Partisan Bias in Professional Macroeconomic Forecasts*

Benjamin S. Kay — Federal Reserve Board
Aeimit Lakdawala — Wake Forest
Jane Ryngaert — Notre Dame

July 24, 2025

Abstract

Using a novel dataset linking professional forecasters to political affiliations, we document partisan bias in GDP forecasts. Republican-affiliated forecasters project higher GDP growth during Republican presidencies. Their forecasts are less accurate at these times, indicating impaired predictive performance. This bias does not extend to inflation, unemployment, or interest rate forecasts. In a model where forecasters combine noisy signals with politically-influenced priors: priors carry more weight when signals about the underlying variable are noisier. This allows ideology to shape growth projections. Finally, we show that partisan bias accompanies public discourse on tax cuts, suggesting divergent beliefs about fiscal policy.

JEL classification: C53, D72, D84, E37

Keywords: partisan bias; professional forecasts; GDP growth forecasts; tax policy expectations;

*We would like to thank Michael Futch for early discussions and assistance in facilitating data access during the initial stages of this project. We would also like to thank our discussant Dean Croushore and seminar participants at NBER Summer Institute 2023, Federal Reserve Bank of Dallas and St. Louis, Bank of Canada, Midwest Macro, Liberal Arts Macro conference, I-85 Macro conference and International Symposium on Forecasting. We are grateful to the Wall Street Journal for making their survey data available to researchers. Michael Kennedy, Jadyn Ives and Tanvi Arora provided excellent research assistance. Finally, we are indebted to Douglas K. Pearce for furnishing early WSJ survey data. Emails: benjamin.s.kay@frb.gov, lakdawa@wfu.edu and jryngaer@nd.edu.

1 Introduction

Professional economic forecasters are perhaps the closest real-world approximation to the full-information rational expectations (FIRE) agents typically assumed in economic models. Operating in competitive environments with incentives for accuracy, these experts have access to sophisticated data, research teams, and forecasting tools that should minimize systematic biases in their predictions. However, a substantial literature documents persistent deviations from FIRE among professional forecasters, attributing these patterns to information rigidities (Coibion and Gorodnichenko, 2015) or cognitive biases such as diagnostic expectations (Bordalo et al., 2020). Crucially, these explanations assume that deviations from FIRE stem from universal frictions that affect all forecasters, rather than systematic differences in the underlying beliefs between forecasters.

We challenge this assumption by documenting a novel source of bias in professional forecasts. In particular, we investigate whether political identity systematically influences economic predictions using publicly available data from the Wall Street Journal (WSJ) Economic Forecasting Survey. Conducted since the early 1980s, this survey uniquely identifies each respondent by name. By linking those names to Federal Election Commission donations, state voter-registration rolls, and partisan employment histories, we build a novel panel that pairs forecasters with political affiliation. The evidence is clear: partisan identity systematically affects GDP growth projections. Specifically, we find that Republican-affiliated forecasters project higher GDP growth relative to their Democratic counterparts when there is a Republican president in office. Because WSJ consensus forecasts closely track those of the more commonly used but anonymous Survey of Professional Forecasters and Blue Chip, our findings call into question the ideological neutrality assumed in a large body of macro-finance research that relies on these professional surveys.

Our ability to document this partisan bias is based on a comprehensive data construction effort. For political donations, we search Federal Election Commission (FEC) records to identify partisan contributions, classifying forecasters whose donations show a clear partisan preference. For voter registration, we use LexisNexis Public Records to identify party affiliations in states where such information is available. For partisan employment, we identify forecasters who worked for partisan elected officials or committees, or held political appointments in the executive branch. The resulting sample consists of an unbalanced panel of forecasters matched with their political affiliation, with macroeconomic forecasts available from 1986 to 2023. Importantly, we find no evidence that our matched sample differs systematically from unmatched forecasters in terms of forecasting behavior, mitigating concerns about selection bias in our partisan identification strategy.

Our baseline difference-in-differences specification reveals that, compared to their Democratic counterparts, Republican-affiliated forecasters project approximately 0.3–0.4 percentage points higher GDP growth under Republican presidents relative to Democratic presidents. This partisan gap is both statistically significant and economically meaningful—representing roughly 10-15% of the average GDP growth rate during our sample period. This effect is remarkably robust. The gap persists in specifications with forecaster fixed effects, confirming that the bias is identified from within-forecaster changes in forecasts as the party of the president changes. The result cannot be explained by differential responses to recessions, despite all recessions in our sample beginning under Republican administrations. The gap remains stable whether we trim outliers, restrict analysis to forecasters identified through single sources, or apply our most stringent classification, requiring unanimous agreement across all partisan indicators.

However, this partisan bias exhibits a pronounced asymmetry. Partisan differences in forecasts emerge specifically during Republican presidencies, whereas under Democratic presidents, average forecasts from Republican and Democratic forecasters are statistically indistinguishable.

Our findings raise a natural question: does partisan optimism signal superior insight or a distortion that degrades forecast accuracy? If forecasters aligned with the party in power had better understanding of policy impacts, their optimism would translate into greater predictive accuracy. Instead, we find that Democratic-affiliated forecasters are more accurate on average, producing lower mean absolute forecast errors for GDP projections under both Democratic and Republican presidents. Both forecaster groups perform worse during Republican administrations, but Democratic forecasters maintain a relative advantage. Importantly, applying the same difference-in-differences strategy used to study forecast levels, we find that Republican forecasters make relatively larger forecast errors when their preferred party is in office—about 0.15 percentage points higher in mean absolute error, representing roughly 10 percent of the typical forecast error. This pattern suggests that partisan optimism comes at the expense of accuracy, indicating a distortion in professional judgment rather than privileged insight into policy effects. More broadly, our findings suggest that simply aggregating across politically diverse forecasters may not eliminate bias or improve forecast accuracy.

We also explore whether broader political control, beyond the presidency, shapes forecasting behavior. Using a Republican Control Index that incorporates party control of the House, Senate, and presidency, we find suggestive evidence that greater Republican control is associated with more optimistic GDP projections from Republican-affiliated forecasters. However, major shifts in congressional control typically coincide with changes in the presidency, making it difficult to separate their independent effects. To address this identification challenge, we examine midterm election windows, when changes in congressional control occur without a presidential transition. The results in this setting are consistently weaker and not robust across specifications. This pattern suggests that the presidency, rather than congressional control, is the primary driver of partisan differences in forecasts.

Although partisan effects are pronounced in GDP forecasts, we find no comparable patterns for other key macroeconomic variables. Using the same empirical strategy, we do not detect statistically significant differences by forecaster affiliation in inflation (CPI), unemployment, or interest rate projections. These empirical patterns raise deep questions about the nature and origin of the partisan bias we uncover. Why is it concentrated in GDP forecasts? Why does it appear primarily during Republican presidencies? What drives this systematic divergence in expectations among highly trained professionals? To address these questions, we develop a simple theoretical framework that formalizes how political identity can shape economic forecasts, even in settings with strong professional incentives for accuracy.

Our model features forecasters who combine noisy signals about the underlying macroeconomic variables with politically influenced prior beliefs to form expectations. A central assumption of the model is that GDP forecasts are based on noisier signals than forecasts for other macroeconomic variables, such as inflation or unemployment. When signals are less informative, forecasters rationally place greater weight on their priors. This mechanism helps explain why partisan bias emerges in GDP forecasts, where priors play a larger role, but is largely absent for more stable indicators where the signal dominates.

We show that our assumption about differential noise in signals about macroeconomic variables is borne out in the data. GDP projections exhibit substantially larger forecast errors. They also exhibit greater cross-sectional disagreement across forecasters than those for other macroeconomic variables. GDP is simply harder to forecast. The model also delivers a clear and testable implication: if signal noise varies over time, the weight forecasters put on their priors, and hence the magnitude of partisan bias, should also vary. In particular, during periods of elevated uncertainty, the model predicts a stronger partisan gap. We validate this prediction empirically. Partisan bias in GDP forecasts increases with both forecast dispersion and absolute forecast errors, i.e. partisan bias intensifies precisely when GDP becomes more difficult to predict.

Having shown when partisan bias is likely to arise, we now turn to how it operates. In particular, the model outlines three distinct channels through which political affiliation can shape forecasts. First, forecasters may attend to different sources of information. Second, they may exhibit pure in-group favoritism when their preferred party is in power. Finally, they may hold systematically different beliefs about the effects of economic policy.

We argue that information differences are unlikely to explain the observed bias. Unlike households, where selective exposure to information is well documented, professional forecasters operate in well-resourced environments with broad access to economic data and research. Moreover, an information story would have to be one-sided: Republican economists would need to absorb distinct information only when a Republican occupies the White House, while Democrats would remain unaffected. Such an asymmetric and presidency-contingent information flow is unlikely. To probe the alternative of pure in-group favoritism, we exploit the largely unexpected 2016 election of Donald Trump in an event-study framework. If partisan cheerleading drives bias, the gap should widen immediately after Election Day or the January 2017 inauguration, as we observe with household survey responses to presidential transitions. Instead, we find that the divergence in GDP forecasts emerges only gradually over the subsequent months and is difficult to reconcile with a pure in-group bias mechanism.

The data support the remaining mechanism, differential beliefs about the growth effects of policy. Republican-affiliated forecasters systematically view tax cuts as more expansionary than Democrats, and this belief appears central to the bias we document. Using Google Trends, we show that tax policy becomes markedly more salient in public discourse under Republican presidents. We also show that Republican forecasters grow more optimistic precisely when that salience rises. We further corroborate this mechanism using an exogenous measure of tax policy shocks from Romer and Romer (2010), finding that Republican forecasters become more optimistic following tax cuts identified as plausibly exogenous. Together, these patterns point to divergent beliefs about policy, rather than information gaps or simple partisan loyalty, as the primary driver of partisan bias in professional macro-forecasts.

Our results bridge two dominant strands in the FIRE-deviation literature: informational frictions (e.g., Mankiw and Reis, 2002; Sims, 2003; Coibion and Gorodnichenko, 2012) and behavioral departures from full rationality (e.g., Woodford, 2013; Gabaix, 2014; Bordalo et al., 2020), showing that they interact rather than operate in isolation. Like Coibion and Gorodnichenko (2015), we find evidence of noisy-signal updating: GDP is sufficiently hard to observe in real time that forecasters rationally lean on their priors. But unlike the standard noisy-information paradigm, those priors are not homogeneous; they are systematically affected by ideology. In contrast, while behavioral models such as diagnostic expectations (Bordalo et al., 2020) allow for biased beliefs, they typically treat the bias as symmetric between agents. Our evidence of partisan asymmetry demands an extension: when the informational signal is weak, heterogeneous politically influenced priors can produce predictable forecast errors even among professionals with identical public information and powerful incentives for accuracy. In this sense, we offer a unified account in which imperfect information processing amplifies, rather than substitutes for, motivated beliefs, implying that any complete model of professional expectations should embed both channels.

Our findings also extends the existing research on partisan bias in economic expectations. A large body of work documents that household economic expectations are heavily influenced by political party affiliation (Bartels, 2002; Gerber and Huber, 2009; Mian et al., 2021; Kamdar and Ray, 2022; Binder, 2023; Farhart and Struby, 2024), with individuals becoming more optimistic about economic conditions when their preferred party holds office. More recently, evidence has mounted that partisan influences extend beyond households to professionals in finance and business (see Kempf and Tsoutsoura (2024) for a recent review). Studies have documented partisan effects among financial professionals, including credit analysts (Kempf and Tsoutsoura, 2021), bank loan officers (Dagostino et al., 2023), and mutual fund managers (Cassidy and Vorsatz, 2024). Parallel work has identified partisan differences in corporate contexts, including entrepreneurial decisions (Engelberg et al., 2022), innovation activity (Engelberg et al., 2023), corporate speech (Cassidy and Kempf, 2024), and merger behavior (Duchin et al., 2023). However, professional forecasters represent a particularly demanding test case for partisan bias. Unlike the settings studied in prior work, where strategic considerations, client relationships, or institutional pressures may influence decisions, forecasters face market incentives for accuracy with transparent, public predictions. Our finding that partisan identity systematically influences even these experts suggests that political beliefs shape economic expectations more fundamentally than previously understood.

The remainder of this paper is organized as follows. Section 2 describes the WSJ data and our partisanship data and classification process. Section 3 presents our empirical results. Section 4 explores possible mechanisms for those results. Section 5 concludes.

2 Data

This section provides a detailed overview of our data sources and our procedure for identifying the partisan affiliation of economic forecasters. Section 2.1 introduces the *Wall Street Journal* (WSJ) Economic Forecasting Survey, which forms the core of our forecasting dataset, and discusses how it compares to other widely used sources. Section 2.2 outlines our overall approach for classifying forecasters by partisanship, drawing on three distinct data sources. Subsection 2.2.1 explains how we use biographical and employment information to identify affiliations based on partisan work history. Subsection 2.2.2 describes how we use campaign contributions recorded by the FEC as a second signal of partisan affiliation. Subsection 2.2.3 details our use of LexisNexis public voter registration records as a third source of partisan data. In Subsection 2.2.4, we describe how we integrate these sources into composite measures of partisanship used in our analysis, and report summary statistics on forecasters' affiliations over time. Finally, Subsection 2.2.5 assesses whether forecasters with identifiable political affiliations are representative of the broader sample by comparing their forecast characteristics to those of unmatched forecasters.

2.1 WSJ Forecasts

The *Wall Street Journal* has been collecting forecasts from 20+ professional economic forecasters since the early 1980s (DeBarros, 2022), evolving over time in both frequency and scope. Initially conducted semiannually (mid-1980s to 2002), it moved to a monthly cycle from 2003 until early 2021, and now operates primarily on a quarterly basis. See About The Wall Street Journal Economic Forecasting Survey (2025) for more details. However, this website currently hosts data that go back only to 2003. For earlier surveys, we use data generously provided by Douglas Pearce who used the data to investigate forecasters' perception of Okun's Law and Taylor rule. (Mitchell and Pearce, 2010a).[1] The WSJ posts each survey wave as a downloadable spreadsheet, which we unify into an unbalanced panel spanning the period for which public data are available. The survey's core focus has remained constant: capturing short- and medium-term projections for GDP, inflation, unemployment, and interest rates, while periodically incorporating additional economic indicators such as exchange rates and oil prices. Each release is accompanied by WSJ articles discussing the panel's consensus and individual estimates.

Unlike virtually all other economic surveys, WSJ's poll is eponymous, identifying each participant by name, together with the firm that employs them.[2] Economists accept this transparency presumably because they use the survey to promote themselves, their firms, and their forecasts. This ability to link political partisanship and biographical data provides a unique laboratory to study how partisanship affects economic forecasting behavior by professional economists. In addition, the four decades of survey data allow us to study multiple political and business cycles.

Despite the WSJ's comprehensive coverage of leading macroeconomic indicators, it has received relatively limited attention in academic research compared to established alternatives like the Blue Chip survey and the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters.[3] However, we find that the WSJ survey yields remarkably consistent results with these widely-used benchmarks. Since our main focus is on GDP forecasts, we plot the 2-quarter ahead consensus GDP forecast from the WSJ survey together with that from the Survey of Professional Forecasters and the Blue Chip Financial Forecast survey in Figure 1.[4] The close alignment demonstrates that insights derived from WSJ survey analysis should generalize well to the broader economics and finance literature that relies on these other professional forecaster surveys.

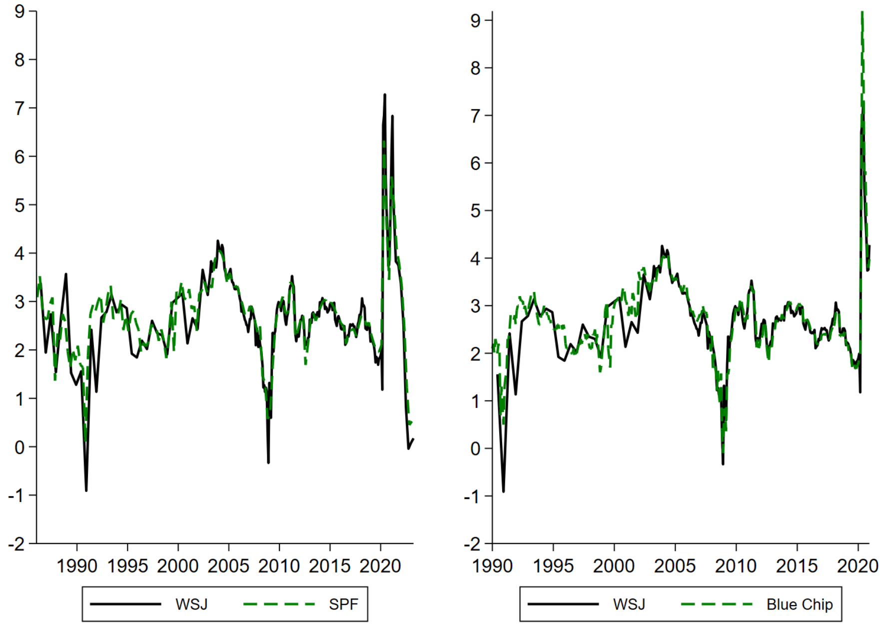
[1] Other academic research has also used this survey data. Early studies compared professional forecasts with market-implied forecasts (Belongia, 1987) and measured forecast error magnitudes (McNees, 1992), with Schuh et al. (2001) extending this analysis through 2000. Other work assessed individual forecaster performance and consensus value (Kolb and Stekler, 1996), long-term forecast accuracy (Greer, 2003; Eisenbeis et al., 2002), and how macroeconomic beliefs affect exchange rate expectations (Dreger and Stadtmann, 2008).

[2] Some other economic surveys provide forecaster identities to insiders, but the WSJ makes this data publicly available.

[3] This is likely due to the greater difficulty of formatting WSJ data into panel form compared to the more standardized formats of SPF and Blue Chip surveys.

[4] Since the SPF is quarterly we use the middle month of the quarter (when the SPF survey is released) and compare it to the corresponding month in the WSJ survey.

Figure 1: GDP forecasts (2 quarter ahead): WSJ vs Blue Chip/SPF



Notes: The figure shows the consensus (mean) two quarter ahead forecast for growth rate of real GDP from the WSJ survey (solid black line) and from the Survey of Professional Forecasters in the left panel and Blue Chip Financial Forecasts in the right panel (dashed green line).

2.2 Finding the Political Affiliation of WSJ Forecasters

We identify economists' partisan affiliations using three approaches: partisan employment from public internet sources, political contribution from FEC records, and voter registration data from LexisNexis. Based on these sources, we assign each economist a single partisan classification that applies throughout our sample period.[5] We next describe our use of these sources in greater detail below.

2.2.1 Identifying Partisanship through Employment

Partisan employment provides our first signal of political affiliation. To identify partisan employment and gather biographical information, we search public internet sources including personal websites, Wikipedia, speaker biographies, CVs, and social media. This biographical data - including age estimates and location information - also helps us accurately match individuals to their campaign donation and voter registration records.[6]

[5] Partisan affiliations can change over the life cycle. For example, it is well documented that college educated white voters have become more likely to vote Democratic in our sample period (Pew Research Center, 2020). At the individual level, about eight percent of voters switched parties between 2018 and 2020 (Pew Research Center, 2020) and 13 percent from 2011 and 2017 (Democracy Fund Voter Study Group, 2020). But more politically engaged voters are much less likely to switch parties (Pew Research Center, 2020). It is well documented that more educated people are generally more politically engaged (Bovens and Wille, 2021), so it is likely that the economists in our sample are less likely than average to switch parties.

[6] Age is estimated from college graduation year when exact birth year is unavailable. Location data ranges from precise street addresses to general metropolitan areas.

We search for forecasters that served as an elected official, worked for partisan elected officials or committees, or held political appointments in the executive branch. For example, we code Richard Berner as "Democratic" based on his Obama administration appointment as director of the Office of Financial Research (2013-2017). In cases of employment with both parties, we assign a "Mixed" classification. This classification applies regardless of whether the employment occurred before, during, or after the forecast period. We find examples of forecasters that have appointed positions in the executive branch, appointed positions in independent agencies, served on legislative branch committees, and volunteered for partisan campaigns. We find no examples of forecasters as candidates for or winners of partisan elections.

2.2.2 Identifying Partisanship through Political Contributions

The second signal of partisanship comes from political donations. We look for partisan political donations by the participating economists in the Federal Election Commission (FEC) database.[7]. To appear in these data a donor must give $200 or more to a single candidate for federal office in a year.[8] This is a strong indication of partisanship because such donations are rare among American adults. Evers-Hillstrom et al. (2020) estimate that just 0.51 percent of the United State population contributed enough to appear in the FEC data. In contrast, 66.8 percent of voting age Americans voted in the 2020 presidential elections (U.S. Census Bureau, 2021).

For each economist we can identify in the FEC data, we count the number of donations by political party. We classify an economist as affiliated with a particular party if at least 80 percent of their total donations (across all time periods) went to that party. If their giving pattern is more mixed (12 cases), we consider their donations politically uninformative. Notably, in 82 percent of cases, economists' donations went exclusively to one party. We exclude donations to employers' Political Action Committees (PACs) from our partisan calculations. We identify employer PACs by matching them against both employer information in the FEC data and employers listed in our biographical records. We exclude employer PACs because the distribution of these funds are typically controlled by the firm and not the employee. For non-employer PACs, we try to classify donations based on the PAC's partisan affiliation (e.g., counting MoveOn donations as Democratic).

To illustrate our methodology, consider Alan Greenspan who submitted forecasts to the WSJ survey while working at Townsend Greenspan prior to becoming Federal Reserve Chair. The FEC data shows he made ten reportable donations: nine to Republican candidates and one to a Republican-affiliated PAC. Since 100 percent of his donations supported Republicans, we classify his partisan affiliation

[7] Publicly available at the FEC's Individual Contributions website

[8] In general, federally registered political committees and campaigns report political donations of $200 with the name, employer, date, recipient, and other contributor details. In some cases, smaller contributions are also reported. We use all contributions as reported.

as Republican. Of course, Alan Greenspan is also categorized as a Republican based on partisan employment because of his appointment as Fed Chair by President Ronald Reagan.

2.2.3 Identifying Partisanship through Voter Registration

The third signal of party affiliation is the respondent's voter registration. We search for each forecaster's affiliation based on voter registration data from LexisNexis Public Records. LexisNexis Public Records licenses these registration data directly from state sources. While LexisNexis covers data from only 23 states, these include states like New York, New Jersey and Connecticut where a lot of the forecasters reside.[9] While the Lexis-Nexis data include third party registrations, no forecasters in our sample have a third party registration.

Unfortunately, voter registration is not widely or reliably available before 2008. Rather than make use of the very limited available within person registration variation, we use the latest available registration for each economist we can match to a registration.

When matching forecaster names in our dataset, we frequently encounter multiple potential matches, particularly with common names. To resolve these ambiguities, we utilize biographical information from various publicly available data, to identify the correct individual. Consider the case of economist Andrew Brimmer in our dataset. By consulting Lexis Nexis public records, in conjunction with his Wikipedia and his Federal Reserve History pages, we confirmed his Democratic Party voter registration and accordingly coded this affiliation in our data.

2.2.4 Identifying Overall Partisanship

We combine these three signals to create our measure of partisanship. Our primary measure of interest is our "Ordered Party" measure, where we use a waterfall from what we regard as the strongest to weakest signals of partisanship to determine the respondent's affiliation.

1. The party is set to the Partisan Employment party if known.
2. If not, and if FEC contribution data shows that 80 percent or more of an individual's donations went to one party, we assign that party affiliation
3. If neither of the above applies, we use party affiliation from LexisNexis voter registration if available
4. If none of these signals exist, we classify the respondent as "Other".

While we will rely on this Ordered Party measure for our baseline results, we validate our findings through various robustness check. First, we construct a more stringent "Strict Party" measure. Under

[9] U.S. Election Assistance Commission (2020) details the availability of state level data more generally.

this classification, we only assign a party affiliation if all available signals (LexisNexis, FEC, and Partisan Employment) agree. If any signals conflict, we classify the respondent as "Other" and exclude them from analyses using this measure.[10] Second, we conduct two additional robustness checks: (i) we restrict our analysis to forecasters whose affiliations we could verify solely through FEC donations, and (ii) we restrict our analysis to forecasters whose affiliations we could verify solely through LexisNexis voter registration. Both approaches yield results that closely align with our baseline findings using the Ordered Party measure.

There are 313 economists in the WSJ survey in our sample. Out of these forecasters, we identify the party affiliation of 140 economists using the Ordered Party measure and 131 using the Strict Party measure.[11] However, we exclude some economists with identified partisan affiliations from our analysis. When a team of economists provides a forecast, that team is coded as partisan only when all members share the same partisan affiliation—a relatively uncommon occurrence (only 3 out of 33 forecasting teams). We also exclude economists who forecast only as part of teams with heterogeneous affiliations or appear no more than once in the data. After these adjustments, our analysis includes forecasts from 122 economists with partisan affiliations under the baseline ordered measure: 62 Republicans and 60 Democrats. The corresponding numbers are 60 Republican and 54 Democratic for the strict party measure.

Figure 2 shows the number of Democrat and Republican affiliated forecasters per period over time. In the early part of the sample (from the mid-80s to the late 90s) there are typically more Republican affiliated forecasters while Democrat affiliated forecasters are slightly higher since then. Later, using forecaster-fixed effects, we control for potential selection bias in who submits forecasts over time. The figure provides no evidence of partisan-driven participation − there are no notable spikes in forecast submissions from either Democratic or Republican-affiliated forecasters around presidential elections.

Appendix Figure A.1 shows the breakdown of our matched forecasters by source of affiliation. We are able to match the most forecasters from voter registration records and the least from partisan employment. This pattern holds for both Democrat and Republican affiliated forecasters.

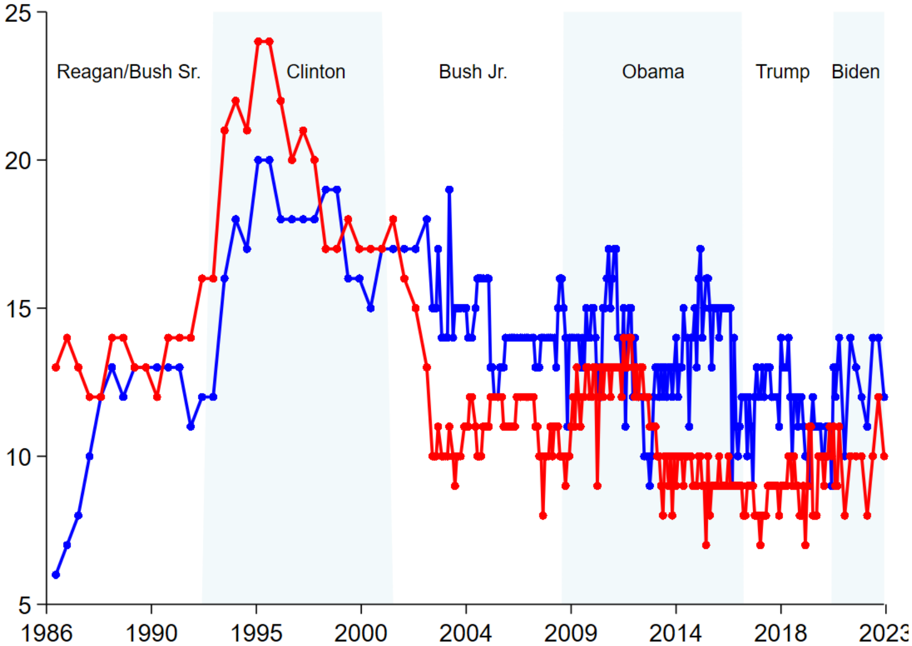
2.2.5 Comparing matched with unmatched forecasters

A potential limitation is that our partisan matching process might only identify strongly partisan forecasters who make their political affiliations public through donations or voter registration, thereby creating a non-representative sample. We address this concern by comparing the forecasting behavior

[10] To see how this works, consider Andrew Brimmer (deceased 2012). Our data shows he has a Democratic party affiliation in LexisNexis, Democratic Partisan Employment, but split FEC donations. Under our Ordered Party measure, we classify him as a Democrat because his Partisan Employment signal (our strongest indicator) shows Democratic affiliation. However, under our Strict Party measure, we classify him as "Other" because his signals are not in complete agreement.

[11] In an additional two cases, the FEC donations are the only observable information but are split.

Figure 2: Number of matched forecasters by party affiliation



Notes: The figure shows the number of matched Democrat affiliated forecasters (blue line) and Republican affiliated forecasters (red line).

of forecasters we can link to partisan affiliation (matched) against those we could not link (unmatched) to assess whether there are systematic differences between these groups.

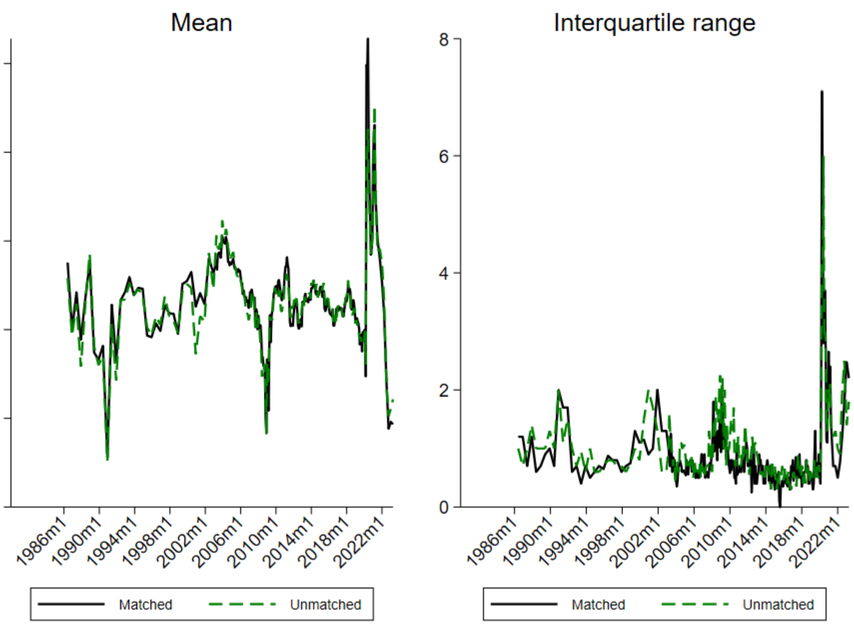
Figure 3 below plots the mean and the interquartile range of the two-quarter ahead GDP forecasts. As can be seen from the figure, the matched forecasters as a group look quite similar to the unmatched forecasters. Moreover, in unreported results, we compare the predictive accuracy of the consensus forecasts from the two groups using the Diebold and Mariano (1995) test and find no statistically significant differences between them. In Section 3.2 we conduct an outlier analysis and find that dropping the most partisan forecasters from our matched group does not materially change the results

In general, our analysis suggests that the matched forecasters in our sample are representative of the broader forecasting population, mitigating concerns about selection bias in our partisan identification strategy.

3 Results

We begin our analysis by examining how presidential party affiliation influences economic forecasts in the baseline sample using the ordered measure of partisan affiliation. We also explore a more granular measure of political control that accounts for House and Senate control (reported in the appendix), but find that partisan bias is primarily driven by presidential transitions. Our analysis of macroeconomic

Figure 3: Comparing GDP forecasts of matched and Unmatched forecasters



Notes: The figure shows the mean and interquartile range of 2-quarter ahead GDP forecasts. The solid black line is for matched forecasters in our baseline sample (i.e. forecasters for whom we have assigned a political affiliation using our ordered measure). The dashed green line shows the unmatched forecasters.

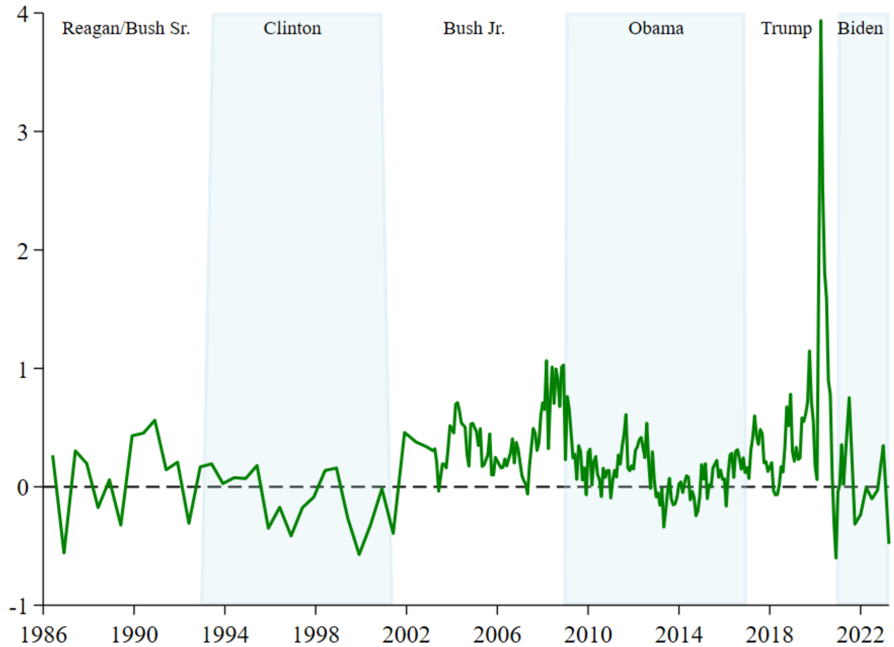
variables focuses primarily on GDP forecasts but we also consider inflation, unemployment, and interest rate forecasts. As detailed in Appendix Section A.1, the forecast horizons change over our sample in the WSJ survey. As a result, not all forecast horizons are available throughout the sample period. We focus on 2-quarter ahead forecasts as these provide the most comprehensive dataset.

3.1 GDP forecasts and forecaster affiliation with party of the president

Our main result is that GDP forecasts are materially affected by the alignment of forecasters' affiliation with the political party of the president. While we demonstrate this through multiple regression specifications that control for fixed effects and potential confounding factors, we first show that the main result can be seen just from plotting the raw forecast data.

Figure 4 plots the difference between the two groups' forecasts: in each period, we calculate the mean forecast across all Republican-affiliated forecasters and subtract from it the mean forecast across all Democrat-affiliated forecasters. The resulting difference is plotted over time, with blue shaded regions indicating periods with Democratic presidents. We use January (inauguration month) as the start of the presidential regime. A value greater than zero represents a month where Republican-affiliated forecasters' average two-quarter-ahead GDP forecast exceeded that of Democrat-affiliated forecasters. Two key patterns emerge from Figure 4. First, during Republican presidencies, the

Figure 4: Difference between Democrat and Republican GDP forecasts



Notes: The figure shows the difference between average Republican-affiliated and average Democrat-affiliated 2-quarter ahead GDP forecast.

difference is consistently positive, indicating that Republican-affiliated forecasters make systematically higher GDP predictions than their Democrat-affiliated counterparts. This pattern holds strongly across the Republican administrations of George W Bush and Trump and to some extent under Reagan and George H. Bush. Second, under Democratic presidents, we observe no systematic difference in either direction. While Democrat-affiliated forecasters were somewhat more optimistic about GDP during the Clinton administration, their forecasts during the Obama and Biden presidencies fluctuated between optimism and pessimism relative to Republican forecasters.

We quantify and perform statistical inference on the differences seen in Figure 4 with a variety of regressions, starting with a simple specification that tests whether the difference in mean forecasts between the two groups varies significantly across presidential party regimes. Denote the macro forecast for forecaster j in month t as $y_{j,t}$. $Rep_j = 1$ for forecasters with Republican affiliation and 0 for Democratic affiliation. The indicator variable $Pres_t = 1$ if the president is Republican (and, zero if Democratic). We estimate Equation 1 using OLS on the forecasts of the ordered matched sample of 122 forecasters from July 1986 to April 2023.

$$y_{j,t} = \beta_0 + \beta_1 Rep_j + \beta_2 Pres_t + \beta_3 Rep_j * Pres_t + \varepsilon_{j,t} \tag{1}$$

From these estimated coefficients we create Table 1, a 2 x 2 table showing forecasts under the four scenarios: Democrat forecasters during Democratic presidencies, Democratic forecasters during Republican presidencies, Republican forecasters during Democratic presidencies, and Republican forecasters during Republican presidencies. For example, the entry where a Democratic forecaster predicts growth under a Republican president represents the average forecast computed using $\beta_0 + \beta_2$. We cluster standard errors at the forecaster level. We focus on 2-quarter ahead GDP forecasts here but the results for the other horizon GDP forecasts are similar, as we discuss in Section 3.2.

Table 1: Differences between Democrat and Republican GDP forecasts

	Republican Forecaster	Democrat Forecaster		Difference (Rep - Dem)
Republican President	3.045	2.652		0.393***
				(0.107)
Democrat President	2.652	2.593		0.059
				(0.102)
Difference (Rep - Dem)	0.393**	0.059	Diff-in-diff	0.334**
	(0.115)	(0.078)		(0.139)

Notes: The table shows the average difference between Democrat and Republican affiliated forecasters by presidential regime, from estimating Equation 1. The sample runs from July 1986 to April 2023. For the differences, standard errors clustered at the forecaster level are reported in parentheses and statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Two features stand out from the table and echo the results in Figure 4. First, when Democrats hold the White House, Democratic and Republican forecasters produce similar GDP predictions (2.59% vs 2.65%, a statistically insignificant difference). However, under Republican presidents, Republican-affiliated forecasters project substantially higher GDP growth (3.05%) compared to Democratic forecasters (2.65%). This gap of 0.39 percentage points is statistically significant. The key focus of our analysis is the difference-in-differences estimate – how the partisan gap in forecasts changes between Democratic and Republican presidencies. This estimate, shown in the bottom right cell, is economically meaningful at 0.33 percentage points and statistically significant at the 5% level.

As discussed above, we do not have a balanced panel as forecasters enter and exit the survey in our sample. One potential concern is that there could be a change in the composition of the survey participants around elections that could be driving our results. The differences-in-differences estimation of Equation 1 averages across forecasters, combining both within-forecaster and between-forecaster variation. We next estimate the more stringent two-way fixed effects (TWFE) specification in Equation 2 that includes both forecaster (γ_j) and time (γ_t) fixed effects. This specification isolates variation within individual forecasters over time, controlling for time-invariant forecaster characteristics and common time trends.

$$y_{j,t} = \gamma_j + \gamma_t + \beta Rep_j * Pres_t + \varepsilon_{j,t} \tag{2}$$

Table 2: Difference between Democrat and Republican GDP forecasts: Alternative specifications

	(1) OLS	(2) TWFE	(3) Recession	(4) FEC only	(5) Voter reg.	(6) Strict aff.
$\text{Rep}_j \times \text{Pres}_t$	0.33**	0.38***	0.33**	0.50***	0.28*	0.38***
	(0.139)	(0.119)	(0.129)	(0.142)	(0.148)	(0.125)
Observations	6,202	6,197	6,197	2,886	4,434	5,879
R-squared	0.016	0.645	0.647	0.667	0.635	0.641
Forecaster F.E.	no	yes	yes	yes	yes	yes
Time F.E.	no	yes	yes	yes	yes	yes
Recession interaction	no	no	yes	no	no	no

Notes: This table reports the difference-in-difference estimate for 2-quarter ahead GDP forecast between Republican and Democratic-affiliated forecasters when there is Republican president relative to a Democrat president. Column 1 shows the OLS difference-in-difference estimate from Equation 1. The next five columns show the two-way fixed-effects estimate. Column 2 is our baseline estimate from Equation 2. Column 3 adds an interaction of forecaster affiliation with NBER recession indicator. Columns 4 and 5 restrict the sample matched only with FEC donations and voter registration respectively. Column 6 uses our alternative "strict" measure of partisan affiliation. The sample runs from July 1986 to April 2023. Standard errors clustered at the forecaster level are reported in parentheses and statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results in the second column of Table 2 show that the TWFE estimate is similar (but slightly larger at 0.38 percentage points) to the OLS estimate reported in column 1 and is also statistically significant at the 1% level. This suggests that our main findings are not driven by changes in the composition of forecasters around elections, but rather reflect genuine differences in forecasting behavior within individual forecasters over time.

Blinder and Watson (2016) document that economic performance in the US has been superior under Democrat presidents. Consistent with this, all the recessions in our sample from 1986 to 2023 start under a Republican president. During Democratic presidencies in our sample, the US experiences a recession only for a few months under the Obama presidency. Moreover, as can be seen from Figure 4, the two episodes with the biggest difference between Democrat and Republican affiliated forecasters is around the 2007-08 recession and the recession caused by the onset of the pandemic in 2020. This raises a natural question. Is it the case that Republican-affiliated forecasters view times around recessions more optimistically than Democrats? And importantly, is this feature really what is driving the results documented above rather than affiliation with the party of the president? To investigate this, we estimate Equation 3, which supplements our TWFE regression with an indicator variable for NBER dated recessions ($Recession_t$) interacted with the indicator for political affiliation of the forecasters.

$$y_{j,t} = \gamma_j + \gamma_t + \beta Rep_j * Pres_t + \delta Rep_j * Recession_t + \varepsilon_{j,t} \tag{3}$$

If our results were driven primarily by differential responses to recessions then we would expect β in this specification to be lower and perhaps even close to zero. The results in the third column in Table 2 shows that β from the Recession regression is similar to our baseline case at 0.33 with statistical significance at the 5% level. This rules out that differential response to recessions is driving our results.

One potential concern with our measurement of partisanship is that different methods of identifying political affiliation might capture systematically different types of partisan forecasters. For instance, individuals who make substantial political donations might represent a particularly engaged and potentially more partisan subset of the population, as the act of making reportable campaign contributions requires both strong political conviction and financial commitment. In contrast, voter registration represents a lower barrier to expressing partisan preferences and might capture a broader, potentially less intensely partisan group of forecasters. Given the relatively rare occurrence of partisan employment in our sample, we lack sufficient observations to estimate a separate regression for forecasters identified through this channel alone.

To investigate this, columns 4 and 5 of Table 2 present results separating forecasters by their method of partisan identification: column 4 restricts the analysis to forecasters identified only through FEC donation records (excluding those found solely in voter registration or through partisan employment), while column 5 uses only those identified through voter registration records (excluding those found solely in FEC data or through partisan employment). While the difference-in-differences estimate is larger in magnitude for the FEC-identified sample (0.50 percentage points in FEC only) compared to the voter registration sample (0.28 percentage points in Voter reg.), both estimates remain statistically significant and economically meaningful. Importantly, despite the potential differences in partisan intensity between these groups, our main finding - that Republican-affiliated forecasters predict relatively higher GDP growth under Republican presidents - holds robustly whether we determine party affiliation through campaign contributions or voter registration records. This consistency suggests our results reflect a general pattern in how partisan identity influences forecasting behavior rather than being driven by particular subgroups of especially partisan forecasters.

Column 6 of Table 2 employs our most stringent classification of partisan affiliation, requiring complete agreement across all available partisan signals. Under this strict measure, we only classify forecasters as partisan when their employment history, campaign contributions, and voter registration records (where available) all consistently indicate the same party affiliation. Any forecaster with conflicting signals—such as Democratic voter registration but Republican campaign donations—is excluded from the analysis. Even with this criterion for partisan classification, we continue to find a significant difference-in-differences estimate of 0.38 percentage points (Strict aff.), nearly identical to our baseline estimate. This robustness to stricter partisan classification further supports our main finding that forecasters' political affiliations systematically influence their GDP growth predictions under presidents of different parties.

3.2 Further Robustness Checks

Our results are not driven by the regime of any one single president. We estimate the TWFE regression of Equation 2 dropping one presidential regime at a time and show the results in Table 3. Consistent with the insight from Figure 4, we see that our estimates (0.27 to 0.46) remain significant and of similar magnitude for all the cases. Unsurprisingly, dropping the Trump presidency, and thus the pandemic sample results in the smallest diff-in-diff estimate. In Section 4.3 we explain from the perspective of a theoretical framework why the highly uncertain environment prevalent in the pandemic is conducive to creating larger differentials among Republicans and Democrats.

Table 3: Difference between Democrat and Republican GDP forecasts: Drop one president at a time

	Reagan/Bush Sr.	Clinton	Bush Jr.	Obama	Trump	Biden
$\text{Rep}_j \times \text{Pres}_t$	0.39***	0.39***	0.46**	0.41**	0.27**	0.36***
	(0.126)	(0.142)	(0.208)	(0.161)	(0.123)	(0.120)
Observations	5,853	5,594	4,475	3,877	5,237	5,944
R-squared	0.640	0.658	0.634	0.667	0.690	0.616

Notes: This table reports the difference-in-difference estimate for 2-quarter ahead GDP forecast between Republican and Democratic-affiliated forecasters when there is Republican president relative to a Democrat president from estimating Equation 2. Each column drops for that president's regime. The sample runs from July 1986 to April 2023. Standard errors clustered at the forecaster level are reported in parentheses and statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We next explore whether forecast horizon affects our results. To this end, we re-estimate the TWFE regression of Equation 2 with 1 quarter ahead, 3 quarter ahead, and forecasts for the 'next year' (with horizons varying from 13 to 23 months depending on timing). Since data availability varies across forecast horizons, we cannot simply compare these estimates to our main 2Q ahead result, which uses the full sample of available 2Q forecasts. Instead, we re-estimate the 2Q ahead specification on each horizon-specific sample for comparison, allowing us to isolate genuine horizon effects from differences in sample composition. For example, the 1Q ahead sample includes only observations where both 1Q and 2Q forecasts are available. The 2Q coefficient estimated on this restricted sample differs from our main 2Q result because it uses fewer observations, not because of methodological differences. Table 4 shows the results.

For 1 quarter ahead forecasts, the diff-in-diff estimate is 0.32 percentage points, compared to 0.41 percentage points for 2Q ahead forecasts estimated on the same sample. Looking at 3Q ahead forecasts, we find an effect of 0.32 percentage points, compared to 0.46 percentage points for 2Q ahead forecasts in that sample. For next year forecasts, the effect is 0.33 percentage points, while the corresponding 2Q ahead estimate is 0.56 percentage points. The estimates remain statistically significant across all specifications.

Table 4: Difference in Democratic and Republican GDP forecasts: Different forecast horizons

	1Q	2Q	3Q	2Q	next year	2Q
$\text{Rep}_j \times \text{Pres}_t$	0.32**	0.41***	0.32***	0.46***	0.33***	0.56***
	(0.158)	(0.135)	(0.114)	(0.142)	(0.129)	(0.184)
Observations	5,394	5,394	4,606	4,606	3,200	3,200
R-squared	0.653	0.644	0.585	0.647	0.659	0.624

Notes: This table reports the difference-in-difference estimate for 2-quarter ahead GDP forecast between Republican and Democratic-affiliated forecasters when there is Republican president relative to a Democrat president from estimating Equation 2. Columns 1, 3 and 5 show the estimate for 1 quarter, 3 quarter and next year forecasts. Since there is missing data for these forecast horizons, Columns 2,4 and 6 shows the corresponding results (with the same observations) for the 2 quarter forecast. The sample runs from July 1986 to April 2023. Standard errors clustered at the forecaster level are reported in parentheses and statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We also rule out that extreme observations are driving our main results. Table 5 examines how our findings on partisan bias in GDP forecasts hold up under different levels of data trimming. The results show that when trimming 1% of the most extreme observations from the tails of the distribution, the interaction coefficient is 0.38 percentage points which is almost identical to our baseline estimate from the full sample. This effect remains statistically significant at the 1% level when increasing the trimming to 5% and 10% of the tails. The insensitivity of the estimated effects across different trimming levels further demonstrates the robustness of our findings of partisan bias.

Table 5: Difference in Democratic and Republican GDP forecasts: Different trimming levels

	1% trimmed	5% trimmed	10% trimmed
$\text{Rep}_j \times \text{Pres}_t$	0.38***	0.34***	0.24***
	(0.119)	(0.097)	(0.064)
Observations	6,197	5,796	5,312
R-squared	0.645	0.691	0.770

Notes: This table reports the difference-in-difference estimate for 2-quarter ahead GDP forecast between Republican and Democratic-affiliated forecasters when there is Republican president relative to a Democrat president from estimating Equation 2. The three columns show results with a 1%, 5% and 10% trimmed sample. The sample runs from July 1986 to April 2023. Standard errors clustered at the forecaster level are reported in parentheses and statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.3 Accuracy of GDP forecasts and forecaster affiliation with party of the president

Having documented that Republican-affiliated forecasters exhibit increased optimism in their GDP predictions under Republican administrations, we now examine whether this optimism improves forecast accuracy. Specifically, we investigate whether forecasters aligned with the ruling party systematically produce smaller forecast errors. To address this, we utilize real-time GDP data to quantify and evaluate prediction accuracy.

We first study the forecast accuracy of Democrat and Republican affiliated forecasters as a group. Specifically, we compare the forecast accuracy of the mean across all Democrat affiliated forecasters to the mean across all Republican affiliated forecasters. Panel A of Table 6 reports the mean forecast errors (actual minus forecast) for 2-quarter ahead GDP forecasts, broken down by forecaster affiliation and presidential party. We also consider the "Consensus forecast" which is the mean across all forecasters in the WSJ survey (including the unmatched forecasters). All forecaster groups exhibit negative mean forecast errors, indicating they tend to be overly optimistic. This systematic bias is consistent with the literature (see for example Bianchi et al. (2022)). However, the degree of optimism varies notably across groups. The optimism bias is particularly pronounced during Republican presidencies for all forecaster groups, with Republican forecasters showing especially strong over-optimism compared to Democratic forecasters.

Panel B confirms these accuracy patterns by examining mean absolute forecast errors. Democratic forecasters produce the most accurate forecasts overall, followed by consensus forecasts, while Republican forecasters have the highest mean absolute errors. This ranking holds consistently across presidential administrations, with all forecaster groups showing substantially higher errors during Republican presidencies. Panel C presents Diebold-Mariano test statistics that formally test these accuracy differences, where negative values indicate the first forecaster in the comparison is significantly more accurate. The results confirm that Democratic forecasters are statistically more accurate than both Republican and consensus forecasters overall and during Republican presidencies, though the advantage over Republican forecasters becomes statistically insignificant during Democratic presidencies. Notably, Republican forecasters perform significantly worse than consensus forecasts, particularly during Republican administrations when the accuracy gap between Democratic and Republican forecasters is most pronounced. The results presented in all the three panels of Table 6 hold when we exclude the sample around the onset of the onset of the pandemic, as shown in the appendix.

While the previous analysis compared the accuracy of Democratic and Republican forecasters using group averages, we now examine this relationship with forecaster-level data, which lets us isolate variation within individual forecasters over time. To this end, we use the forecaster-level data and follow a similar approach that we used to investigate differences in the level of the forecasts in Equation 2. However, here in Equation 4, we use the absolute forecast error as the dependent variable, where $\tilde{y}_{j,t}$ is the real-time realized value of GDP.

$$|\tilde{y}_{j,t} - y_{j,t}| = \gamma_j + \gamma_t + \beta Rep_j * Pres_t + \varepsilon_{j,t} \tag{4}$$

Table 6: Forecast accuracy and Diebold-Mariano tests

Panel A: Mean Forecast Errors			
	All	Rep President	Dem President
Democratic forecast	-0.502	-0.667	-0.329
Republican forecast	-0.761	-1.083	-0.422
Consensus forecast	-0.600	-0.807	-0.382
Panel B: Mean Absolute Forecast Errors			
	All	Rep President	Dem President
Democratic forecast	2.157	2.931	1.345
Republican forecast	2.283	3.143	1.380
Consensus forecast	2.186	2.977	1.356
Panel C: Diebold-Mariano Tests			
	All	Rep President	Dem President
Democratic vs Republican	-2.705***	-2.319**	-1.027
Democratic vs Consensus	-1.693*	-1.236	-0.467
Republican vs Consensus	2.417**	2.490**	1.166

Notes: Panel A reports mean forecast errors (actual - forecast) for 2-quarter ahead GDP forecasts. Negative values indicate forecasts that are optimistic. Panel B reports mean absolute forecast errors. Lower values indicate more accurate forecasts. The Consensus forecast is mean across all forecasters in the WSJ survey. The "All" column shows the average errors across all administrations, while "Rep President" and "Dem President" columns show errors during Republican and Democratic presidential administrations respectively. Panel C reports Diebold-Mariano test statistics where negative values indicate the first forecast in the comparison is more accurate. The sample runs from July 1986 to April 2023. Statistical significance is denoted as: $*** \, p < 0.01$, $** \, p < 0.05$, $* \, p < 0.1$.

Table 7: Absolute forecast error differences in Democratic and Republican GDP forecasts

	Full Sample	Excluding Pandemic
	(1)	(2)
$\text{Rep}_j \times \text{Pres}_t$	0.17**	0.15**
	(0.070)	(0.069)
Observations	6,132	5,887
R-squared	0.974	0.829

Notes: This table reports the difference-in-difference estimate for absolute forecast errors of 2-quarter ahead GDP forecasts between Republican and Democratic-affiliated forecasters when there is a Republican president relative to a Democrat president from estimating Equation 4. The first column shows the full sample from July 1986 to April 2023, while the second column drops October 2019 to September 2020. Standard errors clustered at the forecaster level are reported in parentheses and statistical significance is denoted as: : $*** \, p < 0.01$, $** \, p < 0.05$, $* \, p < 0.1$.

Table 7 reports these results across two specifications. Column (1) shows results for the full sample, while Column (2) excludes the early pandemic period (October 2019 to September 2020) when forecast errors were exceptionally large and volatile. The coefficient on the interaction term is similar across specifications—0.17 percentage points in the full sample and 0.15 percentage points excluding the pandemic period—and statistically significant at the 5% level in both cases. The economic magnitude of this effect is substantial. The 0.15–0.17 percentage point accuracy penalty represents approximately 7–11 percent of typical forecast errors—ranging from 7 percent in the full sample (relative to consensus

MAE of 2.2 pp) to 11 percent when excluding the volatile early pandemic period (relative to consensus MAE of 1.4 percentage points). This represents a meaningful deterioration in predictive performance that is consistent across different sample specifications.

Interestingly, the results in Table 6 and Table 7 suggest that the politically less–diverse subset of Democratic forecasters produces smaller errors than the full, more heterogeneous panel. This finding appears at odds with canonical theory arguing that diversity enhances collective problem-solving (Hong and Page, 2004), as well as recent survey-evidence showing that greater cross-forecaster disagreement (a proxy for informational diversity) improves consensus accuracy (Doelp, 2023). At the same time, it echoes micro-level results indicating that increased team size and heterogeneity can *reduce* precision when coordination costs dominate information gains (Brown and Hugon, 2009). Our setting therefore highlights how the diversity–accuracy relationship is context-dependent: political homogeneity may attenuate noise from partisan disagreement without sacrificing information, thereby improving macroeconomic forecasts.

3.4 Other Macroeconomic Forecasts

Having established evidence of partisan bias in GDP forecasts, a natural question arises: does this bias extend to forecasts of other key macroeconomic indicators? We now investigate the effect of political affiliation on the forecasts of other major macro variables. We focus on inflation (as measured by the CPI), the unemployment rate and the federal funds rate. These are the other variables that are most consistency sampled in the WSJ survey. Just like GDP forecast analysis, we use a 2 quarter forecasting horizon for these three variables. We apply our baseline two-way fixed effects specification (Equation 2) to test for differentials in forecasts across these macro variables. Table 8 presents the results. For all three variables, the interaction coefficient is close to zero and statistically insignificant, indicating no evidence that political affiliation affects these forecasts in the same way it influences GDP forecasts.

These results raise the obvious question: Why is it that partisanship is affecting GDP forecasts but

Table 8: Difference in Democratic and Republican Forecasts: Other macro variables

	CPI	Unemp	FFR
$\text{Rep}_j \times \text{Pres}_t$	0.01	-0.02	0.02
	(0.069)	(0.055)	(0.030)
Observations	6,197	5,531	6,218
R-squared	0.789	0.961	0.987

Notes: This table reports the difference-in-difference estimate for forecasts of various macroeconomic variables between Republican and Democratic-affiliated forecasters when there is a Republican president relative to a Democrat president from estimating Equation 2. Columns 1 through 3 show the estimates for Consumer Price Index (CPI), Unemployment Rate (Unemp) and Federal Funds Rate (FFR)) respectively. The forecasting horizon is 2 quarters for all variables. The sample runs from July 1986 to April 2023. Standard errors clustered at the forecaster level are reported in parentheses. Statistical significance is denoted as: $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

not inflation, unemployment, or interest rate forecasts? We tackle this question in the next section.

4 Mechanisms and Conceptual Framework

This section provides a unified framework to explain both why partisan bias emerges exclusively in GDP forecasts and primarily during Republican administrations. We consider three potential mechanisms through which political identity might influence professional forecasters' judgments. First, there could be information differences driving the differential forecasts of Democrats and Republicans, i.e., that Democrats and Republicans pay attention to different information sources, which might affect their forecasts. Second, forecasters might exhibit a "pure" in-group bias—becoming automatically more optimistic when their affiliated party holds power, regardless of the economic policies undertaken by the administration. Finally, it could be differential evaluations of the effectiveness of the policies implemented by Democrat and Republican presidents. Our model incorporates these mechanisms within a Bayesian framework where forecasters optimally combine noisy signals with politically influenced prior beliefs.

4.1 A Signal Extraction Model with Political Priors

Consider a professional forecaster j with political affiliation $a_j \in \{D, R\}$ (Democrat or Republican) who forecasts macroeconomic variables $i \in \{GDP, \Omega\}$, where GDP represents GDP growth and Ω represents other macroeconomic variables (inflation, unemployment, or interest rates).

Each macroeconomic variable i at time t is allowed to depend on the political party in power $p_t \in \{D, R\}$, and its true value is denoted by $\theta_{i,t}(p_t)$. Each forecaster observes a signal $s_{i,j,t}$ about the fundamental value which combines a common public component and an idiosyncratic private component:

$$s_{i,j,t} = \theta_{i,t}(p_t) + \eta_{i,t} + v_{i,j,t} \tag{5}$$

where $\eta_{i,t}$ represents the common signal noise that is distributed as $\eta_{i,t} \sim N(0, \sigma^2_{\eta,i,t})$ and $v_{i,j,t}$ is forecaster-specific noise with $v_{i,j,t} \sim N(\mu_{v,a_j}, \sigma^2_{v,i,t})$, where $\mu_{v,D}$ and $\mu_{v,R}$ capture potential systematic differences across parties. The common component $\eta_{i,t}$ represents noise in economic data releases or leading indicators, while the idiosyncratic component $v_{i,j,t}$ captures differences in the information to which forecasters are paying attention.

Prior Belief Structure: Forecasters have prior beliefs about macroeconomic variables that follow a normal distribution:

$$\theta_{i,j,t}(p_t) \sim N(\mu_{i,j,t}(p_t), \sigma^2_{prior,i}) \tag{6}$$

Forecasters' prior mean about macroeconomic variables incorporate multiple components:

$$\mu_{i,j,t}(p_t) = \bar{\mu}_i + \beta_{a_j} \cdot \mathbf{1}_{p_t=a_j} + \gamma_{a_j,i}(p_t) \cdot \tau_t \tag{7}$$

where $\bar{\mu}_i$ is the baseline expected value for variable i that is common across forecasters. $\beta_{a_j} \cdot \mathbf{1}_{p_t=a_j}$ captures pure in-group bias that activates when the president's party matches the forecaster's affiliation. $\gamma_{a_j,i}(p_t) \cdot \tau_t$ represents policy-specific beliefs $\gamma_{a_j,i}(p_t)$ modulated by policy salience τ_t.

Bayesian Updating: When forecasters observe the signal $s_{i,j,t}$, they update their beliefs according to Bayes' rule. With normally distributed priors and signals, the posterior mean (which is the optimal forecast under mean-squared error criterion) is a weighted average of the signal and the prior mean:

$$\hat{\theta}_{i,j,t} = w_{i,j,t} \cdot s_{i,j,t} + (1 - w_{i,j,t}) \cdot \mu_{i,j,t}(p_t) \tag{8}$$

where $w_{i,j,t}$ is the weight placed on the signal, given by:

$$w_{i,j,t} = \frac{\sigma^2_{prior,i}}{\sigma^2_{prior,i} + \sigma^2_{\eta,i,t} + \sigma^2_{v,i,t}} \tag{9}$$

We now turn to the key empirical implications of our model, beginning with why partisan bias emerges specifically in GDP forecasts.

4.2 Why Only GDP? The Role of Signal Precision

Recall the signal structure in Equation 5: each forecaster observes a noisy public signal plus idiosyncratic noise. We now impose a restriction on the variance of the public noise.

Assumption: We assume that signals about GDP growth are noisier than signals about other macroeconomic variables:

$$\sigma^2_{\eta,\mathrm{GDP,t}} > \sigma^2_{\eta,\Omega,t} \quad \text{where } \Omega \in \{\text{CPI, Unemployment, FFR}\} \tag{10}$$

If the noise affecting GDP forecasts is indeed larger than for other macroeconomic variables, then GDP should be fundamentally harder to forecast. The data confirms this intuition. Table 9 presents two standardized measures that allow for direct comparability across variables: (1) Scaled RMSE, calculated as the root mean squared error of the consensus forecast divided by the unconditional interquartile range (IQR) of realized outcomes, and (2) Scaled Disagreement, defined as the time-averaged cross-sectional IQR of forecasts normalized by the unconditional IQR of realized outcomes.[12] Both

Table 9: Forecast Accuracy and Disagreement across Variables

	GDP	CPI	Unemp	FFR
Panel A: Full sample				
Scaled RMSE	2.822	0.783	0.477	0.421
Scaled Disagreement	0.437	0.382	0.119	0.114
Panel B: Excluding pandemic				
Scaled RMSE	1.046	0.756	0.173	0.391
Scaled Disagreement	0.446	0.361	0.103	0.112

Notes: This table reports measures of forecast accuracy and disagreement for various macroeconomic variables. Scaled RMSE is the root mean squared error of the consensus forecast (the mean across forecasters at each date) divided by the unconditional interquartile range of the realized series. Scaled Disagreement is the cross-sectional interquartile range of individual forecasts at each date, normalized by the unconditional interquartile range of the realized series and averaged over time. The variables shown are for GDP growth, Consumer Price Index (CPI) inflation, the unemployment rate (Unemp), and the federal funds rate (FFR). Panel A shows results for the full sample from July 1986 to April 2023. Panel B excludes the pandemic period (October 2019 to September 2020).

metrics are substantially higher for GDP than for other macroeconomic variables, providing strong evidence that GDP forecasts involve greater uncertainty and complexity. This pattern holds both in the full sample (Panel A) and when excluding the period around the onset of the pandemic (Panel B), indicating that the greater difficulty in forecasting GDP is not driven by the exceptional volatility during this time. While the exclusion of this period reduces forecast errors and disagreement for all variables, GDP continues to exhibit the highest scaled RMSE and scaled disagreement relative to other macroeconomic indicators.

The greater difficulty in GDP forecasting creates a natural pathway for partisan beliefs to influence forecasts when objective signals lack precision. The assumption about higher noise in GDP signals from Equation 10 combined with Equation 9, implies that forecasters place less weight on signals and more weight on their prior beliefs when forecasting GDP:

$$w_{\text{GDP},j,t} < w_{\Omega,j,t} \quad \text{where } \Omega \in \{\text{CPI, Unemployment, FFR}\} \tag{11}$$

This key insight explains why we observe partisan bias in GDP forecasts but not in other macroeconomic variables, since the partisan bias enters solely through heterogeneous priors.

[12]Since the macroeconomic variables are measured in different units and have different scales of variation, we normalize both measures by the IQR of the realized data to facilitate meaningful cross-variable comparison.

Even with the differential-signal-noise explanation in place, one might still worry that general-equilibrium links should transmit any partisan GDP bias to forecasts of other variables. However, it turns out that numerically the transmission is too small to be detectable. For example let's consider the relationship between unemployment and GDP typically estimated using an Okun's law estimation. A within-forecaster, within-survey-round regression of the expected two-quarter change in the unemployment rate on GDP growth yields a coefficient of $\widehat{\beta}^{\text{Okun}} = -0.06$.[13] Combining this with the average partisan gap in GDP growth forecasts (0.38 percentage points from Column 2 in Table 2) implies an unemployment gap of $\Delta^{\text{partisan}}\hat{u} = (-0.06) \times 0.38 = -0.023$ pp or just over 2 basis points. At an unemployment-rate that typically hovers between 4 and 6 percent, a two-basis-point shift is economically negligible and would not be discernible in standard empirical tests. Similar calculations using Phillips-curve and Taylor-rule coefficients (not shown) imply that any induced gaps in inflation or the interest rate would be smaller still, reinforcing the finding that partisan bias remains confined to GDP forecasts.

Despite inflation forecasts exhibiting the largest forecast errors and disagreement among the non-GDP variables (Table 9)—making them theoretically the most demanding test of our signal noise mechanism—we find no partisan bias. This absence can be explained by conflicting theoretical predictions about the direction any bias should take. Specifically, forecaster optimism when their preferred party is in office could manifest as lower expected inflation (similar to household forecast patterns), but optimism about general economic conditions would simultaneously push toward higher expected inflation through standard macroeconomic relationships like the Phillips curve. Additionally, inflation (and also interest rates) are primarily determined by Federal Reserve monetary policy, and the Fed's institutional design as an independent, technocratic institution likely provides insulation from partisan influence in forecaster expectations. Thus, unlike for GDP, these offsetting theoretical forces leave no clear ex-ante prediction for partisan bias direction in inflation forecasts, making any net effect difficult to detect empirically.

Having established why partisan bias emerges specifically in GDP forecasts, we can now turn to examining its underlying sources. Our theoretical framework suggests three potential mechanisms through which partisan affiliation might influence GDP forecasts. Before evaluating these mechanisms individually, we first test a fundamental prediction of our model: that partisan bias should vary with signal noise.

[13] Mitchell and Pearce (2010b) obtain similar values using the same dataset employed here (WSJ). Three factors explain why this estimate is smaller than the canonical –0.3 to –0.5 rule-of-thumb. First, numerous studies document a post-1990 flattening of the Okun's law relationship (Knotek (2007) and Meyer and Tasci (2012)). Second, our specification absorbs forecaster and time fixed effects, and measurement error in forecasts further attenuates the coefficient (see Daly et al. 2014). Finally, the typical Okun's law coefficient refers to year-over-year growth and four-quarter changes in unemployment; converting to a two-quarter horizon and annualized quarter-on-quarter growth reduces the magnitude.

4.3 Empirical Implication: Partisan Bias Increases with Signal Noise

The model predicts a specific relationship between signal noise and partisan bias that we can examine in the data. Using our model's posterior mean expression: $\hat{\theta}_{i,j,t} = w_{i,j,t} \cdot s_{i,j,t} + (1 - w_{i,j,t}) \cdot \mu_{i,j,t}(p_t)$, we can express the average partisan bias at time t as:

$$\text{Partisan Bias}_{GDP,t} = \left[\frac{1}{N_R} \sum_{j \in J_R} \hat{\theta}_{GDP,j,t} - \frac{1}{N_D} \sum_{j \in J_D} \hat{\theta}_{GDP,j,t} \right] \tag{12}$$

where J_R and J_D represent Republican and Democratic forecasters, N_R and N_D are their counts. Substituting the posterior mean expression and taking averages within each party yields:

$$\text{Partisan Bias}_{GDP,t} = (1 - \bar{w}_t) \underbrace{\left(\bar{\mu}^R_{GDP,t} - \bar{\mu}^D_{GDP,t}\right)}_{\text{PriorGap}_t} + \bar{w}_t \underbrace{\left(\bar{\nu}^R_{GDP,t} - \bar{\nu}^D_{GDP,t}\right)}_{\text{InfoGap}_t}, \tag{13}$$

where $\bar{w}_t \equiv \frac{1}{N_R + N_D} \sum_{j \in J_R \cup J_D} w_{\text{GDP},j,t}$ is the average weight on signals, and for each party $a \in \{R, D\}$: $\bar{\mu}^a_{GDP,t} \equiv \frac{1}{N_a} \sum_{j \in J_a} \mu_{\text{GDP},j,t}$ and $\bar{\nu}^a_{GDP,t} \equiv \frac{1}{N_a} \sum_{j \in J_a} \nu_{\text{GDP},j,t}$ are the average prior mean and idiosyncratic signal component, respectively. The PriorGap_t is the cross-party difference in average prior means—capturing both in-group bias and differing beliefs about policy efficacy. The InfoGap_t represents potential information differences across Democrats and Republicans. In Section 4.6 we argue that party-specific information differences are negligible for professional forecasters. This implies that $\text{InfoGap}_t \approx 0$ and the expression collapses to $(1 - \bar{w}_t)\,\text{PriorGap}_t$. Since $\bar{w}_t$ represents the average weight on signals, and each individual weight is given by $w_{GDP,j,t} = \frac{\sigma^2_{prior,GDP}}{\sigma^2_{prior,GDP} + \sigma^2_{\eta,GDP,t} + \sigma^2_{\nu,GDP,t}}$, an increase in the common signal noise $\sigma^2_{\eta,GDP,t}$ decreases all individual weights and therefore $\bar{w}_t$. This increases $(1 - \bar{w}_t)$, amplifying the effect of any prior gap on partisan bias.

This leads to an empirical prediction: partisan bias should be stronger during periods when signals about the true state of the economy are noisier. Formally, since $\frac{\partial}{\partial \sigma^2_{\eta,GDP,t}}[(1 - \bar{w}_t)] > 0$, we have that partisan bias increases with signal noise whenever $\text{PriorGap}_t \neq 0$

$$\frac{\partial |\text{Partisan Bias}_{GDP,t}|}{\partial \sigma^2_{\eta,GDP,t}} > 0. \tag{14}$$

We test this model implication by examining the relationship between partisan bias and two proxies for signal noise: absolute forecast errors and forecast dispersion (measured by the IQR of forecasts). Table 10 shows that both measures indicate positive and highly significant relationships with partisan bias. Therefore, when forecasting becomes more difficult, partisan differences in forecasts widen. This relationship remains robust even when excluding recession periods, suggesting the mechanism operates consistently across different economic environments.

Table 10: Relationship between Partisan Bias and Noise

	(1)	(2)	(3)	(4)
Dispersion (IQR)	0.391***	0.246***		
	(0.093)	(0.084)		
Absolute forecast error			0.021***	0.015***
			(0.008)	(0.005)
Observations	251	227	248	224
R-squared	0.323	0.185	0.057	0.041
Exclude recessions	no	yes	no	yes

Notes: The table shows the regression of average partisan bias on two measures of noise in GDP forecasts. Average partisan bias is the difference between the average Republican and average Democratic GDP forecasts. "Dispersion (IQR)" is the interquartile range of GDP forecasts across all forecasters. "abs(forecast error)" is the absolute value of the consensus forecast error. Standard errors are reported in parentheses and statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All regressions use data from 1986-2023.

Table 10 thus validates our central mechanism: noisy signals amplify the influence of partisan priors. Combined with the evidence in Table 9 that GDP forecasts are inherently noisier than other variables, these results explain why partisan bias appears primarily in GDP forecasts and intensifies during uncertain periods. We now turn to examining the potential mechanisms that could generate these partisan differences.

4.4 Beliefs about Policy effectiveness

We start with the most promising mechanism for explaining the partisan patterns: differential beliefs about policy effectiveness. Under this mechanism, forecasters' expectations reflect divergent views about the economic models that govern the economy, particularly regarding how presidential policies influence macroeconomic outcomes. Within our framework, this affects the forecast through the term $\gamma_{a_j,i}(p_t) \cdot \tau_t$ in the forecaster prior.

For this to be the operative mechanism consistent with our results, it must be that there are one or more policies that Republicans view as affecting GDP growth more positively than Democrats and that these policies are disproportionately pursued under Republican presidents. Potential examples of such policies include reduced regulation, lower government spending, and lower taxes relative to Democrats. We investigate how these differing policy approaches could differentially affect forecasters' GDP expectations.

We focus primarily on fiscal policy rather than regulation for several reasons. First, fiscal policy changes tend to have immediate and quantifiable impacts on GDP. In comparison, regulatory changes typically work through indirect channels and over longer horizons. Second, fiscal policy receives more prominent coverage in economic news and political discourse. This coverage makes fiscal policy more salient to forecasters. Finally, while regulatory changes are important, they are often industry-specific and difficult to aggregate into a single measure that would systematically influence GDP forecasts.

To capture real-time perceptions of the importance of fiscal policy, we use Google Trends data. These provide normalized indices of search interest, for specific terms, over time and serve as a proxy for the salience of particular economic policies in public and professional discourse. While there are known limitations with Google Trends data (including potential sampling biases and opacity in the normalization process), our comparative approach mitigates these concerns. Since we are only interested in exploring differences across Republican and Democratic-affiliated forecasters, any measurement issues that do not systematically vary across these two groups will not affect our conclusions. We focus on two search terms: "government spending" and "tax cuts".

Table 11: Differences in Google Trend Searches by Presidential Party

	Tax cuts	Govt. spending
Democrat president	9.08	33.46
Republican president	16.38	28.91
Difference	-7.30***	4.55***
	(0.40)	(0.33)

Notes: This table shows the mean of the Google trends searches for "tax cuts" and "government spending" across presidential regimes. The last row shows the difference for the two variables across presidential regimes. The sample runs from January 2004 to April 2023. Robust standard errors are reported in parentheses and statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11 shows the mean of these two series by presidential regime. As expected, there is significantly more search interest in "tax cuts" under Republican presidents, while "government spending" receives more attention under Democratic presidents. These differences are statistically significant at the 1% level, confirming that fiscal policy emphasis does indeed vary systematically by presidential party, with Republicans associated with tax cut discussions and Democrats with government spending discourse.

To investigate if these differences in fiscal policy emphasis play a role in the partisan GDP forecast differentials, we estimate our baseline two-way fixed effects regression, replacing the indicator for presidential regime with the Google Trends measures for tax cuts and government spending:

$$y_{j,t} = \gamma_j + \gamma_t + \beta Rep_j * \text{tax cuts}_t + \delta Rep_j * \text{goverment spending}_t + \varepsilon_{j,t} \tag{15}$$

To aid in interpreting the coefficients, we standardize both Google Trends variables to have unit standard deviation. Table 12 shows the results from this estimation. The coefficient on the interaction between Republican forecaster affiliation and tax cut search intensity (0.09) is positive and statistically significant at the 5% level. This indicates that when public interest in tax cuts increases by one standard deviation, Republican forecasters are on average more optimistic relative to Democratic forecasters, projecting GDP growth 0.09 percentage points higher. Conversely, the interaction between Republican affiliation and government spending search intensity is negative (-0.04). Therefore, when interest in government spending increases, Republican forecasters on average are relatively pessimistic about GDP. However, this coefficient is smaller and statistically insignificant.

Table 12: Fiscal policy Google searches and GDP Forecasts

$\text{Rep}_j \times \text{tax cuts}_t$	0.09 **
	(0.044)
$\text{Rep}_j \times \text{government spending}_t$	-0.04
	(0.034)
Observations	4,847
R-squared	0.647

Notes: This table shows the differential effect of intensity of Google Trend searches for "tax cuts" and "government spending", based on forecaster affiliation, estimated from Equation 15. The sample runs from January 2004 to April 2023. Standard errors clustered at the forecaster level are reported in parentheses and statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Republican forecasters appear to be relatively more optimistic about economic growth prospects when tax cuts are salient in public discourse, aligning with the view—often associated with Republicans—that reducing taxes can stimulate growth. Meanwhile, a negative, but small and statistically insignificant response to "government spending" searches suggests a smaller role, if any, for spending to make Democratic forecasters relatively more relatively optimistic. This asymmetry suggests that partisan differences in GDP forecasts are linked specifically to views on the growth effects of tax cuts rather than fiscal policy more broadly.

To further explore the effects of tax-induced fiscal policy shocks on partisan forecasts, we employ the exogenous tax shocks constructed by Romer and Romer (2010), referred to as RR henceforth. The RR measure identifies tax changes that were motivated by either deficit reduction concerns or long-run growth considerations, rather than in response to current economic conditions. We use their measure of exogenous tax changes expressed as a percentage of nominal GDP and excluding retroactive tax changes to ensure proper timing of the policy intervention.

Tax shocks from the literature (including the RR measure) typically end 10–20 years before 2023 and thus do not cover our entire sample period. Moreover, because we need to estimate the dynamic causal impact of these shocks, we begin our sample in 2003, when the WSJ survey changed from bi-annual to monthly frequency. This timing leaves only a limited overlap between existing tax shock measures and our forecast data. We therefore extend the RR measure to include the 2017 Tax Cuts and Jobs Act (TCJA) following the approach of Howes (2019).[14] This approach is methodologically

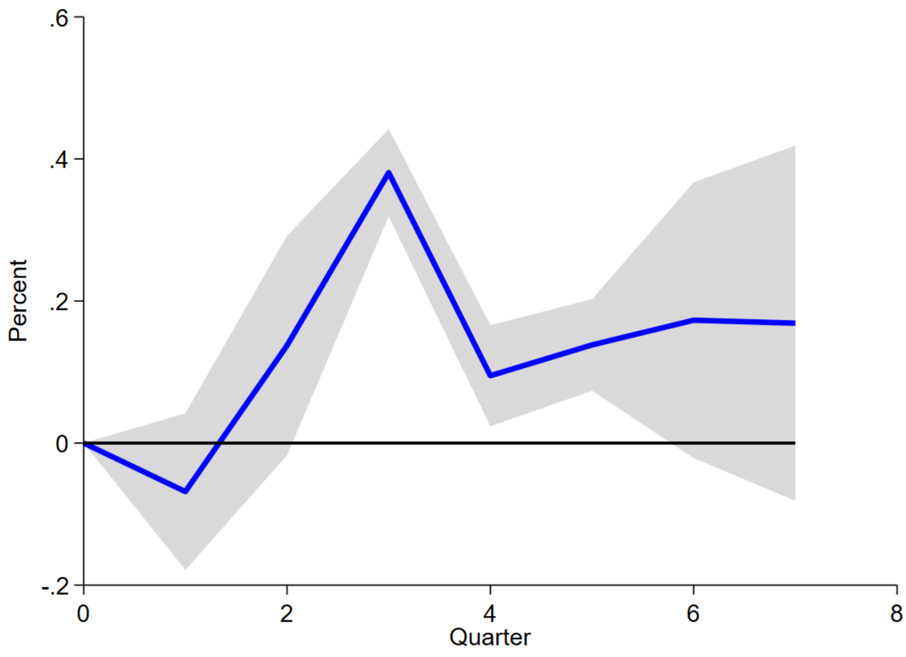
[14]Howes applies the Romer-Romer narrative methodology to the TCJA, carefully examining legislative history and congressional records to identify the motivation behind the tax changes. He classifies TCJA components as either exogenous (motivated by long-run growth objectives) or endogenous (responding to cyclical conditions), and quantifies their magnitude and timing based on Joint Committee on Taxation revenue estimates.

consistent with the original RR tax shock series, while extending it to cover the most significant tax legislation during our sample period.

We then use the updated RR tax measure in a local projection framework (Jordà, 2005). Since the RR shocks are available at a quarterly frequency, we aggregate our monthly forecast data to quarterly by averaging over each quarter. To study how these tax shocks differentially affect forecasters based on their political affiliation, we could in principle run panel local projections. However, as mentioned previously, our unbalanced panel—where forecasters enter and exit the sample—significantly reduces the data available for identification in such a specification.

To overcome this limitation, we first compute quarterly means by forecaster affiliation. Next, we calculate the difference between Republican and Democratic averages for each quarter. Finally, we estimate local projections of this difference on the RR tax shock. We run the regression (Rep. $\text{Forecast}_{t+h} -$ Dem. $\text{Forecast}_{t+h}) = \alpha_h + \beta_h \cdot \text{Tax Shock}_t + \varepsilon_{t+h}$ where we scale the shock so that an increase in the variable represents a tax cut. This allows us to estimate the dynamic causal effect of tax changes on the difference between Republican and Democratic forecasters' GDP projections.

Figure 5: Difference in Democratic and Republican Forecasts: Response to tax shock



Notes: The figure shows the dynamic response of the difference between the average Republican and Democratic 2-quarter ahead GDP forecast to a tax cut (using Romer and Romer (2010) exogenous tax shock). 90% confidence intervals are reported with shaded regions. The sample runs from 2003:Q1 2023:Q1.

Figure 5 presents the dynamic responses of the Republican-Democratic forecast gap to an exogenous tax increase (i.e. β_h). The results reveal a clear pattern: following a tax cut, Republican forecasters become more optimistic relative to Democratic forecasters, with the effect emerging gradually and peaking around 3 quarters after the policy change.

The evidence from both Google Trends salience measures and exogenous tax shocks consistently points to differential beliefs about fiscal policy effectiveness as the primary mechanism driving partisan bias in GDP forecasts. To complete our analysis of potential mechanisms, we next examine two alternative explanations. First, whether pure in-group favoritism independent of policy views could generate the observed bias. Second, whether systematic differences in information sources might account for the partisan patterns.

4.5 Pure in-group bias

Here, we take up the the potential role of pure in-group bias in driving the partisan differences across Republicans and Democrats. In the forecaster's prior, this term is represented by $\beta_{a_j} \cdot \mathbf{1}_{p_t=a_j}$. This term captures how forecasters become more optimistic when the president belongs to their affiliated party. An important implication of pure in-group bias is that it should manifest immediately upon a president's election or inauguration, since it is unrelated to any economic policies actually implemented by the president. Indeed, household economic expectations shift almost instantaneously following presidential transitions (Mian et al., 2021). Thus, a straightforward test for the existence of pure in-group bias is to examine whether partisan differences emerge immediately following the election or inauguration of a president.

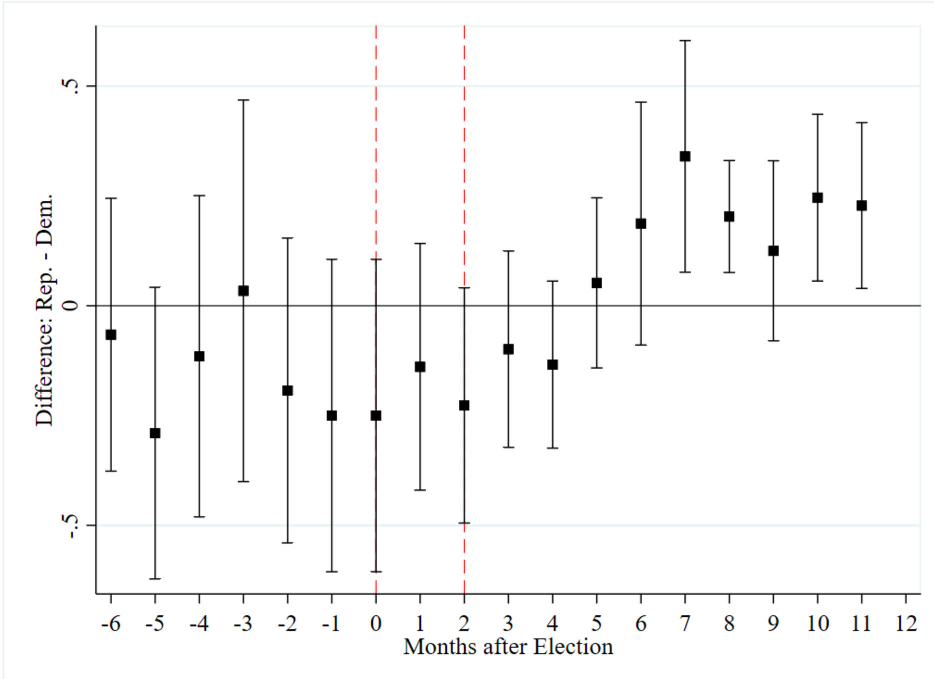
Identifying the precise timing of partisan bias emergence is challenging. Presidential election results are typically anticipated in our sample, creating anticipatory effects in forecasts. If forecasters expect their affiliated party's candidate to win, partisan bias may begin influencing their projections before the election date. The 2016 presidential election, however, provides a natural experiment. With polling and forecasting models giving Hillary Clinton a very high probability of winning, Donald Trump's victory was largely unexpected. The surprise of president Trump's victory allows us to treat the 2016 election as an exogenous shock, effectively eliminating anticipation effects. By examining how Republican and Democratic forecasters adjusted their GDP projections around this unexpected result, we can better identify the timing of partisan bias and gain insights into its underlying mechanisms.

We estimate the partisan forecast effects of the 2016 election surprise using the following regression:

$$y_{j,t} = \gamma_j + \gamma_t + \sum_{k=-6}^{12} \zeta_k Rep_j \cdot \mathbf{1}_{t=t_0+k} + \epsilon_{j,t}, \tag{16}$$

where t_0 is the election date and ζ_k is a separate date fixed effect for Republicans. Figure 6 presents the results with 95% confidence intervals. The interpretation of each ζ_k is the difference between the expectations of Republicans and those of Democrats in the same period. The first vertical dotted red

Figure 6: Event-study of 2016 Election



line indicates the November election date, while the second marks the January inauguration.

Republican forecasters' optimism (relative to Democrats) does not emerge immediately. The difference between Republican and Democrat-affiliated forecasters remains statistically indistinguishable from zero around both the election and inauguration dates. However, several months into the Trump administration, we observe the partisan gap widening and becoming statistically significant, peaking approximately 7 months after the election. Pure partisan cheerleading would have emerged quickly following the election.

Moreover, pure in-group bias would require an implausible asymmetry: Republican forecasters would need to systematically exhibit partisan cheerleading while Democratic forecasters do not, and this difference would need to persist consistently across four decades. These considerations suggest that pure in-group favoritism is unlikely to be the primary mechanism driving our results.

4.6 Information differences

Another potential explanation for the partisan patterns we observe is that forecasters with different political affiliations might systematically expose themselves to distinct news sources or economic indicators, leading to divergent GDP projections. However, several factors make this explanation unlikely to account for our findings.

First, an information-based explanation would require an implausible asymmetric pattern. Republican forecasters would need to selectively attend to relatively optimistic information when Republicans hold the presidency, but show no corresponding bias toward pessimistic information under Democratic presidents. Moreover, Democratic forecasters would need to remain unbiased regardless of which party is in power. The required asymmetry is not something we observe in household expectations, where information differences and selective exposure to partisan media sources appear to play an important role in driving symmetric partisan bias: Republican households are more optimistic under Republican presidents and more pessimistic under Democratic presidents, while Democratic households show the reverse pattern (Bartels, 2002; Gerber and Huber, 2009; Peterson and Iyengar, 2021).

Second, our sample consists of professional forecasters at leading financial institutions, investment banks, economic consulting firms, and academic institutions. These organizations typically invest heavily in data acquisition, economic research teams, and sophisticated forecasting tools. Such forecasters face strong market incentives for accuracy—their compensation, professional advancement, and institutional reputation all depend on forecast precision. Unlike households whose information consumption may be driven by confirmation bias or partisan media preferences, professional forecasters operate in competitive environments where persistent information neglect would be costly.

Finally, the gradual emergence of partisan differences following the 2016 election is difficult to reconcile with a simple information filtering story. If Republican forecasters were simply switching to different information sources after Trump's election, we might expect a more immediate shift in their forecasts rather than the delayed pattern we observe.

These considerations suggest that selective exposure to or processing of information is unlikely to be the primary driver of the partisan bias we document.

5 Conclusion

This paper demonstrates that partisan bias substantially affects professional forecasters' GDP predictions, with Republican-affiliated forecasters projecting relatively higher GDP growth when Republicans control the presidency. To establish these findings, we create a novel dataset by matching professional forecasters in the Wall Street Journal Economic Forecasting Survey to their political affiliations using publicly available sources including FEC donation records, voter registration data, and partisan employment histories. Our analysis reveals several key insights about how partisanship influences economic forecasting.

First, the partisan effect is economically meaningful and highly robust. Republican forecasters predict GDP growth approximately 0.3–0.4 percentage points higher under Republican presidents compared to Democratic forecasters, with the bias stemming from Republican forecasters' increased optimism during Republican presidencies rather than symmetric partisan effects across both groups.

Second, partisan bias appears uniquely in GDP forecasts, with no corresponding effect in inflation, unemployment, or interest rate forecasts. Third, our analysis of forecast accuracy reveals that partisan optimism comes at the cost of predictive performance. Republican forecasters exhibit relatively larger forecast errors during Republican presidencies, suggesting that partisan sentiment distorts professional judgment even among highly trained experts.

To help explain these empirical patterns, we develop a theoretical framework showing how the interaction between signal quality and politically-influenced prior beliefs can generate partisan bias in professional settings. The model provides insight into why partisan bias emerges specifically in GDP forecasts—where signals are inherently noisier—while being absent from other macroeconomic variables with more precise signals. Our examination of underlying mechanisms points to differing beliefs about economic policy effectiveness, particularly regarding tax policy, as the most plausible explanation for the partisan differences we observe. The evidence suggests that Republican forecasters genuinely believe tax cuts have larger growth effects than Democratic forecasters do, rather than reflecting simple in-group favoritism or differences in information sources.

References

Bartels, L. M. (2002). Beyond the running tally: Partisan bias in political perceptions. *Political Behavior 24*(2), 117–150.

Belongia, M. T. (1987). Predicting interest rates: A comparison of professional and market-based forecasts. Technical Report March 1987, Federal Reserve Bank of St. Louis Review.

Bianchi, F., S. C. Ludvigson, and S. Ma (2022). Belief distortions and macroeconomic fluctuations. *American Economic Review 112*(7), 2269—-2315.

Binder, C. (2023). Political party affiliation and inflation expectations. *Brookings Papers on Economic Activity 2023*(1), 215–258.

Blinder, A. S. and M. W. Watson (2016). Presidents and the us economy: An econometric exploration. *American Economic Review 106*(4), 1015–1045.

Bordalo, P., N. Gennaioli, Y. Ma, and A. Shleifer (2020). Overreaction in macroeconomic expectations. *American Economic Review 110*(9), 2748–82.

Bovens, M. and A. Wille (2021). Education, inequality, and political behavior. In *Oxford Research Encyclopedia of Politics*. Oxford University Press.

Brown, L. D. and A. Hugon (2009). Team earnings forecasting. *Review of Accounting Studies 14*(4), 587–607.

Cassidy, W. and E. Kempf (2024). Partisan corporate speech.

Cassidy, W. and B. Vorsatz (2024). Partisanship and portfolio choice: Evidence from mutual funds. *Available at SSRN 3977887 No column information*(No number information), No page information.

Coibion, O. and Y. Gorodnichenko (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy 120*(1), 116–159.

Coibion, O. and Y. Gorodnichenko (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review 105*(8), 2644–78.

Dagostino, R., J. Gao, and P. Ma (2023). Partisanship in loan pricing. *Journal of Financial Economics 150*(3), 103717.

Daly, M. C., J. Fernald, Òscar Jordà, and F. Nechio (2014, April). Interpreting deviations from okun's law. *Federal Reserve Bank of San Francisco Economic Letter NA*(2014-12), NA.

DeBarros, A. (2022). About the wall street journal economic forecasting survey. *The Wall Street Journal 0*(0), 0.

Democracy Fund Voter Study Group (2020). Party hoppers: Understanding voters who switch political parties. Accessed: 2025-02-11.

Diebold, F. X. and R. S. Mariano (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics 13*(3), 253–263.

Doelp, P. (2023, December). Forecast accuracy and forecaster disagreement in the survey of professional forecasters. Research Brief RB 2023-DEC-31, Federal Reserve Bank of Philadelphia.

Dreger, C. and G. Stadtmann (2008). What drives heterogeneity in foreign exchange rate expectations: insights from a new survey. *International Journal of Finance & Economics 13*(4), 360–367.

Duchin, R., A. E. K. Farroukh, J. Harford, and T. Patel (2023). The economic effects of political polarization: Evidence from the real asset market*. In *No book title*.

Eisenbeis, R., D. F. Waggoner, and T. A. Zha (2002). Evaluating wall street journal survey forecasters: A multivariate approach. Technical report, SSRN.

Engelberg, J., J. Guzman, R. Lu, and W. Mullins (2022). Partisan entrepreneurship. Technical report, National Bureau of Economic Research.

Engelberg, J., R. Lu, W. Mullins, and R. R. Townsend (2023). Political sentiment and innovation: Evidence from patenters. Technical report, National Bureau of Economic Research.

Evers-Hillstrom, K., D. Weber, A. Massoglia, A. Mayersohn, G. Haley, S. Bryner, and A. Baumgart (2020). More money, less transparency: A decade under citizens united. Technical report, Center for Responsive Politics.

Farhart, C. E. and E. Struby (2024). Inflation expectations and political polarization: evidence from the cooperative election study. *Carlton College Department of Economics Working Paper Series NA*(NA), NA.

Gabaix, X. (2014). A sparsity-based model of bounded rationality. *The Quarterly Journal of Economics 129*(4), 1661–1710.

Gerber, A. S. and G. A. Huber (2009). Partisanship and economic behavior: Do partisan differences in economic forecasts predict real economic behavior? *American Political Science Review 103*(3), 407–426.

Greer, M. (2003). Directional accuracy tests of long-term interest rate forecasts. *International Journal of Forecasting 19*(2), 291–298.

Hong, L. and S. E. Page (2004). Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proceedings of the National Academy of Sciences 101*(46), 16385–16389.

Howes, C. (2019). The aggregate effects of targeted tax cuts. Working paper, University of Texas at Austin. March 2019.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.

Kamdar, R. and W. Ray (2022). Polarized expectations, polarized consumption. Technical report, SSRN.

Kempf, E. and M. Tsoutsoura (2021). Partisan professionals: Evidence from credit rating analysts. *The journal of finance 76*(6), 2805–2856.

Kempf, E. and M. Tsoutsoura (2024). Political polarization and finance. *SSRN Electronic Journal No column information*(No number information), No page information.

Knotek, E. S. (2007). How useful is okun's law? *Federal Reserve Bank of Kansas City Economic Review 92*(4), 73–103.

Kolb, R. and H. O. Stekler (1996). How well do analysts forecast interest rates? *Journal of Forecasting 15*(5), 385–394.

Mankiw, N. G. and R. Reis (2002, November). Sticky information versus sticky prices: A proposal to replace the new keynesian phillips curve. *The Quarterly Journal of Economics 117*(4), 1295–1328.

McNees, S. K. (1992). How large are economic forecast errors? *New England Economic Review 1*(Jul), 25–42.

Meyer, B. and M. Tasci (2012, August). An unstable okun's law, not the best rule of thumb. *Federal Reserve Bank of Cleveland Economic Commentary NA*(2012-08), NA.

Mian, A., A. Sufi, and N. Khoshkhou (2021). Partisan bias, economic expectations, and household spending. *The Review of Economics and Statistics 150*(3), 1–46.

Mitchell, K. and D. K. Pearce (2010a). Do wall street economists believe in okun's law and the taylor rule? *Journal of Economics and Finance 34*(2), 196–217.

Mitchell, K. and D. K. Pearce (2010b). Do wall street economists believe in okun's law and the taylor rule? *Journal of Economics and Finance 34*(2), 196–217.

Office of the House Historian (2023). Party government since 1857. Technical report, U.S. House of Representatives.

Peterson, E. and S. Iyengar (2021). Partisan gaps in political information and information-seeking behavior: Motivated reasoning or cheerleading? *American Journal of Political Science 65*(1), 133–147.

Pew Research Center (2020). Voters rarely switch parties, but recent shifts further educational, racial divergence. Accessed: 2025-02-11.

Romer, C. D. and D. H. Romer (2010). The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks. *American economic review 100*(3), 763–801.

Roper, L. D. (2002). Party control of u.s. government. Technical report, Personal Website.

Schuh, S. et al. (2001). An evaluation of recent macroeconomic forecast errors. *New England Economic Review January/February*(1), 35–36.

Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics 50*(3), 665–690.

U.S. Census Bureau (2021, April). 2020 presidential election voting and registration tables now available. Press release. Accessed June 11, 2025.

U.S. Election Assistance Commission (2020, October). Availability of state voter file and confidential information. PDF document. Accessed June 11, 2025.

Woodford, M. (2013). Macroeconomic analysis without the rational expectations hypothesis. *Annu. Rev. Econ. 5*(1), 303–346.

Appendix

A.1 Construction of Fixed Horizon Forecasts

For most of our sample, the WSJ Survey is conducted monthly and contains forecasts of several macroeconomic and financial variables. We focus on GDP growth, CPI inflation, the federal funds rate, and the unemployment rate. We primarily focus on fixed-horizon two-quarter-ahead forecasts. We now describe how we construct these forecasts from the data provided in the WSJ Survey.

The survey prompts respondents to give GDP growth forecasts for specific quarters, typically spanning from the current quarter to three to four quarters out. Thus for GDP growth, the survey directly provides a fixed-horizon forecast in each survey month.[15] Table A.1 describes the availability of data at horizons from 0 to 4 quarters ahead. The two-quarter ahead forecast is available in 100 percent of survey periods starting in December of 1985. For this reason, we focus on this variable for the majority of our analysis.

Table A.1: GDP Forecast Data Availability

Forecast Horizon	Share of Periods
$h = 0$	0.85
$h = 1$	0.90
$\mathbf{h = 2}$	**1.00**
$h = 3$	0.77
$h = 4$	0.55
$N = 251$	

Notes: The table presents the share of observations from December 1985 that include GDP growth forecasts at various horizons. A horizon of zero indicates a forecast for the current periods quarter-over-quarter annualized GDP growth, the nowcast. Horizons 1 to 4 indicate quarter-ahead to year-ahead forecasts.

Table A.2: Other Variable Forecast Availability

Variable	$h = 1$	$h = 2$	$h = 3$
CPI	0.41	0.59	0.41
Fed. Funds.	0.41	0.59	0.41
Unemployment	0.41	0.51	0.41

Notes: The table shows the share of survey periods December 1985 and on that contain forecasts for CPI inflation, the Federal Funds rate and the unemployment rate at horizons from one to three quarters ahead. The two-quarter forecast is available for the majority of survey periods. When the two-quarter forecast is not available, the one-quarter and three-quarter forecasts typically are available.

Forecasts of other variables (unemployment rate, CPI inflation, and federal funds rate) are elicited

[15] Technically, the exact time horizon varies depending on when within the quarter the survey is conducted. For example, a January 2019 survey asking for the two-quarter ahead forecast targets Q3 2019 (ending in September), creating a 9-month horizon. The same two-quarter ahead forecast collected in February 2019 would have only an 8-month horizon to the same target quarter.

by asking for the value of that variable in either May and November or June and December of a given year. We assign each target date to its corresponding quarter and calculate the forecast horizon as the number of quarters between the survey quarter and the target quarter. This approach creates varying forecast horizons depending on when the survey is conducted. Surveys conducted in even-numbered quarters (Q2, Q4) yield two-quarter and four-quarter ahead forecasts, while surveys in odd-numbered quarters (Q1, Q3) yield one-quarter and three-quarter ahead forecasts. Table A.2 shows the availability of forecasts at different horizons for these variables. To maintain consistency with our GDP analysis, when a two-quarter ahead forecast is unavailable for these variables, we construct a proxy by averaging the available one-quarter and three-quarter ahead forecasts.

A.2 Matched forecasters by source of party affiliation

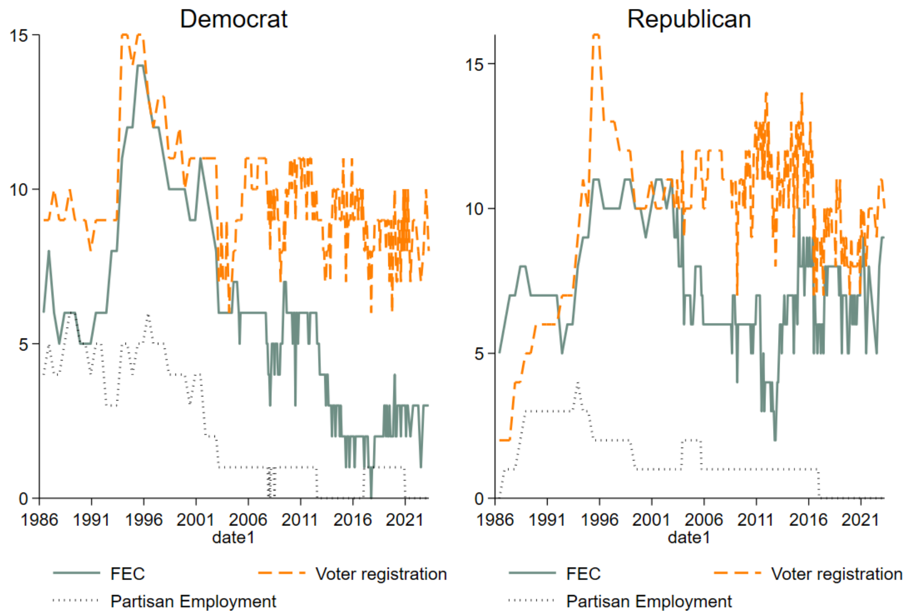


Figure A.1: Number of matched forecasters by source of party affiliation

A.3 Forecast Accuracy

Table A.3: Forecast accuracy and Diebold-Mariano tests: Excluding pandemic

Panel A: Mean Forecast Errors			
	All	Rep President	Dem President
Democratic forecasts	-0.451	-0.581	-0.329
Republican forecasts	-0.652	-0.897	-0.422
Consensus forecasts	-0.542	-0.712	-0.382
Panel B: Mean Absolute Forecast Errors			
	All	Rep President	Dem President
Democratic forecasts	1.349	1.353	1.345
Republican forecasts	1.450	1.523	1.380
Consensus forecasts	1.380	1.406	1.356
Panel C: Diebold-Mariano Tests			
	All	Rep President	Dem President
Democratic vs Republican	-2.796***	-1.948*	-1.027
Democratic vs Consensus	-1.741*	-1.286	-0.467
Republican vs Consensus	2.997***	2.294**	1.166

Notes: Panel A reports mean forecast errors (actual - forecast) for 2-quarter ahead GDP forecasts. Negative values indicate forecasts that are too too high (over-forecasting). Panel B reports mean absolute forecast errors. Lower values indicate smaller errors (more accurate forecasts). The "All" column shows the average errors across all administrations, while "Rep President" and "Dem President" columns show errors during Republican and Democratic presidential administrations respectively. Panel C reports Diebold-Mariano test statistics where negative values indicate the first forecast in the comparison is more accurate. The sample runs from July 1986 to April 2023, excluding October 2019 to September 2020. Statistical significance is denoted as: $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

A.4 More Granular Measure of Political Control

Our analysis in the main text has focused on using the party of the president to characterize political control. Here we explore whether changes in control of the House or Senate are also related to differentials in forecasts, as the legislative branch plays a crucial role in fiscal policy decisions and budget processes that can significantly impact economic outcomes.

We use an adaptation of David Roper's Democrat Control Index (Roper, 2002), inverting the scale to create a Republican Control Index where increasing values correspond to increasing Republican control. The Republican Control Index ranges from 0 to 7, with 0 representing complete Democratic control (of the House, Senate, and presidency) and 7 representing complete Republican control. To verify the specific party control configuration of the US government throughout our sample period, we reference the U.S. House website's authoritative records on party government (Office of the House Historian, 2023).

Appendix Table A.4 shows the details of how the measure assigns a score for the different combinations of political control and Appendix Figure A.2 illustrates how this measure varies during our sample period. Notable periods include the early Clinton years when Democrats controlled all three branches (index value of 0), the early George W. Bush administration when Republicans achieved complete control (index value of 7), and similar transitions to unified party control under Presidents Obama (Democratic control, index value of 0) and Trump (Republican control, index value of 7).

Table A.4: A diagram showing the Republican Party Control Index (Inverted Roper Measure)

Republican Control	**Republican Party Control Index**	**Democratic Control**
President, House, and Senate	7	Nothing
President and House	6	Senate
President and Senate	5	House
President	4	House and Senate
House and Senate	3	President
House	2	President and Senate
Senate	1	President and House
Nothing	0	President, House, and Senate

Source: Roper (2002)

We first use our two-way fixed effects specification and replace the presidential indicator variable with the Roper measure.

$$y_{j,t} = \gamma_j + \gamma_t + \beta Rep_j * Roper_t + \varepsilon_{j,t} \tag{17}$$

The first column of Appendix Table A.5 presents results using our full sample. The interaction coefficient is 0.05 and statistically significant at the 10% level. This magnitude implies that moving from complete Democratic control (Roper index = 0) to complete Republican control (Roper index =

7) is associated with Republican-affiliated forecasters providing GDP forecasts that are 0.35 percentage points higher relative to Democratic-affiliated forecasters. This effect size is comparable to our baseline presidential party results, which is unsurprising given that major changes in the Roper index typically coincide with presidential transitions, as shown in Appendix Figure A.2.

Table A.5: Difference in Democratic and Republican GDP forecasts by Roper measure

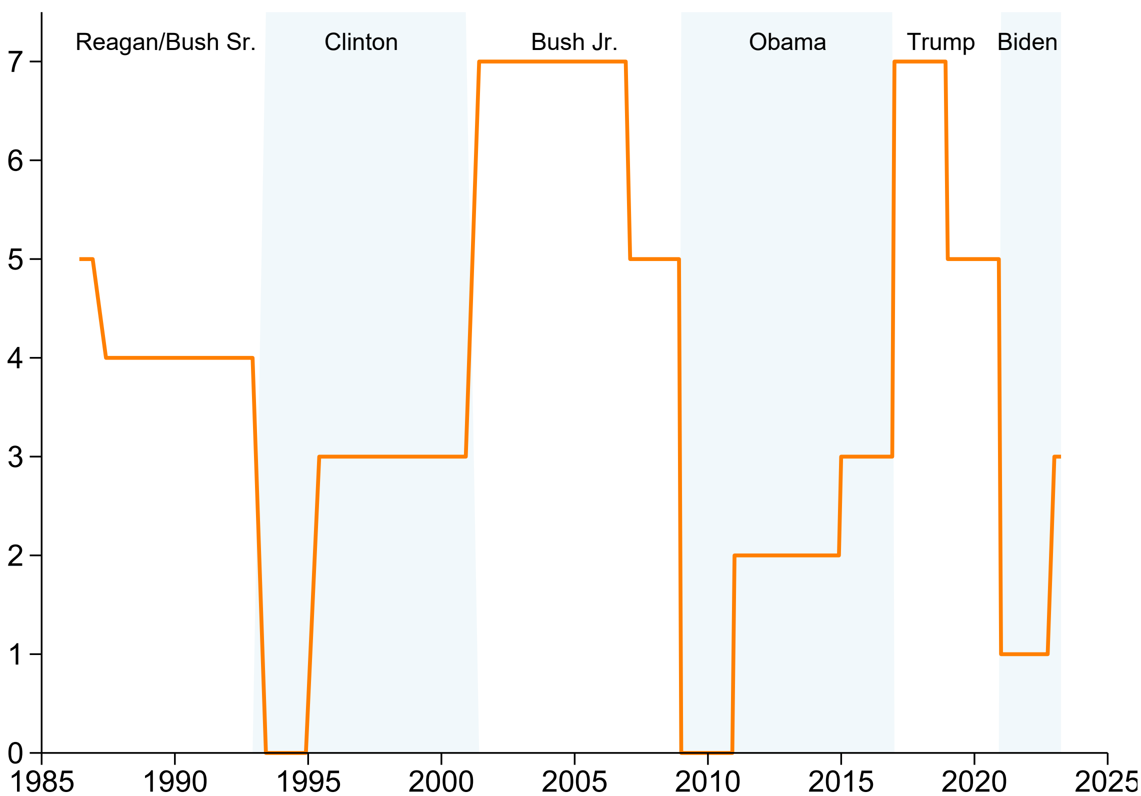
	All elections	Mid-term elections
$\text{Rep}_j \times \text{Roper}_t$	0.05^{**}	0.05
	(0.026)	(0.030)
Observations	6,197	1,850
R-squared	0.643	0.729

Notes: This table reports the average difference between Democratic and Republican-affiliated forecasters by Roper Republican Control Index, estimated using the two-way fixed effects specification in Equation 17. The first column uses the full sample from July 1986 to April 2023. The second column uses only data from a one year window around mid-term elections. Standard errors clustered at the forecaster level are reported in parentheses and statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To isolate the effects of legislative control changes from presidential transitions, we focus on mid-term elections in the second column. We restrict our analysis to a 1 year window around each mid-term election, from June of the election year through June of the following year, motivated by the semi-annual availability of our forecasts in the pre-2003 sample. This window captures the period when control of Congress may change while keeping the president constant, allowing us to identify the pure effects of House and Senate control shifts. The second column shows an interaction coefficient of 0.05, similar in magnitude to the full sample but not statistically significant at conventional levels (p = 0.13). This suggests that a one-point increase in the Roper index—such as Republicans gaining control of the House—is associated with a 5 basis point differential in GDP forecasts. However, given the lack of statistical significance and sensitivity to window specification in unreported robustness checks, we interpret this result with caution.

Additional (unreported) specifications allowing for non-linearities similarly fail to yield systematically robust results. Part of the identification challenge is that while many forecasters appear in the sample under both Democratic and Republican presidents, fewer forecasters are observed across all possible combinations of congressional control, limiting our ability to isolate the independent effects of changes in legislative majorities. Overall, the evidence suggests that partisan bias in forecasts is primarily tied to changes in the party of the president rather than to changes in the control of Congress.

Figure A.2: Republican Control Index (Inverted Roper Measure)



The figure shows the Republican Control Index (an inverted version of the Roper measure of political control). A value of 7 represents complete Republican control of the House, Senate and presidency while a value of 0 represents complete Democratic control.

Source: Office of the House Historian (2023) and Roper (2002).