics. Specifically, we investigate the heterogeneous effects across political parties, age, and tenure.

To this end, we estimate the following specification:

$$Forecast\ Error_{i,j,q,t} = \beta_1 Misalign_{i,t} + \beta_2 Misalign_{i,t} \times I_{i,t} + \beta_3 I_{i,t} + \Gamma Z_{i,j,q,t} + \alpha_{j,q} + \gamma_i + \theta_b + \tau_t + \varepsilon_{i,j,q,t}, \tag{4}$$

where $I_{i,t-1,s}$ is a dummy variable based on forecast and manager characteristics. All other empirical specifications are the same as in Eq. (2). First, we examine whether the prior results are stronger for analysts who are affiliated with a particular political party. To this end, we interact *Misalign* with two dummy variables *Dem* and *Rep* that equal to one if the analyst is affiliated with the Democratic and Republican parties, respectively. We report the results in column (1) of Table 4. Our base group of misaligned analysts are those affiliated with parties that are neither Democratic nor Republican. The negative relationship between *Misalign* and *Forecast Error* is weaker for Democratic analysts. When analysts are affiliated with the Republican party, we do not find any differential effects.

Second, We interact *Misalign* with *High Age*, a dummy variable equal to one if the analyst's age is in the top quintile. In column (2) of Table 4, we find that the partisan misalignment effect is much stronger for analysts that are top age quintile. Specifically, the coefficient estimates on *Misalign* for *High Age* analysts are 114% higher than the rest of the sample. Our results are inline with studies in behavioral psychology. De Neys and Van Gelder (2009) found that when belief and logic conflicted, older adults had a weaker ability to inhibit inappropriate beliefs, leading to more frequent bias-dominated logic failures. In a controlled experiment, Tsujii et al. (2010) found that older adults exhibited a larger belief–bias than young adults through the examination of the inferior frontal cortex (IFC) activity differences in younger and older adults. As expected, bias in older analysts had a greater impact on their reasoning than in their younger counterparts.

Finally, we examine whether longer work experience can attenuate the negative relationship between *Misalign* and *Forecast Error*. Empirically, we interact *Misalign* with *High Tenure*, a dummy variable equal to one if the analyst's tenure is in the top quintile. We calculate tenure as the natural logarithm of one plus the number of quarters since the analyst's first earnings forecast for a given broker. We report the results in column (3) of Table 4. Interestingly, we do not find a differential effect for analysts with long tenure with a brokerage.

3.4 Robustness

In this subsection, we provide a battery of robustness of our results in Table 3.

First, we test whether The way we code mechanically drives our results *Misalign* (e.g., coding unaffiliated analysts as not misaligned). To this end, we re-estimate Eq. (1) using different subsamples. We exclude all unaffiliated analysts in column (1) of Table 5. Furthermore, in column (2) of Table 5, we keep only analysts who are affiliated with either the Democratic or the Republican party. In both subsample analyses, our results are consistent with our previous findings. The coefficient estimates on *Misalign* are negative and significant at the 1% level and have larger economic magnitudes.

Second, we assess the robustness of our results with respect to alternative methods of computing the standard errors. Specifically, we triple cluster our standard error by analyst, firm, and year-quarter. The results in column (3) of Table 5 show that the standard errors are similar to the double-clustered standard errors. Finally, we include additional (i.e., party, voter state, and firm $\times$ broker) fixed effects to control for other possible time-invariant effects. In columns (4)–(7), we show that our previous findings are robust to the inclusion of additional fixed effects.

4 Conclusion

Our paper tests whether partisan beliefs bias analysts' forecasts. We address this question in the context of analysts' earnings forecast errors on firms in the S&P 500. We construct a novel dataset that tracks analysts (gender, age, location, and political affiliation), firm, and brokerage characteristics. Our model demonstrates that politically misaligned analysts suffer from significantly worse earnings forecasts error. Our estimation is robust to numerous fixed effects and clustering. Our robustness checks dismantle arguments that analysts' intrinsic characteristics, firm composition, brokerage policies, and time-varying conditions confound the partisan effect. Our analysis furthers the academic discourse on the partisan and competition channels. We supply evidence that the changes in earnings forecasts error between politically misaligned and aligned analysts are contingent on their differences in economic expectations.

Our research is the first to supply evidence that analysts' partisan beliefs impact earnings forecasts for SP500 firms. Our findings contribute to the literature which examines the role of partisan beliefs in shaping asset pricing. Furthermore, our research proposes that partisan beliefs not only increase discord among investors but also affect asset pricing. This paper advances our understanding of the consequences of partisan beliefs on financial markets.

Future research may explore analysis recommendations that may have more salience on asset pricing than earnings forecasts. Further research might also address the impact of competition on the partisan effect. Finally, the role of age and gender warrant further research in the securities market.

References

Addoum, Jawad M., and Alok Kumar, 2016, Political sentiment and predictable returns, *The Review of Financial Studies* 29, 3471—-3518.

Arikan, Mazhar, Mehmet Kara, Adi Masli, and Yaoyi Xi, 2022, Political euphoria and corporate disclosures: An investigation of ceo partisan alignment with the president of the united states, *Journal of Accounting Economics* 75, 101552.

Babenko, Ilona, Viktar Fedaseyeu, and Song Zhang, 2020, Do ceos affect employees' political choices?, *The Review of Financial Studies* 33, 1781—-1817.

Becker, Gary Stanley, 1971, The economics of discrimination, 2nd edition.

Bradley, Daniel, Sinan Gokkaya, and Xi Liu, 2017, Before an analyst becomes an analyst: Does industry experience matter?, *Journal of Finance* 72, 751–792.

Cassidy, Will, and Vorsatz Blair, 2021, Partisanship and portfolio choice: Evidence from mutual funds, *Available at SSRN: https://ssrn.com/abstract=3977887*.

Clement, Michael B, Lisa Koonce, and Thomas J Lopez, 2007, The roles of task-specific forecasting experience and innate ability in understanding analyst forecasting performance, *Journal of Accounting and Economics* 44, 378–398.

Dagostino, Ramona, Janet Gao, and Pengfei Ma, 2020, Partisanship in loan pricing, *Available at SSRN 3701230*.

Engelberg, Joseph, Jorge Guzman, Runjing Lu, and William Mullins, 2022, Partisan entrepreneurship, *Available at SSRN: https://ssrn.com/abstract=3821106*.

Engelberg, Joseph, Matthew Henriksson, Asaf Manela, and Jared Williams, 2023, The partisanship of financial regulators, *Available at SSRN: https://ssrn.com/abstract=3481564*.

Evans, Richard B., Melissa Porras Prado, Antonino Emanuele Rizzo, and Rafael Zambrana, 2019, Identity, diversity, and team performance: Evidence from u.s. mutual funds, *Available at SSRN: https://ssrn.com/abstract=3505619*.

Fos, Vyacheslav, Elisabeth Kempf, and Margarita Tsoutsoura, 2022, The political polarization of corporate america, *Available at SSRN: https://ssrn.com/abstract=4142685*.

Green, T Clifton, Russell Jame, Stanimir Markov, and Musa Subasi, 2014, Access to management and the informativeness of analyst research, *Journal of Financial Economics* 114, 239–255.

Jannati, Sima, Alok Kumar, Alexandra Niessen-Ruenzi, and Justin Wolfers, 2021, In-group bias in financial markets, *Available at SSRN: https://ssrn.com/abstract=2884218*.

Jiang, Danling, Alok Kumar, and Kelvin Law, 2016, Political contributions and analyst behavior, *Review of Accounting Studies* 21, 37–88.

Kempf, Elisabeth, and Margarita Tsoutsoura, 2021, Partisan professionals: Evidence from credit rating analysts, *Journal of finance* 76, 2805–2856.

Table A1: Variable Definitions

Forecast Error	Difference between the forecast earnings and the actual earnings, scaled by the price of the stock as of the previous month-end, multiplied by 100.
Misalign	A dummy variable that equals one if the analyst's party affiliation does not match that of the president.
Num Covered	The natural logarithm of the number of firms covered by the analyst in a given quarter.
Distance	The natural logarithm of the number of days between the forecast issue date and the fiscal period end date.
Tenure	The natural logarithm of one plus the number of quarters since the analyst's first earnings forecast for a given broker.
Age	The natural logarithm of the age of the analyst in years.
High Tenure	A dummy variable equal to one if the analyst's tenure is in the top quintile.
High Age	A dummy variable equal to one if the analyst's age is in the top quintile.
Dem	A dummy variable equal to one if the analyst is affiliated with the Democratic party.
Rep	A dummy variable equal to one if the analyst is affiliated with the Republican party.

Figure 1: Partisan Conflict Index, 12-Month Rolling Average

The figure plots the 12 month rolling average of the PCI index

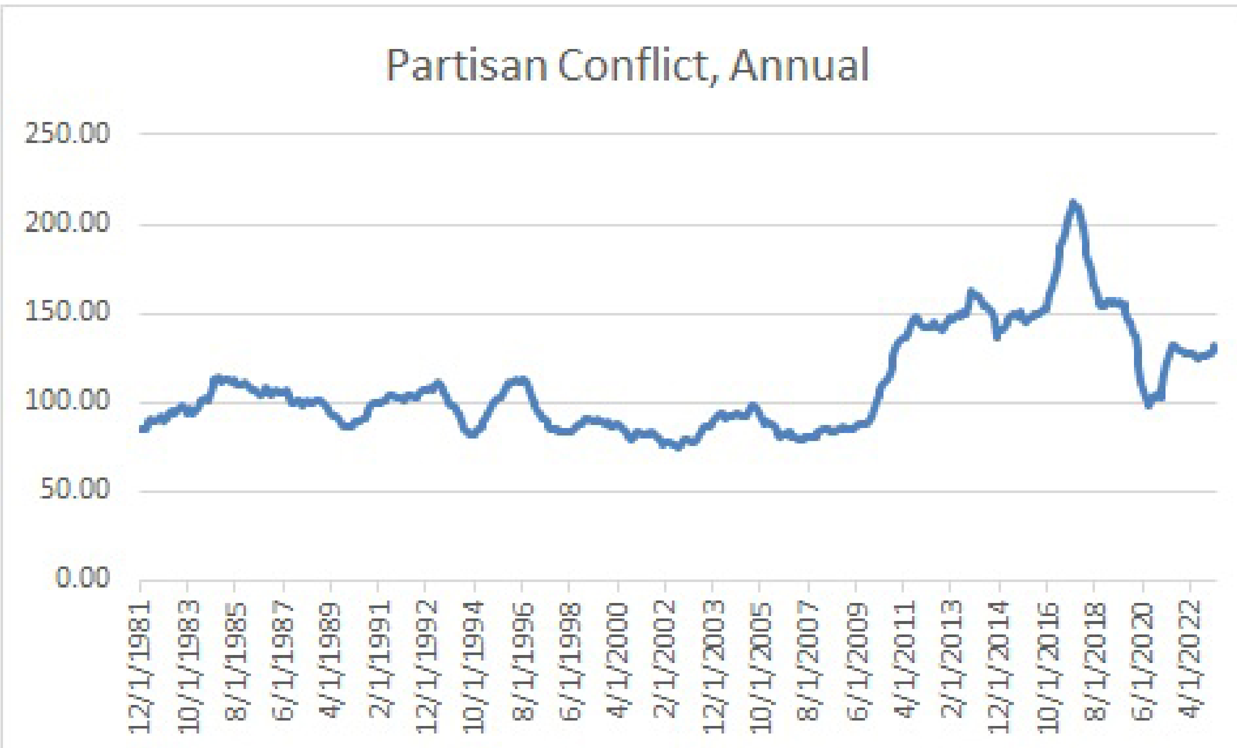

Figure 2: Event Study around Presidential Elections

The figure plots the results from the event study around the presidential elections, during which the party of the president changed. The horizontal axis indicates the n^{th} 90-day periods before or after the presidential elections, where the base period ($i.e., EventTime = 0$) is the first 90-day period immediately after the presidential election. The vertical axis shows the coefficient estimates for β_n from Eq. (2). We also report the 95% confidence intervals. Standard errors are double-clustered by analyst and firm.

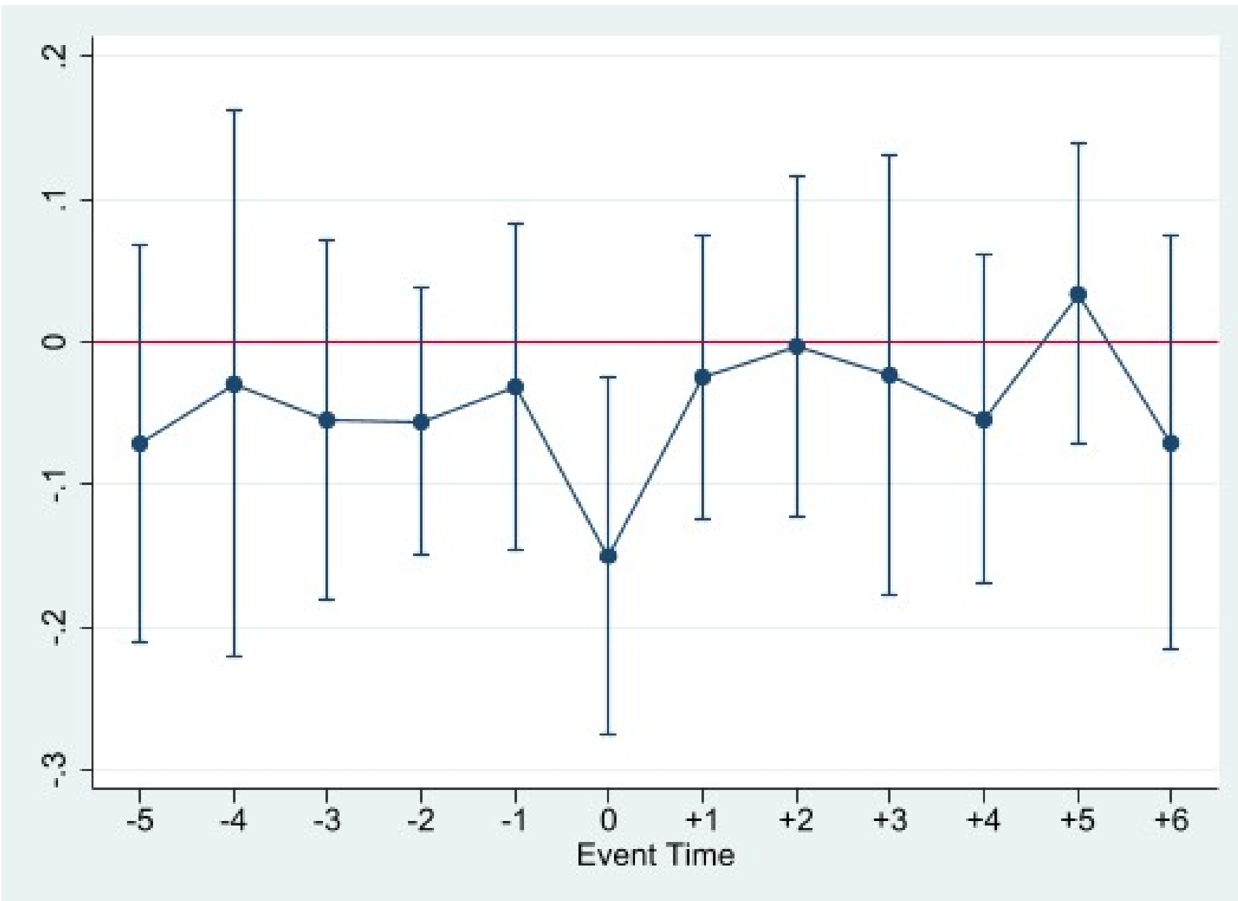

Figure 3: Event Study around the 2016 Presidential Election

The figure plots the results from the event study around the 2016 presidential elections. The horizontal axis indicates the n^{th} 90-day periods before or after the presidential elections, where the base period (*i.e.*, $EventTime = 0$) is the first 90-day period immediately after the presidential election. The vertical axis shows the coefficient estimates for β_n from Eq. (3). We also report the 95% confidence intervals. Standard errors are double-clustered by analyst and firm.

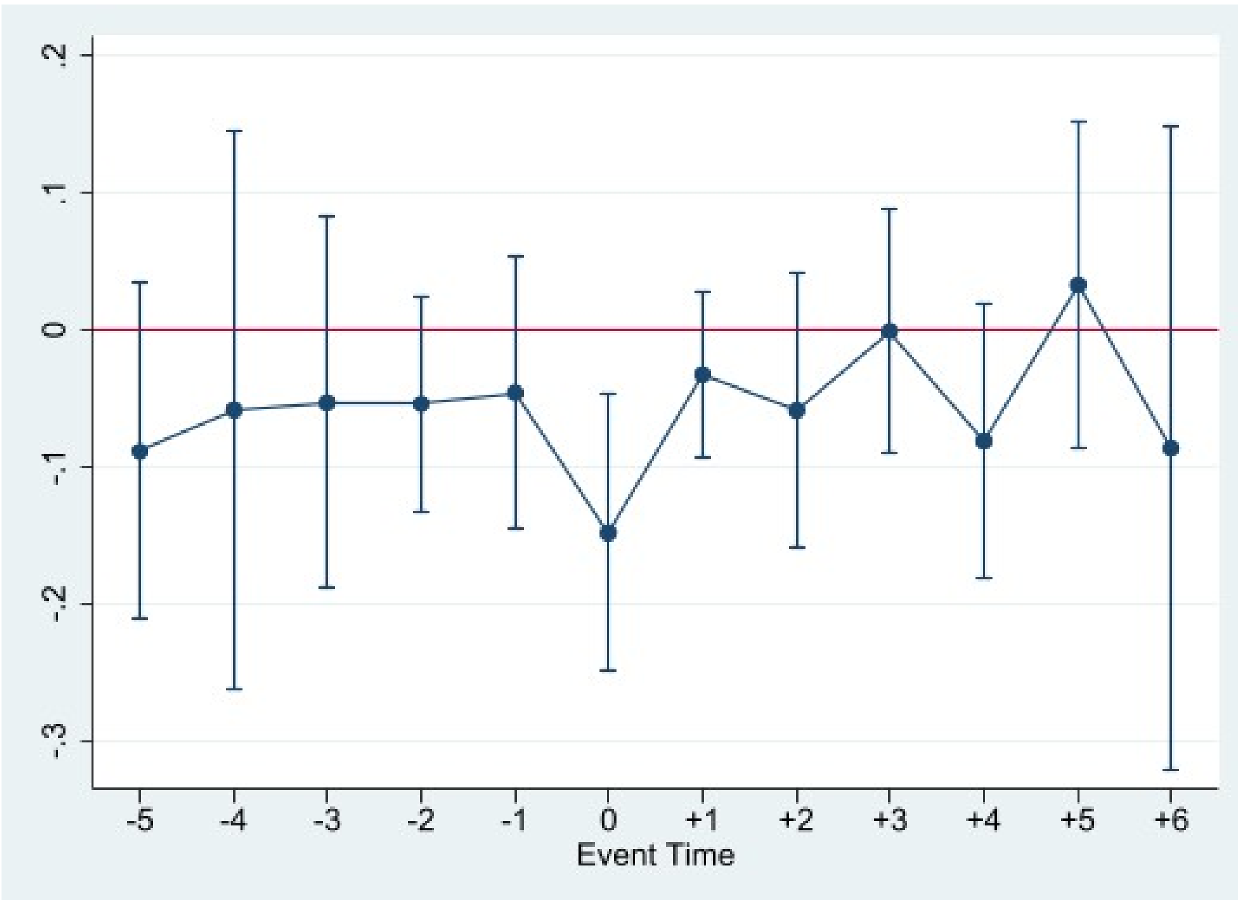

Table 1: Descriptive Statistics

This table reports summary statistics for the main variables used in the analyses. *Forecast Error* is the difference between the forecast earnings and the actual earnings, scaled by the price of the stock as of the previous month-end, multiplied by 100. *Misalign* is a dummy variable that equals one if the analyst's party affiliation does not match that of the president. *Num Covered* is the natural logarithm of the number of firms covered by the analyst in a given quarter. *Distance* is the natural logarithm of the number of days between the forecast issue date and the fiscal period end date. *Tenure* is the natural logarithm of one plus the number of quarters since the analyst's first earnings forecast for a given broker. *Age* is the natural logarithm of the age of the analyst in years. *Dem* is a dummy variable equal to one if the analyst is affiliated with the Democratic party. *Rep* is a dummy variable equal to one if the analyst is affiliated with the Republican party. Variable definitions are in Table A1 of the Appendix.

	(1)	(2)	(3)	(4)	(5)
	Mean	Std. Dev.	25^{th} Pctl	Median	75^{th} Pctl
Forecast Error	0.02	0.50	-0.12	-0.03	0.04
Misalign	0.38	0.49	0.00	0.00	1.00
Tenure	12.85	10.74	4.00	11.00	19.00
Num Covered	6.08	3.49	3.00	5.00	8.00
Distance	134.69	137.03	56.00	70.00	166.00
Age	45.32	9.63	38.00	44.00	52.00
Dem	0.28	0.45	0.00	0.00	1.00
Rep	0.34	0.47	0.00	0.00	1.00
Other	0.05	0.22	0.00	0.00	0.00
Noparty	0.33	0.47	0.00	0.00	1.00

Table 2: Party Affiliation Distribution by State

This table presents the distribution of party affiliations of the analysts. Since analysts can change party affiliation during our sample, we report the distribution at the forecast level.

	(1)	(2)	(3)	(4)	(5)
State	%Forecasts	Democrat	Republican	Other	Unaffiliated
Arkansas	5.35%	255	205	255	557
Colorado	1.67%	0	394	0	3
Connecticut	18.96%	331	2675	81	1424
District of Columbia	0.31%	25	48	0	0
Florida	3.56%	284	452	1	109
Louisiana	0.45%	0	0	0	108
Minnesota	7.63%	0	0	0	1815
New Mexico	0.23%	55	0	0	0
New York	41.78%	4402	2877	1111	1550
Ohio	2.81%	136	174	0	359
Pennsylvania	4.34%	307	582	0	144
Texas	12.61%	487	1500	0	1014
Wisconsin	0.31%	0	0	0	73

Table 3: Partisan Misalignment and Forecast Error

This table reports the OLS regression results of the effect of analyst partisanship on forecast error. The dependent variable is *Forecast Error*, the difference between the forecast earnings and the actual earnings, scaled by the price of the stock as of the previous month-end, multiplied by 100. The key independent variable is *Misalign*, a dummy variable that equals one if the analyst's party affiliation does not match that of the president. Variable definitions are in Table A1 of the Appendix. We also include firm × fiscal quarter, broker, year-quarter, and analyst fixed effects in the regressions. T-statistics are reported in parentheses and standard errors are double-clustered by analyst and firm. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
Misalign	-0.058*	-0.050**	-0.108**	-0.105***
	(-1.766)	(-2.154)	(-2.359)	(-2.885)
Tenure	-0.026*	-0.018*	-0.078***	-0.047**
	(-1.811)	(-1.685)	(-2.920)	(-2.032)
Num Covered	0.052**	0.029	0.090***	0.046*
	(2.529)	(1.562)	(3.198)	(1.912)
Distance	0.121***	0.064***	0.113***	0.062***
	(5.633)	(3.926)	(5.059)	(3.743)
Firm × Fiscal Quarter Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects		Yes		Yes
Analyst Fixed Effects			Yes	Yes
Observations	10,039	10,037	10,029	10,027
Adjusted R-squared	0.608	0.685	0.630	0.701

Table 4: Partisan Misalignment, Forecast Error, and Analyst Characteristics

This table reports the OLS regression results of how analyst characteristics impact the effect of analyst partisanship on forecast error. The dependent variable is *Forecast Error*, the difference between the forecast earnings and the actual earnings, scaled by the price of the stock as of the previous month-end, multiplied by 100. The key independent variable is *Misalign*, a dummy variable that equals one if the analyst's party affiliation does not match that of the president. *Dem* is a dummy variable equal to one if the analyst is affiliated with the Democratic party. *Rep* is a dummy variable equal to one if the analyst is affiliated with the Republican party. *High Age* is a dummy variable equal to one if the analyst's age is in the top quintile. *High Tenure* is a dummy variable equal to one if the analyst's tenure is in the top quintile. Variable definitions are in Table A1 of the Appendix. We also include Firm × fiscal quarter, broker, year-quarter, and analyst fixed effects in the regressions. T-statistics are reported in parentheses and standard errors are double-clustered by analyst and firm. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
Misalign	-0.233***	-0.079***	-0.079**
	(-3.370)	(-2.738)	(-2.583)
Misalign × Dem	0.157*		
	(1.793)		
Misalign × Rep	0.037		
	(0.312)		
Misalign × High Age		-0.090**	
		(-2.027)	
Misalign × High Tenure			-0.007
			(-0.183)
Dem	-0.059		
	(-0.827)		
Rep	-0.137*		
	(-1.731)		
High Age		0.070**	
		(2.225)	
High Tenure			0.048
			(1.593)
Tenure	-0.050*	-0.043**	
	(-1.752)	(-2.181)	
Num Covered	0.060**	0.038**	0.029
	(1.995)	(1.991)	(1.490)
Distance	0.073***	0.053***	0.051***
	(3.542)	(3.794)	(3.815)
Firm × Fiscal Quarter Fixed Effects	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes
Analyst Fixed Effects	Yes	Yes	Yes
Observations	10,027	9,683	10,027
Adjusted R-squared	0.729	0.681	0.681

Table 5: Robustness: Partisan Misalignment and Forecast Error

This table reports the OLS regression results of the effect of partisan misalignment and forecast error with alternative specifications. The dependent variable is *Forecast Error*, the difference between the forecast earnings and the actual earnings, scaled by the price of the stock as of the previous month-end, multiplied by 100. The key independent variable is *Misalign*, a dummy variable that equals one if the analyst's party affiliation does not match that of the president. Variable definitions are in Table A1 of the Appendix. Column (1) excludes analysts who are unaffiliated with any political party. Column (2) includes only analysts who are affiliated with the Democratic or the Republican parties. Column (3) triple-clusters the standard errors by analyst, firm, and year-quarter. Column (4)–(7) include various fixed effects, including party, voter state, and firm × broker fixed effects. All other empirical specifications are the same as in Table 3. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Exclude Unaffiliated	Only Dem. or Rep.	Triple Clustering	Additional Fixed Effects			
Misalign	-0.157***	-0.189***	-0.105***	-0.098**	-0.103***	-0.094**	-0.138**
	(-3.458)	(-4.020)	(-2.813)	(-2.372)	(-2.660)	(-2.238)	(-2.476)
Tenure	-0.002	-0.002	-0.047*	-0.049**	-0.044*	-0.045*	-0.059**
	(-0.082)	(-0.088)	(-1.975)	(-2.037)	(-1.881)	(-1.840)	(-2.515)
Num Covered	0.017	0.018	0.046*	0.044*	0.047*	0.045*	0.086***
	(0.680)	(0.608)	(1.745)	(1.795)	(1.784)	(1.671)	(3.190)
Distance	0.024*	0.026*	0.062***	0.062***	0.061***	0.061***	0.115***
	(1.885)	(1.827)	(3.296)	(3.750)	(3.228)	(3.224)	(4.813)
Firm × Fiscal Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Party Fixed Effects				Yes		Yes	
Voter State Fixed Effects					Yes	Yes	
Firm × Broker Fixed Effects							Yes
Observations	5,254	4,542	10,027	10,027	10,027	10,027	9,900
Adjusted R-squared	0.752	0.741	0.701	0.701	0.701	0.701	0.635