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OVERCONFIDENCE IN POLITICAL BEHAVIOR

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ABSTRACT

This paper studies, theoretically and empirically, the role of overconfidence in political behavior. Our model of overconfidence in beliefs predicts that overconfidence leads to ideological extremeness, increased voter turnout, and increased strength of partisan identification. Moreover, the model makes many nuanced predictions about the patterns of ideology in society, and over a person's lifetime. These predictions are tested using unique data that measure the overconfidence, and standard political characteristics, of a nationwide sample of over 3,000 adults. Our predictions, eight in total, find strong support in this data. In particular, we document that overconfidence is a substantively and statistically important predictor of ideological extremeness and voter turnout.

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1 Introduction

Without heterogeneity in *ideology*—preferences and opinions—there would be no need for the institutions studied by political economists. However, the sources of ideology have received scant attention: since Marx, political economists have largely viewed ideology as driven by wealth or income (Meltzer and Richard, 1981; Acemoglu and Robinson, 2000, 2001, 2006).[1]

This paper proposes a complementary theory in which differences in ideology are also due to imperfect information processing. This theory predicts that *overconfidence* in one's own beliefs leads to ideological extremeness, increased voter turnout, and stronger identification with political parties. Our predictions find strong support in a unique dataset that measures the overconfidence, and standard political characteristics, of a nationwide sample of over 3,000 adults. In particular, we find that overconfidence is the most reliable predictor of ideological extremeness, and an important predictor of voter turnout in our data.

Adopting a behavioral basis for ideology may help answer puzzling questions, such as why politicians and voters are becoming more polarized despite the increased availability of information (McCarty et al., 2006), or why political rumors and misinformation such as, "Global warming is a hoax", are so persistent (Berinsky, 2012).[2] Moreover, as behavioral findings deepen our understanding of market institutions (Bertrand, 2009; Baker and Wurgler, 2013), a behavioral basis for ideology promises greater understanding of the design and consequences of political institutions (Callander, 2007; Bisin et al., 2011).

In our model, overconfidence and ideology arise due to imperfect information processing. Citizens passively learn about a state variable through their experiences. However, to varying degrees, citizens underestimate how correlated these experiences are, and thus, have different levels of overconfidence about their information. This underestimation—which we term *correlational neglect*—may have many sources. For example, citizens may choose to get

[1] Political scientists also study identity politics; the closest analog in economics is the study of ethnicity as the basis for coalition formation in distributive politics (Alesina et al., 1999; Padró-i-Miquel, 2007).

[2] In early 2013, 37% of U.S. voters agreed with this statement (Public Policy Polling, 2013). Only 41% believe global warming is caused by human activity, compared with 97% of climate scientists (Yale Project on Climate Change Communication, 2013). Similar levels of agreement with other political rumors or "conspiracy theories" are regularly found among voters (Berinsky, 2012; Public Policy Polling, 2013).

information from a biased media outlet, but fail to fully account for the bias. Indeed, unbeknownst to most users, Google presents different news sources for the same search depending on a user's location.[3] Alternatively, exchanging information on a social network could lead to correlational neglect if citizens fail to understand that much of the information comes from people similar to themselves, if they fail to recognize the influence of their own previous reports on others' current reports (DeGroot, 1974; DeMarzo et al., 2003), or if they fail to account for the presence of rational herds (Eyster and Rabin, 2010). Recent laboratory experiments find strong evidence of correlational neglect (Enke and Zimmerman, 2013).

Our primary theoretical result is that overconfidence and ideological extremeness are connected. This follows an uncomplicated logic. For example, consider a citizen who notes the number of people in her neighborhood who are unemployed, and uses this information to deduce the state of the national economy. Suppose further that she lives in a neighborhood with high unemployment. If the citizen believes that the employment status of each person is relatively uncorrelated, she will think she has a lot of information about the state of the national economy—she will be overconfident—and favor generous aid to the unemployed and loose monetary policy. If, instead, she realizes that local unemployment has a common cause—say, a factory shutting down—then she will understand that she has comparatively little information about the national economic situation, and believe that although the situation is bad, it is not likely to be dire, and will support more moderate policies.

Our data—from the 2010 Cooperative Congressional Election Survey (CCES)—strongly supports this prediction. We document that a one-standard-deviation change in overconfidence is related to 15–22% of a standard-deviation change in ideological extremeness, depending on the specification. This relationship is as large as, and much more stable than, the relationship between extremeness and demographics. Indeed, the range of correlations for most demographics include points that are statistically indistinguishable from zero, suggesting that overconfidence is an important and distinct predictor of ideological extremeness.

The size and complexity of this data allows for the testing of more subtle predictions. For

[3] See: *http://vimeo.com/51181384*.

example, the model predicts that older citizens will be more overconfident, and will generally be more ideologically extreme. Moreover, if more overconfident citizens are, on average, more conservative, ideology should be more correlated with overconfidence for conservatives than for liberals. These results find robust support in the data.

To extend this model to voter turnout, we posit an expressive voting model in which the expressive value of voting is increasing with a citizen's belief that one party's policy is better for her (Fiorina, 1976; Brennan and Hamlin, 1998). Similarly, strength of partisan identification is modeled as the probability a citizen places on her favored party's policy being better for her.

As more overconfident citizens are more likely to believe that one or the other party is likely to have the right policy for them, they are more likely to turn out to vote. This is true even conditional on ideology. The opposite conditional statement also holds: more ideologically extreme citizens are more likely to vote, conditional on overconfidence. Thus, our model matches the well-known empirical regularity that more ideologically extreme citizens are more likely to vote. Similar predictions hold for strength of partisan identification.

This second set of predictions are, once again, robustly supported by the data. Using verified voter turnout data we document that a one-standard-deviation change in overconfidence is associated with 7–19% increase in voter turnout. This is a more important predictor of turnout in our data than income, education, race, gender, or church attendance.

Finally, we theoretically analyze whether our results would be altered by citizens communicating their ideology to each other. Even assuming that citizens are Bayesian—albeit overconfident in the precision of their own signals—allowing for communication strengthens our results. Intuitively, this occurs because more-overconfident citizens will attribute differences in ideology to anything other than their information being incorrect, and hence update less than less-overconfident citizens, accentuating the correlation between ideological extremeness and overconfidence.

The remainder of this section provides more details on the behavioral phenomena of overconfidence, and connects our work to the literature.

1.1 What is Overconfidence?

Overconfidence describes related phenomena in which a person thinks some aspect of his or hers, usually performance or information, is better than it actually is. These phenomena are the subject of a large literature in psychology, economics, and finance, having been first documented by Alpert and Raiffa (1969/1982). This literature has documented overconfidence in a wide range of contexts, and among people from a wide range of backgrounds and countries. Two features of this literature are of particular importance to our empirical exercises: men are more overconfident than women (for example, Lundeberg et al., 1994), and overconfidence is treated as a personality trait—that is, some people are simply more overconfident than others.

Moore and Healy (2007, 2008) divide overconfidence into three, often conflated, categories: over-estimation, over-placement, and over-precision. Over-estimation is when people believe that their performance on a task is better than it actually is. Over-placement is when people believe that they perform better than others—as in the classic statement that, "93% of drivers believe that they are better than average."[4]

In this paper we focus on over-precision: the belief that one's information is more precise than it actually is. There are two reasons for this focus. First, while over-estimation and over-placement often suffer from reversals,[5] this does not seem to be the case for over-precision. In other words, it appears that (almost) everyone exhibits over-precision (almost) all the time (Moore and Healy, 2007, 2008). Second, over-precision has a very natural interpretation in political contexts: it is the result of people believing that their own experiences are more informative about policy than they actually are. Despite our narrower focus, we continue to use the term overconfidence.

Overconfidence is usually a modeling fundamental. By contrast, we derive it as a consequence of correlational neglect. We model a citizen who has many experiences that she believes to be relatively uncorrelated signals of the state. However, she neglects that these

[4] Interestingly, this may be perfectly rational; see Benoît and Dubra (2011).

[5] That is, people tend to perceive their performance as better than it actually is when a task is easy, and worse when the task is difficult (Erev et al., 1994).

experiences are all happening to her, and thus, highly correlated. The greater the neglect of correlation, the greater the information the citizen (incorrectly) believes she has received, leading to overconfidence.

1.2 Literature

This work contributes to the emerging literature on behavioral political economy, which applies findings from behavioral economics to understand the causes and consequences of political behavior.[6] This approach promises to allow political economists to integrate the insights of a half-century of psychology-based political behavior studies.

A particular appeal of applying behavioral insights to political economy is that many of the feedback mechanisms that have led scholars to doubt the importance of behavioral phenomena in markets do not seem to exist in politics. In particular, as an individual's political choice is unlikely to be pivotal, citizens who make poor political choices do not suffer worse consequences than those who make good political choices. Moreover, this lack of direct feedback drastically reduces a citizen's ability to learn of her bias. This is in stark contrast to markets, where poor choices directly impact the decision-maker, which some scholars argue will eliminate behavioral biases. Furthermore, behavioral traits that may be detrimental in markets may, in some cases, be useful in facilitating collective action (Benabou and Tirole, 2002, 2006; Benabou, 2008).

Our model of correlational neglect is closest in spirit to social-learning models where people exchange information, but fail to recognize the influence of their own previous reports on others' current reports. Hence people "double count" information (DeGroot, 1974; DeMarzo et al., 2003; Golub and Jackson, 2010, studies the learning paths of such networks). Recent field experiments show that this model fits data better than a fully Bayesian model (Chandrasekhar et al., 2012).

This paper is related to a number of additional literatures. First and foremost, the

[6] This literature is small, and includes Matsusaka (1995); Bendor et al. (2003, 2011); Callander and Wilson (2006, 2008); Bisin et al. (2011); Degan and Merlo (2011); and Lizzeri and Yariv (2012).

study of ideology, voting, and partisan identification are the subject of massive literatures in political science. Second, overconfidence is the focus of a large literature in behavioral economics and finance (see, for example, Odean, 1998; Daniel et al., 1998; Camerer and Lovallo, 1999; Santos-Pinto and Sobel, 2005). Third, our modeling technique comes from the small literature that utilizes the normal learning model.[7] Fourth, this paper is related to the literature that strives to understand how political behaviors are tied to personality traits. Recent work in this literature has focused on the "Big Five" personality traits (see, for example, Gerber et al., 2010, 2012). Overconfidence is often seen as akin to a personality trait, although it is orthogonal to the "Big Five" (Moore and Healy, 2007). Finally, our model of voter turnout is consistent with voters being either choice- or regret-avoidant (Matsusaka, 1995; Degan and Merlo, 2011).[8]

2 Framework and Data

This section presents our model, and formally defines correlational neglect and overconfidence. This is followed by a discussion of our data, and how we use it to construct measures of overconfidence, ideology, voter turnout, and partisan identification.

2.1 Theoretical Framework

There is a unit measure of citizens $i \in [0, 1]$. Each citizen i has a utility for actions which depends on the state. A citizen's beliefs about the state are determined by her experiences. We emphasize that the state is just part of the citizens' belief formation process, nothing

[7] Although the literature is not large, it cannot be completely reviewed here. Early papers include Zechman (1979), Achen (1992). For a recent review, see the introduction of Bullock (2009). In this literature, our model is closest to Blomberg and Harrington (2000), which studies a model in which citizens have priors with heterogeneous means and precisions. Citizens all observe public signals of the state. Those that start with extreme and precise beliefs end up retaining those beliefs, while those with extreme and imprecise beliefs converge to the center. While similar in some respects to our model, there are substantive differences. For example, Blomberg and Harrington (2000) predicts that citizens who receive more signals, such as older citizens, should be less ideologically extreme—as Bayesian citizens will converge to the truth. By contrast, in our model (and data), citizens who receive more signals can also become more ideologically extreme as they become more overconfident.

[8] For a discussion of how our results relate to other models of voter turnout, see Appendix D.

more. In particular, it is not the "truth".

Utilities: Each citizen i has a standard quadratic-loss utility over actions $a_i \in \mathbb{R}$, which depends on the state $x \in \mathbb{R}$, and a preference bias b_i

$$U(a_i, b_i|x) = -(a_i - b_i - x)^2.$$

Throughout this paper a_i is the policy that a citizen would like to see implemented by government. A citizen's preference bias is an i.i.d. draw from a normal distribution with mean 0 and precision τ_b. We write this as $b_i \sim \mathcal{N}[0, \tau_b]$.

With uncertainty about the state, it is straightforward to show that the policy preferred by citizen i will be $a_i = b_i + \mathbb{E}_i[x]$, where $\mathbb{E}_i$ is the expectation taken over citizen i's beliefs. We define this quantity as the citizen's *ideology*,

$$\mathcal{I}_i = b_i + \mathbb{E}_i[x], \tag{1}$$

and ideological extremeness as $\mathcal{E}_i = |\mathcal{I}_i|$.

Experiences, Beliefs, and Correlational Neglect: The core of the model is the process by which citizens form beliefs over the state. In our model, each citizen is well-calibrated about the informativeness of individual experiences, but underestimates how correlated her experiences are. This will lead to varying degrees of overconfidence in the population.

Each citizen starts with a normal prior $\mathcal{N}[\pi, \tau]$ over the state, which has a common mean π, and a common precision τ. For simplicity, we normalize $\pi = 0$ throughout. Citizens have multiple experiences over time, which are signals about the state, $e_{it} = x + \varepsilon_{it}$, $t \in \{1, 2, \ldots, n_i\}$. Each $\varepsilon_{it} \sim \mathcal{N}[0, 1]$, and the signals are correlated, with $\text{Corr}[\varepsilon_{\text{it}}, \varepsilon_{\text{it}'}] = \rho$.[9]

[9] Formally, ε_i is distributed according to a mean-zero multinomial normal with covariance matrix

$$\Sigma_{\varepsilon_i} = \begin{pmatrix} 1 & \rho & \cdots & \rho \\ \rho & 1 & \cdots & \rho \\ \vdots & \vdots & \ddots & \vdots \\ \rho & \rho & \cdots & 1 \end{pmatrix}. \text{ However, citizen } i \text{ believes that } \Sigma_{\varepsilon_i} = \begin{pmatrix} 1 & \rho_i & \cdots & \rho_i \\ \rho_i & 1 & \cdots & \rho_i \\ \vdots & \vdots & \ddots & \vdots \\ \rho_i & \rho_i & \cdots & 1 \end{pmatrix}.$$

Each ε_{it} has unit variance, so $\text{Corr}[\varepsilon_{it}, \varepsilon_{it'}] = \text{Cov}[\varepsilon_{it}, \varepsilon_{it'}] = \rho$.

Alternatively, we could model the state in a multi-dimensional space with multi-dimensional errors over time, and citizens either underestimate the amount of correlation between dimensions, or across time, or both. This does not add to the testable predictions of the model, see Appendix D.

However, citizen i underestimates this correlation: she believes $\text{Corr}[\varepsilon_{it}, \varepsilon_{it'}] = \rho_i \in [0, \rho)$.

Definition. *A citizen suffers from* **correlational neglect** *when* $\rho_i < \rho$.

The magnitude of correlational neglect varies by citizen, and is an i.i.d. draw from F_{ρ_i}, which is independent of the distribution of experiences and preference biases $\rho_i \perp (e_{it}, b_i)$.[10] Except where noted, we assume that all citizens receive the same number of signals, that is, we set $n_i = n$, $\forall i$.

Overconfidence: As our data measures overconfidence, our theoretical results are in terms of this variable. Denote the precision of citizen i's posterior belief as $\kappa_i + \tau$, which we refer to as the citizen's *confidence*. Additionally, denote by $\kappa + \tau$ the posterior belief the citizen would have if she had accurate beliefs about the correlation between signals.

Definition. **Overconfidence** *is the difference between a citizen's confidence, and how confident she would be if she were properly calibrated,* $\kappa_i - \kappa$. *Given two citizens* i *and* j, *we say that* i *is* **more overconfident** *than* j *if* $\kappa_i \geq \kappa_j > 0$.[11]

As κ and τ are the same for all citizens, we denote a citizen's level of overconfidence as κ_i.

2.2 Data

Our data comes from the Harvard and Caltech modules of the 2010 Cooperative Congressional Election Study (CCES) (Alvarez, 2010; Ansolabehere, 2010a,b). This data is unique (as far as we know) in that it allows a survey-based measure of overconfidence in beliefs as well as political characteristics.

The CCES is an annual cooperative survey. Participating institutions purchase a module of at least 1,000 respondents, who are asked 10–15 minutes of custom questions. In addition, every respondent across all modules is asked the same battery of basic demographic and

[10] Note that we also assume $b_i \perp e_{it}$. All of our results hold in the more general case in which $\pi_i | \rho_i \sim \mathcal{N}[0, \tau_\pi]$, $\tau | \rho_i \sim F_\tau(\cdot)$ over $[\underline{\tau}, \overline{\tau}] \in (0, \infty)$, and ρ varies by citizen—subject to the constraint that $\rho_i \perp \rho$, and for each citizen, $\rho_i < \rho$. These complications do not add to the testable predictions of the model, so we omit them.

[11] All results hold defining overconfidence as κ_i / κ.

political questions. The complete survey is administered online by Knowledge Networks. Each module uses a matched-random sampling technique to achieve a representative sample, with over-sampling of certain groups (Ansolabehere, 2012; Ansolabehere and Rivers, 2013).

2.2.1 Overconfidence

The most important feature of this data, for our purposes, is that it allows for a measure of overconfidence. This measure is constructed from four subjective questions about respondent confidence in their guesses about four factual quantities, adjusting for a respondent's accuracy on the factual question. This is similar to the standard psychology measure in that it elicits confidence and controls for knowledge. However, it differs in that we cannot say for certain whether a given respondent is overconfident, just that their confidence, conditional on knowledge, is higher or lower than another respondent. Therefore, we use previous research, which shows that (almost) everyone exhibits over-precision (almost) all the time (Moore and Healy, 2007, 2008), to argue that this is a measure of overconfidence.[12]

The factual and confidence questions were asked as part of another set of studies (Ansolabehere et al., 2011, 2013). Respondents were asked their assessment of the current unemployment and inflation rate, and what the unemployment and inflation rate would be a year from the date of the survey. Respondents were then asked their confidence about their answer to each factual question on a qualitative, six-point scale.

Confidence reflects both knowledge and overconfidence, so subtracting knowledge from confidence leaves overconfidence.[13] To subtract knowledge, we deduct points from a respondent's reported confidence based on his or her accuracy, and thus knowledge, on the corresponding factual question. This is implemented conservatively: we regress confidence on an arbitrary, fourth-order polynomial of accuracy, and use the residual as a measure of

[12] Psychological studies typically elicit a large (up to 150) number of 90% confidence intervals and count the percent of times that the actual answer falls within a subject's confidence interval. This number, subtracted from 90, is used as a measure of overconfidence. Our measure has advantages over the typical psychology approach—see Appendix B, which also contains all survey questions.

[13] Theoretically, we need to control for the precision a citizen would have if they were properly calibrated. As we do not observe this, we control for accuracy, which is, in our theory, correlated.

Table 1: Overconfidence is correlated with gender and age, but not education or income.

Dependent Variable:		Overconfidence			Confidence	
Gender (Male)	0.45***	0.44***	0.43***	0.48***	0.47***	0.46***
	(.078)	(.080)	(.079)	(.077)	(.078)	(.0022)
Age (in years)	0.012***	0.013***	0.012***	0.013***	0.014***	0.013***
	(.0023)	(.0024)	(.0023)	(.0022)	(.0023)	(.0022)
Education		$F = 1.12$			$F = 2.03$	
		$p = 0.36$			$p = 0.08$	
Income			$F = 1.33$			$F = 1.82$
			$p = 0.21$			$p = 0.05$
N			2,927			

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. All specifications estimated using WLS with CCES sampling weights.

overconfidence.[14] This allows the regression to pick the points to deduct for each level of accuracy, such that knowledge absorbs as much variation as possible.

Each of the resultant overconfidence measures are measured with error, as some respondents with little knowledge will randomly provide accurate answers. Thus, we use the first principal component of the four measures.[15] Finally, to standardize regression coefficients, we subtract the minimum level of overconfidence, and divide by the standard deviation.

In keeping with previous research, overconfidence is strongly correlated with a respondent's gender, as shown in Table 1. Section 3.4 predicts that overconfidence is correlated with age. This is also clear in Table 1. This predicted relationship leads us to cluster standard errors by age.[16] Additionally, as the CCES over-samples certain groups, such as voters, we

[14] That is, we use a semi-nonparametric sieve method to control for knowledge (Chen, 2007). Ideally one would impose a monotonic control function, however, doing so is methodologically opaque, see Athey and Haile (2007); Henderson et al. (2009). In keeping with the treatment of these factual questions in Ansolabehere et al. (2011, 2013), we topcode responses to the unemployment and inflation questions at 25, limiting a respondent's inaccuracy.

[15] Consistent with each measure consisting of an underlying dimension plus i.i.d. measurement error, the first principal component weights each of the four questions approximately equally. Also consistent with this structure, our results are substantively similar using any one of the four questions in isolation. So, for example, they hold if we use only variables pertaining to present conditions, or only to future predictions.

[16] Age also has a greater intraclass correlation than state of residence, education, or income, making age the most conservative choice. Because the intraclass correlation is small for all of these variables, thus, clustering on any one of them produces similar results that are also similar to heteroskedastistic-consistent standard errors. Classical standard errors are approximately 25% smaller.

estimate specifications using WLS and the supplied sample weights (Ansolabehere, 2012).

However, overconfidence is uncorrelated with education or income. Note that these latter controls are ordered categorical variables, so we provide F-tests on the five and fifteen dummy variables that, respectively, represent these categories. For comparison, we construct a confidence measure from the first principal component of confidence scores. Education and income are related to this measure, providing some confirmation that actual knowledge has been purged from the overconfidence measure.

While the data we use to elicit overconfidence is quite similar to that used in psychology, there are some differences. First, we use questions about economic measures—unemployment, inflation—as opposed to general knowledge questions—for example, "When was Shakespeare born?" Second, these questions elicit confidence directly, while studies in psychology typically elicit confidence intervals. To understand whether our slightly different approach provides similar results, we added four general knowledge questions—eliciting confidence with an interval—to the 2011 CCES. The 2011 CCES also included the confidence questions from the 2010 version. The main finding is reassuring: the results we can test in the (more limited) 2011 CCES hold using general knowledge-based measures of overconfidence. These results can be found in Section 3.2, and more about using surveys to measure overconfidence can be found in Appendix B.

2.2.2 Dependent Variables

The predictions in this paper concern three types of dependent variables: ideology, voter turnout, and strength of partisan identification.

Ideology: This study uses one main and two alternative measures of ideology. The main measure is scaled ideology from Tausanovitch and Warshaw (2011), which they generously provided to us. This measure is generated using item response theory (IRT) to scale responses to eighteen issue questions asked on the CCES—for example, questions about abortion and gun control. A similar process generates the Nominate Scores used to evaluate the ideology of members of Congress (Poole and Rosenthal, 1985).[17]

Our alternative measures of ideology are direct self-reports. The CCES twice asks respondents to report their ideology: from extremely liberal to extremely conservative. The first elicitation is when the respondent agrees to participate in surveys (on a five point scale), and the second when taking the survey (on a seven point scale). We normalize each of these measures to the interval $[-1, 1]$, and average them. Those that report they "don't know" are either dropped from the sample, or treated as moderates (0). Results are presented for both cases. These self-reported measures are imperfectly correlated with scaled ideology (0.42).

To generate measures of ideological extremeness, we take the absolute value of these measures. All three measures of ideology and ideological extremeness are divided by their standard error to standardize regression coefficients.

Voter Turnout: Turnout is ascertained from the voting rolls of the state that a respondent lives in. Voter rolls vary in quality between states, but rather than trying to control for this directly, we include state fixed effects in most of our specifications.[18]

Partisan Identification: At the time of the survey, respondents were asked whether they identify with the Republican or Democratic Party, or consider themselves to be an independent. If they report one of the political parties—for example the Democrats—they are then asked if they are a "Strong Democrat" or "Not so Strong Democrat". Those who report they are independents are asked if they lean to one party or the other, and are allowed to say that they do not lean toward either party. Those who report they are strong Democrats or Republicans are coded as strong partisan identifiers. Independents—those who do not lean toward either party—are coded as either strong party identifiers, weak party identifiers, or are left out of the analysis. Results are presented for all three resultant measures.

[17] There are many ways to aggregate these individual issues into ideology. For example, one could aggregate groups of related issues into different ideological dimensions. We prefer to use a measure generated by other scholars to eliminate concerns about specification searching, see Appendix D.

[18] The state of Virginia did not make their rolls available, so the 60 respondents from Virginia are dropped from turnout regressions (see Ansolabehere and Hersh, 2010). Classifying as non-voters the 42 respondents who were found to have voted in the primary but not the general election does not change the results.

Table 2: Controls used in statistical tests.

Type	Number of Categories
Income	16 categories
Education	6 categories
Gender	2 categories
Race	8 categories
Hispanic	3 categories
Religion	12 categories
Church attendance	8 categories
Union / union member in household	8 categories
State—including DC, and missing	52 categories
Total	115 categories

2.2.3 Controls

Our theory makes no predictions about which variables should be included as controls. Thus, we follow a "kitchen sink" approach. Although the controls are not theoretically motivated, they are useful in understanding the substantive significance of the relationship between overconfidence and the various dependent variables.

The CCES provides demographic controls as categories: for example, rather than providing years of education, it groups education into categories such as "Finished High School". Thus, we introduce a dummy variable for each category of each demographic control. We also include a category for missing data for each variable. The controls, and number of categories they contain, can be found in Table 2.

3 Ideological Extremeness and Overconfidence

The first set of theoretical and empirical results concern the relation between ideological extremeness and overconfidence.

3.1 Ideological Extremeness

Our first theoretical result is:

Proposition 1. *Overconfidence and ideological extremeness are positively correlated.*

Proof. All proofs are in Appendix A. ■

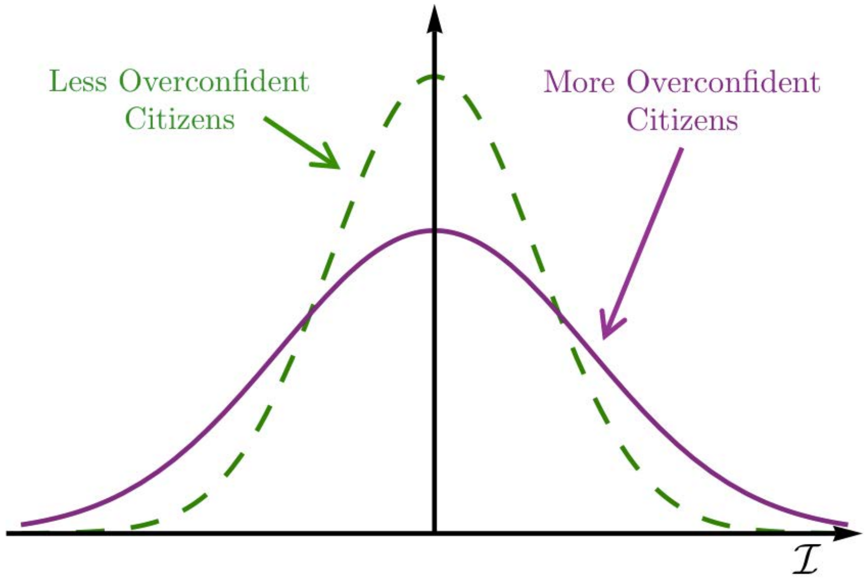
To build the intuition underlying this result it is useful to rewrite our model as one in which citizens receive only a single signal, but overestimate its precision. Specifically, we can model each citizen as if they have a single experience $e_i = x + \varepsilon_i$, where $\varepsilon_i \sim \mathcal{N}[0, \kappa]$, $\forall i$. However, citizens overestimate the precision of this signal: that is, they believe that $\varepsilon_i \sim \mathcal{N}[0, \kappa_i]$, where $\kappa_i \geq \kappa$. If we properly define e_i, κ and κ_i, then this "model" will give some of the same results.

Lemma 2. *Define* $e_i \equiv \frac{1}{n}\sum_{t=1}^{n} e_{it}$. *Then* $\kappa = \frac{n}{1+(n-1)\rho}$, *and* $\kappa_i = \frac{n}{1+(n-1)\rho_i}$.

Consider two citizens with the same preference bias $b = 0$ and the same experience $e \geq 0$, but two different levels of overconfidence κ_1 and κ_2, with $\kappa_1 > \kappa_2$. Using the definition of ideology in (1) and Bayes rule $\mathcal{I}_i = b_i + \mathbb{E}_i[x] = \frac{\kappa_i e}{\tau+\kappa_i}$. As citizens' mean beliefs, and hence ideology, are increasing in κ_i, then the more-overconfident citizen will have a more extreme ideology. Intuitively, the more-overconfident citizen believes her experience is a better signal of the state, and hence updates more, becoming more extreme.

To see that this results in a positive correlation, we examine the entire distribution of ideologies. The logic above implies that the distribution of ideologies for those who are more overconfident will be more spread out than the distribution for those who are less overconfident. Figure 1 shows the distribution of ideologies for two levels of overconfidence with $x = 0$. In that figure, as one moves further from the ideological center, citizens are more likely to be more overconfident, generating a positive correlation between overconfidence and ideological extremeness. The simplicity of the figure is driven by the assumption that $x = 0$: if $x \neq 0$, the distributions will not be neatly stacked on top of each other, and the relationship

Figure 1: Overconfidence and Ideological Extremeness are Correlated



will be more complex—but Proposition 1 shows that there is a positive correlation between overconfidence and ideological extremeness for any value of x.[19]

3.1.1 Empirical Analysis

We now test this prediction in survey data. Table 3 presents the results of regressing ideological extremeness—from the scaled ideology measure of Tausanovitch and Warshaw (2011)—on overconfidence.

The relationship between ideological extremeness and overconfidence is statistically very robust, no matter what additional (non-theoretically motivated) controls are added to the regressions—with t-statistics on this novel result between ∼5.5 and ∼7.5.[20] For comparison, previous research has shown that gender is the most robust predictor of overconfidence. In Table 1 the t-statistic on gender, as a regressor of overconfidence, is ∼5.5. It is also worth noting that the control that leads to the greatest attenuation of the coefficient on overconfidence is gender. This is reassuring: the control that really matters is the one found to be correlated with overconfidence in prior research.

[19] The proof of Proposition 1—after applying Lemma 2—does not rely on the normal distribution of beliefs and experiences. For more discussion, see Appendix D.

[20] The closest empirical result we are aware of appears in Footnote 14 of Kuklinski et al. (2000), which notes a strong correlation (0.34) between strength of partisan identification and confidence in incorrect opinions.

Table 3: Ideological extremeness is robustly related to overconfidence.

Dependent Variable: Scaled Ideological Extremeness					
Overconfidence	0.22*** (.029)	0.18*** (.028)	0.19*** (.027)	0.20*** (.031)	0.15*** (.027)
Income, Education Race, Hispanic		Y			
Union, Religion Church, State			Y		
Gender (Male)				0.16*** (.058)	
All Controls					Y
N			2,868		

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. All specifications estimated using WLS with CCES sampling weights.

Table 4: Self-reported ideological extremeness is robustly related to overconfidence.

Treatment of "Don't Know"	Centrist (0)		Missing (.)	
Overconfidence	0.20*** (.032)	0.17*** (.031)	0.17*** (.035)	0.16*** (.030)
All Controls	N	Y	N	Y
N	2,910		2,754	

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. All specifications estimated using WLS with CCES sampling weights.

In Table 4, we study similar relationships for self-reported ideology, and once again find robust support for the theory. As discussed in Section 2.2.2, there are two measures of self-reported ideology. These measures treat respondents who answered they "don't know" their ideological disposition differently: in one they are treated as centrist (0), in the other they are removed from the data (.). Table 4 considers both measures, and shows that the robust relationship found in Table 3 between ideological extremeness and overconfidence also exists for self-reported ideology. One other pattern in Table 4 is worth noting: classifying as centrist those who report they "don't know" their ideological disposition increases the correlation

Table 5: Overconfidence is a substantively important predictor of ideological extremeness.

A one standard deviation change in ________ is associated	with a ________ standard deviation change in ideological extremeness. Minimum	Maximum
Income	2%	28%
Education	2%	25%
Race (Black)	5%	13%
Church attendance	1%	15%
Gender (Male)	1%	13%
Overconfidence	**15%**	**22%**

Notes: The minimum and maximum effect size come from regressions with no other variables, and all other variables respectively across the three different measures of ideology. Effect sizes for categorical variables are based on entering them linearly in regressions.

between overconfidence and ideological extremeness. This appears intuitive: those who express a low level of confidence about their answer to factual questions are also likely to be relatively less confident about their ideological leanings.

While we have shown that the relationship between ideological extremeness and overconfidence is statistically robust, is it substantively important? Table 5 suggests the answer is yes. In particular, it shows the change in ideological extremeness associated with a one-standard-deviation change in some demographics. As the table shows, overconfidence is almost as predictive of ideological extremeness as education and income, and more predictive than race, gender, or church attendance. Moreover, as this relationship is more consistent across specifications, it suggests that overconfidence is a separate phenomena that is not captured by standard controls.

3.2 Discussion of Identification

Before discussing more results, we briefly address the twin issues of identification and causality. For our results to be identified, correlational neglect, and thus overconfidence, must be something akin to a personality trait: set early in life, with changes unrelated to political conditions. While this is plausible, and we assume it is true, it is not testable with our data.

We can gain additional insights by considering what it would mean for our results to not be identified. There are two classes of issues that seem especially worrying: reverse causality and third-factor causation.

Reverse causality implies that ideological extremeness causes overconfidence. If this were the case, it must be that something else, say, attending political rallies as a child, causes ideological extremeness, and this in turn causes overconfidence. However, overconfidence has been shown to cause many other behaviors, such as inefficiently high levels of equity trading (Grinblatt and Keloharju, 2009). This would then imply that political rallies cause overtrading on the stock market. While this is possible, it does not seem plausible.

However, one might object to the factual questions used to measure overconfidence on the grounds that they are inherently ideological. While Ansolabehere et al. (2011) find this is not the case, we can also examine other ways of eliciting overconfidence. In particular, we were allowed to place several questions on the 2011 CCES that would measure overconfidence on general knowledge-related items, such as the year of Shakespeare's birth and the population of Spain. Moreover, confidence was elicited using a confidence interval. While the 2011 survey is limited in other ways—it was much shorter and smaller, only allowed for self-reported ideology, and did not contain voter turnout data—it allows us to check our previous results.[21]

The first panel of Table 6 shows that the results are substantively unchanged in the 2011 data, and by the use of a general knowledge-based overconfidence measure. The results here are analogous to the first two columns of Table 4. As can be seen, the results are not statistically different between years or measures. We believe this should eliminate concerns that the correlation between ideological extremeness and overconfidence is driven by the questions we use to measure overconfidence.

However, different parts of the variation in the two measures may drive the results. In order to assuage such concerns, we instrument our economy-based overconfidence measure with the general knowledge-based measure. The first stage shows that there may be some reason

[21] For more on measuring overconfidence on surveys, and the text of all questions, see Appendix B.

Table 6: A general knowledge-based measure of overconfidence produces the same results.

Panel A: WLS				
Dependent Variable:	Self-Reported Ideological Extremeness ("Don't Know" treated as centrist)			
Overconfidence (Economy)	0.16*** (.047)	0.14*** (.035)		
Overconfidence (General Knowledge)			0.17*** (.043)	0.10** (.042)
All Controls	N	Y	N	Y
N	989			

Panel B: 2SLS				
Dependent Variable:	Overconfidence (Economy)	Extremeness	Overconfidence (Economy)	Extremeness
Overconfidence (Economy)		0.49*** (.15)		0.33** (.14)
Overconfidence (General Knowledge)	0.35*** (.049) F=51		0.30*** (.044) F=48	
All Controls	N	N	Y	Y
N	989			

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (69 clusters), in parentheses. The first stage specifications also present an F test on excluding the instrument, Overconfidence (General Knowledge). Each stage of 2SLS is implemented via WLS.

for concern, as the unconditional correlation between the two measures is 0.35. However, in the second stage, the coefficient on the economy-based measure increases by approximately a factor of three. This indicates that there is significant measurement error in both measures, and that we may be understating the magnitude of results compared to what one would find with a less-noisy measure of overconfidence.

Third-factor causation may also be the result of measurement problems. In particular, some survey respondents may simply enjoy picking extreme answers. These respondents would reply that they are certain of their answers to factual questions, and also report that they are ideologically extreme. This is not a concern for us: our main ideology measure—from Tausanovitch and Warshaw (2011)—is constructed by splitting the possible answers to each issue question into two groups, one group coded as for, the other against.[22] That is, all respondents who indicate a similar position are coded the same way, regardless of the extremity of their position. This eliminates concerns that our results concerning ideological extremeness are driven by respondents who simply like to choose extreme answers on surveys.

Finally, there may be "something else" that causes both ideology and overconfidence: for example, particular patterns of brain development. To our knowledge, current research does not suggest any obvious third factors that would explain all eight of our empirical findings. If such a third factor could be found, it would clearly be very important. Even if that occurs, we believe our theory and results will still provide useful insights into the unconditional relationship between overconfidence and political characteristics.

3.3 When Average Ideology Changes with Overconfidence

While Proposition 1 holds for all values of the state x, a more nuanced prediction is possible when $x > 0$. As the value of x is not observable, we instead make the prediction in terms of an implication of $x > 0$. Also, as the midpoint of the ideology scale is arbitrary, we use a data-driven midpoint for this proposition: in particular, we define $\mathcal{I}_M$ as the median ideology in the population, and define $\mathcal{E}_M = |\mathcal{I} - \mathcal{I}_M|$.[23] We also define the minimum level of overconfidence $\underline{\kappa} = \inf\{\kappa | F_{\kappa_i}(\kappa) > 0\}$.

Proposition 3. *Assume $x < \sqrt{2/\kappa}$, $\underline{\kappa}/\tau \geq (\sqrt{\pi/2} - 1)^{-1}$, and τ_b is large.*[24] *Then, if $\mathbb{E}[\mathcal{I}_i|\kappa_i]$ is increasing in κ_i,*

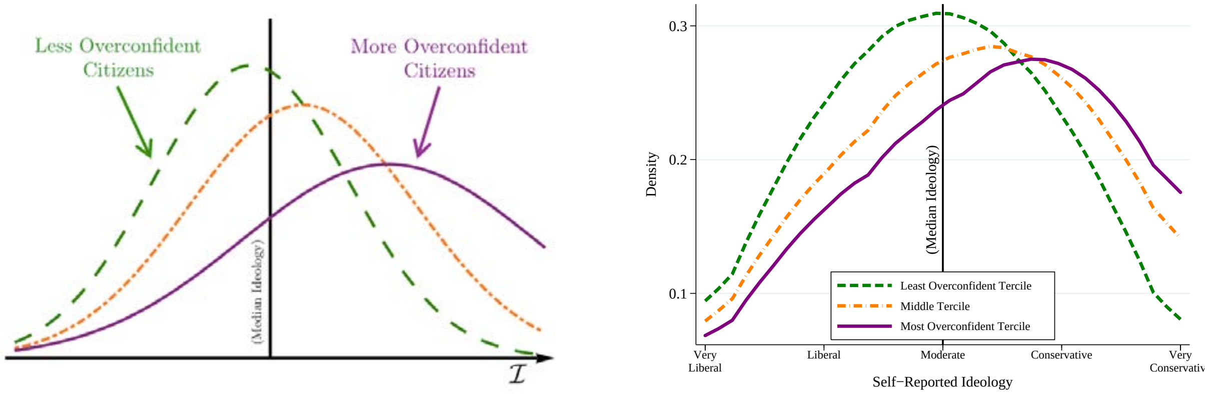
$$\text{Cov}[\mathcal{E}', \kappa_i | \mathcal{I}_i \geq \mathcal{I}_M] > \text{Cov}[\mathcal{E}', \kappa_i | \mathcal{I}_i \leq \mathcal{I}_M]. \tag{2}$$

[22] If an issues question had an odd number of responses, the middle response is randomly coded as either for or against for all respondents.

[23] For all three ideology measures, median ideology is very close to zero. As such, using this measure of extremeness would not change any of our other empirical results.

[24] While our proof only holds given the constraints above, numerical simulations suggest the proposition holds for all parameter values when $x > 0$. The use of covariances here is for tractability, and our empirical results also hold for correlations.

Figure 2: The theoretical structure of Proposition 3, and the data used to test it.



(a) Theory: When average ideology is increasing in overconfidence.

(b) Data: Distribution of self-reported ideology by tercile of overconfidence. (Smoothed using an Epanechnikov kernel, bandwidth 0.8.)

The proposition states that if average ideology is increasing in overconfidence, than the covariance between overconfidence and extremeness is larger for those to the right-of-center than for those to the left-of-center. This is a subtle, mathematical, prediction of the theory. The mathematical intuition is illustrated in Figure 2(a), which uses three different levels of κ_i. Moving right from median ideology, average overconfidence is quickly increasing, along with ideological extremeness measured from the median point. This leads to a large covariance between overconfidence and ideological extremeness. Moving to the left from median ideology, ideological extremeness measured from the median point is also increasing, but average overconfidence initially decreases. Eventually, average overconfidence will increase, but this occurs in a region that contains a relatively small measure of citizens. Thus, the covariance to the left will be either small and negative or small and positive, depending on the relative measure of citizens in the regions with positive and negative covariances. Either way, the covariance between overconfidence and ideological extremeness, measured from the median, will be smaller for left-of-center citizens than right-of-center citizens.

3.3.1 Empirical Analysis

Initial support for Proposition 3 comes from a comparison of Figure 2(a), generated by theory, and Figure 2(b), generated from the data.

Table 7: There is a greater covariance between extremeness and overconfidence for right-of-center citizens than left of center citizens.

Ideology Measure:	Scaled		Self-Reported Treatment of "Don't Know" Centrist		Self-Reported Treatment of "Don't Know" Missing	
	Left of Median	Right of Median	Left of Median	Right of Median	Left of Median	Right of Median
Covariance with Overconfidence	0.014	0.099***	0.0083	0.13***	-0.012	0.11***
	(.013)	(.014)	(.017)	(.015)	(.014)	(.012)
Difference	0.085***		0.12***		0.13***	
	(.019)		(.022)		(.018)	
All Controls	Y	Y	Y	Y	Y	Y
N	1,367	1,502	1,448	1,990	1,322	1,859

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. We use the Frisch-Waugh-Lovell Theorem to compute conditional covariances. The N of the two regressions may not sum to the N in previous tables due to the fact that those respondents with the median ideology are included in both regressions and the median is determined using sample weights. Extremeness is measured from median ideology, as required by Proposition 3. Similar results hold using partial correlations.

A more rigorous analysis requires that we first establish the hypothesis of the proposition: average ideology is increasing in overconfidence. Indeed, for all three measures of ideology, those in the middle and highest tercile of overconfidence are significantly further to the right than those in the lowest tercile. The difference between the first and second tercile (with clustered standard error) for the scaled ideology measure is 0.30 (.061), and the difference between the first and third is 0.58 (.054).[25]

As the hypothesis of the proposition is met, Table 7 tests to see whether the conclusion is confirmed by the data. Ideological extremeness has a substantially higher covariance with overconfidence for those to the right of center than for those to the left of center.[26]

[25] For the self-reported measure with "don't know" treated as ideologically centrist, the corresponding differences are 0.28 (.054) and 0.47 (.054). When treating "don't know" as missing, the differences are 0.30 (.063) and 0.51 (.058). For all three measures, differences between the terciles are statistically significant.

[26] Another obvious prediction from Figure 2(a) is that the variance of ideology is increasing in overconfidence. We cannot test this prediction because ideology is an ordinal, not cardinal, measure. There exists a monotonic transformation of each ideology measure—in particular, one that reduces ideological differences in the center and increases them toward the extremes—that makes the data appear to support this prediction, but other transformations create the opposite impression. Along the same lines, Tausanovitch and Warshaw (2011) use techniques to maximize discrimination in the tails, so their estimates of ideology are bimodal, producing a slightly different picture than Figure 2(b).

One might be concerned that there is a relationship between overconfidence and conservatism, rather than overconfidence and extremeness. That is, formally, $\mathcal{I}_i = g(\kappa_i)$ with $g' > 0$. It is straight-forward to show this is consistent with the data for those who are right-of-center, however, for those left-of-center, it predicts a negative covariance between ideological extremeness and overconfidence. Table 7 clearly shows this is not the case. An in-depth discussion of this point can be found in Appendix C.

3.4 Age, Overconfidence, and Ideology

We now extend the analysis to the more general case in which citizens have different numbers of experiences (signals), $n_i \geq 2$. Under the assumption that citizens have more experiences as they age, we can make predictions about how age, overconfidence and ideology are related.

Proposition 4. *Overconfidence is increasing with the number of experiences. Further, if* $\rho \geq \frac{1+\rho_i\tau}{1+2\tau-\rho_i\tau}$ *then ideological extremeness is, on average, increasing with the number of experiences, that is,* $\mathbb{E}[\mathcal{E}_i|n]$ *is increasing in* n*.*

This proposition provides a potential answer to the first puzzle posed in the introduction: why politicians and voters are becoming more polarized, despite the increased availability of information through the internet (McCarty et al., 2006). The second part of the proposition suggests that an increase in the number of signals can actually increase ideological extremeness, and thus, polarization. Note that this occurs even if media consumption is not more polarized, as seems to be the case (Gentzkow and Shapiro, 2011).

To build intuition for Proposition 4, consider the extreme case in which $\rho_i = 0$ and $\rho = 1$; that is, when experiences are perfectly correlated, but citizen i believes that they are independent. In this case, each experience is identical, so it will make the citizen more confident without increasing her information—leading to the first part of the proposition. Moreover, each experience makes a citizen more extreme, as her posterior shifts closer and closer to the signal—leading to the second part of the proposition.

While the condition in the second part of Proposition 4 holds for a wide range of parameters, the fact that ideological extremeness can increase with the number of signals sets our model apart from fully Bayesian models. Specifically, in a fully Bayesian model, as the number of signals increases, all citizens' beliefs must converge to x, and thus ideological extremeness will decrease with the number of signals. This will also be the case in the "model" of Lemma 2, extended to allow for citizen's to receive multiple, independent signals. Therefore, a test of this result can be seen not just as a test of a single prediction of our model, but a test of the modeling methodology itself.[27]

3.4.1 Empirical Analysis

As we do not observe the number of signals a respondent receives, we assume that older respondents receive more signals than younger respondents, and test whether overconfidence and ideological extremeness are increasing with age in Figure 3.[28]

Each panel of Figure 3 shows a smoothed, non-parametric fit with 95% confidence intervals, and three-year averages of the data. The first panel shows that, in accordance with Proposition 4, overconfidence increases with age, except, possibly, among those older than 80—who account for less than 1% of the data.[29] The second panel shows that ideological extremeness increases with age, consistent with our theory.[30] The third and fourth panels show that the increase in ideological extremeness is due to both a slight rightward shift in ideology, and an increase in ideological dispersion with age. The increase in dispersion is implied by Proposition 4, while the rightward shift is consistent with the theory if $x > 0$, which is also consistent with Figure 2(b). It is worth noting that this increase in dispersion holds both right- and left-of-center, casting further doubt on the idea that "something" is causing both overconfidence and conservatism: for more, see Section 3.3 and Appendix C.

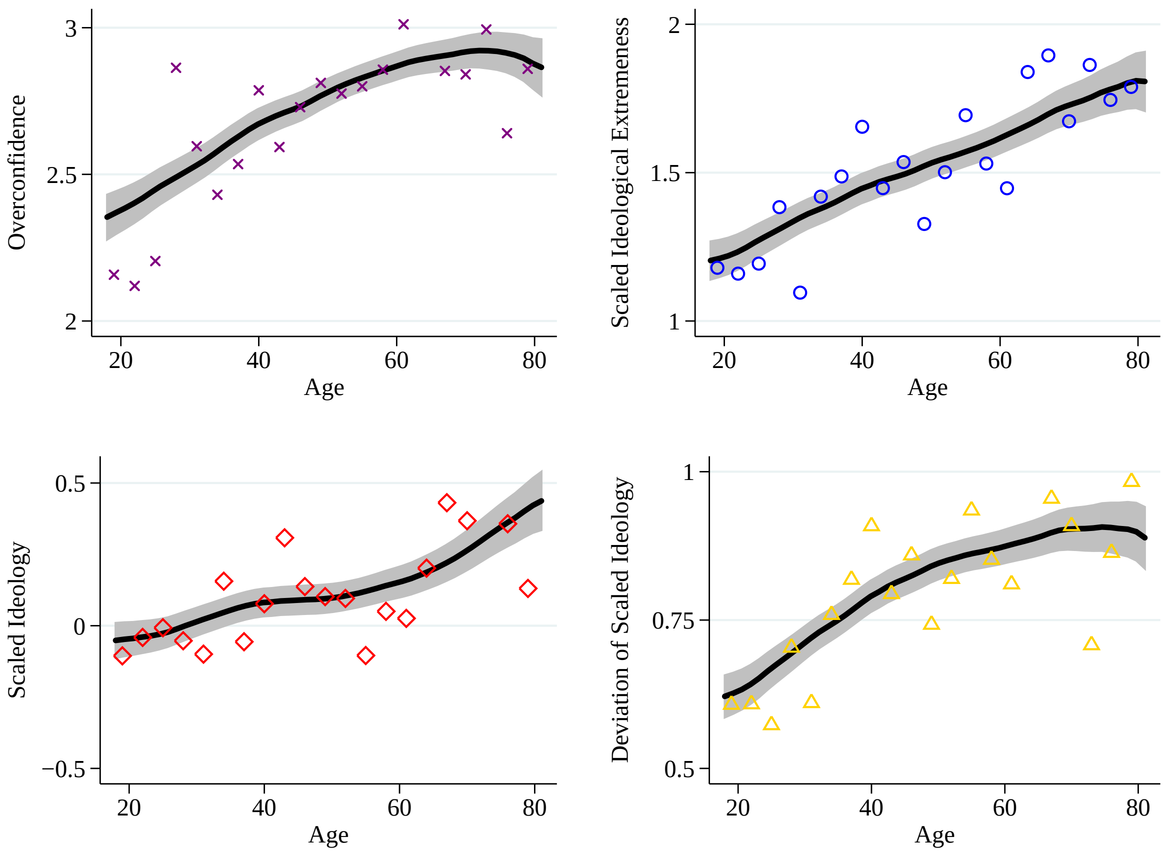
[27] Of course, this is an imperfect test. Our model allows ideological extremeness to increase or decrease with age, so there is no way to reject our model here, only fully Bayesian models.

[28] Another plausible interpretation is that the number of signals is increasing with media consumption. The results in Figure 3 are statistically and substantively more significant when age is replaced by self-reported media usage. However, we focus on age, as the literature suggests that media consumption may be caused by ideological extremeness (Mullainathan and Shleifer, 2005; Gentzkow and Shapiro, 2006).

[29] This is consistent with previous research that finds older people are more overconfident, see Hansson et al. (2008). For regression results on the data in Figure 3, see Appendix D.

[30] When this is the case, all of our results hold mechanically with a distribution of ages.

Figure 3: Age, Overconfidence, and Ideology



Notes: Each point is the average for three years of age. Trendiness, in black, and 95% confidence intervals, in gray, use an Epanechnikov kernel with a bandwidth of 8.

4 Turnout and Partisan Identification

To analyze turnout and partisan identification, we must specify how citizens make these political choices. We posit an expressive voter model in which the expressive value of voting is increasing with a citizen's belief that one party's policy is better for her (Fiorina, 1976; Brennan and Hamlin, 1998).[31]

[31]For a discussion of other models of voter turnout, see Appendix D.

4.1 Formalization

Turnout and partisan identification will depend on the policy positions adopted by parties. We assume there are two parties committed to platforms L and R, with $L = -R$.[32] Denote by $U_j(b_i|x)$ the utility that a citizen with preference bias b_i receives from the platform of party j when the state is x. Party R's position will be better for citizen i in state x when $U_R(b_i|x) > U_L(b_i|x)$. As in the above description, we assume citizen i turns out to vote if and only if

$$\left|\text{Prob}_i[U_R(b_i|x) > U_L(b_i|x)] - \frac{1}{2}\right| - c_i > 0. \tag{3}$$

We assume the c.d.f. F_c is strictly increasing on $\left(0, \frac{1}{2}\right)$, and $c_i \perp (b_i, \rho_i, e_{it})$. Appendix D shows that (3) produces the same comparative statics as the canonical voting model of Riker and Ordeshook (1968) with a large electorate, and regret- or choice-avoidant voters (Matsusaka, 1995; Degan and Merlo, 2011).

Finally, we model strength of partisan identification using the left-hand side of (3), but with a (possibly different) distribution of costs F_c'.[33]

4.2 Predictions

This model of turnout gives several predictions:

Proposition 5.

1. *More ideologically extreme citizens are more likely to turn out to vote.*

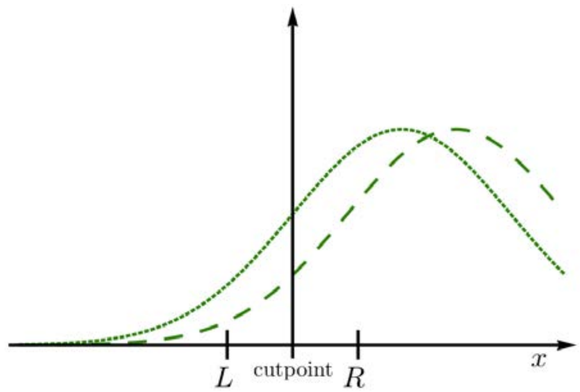
2. *Conditional on overconfidence, more ideologically extreme citizens are more likely to turn out.*

3. *Conditional on ideology, more overconfident citizens are more likely to turn out.*

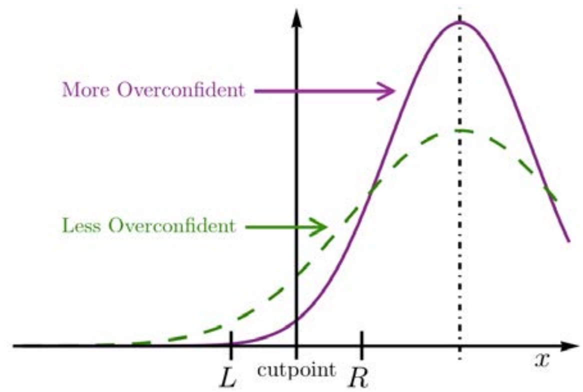
[32]Symmetric divergence can be generated from a Calvert (1985) model with policy and office motivated parties that are uncertain about the median voter's ideology due to the random realization of x.

[33]We adopt this formulation to simplify and shorten the exposition. Identical predictions are obtained from a more complex model of partisan identification that we discuss in Appendix D.

Figure 4: Intuition for Proposition 5 and Corollary 6.



(a) More ideologically extreme citizens are more likely to turn out.



(b) More overconfident citizens are more likely to turn out, conditional on ideology

The first part of Proposition 5 is a well-documented empirical regularity: more ideologically extreme citizens are more likely to turn out. The second part of Proposition 5 makes a stronger prediction: more ideologically extreme citizens are more likely to turn out, even controlling for overconfidence. Figure 4(a) helps build intuition. It depicts the posterior of two citizens with the same level of overconfidence, but different ideologies. While both prefer R to L, the more extreme citizen assigns a higher probability to R having the correct policy, and hence is more likely to turn out.

The third part of Proposition 5 describes the role of overconfidence in turnout: more overconfident citizens are more likely to turn out, even controlling for ideology. The intuition is apparent from Figure 4(b), which shows the posterior of two citizens, both with $b = 0$ and the same posterior mean $\mathbb{E}_i[x]$, but different levels of overconfidence. While both citizens prefer R to L, the more overconfident citizen assigns a higher probability to R having the correct policy—and hence, will be more likely to turn out.

The final predictions examined in survey data concern the strength of partisan identification. These results follow directly from Proposition 5, as (3) characterizes both turnout and partisan identification.

Corollary 6. *Strength of partisan identification is increasing in overconfidence, both conditional on, and independent of, ideological extremeness. Moreover, conditional on overconfidence, strength of partisan identification is increasing in ideological extremeness.*

Table 8: Turnout is increasing with ideological extremeness and overconfidence, as predicted by Proposition 5.

Dependent Variable:	Turnout Decision					
Overconfidence	0.096*** (.017)	0.056*** (.017)	0.048*** (.017)	0.046*** (.017)	0.054*** (.0090)	0.038** (.017)
Ideological Extremeness		0.18*** (.014)	0.17*** (.014)	0.17*** (.014)	0.18*** (.0089)	0.16*** (.014)
Income, Education Race, Hispanic			Y			
Union, Religion Church, State				Y		
Gender (Male)					0.014 (.030)	
All Controls						Y
N	2,808					

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. All specifications estimated using WLS with CCES sampling weights.

4.3 Empirical Analysis

We test Proposition 5 using verified voter turnout from the 2010 CCES.[34] The results, shown in Table 8, are robustly supportive of the proposition: more ideologically extreme citizens are more likely to vote, even conditional on overconfidence; and more overconfident citizens are more likely to vote, even conditional on ideological extremeness.

To get a full accounting of the effect of overconfidence on turnout, we need to first account for the fact that overconfidence also leads to ideological extremeness. Doing so, a one-standard deviation increase in overconfidence is associated with a 15–19% (depending on the specification) increase in turnout—a 7.5–9.5 percentage point increase versus a baseline turnout rate of 51% in the data. This effect is substantively important as it is larger than the effect of income, education, race, gender, or church attendance, and 47–54% of the effect size associated with ideological extremeness—all known to be important correlates of turnout.

We now examine partisan identification. As noted in Section 2.2.2 we construct three

[34] One of the advantages of the CCES dataset is that it provides verified voter turnout in addition to self-reported turnout, which is known to be unreliable. Our results also hold, and indeed are stronger, if we use self-reported turnout.

Table 9: Overconfidence is correlated with strength of partisan identification, even controlling for ideological extremeness.

Treatment of Independents:	Strong (1)		Weak (0)		Missing (.)	
Overconfidence	0.050*** (.016)	0.050*** (.015)	0.052*** (.013)	0.044*** (.012)	0.060*** (.015)	0.054*** (.013)
Ideological Extremeness		0.071*** (.014)		0.13*** (.011)		0.12*** (.012)
All Controls	N	Y	N	Y	N	Y
N	2,868				2,545	

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. All specifications estimated using WLS with CCES sampling weights.

measures of partisan identification, all of which code someone who identifies as a "Strong Democrat" or "Strong Republican" as a strong partisan identifier (1), and most others as weak partisan identifiers (0). The three measures differ in how they treat those who identify as "Independent". Although the theory does not ascribe any particular status to independents, it is possible that they are strongly invested in their political identity. Therefore, the three different measures code independents as strong partisan identifiers (1), weak partisan identifiers (0), or drops these respondents altogether (.). Table 9 then regresses these three measures on overconfidence and ideological extremeness.

The results in Table 9 are consistent with theory, no matter which measure is used. Doing the same accounting exercise as above, a one standard-deviation change in overconfidence is associated with a 9–12% increase in the probability a respondent classifies themselves a a strongly partisan—a 4.5–6 percentage point increase from a mean rate of 54%, 44% and 49%, respectively, for the three different measures. This is 48–95% of the effect size associated with ideological extremeness.

One other pattern in Table 9 is worth noting: ideological extremeness is a better predictor of strength of partisan identification when independents are treated as weak partisan identifiers or left out altogether. Intuitively, there are few respondents who hold extremely conservative or liberal views, but identify as independent.

Note that Proposition 5 and Corollary 6 predict that correlations between overconfidence and turnout or partisan identification should exist even if ideology is entered as fixed effects. We present fixed-effect specifications using the discrete, alternative measures of ideology in Appendix D.

5 Communication between Citizens

We have assumed that citizens only receive information from within their social network, or from their own experiences. But what if they could also learn the point of view of citizens outside their network, or receive information from public sources? In this section we show theoretically that this would, interestingly, strengthen the correlation between overconfidence and ideological extremeness. This occurs because when more-overconfident citizens meet someone with a different ideology, they attribute this difference to factors other than the information of the other citizen—as, by construction, they believe that "they know better". Therefore, more-overconfident citizens will tend to update less than less-overconfident citizens, making more-overconfident citizens relatively more extreme.

We illustrate this pattern in two ways. First we consider citizens with arbitrary preference biases, b_i, who are unaware that other citizens may be overconfident. Second, citizens are aware that others may be overconfident, but there are no preference biases ($b_i = 0$, $\forall i$). In the first case, citizens will attribute disagreement to the bias of others; in the second, they will attribute it to others' overconfidence. More-overconfident citizens will attribute more of the difference to these other factors.

Throughout this section we assume that after n private signals, each citizen i meets another, randomly chosen, citizen j and is told her ideology. It is straightforward to extend the analysis to citizens meeting any finite number of other citizens, or observing any finite number of public signals with known precision.[35]

[35] Matching with like-minded individuals is encompassed by correlational neglect. If there is uncertainty about the distribution of overconfidence in the population, or the mean preference bias in the population, our results extend to public signals about the summary statistics of the distribution of ideology.

5.1 Unawareness of Overconfidence

As noted above, we begin by assuming citizens are unaware of overconfidence.

Proposition 7. *When citizen i is told the ideology of citizen j, and she believes $\kappa_j = \kappa$:*

1. *The ideology of citizen i after communication is $\alpha_i \mathcal{I}_i + \beta_i \mathcal{I}_j$ for some $\alpha_i, \beta_i \in \mathbb{R}_{++}$, where α_i is increasing in κ_i and β_i is decreasing in κ_i.*

2. *If $\mathcal{I}_j \neq (\mathcal{I}_i - b_i)\frac{\kappa}{\kappa+\tau}$, then $|\mathbb{E}_i[b_j]|$ is increasing in κ_i.*

When i meets j, she knows that the difference in their ideologies may have two sources: different preference biases and different information. The more overconfident citizen i is, the more confident she is that she and j received similar signals. Thus, she believes their difference in ideologies is due to differences in preference biases, b. In turn, this leads i to only slightly update her beliefs.

This intuition also characterizes how overconfident citizens would update in the face of media reports contradicting their point of view. As long as there is some chance that the media is biased, more-overconfident citizens will attribute the contradiction to media bias, and, hence, update less.

5.2 No Preference Biases

Next, we consider the case in which citizens are (correctly) aware of the fact that others are overconfident. For simplicity, we assume that all citizens have no preference bias ($b_i = 0, \forall i$), and that this is common knowledge. Define F_{κ_i} as the distribution of posterior precisions in the population, and $\underline{\kappa} = \inf\{\kappa | F_{\kappa_i}(\kappa) > 0\}$, then:

Proposition 8. *Suppose $b_i = 0$, $\forall i$. When citizen i is told the ideology of citizen j:*

1. *The ideology of citizen i after communication is $\gamma_i \mathcal{I}_i + \delta_i \mathcal{I}_j$ for some $\gamma_i, \delta_i \in \mathbb{R}_{++}$, where γ_i is increasing in κ_i and δ_i is decreasing in κ_i.*

2. *$\mathbb{E}_i[\kappa_j]$ is increasing in κ_i if i and j are on opposite sides of the aisle, $(\mathcal{I}_i * \mathcal{I}_j < 0)$* or if j is more ideological extreme than i $(\mathcal{E}_j > \mathcal{E}_i)$.

3. $\mathbb{E}_i[\kappa_j]$ is decreasing in κ_i if i and j are on the same side of the aisle $(\mathcal{I}_i * \mathcal{I}_j > 0)$, and $\mathcal{E}_i > \frac{\tau+\kappa}{\underline{\kappa}} \mathcal{E}_j$.

Proposition 8 has a similar form, and intuition, to Proposition 7. When a citizen meets someone with a different ideology, she can attribute the difference to either differences in information, or in how the other citizen processes information. Following the logic above, more-overconfident citizens attribute more of the difference to other citizens' overconfidence.

However, the other parts of Proposition 8 are more nuanced. In particular, if the other citizen is more extreme, or is on the other side of the aisle, the first citizen attributes this to overconfidence. But when the other citizen is on the same side of the aisle but is less extreme, the first citizen believes that the other under-interprets her information, that is, she "lacks the courage of her convictions".

Proposition 7 and 8 both imply that communication causes more overconfident citizens to have *relatively* more dispersed ideologies. This leads to a greater correlation between overconfidence and ideological extremeness.

Finally, these results return us to briefly consider a puzzle presented in the introduction: why political rumors and misinformation are so persistent (the first, that citizens are more polarized despite the increased availability of information, was briefly discussed in Section 3.4). Our model suggests a possible answer: it is very difficult to persuade overconfident citizens that their prior is incorrect as they will tend to attribute contradictory information to others' biases.

6 Conclusion

This paper introduces a novel model of overconfidence and draws implications for political behavior. These implications are tested using unique survey data. Overconfidence is theoretically and empirically related to the central political characteristics of ideology, ideological extremeness, voter turnout, and strength of partisan identification.

We conclude by returning to the introduction, where we noted that a behavioral basis for ideology promises to deepen our understanding of political institutions. While we leave this to future work, we illustrate the usefulness of our findings by sketching a model of primaries with overconfident voters.

Two parties have a primary to nominate candidates for executive office. Between the primaries and the general election, nature will send each voter a signal of the state. It is well known that primary voters are more ideologically extreme than the general electorate. Based on the evidence presented above, these voters are also more overconfident. Thus, although primary voters know the ideology of the median voter at the time of the primary, they expect nature's signals to agree with their beliefs, drawing the median voter toward their ideology. Thus, primary voters will select divergent candidates. Moreover, the losing candidates' partisans will think the median voter ignored "the truth". We believe this sketch provides some insight into the nomination of, and partisan reactions to the defeat of, John Kerry in 2004, and Mitt Romney in 2012 (Ortoleva and Snowberg, 2013).

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Appendix A Proofs

Proof of Lemma 2: The posterior likelihood in the model is proportional to

$$\begin{aligned}
\mathcal{L}(x|e_i) &\propto \mathcal{L}(e_i|x)\mathcal{L}_0(x) \\
&\propto \exp\left\{-\frac{1}{2}\begin{pmatrix} x-e_{i1} \\ x-e_{i2} \\ \vdots \\ x-e_{in_i}\end{pmatrix}^T \begin{pmatrix} 1 & \rho_i & \cdots & \rho_i \\ \rho_i & 1 & \cdots & \rho_i \\ \vdots & \vdots & \ddots & \vdots \\ \rho_i & \rho_i & \cdots & 1 \end{pmatrix} \begin{pmatrix} x-e_{i1} \\ x-e_{i2} \\ \vdots \\ x-e_{in_i}\end{pmatrix}\right\} \exp\left\{-\frac{1}{2}x^2\tau\right\} \\
&= \exp\left\{-\frac{1}{2}\left(\frac{nx^2 - 2x\sum_{t=1}^{n_i} e_{it}}{1+(n_i-1)\rho_i} + C\right)\right\}\exp\left\{-\frac{1}{2}x^2\tau\right\} \\
&\propto \exp\left\{-\frac{1}{2}\frac{n_i+\tau(1+(n_i-1)\rho_i)}{1+(n_i-1)\rho_i}\left(x - \frac{\sum_{t=1}^{n_i} e_{it}}{n+\tau(1+(n_i-1)\rho_i)}\right)^2\right\}
\end{aligned}$$

where C is constant with respect to x. Thus, defining $e_i = \frac{1}{n_i}\sum_{t=1}^{n_i} e_{it}$, the posterior belief of a citizen is distributed according to

$$\mathcal{N}\left[\frac{n_i e_i}{n_i+\tau(1+(n_i-1)\rho_i)}, \frac{n_i+\tau(1+(n_i-1)\rho_i)}{1+(n_i-1)\rho_i}\right].$$

Substituting $\rho_i = \frac{n_i - \kappa_i}{(n_i-1)\kappa_i}$ the posterior is given by $\mathcal{N}\left[\frac{\kappa_i e_i}{\kappa_i+\tau}, \kappa_i+\tau\right]$, which is the same as the posterior that a citizen would have if they received a single signal $e_i = x + \varepsilon_i$, where the citizen believes $\varepsilon_i \sim \mathcal{N}[0, \kappa_i]$. Finally, note that $\mathbb{E}[e_i] = x$, and

$$\text{Var}[e_i] = \left(\frac{1}{n}\right)^2 \sum_{t=1}^{n} \text{Var}[\varepsilon_{it}] + 2\left(\frac{1}{n}\right)^2 \frac{n(n-1)}{2}\text{Cov}[\varepsilon_{it}, \varepsilon_{it'}] = \frac{1}{n} + \frac{n-1}{n}\rho.$$

Thus, $e_i \sim \mathcal{N}\left[x, \frac{n}{1+(n-1)\rho}\right] \equiv \mathcal{N}[x, \kappa]$. ■

Proof of Proposition 1: $\text{Corr}[\mathcal{E}, \kappa_i] > 0 \iff \text{Cov}[\mathcal{E}, \kappa_i] > 0$. If $b_i = 0$, $\forall i$, then using (1) and Lemma 2, $\mathcal{E}_i = |\mathcal{I}_i| = \frac{\kappa_i}{\kappa_i+\tau}|e_i|$, and

$$\text{Cov}[\mathcal{E}, \kappa] = \mathbb{E}\left[\frac{\kappa_i^2}{\kappa_i+\tau}|e_i|\right] - \mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}|e_i|\right]\mathbb{E}[\kappa_i] = \mathbb{E}[|e_i|]\text{Cov}\left[\frac{\kappa_i}{\kappa_i+\tau}, \kappa_i\right] > 0$$

where Cov $\left[\frac{\kappa_i}{\kappa_i+\tau}, \kappa_i\right] > 0$ because $\frac{\kappa_i}{\kappa_i+\tau}$ is an increasing function of κ_i (Schmidt, 2003). As $b_i \perp (\rho_i, e_i)$, this holds when $\mathcal{I}_i = b_i + \frac{\kappa_i}{\kappa_i+\tau}$. ■

Proof of Proposition 3: $\mathbb{E}[\mathcal{I}_i|\kappa_i] \iff x > 0$. Define $\overline{e}(\kappa_i) \equiv \frac{\kappa_i+\tau}{\kappa_i}\mathcal{I}_M$, and Φ_κ and ϕ_κ as the c.d.f. and p.d.f., of a normal distribution with mean 0 and precision κ. Then

$$
\begin{aligned}
&\text{Cov}[\mathcal{E}', \kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] \\
&= \mathbb{E}[(\mathcal{I}_i - \mathcal{I}_M)\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] - \mathbb{E}[\mathcal{I}_i - \mathcal{I}_M|\mathcal{I}_i \geq \mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] \\
&= \mathbb{E}[\mathcal{I}_i\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] - \mathbb{E}[\mathcal{I}_i|\mathcal{I}_i \geq \mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] \\
&= \mathbb{E}[(\mathcal{I}_i - b_i)\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] - \mathbb{E}[\mathcal{I}_i - b_i|\mathcal{I}_i \geq \mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] \\
&\quad + \mathbb{E}[b_i\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] - \mathbb{E}[b_i|\mathcal{I}_i \geq \mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] \\
&= \mathbb{E}[(\mathcal{I}_i - b_i)\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] - \mathbb{E}[\mathcal{I}_i - b_i|\mathcal{I}_i \geq \mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] + \text{Cov}[b_i, \kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] \\
&= \frac{1}{\text{Prob}[\mathcal{I}_i \geq \mathcal{I}_M]} \int_{\underline{\kappa}}^{\infty}\int_{\overline{e}(\kappa_i)}^{\infty} \left(\frac{\kappa_i^2 e_i}{\kappa_i+\tau} - \frac{\kappa_i e_i}{\kappa_i+\tau}\mathbb{E}[\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M]\right) d\Phi_\kappa[e_i]dF_{\kappa_i} + \text{Cov}[b_i, \kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] \\
&= 2\int_{\underline{\kappa}}^{\infty}\left(\frac{\kappa_i^2}{\kappa_i+\tau} - \frac{\kappa_i}{\kappa_i+\tau}\mathbb{E}[\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M]\right)\mathbb{E}[e_i|e_i \geq \overline{e}(\kappa_i)]\Phi_\kappa[x - \overline{e}(\kappa_i)]dF_{\kappa_i} + \text{Cov}[b_i, \kappa_i|\mathcal{I}_i \geq \mathcal{I}_M] \\
&= 2\left(\mathbb{E}\left[\frac{\kappa_i^2}{\kappa_i+\tau}\zeta(\kappa_i)\right] - \mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\zeta(\kappa_i)\right]\mathbb{E}[\kappa_i|\mathcal{I}_i \geq \mathcal{I}_M]\right) + \text{Cov}[b_i, \kappa_i|\mathcal{I}_i \geq \mathcal{I}_M]
\end{aligned}
$$

where $\zeta(\kappa_i) := \mathbb{E}[e_i|e_i \geq \overline{e}(\kappa_i)]\Phi_\kappa[x - \overline{e}(\kappa_i)]$. Similarly,

$$
\begin{aligned}
&\text{Cov}[\mathcal{E}', \kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] \\
&= \mathbb{E}[(\mathcal{I}_M - \mathcal{I}_i)\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] - \mathbb{E}[\mathcal{I}_M - \mathcal{I}_i|\mathcal{I}_i \leq \mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] \\
&= \mathbb{E}[-(\mathcal{I}_i - b_i)\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] - \mathbb{E}[-(\mathcal{I}_i - b_i)|\mathcal{I}_i \leq \mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] \\
&\quad -\mathbb{E}[b_i\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] + \mathbb{E}[b_i|\mathcal{I}_i \leq \mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] \\
&= \mathbb{E}[-(\mathcal{I}_i - b_i)\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] - \mathbb{E}[-(\mathcal{I}_i - b_i)|\mathcal{I}_i \leq \mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] - \text{Cov}[b_i, \kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] \\
&= \frac{1}{\text{Prob}[\mathcal{I}_i \leq \mathcal{I}_M]} \int_{\underline{\kappa}}^{\infty}\int_{-\infty}^{\overline{e}(\kappa_i)} \left(-\frac{\kappa_i^2 e_i}{\kappa_i+\tau} + \frac{\kappa_i e_i}{\kappa_i+\tau}\mathbb{E}[\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M]\right) d\Phi_\kappa[e_i]dF_{\kappa_i} - \text{Cov}[b_i, \kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] \\
&= 2\int_{\underline{\kappa}}^{\infty}\left(\frac{\kappa_i^2}{\kappa_i+\tau} - \frac{\kappa_i}{\kappa_i+\tau}\mathbb{E}[\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M]\right)\mathbb{E}[-e_i|e_i \leq \overline{e}(\kappa_i)]\Phi_\kappa[-(x - \overline{e}(\kappa_i))]dF_{\kappa_i} \\
&\quad -\text{Cov}[b_i, \kappa_i|\mathcal{I}_i \leq \mathcal{I}_M] \\
&= 2\left(\mathbb{E}\left[\frac{\kappa_i^2}{\kappa_i+\tau}\xi(\kappa_i)\right] - \mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\xi(\kappa_i)\right]\mathbb{E}[\kappa_i|\mathcal{I}_i \leq \mathcal{I}_M]\right) - \text{Cov}[b_i, \kappa_i|\mathcal{I}_i \leq \mathcal{I}_M].
\end{aligned}
$$

Combining the above, we have that (2) holds if and only if:

$$\mathbb{E}\Bigg[\frac{\kappa_i}{\kappa_i+\tau}\Bigg(\kappa_i\big(\zeta(\kappa_i)-\xi(\kappa_i)\big)-\big(\zeta(\kappa_i)\mathbb{E}[\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]-\xi(\kappa_i)\mathbb{E}[\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]\big)\Bigg)\Bigg]$$
$$+\big(\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]+\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]\big)>0.$$

Claim 1.

$\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]+\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]=-\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]\big(\mathbb{E}[\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]-\mathbb{E}[\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]\big)$.

Proof.

$$\begin{aligned}
&\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]+\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]\\
=\;&\mathbb{E}[b_i\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]-\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]+\mathbb{E}[b_i\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]-\mathbb{E}[b_i|\mathcal{I}_i\leq\mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]\\
=\;&2\left(\frac{1}{2}\mathbb{E}[b_i\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]+\frac{1}{2}\mathbb{E}[b_i\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]\right)-\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]\\
&-\mathbb{E}[b_i|\mathcal{I}_i\leq\mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M].
\end{aligned}$$

Note that as $\{\mathcal{I}_i:\mathcal{I}_i\leq\mathcal{I}_M\}\cup\{\mathcal{I}_i:\mathcal{I}_i\geq\mathcal{I}_M\}=\mathbb{R}$, and $\mathrm{Prob}[\mathcal{I}_i\leq\mathcal{I}_M]=\mathrm{Prob}[\mathcal{I}_i\geq\mathcal{I}_M]=\frac{1}{2}$, we have

$$\frac{1}{2}\mathbb{E}[b_i\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]+\frac{1}{2}\mathbb{E}[b_i\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]=\mathbb{E}[b_i\kappa_i].$$

Since b_i and κ_i are independent, then $\mathrm{Cov}(b_i,\kappa_i)=0$, thus $\mathbb{E}[b_i,\kappa_i]-\mathbb{E}[b_i]\mathbb{E}[\kappa_i]=0$. Since $\mathbb{E}[b_i]=0$, then $\mathbb{E}[b_i,\kappa_i]=0$. Thus

$$\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]+\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]=-\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]-\mathbb{E}[b_i|\mathcal{I}_i\leq\mathcal{I}_M]\mathbb{E}[\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M].$$

Note that $\frac{1}{2}\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]+\frac{1}{2}\mathbb{E}[b_i|\mathcal{I}_i\leq\mathcal{I}_M]=\mathbb{E}[b_i]=0$, so $\mathbb{E}[b_i|\mathcal{I}_i\leq\mathcal{I}_M]=-\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]$, and thus

$$\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]+\mathrm{Cov}[b_i,\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]=-\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]\big(\mathbb{E}[\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]-\mathbb{E}[\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]\big)$$

■

Using Claim 1, to prove (2) it is sufficient to show

$$\mathbb{E}\Bigg[\frac{\kappa_i}{\kappa_i+\tau}\Bigg(\kappa_i\big(\zeta(\kappa_i)-\xi(\kappa_i)\big)-\big(\zeta(\kappa_i)\mathbb{E}[\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]-\xi(\kappa_i)\mathbb{E}[\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]\big)\Bigg)\Bigg]$$
$$-\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]\big(\mathbb{E}[\kappa_i|\mathcal{I}_i\geq\mathcal{I}_M]-\mathbb{E}[\kappa_i|\mathcal{I}_i\leq\mathcal{I}_M]\big)>0. \tag{4}$$

Simplifying $\zeta(\kappa_i)$ and $\xi(\kappa_i)$, we have that

$$\begin{aligned}
\zeta(\kappa_i) &= \int_{\overline{e}(\kappa_i)}^{\infty} e_i \frac{\exp(-\frac{(e_i-x)^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} de_i = \int_{\overline{e}(\kappa_i)-x}^{\infty} (t+x) \frac{\exp(-\frac{t^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} dt = \\
&= \int_{\overline{e}(\kappa_i)-x}^{\infty} t \frac{\exp(-\frac{t^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} dt + x \int_{\overline{e}(\kappa_i)-x}^{\infty} \frac{\exp(-\frac{t^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} dt = \int_{\overline{e}(\kappa_i)-x}^{\infty} t \frac{\exp(-\frac{t^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} dt + x\Phi_\kappa[x-\overline{e}(\kappa_i)] \\
&= \frac{1}{\kappa} \int_{\frac{(x-\overline{e}(\kappa_i))^2}{2/\kappa}}^{\infty} \frac{\exp(-h)}{\sqrt{2\pi/\kappa}} dh + x\Phi_\kappa[x-\overline{e}(\kappa_i)] = \frac{\phi_\kappa[x-\overline{e}(\kappa_i)]}{\kappa} + x\Phi_\kappa[x-\overline{e}(\kappa_i)], \\
\xi(\kappa_i) &= \int_{-\infty}^{\overline{e}(\kappa_i)} -e_i \frac{\exp(-\frac{(e_i-x)^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} de_i = \int_{-\infty}^{\overline{e}(\kappa_i)-x} -(t+x) \frac{\exp(-\frac{t^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} dt \\
&= \int_{-\infty}^{\overline{e}(\kappa_i)-x} -t \frac{\exp(-\frac{t^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} dt - x \int_{-\infty}^{\overline{e}(\kappa_i)-x} \frac{\exp(-\frac{t^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} dt \\
&= \int_{-\infty}^{\overline{e}(\kappa_i)-x} -t \frac{\exp(-\frac{t^2}{2/\kappa})}{\sqrt{2\pi/\kappa}} dt - x\Phi_\kappa[-(x-\overline{e}(\kappa_i))] = \\
&= \frac{1}{\kappa} \int_{\frac{(x-\overline{e}(\kappa_i))^2}{2/\kappa}}^{\infty} \frac{\exp(-h)}{\sqrt{2\pi/\kappa}} dh - x\Phi_\kappa[-(x-\overline{e}(\kappa_i))] = -x\Phi_\kappa[-(x-\overline{e}(\kappa_i))] + \frac{\phi_\kappa[x-\overline{e}(\kappa_i)]}{\kappa}.
\end{aligned}$$

Define $\alpha(\kappa_i) \equiv 2\Phi_\kappa[x-\overline{e}(\kappa_i)] - 1$, and note that

$$\begin{aligned}
\mathbb{E}[\kappa_i | \mathcal{I}_i \geq \mathcal{I}_M] &= \frac{1}{\text{Prob}[\mathcal{I}_i \geq \mathcal{I}_M]} \int_{\underline{\kappa}}^{\infty} \kappa_i \Phi_\kappa[x-\overline{e}(\kappa_i)] dF_{\kappa_i} \\
&= \mathbb{E}[\kappa_i] + \int_{\underline{\kappa}}^{\infty} \kappa_i (2\Phi_\kappa[x-\overline{e}(\kappa_i)] - 1) dF_{\kappa_i} \\
&= \mathbb{E}[\kappa_i] + \mathbb{E}[\kappa_i \alpha(\kappa_i)] \\
\mathbb{E}[\kappa_i | \mathcal{I}_i \leq I] &= \frac{1}{\text{Prob}[\mathcal{I}_i \leq \mathcal{I}_M]} \int_{\underline{\kappa}}^{\infty} \kappa_i (1 - \Phi_\kappa[x-\overline{e}(\kappa_i)]) dF_{\kappa_i} \\
&= \mathbb{E}[\kappa_i] - \int_{\underline{\kappa}}^{\infty} \kappa_i (2\Phi_\kappa[x-\overline{e}(\kappa_i)] - 1) dF_{\kappa_i} \\
&= \mathbb{E}[\kappa_i] - \mathbb{E}[\kappa_i \alpha(\kappa_i)].
\end{aligned}$$

Thus, (2) holds if and only if

$$\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\big(\zeta(\kappa_i) - \xi(\kappa_i)\big)\big(\kappa_i - \mathbb{E}[\kappa_i]\big)\right] > \left(\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\big(\zeta(\kappa_i) + \xi(\kappa_i)\big)\right] + 2\mathbb{E}[b_i | \mathcal{I}_i \geq \mathcal{I}_M]\right) \mathbb{E}[\kappa_i \alpha(\kappa_i)]$$

Note that

$$\begin{aligned}
\zeta(\kappa_i) - \xi(\kappa_i) &= x\Phi_\kappa[x - \overline{e}(\kappa_i)] + \frac{\phi_\kappa[x - \overline{e}(\kappa_i)]}{\kappa} - \big(- x\Phi_\kappa[-(x - \overline{e}(\kappa_i))] + \frac{\phi_\kappa[x - \overline{e}(\kappa_i)]}{\kappa}\big) \\
&= x \\
\zeta(\kappa_i) + \xi(\kappa_i) &= x\Phi_\kappa[x - \overline{e}(\kappa_i)] + \frac{\phi_\kappa[x - \overline{e}(\kappa_i)]}{\kappa} - x\Phi_\kappa[-(x - \overline{e}(\kappa_i))] + \frac{\phi_\kappa[x - \overline{e}(\kappa_i)]}{\kappa} \\
&= x\big(\Phi_\kappa[x - \overline{e}(\kappa_i)] - \Phi_\kappa[-(x - \overline{e}(\kappa_i))]\big) + \frac{2}{\kappa}\phi_\kappa[x - \overline{e}(\kappa_i)] \\
&= \alpha(\kappa_i) \cdot x + \frac{2}{\kappa}\phi_\kappa[x - \overline{e}(\kappa_i)].
\end{aligned}$$

Thus, (4) holds if and only if

$$x{\cdot}\mathrm{Cov}\left[\frac{\kappa_i}{\kappa_i + \tau}, \kappa_i\right] > \left(\mathbb{E}\left[\frac{\kappa_i}{\kappa_i + \tau}\left(\alpha(\kappa_i) \cdot x + \frac{2}{\kappa}\phi_\kappa[x - \overline{e}(\kappa_i)]\right)\right] + 2\mathbb{E}[b_i|\mathcal{I}_i \geq \mathcal{I}_M]\right)\mathbb{E}[\kappa_i\alpha(\kappa_i)].$$

Since $\mathbb{E}[\alpha(\kappa_i)] = \mathbb{E}[2\Phi_\kappa[x - \overline{e}(\kappa_i)] - 1] = 2\mathrm{Prob}[\mathcal{I}_i \geq \mathcal{I}_M] - 1 = 0$, then we have $\mathbb{E}[\kappa_i\alpha(\kappa_i)] = \mathrm{Cov}[\alpha(\kappa_i), \kappa_i]$. Therefore (2) holds if and only if:

$$x{\cdot}\mathrm{Cov}\left[\frac{\kappa_i}{\kappa_i + \tau}, \kappa_i\right] > x{\cdot}\mathrm{Cov}\left[\alpha(\kappa_i)\left(\mathbb{E}\left[\frac{\kappa_i}{\kappa_i + \tau}\left(\alpha(\kappa_i) + \frac{2}{x\kappa}\phi_\kappa[x - \overline{e}(\kappa_i)]\right)\right] + 2\mathbb{E}[b_i|\mathcal{I}_i \geq \mathcal{I}_M]\right), \kappa_i\right].$$

Define $T(\kappa_i) \equiv \frac{\kappa_i}{\kappa_i+\tau} - \alpha(\kappa_i)\left(\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\left(\alpha(\kappa_i) + \frac{2}{x\kappa}\phi_\kappa[x - \overline{e}(\kappa_i)]\right)\right] + 2\mathbb{E}[b_i|\mathcal{I}_i \geq \mathcal{I}_M]\right)$. Since $x > 0$, then the expression above is equivalent to $\mathrm{Cov}[T(\kappa_i), \kappa_i] > 0$. To prove the proposition it is sufficient to show that if the condition in the proposition holds we have $T'(\kappa_i) > 0$. Note

$$\begin{aligned}
T'(\kappa_i) &= \frac{\tau}{(\kappa_i + \tau)^2} - 2\phi_\kappa[x - \overline{e}(\kappa_i)]\frac{\tau}{\kappa_i^2} \cdot \mathcal{I}_M \cdot \\
&\qquad \left(\mathbb{E}\left[\frac{\kappa_i}{\kappa_i + \tau}\left(\alpha(\kappa_i) + \frac{2}{x\kappa}\phi_\kappa[x - \overline{e}(\kappa_i)]\right)\right] + 2\mathbb{E}[b_i|\mathcal{I}_i \geq \mathcal{I}_M]\right) > 0 \\
\iff \frac{\kappa_i^2}{(\kappa_i + \tau)^2} &> 2\phi_\kappa[x - \overline{e}(\kappa_i)] \cdot \frac{\mathcal{I}_M}{x} \cdot \left(\mathbb{E}\left[\frac{\kappa_i}{\kappa_i + \tau}\left(\alpha(\kappa_i) \cdot x + \frac{2}{\kappa}\phi_\kappa[x - \overline{e}(\kappa_i)]\right)\right] + 2\mathbb{E}[b_i|\mathcal{I}_i \geq \mathcal{I}_M]\right)
\end{aligned}$$

To show this holds, we bound both the LHS and RHS. We start by noting that as ϕ_κ is the normal p.d.f. with mean 0 and precision κ, then $\phi_\kappa[x-\overline{e}(\kappa_i)] < \phi_\kappa[0] = \sqrt{\kappa}/\sqrt{2\pi}$. Thus:

$$\begin{aligned}\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\left(\alpha(\kappa_i)\cdot x+\frac{2}{\kappa}\phi_\kappa[x-\overline{e}(\kappa_i)]\right)\right] &< \frac{2}{\sqrt{2\pi\kappa}}+x\cdot\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\alpha(\kappa_i)\right] \\ x\cdot\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\alpha(\kappa_i)\right] &\leq x\int_{x-\overline{e}(\kappa_i)\geq 0}\alpha(\kappa_i)\frac{\kappa_i}{\kappa_i+\tau}dF_{\kappa_i}\end{aligned}$$

Further, as $x>0$ we have $\text{Prob}[\mathcal{I}_i \geq x] = \text{Prob}\left[e_i \geq \frac{\kappa_i+\tau}{\kappa_i}x\right] < \text{Prob}[e_i \geq x] = \frac{1}{2} = \text{Prob}[\mathcal{I}_i \geq \mathcal{I}_M]$, which implies $x > \mathcal{I}_M$. Thus, as $\alpha(\kappa_i) = 2\Phi_\kappa\left[x-\frac{\kappa_i+\tau}{\kappa_i}\mathcal{I}_M\right]-1 = \frac{\sqrt{\kappa}}{\sqrt{2\pi}}\int_{-(x-\frac{\kappa_i+\tau}{\kappa_i}\mathcal{I}_M)}^{x-\frac{\kappa_i+\tau}{\kappa_i}\mathcal{I}_M} e^{-\frac{\kappa t^2}{2}}dt$ and $1 \geq e^{-\frac{\kappa t^2}{2}}$ for all t (as $\kappa > 1$ by construction),

$$\alpha(\kappa_i) \leq \frac{\sqrt{\kappa}}{\sqrt{2\pi}}2(x-\overline{e}(\kappa_i)) \leq \frac{\sqrt{\kappa}}{\sqrt{2\pi}}2(x-\mathcal{I}_M) \text{ when } x-\overline{e}(\kappa_i)\geq 0.$$

and thus

$$\begin{aligned}\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\left(\alpha(\kappa_i)\cdot x+\frac{2}{\kappa}\phi_\kappa[x-\overline{e}(\kappa_i)]\right)\right] &< x\cdot\text{Prob}[x-\overline{e}(\kappa_i)\geq 0]\cdot\frac{2\sqrt{\kappa}(x-\mathcal{I}_M)}{\sqrt{2\pi}}+\frac{2}{\sqrt{2\pi\kappa}} \\ &< \frac{x(x-\mathcal{I}_M)\sqrt{\kappa}}{\sqrt{2\pi}}+\frac{2}{\sqrt{2\pi\kappa}}\end{aligned}$$

Finally, $\frac{\mathcal{I}_M(x-\mathcal{I}_M)\sqrt{\kappa}}{\sqrt{2\pi}}+\frac{2}{\sqrt{2\pi\kappa}}\frac{\mathcal{I}_M}{x}$ is increasing in $\mathcal{I}_M$ when $\mathcal{I}_M < x < \sqrt{\frac{2}{\kappa}}$, so

$$\frac{2}{\pi} > \frac{\mathcal{I}_M(x-\mathcal{I}_M)\kappa+2\frac{\mathcal{I}_M}{x}}{\pi} > 2\phi_\kappa[x-\overline{e}(\kappa_i)]\cdot\frac{\mathcal{I}_M}{x}\cdot\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\left(\alpha(\kappa_i)\cdot x+\frac{2}{\kappa}\phi_\kappa[x-\overline{e}(\kappa_i)]\right)\right].$$

Thus, when τ_b is large enough, then $\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]$ is small, and

$$\frac{2}{\pi} > 2\phi_\kappa[x-\overline{e}(\kappa_i)]\cdot\frac{\mathcal{I}_M}{x}\cdot\left(\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\left(\alpha(\kappa_i)\cdot x+\frac{2}{\kappa}\phi_\kappa[x-\overline{e}(\kappa_i)]\right)\right]+2\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]\right)$$

Therefore, as $\frac{\kappa_i}{\kappa_i+\tau}$ is increasing in κ_i, and if $\underline{\kappa} \geq \frac{\tau}{\sqrt{\frac{\pi}{2}-1}}$, then $\frac{\kappa_i^2}{(\kappa_i+\tau)^2} \geq \frac{\underline{\kappa}^2}{(\underline{\kappa}+\tau)^2} \geq \frac{2}{\pi}$ and

$$\frac{2}{\pi} > 2\phi_\kappa[x-\overline{e}(\kappa_i)]\cdot\frac{\mathcal{I}_M}{x}\cdot\left(\mathbb{E}\left[\frac{\kappa_i}{\kappa_i+\tau}\left(\alpha(\kappa_i)\cdot x+\frac{2}{\kappa}\phi_\kappa[x-\overline{e}(\kappa_i)]\right)\right]+2\mathbb{E}[b_i|\mathcal{I}_i\geq\mathcal{I}_M]\right)$$

so $T(\kappa_i)$ is increasing in κ_i, and therefore $\text{Cov}[T(\kappa_i),\kappa_i] > 0$, so (2) holds. ■

Proof of Proposition 4: For a given ρ_i, a citizens' overconfidence after n_i signals is given by:

$$\frac{n_i + \tau(1 + (n_i - 1)\rho_i)}{1 + (n_i - 1)\rho_i} - \frac{n_i + \tau(1 + (n_i - 1)\rho)}{1 + (n_i - 1)\rho} > 0 \iff \rho_i < \rho$$

The difference in overconfidence between the citizen at age $n_i + 1$ and age n_i is given by

$$\frac{n_i(\rho - \rho_i)(2 + (n_i - 1)(\rho + \rho_i - \rho\rho_i)}{(1 + (n_i - 1)\rho_i)(1 + n_i\rho_i)(1 + (n_i - 1)\rho)(1 + n\rho)} > 0$$

which is positive because $0 < \rho_i < \rho < 1$ and $n_i \geq 2$. When $\rho_i < \rho$, the increase in a citizens posterior precision will be in excess of the new information transmitted, so older citizens will be more overconfident.

To establish that $\mathbb{E}[\mathcal{E}_i|n]$ is increasing in n if $\rho \geq \frac{1+\rho_i\tau}{1+2\tau-\rho_i\tau}$, consider a citizen who observes n_i signals e_{it} who believes that the correlation between those signals is ρ_i. Following Lemma 2 define $e_i = \dfrac{1}{n_i}\displaystyle\sum_{t=1}^{n_i} e_{it}$, and her mean belief is $\frac{n_i e_i}{n_i+\tau(1+(n_i-1)\rho_i)}$. In turn, e_i is distributed according to $e_i \sim \mathcal{N}\left[x, \frac{n_i}{1+(n_i-1)\rho}\right]$. Thus, the mean belief of citizens with ρ_i is distributed according to a normal distribution with mean $\frac{n_i x}{n_i+\tau(1+(n_i-1)\rho_i)}$ and variance $\frac{1+(n_i-1)\rho}{n_i} \cdot \frac{n_i^2}{(n_i+\tau(1+(n_i-1)\rho_i))^2}$.

$\mathcal{I}_i|n_i, \rho_i$ is distributed as a normal, so $\mathcal{E}_i|n_i, \rho_i$ is distributed as a folded normal. When $y \sim \mathcal{N}\left[\mu, \frac{1}{\sigma^2}\right]$, then

$$\mathbb{E}[|y|] = 2\sigma\,\phi\left[\frac{\mu}{\sigma}\right] + \mu\left(1 - 2\Phi\left[-\frac{\mu}{\sigma}\right]\right), \qquad \frac{d}{d\sigma}\mathbb{E}[|y|] = 2\phi\left[\frac{\mu}{\sigma}\right] > 0$$

where Φ is the standard normal c.d.f., and ϕ is the standard normal p.d.f. Thus, it is sufficient to show that the variance of $\mathcal{I}_i|n_i, \rho_i$ is increasing in n_i as this implies $\mathcal{E}_i|n_i, \rho_i$ will be increasing in n_i for all ρ_i. That is, we need to show

$$\frac{1 + n\rho}{n + 1} \cdot \frac{(n + 1)^2}{(n + 1 + \tau(1 + n\rho_i))^2} - \frac{1 + (n - 1)\rho}{n} \cdot \frac{n^2}{(n + \tau(1 + (n - 1)\rho_i))^2} \geq 0 \qquad (5)$$

We will argue that the LHS increasing in ρ. We first show that the derivative of the LHS with respect to ρ is positive, that is

$$n(1+n)(n+(1+(n-1)\rho_i)\tau)^2-(n-1)n(1+n+(1+n\rho_i)\tau)^2\geq 0$$

which, in turn, is equal to

$$n+n^2+2n\tau+2n^2\tau+2n\tau^2-2n\rho_i\tau^2+2n^2\rho_i\tau^2+n\rho_i^2\tau^2-n^2\rho_i^2\tau^2\geq 0.$$

Since $\rho_i\in[0,1)$, $n_i\geq 2$, and $\tau>0$, then we must have $2n\tau^2-2n\rho_i\tau^2\geq 0$ and $2n^2\rho_i\tau^2-n^2\rho_i^2\tau^2\geq 0$, which implies that that the condition is satisfied.

Since this the LHS of (5) increasing in ρ, and a since we know $\rho\geq\frac{1+\rho_i\tau}{1+2\tau-\rho_i\tau}$, then it suffices to show that this condition holds when $\rho=\frac{1+\rho_i\tau}{1+2\tau-\rho_i\tau}$. Replacing ρ with this value and solving yields

$$\frac{(\rho_i-1)^2\tau^2(1+2n+(2+(2n-1)\rho_i)\tau)}{1+(2-\rho_i)\tau}\geq 0,$$

which is always true since $\rho_i\in[0,1)$, $n\geq 1$, and $\tau>0$. ■

Proof of Proposition 5 and Corollary 6: Consider an individual i with ideology $\mathcal{I}$, overconfidence κ_i, and preference bias b_i. Suppose, without loss of generality that $\mathcal{I}_i>0$. Note that $\mathbb{E}_i[x]=\mathcal{I}_i-b_i$. This means that we have $U_R(b_i|x)>U_L(b_i|x)$ if and only if $x>-b_i$. Thus, $\text{Prob}_i[U_R(b_i|x)>U_L(b_i|x)]=\text{Prob}_i[x>-b_i]=1-\text{Prob}_i[x<-b_i]$. By construction this is equal to

$$1-\Phi\left[(-b_i-(\mathcal{I}_i-b_i))\sqrt{\tau+\kappa_i}\right]=\Phi\left[\mathcal{I}_i\sqrt{\tau+\kappa_i}\right]. \tag{6}$$

As $\mathcal{I}_i>0$, $\mathcal{I}_i\sqrt{\tau+\kappa_i}$ must be strictly increasing in κ_i conditional on $\mathcal{I}_i$, and in $\mathcal{I}_i$ conditional on κ_i. The same must therefore hold for $\Phi[\mathcal{I}_i\sqrt{\tau+\kappa_i}]$, and hence for $\text{Prob}_i[U_R(b_i|x)>U_L(b_i|x)]$. Note that specular results hold conditional on $\mathcal{I}_i<0$. Thus, we can replace $\mathcal{I}_i$ with $\mathcal{E}_i=|\mathcal{I}|$ in (6).

Finally, $F_c(\cdot)$ and $F_c'(\cdot)$ are c.d.f.s and thus increasing in their arguments. This, together with the previous argument gives the second and third parts of the proposition and corollary. This, combined with Proposition 1 gives the first part of Proposition 5 and Corollary 6. ■

Proof of Proposition 7: The posterior of citizen i about the bias of citizen j after observing $\mathcal{I}_j$ is:

$$\begin{aligned}\mathcal{L}(b_j|\mathcal{I}_j) &\propto \mathcal{L}(\mathcal{I}_j|b_j)\mathcal{L}(b_j)\\ &\propto \left[\int_{-\infty}^{+\infty}\exp\left\{-\frac{\kappa}{2}\left(x-\frac{\kappa+\tau}{\kappa}(\mathcal{I}_j-b)\right)^2\right\}*\exp\left\{-\frac{\kappa_i+\tau}{2}(x-\mathcal{I}_i)^2\right\}\mathrm{d}x\right]*\exp\left\{-\frac{\tau_b b_j^2}{2}\right\}\end{aligned}$$

This is a normal distribution with mean

$$\left(\mathcal{I}_j\frac{\kappa+\tau}{\kappa}-(\mathcal{I}_i-b_i)\right)*\frac{\kappa(\kappa_i+\tau)(\kappa+\tau)}{(\kappa+\tau)\left(\tau^2+\tau\kappa+\tau_b\kappa\right)+\kappa_i\left(\tau^2+2\tau\kappa+\kappa\tau_b+\kappa^2\right)}$$

where the second term is positive and increasing in κ_i. Thus, if $\mathcal{I}_j > (\mathcal{I}_i - b_i)\left(\frac{\kappa}{\kappa+\tau}\right)$, then $\mathbb{E}_i[b_j] > 0$ and $\mathbb{E}_i[b_j]$ is increasing in κ_i. If $\mathcal{I}_j < (\mathcal{I}_i - b_i)\left(\frac{\kappa}{\kappa+\tau}\right)$, then $\mathbb{E}_i[b_j] < 0$ and $\mathbb{E}_i[b_j]$ is decreasing in κ_i. Thus, $|\mathbb{E}_i[b_j]|$ is increasing in κ_i.

The existence of $\alpha_i, \beta_i \in \mathbb{R}_{++}$ s.t. the ideology of citizen i after communication is $\alpha_i\mathcal{I}_i + \beta_i\mathcal{I}_j$ is a standard result of Bayesian updating. $\alpha_i + \beta_i \neq 1$ because ideology is a signal of both bias and beliefs. The fact that α_i increases and β_i decreases in κ_i is a direct consequence of the standard result that citizens with a high prior precision update less, and also because here they will tend to assign a higher probability to the fact that the differences in ideologies are due to differences in preference biases. In particular, solving for $\alpha_i, \beta_i \in \mathbb{R}_+$:

$$\alpha_i = \frac{(\kappa_i+\tau)\left(\tau^2+2\tau\kappa+\kappa\tau_b+\kappa^2\right)}{(\kappa+\tau)\left(\tau^2+\tau\kappa+\tau_b\kappa\right)+\kappa_i\left(\tau^2+2\tau\kappa+\kappa\tau_b+\kappa^2\right)}, \qquad \beta_i = \frac{\kappa(1-\alpha_i)}{\kappa+\tau}$$

and thus

$$\frac{d\alpha_i}{d\kappa_i} = \frac{\tau_b\kappa^2(\tau_b\kappa+(\kappa+\tau)^2)}{(\kappa_i+\tau)(\kappa+\tau)^2+\tau_b\kappa(\kappa_i+\kappa+\tau)^2} > 0.$$

Thus, α_i is increasing in κ_i, so β_i is decreasing in κ_i. ■

Proof of Proposition 8: We begin with the second and third parts of the proposition.

By Bayes' rule: $\mathcal{L}(\kappa_j|\mathcal{I}_j) \propto \mathcal{L}(\mathcal{I}_j|\kappa_j)\mathcal{L}(\kappa_j)$. Note that $\mathcal{L}(\mathcal{I}_j|\kappa_j) = \phi_{\mathcal{I}_i,\kappa_i+\tau}\big(\mathcal{I}_j(\frac{\tau+\kappa_j}{\kappa_j})\big)$, where $\phi_{\mu,\tau}(\cdot)$ denotes the p.d.f. of a normal distribution with mean μ and precision τ. To prove that $\mathbb{E}_i[\kappa_j]$ is increasing in κ_i, it is sufficient to prove that, for any $\kappa_j, \kappa_j' \in \text{supp}(F)$, $\kappa_j < \kappa_j'$, the ratio

$$\begin{aligned}
\frac{\mathcal{L}(\mathcal{I}_j|\kappa_j')}{\mathcal{L}(\mathcal{I}_j|\kappa_j)} &= \frac{\sqrt{\frac{\kappa_i+\tau}{2\pi}}\exp\left\{-\frac{(\kappa_i+\tau)}{2}\left(\mathcal{I}_j\left(\frac{\tau+\kappa_j'}{\kappa_j'}\right)-\mathcal{I}_i\right)^2\right\}}{\sqrt{\frac{\kappa_i+\tau}{2\pi}}\exp\left\{-\frac{(\kappa_i+\tau)}{2}\left(\mathcal{I}_j\left(\frac{\tau+\kappa_j}{\kappa_j}\right)-\mathcal{I}_i\right)^2\right\}} \\
&= \exp\left\{-\frac{\kappa_i+\tau}{2}\left(\left(\mathcal{I}_j\left(\frac{\tau+\kappa_j'}{\kappa_j'}\right)-\mathcal{I}_i\right)^2-\left(\mathcal{I}_j\left(\frac{\tau+\kappa_j}{\kappa_j}\right)-\mathcal{I}_i\right)^2\right)\right\}
\end{aligned}$$

is increasing in κ_i. This holds if and only if

$$\left(\mathcal{I}_j\left(\frac{\tau+\kappa_j'}{\kappa_j'}\right)-\mathcal{I}_i\right)^2 < \left(\mathcal{I}_j\left(\frac{\tau+\kappa_j}{\kappa_j}\right)-\mathcal{I}_i\right)^2 \tag{7}$$

for all $\kappa_j, \kappa_j' \in \text{supp}(F)$, $\kappa_j < \kappa_j'$. If the converse of (7) holds for all $\kappa_j, \kappa_j' \in \text{supp}(F)$, $\kappa_j < \kappa_j'$, this is sufficient for $\mathbb{E}_i[\kappa_j]$ to be decreasing in κ_i.

As $\frac{\tau+\kappa_j}{\kappa_j}$ is decreasing in κ_j, $\mathcal{E}_j(\frac{\tau+\kappa_j'}{\kappa_j'}) < \mathcal{E}_j(\frac{\tau+\kappa_j}{\kappa_j})$ since $\kappa_j < \kappa_j'$. This implies (7) holds if $\mathcal{I}_i * \mathcal{I}_j < 0$ or $\mathcal{E}_j > \mathcal{E}_i$. By contrast, the converse holds $\kappa_j, \kappa_j' \in \text{supp}(F)$, $\kappa_j < \kappa_j'$ if $\mathcal{I}_i * \mathcal{I}_j > 0$, and $\mathcal{E}_i > \frac{\tau+\underline{\kappa}_j}{\underline{\kappa}_j}\mathcal{E}_j$.

Finally, as in the Proof of Proposition 7, the first part follows from standard properties of Bayesian Updating. ■

Appendix B Survey Details—Not for Publication

The typical way psychologists measure overconfidence is not well suited to surveys. They often use a very large number of questions—up to 150 (see, for example, Alpert and Raiffa, 1969/1982; Soll and Klayman, 2004)—and elicit confidence using confidence intervals, which may be difficult for the average survey respondent to understand (see, for example, Juslin et al., 1999; Rothschild, 2011).

Our methodology for measuring overconfidence on surveys uses three innovations. The first two are due to Ansolabehere et al. (2011). First, the questions we use are about either quantities that everyone knows the scale of, such as dates, or the scale is provided, as in the case of unemployment or inflation. That is, when asking about unemployment rates, the question gives respondents the historical minimum, maximum, and median of that rate. This has been shown to reduce the number of incorrect answers simply due to a respondent not knowing the appropriate scale (Ansolabehere et al., 2013). Second, confidence is elicited on a qualitative scale, which is easily understandably by survey respondents and allows for more conservative controls for actual knowledge.

The third innovation is a modification of the second, and was only utilized on the 2011 CCES. For our general knowledge questions—the year the telephone was invented, the population of Spain, the year Shakespeare was born, and the percent of the U.S. population that lives in California—we elicited confidence using an inverted confidence interval.[1] That is, rather than asking for a confidence interval directly, which we felt may have been too challenging for survey respondents, we asked them to give their estimates of the probability that the true answer was in some interval around their answer. So, for example, after giving their best guess as to the date of Shakespeare's birth, respondents were asked:

> What do you think the percent chance is that your best guess, entered above, is within 50 years of the actual answer?

Given a two-parameter distribution, such as a normal, this is enough to pin down the variance of a respondent's belief.

The sum total of these innovations is that overconfidence can be elicited using a small number of questions that are understandable to most survey respondents, rather than just to university undergraduates.

[1]Note that these general knowledge questions were all from previous research on overconfidence.

Appendix B.1 Survey Questions

We next present the text of the questions used to construct our overconfidence measure on the 2010 and 2011 CCES, as described in Section 2.2.1. Instructions in brackets indicate limitations on possible answers implemented by the survey company—these were not displayed to respondents. If a survey respondent tried to enter, say, text where only a positive number was allowed, they would be told to edit their entry to conform with the limitations placed on the response field. If a respondent tried to skip a question, the survey would request that the respondent give an answer. If the respondent tried to skip the same question a second time, they were allowed to do so.

1. The unemployment rate is the percent of people actively searching work but not presently employed. Since World War II it has ranged from a low of 2 percent to a high of 11 percent.

   What is your best guess about the unemployment rate in the United States today? Even if you are uncertain, please provide us with your best estimate of the percent of people seeking work but currently without a job in the United States.

   ____% [only allow a positive number]

2. How confident are you of your answer to this question?

   - No confidence at all
   - Not very confident
   - Somewhat unconfident
   - Somewhat confident
   - Very confident
   - Certain

3. The inflation rate is the annual percentage change in prices for basic goods like food, clothing, housing, and energy. Since World War II it has ranged from a high of 14 percent (a 14% increase in prices over the previous year) to a low of -2 percent (a 2% decline in prices over the previous year).

   What is your best guess about the inflation rate in the United States today? Even if you are uncertain, please provide us with your best estimate of about what percent do you think prices went up or down in the last 12 months.

   Do you think prices went up or down?

- Up
- Down

4. By what percent do you think prices went up or down?

    ____% [only allow a positive number]

5. How confident are you of your answer to this question?

    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident
    - Certain

6. The unemployment rate is the percent of people actively searching work but not presently employed. Since World War II it has ranged from a low of 2 percent to a high of 11 percent.

    What do you expect the unemployment rate to be a year from now? Even if you are uncertain, please provide us with your best estimate of the percent of people who will be seeking but without a job in the United States in November, 2011.

    ____% [only allow a positive number]

7. How confident are you of your answer to this question?

    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident
    - Certain

8. The inflation rate is the annual percentage change in prices for basic goods like food, clothing, housing, and energy. Since World War II it has ranged from a high of 14 percent (a 14% increase in prices over the previous year) to a low of -2 percent (a 2% decline in prices over the previous year).

    What do you expect the inflation rate to be a year from now? Even if you are uncertain, please provide us with your best estimate of about what percent do you expect prices to go up or down in the next 12 months.

    Do you expect prices to go up or down?

- Up
- Down

9. By what percent do you expect prices to go up or down?
   ____% [only allow a positive number]
10. How confident are you of your answer to this question?
    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident
    - Certain

Next, we list the questions from the 2011 CCES used to construct the overconfidence measures discussed in Section 3.2. Note that the unemployment questions were changed from 2010, in accordance with the evolving research agenda of Ansolabehere et al..

1. In what year was the telephone invented? Even if you are not sure, please give us your best guess.

   ____
2. How confident are you of your answer to this question?
   - No confidence at all
   - Not very confident
   - Somewhat unconfident
   - Somewhat confident
   - Very confident
   - Certain
3. As a different way of answering the previous question, what do you think the percent chance is that your best guess, entered above, is within 25 years of the actual answer?
   ____%
4. What is the population of Spain, in millions? Even if you are not sure, please give us your best guess.

   ____

5. How confident are you of your answer to this question?
    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident
    - Certain
6. As a different way of answering the previous question, what do you think the percent chance is that your best guess, entered above, is within 15 million of the actual answer?
   ____%
7. In what year was the playwright William Shakespeare born? Even if you are not sure, please give us your best guess.
   ____
8. How confident are you of your answer to this question?
    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident
    - Certain
9. As a different way of answering the previous question, what do you think the percent chance is that your best guess, entered above, is within 50 years of the actual answer?
   ____%
10. What percent of the US population lives in California? Even if you are not sure, please give us your best guess.
    ____
11. How confident are you of your answer to this question?
    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident

- Certain

12. As a different way of answering the previous question, what do you think the percent chance is that your best guess, entered above, is within 5 percentage points of the actual answer?

    ____%

13. According to the Bureau of Labor Statistics, since World War II the most non-agricultural jobs the US economy has lost in a year is 5.4 million. The most jobs gained in a year has been 4.2 million. Over the same period, the US economy has gained an average of 1.4 million jobs a year.

    What is your best guess about the number of jobs gained or lost in the last year?

    Over the past year, I think the US economy has overall

    - Lost jobs
    - Gained jobs

14. How many jobs do you think have been lost or gained over the past year?

    ____ million jobs [only allow a positive number]

15. How confident are you of your answer to this question?

    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident
    - Certain

16. The inflation rate is the annual percentage change in prices for basic goods like food, clothing, housing, and energy. Since World War II it has ranged from a high of 14.4. percent (a 14.4% increase in prices over the previous year) to a low of -1.2 percent (a 1.2% decline in prices over the previous year).

    What is your best guess about the inflation rate in the United States today?

    Do you think prices went up or down?

    - Up
    - Down

17. By what percent do you think prices went up or down?

    ____% [only allow a positive number]

18. How confident are you of your answer to this question?

    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident
    - Certain

19. According to the Bureau of Labor Statistics, since World War II the most non-agricultural jobs the US economy has lost in a year is 5.4 million. The most jobs gained in a year has been 4.2 million. Over the same period, the US economy has gained an average of 1.4 million jobs a year.

    What is your best guess about the number of jobs that will be gained or lost over the next year?

    Over the next year, I think the US economy will overall

    - Lose jobs
    - Gain jobs

20. How many jobs do you think the US economy will lose or gain over the next year?

    ____ million jobs [only allow a positive number]

21. How confident are you of your answer to this question?

    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident
    - Certain

22. The inflation rate is the annual percentage change in prices for basic goods like food, clothing, housing, and energy. Since World War II it has ranged from a high of 14.4. percent (a 14.4% increase in prices over the previous year) to a low of -1.2 percent (a 1.2% decline in prices over the previous year).

    What do you expect the inflation rate to be a year from now?

    Do you expect prices to go up or down?

    - Up
    - Down

23. By what percent do you expect prices to go up or down?
    ____% [only allow a positive number]

24. How confident are you of your answer to this question?
    - No confidence at all
    - Not very confident
    - Somewhat unconfident
    - Somewhat confident
    - Very confident
    - Certain

Appendix C Historical Data—Not for Publication

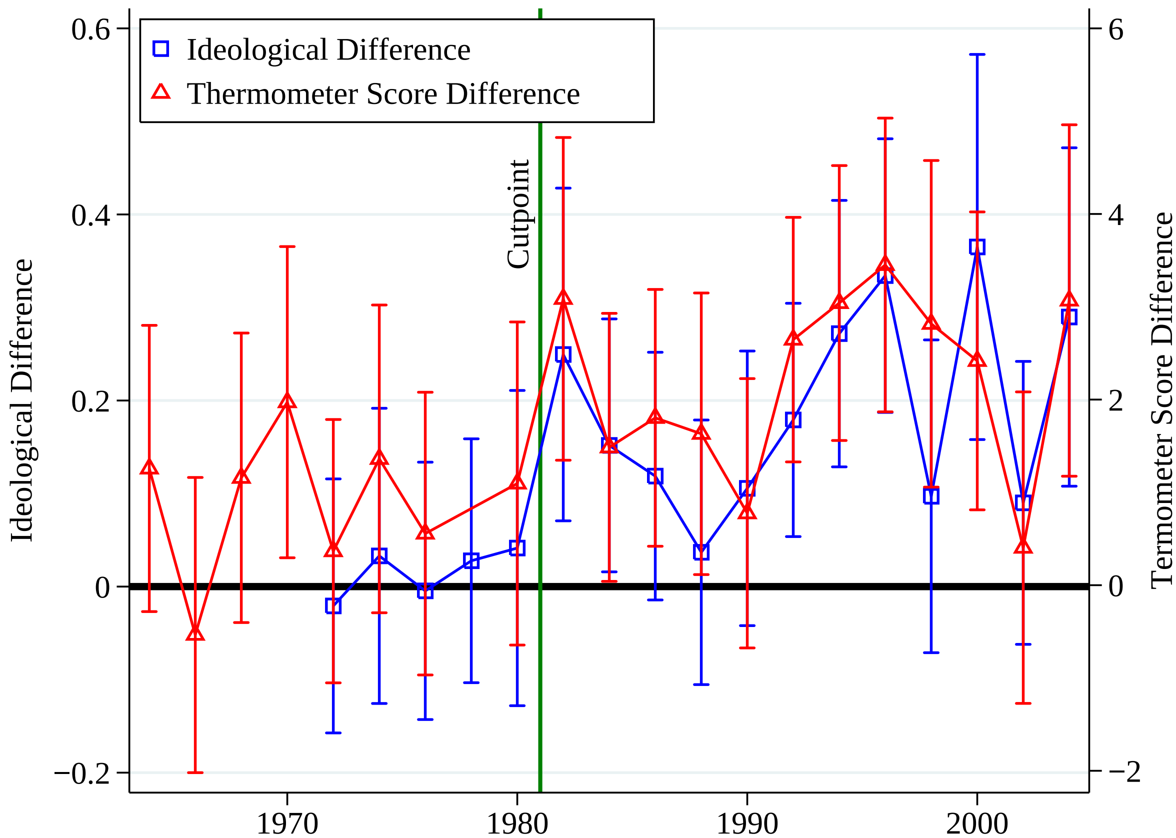
While the results in the text support our theory, they raise the concern, briefly discussed in Section 3.3, that overconfidence and conservatism are somehow linked in a way not accounted for in our theory. This section contains a limited, post-hoc, analysis to address this concern, and concludes by gathering together a number of facts in order to construct a post-hoc rationalization of this fact that goes beyond the findings in Section 3.3.

As the data in the text are the only we are aware of that provide both good measures of political ideology and of overconfidence, we turn to a survey with greater coverage over time, but more limited measures of ideology, and only a proxy for overconfidence: the American National Election Study (ANES). In particular, we follow a strategy based on the fact that many studies over time, including ours, have found men to be more overconfident then women and use male as a proxy for "more overconfident".[1]

To begin the analysis we add a basic result.

[1] Barber and Odean (2001) use male as an instrument for overconfidence in a study of financial risk taking. We have not adopted this strategy as being male is likely correlated with numerous other factors which may also affect the dependent variables we are interested in (Grinblatt and Keloharju, 2009). The curious reader may be interested to know that doing so approximately triples the effect size of overconfidence in the regressions presented in the main text.

Figure 5: Men became significantly more conservative after 1980.



Note: Thermometer scores were not collected in 1978.

Proposition C.1. *If more overconfident citizens have the same average ideology as less overconfident citizens, then overconfidence is equally correlated with ideological extremeness for both those to the right and to the left of center.*

Proof of Proposition C.1: Consider two citizens with $\kappa_1 > \kappa_2$. As $\mathbb{E}[\mathbb{E}_i[\mathcal{I}|\kappa]] = \frac{\kappa x}{\tau+\kappa}$, we have that $\frac{\kappa_1 x}{\tau+\kappa_1} = \frac{\kappa_2 x}{\tau+\kappa_2} \iff x = 0$. Thus, $\mathcal{I}|\kappa \sim \mathcal{N}\left[0, \frac{\tau_b(\tau+\kappa)^2}{\tau_b\kappa^2+(\tau+\kappa)^2}\right]$. As this is symmetric about zero for all κ, it implies $\text{Cov}[\mathbb{E}[\mathcal{E}|\kappa, \mathcal{I} \geq 0], \kappa] = \text{Cov}[\mathbb{E}[\mathcal{E}|\kappa, \mathcal{I} \leq 0], \kappa]$ and $\text{Var}[\mathcal{I}|\mathcal{I} \geq 0] = \text{Var}[\mathcal{I}|\mathcal{I} \leq 0]$. Finally, as this implies $f(\kappa|\mathcal{I} \geq 0) = f(\kappa|\mathcal{I} \leq 0) = f(\kappa)$, thus, $\text{Var}[\kappa|\mathcal{I} \geq 0] = \text{Var}[\kappa|\mathcal{I} \leq 0]$. Taken together this implies $\text{Corr}[\mathcal{E}, \kappa|\mathcal{I} \geq 0] = \text{Corr}[\mathcal{E}, \kappa|\mathcal{I} \leq 0]$. ■

Next, we investigate if there is variation over time in the difference between the average ideology of men and women. In particular, we have both self-reported ideology and the difference between respondent's thermometer scores for "liberals" and "conservatives", which is intended as a measure of ideology. Figure 5 plots the difference between men and women on both of these scales over time with 95% confidence intervals in each year we have data. There is a clear rightward shift for men between 1980 and 1982. We divide the sample into two parts around 1981, and conduct a similar analysis to Table 7. The results can be found in Table C.1.

Table C.1: Data from the ANES is broadly consistent with Proposition 3 and Proposition C.1.

Time Frame	Up to 1980			1982 and After		
Dep. Variable	Ideology	Extremeness		Ideology	Extremeness	
Sample		Left of Median	Right of Median		Left of Median	Right of Median
Panel A: Self-Reported Ideology						
Male	0.013	0.14***	0.10***	0.18***	0.044**	0.16***
	(.032)	(.027)	(.025)	(.022)	(.019)	(.017)
Difference		0.035			0.11***	
		(.037)			(.025)	
Year Fixed Effects	Y	Y	Y	Y	Y	Y
N	6,880	4,241	5,132	15,183	8,808	11,395
Panel B: Thermometer Scores						
Male	0.88***	0.72***	1.62***	2.17***	-0.092	1.96***
	(.28)	(.24)	(.25)	(.23)	(.19)	(.21)
Difference		0.89**			2.05***	
		(.35)			(.28)	
Year Fixed Effects	Y	Y	Y	Y	Y	Y
N	11,439	6,551	8,709	18,105	10,455	12,992

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors in parentheses. The N of the split-sample regressions do not sum to the N of the ideology regression due to the fact that those respondents with the median ideology are included in both regressions.

The results in Table C.1 are broadly consistent with the patterns predicted by Proposition 3 and Proposition C.1. For self-reported ideology, there is no statistical difference in average ideology between men and women before 1982, and, consistent with Proposition C.1, men are equally more ideologically extreme, regardless of their ideological direction. After 1982, men are significantly further to the right then women on average, and, consistent with Proposition 3, being male exhibits greater correlation with ideological extremeness for those to the right of the population median than for those to the left of the median.[2] For the thermometer scores, the difference in correlation between right and left expands as the ideological difference between men and women increases.

While the results presented here are broadly consistent with theory, and suggest that overconfidence and ideological extremeness are correlated for both left and right, depending on the time-frame under study, further research is needed. In particular, gender is correlated with a multitude of political differences, and the shift in ideology that occurred in the 1980s has many potential explanations that have nothing to do with overconfidence. We believe it is best to note that the available data is consistent with theory, but that better data is clearly needed.[3]

Is There a Connection between Overconfidence and Conservatism? Figure 2(b) shows a clear correlation between overconfidence and conservatism. But is this a more general phenomenon? While our data is limited, and our thinking about this issue is decidedly post-hoc, we believe the answer is no.

There are three pieces of weak evidence against a more general relationship between overconfidence and conservatism. The first piece is noted in Section 3.3: if overconfidence and

[2] The magnitudes of the coefficients are similar in magnitude to the coefficient on gender in the analysis of the 2010 CCES in Sections 3.1 and 3.3. After 1988, the self-reported ideological extremeness measure exhibits no statistically significant correlation with gender for those to the left of the median, which is consistent with the analysis in Table 7.

[3] Another proxy for overconfidence, especially given the results in Section 3.4, is age. However, across the the entire timespan of the ANES cumulative dataset, age has a roughly constant, statistically significant, positive correlation with ideology. That is, the hypothesis of Proposition C.1 is never met, and thus, there is no way to contrast that proposition with the results in Section 3.3.

conservatism were both caused by some underlying factor, then there should be a negative correlation between extremeness and overconfidence for those left-of-center in Table 7, yet there is not. Second, as noted in Section 3.4 older people on both the left and the right are more ideologically extreme. Third is the analysis in this section, which suggests that in the past overconfidence was equally linked to liberalism and conservatism.

So if there is no general relationship between overconfidence and conservatism, what can explain this relationship in 2010 (and 2011)? This relationship, and the facts above are consistent with our theory, if we add that ideological direction, left or the right, is the product of a person's environment when they became politically active. To put this another way, correlational neglect gives people the tendency to become both more ideologically extreme and more overconfident as they age. However, the theory makes no prediction about which ideological direction they will tend towards, and it is known that this responds to environmental factors when a person first becomes politically active (Meredith, 2009; Mullainathan and Washington, 2009). As the most ideologically extreme and overconfident people in 2010 began participating in politics in the late 70s and 80s, when conservatism was in the ascendency, this would rationalize the patterns we see in the data. This further implies that in other periods in time it may appear that there is a relationship between overconfidence and liberalism.

Appendix D Other Specifications—Not for Publication

Appendix D.1 Theoretical

This section addresses, in a casual way, a number of theoretical questions that have been posed to us. While the result of our inquiry into these questions did not produce results that merit a discussion in the main text, we thought it would be useful to record the results.

Distributional Assumptions Throughout the paper we make heavy use of normal distributions. This has advantages for both tractability and interpretation. In particular, tractability is helped by the fact that a normal is a self-conjugate prior, and that properties of the normal are well studied in statistics. The advantage in interpretation comes from the fact that the normal is a two-parameter distribution (the mean and precision), so it is straightforward to implement and interpret overconfidence as a function of precision without worrying about the effects of higher (or lower) order moments.

However, this leads to questions about how much our results are driven by the use of normal distributions. Or, conversely, many seminar attendees have conjectured that it would be straight-forward to extend our results to well-behaved distributions. Here we give some guidance on these questions.

We start by discussing how our results might generalize to other distributions. Without the normal distribution, the correlational neglect model becomes intractable. The value of this model is that it allows us to make predictions about the role of age that could not be obtained under any fully Bayesian model, as discussed in Section 3.4.

However if one is willing to put aside these predictions, it is possible to discuss the role of the normal when citizens receive uncorrelated signals they over-interpret (as in the "model" of Lemma 2). The proof of Proposition 1 (once Lemma 2 is applied), for example, requires only that the posterior belief of a citizen be given by $f(\kappa_i) * e_i$, where $f(\cdot)$ is increasing. This could be generalized to a large family of likelihood functions with the property that the perceived likelihood function for a citizen with overconfidence κ_i second-order-stochasticlly dominates the perceived likelihood function for a citizen with overconfidence κ_j when $\kappa_i > \kappa_j$. Moreover, we have verified that our results hold with a uniform (or beta) prior with binary signals that are interpreted as being of various strengths, depending on a citizen's level of overconfidence.

If one uses a support with only two possible states, then our results may not always hold. However, it is known that such a setup (without overconfidence) produces perverse results: see McMurray (2012). In particular, with only two states, the precision of beliefs may decrease, rather than increase with more signals. However, this would be inconsistent empirical results in Section 3.4.

Multi-Dimensional Issue Spaces: Our theory has implications for how ideology on different dimensions would be related to overconfidence. For example, if the information on a given dimension were all public, with agreed upon correlational structure, then there should be no relationship between ideology and overconfidence on that dimension. While this implication is straight-forward to work out, we did not feel that it was testable with current data.

In particular, in order to test this, one would need to know quite a bit about where citizens get their data from, and how citizens infer about how this data affects them. For example, even if most economic information is public, how that information relates to a citizen's permanent income is more opaque. Learning about that relationship would entail seeing how nationwide economic performance seemed to affect a citizen's own employment situation. As these very personal signals would have an unknown correlational structure, there is plenty of room for correlational neglect.

Likewise, positions on a social issue like gay marriage may appear to have no informational content at all, and hence, there should be no relationship between overconfidence and ideology on this dimension. However, it is perfectly reasonable that one's position on gay marriage may depend on beliefs about the likelihood that a loved one, say a child, is gay. This likelihood may be drawn, in part, from the number of openly gay people in a citizen's social environment. If a citizen neglects the fact that they live in a religious community where others are not open about their sexuality, then they will tend to underestimate the probability that a loved may turn out to be gay. This will lead to both overconfidence and more extreme positions, as before.

We believe that applying our theory to multi-dimensional spaces would be interesting, and possibly fruitful. We refrain from doing so in this paper because it does not add to the predictions we can test in our data.

Appendix D.1.1 Voting

Our model of voter turnout, and partisan identification, is based on a specific form of expressive voting (Fiorina, 1976; Brennan and Hamlin, 1998). In particular a citizen i votes if and only if

$$\left|\text{Prob}_i[U_R(b_i|x) > U_L(b_i|x)] - \frac{1}{2}\right| - c_i > 0, \tag{8}$$

where c_i is an i.i.d. draw from some distribution F_c, which is strictly increasing on $\left(0, \frac{1}{2}\right)$. In addition $c_i \perp (\rho_i, b_i, e_{it})$.

While any political economy model where turnout is exogenous implicitly uses an expressive voting model (and others use it more explicitly, see Knight, 2013), there are a number of other approaches in the political economy literature. As each approach has its partisans, we thought it worthwhile to discuss those models, and show, where possible, how our model relates to them.

Before discussing alternative models, we should note that we focused on the expressive approach because we believe it is correct, and because it is compatible (as shown below) with a promising approach in the literature, that voters are choice- or regret-avoidant (Matsusaka, 1995; Degan and Merlo, 2011).

In addition, this modeling approach allows for both non-trivial turnout and strong partisan identification even if the policies proposed by political parties are similar to each other, as seems to be the case in reality (Snowberg et al., 2007a,b). This is generally not possible in more traditional models. To make this specific, suppose that both parties propose very similar platforms, and consider a citizen who is very confident that the best policy for her is proposed by party R. According to our model, this citizen would strongly identify with, and turn out to vote, for party R. However, if these behaviors were rooted in expected utility, and the parties espoused similar platforms, this would not hold. For any reasonably smooth utility function there is a small difference in utility between the two parties—and hence no reason to strongly identify with one party or the other, or turnout.

Pivotal Voting: In these models, the turnout decision is driven largely by whether or not a voter is likely to be pivotal—that is, change the outcome of the election (Riker and Ordeshook, 1968). In this model a citizen turns out to vote if and only if

$$pB_i - C_i + D_i > 0 \tag{9}$$

where p is the probability an individual citizen's vote is pivotal—that is, changes the winner of the election—and B_i is the benefit to the citizen of the citizen's favored candidate winning over the other candidate. The remaining terms, C_i and D_i, are the instrumental costs and benefits of voting, which are unrelated to the outcome of the election.

It seems reasonable to assume that more-overconfident citizens would over-estimate their probability of being pivotal. This would lead to the prediction that more overconfident citizens would be more likely to turnout.

However, whether or not more ideologically extreme people are more likely to turn out will depend on their utility function. It is well known in the literature on pivotal voting than in order for more ideologically extreme people to be more likely to turnout, utilities need to be very concave: that is, they care much more about small differences in policy when those policies are very far away from their ideal, than when those policies are close to them. Adding overconfidence adds some additional issues: in particular, in order to have more extreme citizens be more likely to turn out the utility function has to be more concave than a quadratic loss function. We have examined a quartic loss-function, and even this degree of concavity will not guarantee the result: it holds only for specific parameters and values of the fourth moment of the distribution of beliefs.

Finally, we do not know if it is possible to replicate our conditional predictions about the role of overconfidence and extremeness using a pivotal voter model. As such, it seems that turning in our model for a pivotal voter model would be a poor choice.

Group Utilitarian: In the group-utilitarian framework a citizen votes not just because voting may improve her utility, but because it will improve the utility of others like her as well (Coate and Conlin, 2004; Feddersen and Sandroni, 2006). In these models there is heterogeneity in the costs of voting, and this selects who, from a group, actually turns out. In order to use our model of overconfidence, there needs to be a mapping from beliefs to the cost of voting. An expression for the cost of voting like the left-hand-side of (8) works, and once this is nested in the group-utilitarian framework will produce the same comparative statics as in Proposition 5. This occurs because in the group utilitarian framework those with the lowest costs of voting vote (up to some threshold), and the overconfident, and ideologically extreme, have the lowest costs according to (8). While it would have been possible to use the full group-utilitarian framework in Section 4.2, we felt that, for concision, it was best to avoid that machinery and show directly the important assumption that gives the predictions in that section.

The remaining two models we discuss—like the expressive voting model—focus on the idiosyncratic costs and benefits of turning out to vote. In particular, they focus on large elections where the number of voters grows large, and hence, $p_i \to 0$.

Regret Avoidance: Matsusaka (1995) argues that voter turnout is driven in part by whether citizens anticipate they will regret their vote. We view this theory as descriptively accurate: indeed, we ran a survey on a convenience sample using Mechanical Turk, and found that over 60% of respondents reported that they took into account whether they might regret their vote when deciding whether or not to vote. Almost 40% could name someone they regretted voting for.[1]

[1]For more on regret-avoidance, see Connolly and Zeelenberg (2002), Zeelenberg (1999), Zeelenberg et al. (2001). Models of regret have then been frequently used to explain behavioral patterns which are not compatible with standard, expected-utility, models (Bell, 1982; Loomes and Sugden, 1982; Loomes and Sugden, 1987; Sugden, 1993; and Sarver, 2008). Indeed, Matsusaka's approach is a direct instantiation of

It is straightforward to show that our model is consistent with a model of regret-avoident voting. In particular, as $p_i \to 0$, a citizen's turnout decision depends only on the idiosyncratic, instrumental costs and benefits of voting in (8), C_i and D_i. We decompose the instrumental cost into two parts: direct costs C_i', such as the opportunity cost of going to vote, and a regret penalty $\mathcal{R}_i$ that accuser if the citizen votes for a candidate whose platform turns out to be worse for the citizen, given the state. That is

$$D_i - C_i \equiv D_i - \mathcal{R}_i \mathbb{I}_{\text{vote=wrong}} - C_i'$$

with D_i, $\mathcal{R}_i$ and C_i' i.i.d. draws from some (possibly different) distributions.[2] We then have:

Proposition D.1. *In large elections when $D_i - C_i \equiv D_i - \mathcal{R}_i \mathbb{I}_{\text{vote=wrong}} - C_i'$, comparative statics on voter turnout and partisan identification are the same as comparative statics on*

$$\left| Prob_i[U_R(b_i|x) > U_L(b_i|x)] - \frac{1}{2} \right| - c_i > 0.$$

Proof of Proposition D.1: When elections are large $p \to 0$ in (9). Supposing citizen i favors candidate R if he or she were to vote, citizen i will vote if and only if

$$\begin{aligned}
D_i - \mathcal{R}_i \mathbb{E}[\mathbb{I}_{\text{vote=wrong}}] - C_i' &> 0 \\
\text{Prob}[\text{vote} = \text{wrong}] &< \frac{D_i - C_i'}{\mathcal{R}_i} \\
1 - \text{Prob}[U_R(b_i|x) > U_L(b_i|x)] &< \frac{D_i - C_i'}{\mathcal{R}_i} \\
\text{Prob}[U_R(b_i|x) > U_L(b_i|x)] - \frac{1}{2} &> \frac{1}{2} - \frac{D_i - C_i'}{\mathcal{R}_i} \equiv c_i.
\end{aligned}$$

The absolute value follows from considering the case where i favors candidate L. ■

We chose to display this chain of logic here to simplify and shorten exposition in the text.

Sugden (1993), applied to politics.

[2] We emphasize that, although we pick a particular formalization, (expected) regret can be seen as either a reduction in the benefit of voting, or an increase in the cost of voting.

Choice Avoidance: Degan and Merlo (2011) use the same idea as Matsusaka (1995). However, they note that as it is unlikely that a citizen will discover the actual state, they will not anticipate regretting their decision; instead, they discuss their model in terms of choice avoidance. It should be clear from the form of (8) that citizens who make their voting decision in this way are choice-avoidant. In particular, a citizen avoids choice unless the choice is clear.[3]

Appendix D.1.2 Strength of Partisan Identification

Our initial model of strength of partisan identification assumed that citizens would invest in a partisan identity only if they believed there was a sufficiently high probability that they would stay on the same side of the ideological spectrum as they received more signals.

This yields the same predictions as Corollary 6. More overconfident citizens would believe that, with high-probability, future signals would just confirm what they already knew. As such, there is little chance that they would end up on the opposite side of the ideological spectrum. Thus, more-overconfident citizens would be more likely to strongly identify with a party.

More ideologically extreme citizens would know that they would need a more extreme signal that the state is on the other side of the ideological spectrum in order to cross-over to that side. As such, there is little chance they would end up on the opposite side, and they would thus be more likely to strongly identify with a party.

We removed this additional model from the text of the paper in order to simplify and shorten the exposition.

[3]For examples of choice avoidance in other contexts see Iyengar et al. (2004), Iyengar and Lepper (2000), Boatwright and Nunes (2001), Shah and Wolford (2007), Schwartz (2004), Choi et al. (2009), DellaVigna (2009), Reutskaja and Hogarth (2009), and Bertrand et al. (2010).

Appendix D.2 Empirical

In the text we present our preferred specifications. Here we provide additional specifications that we excluded from the text for brevity.

First, in Table D.1 we present the regression equivalent of Figure 3. The age variable is divided by its standard deviation, as are the dependent variables, to standardize regression coefficients. Note that the coefficients on age are highly statistically significant in all uncontrolled regressions, which match the visual patterns in the figure. However, the rightward drift in Panel C of the figure is statistically insignificant after adding controls. We do not find this particularly problematic, however, as this result is not a prediction of the theory. Moreover, our alternative measures of ideology display a rightward drift even when including all controls, and this pattern is well-documented in the literature.

Next, we present analogs of Tables 8 and 9 but use fixed effects to control for self-reported ideology. The results are slightly stronger using this specification. We refrained from using these specifications in the text in order to focus on our preferred measure of ideology, the scaled ideology measure of Tausanovitch and Warshaw (2011). Table D.2 presents the results for turnout, and Table D.3 presents the results for strength of partisan identification.

In the text we present WLS specifications with CCES supplied sample weights because the CCES oversamples certain groups. Some readers may prefer OLS specifications, so we present them here. In particular, OLS analogs of Tables 3, 4, 6, 7, 8, and 9 are presented in Tables D.4–D.9. The results are substantively and statistically similar, although the coefficients tend to be a bit smaller than the WLS specifications presented in the paper.

Table D.1: Regressions support the visual patterns in Figure 3.

Dependent Variable:	Overconfidence		Extremeness		Ideology		Deviation	
Age	0.20***	0.19***	0.18***	0.17***	0.12***	0.023	0.17***	0.17***
	(.037)	(.035)	(.031)	(.031)	(.030)	(.028)	(.033)	(.034)
All Controls	N	Y	N	Y	N	Y	N	Y
N	2,927				2,868			

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. All specifications estimated using WLS with CCES sampling weights.

Table D.2: Turnout results are similar when using fixed effects for ideology.

Dependent Variable:	Turnout Decision					
Overconfidence	0.056***	0.038**	0.068***	0.048***	0.074***	0.054***
	(.017)	(.017)	(.018)	(.017)	(.021)	(.018)
Ideological Extremeness	0.18***	0.16***				
	(.014)	(.014)				
Ideology Fixed Effects (DK as Centrist)			F=9.21	F=4.93		
			p=0.00	p=0.00		
Ideology Fixed Effects (DK dropped)					F=4.18	F=2.79
					p=0.00	p=0.00
All Controls	N	Y	N	Y	N	Y
N	2,808		2,849		2,696	

<u>Notes:</u> ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. All specifications estimated using WLS with CCES sampling weights.

Table D.3: Partisan identification results are similar when using fixed effects for ideology.

Treatment of Independents	Strong (1)		Weak (0)		Missing (.)	
Overconfidence	0.049***	0.055***	0.042***	0.045***	0.050***	0.049***
	(.015)	(.015)	(.012)	(.014)	(.013)	(.014)
Ideology Fixed Effects (DK as Centrist)	F=11.6		F=18.0		F=15.7	
	p=0.00		p=0.00		p=0.00	
Ideology Fixed Effects (DK dropped)		F=8.67		F=14.2		F=13.1
		p=0.00		p=0.00		p=0.00
All Controls	Y	Y	Y	Y	Y	Y
N	2,910	2,754	2,910	2,754	2,587	2,479

<u>Notes:</u> ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. All specifications estimated using WLS with CCES sampling weights.

Table D.4: Ideological extremeness is robustly related to overconfidence in unweighted specifications.

Dependent Variable: Scaled Ideological Extremeness					
Overconfidence	0.20*** (.022)	0.16*** (.022)	0.18*** (.022)	0.17*** (.024)	0.12*** (.024)
Income, Education Race, Hispanic		Y			
Union, Religion Church, State			Y		
Gender (Male)				0.25*** (.033)	
All Controls					Y
N			2,868		

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses.

Table D.5: Self-reported ideological extremeness is robustly related to overconfidence in unweighted specifications.

Treatment of "Don't Know"	Centrist		Missing	
Overconfidence	0.14*** (.016)	0.11*** (.016)	0.12*** (.018)	0.10*** (.018)
All Controls	N	Y	N	Y
N	2,910		2,754	

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses.

Table D.6: A general knowledge-based measure of overconfidence produce similar results to Table D.5.

Panel A: OLS				
Dependent Variable:	Self-Reported Ideological Extremeness ("Don't Know" treated as centrist)			
Overconfidence (Economy)	0.14*** (.032)	0.11*** (.033)		
Overconfidence (General Knowledge)			0.16*** (.034)	0.093** (.037)
All Controls	N	Y	N	Y
N	989			

Panel B: 2SLS				
Dependent Variable:	Overconfidence (Economy)	Extremeness	Overconfidence (Economy)	Extremeness
Overconfidence (Economy)		0.50*** (.12)		0.32** (.13)
Overconfidence (General Knowledge)	0.31*** (.031) F=96.2		0.29*** (.034) F=69.5	
All Controls	N	N	Y	Y
N	989			

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (69 clusters), in parentheses. The first stage specification also present an F test on excluding the instrument, Overconfidence (General Knowledge).

Table D.7: Covariances left and right of center are similar using unweighted specifications..

Measure:	Scaled		Self-Reported Treatment of "Don't Know" Centrist		Self-Reported Treatment of "Don't Know" Missing	
	Left of Median	Right of Median	Left of Median	Right of Median	Left of Median	Right of Median
Covariance with Overconfidence	0.00066	0.076***	-0.0094	0.067***	-0.026*	0.093***
	(.011)	(.0086)	(.014)	(.0094)	(.014)	(.025)
Difference	0.075***		0.076***		0.087***	
	(.014)		(.017)		(.017)	
All Controls	Y	Y	Y	Y	Y	Y
N	1,434	1,434	1,608	1,456	1,472	1,426

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses. The N of the two regressions may not sum to the N in those other tables due to the fact that those respondents with the median ideology are included in both regressions. Extremeness is measured from median ideology, as required by Proposition 3.

Table D.8: Turnout results are similar when using unweighted specifications.

Dependent Variable:	Turnout Decision					
Overconfidence	0.071***	0.042***	0.036***	0.035***	0.034***	0.025***
	(.011)	(.0091)	(.0094)	(.0096)	(.0096)	(.010)
Ideological Extremeness		0.14***	0.12***	0.13***	0.14***	0.11***
		(.011)	(.011)	(.010)	(.011)	(.010)
Income, Education Race, Hispanic			Y			
Union, Religion Church, State				Y		
Gender (Male)					0.060***	
					(.019)	
All Controls						Y
N	2,808					

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses.

Table D.9: Overconfidence is correlated with strength of partisan identification, even controlling for ideological extremeness.

Treatment of Independents	Strong (1)		Weak (0)		Missing (.)	
Overconfidence	0.039^{***}	0.038^{***}	0.037^{***}	0.031^{***}	0.044^{***}	0.039^{***}
	(.010)	(.0098)	(.0092)	(.0085)	(.010)	(.0095)
Ideological Extremeness		0.078^{***}		0.12^{***}		0.12^{***}
		(.0089)		(.0086)		(.0090)
All Controls	N	Y	N	Y	N	Y
N	2,868				2,545	

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% level with standard errors, clustered by age (73 clusters), in parentheses.