Political Rational Inattention: A New Measure With an Application to Political Polarization*

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Abstract

Attention to political information stands at the core of political theory, yet measuring it is a challenging endeavor. We propose a novel measure of political rational inattention, based on political forecast data. Capitalizing on the unique features of the American National Election Studies, which recurrently collect political forecast data in daily frequency prior to elections, we construct a state-by-year data series of political rational inattention, covering the period 1952-2020 in U.S. presidential election years. Examining key patterns, we show that political and economic attention are complementary, in contrast to limited attention hypotheses. Thereafter, we consider an application of this measure within the context of political polarization. First, we present a rational inattention, persuasion model that illustrates how heightened societal attention may exacerbate political polarization. Second, we empirically test the model's predictions via detailed individual-data on political opinions, finding that state (societal) political attention fuels political polarization: a standard deviation increase in attention raises the extent of average polarization by 6%.

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1 Introduction

Attention to political information takes a fundamental role in the analyses of central political phenomena, ranging from mobilization and manipulation, to electoral outcomes and policy design.[1] This centrality is especially prominent in the age of social media and the internet, in which the availability and granularity of information has vastly increased, while the capacity to process it (attention) remained limited. Despite its importance, however, empirical measurements of such attention constraints within the political context remained largely unexplored. Previous studies have approached this by developing various metrics to assess related constructs such as political knowledge (e.g., Carpini and Keeter (1996)), informedness (e.g., Shi and Svensson (2006)), and political interest (e.g., Matějka and Tabellini (2021)). These measures, however, fail to account for the capacity of information processing related to politics, which is central for measuring the extent to which attention is diverted to politics over other matters. For instance, measures of political knowledge may rather reflect improved access to information dissemination, and in broader measures, such as in the case of informedness, often proxied by education or literacy levels, the detachment from attention is even larger.

We address this gap in the literature by offering a novel measure of political rational inattention, which accounts for the extent of information processing related to politics. We draw on the methodology developed in Coibion and Gorodnichenko (2015), and apply it within the context of politics. Our proposed method is based on political forecast data, and revisions thereof, based on the notion that on average, forecasts gradually move in the direction of the true value. The proposed methodology compares a forecast error (difference between the true value and the forecast) to a forecast revision (difference between forecasts in two consecutive periods). The basic idea is that a forecast revision, representing a procedure of information processing, demonstrates *attention* to informative signals if it goes in the same direction of the forecast error. This approach enables tracking political attention consistently across time and space, depending on data availability.

Similar to macroeconomic expectations-based attention measures (see, e.g., Coibion and Gorodnichenko (2015); Goldstein (2023)), implementing this methodology under a political orientation requires recurrently sampled forecast data over a major political event. We, thus, capitalize on the unique features of the American National Election Studies (ANES), a comprehensive national survey

[1] Related notions of *rational ignorance*, and political *informedness* date back to Downs (1957) and Riker and Ordeshook (1968). Additional examples include Matějka and Tabellini (2021), Perego and Yuksel (2022a), Levy (2021), among others. Maćkowiak et al. (2023) provide a synthesis of the literature, reviewed in the next section.

of voters in the U.S. with standardized measures across waves (ANES (2022)), covering a wide period (1952-2020). During election years, the ANES asks respondents –prior to election– who they think will be elected President (i.e., the Democrat of Republican candidate) in November of that year.[2] Importantly, during the pre-election survey wave, the ANES asks this question recurrently in daily frequency, up to 77 days prior to election date. Notably, this recurrence is within states; i.e., a different group of respondents is surveyed in each day prior to election, yet within the same state (their state of residency), providing up to 77 expectation sampling cycles for each state in each election. This feature, in turn, enables examining forecast errors and revisions across states and time, given that the true value is the election outcome.

Applying this method via the ANES data, we construct a state-by-year data series of political attention measures, covering the period 1952-2020 in (presidential) election years.[3] As a first step, we examine key patterns in this measure. Interestingly, we find that political attention co-moves with income at the cross-section, yet over time it is counter-cyclical, similar to the patterns of macroeconomic attention documented in previous studies (Coibion and Gorodnichenko (2015); Goldstein (2023); Roth et al. (2022)). Digging deeper into the relationship with economic attention, we employ an economics-related expectations data in the ANES, inquiring into expected unemployment in the 12 months following the survey, to construct an equivalent attention measure, following the same methodology, yet for economics. Derived from the same survey, this measure has similar coverage to that of the constructed political attention data series, with variation across states and years.[4] This case as well points at co-movements of political and economic attention, suggesting that the two are complementary (rather than substitutable), although attention is a limited resource. These observations, while being in contrast to limited attention hypotheses (e.g., Gabaix (2019)), add to recent evidence pointing at complementarities between the attention given to the economy and that given to other endeavors (e.g., Goldstein and Raveh (2024)).

Our proposed measure can be applied in the analysis of a a vast array of political phenomena. To introduce one such application, we consider the case of political polarization.[5] The latter has been at the center of policy debates, in light of the steep increase in affective polarization and partisanship in

[2]U.S. presidential elections are held in November of an election year.

[3]With the exclusion of 2012, in which the noted political expectation question was not asked.

[4]Unlike the expectations-based macroeconomic attention measures derived from the Survey of Professional Forecasters (e.g., Coibion and Gorodnichenko (2015) which do not variate across the geographical dimension.

[5]Political polarization is regarded as the extent to which individuals feel more positively toward their own political group while harboring negative emotions and hostility toward the opposing group (Campbell (1980)).

recent decades, and has been shown to inflict various adverse effects.[6] We examine, theoretically and empirically, the potential role of state political attention, regarded as *societal* attention, in inducing political polarization.

Our theoretical model integrates two influential frameworks in information economics: rational inattention and Bayesian persuasion. We study a setting in which an informed sender strategically designs signals for a rational but attention-constrained receiver. The model captures a process that may be described as *rational indoctrination*: belief formation driven by strategic information design within a fully Bayesian framework. It shows how limits to information processing affect the transmission of information, and how such constraints can lead to belief polarization even when all agents are fully rational. Three central features distinguish our approach: an infinite-dimensional state space, and two forms of attention constraints imposed on the receiver. We now elaborate on each.

Many studies in the literature assume a one-dimensional state space, typically a binary one, which necessarily reduces the problem to a single "right" or "wrong" answer. That is, if the state is either 0 or 1, then one side must be right while the other has to be wrong. We, however, use a multi-dimensional state space. This is not merely a technical choice but a conceptual one. On the technical side, following the recent studies of Burdzy and Pitman (2020) and Arieli et al. (2021), drawing on the agreement theorem of Aumann (1976), there exists a theoretical bound on the separation of posterior beliefs in one dimension. Even under a broad interpretation of polarization, there is a fundamental limit to the degree of anti-correlation that can arise when beliefs concern a single binary state (see the broader discussion in the literature review in Section 2). Thus, defining polarization within a one-dimensional framework is inherently too restrictive. On the conceptual side, real-world politics and ideological debates involve trade-offs across many fronts. One-dimensional models obscure this richness. In contrast, our infinite-dimensional framework allows for nuanced persuasion across many distinct issues, each with its own underlying truth, thus encompassing the trade-offs of different political ideologies.

The next feature of our model involves bounds on the receiver's attention. The receiver is rational and unbiased but constrained in two ways. First, there is a fixed cost to processing any signal, regardless of its content. Second, processing more informative signals incurs a variable cost, measured by standard mutual information. These combine into an attention budget that limits how many

[6]For instance, in the U.S. case, our focus in this study, it has been demonstrated that political elites have undergone significant partisan polarization over recent decades (see, e.g., Hetherington (2009) for a survey of the evidence). This, in turn, have been shown to induce adverse effects via various dimensions, including increased corruption (Melki and Pickering (2020)), inequality (Stewart et al. (2020)), conflict (Esteban and Ray (2011), Montalvo and Reynal-Querol (2005)), and poor government policies (Campos and Kuzeyev (2007)).

dimensions the receiver can attend to and how deeply she can process each of them.

Within these constraints, the sender designs biased yet informative signals across many dimensions. These signals are carefully constructed to nudge the receiver's beliefs in the sender's preferred direction, while remaining credible enough to be processed. The sender essentially acts as an information source that consistently promotes a specific ideology, with high probability.[7] As attention increases, the receiver absorbs more information and updates her beliefs across more dimensions. Yet paradoxically, this increased attention can lead to greater belief divergence. Specifically, while the divergence in each individual dimension remains limited, it occurs *in every dimension with probability that tends to* 1, thus generating a substantial aggregate effect across the full ideological space.

Extending the model to two sender–receiver pairs, each with opposing agendas, we find that as attention increases, their respective posterior beliefs diverge with high probability. To the best of our knowledge, this contrasts with most theoretical studies in the literature that consider Bayesian agents (with no misperceptions), and typically prove that ex-post disagreements decrease as agents become more exposed and attentive to informative signals. For example, the main result of Matějka and McKay (2015) elegantly shows how reducing information costs leads to objectively more accurate decisions. The recent important study by Nimark and Sundaresan (2019), building on Matějka and McKay (2015), states that "Cheaper information thus decreases permanent disagreement on the extensive margin;" see a broader discussion of this issue in Section 2. In contrast, our analysis illustrates how strategic information design, even with ex-ante homogeneous Bayesian agents, can lead to rational indoctrination across an ideological landscape.

The model's predictions are corroborated by the empirical analysis. Employing our constructed data series of political rational inattention across U.S. states and years, we undertake an empirical investigation of the effect of state (societal) political attention on individuals' extent of political polarization in the U.S. To measure the latter, we construct a measure of political (partisan) polarization, following the standard definition in the literature (e.g., Stewart et al. (2020)), vis-à-vis (absolute value) differences in reported warmth (thermometer) feelings, on a scale 1-100, concerning views on the Democratic and Republican parties. This measure maps to the endogenous polarization metric introduced in the analytical framework as it reports the extent to which individuals identify with an ideology while concurrently disliking the other, eliminating moderate views. Importantly, the nature

[7]This result resonates with studies on the political impact of media competition and bias, such as Gentzkow and Shapiro (2006); DellaVigna and Kaplan (2007); Prior (2007); Gentzkow et al. (2015); Lelkes et al. (2017a); Darr et al. (2018); Perego and Yuksel (2022b).

of this data enables a within-state framework, which helps address concerns about subjectivity in thermometer reports across geographic locations and time.

To that end, we assembled the data of respondents to the ANES, across the 50 U.S. states (based on respondents' reports of state of residence) and over the period 1980-2020, in presidential election years, limited by the availability of our baseline measures. To exploit the full extent of variation in our data, the unit of analysis is at the respondent level, covering about $19,000$ individuals, considered under a state-level perspective. Our identification strategy throughout the analysis relies primarily on the plausible exogeneity of state-level treatment to individuals' opinions. In addition, we undertake an instrumental variable (IV) approach in which our proposed instrument for political attention is the extent to which individuals are opinionated on an issue that is not directly related to politics; i.e., whether they express any explicit opinion (in favor, or oppose), rather than *which* opinion. Our focus is on individuals' opinions on laws to protect homosexuals against discrimination. Our identifying assumption is that, on one hand, being opinionated on a matter that concerns society, irrespective of its direct political context, is reflective of general attention to societal matters, including politics; yet, on the other hand, being opinionated on such a matter is not revealing of partisan identity, nor of differences in political opinions (polarization). This assumption induces a potentially viable first-stage (validated within the analysis), while concurrently holding the exclusion restriction.

In a preliminary analysis, we first illustrate via the ANES data, that individuals who actively participate in the political discourse (considering various channels, ranging from contacting public officials, to attending political rallies and providing campaign donations) are associated with more extreme (polarized) political views, supporting the initial theoretical implication.[8] Thereafter, in our main analysis, we find that an increase in the extent of societal political attention raises the degree of individuals' political polarization, in an economically meaningful and robust magnitude. Specifically, our baseline estimates indicate that a one standard deviation of societal political attention increases the average extent of political polarization by about 7%. In addition, we find that this increase is triggered primarily by an in-group bias, in which individuals increase their warmth towards the party with which they identify.

We show that the main result is robust to the inclusion of controls across various related dimensions, including measures at the state, respondent, and interview levels, as well as to different specifications,

[8] I.e., active involvement in political debates, representing greater efforts to control the discourse, and extreme opinions are indeed positively associated.

estimation methods (including the noted IV approach), sample restrictions, and different polarization as well as attention measures. Testing for underlying potential mechanisms, via heterogeneity analyses that consider the main controls and additional differences in political institutions, we find that the effect of societal political attention on polarization intensifies under various state characteristics including inequality, strong parties, and no baseline budgeting rules; importantly, however, the main effect driven via attention remains to hold in all cases.

The next section reviews the related literature and places the current contribution within it. Section 3 presents our methodology for measuring political rational inattention. Section 4 presents an application of our proposed measure in the context of political polarization vis-a-vis theoretical and empirical analyses. Section 5 concludes and the appendices present data, as well as technical details.

2 Related literature

The paper is related to a number of literature strands. First, the literature on the role of information in political economy. Information plays a pivotal role in the analysis of political phenomena, emphasizing for instance misinformation (Kartal and Tyran (2022)), media bias (Ershov and Morales (2024)), voter knowledge (Angelucci and Prat (2024)), and transparency (Grossman et al. (2024)), with implications for a host of central issues such as accountability, corruption, and polarization, among others. This line of research, however does not touch on the *capacity* to process political information, which is limited in nature. Recent studies considered the potential role of political rational inattention more explicitly, and its impact on policy design (Matějka and Tabellini (2021)), manipulation (Murtinu et al. (2022)), and pandering (Trombetta (2020)). Empirically, however, the measures employed in these studies do not reflect information processing. Matějka and Tabellini (2021) examine responses to a question on the extent to which respondents follow political and governmental affairs, without accounting for revisions in thereof, or comparisons to objective outcomes, while Trombetta (2020) considers a broader proxy of economic literacy. The current effort offers a novel measure of political rational inattention, which accounts for the processing of political information, shedding light on the extent to which individuals pay attention to politics over other endeavors, at the U.S. state level, and over time.[9] Applying this measure within the context of political polarization, we further unravel a new attention-polarization nexus, showing that societal political attention affects polarization patterns.

[9]Nonetheless, in the analysis we examine the association of our proposed measure with those employed in previous studies, pointing at positive correlations.

Second, the literature on empirical measures of rational inattention. Seminal works by Sims (2003) and Maćkowiak and Wiederholt (2009, 2015) have introduced the idea of rational inattention, where limited attention to economic conditions is micro-founded, based on the idea that people optimally choose how much costly information should be acquired. The literature proposes and analyzes empirical measures of attention, focusing most notably on survey data, mostly from professional forecasters. While parameters of inattention can be estimated indirectly, based on an underlying macroeconomic model, survey data on macroeconomic expectations can provide more direct estimates. The recent literature has provided such estimates, using expectations data both at the mean level (Coibion and Gorodnichenko (2012, 2015)) and at the individual level (Andrade and Le Bihan (2013); Goldstein (2023); Kohlhas and Walther (2021)). In particular, it was found that inattention to information has largely increased following the Great Moderation and it varies with the business cycle, where recessions induce a growing attention. We contribute to this literature by extending the noted expectations-based methodology to contexts outside the realm of macroeconomics, namely political economy in our case. In addition, we show that political rational inattention exhibits patterns that are reminiscent of those reported over macroeconomic attention, rising in times of economic declines, and more generally that political and economic attention tend to be complementary, despite the limited capacity of attention.[10]

Third, the literature on the determinants of political polarization. The literature has identified a host of explanations for the observed patterns of political polarization. Key determinants include economic declines (Gidron et al. (2020); López and Ramírez (2004), inequality (Stewart et al. (2020)), globalization (Autor et al. (2020)), media exposure and the rise of "echo chambers" (Lelkes et al. (2017b); Darr et al. (2018); Melki and Sekeris (2019); Waller and Anderson (2021)), institutions (McCarty et al. (2009)), social identity dynamics (Mason (2015)), and windfalls (Ikan et al. (2025)). Our study highlights a new potential determinant, namely societal political attention. We show, theoretically and empirically, that an increase in society's attentiveness to political matters may polarize the distribution of political (partisan) opinion. Theoretically, we present a mechanism that links rational inattention to political opinions; empirically, we employ our constructed data series of political rational inattention and show that it induces a positive impact on political polarization across U.S. states.

Last, our theoretical model builds on two major branches of information economics: Bayesian persuasion, as developed by Kamenica and Gentzkow (2011), and rational inattention, as introduced

[10]More generally, these results support the view that the attention given to different tasks can be complementary, as pointed by evidence in a number of recent studies including Goldstein and Raveh (2024); Miyahara et al. (2006); Schmitt and Schlatterer (2021).

by Sims (2003). Their combination, commonly referred to as costly persuasion (see Gentzkow and Kamenica, 2014), has been explored in various contexts. However, our approach is new by the combination of persuasion over multiple dimensions and two distinct forms of cognitive costs- a fixed cost per dimension, and a variable cost based on mutual information, using Shannon's entropy function (see Shannon (1948) and Sims, 2003). This combination drives our main theoretical insight that higher attention can lead to greater polarization, even among ex-ante homogeneous, fully Bayesian agents.

A large body of recent theoretical work seeks to explain belief polarization within a Bayes-rational framework. Most of these models conclude, naturally, that greater attention (i.e., more information) should reduce disagreement and align beliefs. For instance, the foundational study by Matějka and McKay (2015) shows that increased attention improves objective decision accuracy, as formalized in their equation (1) and theorem 1. Building on this, Nimark and Sundaresan (2019) argues that the probability of permanent disagreement declines as information becomes cheaper (see Section 4.3, particularly the final paragraph). This literature stands in contrast to our result on rational indoctrination. In our model, attention leads to small but systematic belief shifts across many dimensions. While each individual shift may be modest, their accumulation results in substantial polarization.

An important exception is the recent study by Bowen et al. (2023), which shows that greater attention can increase polarization. However, their result requires that agents hold misperceptions about the source of information, thereby introducing behavioral biases. In contrast, our model assumes fully Bayesian and unbiased agents, such that polarization emerges not from misperception, but from the strategic design of information under cognitive constraints.

The key conceptual point behind our result is that political identities are multi-dimensional. Reducing them to a single axis cannot capture the richness of ideological structures.[11] Technically, this matters because fully rational models impose limits on posterior divergence in single dimensions. The studies by Burdzy and Pitman (2020) and Arieli et al. (2021), building on Aumann (1976), show that the extent of belief separation in one dimension is strictly bounded. For example, in a one-dimensional symmetric set-up, one can get (with probability 1) a distance of 0.5 between posterior beliefs by not giving any information to one agent (so that the posterior equals the prior of 0.5), while revealing the true state to the other agent (leading to posteriors of either 0 or 1). While this maximizes distance between posterior beliefs, it is not the mechanism by which real-world polarization operates. Instead,

[11]This should not be confused with reducing multi-dimensional positions to a one-dimensional index for empirical purposes, such as a "thermometer" score.

our notion of polarization focuses not on the distance between posteriors per se, but on the systematic directional shift of beliefs in opposite directions and across many dimensions with high probability.

Finally, our model builds on several ideas in the persuasion and media bias literature. The sender's strategic role resembles the biased media environment studied in Gentzkow and Shapiro (2006), and the multi-dimensional nature of belief formation parallels models in Matějka and Tabellini (2021), Yuksel (2022) and Hu et al. (2024). However, a key distinction is that we do not rely on heterogeneity in preferences or priors to generate disagreement: our results show that polarization among ex-ante homogeneous and unbiased receivers can arise endogenously from the interaction of attention constraints and multidimensional persuasion.

3 Measuring Political Attention

This section develops a method for measuring political attention based on political forecast data from the ANES. After describing the dataset, we present our method for measuring attention and highlight key patterns in the new measure. The effect of attention on polarization is examined in the following sections—first theoretically and then empirically—building on the new measure.

3.1 The ANES

The ANES is a comprehensive national survey of voters, conducted biennially until 2004 and quadrennially thereafter, on a representative sample of voting-eligible U.S. residents before and/or after elections (Presidential or House/Senate, depending on the survey year), starting in 1948. We use the ANES cumulative survey data, which merges and standardizes survey variables across a pooled cross-section of survey waves.

The survey questions are designed to capture voter behavior and public opinion. In this paper, we focus on two questions presented before the election regarding: (i) the 'feelings thermometer' and (ii) the expected outcome of the election. The former question is used to measure polarization, as explained in Section 4.2. The latter question is used to measure attention based on our methodology. The analysis covers presidential election years for which our main questions of interest are available, spanning the period from 1952 to 2020 (except for 2012, in which the question on expectations was absent). Our sample includes approximately 35,000 individuals. Additional questions from the ANES are used to extend our analysis and provide robustness checks. An outline of all questions and descriptive statistics

is provided in Appendix A.

In this section, we focus on the question regarding the expected outcome of the election (ii), asking the following:

"Who do you think will be elected President in November?"

We concentrate on the two-party expectations, specifically the binary expectations of a Democratic (0) or Republican (1) victory. In our baseline measure of political attention, we exclude "Don't know" responses to align with the actual outcome of the election. However, an alternative measure will take these responses into account.

3.2 The measure of attention

Suppose that forecasters form expectations about the random variable X in period t. The prior belief of forecaster i, formed in period $t-1$, is that $X \sim \mathcal{N}(\mu_i, \tau_x^{-1})$, hence $\mathbb{E}^i_{t-1}[X] = \mu_i$. In period t, the forecaster revises her forecast based on a private signal $y^i_t = X + \omega^i_t$, which contains idiosyncratic noise $\omega^i_t \sim$ i.i.d. $\mathcal{N}(0, \tau_y^{-1})$.

The optimal revised forecast that minimizes the mean-squared error is given by:

$$\mathbb{E}^i_t[X] = \mathbb{E}^i_{t-1}[X] + \kappa(y^i_t - \mathbb{E}^i_{t-1}[X]) \ , \tag{1}$$

where $\kappa = \frac{\tau_y}{\tau_x + \tau_y}$ is the optimal weight placed on the new signal. Thus, the level of attention to new information can be measured by estimating κ. Following Coibion and Gorodnichenko (2015), κ can be estimated using forecast data at the aggregate level by regressing the average forecast error on the average forecast revision. Specifically, by averaging equation (1) across i and rearranging, we obtain the following specification:

$$X - \bar{\mathbb{E}}^i_t[X] = c + \beta(\bar{\mathbb{E}}^i_t[X] - \bar{\mathbb{E}}^i_{t-1}[X]) + \epsilon_t \ , \tag{2}$$

where $\bar{\mathbb{E}}^i_t[X]$ is the cross-sectional average forecast, $c = 0$, and $\beta = \frac{1-\kappa}{\kappa}$. Thus, k can be estimated from the coefficient on the forecast revision. The intuition behind this simple specification is that, due to the partial weight placed on the new signal, the forecast - on average - gradually moves in the direction of the true value X. Hence, the average ex-post forecast error would be positively correlated with the average forecast revision.

In our setting of political forecasts, specification (2) could be applied directly if the forecasts referred to a continuous variable, such as the share of votes supporting a candidate. However, the forecasts in the survey refer to the winning candidate. Suppose that a participant revises their expected share of votes for the Republican candidate from 55% to 60%. Despite this revision, the reported forecast still indicates a Republican win in the presidential election.

As a result, we propose a nonparametric measure of political attention based on the general idea, implied by specification (2), that the average forecast should move in the direction of the outcome. Specifically, we define the outcome variable rep, which takes the value 1 in the case of a Republican win and 0 otherwise. Corresponding to this outcome, we recast a participant's response in the survey as a forecast, $F_t^i(rep)$, which takes the value 1 if the participant expects a Republican win and 0 otherwise. The average forecast across participants, $\bar{F}_t^i(rep)$, ranges between 0 and 1.

Thus, in the spirit of specification (2), we examine the average forecast error, $rep - \bar{F}_t^i(rep)$, and the average forecast revision, $\bar{F}_t^i(rep) - \bar{F}_{t-1}^i(rep)$. If both have the same sign, the revision demonstrates attention to informative signals in the direction of the outcome. By contrast, opposite signs indicate inattention. Hence, our primary measure of attention is defined as follows:

$$attention = \frac{\sum_{k=1}^{N} \mathbf{1}\left(sgn(rep - \bar{F}_t^i(rep)) = sgn(\bar{F}_t^i(rep) - \bar{F}_{t-1}^i(rep))\right)}{N}, \tag{3}$$

Thus, the measure of attention represents the share of forecast revisions that move in the direction of the outcome, relative to the total number of revisions N. Importantly, this measure accounts for the complete spectrum of information, including for instance misinformation or fake news, which may be prominent in political contexts, as the focus is on the *processing* of information (revision), rather than its type.

In the ANES, forecasts are not revised at the individual level. However, following specification (2), our measure relies on forecast revisions at the aggregate level, making it applicable in our setting. The definition of a revision in terms of time is somewhat arbitrary though. Forecasts in the ANES are collected daily, up to 77 days before the election. To balance the number of participants with the number of revisions, we divide this period into six time windows of 12-13 days each. Within each window, we compute the average forecast across participants to obtain $\bar{F}_t^i(rep)$. Consequently, we obtain five revisions, $\bar{F}_t^i(rep) - \bar{F}_{t-1}^i(rep)$, for each election.[12]

[12]Our findings are robust to this choice. We obtain similar results whether revisions are computed on a daily basis or defined as a single revision per election.

To measure variations in political attention based on the structure of the ANES, we apply our measure at two levels: presidential elections and U.S. states. For each election and state, we calculate the average forecast $\bar{F}_t^i(rep)$ across participants and derive the corresponding forecast error and revision. To measure $attention_t$ at the election level, we compute the attention measure for year-t elections across states. The number of revisions N in this calculation is therefore the number of states multiplied by 5 (the number of revisions before an election). To measure $attention_j$ at the state level, we compute the attention measure for state j across elections. The number of revisions N in this calculation is therefore the number of elections multiplied by 5.

Figures 1 and 2 show the estimates of attention along both dimensions, illustrating key patterns that are consistent with rational inattention theories. Panel A in Figure 1 presents the distribution of $attention_j$ across U.S. states. The state-level estimates follow a roughly normal distribution, with a mean of 0.578 and a standard deviation of 0.077. Thus, in the average state, 58% of the revisions in political forecasts are made in the direction of the election outcome – 8% more than the benchmark of randomly revised forecasts. Panel B presents a scatterplot of the estimates against the (in)accuracy of the forecasts, measured by the mean absolute error. Importantly, we observe a positive relation, where states with higher levels of attention make smaller forecast errors. Hence, the cross-sectional variation in our measure aligns with an attention-based interpretation.

Figure 2 plots the time variation of attention across elections ($attention_t$), ranging from 50% to almost 70%. While many factors could account for this variation, the figure illustrates an interesting relationship with the economic situation, specifically the U.S. unemployment rate. Interestingly, political attention appears to increase following a rise in unemployment. The economic literature on rational inattention documents a rise in economic attention during periods of adverse economic conditions (Coibion and Gorodnichenko (2015); Goldstein (2023)). Political science literature has long recognized that economic conditions are a prominent predictor of election outcomes (see Fair (2020), for a review). The pattern in Figure 2 appears consistent with both of these findings.

Our case study in this paper is the potential attention-polarization nexus. To examine this, we construct the measure $attention_jt$, which varies across both states and elections. This measure is simply calculated as the product of the two previously defined measures, namely $attention_j \times attention_t$. Thus, $attention_jt$ is designed to resemble the familiar shift-share instruments. This design will be useful for identifying the effect of attention on polarization in Section 4.2.

Table 1 reports several interesting properties of $attention_jt$, based on panel regressions. In Panel

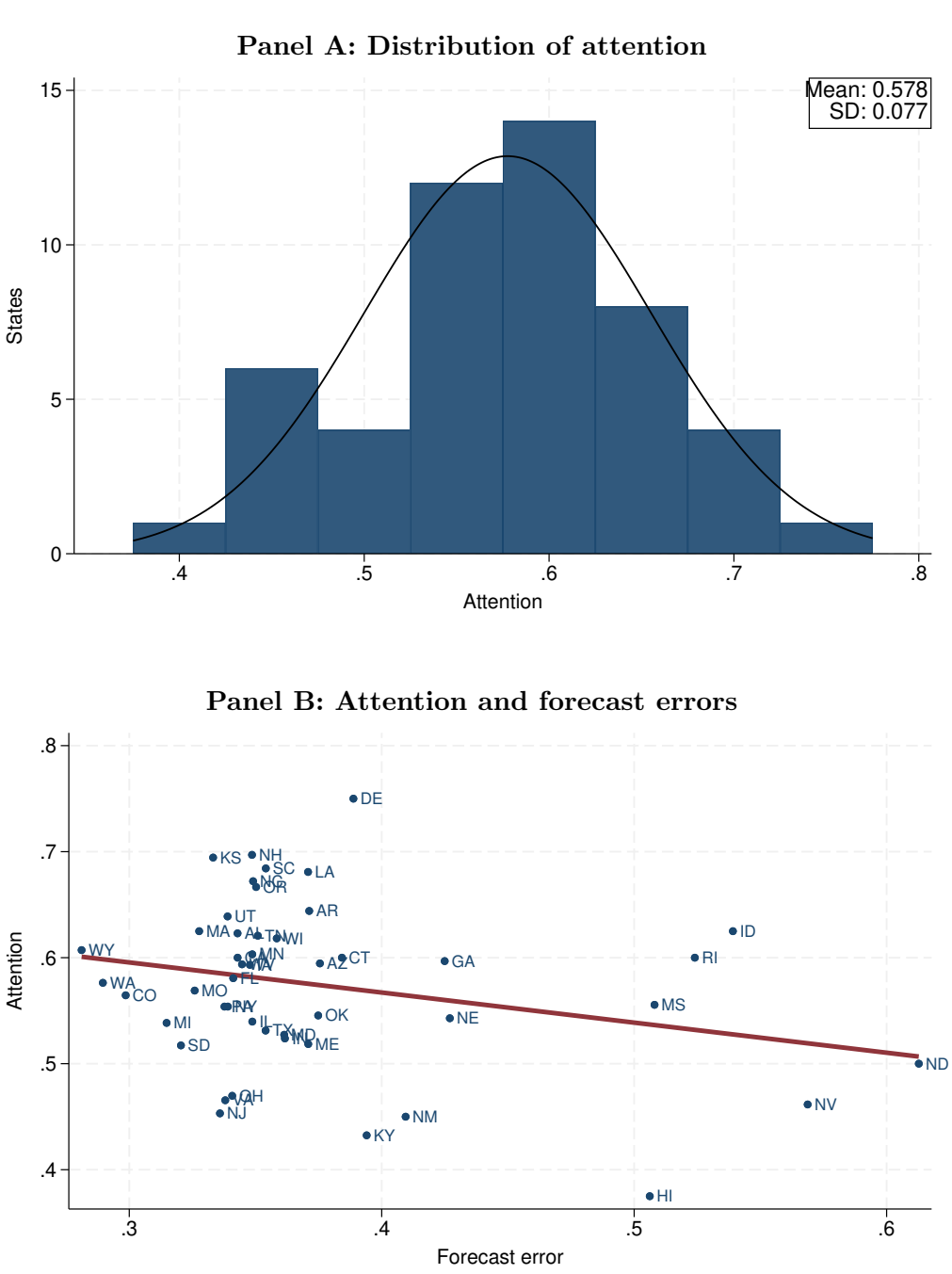

Figure 1: The figure plots the estimates of $attention_j$ across U.S. states, based on the political forecast data from the ANES. Panel A shows the distribution of estimates, with a normal distribution approximation indicated by the black line. Panel B plots the estimates of political attention against the mean absolute errors of the forecasts, calculated for each state.

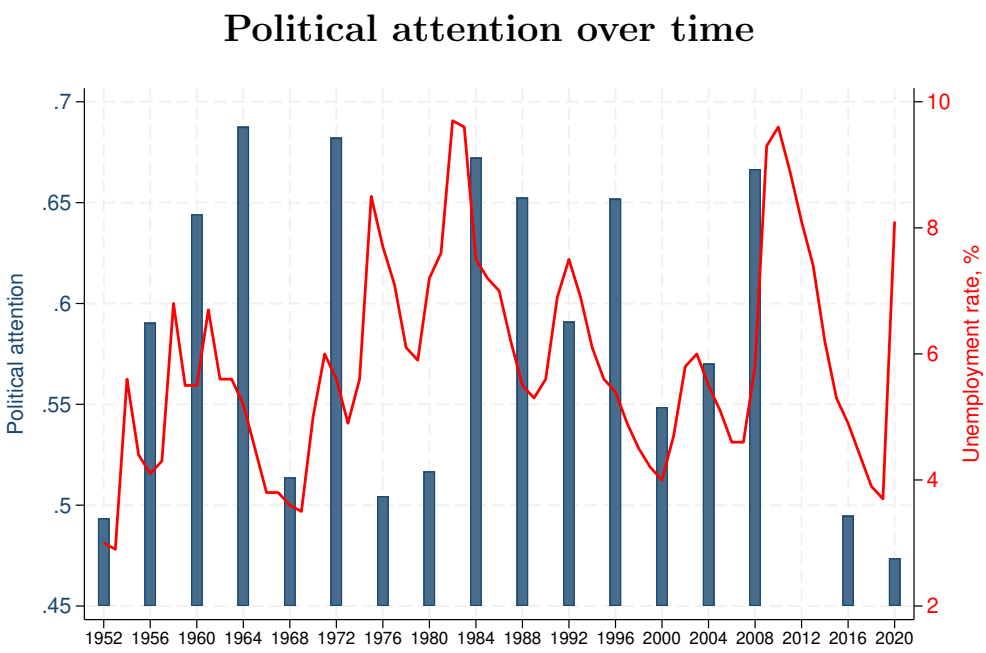

Figure 2: The figure plots the estimates of $attention_t$ for each presidential election from 1952 to 2020 (except for 2012), based on the political forecast data from the ANES. The blue bars represent the estimates (left axis), while the red line shows the U.S. unemployment rate over the period (right axis).

A, we further examine the link between political attention and economic conditions by regressing $attention_jt$ on the growth rate of the GDP at the state level. Strikingly, we document a significant coefficient, but its sign flips from positive to negative when fixed effects are included in the regression. Thus, within a given state, political attention increases during periods of economic slowdown, consistent with the time pattern documented in Figure 2 at the national level. However, the positive coefficient estimated without fixed effects suggests that the cross-sectional relationship between political attention and economic growth differs. This shifting correlation mirrors evidence documented in recent studies on economic attention (Goldstein and Raveh (2024)). According to this evidence, attention to information, as measured in macroeconomic expectations, tends to increase during recessions (Coibion and Gorodnichenko (2015); Roth et al. (2022); Goldstein (2023)). However, cross-sectionally, wealthier individuals tend to have more accurate macroeconomic expectations (Bruine de Bruin et al. (2010); Das et al. (2020)).

Panel B delves further into the relationship between political and macroeconomic attention by regressing our political attention measure on an equivalent measure of macroeconomic attention. We

Table 1: Political attention – panel regressions

Dependent variable: Attention	(1)	(2)
Panel A		
Growth	0.168***	-0.005*
	(0.039)	(0.003)
Fixed effects	No	Yes
R-squared	0.026	0.992
Obs.	700	700
Panel B		
Unemployment_attention	2.467***	0.056***
	(0.077)	(0.002)
R-squared	0.789	0.532
Observations	250	250
Panel C		
TV_exposure	0.046***	0.027
	(0.009)	(0.017)
R-squared	0.508	0.684
Observations	497	237
Panel D		
Previous measures	0.12***	0.004***
	(0.01)	(0.0001)
R-squared	0.575	0.96
Observations	133	44

Notes: The table reports coefficient estimates from panel regressions of political attention. 'Attention' is the baseline measure of political rational inattention outlined in the text. In Panel A, attention is regressed on the state-level growth rate in GDP (election year relative to the previous year), with and without fixed effects for state and election. In Panel B political attention is regressed on a measure of attention to unemployment, based on qualitative unemployment forecasts in the ANES. The realized unemployment for the attention measure is computed by comparing the unemployment rates in December of the election year and the following year (Column 1), or by comparing the average rates of these same years (Column 2). In Panel C, political attention is regressed on TV exposure to political campaigns in Column 1 (question VCF0724 in the ANES) or on exposure to TV news in Column 2 (question VCF9035 in the ANES). In Panel D, political attention is regressed on the extent to which respondents follow information on politics and government (question VCF9259 in the ANES) in Column 1 or on states' extent of internet access in Column 2. The regressions in Panels B, C, D include state effects. Clustered standard errors are in parentheses. ***, **, * denote significance at 1, 5 and 10% levels.

apply the same methodology used for our measure to another ANES question, which asks about expectations for the unemployment rate over the next 12 months. The response is qualitative: more unemployment, about the same, or less unemployment than now. To derive forecast errors and revisions, we encode the responses and the corresponding outcomes as -1, 0, and 1, respectively. Due to ambiguity in defining the outcome, we compute the forecast errors for the attention measure in two ways. One method compares the unemployment rates in December of the election year and the following year, while the other compares the average unemployment rates of these same years. The two resulting measures of attention to unemployment are quite similar, and both are significantly correlated with the measure of political attention, as reported in Panel B of Table 1. Hence, political

and economic attention behave as complements rather than as substitutes competing for attention capacity. This result further illustrates how attention to elections is related to the economic environment at the U.S. state level.

Panel C also reports a positive relationship between the political attention measure and responses to two ANES questions regarding exposure to political campaigns and news on TV. These questions can be viewed as proxies for political attention. Although they do not appear systematically in the survey, as political expectations do in our measure, we will later use them as robustness checks for the effect of political attention on polarization. Finally, Panel D reports similar results over the association of our constructed political attention, and those employed in previous studies. Specifically, Column 1 considers the measure used in Matějka and Tabellini (2021) for political attention (the extent to which respondents follow information on politics and government), and Column 2 considers a measure reminiscent of the one used in Shi and Svensson (2006) for informedness (the extent of internet access).[13]

3.3 Alternative measures

Additional robustness checks in Section 4.2 will be based on two alternative measures of attention applied to political expectations. As explained above, our primary measure builds on specification (2) of Coibion and Gorodnichenko (2015) and requires that attentive forecasters revise their forecasts, on average, toward the outcome. One alternative measure will use informative political signals instead of the election outcome, while the other will be based on the relationship between attentiveness and persistence in expectations following Goldstein (2023):

I. One of the main questions in the ANES concerns a respondent's intended vote in the upcoming election. Thus, the survey provides poll results that can serve as proxies for informative signals about the election outcome. We replace the election outcome, rep, in our primary measure with these signals. Unlike the election outcome, the poll outcome varies over time. Our alternative measure assesses the extent to which the dynamics of forecasts align with the dynamics of political signals.[14]

II. Goldstein (2023) proposes an alternative approach for measuring the weight k placed on new informa-

[13]These measures, described in the table notes, are considered under their state-year averages. States' internet access measure is derived from Bromley-Trujillo and Poe (2020), available for 2004-2010.

[14]Since this measure compares forecasts to poll signals we also account for voter turnout and compute the rate of forecasting a Republican win relative to all respondents, including those responding "Don't know" to the question. These responses were excluded in the baseline measure, which compares forecasts to the election outcome.

tion in equation (1), using the following specification:

$$\mathbb{E}_t^i[X] - \bar{\mathbb{E}}_t^i[X] = c + \gamma(\mathbb{E}_{t-1}^i[X] - \bar{\mathbb{E}}_{t-1}^i[X]) + \epsilon_t \ .$$

It can easily be shown that $\gamma = 1 - k$, which represents the complementary weight placed on the prior, or the level of inattention. According to this specification, inattention corresponds to the persistence of deviations in individual expectations from the mean. Intuitively, deviations from the mean should be more persistent if individuals rely more on their priors, whereas greater attention to new signals implies lower persistence. Given the limitations of our data, as discussed above, our alternative measure of political attention applies this idea non-parametrically:

$$attention = \frac{\sum_{k=1}^{N} \mathbf{1}\left(sgn(\bar{F}_t^i(rep) - \bar{\bar{F}}_t^i(rep)) \neq sgn(\bar{F}_{t-1}^i(rep) - \bar{\bar{F}}_{t-1}^i(rep))\right)}{N} \ ,$$

where $\bar{F}_{t-1}^i(rep)$ is the average forecast at the state level, as before, while $\bar{\bar{F}}_t^i(rep)$ is the average forecast at the national level. We examine the deviations of state-level forecast from national-level forecasts and measure the share of deviations that are not persistent —in the sense that the direction of deviation is opposite to the direction of the lagged deviation. Notice that instead of examining persistence at the individual level, which is not possible in the ANES, we assess the persistence of expectations at the state level. This approach relies on the plausible assumption that informative signals could also vary at the state level.

4 Application to Political Polarization

Our proposed measure of political rational inattention can be applied to the study of a vast array of political phenomena, as suggested by the discussion in Section 2, highlighting theoretical foundations of various facets concerning attention to political information. To illustrate the applicability of our measure in this context, through one example, we consider its potential role in shedding light on a central political phenomenon in recent decades, namely political polarization. Hence, in this section we examine, theoretically and empirically, whether political attention may induce political polarization. We do so by, first, laying out the theoretical foundations, in the next sub-section, and thereafter empirically testing the analytical predictions using our constructed measure of political attention.

4.1 A Bayes-rational model of indoctrination

We develop a model of strategic information transmission in a countably infinite binary state space, incorporating rational inattention constraints. In this model, a sender aims to persuade a receiver to choose specific actions, while the receiver seeks to align her actions with as many realized states as possible. The receiver, however, is bounded by her information-processing capacity: she incurs a fixed cost for processing any signal, and a variable cost equal to the informativeness of that signal, measured via mutual information.

This framework captures the informational complexity faced by individuals who must decide on diverse and heterogeneous policy issues. The state dimensions can be interpreted as representing specific policies or decisions that individuals aim to understand. It reflects the idea that political agendas and identities aggregate an overwhelming number of decisions that corresponds to different dimensions of the state. A central feature of our model is the incorporation of rational inattention: individuals cannot process all available signals and must choose what to attend to, subject to cognitive constraints.

Formally, consider a countable set of *state indices* $\mathbb{N} = \{1, 2, \dots\}$. For each $n \in \mathbb{N}$, a binary state $\omega_n \in \{0, 1\}$ is drawn independently with equal probability, $\mathbb{P}(\omega_n = 1) = \mathbb{P}(\omega_n = 0) = \frac{1}{2}$. Let $\omega = (\omega_1, \omega_2, \dots) \in \Omega = \{0, 1\}^{\mathbb{N}}$ denote the full vector of binary state variables.

Upon observing the full realization ω, the sender commits to a signaling scheme designed to influence the receiver's decision. The signaling scheme is a *separable* Blackwell experiment[15] $S = (S_1, S_2, \dots)$, where each S_n is a random variable with distribution $S_n(\cdot \mid \omega_n)$ over some finite and non-degenerate signal space $\mathcal{S}$. That is, each signal component S_n depends only on the corresponding state component ω_n. For each n, let s_n denote a realization of S_n.

Although the sender broadcasts a full vector of signals, the receiver cannot process all of them due to cognitive costs. Specifically, processing information along dimension n incurs two types of cost:

1. A *fixed effort cost* $c_0 > 0$, paid whenever the receiver attends to signal S_n;

2. A *variable bandwidth cost* equal to the Shannon mutual information,[16]

$$I_n \;=\; I(\omega_n; S_n) := H(\omega_n) - H(\omega_n \mid S_n),$$

[15] See Blackwell (1951).

[16] See Shannon (1948). Note that one can use other measures of information, as shown in Frankel and Kamenica (2019).

where $I(\omega_n; S_n)$ denotes the *mutual information* between the binary state ω_n and the random signal S_n and $H(\cdot)$ is the standard entropy function (all logarithms are natural unless noted otherwise).[17]

The mutual information quantifies the expected reduction in uncertainty about ω_n after observing S_n, and reflects the informativeness of the signal. All costs are common knowledge.

The variable costs across attended dimensions must respect an exogenous (attention) budget $C > 0$. Thus, the receiver can only process a finite number of sufficiently informative signals. Upon observing the experiment's structure, she decides which signal components to attend to. Because all indices are ex-ante symmetric, the receiver's optimal attention set is a prefix: she chooses the largest k such that the variable cost fits the budget, that is:

$$N = \max \left\{ k \in \mathbb{N} \cup \{0\} : \sum_{n=1}^{k} I_n \leqslant C \right\},$$

where I_n is computed from the announced experiment.[18] Only for these indices does the receiver observes realizations $s = (s_1, \ldots, s_N)$ and thereby forms posteriors $P_n = \Pr(\omega_n = 1 \mid s_n)$ for every $n \leqslant N$.

The model unfolds as follows. First, the sender observes the full state vector ω and commits to a separable signaling scheme $S = (S_1, S_2, \ldots)$. Then, the receiver observes the structure of the signals and selects a subset of dimensions $\{1, 2, \ldots, N\}$ to process. Next, signals are realized and the receiver observes realizations s_n for the dimensions she attends to. Finally, based on these realizations, the receiver takes an action $a \in \{0,1\}^N$.

Given a posterior vector $(P_1, \ldots, P_N)$ for the attended dimensions based on the realized signals $s = (s_1, \ldots, s_N)$, the receiver chooses an action $a \in \{0,1\}^N$ to maximize the marginal accuracy gain (relative to the prior) net of the fixed cost:

$$u^R(a \mid s) \;=\; \sum_{n=1}^{N} \left[\mathbb{P}(\omega_n = a_n \mid s_n) - \tfrac{1}{2} - c_0 \right],$$

[17] For a discrete random variable X with support $\mathcal{X}$ and probability mass function $p(x) = \Pr(X = x)$, the Shannon entropy is $H(X) = -\sum_{x \in \mathcal{X}} p(x) \ln p(x)$. For jointly distributed discrete random variables X and Y, the conditional entropy of X given Y is $H(X \mid Y) = \sum_{y \in \mathcal{Y}} \Pr(Y = y) H(X \mid Y = y)$. Thus, the mutual information between X and Y is defined as $I(X;Y) = H(X) - H(X \mid Y)$.

[18] This decision is evidently endogenous as it depends on $\{I_n : n \in \mathbb{N}\}$. Yet, one can always reorder the indices accordingly.

where the uniform prior 1/2 serves as a benchmark, and the term in brackets is the marginal accuracy gain (relative to the prior) net of the fixed cost. Since c_0 is constant, it does not affect the choice of a, but ensures that only dimensions with sufficiently high marginal gain are processed in the first place. Specifically, given a posterior belief $P_n \in [0,1]$, notice that $v(P_n) = \max\{P_n, 1-P_n\}$ is the receiver's expected payoff (ignoring the fixed components c_0 and $\frac{1}{2}$) when she chooses the action that maximizes her probability of matching the true realization of ω_n. The sender's objective is to maximize $\sum_{n=1}^{N}[\Pr(a_n = 1) - \frac{1}{2}]$ by choosing the appropriate experiment S.

Two more clarifications are in order. First, note that the fixed cost c_0 imposes a lower bound on I_n for every dimension n, so N is finite (see the analysis in the following section). Second, to avoid trivial solutions, we henceforth focus on the regime where $c_0 \ll \frac{1}{2}$. If $c_0 \geqslant \frac{1}{2}$, then the receiver would optimally ignore all signals.

4.1.1 Preliminary case: one dimension

Before elaborating on the infinite-dimensional case, we begin by analyzing a baseline persuasion environment with a single binary state $\omega \in \{0,1\}$, drawn under a uniform prior. The sender observes the true state and commits to an experiment S. The experiment S must satisfy three conditions: (i) Bayes' plausibility, (ii) the receiver's fixed cognitive cost constraint $c_0 > 0$, and (iii) the mutual information budget condition $I(\omega; S) \leqslant C$.

Taking all these into account, we claim that the sender does not require more than two signals (i.e., realizations). That is, for any experiment that generates more than two posteriors, we can devise an experiment based on two signals s_H and s_L, without reducing the sender's payoff. To see this, notice that the receiver's payoff is a linear function of the posterior on each side of the prior (namely, $v(p) = \max\{p, 1-p\}$). Therefore, the sender can contract any two posteriors that lie strictly above (or strictly below) $p = 0.5$ while maintaining Bayes' plausibility and the fixed cost constraint. Moreover, mutual information is convex in the experiment (see, e.g., Theorem 2.7.4 in Cover and Thomas, 2006), so the same contraction weakly reduces $I(\omega; S)$. Iterating this procedure until no side of the prior hosts more than one posterior, we get an experiment with exactly two posterior beliefs, one above and one below $\frac{1}{2}$, without lowering the sender's payoff. Hence, without loss of generality, we may restrict attention to a *binary* experiment $S \in \{s_H, s_L\}$ characterized by the pair (α, β), where $\alpha = \Pr(S = s_H \mid \omega = 1)$, $\beta = \Pr(S = s_H \mid \omega = 0)$ and $0 \leqslant \beta < \alpha \leqslant 1$.

A straightforward computation (see Theorem 2.4.1 in Cover and Thomas, 2006) shows that

$$\begin{aligned} I(\omega; S) &= H(\omega) - H(\omega|S) \\ &= H(S) - H(S|\omega) \\ &= h\left(\tfrac{\alpha+\beta}{2}\right) - \left[\Pr(\omega=0)H(S|\omega=0) + \Pr(\omega=1)H(S|\omega=1)\right] \\ &= h\left(\tfrac{\alpha+\beta}{2}\right) - \tfrac{1}{2}\left[h(\alpha) + h(\beta)\right], \end{aligned}$$

where $h(p) = -p\ln p - (1-p)\ln(1-p)$ is the binary entropy function (i.e., the entropy function for a Bernoulli variable with parameter p). For now, let us assume that the budget constraint C is slack, meaning it is large enough to accommodate any experiment $S \in \{s_H, s_L\}$.

From the receiver's perspective, the signal leads the receiver to choose correctly with probability $\frac{1}{2}(\alpha + 1 - \beta)$, while her accuracy without processing is only $\frac{1}{2}$. Therefore, the ex-ante accuracy gain from processing is

$$g(\alpha, \beta) = \tfrac{1}{2}(\alpha - \beta),$$

and the receiver chooses to process the signal only if this gain exceeds the fixed cost, namely, if $\alpha - \beta \geqslant 2c_0$. This threshold defines the processing constraint. Conditional on processing, the receiver optimally chooses $a = 1$ if and only if the observed signal is s_H.

The sender's expected payoff depends on the unconditional probability of s_H given by $\Pr(a = 1) = \Pr(S = s_H) = \frac{1}{2}(\alpha + \beta)$. The sender's objective is to choose the signal that maximizes this success probability subject to the receiver's processing constraint. It is thus optimal for the sender to select the *minimum required gap* $\alpha - \beta = 2c_0$. Widening the gap beyond this point is counter-productive for the sender because $\frac{1}{2}(\alpha+\beta) = \alpha - \frac{\Delta}{2}$ which decreases as a function of $\Delta := \alpha - \beta \geqslant 2c_0$. Once the gap is fixed, the sender can increase both probabilities as high as possible to maximize $\alpha + \beta$. Because the budget constraint is non-binding, the optimal choice is $(\alpha, \beta) = (1, 1 - 2c_0)$ which yields an expected payoff of $\frac{1}{2} - c_0$ for the sender. This one-dimensional logic forms the essential building block for the multi-dimensional persuasion setting.

If we do not assume that the budget constraint is slack, then the sender may not be able to shift α upwards to tilt the posterior mass toward the preferred message s_H, given the fixed gap $\alpha - \beta = 2c_0$. Whether that is feasible depends on how the variable information cost behaves in α. Because the gap

is fixed, we can formulate I as a function of α and (with some abuse of notation) get

$$I(\alpha) = h(\alpha - c_0) - \frac{1}{2}\left[h(\alpha) + h(\alpha - 2c_0)\right].$$

Note that the binary entropy function $h(\cdot)$ is strictly concave with a maximum at 0.5 and tends to zero when approaching the boundaries 0 and 1. See Figure 3a. Using the symmetry of h around 1/2, its derivatives, and Jensen's inequality, we can prove that $I(\alpha)$ is convex, symmetric around $\frac{1}{2} + c_0$, and has a unique minimum at $\alpha = \frac{1}{2} + c_0$, where $\alpha \in [2c_0, 1]$. See Figure 3b and Appendix B. Consequently, the symmetric experiment $(\alpha, \beta) = \left(\frac{1}{2} + c_0, \frac{1}{2} - c_0\right)$ minimizes the information cost, whereas the polar experiment $(1,\, 1 - 2c_0)$ maximizes it.

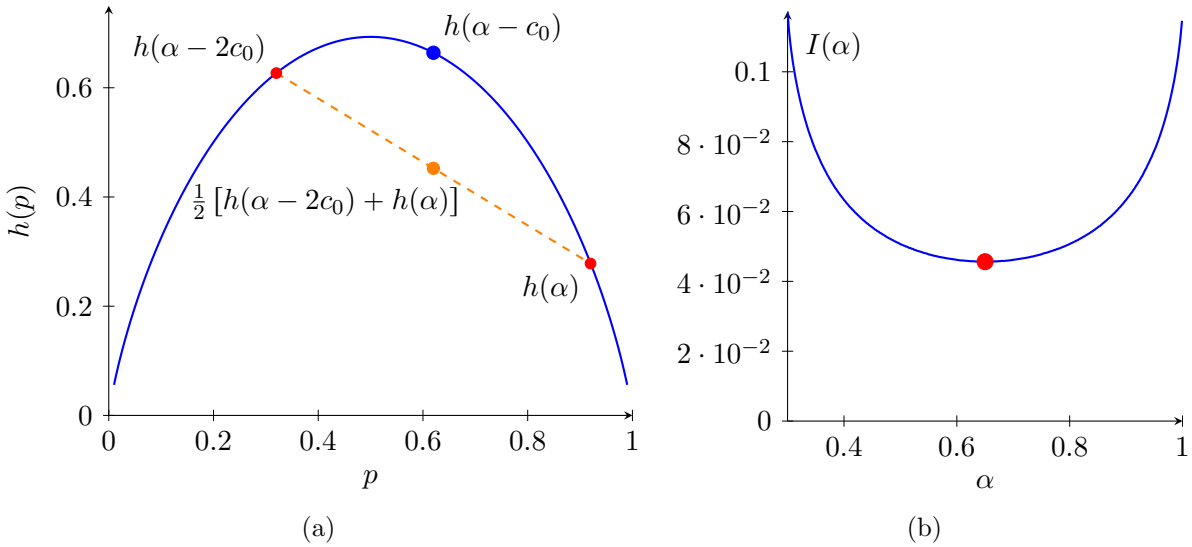

Figure 3: Graph 3a (left) illustrates a binary entropy function $h(p)$ with key points marked, given $c_0 = 0.3$ and $\alpha = 0.92$. Graph 3b (right) depicts the mutual information $I(\alpha)$ given $c_0 = 0.15$.

Note that the symmetric experiment yields an expected payoff of zero for the sender (relative to the benchmark given by the prior), as the posterior symmetrically splits to both sides and the receiver is ex-ante equally likely to choose either action. The polar experiment, on the other hand, generates a posterior greater than half with probability $1 - c_0$, thus yields an expected payoff of $\frac{1}{2} - c_0$ for the sender, as previously stated. The following Proposition 1 summarizes these results. (The proof follows from the previous analysis, thus omitted.)

Proposition 1. *Assume that $C \in (I(0.5 + c_0), I(1))$ and $N = 1$ is fixed. Then, the conditional probability α and the expected payoff of the sender strictly increases in C. If $C = I(1)$, then the*

receiver's posterior distribution is $\frac{1}{2-2c_0}$ *with probability* $1-c_0$.

Notice the inherent persuasion trade-off concerning c_0. If c_0 tends to 0, then with high probability the posterior is slightly above half. If c_0 is closer to 0.5, then with a probability slightly above half, the posterior is close to 1. In other words, the persuasion varies depending on the fixed cost.

The gap $\alpha - \beta = 2c_0$ ensures that the mutual information function $I(\alpha)$ remains strictly positive, because uninformative signals are completely ignored. Therefore, even at its minimum $I\left(\frac{1}{2}+c_0\right)$ is bounded away from 0. More formally,

$$\begin{aligned} I\left(\tfrac{1}{2}+c_0\right) &= h\left(\tfrac{1}{2}\right) - \tfrac{1}{2}\left[h\left(\tfrac{1}{2}+c_0\right) + h\left(\tfrac{1}{2}-c_0\right)\right] \\ &= h\left(\tfrac{1}{2}\right) - h\left(\tfrac{1}{2}+c_0\right) \\ &> \ln(2) - (\ln(2) - 2c_0^2) = 2c_0^2, \end{aligned}$$

where the inequality follows from the Taylor expansion of h around $p = \frac{1}{2}$ (one can verify that all relevant derivatives are negative). We can therefore conclude that $N \leqslant \left\lfloor \frac{C}{I(0.5+c_0)} \right\rfloor$, so that the receiver cannot attend to more than $\left\lfloor \frac{C}{I(0.5+c_0)} \right\rfloor$ sufficiently informative and independent experiments.

In addition, in case $\alpha = 1$ we get

$$\begin{aligned} I(1) &= h(1-c_0) - \frac{1}{2}\left[h(1) + h(1-2c_0)\right] \\ &= h(1-c_0) - \frac{1}{2}h(1-2c_0) \\ &= -(1-c_0)\ln(1-c_0) - c_0\ln(c_0) + \tfrac{1}{2}(1-2c_0)\ln(1-2c_0) + c_0\ln(2c_0) \\ &= \tfrac{1}{2}F(2c_0) - F(c_0) + c_0\ln(2), \end{aligned}$$

where $F(x) = (1-x)\ln(1-x)$. Note that F is convex, so $\frac{1}{2}F(2c_0)+\frac{1}{2}F(0) \geqslant F\left(\frac{1}{2}\cdot 2c_0 + \frac{1}{2}\cdot 0\right) = F(c_0)$, therefore $\frac{1}{2}F(2c_0) \geqslant F(c_0)$. Plugging this into the previous equation yields $I(1) \geqslant c_0\ln(2)$. So, in the polar case of $\alpha = 1$, the receiver can attend to at most $\left\lfloor \frac{C}{I(1)} \right\rfloor$ such experiments.

Remark 1. *We henceforth assume that* C *is sufficiently large such that* $\left\lfloor \frac{C}{I(0.5+c_0)} \right\rfloor \geqslant 1$. *Otherwise, the receiver cannot attend any signal due to a too restrictive* C *relative to* c_0*, and persuasion becomes completely infeasible.*

4.1.2 General Case: infinite dimensions.

Having characterized the one-dimensional benchmark, we now turn to the full model with a countably infinite vector of binary states. The different dimensions are independent in all aspects except for the mutual information budget constraint. Therefore, once the number N of dimensions is fixed (by the sender), the problem becomes rather straightforward.

In order to fix N, recall that $\sum_{n=1}^{N} I_n \leqslant C$. If the sender chooses either the symmetric experiment or the polar one in every dimension, then the number of attended dimensions is bounded by $\frac{C}{I(0.5+c_0)}$ and $\frac{C}{I(1)}$, respectively. Because these are the two extreme cases, we can fix $1 \leqslant N \leqslant \left\lfloor \frac{C}{I(0.5+c_0)} \right\rfloor$ and consider the sender's problem. Denote $\alpha_n = \Pr(S_n = s_H \mid \omega_n = 1)$ and $\beta_n = \Pr(S_n = s_H \mid \omega_n = 0)$ where $0 \leqslant \beta_n < \alpha_n \leqslant 1$ and $n = 1, \ldots, N$, as in the one-dimensional case. The previous analysis holds in every attended dimension n, including the gap $\alpha_n - \beta_n = 2c_0$, and we again conclude that $\Pr(a_n = 1) - \frac{1}{2} = \frac{\alpha_n + \beta_n - 1}{2} = \alpha_n - c_0 - \frac{1}{2}$. Therefore, conditional on N attended signals, the sender maximizes

$$\begin{aligned} \max_{\alpha_1,\ldots,\alpha_N} \quad & \sum_{n=1}^{N} \left(\alpha_n - c_0 - \frac{1}{2} \right) \\ \text{s.t.} \quad & \alpha_n \in \left[\tfrac{1}{2} + c_0,\, 1 \right] \quad \text{for all } n = 1, \ldots, N, \\ & \sum_{n=1}^{N} I(\alpha_n) \;\leqslant\; C. \end{aligned}$$

Notice that the mutual information $I(\alpha_n)$ is increasing and convex given $\alpha_n \in \left[\frac{1}{2} + c_0,\, 1 \right]$, so the optimal solution is symmetric $\alpha_1 = \alpha_2 = \cdots = \alpha_N$ (otherwise, we can shift some weight between dimensions while reducing the budget constraint; this also implies that $N \geqslant \left\lfloor \frac{C}{I(1)} \right\rfloor$). Therefore, we can reformulate the problem to optimize over N as follows:

$$\begin{aligned} \max_{\alpha, N} \quad & N \left(\alpha - c_0 - \frac{1}{2} \right) \\ \text{s.t.} \quad & \tfrac{1}{2} + c_0 \leqslant \alpha \leqslant 1, \\ & N \cdot I(\alpha) \;\leqslant\; C. \end{aligned}$$

We can reduce the dimension of the optimization problem by defining $N(\alpha) = \left\lfloor \frac{C}{I(\alpha)} \right\rfloor$, so that for every admissible precision level $\alpha \in [\frac{1}{2} + c_0, 1]$, the largest integer number of experiments consistent with the information budget is $N(\alpha)$. Because $I(\alpha)$ is strictly increasing on this interval, $N(\alpha)$ is weakly decreasing, and the original mixed–integer problem can be rewritten as the single-variable

maximization

$$\max_{\alpha\in[\frac{1}{2}+c_0,\,1]} \; N(\alpha)\big(\alpha - c_0 - \tfrac{1}{2}\big), \tag{4}$$

whose objective is piecewise linear in α and drops at the jump points of $N(\alpha)$. Let $\alpha(C)$ be the *intensive margin* solution for the optimization given in (4).

Alternatively, we can optimize over N rather than over α. Since the sender strives to exhaust the receiver's attention for every $N \geqslant 1$, the optimization increases α until the inequality $N \cdot I(\alpha) \leqslant C$ is tight or until the upper bound $\alpha = 1$ is reached. This yields the frontier value

$$\alpha_N \;:=\; \max\big\{\alpha \in [\tfrac{1}{2} + c_0, 1] \mid N \cdot I(\alpha) \leqslant C\big\}.$$

As I is monotone in the relevant interval, α_N is uniquely characterized by $N \cdot I(\alpha_N) = C$, except when $\alpha_N = 1$ and $N \cdot I(1) < C$. The maximal objective attainable is therefore

$$\max_{1\leqslant N\leqslant \left\lfloor \frac{C}{I(0.5+c_0)} \right\rfloor} \; N\big(\alpha_N - c_0 - \tfrac{1}{2}\big), \tag{5}$$

which reduces the complexity of the problem to a finite number of values. Let $N(C)$ be the *extensive margin* solution for the optimization given in (5). We can now build on these optimization problems to conclude that a higher attention (i.e., budget C) weakly increases either the intensive margin or the extensive one, and a significant increase in attention always increases the latter. This result is captured in the following Proposition 2:

Proposition 2. *If attention C increases, then either the intensive margin $\alpha(C)$ or the extensive margin $N(C)$ weakly increases, and there exists $C' > C$ such that $N(C') > N(C)$.*

Proof. The proof is straightforward. For any fixed $N \geqslant 1$, both $\left\lfloor \frac{C}{I(0.5+c_0)} \right\rfloor$ and α_N weakly increase as a function of C, which implies that $N\big(\alpha_N - c_0 - \frac{1}{2}\big)$ weakly increases as well. So the sender's expected payoff in equilibrium weakly increases in C, implying that either the extensive margin or the intensive margin weakly increase. For the second part of the proof, recall that $N(C)$ is bounded from below by $\left\lfloor \frac{C}{I(1)} \right\rfloor$, so $\lim_{C\to\infty} N(C) \geqslant \lim_{C\to\infty} \left\lfloor \frac{C}{I(1)} \right\rfloor = \infty$, as needed. □

A natural extension to Propositions 1 and 2 concerns the case of a finite number of dimensions $N > 1$, i.e., an exogenous bound on N. If indeed the number of dimensions is finite, yet greater than

1, then we can combine the results of the two propositions to derive the following Corollary 1. (The proof follows from previous analysis and results, thus omitted.)

Corollary 1. *Assume that $N > 1$ is exogenously bounded from above and fix $C \in [I(0.5 + c_0), I(1)]$. Then, there exists $C' > C$ such that in every dimension n, the receiver's posterior distribution is $\frac{1}{2-2c_0}$ with probability $1 - c_0$.*

An interesting feature of the finite-dimension case is the adjustment on both the intensive and extensive margins: as the attention C increases, the receiver eventually attends to all dimensions and in every dimension, with probability $1 - c_0$, the posterior tends toward $\frac{1}{2-2c_0}$.

4.1.3 From attention to polarization

The transition from attention to polarization goes through a dual persuasion problem. Consider two senders, A_0 and A_1, and two receivers, B_0 and B_1, one for each sender respectively. Similarly to the baseline model, every Sender A_i tries to maximize the sum of probabilities that Receiver B_i chooses $a_n = i$ in every state n. These senders are essentially different sources of information (news outlets, politicians, acquittances and so on) conveying noisy informative signals to their audiences. The two senders and receivers are confined to the same framework and constraints as before.

The analysis in previous sections holds for each persuasion problem, thus allowing us to study the receivers' joint distribution of posterior beliefs on the entire state space. Focusing first on the one-dimensional problem, assume that $C \in (I(0.5 + c_0), I(1))$ and $N = 1$ is fixed. Conditional on $\omega_1 = 1$, the following Table 2 presents the joint posterior beliefs and signal realization probabilities.

Signal S_A	**Signal** S_B	**Beliefs** (P_A, P_B)	**Probability (given** $\omega = 1$**)**
s_H	s_H	$\left(\frac{\alpha}{2\alpha - 2c_0}, \frac{\alpha - 2c_0}{2\alpha - 2c_0}\right)$	$\alpha \cdot (\alpha - 2c_0)$
s_H	s_L	$\left(\frac{\alpha}{2\alpha - 2c_0}, \frac{\alpha}{2\alpha - 2c_0}\right)$	$\alpha \cdot (1 - \alpha + 2c_0)$
s_L	s_H	$\left(\frac{\alpha - 2c_0}{2\alpha - 2c_0}, \frac{\alpha - 2c_0}{2\alpha - 2c_0}\right)$	$(1 - \alpha) \cdot (\alpha - 2c_0)$
s_L	s_L	$\left(\frac{\alpha - 2c_0}{2\alpha - 2c_0}, \frac{\alpha}{2\alpha - 2c_0}\right)$	$(1 - \alpha) \cdot (1 - \alpha + 2c_0)$

Table 2: Joint posterior beliefs and signal realization probabilities given $\omega = 1$.

If attention is low, namely, in case α is close to $\frac{1}{2} + c_0$, then the receivers choose different actions with probability close to 0.5. Essentially a random draw. However, if attention increases and α tends

to 1, then with probability $1-2c_0$, the *realized* actions differ. See Table 3. Note, again, the trade-off that originated from the fixed cost: a small c_0 yields posteriors close to 0.5 with high probability, whereas a higher cost yields posteriors that are further apart but with a smaller probability. This trade-off is rather evident given the Bayes' plausibility condition. A similar image emerges when $\omega = 0$.

Signal S_A	**Signal** S_B	**Beliefs** (P_A, P_B)	**Probability (given** $\omega = 1$**)**
s_H	s_H	$\left(\frac{1}{2-2c_0}, \frac{1-2c_0}{2-2c_0}\right)$	$1-2c_0$
s_H	s_L	$\left(\frac{1}{2-2c_0}, \frac{1}{2-2c_0}\right)$	$2c_0$

Table 3: Joint posterior beliefs and signal realization probabilities given $\omega = 1$ and $\alpha = 1$.

4.1.4 Testable hypothesis

We extend the previous analysis and results to a setting with multiple states, where N is exogenously bounded from above. Doing so, we conclude that once attention increases, the posteriors of both receivers split around half, with a probability of $1-c_0$. (The proof follows from previous analysis, thus omitted.)

Corollary 2. *Assume that $N > 1$ is bounded from above. Fix $C \in [I(0.5+c_0), I(1)]$ and consider some dimension $1 \leqslant n \leqslant N$. There exists $C' > C$ such that, with probability $1-c_0$, Receivers B_0 and B_1 choose (in dimension n) actions 0 and 1, respectively. Thus, given this C', the expected number of dimensions in which the receivers' actions differ is $N(1-c_0)$.*

Assuming that the fixed cost is small and attention increases, we reach ex-post polarization in a given dimension with high probability (namely, $1-c_0$), that eventually translates to the receivers' actions. As attention increases, the polarization occurs across both the extensive margin (across all dimensions) and the intensive margin (in every dimension with high probability). Leading us to the conclusion that higher attention can effectively increase polarization.

4.2 Empirical testing

The model above explains how societal political attention may increase polarization. In this section we put this prediction into empirical testing. Specifically, we consider the potential impact of state

political attention on the patterns of individuals' political polarization in the U.S., in presidential election years over the period 1980-2020.

Our focus is on individuals' political polarization. We measure the latter via (the absolute value of) differences in respondents' responses in the ANES concerning their feelings towards the Democratic and Republican parties.[19] This difference, as we further outline below, indicates the extent to which individuals empathize with a party while disliking the other, eliminating empathy for the moderate views, and hence mapping to the endogenous polarization concept introduced in the model. Focusing on the gubernatorial context enables undertaking within-state analyses, and thus mitigate concerns related to the extent of subjectivity in the reported views across states and time. Importantly, ANES surveys employ standardized measures across waves, making them ideal for examining polarization patterns over times.

The analysis is, therefore, undertaken at the respondent level, under a state-level perspective which considers societal political attention. Considering a federal setup provides ample within and cross state variation in political attention, as noted previously, as well as in polarization, as reported below, in addition to variation in key aspects of the analysis including political institutions, and various politico-economic measures. These features follow the framework studied in the theoretical analysis, and allow identifying the causal link running from societal political attention to political polarization. Next, we describe the data and methodology in more detail.

4.2.1 Data and methodology

We examine the data of respondents to the ANES, across the 50 U.S. states, covering the period 1980-2020, in election years.[20] All variables are outlined in the Data Appendix, including descriptive statistics of the key variables, presented in Table 11. The analysis is based primarily on two key measures, namely societal political attention, and polarization. The former was outlined in detail previously; hence, we outline the details of the latter next.

Polarization We measure polarization via data from the ANES (ANES (2022)). The ANES is a comprehensive national survey of voters, undertaken biennially up to 2004 and quadrennially there-

[19] Following the definition of polarization outlined in Stewart et al. (2020).

[20] The sample size and period are restricted by the availability of our baseline measures of political attention and polarization. The latter is available starting in 1978, and the former is available for presidential election years, hence providing the noted sample period.

after, on a representative sample of voting-legible U.S residents, before and/or after elections (Presidential or House/Senate, depending on the survey year), starting in 1948. We employ the ANES cumulative survey data which merges and standardizes survey variables across a pooled cross-section of survey waves. The analysis covers all years for which our main measures of interest (attention and polarization) are available, namely 1980-2020, in presidential election years.

We consider partisan polarization, in which individuals identify more strongly with one political party while concurrently identifying less with the other party, mapping to the polarization criterion introduced in the analytical framework. Turning to ANES, we adopt the 'feelings thermometer' concerning views on the Democratic and Republican parties, evaluated consistently over time. Feelings thermometers have long been a standard part of election surveys, and are administered on a 100 point scale, with 0 corresponding to strong negative feelings towards a party, and 100 corresponding to strong positive feelings. Intuitively, if an individual gives a high score to one party and a low score to another, this indicates a high degree of partisan polarization, i.e., a large net positive feeling towards a preferred party. Hence, our baseline measure of political polarization considers the absolute value of the difference between individuals' thermometer values concerning the Democratic and Republican parties. Notably, thermometer responses concerning Democratic-Republican parties' values are recorded post-election in each wave, late in the year (noting that elections in the U.S. are held in November).[21]

Using the ANES presents several advantages for our hypotheses testing. First, the ANES is a central data source of political opinions in the U.S. across time, employed previously in several seminal studies (e.g., Kuziemko and Washington (2018), Shachar and Nalebuff (1999)), and is well suited for examining public opinions over time (ANES (2022)). Second, it provides a rich set of respondent-level measures, ranging from individuals' income to their party identification and political engagement, essential to the analysis. Last, it also reports individuals' congressional district of residence, covering all U.S. states, and hence enables matching our (state-level) treatment and adding congressional district fixed effects, thus undertaking a within congressional district analysis that addresses concerns related to the extent of subjectivity in thermometer values across states and time.

Our sample covers 19,646 individuals. Figure 4 presents the cross-sectional distribution of our (baseline) polarization measure across U.S. states. As the figure illustrates, there is significant cross-state variation. The state averages range from 22 (Wyoming) to slightly over 42 (Vermont). Overall, the average polarization level is about 34, with a standard deviation of 29, ranging from 0 to 99. The

[21] We account for the timing of interview, in terms of number of days post-election, within the analysis.

bias towards relatively small thermometer differences is clear; about 25% (5%) of the sample report differences in the lower (upper) 10% percentile (i.e., values between 0 to 10 (90 to 99)).

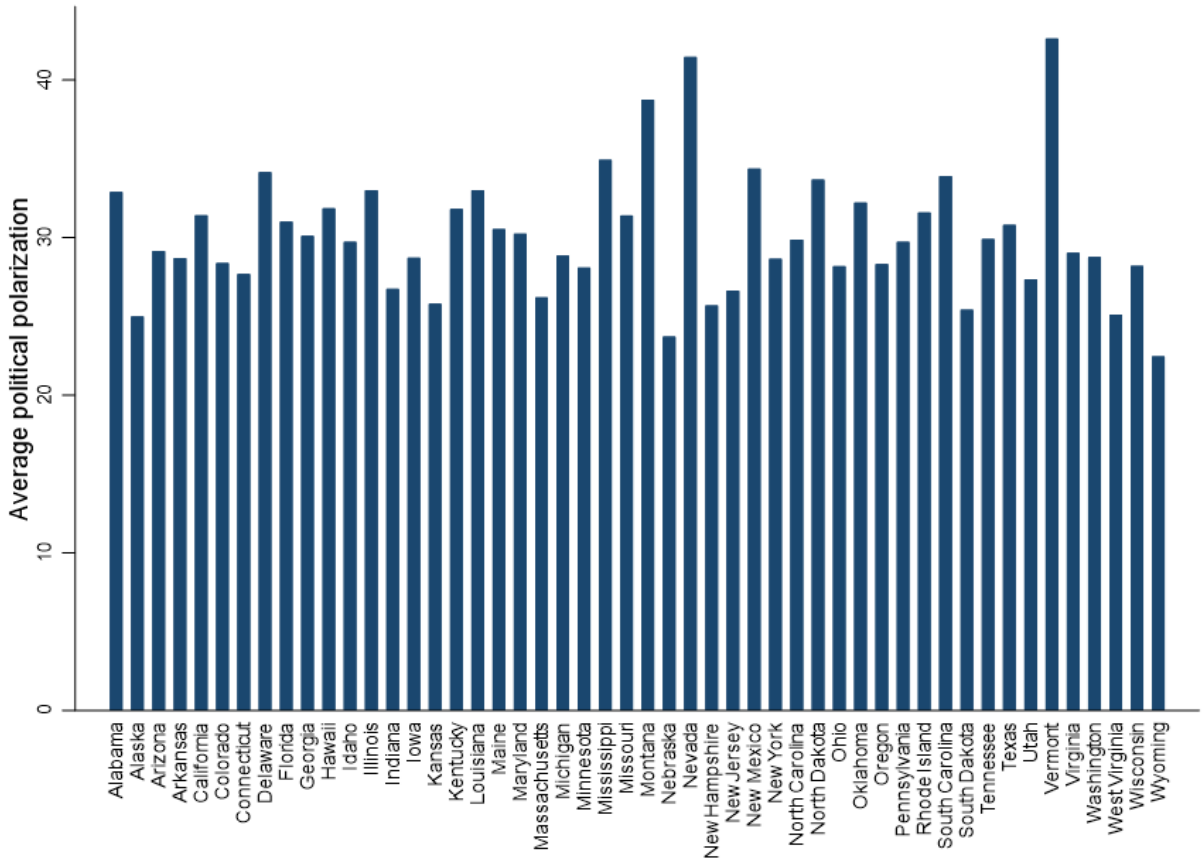

Figure 4: The figure presents the average political polarization across the 50 U.S. states, over the period 1980-2020.

Methodology and identification Using these primary measures, in addition to further respondent and state level controls noted below, as well as throughout the analysis, we estimate the impact of political attention on the extent of polarization, in election years over the period 1980-2020. Identification rests on the plausible exogeneity of the state political attention measure to individual-level opinions. Indeed, we assume that individuals on their own do not alter state-level indicators, including societal political attention. In addition, as outlined previously, the treatment is the outcome of an interaction of cross-sectional and temporal estimates, each being plausibly exogenous to state-by-year indicators. Specifically, this is so because the former (latter) considers within-state (within-year) expectations

across all years (across all states).[22] Further, noting that the ANES data is composed of a pooled cross-section of individuals, identification is further based on the assumption that within congressional districts and years subjective differences in thermometer interpretations across individuals are similar over the opinion spectrum;[23] notably, other (cross-state and time) potential subjective differences are captured by the fixed effects, as further noted below.

Throughout the analysis we estimate models of the following type, for respondent i, state j, year t, and congressional district c:

$$polarization_{i,c,t} = \alpha + \beta(attention)_{j,t} + \gamma(\mathbf{X})_{i,j,t} + \zeta_c + \nu_t + \epsilon_{i,c,t} \ , \tag{6}$$

where *polarization*, and *attention* denote the polarization, and political attention measures outlined above. In addition, $\mathbf{X}$ is a vector of controls at the respondent-year and/or state-year level which varies across specifications and outlined across the analysis; In all cases, however, it includes state-by-year time trends, to control for the upward trend in the extent of polarization over time, and survey weights.[24] Finally, ζ and ν are congressional district and year fixed effects, respectively. Albeit considering a treatment at the state level, we exploit the reports of congressional district of residence to add fixed effects at a more granular level (congressional district), which addresses further heterogeneity, while accounting also for state fixed effects, given that congressional districts are state-fixed. Notably, these fixed effects control for key factors. The within congressional district approach enables addressing regulatory impacts as well as effects of social political approaches related to, for instance, containment of partisanship and related phenomena. The time fixed effects absorb national impacts, ranging from business cycles to technological shocks. Importantly, both in addition control for subjective differences in thermometer reports across space and time.

This setting considers a state-level perspective, as it examines the impact of societal (state-level)

[22] Nonetheless, later in the analysis we further address this by employing an IV approach, in which attention is instrumented by expressions of interest in issues unrelated to politics.

[23] In this case, individuals may differ in their thermometer interpretations; i.e., for some individuals a score of 50 may seem high, while others may interpret it as being low. Nonetheless, assuming that individuals apply their subjective interpretations similarly across the opinion spectrum, judging partisan views on the same subjective scale, the *difference* in thermometer values, which is what the outcome variable ultimately captures, is comparable across individuals and hence informative. Indeed, regressing the difference between individuals' Republican party thermometer and the mean Republican party thermometer within congressional districts and years, on the same difference using Democratic party thermometer values, yields a statistically precise positive estimate, indicating that deviations of individuals' opinions from the mean co-move across the opinion spectrum.

[24] ANES reports the survey weights of each respondent, in an attempt to reach a representative sample; consequently, some observations have a weight of less than 1, while others take a relatively larger portion, exceeding a weight of 1.

political attention. Nonetheless, to exploit the full extent of variation in the ANES data, we concurrently maintain its respondent-level frequency throughout the analysis. To address the potential correlation of ads within state-year cells, we cluster the standard errors at the treatment level.[25] Specifically, throughout the analysis we adopt a conservative two-way clustering approach, in which the standard errors are clustered by states and years concurrently.[26] Importantly, albeit being conservative, this approach yields a relatively large number of clustering groups, mitigating concerns related to potential Moulton bias, and statistical inference under few clustering groups. Our focus throughout the analysis is on the characteristics of β, namely its sign, magnitude and statistical preciseness, which give an estimate for the contemporaneous impact of political attention on polarization. Our contemporaneous approach is driven by the timing of the survey parts pertaining to the analysis, which, as noted, are undertaken late in each given year.

4.2.2 Preliminary analysis: extremism and efforts

The initial theoretical outcome is based on the conjecture that extreme voices put more effort in voicing their opinions, thus eventually controlling the political discourse. In this preliminary analysis, we examine the validity of this association via the ANES data. To do so, we examine the individual-level association between the baseline measure of polarization, and six measures of participation in the political discourse, namely whether an individual attempted the following during the campaign: attending political meetings/rallies, influencing the vote of others, working for the party or candidate, displaying candidate's button/sticker, and donating money to party or candidate. Each such measure is a binary variable, taking the value 1 (0) in case of an attempt (otherwise). In effect, we estimate the following variant of Equation (6):

$$polarization_{i,c,t} = \alpha + \beta z_{i,c,t} + \zeta_c + \nu_t + \epsilon_{i,c,t} \ , \tag{7}$$

with z denoting each of the six noted measures of participation. The results are reported in Columns 1-5 of Table 4, respectively. The estimated βs are positive and statistically precise in all cases, pointing at a clear positive association between the extent of participation in the political discourse (efforts)

[25] This setting, in which standard errors are clustered at the treatment level, is consistent with the approach adopted in related studies that similarly examined the impact of an aggregated treatment on a disaggregated outcome. See e.g., Cust et al. (2019), Ebenstein et al. (2016), Pelzl and Poelhekke (2021), or Topalova and Khandelwal (2011), among many others.

[26] Cases that yield highly singular variance matrix are clustered by state.

and polarization (extremism). This observation supports the initial theoretical outcome, motivating an examination of the key theoretical predictions, which we do next.

Table 4: Extremism and efforts

Dependent variable: Polarization	(1) Political rallies	(2) Influence others	(3) Political work	(4) Button / Sticker	(5) Political donations
z	9.22***	10.84***	12.27***	12.51***	12.45***
	(0.94)	(0.41)	(1.41)	(0.84)	(1.15)
CD fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.05	0.08	0.05	0.06	0.06
Observations	17208	17204	17199	17210	17196

Notes: Standard errors are robust, clustered by state and year, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is polarization. All regressions include congressional district (CD) and year fixed effects, survey weights, state-by-year time trends, and an intercept. The complete sample includes respondents to the U.S. American National Elections Survey, covering presidential election years over the period 1980-2020. In each column, 'z' denotes the measure noted at the title of it, namely 'Political rallies', 'Influence others', 'Political work', 'Button / Sticker', and 'Political donations', respectively (each outlined in the text). For further information on variables see data Appendix.

4.2.3 Main empirical results

This sub-section outlines the main results of the empirical analysis. We start with the baseline outcomes, and continue to additional examinations and robustness tests thereafter.

Political attention and polarization We turn to the main analysis. We estimate various versions of Equation (6). Results appear in Table 5. Column 1 represents our baseline specification. The estimated β is positive and statistically significant. Political attention increases polarization, consistent with the main prediction of the model. Furthermore, The magnitude is non-trivial. A one standard deviation of *attention* increases average *polarization* 6%.[27]

Next, in Columns 2-3 we examine the source of the change in affective polarization; i.e., whether it is the in-group and/or out-group opinions that are affected. For instance, Gidron et al. (2020) find that economic factors primarily affect out-group feelings, pointing at the potential source of change in our baseline outcome. To examine this, we consider individuals' direct thermometer values of the party they (do not) identify with, representing the in-group (out-group) case. These measures are

[27] This is computed by multiplying a one standard deviation of *attention* (0.06) by the estimated β (31.87), and dividing by the average *polarization* (34.17).

Table 5: Political attention and polarization

Dependent variable: Polarization	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Dep. Var: In-group Thermometer	Dep. Var: Out-group Thermometer	Respondent characteristics	Interview characteristics	State characteristics
Attention	31.87***	28.62***	-3.25	29.4**	36.26***	34.83***
	(8.01)	(8.32)	(9.23)	(9.78)	(6.31)	(8.61)
CD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Respondent controls	No	No	No	Yes	No	No
Interview controls	No	No	No	No	Yes	No
State controls	No	No	No	No	No	Yes
R-squared	0.04	0.05	0.11	0.05	0.04	0.04
Observations	19646	19646	19646	19646	18029	19646

Notes: Standard errors are robust, clustered by state and year, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is polarization (In Column 2 (3) it is in- (out-)group thermometer value. All regressions include congressional district (CD) and year fixed effects, survey weights, state-by-year time trends, and an intercept. The complete sample includes respondents to the U.S. American National Elections Survey, covering presidential election years over the period 1980-2020. 'Attention' is the baseline measure of political rational inattention outlined in the text. Respondent controls include: income, party identification, and gender. Interview controls include: mode, language, and timing. State controls include: electoral competition, population, and inequality. For further information on variables see data Appendix.

then employed as the outcome variable, in lieu of *polarization*, in Column 2 (3). The results indicate that political attention increases the in-group thermometer values (i.e., further liking it) of individuals, while not affecting the out-group values, thus pointing at the source of the impact on the extent of polarization.

The next columns include various controls in $\mathbf{X}$; each case addresses a different facet of the polarization reports examined.[28] We outline the controls considered in each case (referring to the Data Appendix for the complete description of each measure), which in turn alter sample sizes, depending on the measures' availability and coverage. In Column 4 we examine the role of respondent factors, as they may impact the extent of thermometer values reported. For instance, it has been shown that income may be associated with polarization (Gunderson (2022)). Hence, we add the following respondent controls: income level, political engagement, party identification, and gender.

In Column 5 we account for the potential impact of interview characteristics. Specifically, we consider three measures, namely the mode, language, and timing of interview. The first measure considers whether the interview was held in person, over the phone, online, or through video; the second addresses the language in which the interview was held, including English, Spanish, French, or other; the third reports the timing of the interview, measured as the number of days from the day

[28] We distinguish between facets, rather than consider them jointly, as the latter option restricts the sample considerably.

of election (within the corresponding year). Each of these factors may affect respondents' reported measures; for instance, assuming that the interest in political debates peaks at, or around, election day, the farther the interview is from election day the subtler may be respondents' attitudes towards them.

In Column 6 we consider statewide politico-economic factors that go beyond the previously considered individual co-variates. First, states' electoral competition. The latter enhances salience, and may affect polarization, as noted by Bassan-Nygate and Weiss (2022). To account for that, we include the state-year average of a binary indicator that takes the value 1 (0) in case the respondent expects a close presidential race (a certain win by one of the candidates). Second, income inequality. Previous studies noted that income and political polarization are associated (e.g., Stewart et al. (2020)), hence we control for income inequality via the state-year average of respondents' income distance from the mean state income. Last, population size. Larger, more populous societies, may incur greater heterogeneity that manifests to polarization-triggering echo-chamber effects (e.g., Prior (2007)), or may decrease investment in political information (e.g., Martinelli (2006)) hence affecting the extent of societal attention, thus we include state-year population size.

Columns 4-6 report the estimated βs.[29] Notably, the outcome in each case is reminiscent of that estimated under the baseline case (Column 1). Specifically, we note that β is positive, statistically precise, and with a largely similar magnitude, in each case. Put together, we note that the main observed patterns are robust to addressing the various noted co-variates.

Potential mechanisms The baseline results indicate that, consistent with the theoretical analysis, political attention increases the extent of polarization. Next, we consider various potential underlying mechanisms. To do so, we undertake an heterogeneity analysis with respect to the key controls considered in the baseline examinations, namely those related to respondent and state characteristics as well as additional ones related to state institutions. We examine each case separately. Hence, we estimate the following variation of Equation (6):

$$polarization_{i,c,t} = \alpha + \beta(attention)_{j,t} + \gamma(z)_{\Theta\in((i,t),(j),(j,t))} + \delta(attention * z)_{\chi\in((\Theta,t),(\Theta))} + \zeta_c + \nu_t + \epsilon_{i,c,t} \ , \quad (8)$$

[29]The separate effects of the various key co-variates are reported and analyzed in the following sub-section which considers potential underlying mechanisms.

where z is an alternating measure across specifications (in conjunction with corresponding alternations of Θ, depending on z's variation), outlined separately for each of the three cases (respondent, state, and institutional features). In each case we report the coefficients of interest, namely β, γ (if not absorbed by the fixed effects), and δ.

I. Respondent characteristics: Examining heterogeneities across respondent-level measures, z in this case denotes one of the following respondent-level measures outlined above: income, party identification, and gender. Results appear in Table 6. We observe that none of the co-variates are robustly associated with polarization, including when interacted with *attention*. Importantly, however, β retains its characteristics in all cases, in terms of sign, magnitude, and significance, pointing at patterns similar to the baseline case, including in Column 4 in which all the underlying channels are considered concurrently. The main outcome is, therefore, robust to the inclusion of the key respondent-level potential mechanisms.

Table 6: Potential mechanisms – Respondent characteristics

Dependent variable: Polarization	(1)	(2)	(3)	(4)
	Income	Party	Gender	All
Attention	33.79**	35.74***	40.58***	46.93**
	(11.14)	(11.41)	(14.9)	(18.17)
Income	0.44			0.41
	(0.74)			(1.05)
Party		-0.33		-0.26
		(0.86)		(0.85)
Gender			3.13	3.24
			(2.34)	(2.33)
Attention X Income	-0.57			0.18
	(1.61)			(2.89)
Attention X Party		-1.91		-2.16
		(2.58)		(2.54)
Attention X Gender			-5.88	-6.7
			(6.89)	(6.86)
R-squared	0.04	0.05	0.04	0.05
Observations	19646	19646	19646	19646

Notes: Standard errors are robust, clustered by state and year, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is polarization. All regressions include congressional district (CD) and year fixed effects, survey weights, state-by-year time trends, and an intercept. . The complete sample includes respondents to the U.S. American National Elections Survey, covering presidential election years over the period 1980-2020. 'Attention' is the baseline measure of political rational inattention outlined in the text. 'Income' is respondent's income level. 'Party' is respondent's party identification. 'Gender' is respondent's gender. For further information on variables see data Appendix.

II. State characteristics: Undertaking similar analysis for the key state-level measures, z in this case represents one of the following state-level measures outlined above: population, electoral competition, and inequality, in addition to land area, as additional cross-sectional proxy for size. The results, which appear in Table 7, indicate that population size increases polarization, and even more so under high societal attention, consistent with the previously noted heterogeneity hypothesis. In addition, inequality also raises polarization under high societal attention. Notably, the main observed patterns (noted via the βs) remain to hold under the consideration of the different state-level channels, also when all of them are considered jointly in Column 6.

Table 7: Potential mechanisms – State characteristics

Dependent variable: Polarization	(1)	(2)	(3)	(4)	(5)
	Area	Population	Electoral competition	Inequality	All
Attention	32.05***	36.69***	35.06***	23.19***	34.02***
	(9.55)	(8.7)	(7.91)	(6.43)	(7.26)
Population		1.69***			1.39***
		(0.52)			(0.21)
Electoral competition			30.67		30.28
			(28.14)		(30.83)
Inequality				-2.76**	-2.83*
				(1.11)	(1.24)
Attention X Area	-0.00001				-0.00004
	(0.00002)				(0.00005)
Attention X Population		-0.12			0.11
		(0.14)			(0.18)
Attention X Electoral_competition			-140.32		-137.79
			(79.2)		(86.26)
Attention X Inequality				7.89**	8.05**
				(2.97)	(3.21)
R-squared	0.04	0.04	0.04	0.04	0.04
Observations	19646	19646	19646	19646	19646

Notes: Standard errors are robust, clustered by state and year, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is polarization. All regressions include congressional district (CD) and year fixed effects, survey weights, state-by-year time trends, and an intercept. The complete sample includes respondents to the U.S. American National Elections Survey, covering presidential election years over the period 1980-2020. 'Attention' is the baseline measure of political rational inattention outlined in the text. 'Area' is state land area. 'Population' is state population. 'Electoral competition' is the extent to which presidential elections in the state are close. 'Inequality' is state income inequality. For further information on variables see data Appendix.

III. Institutional characteristics: Additional potential political mechanisms relate to cross-state institutional differences. U.S. states present various institutional differences that may be pivotal for our

analysis, as they relate to incumbent behavior, which may crucially affect various aspects of political debates. We, hence, consider cross-sectional differences in the institutional settings that have been reported in previous research to affect states' incumbent behavior (see, e.g., Raveh and Tsur (2023)). While such differences are captured via the state fixed effects, we look into the role of their interaction with *attention*. In this case z represents an indicator for one of the examined institutional features. The descriptions and cross-sectional state divisions of each of the institutional differences mentioned below are outlined in the Data Appendix, together with their sources.

We examine the roles of the following cross-state institutional differences: baseline budgeting rules; direct democracy; line item veto; party strength; tax and expenditure limitations; combined tax and spending committees in the legislature; gubernatorial and/or legislature term limits. Results appear in Columns 1-7, of Table 8, examining each of these cases, respectively, in addition to Column 8 in which they are considered jointly. The estimates indicate that with the exception of baseline budgeting rules and party strength, via which political attention decreases and increases polarization, respectively, the examined institutional differences do not transmit the impact of attention to polarization. Political attention on its own, on the other hand, retains its effect on polarization in all cases, including in the one that considers all institutional differences concurrently. Our main outcome is, thus, robust to considering major state institutional differences.

4.2.4 Different measures

The baseline analysis employed specific *polarization*, and *attention* measures. In this sub-section we examine the robustness of the results to the adoption of various alternatives. Results appear in Table 9, and follow the baseline specification (Column 1 of Table 5), yet with the examined alternative in lieu of either the baseline measure noted. Starting with *polarization*, we examine an alternative measure, at the state level. Considering the latter enables examining a standard measure, used previously in the literature, and mapping the outcome to the treatment level. This mapping, in turn, also enables more generally to test the main hypothesis under a complete state-level perspective in which both the treatment and outcome variables are aggregated to the same level. This measure, constructed by Enns and Koch (2013), examines the extent of partisanship, by summing population shares of individuals who identify as Democrats and those who identify as Republicans, and it is available annually (albeit for different periods, as outlined in the appendix).

Table 8: Potential mechanisms – State institutions

Dependent variable: Polarization	(1) Baseline budget	(2) Direct democracy	(3) Line item veto	(4) Party strength	(5) Tax and spending limits	(6) Combined committees	(7) Term limits	(8) All
Attention	35.21***	30.67***	31.78***	41.63***	33.6***	31.1***	30.52***	51.11***
	(10.44)	(8.61)	(8.63)	(10.24)	(9.39)	(8.58)	(6.39)	(14.08)
Attention X Baseline	-5.95***							-7.81***
	(2.11)							(2.17)
Attention X DirDem		-2.34***						3.31
		(0.69)						(2.3)
Attention X Veto			0.31					-6.78
			(3.02)					(3.81)
Attention X ParStrength				5.67**				8.39***
				(2.31)				(1.45)
Attention X TaxLimit					-2.53			-2.69
					(2.52)			(3.17)
Attention X Combined						4.08		4.67
						(2.46)		(3.57)
Attention X TL							1.15	3.49
							(2.69)	(1.97)
R-squared	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Observations	19646	19646	19646	19646	19646	19646	19646	19646

Notes: Standard errors are robust, clustered by state and year, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1%level of significance. The dependent variable is polarization. All regressions include congressional district (CD) and year fixed effects, survey weights, state-by-year time trends, and an intercept. The complete sample includes respondents to the U.S. American National Elections Survey, covering presidential election years over the period 1980-2020. 'Attention' is the baseline measure of political rational inattention outlined in the text. The various institutional heterogeneities (interacted with 'Attention') are absorbed by the CD fixed effects and hence not reported separately. State institutional heterogeneities include: 'Baseline': baseline budgeting rules; 'DirDem': direct democracy (voter initiative); 'Veto': line item veto. 'ParStrength': party strength; 'TaxLimit': tax and expenditure limitations; 'Combined': combined tax and spending committees in the legislature; 'TL': The existence of gubernatorial and/or legislature term limits over the sample period. For further information on variables see data Appendix.

Next, we examine various alternative *attention* measures. The first two measures, derived directly from the ANES survey, examine a facet of political attention. The first reports whether respondents watched TV programs concerning election campaigns, whereas the second reports the number of days respondents watched national TV news in the week prior to the survey. Notably, both measures provide a direct observation over aspects of individuals' political attention.[30] The two latter measures are the two alternative measures outlined in detail in sub-section 3.3.

Each of these cases appear in Columns 1-5, in the order described, respectively.[31] Notably, in all cases the impact of political attention remains positive and significant, similar to the baseline analysis, and together with the estimated β, the main outcome is reaffirmed and robust to the examination of alternative measures.

[30] In that sense, these measures are reminiscent of the one employed in Matějka and Tabellini (2021). However, unlike our baseline measure, these proxies are subjective and are not based on an underlying theory, and therefore are explored as additional potential treatments, for robustness.

[31] Columns 4-5 represent the first and second alternatives in the order presented in sub-section 3.3, respectively.

Table 9: Different measures

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Partisanship (state-level)	Polarization	Polarization	Polarization	Polarization
Attention	64.51**				
	(30.73)				
Watch political campaigns		1.73***			
		(0.24)			
Watch TV news			1.13***		
			(0.09)		
Attention_first_alt				34.94**	
				(15.71)	
Attention_second_alt					33.41**
					(13.97)
CD fixed effects	No	Yes	Yes	Yes	Yes
State fixed effects	Yes	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared, within	0.85	0.03	0.03	0.02	0.04
Observations	315	13354	12412	19646	19646

Notes: Standard errors are robust, clustered by state, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is respondent polarization (Columns 2-5); state ideological partisanship (Column 1). Columns 2-5 include congressional district (CD) and year fixed effects, survey weights, state-by-year time trends, and an intercept (Column 1 includes state and year fixed effects, and an intercept). The complete sample includes respondents to the U.S. American National Elections Survey, covering the period 1980-2020 in election years (Columns 2-5), or the 50 U.S states covering the period 1976-2010 in election years (Column 1). 'Attention' ('Attention_first/second_alt') is the baseline measure (alternative measures) of political rational inattention outlined in the text. 'Watch political campaigns' is a dummy variable that captures whether the respondent reports watching political campaigns. 'Watch TV news' reports the number of days of the week precedent to the survey week in which the respondent watched TV news. For further information on variables see data Appendix.

4.2.5 Additional tests

We undertake additional robustness tests to the main specification. All cases follow the baseline specification (Column 1 of Table 5), with case-specific modifications as noted below. Results of this sub-section appear in Table 10. First, we further address the endogeneity concern. Relaxing the assumption that individual characteristics do not alter societal indicators, for instance potentially in cases of influential individuals and relatively homogeneous societies, the societal political attention measure may be endogenous to individuals' opinions. To address that we take an IV approach, in which our proposed instrument is whether individuals are opinionated on an issue that is not directly related to politics. Notably, we consider whether respondents have an opinion on a matter, not *which* opinion. Specifically, respondents are asked if they favor or oppose laws to protect homosexuals against discrimination. The proposed instrument, a binary indicator, takes the value 1 if the respondent reported being in favor or oppose; otherwise, if the respondent expressed no opinion (not replying, or

otherwise replying 'don't know'), the instrument takes the value 0. We consider the state-year average of this measure, consistent with the variation of our treatment (*attention*).

We follow two identifying assumptions. First, being opinionated on a societal matter, even if detached from politics, is complementary to the extent of attention given to politics; i.e., we assume that opinionated individuals are concurrently politically attentive.[32] Second, being opinionated (again, irrespective of the opinion itself) on a societal matter, indirectly related to politics, does not directly reflect on the *type* of political opinions held, nor on the extent of ideological differences in such opinions (polarization). Put together, we thus assume that our proposed instrument may affect the outcome (*polarization*) only via its effect on the seemingly endogenous variable (*attention*). The first assumption, therefore, points at a potentially viable first-stage, whereas the second one ensures the exclusion restriction is met.

Column 1 presents the first-stage result. The estimated coefficient on the proposed instrument, *opinion*, is positive and statistically precise, consistent with our first identifying assumption, and the F-statistic stands at 12.38, pointing at a viable first-stage. Thereafter, the second-stage results are presented in Column 2. The estimated β remains positive and significant, consistent with the baseline outcome; thus, political attention raises polarization also under this methodology. Notably, the magnitude of the estimate rises significantly compared to the baseline case; however, accounting for the first and second moments of the fitted values of the first-stage (being less dispersed under a lower mean relative to the baseline *attention*), the scope of the effect is largely similar to that under the baseline estimation.

Second, we further examine the role of the time dimension. Polarization behaves differently over time, as previous studies have shown that it becomes more prominent in recent decades (e.g., Hetherington (2009)); this observation, in turn, implies that *attention* may bear different impacts on *polarization* across different periods. To examine that, we look into the impact of *attention* on *polarization* in the earlier part of our sample period (pre-1985), together with its impact in the later part (post-1984). We do this by interacting *attention* with a pre-1985 indicator, and separately with a post-1984 indicator, and then estimating the baseline model with both terms included and *attention* excluded, giving us both effects concurrently. The results in Column 3 illustrate that the main effect is maintained across the two periods, and in a largely similar magnitude, suggesting that the main

[32]This assumption is based on recent studies pointing at complementarities between the attention given to seemingly unrelated actions; see, e.g., Goldstein and Raveh (2024) for the case of complementarity between the attention given to the skies and that given to the economy, as well as references therein for additional examples.

effect is not only applicable across the sample period, but also largely stable.

Last, we test different clustering levels. The baseline analysis follows a conservative two-way clustering approach at the state and year level. To examine the robustness of the main result to this approach, in Columns 4 and 5 we estimate the main specification following a one-way approach, clustering separately by state, and year, respectively. The results indicate that the main effect is robust to these modifications.

Table 10: Additional tests

	(1)	(2)	(3)	(4)	(5)
	IV - first stage	IV - second stage	Time heterogeneity	Clustering by state	Clustering by year
Dependent variable:	Attention	Polarization	Polarization	Polarization	Polarization
Attention		618.99***		31.87***	31.87**
		(119.81)		(8.91)	(11.45)
Opinion	0.004***				
	(0.001)				
Population					
Attention X Population					
Attention X Pre_1985			36.61***		
			(11.16)		
Attention X Post_1984			31.08***		
			(9.33)		
F_statistic (1st stage)	12.38				
CD fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.11	0.07	0.04	0.04	0.04
Observations	15774	15774	19646	19646	19646

Notes: Notes: Standard errors are robust, clustered by state and year (state in Column 5; year in Column 6), and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is polarization (Attention in Column 1). All regressions include congressional district (CD) and year fixed effects, survey weights, state-by-year time trends, and an intercept. The complete sample includes respondents to the U.S. American National Elections Survey, covering presidential election years over the period 1980-2020. 'Attention' is the baseline measure of political rational inattention outlined in the text. 'Opinion' is the state-year average of a dummy variable that captures whether the respondent has an opinion on laws to protect homosexuals against discrimination. 'Pre_1985' ('Post_1984') is a dummy variable that captures years prior to (post) 1985 (1984). For further information on variables see data Appendix.

5 Conclusion

This study introduced and developed a novel empirical measure of political rational inattention, addressing a gap in the literature concerning the measurement of attention constraints within political contexts. Drawing on forecast revisions relative to actual electoral outcomes from the ANES, the

proposed measure quantifies political attention based on the consistency of forecast revisions with actual election results. This innovative approach allows for systematic, empirical tracking of political rational inattention across states and over time, covering U.S. presidential elections from 1952 to 2020. In effect, it adapts methodologies from macroeconomic expectations literature to the political domain, presenting a direct and empirically tractable measure of political rational inattention that captures the active processing and revision of political information. This approach significantly enhances previous indirect measures such as education or political knowledge proxies, offering scholars and policymakers a more precise tool to examine the dynamics and implications of political information processing.

Applying this newly developed measure, we first identified key empirical patterns, such as the complementary relationship between political and economic attention, providing insights that challenge traditional limited-attention hypotheses. As an illustrative application, we explored the potential role of societal political attention in influencing political polarization. To do so, we first proposed a theory linking political rational inattention to political polarization; thereafter, we examined this nexus empirically, using our constructed data series of political rational inattention. Our empirical analysis, leveraging detailed individual-level data over four decades, demonstrated a clear relationship, reaffirming the analytical results: increased political attention was associated with heightened polarization, primarily through enhanced in-group party identification. These illustrative findings underscore the broader applicability and analytical power of our measure.

Finally our analysis bears various policy implications. The illustrative findings suggest potential avenues for managing polarization through the lens of attention regulation. Policymakers might benefit from promoting balanced information environments, transparency in political communication, and public education initiatives that enhance citizens' ability to critically process political information. Ultimately, by recognizing the significant impact of societal attention allocation on political outcomes, policymakers can more effectively design interventions to foster healthier democratic engagement and mitigate polarization risks.

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Appendix

A Data

We use a pooled cross-section of respondents to the American National Election Studies (ANES (2022)), covering the period 1980-2020, in (presidential) election years, across the 50 U.S. states. Specifically, the data is derived from ANES' time-series cumulative data, which merges and standardizes survey variables across years. Additional standard state variables are derived from the U.S. Bureau of Economic Analysis (BEA). Variables in monetary-values are in current $USD. Descriptive statistics of the key variables are presented in Table 11.

Table 11: Descriptive statistics

	Mean	Std. Dev.	Min.	Max.
Polarization (respondent)	34.17	29.33	0	99
In-group thermometer (respondent)	71.10	19.08	0	99
Out-group thermometer (respondent)	36.93	24.99	0	99
Political attention (state)	0.32	0.06	0.17	0.5
Political attention_first alternative (state)	0.12	0.04	0.02	0.38
Political attention_second alternative (state)	0.09	0.04	0.0003	0.34
Income (respondent)	2.68	1.32	1	5
Party identification (respondent)	3.59	2.13	1	7
Gender (respondent)	1.55	0.50	1	3
Mode of interview (respondent)	1.13	1.72	0	5
Language of interview (respondent)	0.50	2.04	0	7
Timing of interview (respondent)	26.13	25.28	0	99
Influence others (respondent)	0.33	0.47	0	1
Attending political rallies (respondent)	0.07	0.26	0	1
Political work (respondent)	0.04	0.20	0	1
Button/Sticker (respondent)	0.12	0.33	0	1
Political donations (respondent)	0.12	0.32	0	1
Opinion (state)	0.92	0.11	0	1
Watch political campaigns (respondent)	1.53	0.72	0	2
Watch TV news (respondent)	4.24	2.73	0	7
Partisanship (state)	66.18	8.96	38.96	93.92
Area (sq miles, state)	81275.35	64919.31	1545	665384
Population (state)	11900000	19500000	432880	212000000
Electoral competition (state)	0.06	0.08	0	0.69
Inequality (state)	1.09	0.72	0.08	3.14

Notes: See Appendix for detailed description of variables.

Respondent-related variable definitions (source: ANES)[33]

[33]Variables in this group are at the respondent-level.

Polarization: The absolute value of the difference between the Democratic party's thermometer (variable VCF0218 in the survey) and the Republican party's thermometer (variable VCF0224 in the survey), each reporting the respondent's feelings towards the corresponding group, on a scale between 0 and 100, where higher (lower) score represents a (un)favorable feeling. This measure is available starting in 1978.

In-group thermometer: The thermometer value of the group with which the respondent identifies. Specifically, the higher value of either the Democratic party's thermometer (variable VCF0218 in the survey) or Republican party's thermometer (variable VCF0224 in the survey), or either in case of equivalence; each variable reports the respondent's feelings towards the corresponding group, on a scale between 0 and 100, where higher (lower) score represents a (un)favorable feeling. This measure is available starting in 1978.

Out-group thermometer: The thermometer value of the group with which the respondent does not identify. Specifically, the lower value of either the Democratic party's thermometer (variable VCF0218 in the survey) or Republican party's thermometer (variable VCF0224 in the survey), or either in case of equivalence; each variable reports the respondent's feelings towards the corresponding group, on a scale between 0 and 100, where higher (lower) score represents a (un)favorable feeling. This measure is available starting in 1978.

Watch political campaigns: A dummy variable that captures whether the respondent watches TV programs about the election campaigns (variable VCF0724 in the survey).

Watch TV news: The number of days the respondent watched national TV news in the past week (variable VCF9035 in the survey).

Income: Respondent's income level (variable VCF0114 in the survey), taking the values 1-5, each representing the following income groups, which classify ranking in the population's income distribution: 1. 0 to 16 percentile; 2. 17 to 33 percentile; 3. 34 to 67 percentile; 4. 68 to 95 percentile; 5. 96 to 100 percentile.

Party identification: Respondent's party identification (variable VCF0301 in the survey, taking the values 1-7 according to the following classifications: 1. Strong Democrat; 2. Weak Democrat; 3. Independent - Democrat; 4. Independent - Independent; 5. Independent - Republican; 6. Weak Republican; 7. Strong Republican.

Gender: Respondent's gender (variable VCF0104 in the survey), taking the values 1-3 according to the following categories: 1. Male; 2. Female; 3. Other.

Mode of interview: Respondent's mode of interview (variable VCF0017 in the survey), taking the values 0-5 according to the following categories: 0. Personal; 1-2. Telephone (partial, for different parts); 3. All telephone; 4. All internet; 5. All video (2020 only).

Language of interview: Respondent's language of interview (variable VCF0018b in the survey), taking the values 0-7 according to the following categories: 0. English; 1. Spanish; 3. French; 4. Either Spanish or French; 5. Non-English language other than Spanish or French; 7. Non-English language but NA which language.

Timing of interview: Respondent's timing of interview (variable VCF1016 in the survey) measured as the number of days from day of election (presidential or House/Senate races, depending on the year).

Influence others: A binary variable that takes the value 1 (0) if the respondent reported attempting to influence the vote others during the campaign (variable VCF0717 in the survey).

Political rallies (engagement): A binary variable that takes the value 1 (0) if the respondent reported attending political rallies during the campaign (variable VCF0718 in the survey).

Political work: A binary variable that takes the value 1 (0) if the respondent reported working for party or candidate during the campaign (variable VCF0719 in the survey).

Button/Sticker: A binary variable that takes the value 1 (0) if the respondent reported displaying candidate button/sticker during the campaign (variable VCF0720 in the survey).

Political donations: A binary variable that takes the value 1 (0) if the respondent reported donating money to party or candidate during the campaign (variable VCF0721 in the survey).

State-related variable definitions[34]

Political attention: The baseline, first, and second alternative, state-year measures of political attention based on the political expectation variables. These measures are described in detail in the text.

Economic attention: A measure of economic attention based on the unemployment expectation variable. The measure is analogous to the state-year political attention measure, as described in detail in the text.

Opinion: The state-year average of a dummy variable that captures whether the respondent has an opinion on laws to protect homosexuals against discrimination; i.e., whether the respondent expressed any opinion in replying to variable VCF0876a in the ANES, either 'Favor' or 'Oppose', denoted as '1', or otherwise (having no opinion), denoted as '0'.

[34]Unless specified otherwise, variables in this group are at the U.S. state level.

Partisanship: The sum of shares of surveyed individuals who identify as Democrats and those who identify as Republicans, as constructed in Enns and Koch (2013). Available annually, 1976-2010.

Electoral competition: State-year average of a binary indicator that takes the value 1 (0) in case the respondent expects a close presidential race (a certain win by one of the candidates), based on variable VCF0714 in the ANES.

Inequality: The state-year average of respondent's income distance from state mean, measured as the difference between the respondent's reported income group (via the *income* variable defined above), and the state-year average of it.

Population: Total state-year population. Source: U.S. Bureau of Economic Analysis.

Area Total state area in square miles. Source: U.S. Census Bureau.

State political institutions

Baseline budgeting rules: States are divided based on a binary variable that is 1 for states that use current services baseline, and 0 if they use last year's dollar budget as a baseline. The former group includes: AR, AZ, CT, CO, DE, HI, ME, MA, NV, NC, OH, PA, VT, VA, WV, WY. Source: Crain and Crain (1998).

Direct democracy: States are divided based on a binary variable that is 1 for states that have voter initiatives, and 0 otherwise. The former group includes: AK, AR, AZ, CA, CO, FL, ID, IL, MA, ME, MI, MO, MT, NE, NV, ND, OH, OK, OR, SD, UT, WA, WY. Source: Matsusaka (1995).

Line item veto: States are divided based on a binary variable that is 1 for states that have gubernatorial line item veto, and 0 otherwise. The latter group includes: HI, IN, ME, NC, NH, NV, RI, VT. Source: ACIR (1987).

Party strength: States are divided based on a binary variable that is 1 for states with relatively stronger parties based on the Mayhew Index (Mayhew (1986)), and 0 otherwise. The latter group includes: CT, DE, IL, KY, MD, MO, NJ, NY, OH, PA, RI, WV. Source: Primo and Snyder (2010).

Tax and expenditure limitations: States are divided based on a binary variable that is 1 for states that have tax and expenditure limitations, and 0 otherwise. The former group includes: AK, AZ, CA, CO, HI, ID, LA, MI, MT, NV, OR, RI, SC, TN, TX, UT, WA. Source: ACIR (1987).

Combined committees: States are divided based on a binary variable that is 1 for states that have combined tax and expenditure committees, and 0 otherwise. The former group includes: AK, AL, CA, FL, HI, KS, KY, MA, ME, NJ, NY, OK, SC, TN, WI, WV. Source: ACIR (1987).

Term limits: States are divided based on a binary variable that is 1 for states that had gubernatorial

and/or legislature term limits over the sample period, and 0 otherwise. The former group includes: AK, AL, AR, AZ, CA, CO, DE, FL, GA, HI, ID, IN, KS, KY, LA, MA, MD, ME, MI, MO, MS, MT, NC, NE, NJ, NM, NV, OH, OK, OR, PA, RI, SC, SD, TN, UT, VA, WA, WV, WY. Source: National Governors Association.

B Proofs

Proposition 3. *Define* $I(\alpha) = h(\alpha - c_0) - \frac{1}{2}\left[h(\alpha) + h(\alpha - 2c_0)\right]$. *Then,*

- $I(\alpha) = I(1 + 2c_0 - \alpha)$ *for every* $\alpha \in [2c_0, 1]$*;*
- I *is strictly convex on* $[2c_0, 1]$*;*
- I *attains its unique minimum at* $\alpha^* = \frac{1}{2} + c_0$.

Proof. Fix $\alpha \in [2c_0, 1]$ and define $\widetilde{\alpha} = 1 + 2c_0 - \alpha$. Using the identity $h(1-p) = h(p)$ for the binary entropy function:

$$\begin{aligned} I(\widetilde{\alpha}) &= h(\widetilde{\alpha} - c_0) - \frac{1}{2}\Big[h(\widetilde{\alpha}) + h(\widetilde{\alpha} - 2c_0)\Big] \\ &= h(1 + c_0 - \alpha) - \frac{1}{2}\Big[h(1 + 2c_0 - \alpha) + h(1 - \alpha)\Big] \\ &= h(\alpha - c_0) - \frac{1}{2}\Big[h(\alpha - 2c_0) + h(\alpha)\Big] \\ &= I(\alpha). \end{aligned}$$

Hence I is symmetric around $\alpha^* = \frac{1}{2} + c_0$.

Moving on to prove that I is strictly convex. Set $g(p) = \frac{1}{p} + \frac{1}{1-p}$, so $h''(p) = -g(p)$. Then,

$$I''(\alpha) = h''(\alpha - c_0) - \tfrac{1}{2}h''(\alpha) - \tfrac{1}{2}h''(\alpha - 2c_0) = -\Big[g(\alpha - c_0) - \tfrac{1}{2}g(\alpha) - \tfrac{1}{2}g(\alpha - 2c_0)\Big].$$

One can easily verify that g is strictly convex. Therefore, using Jensen's inequality, we deduce that $g(\alpha - c_0) < \frac{1}{2}\big[g(\alpha) + g(\alpha - 2c_0)\big]$, so $I''(\alpha) > 0$ and I is strictly convex.

Now we need to prove that the function I as a unique minimum at $\alpha^* = \frac{1}{2} + c_0$. Since $h'(p) = \ln\big(\frac{1-p}{p}\big)$, we get $h'\big(\frac{1}{2}\big) = 0$ and $h'\big(\frac{1}{2} - c_0\big) = -h'\big(\frac{1}{2} + c_0\big)$. Note that $I'(\alpha) = h'(\alpha - c_0) - \frac{1}{2}h'(\alpha) - \frac{1}{2}h'(\alpha - 2c_0)$, therefore $I'(\alpha^*) = 0$. Using the strict convexity and symmetry of I, we conclude that $\alpha^* = \frac{1}{2} + c_0$ is its unique minimum. □