A Theory of Rigid Extremists and Flexible Moderates with an Application to the U.S. Congress

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Diversity of opinion is an endemic feature of society. Different people can hold divergent opinions on a subject. They can also differ in the intensity with which they hold their opinions. Some people are vehement and uncompromising. Their views seem relatively impervious to contradictory evidence and the opinions of others. Then there are people who hold their opinions tentatively and show a willingness and inclination to modify them as new information comes to light. Heterogeneity in how people form new opinions in response to new facts and the opinions of others has been documented (for example, Walter Mischel and John Schopler, 1959). Psychologists refer to such a personality trait as lying along a rigidity-flexibility dimension.[1]

By way of example, consider an influential segment of society: politicians. As reflected in their espoused ideologies, politicians differ in their opinions concerning what is the ideal society and what are the appropriate means for achieving it. Empirically, there are vast ideological differences among politicians with some being extreme and some being mainstream. On top of this heterogeneity, we find that some politicians are notorious for being uncompromising while others, contrarily, have built a reputation for accommodation. Examples of recent vintage include Newt Gingrich and Ronald Reagan in the rigid category and George Bush and Bill Clinton in the flexible one.[2]

That there should be extensive differences among people in their opinions and their rigidity is hardly surprising in light of the diversity of backgrounds and the complexity of the environment that people must interpret and act upon. What *is* intriguing, however, is the apparent relationship between these two traits. Casual observation and what data are available suggest that individuals with relatively extreme views tend to be relatively rigid. As an example, a survey of enlisted soldiers were queried about their attitudes toward a variety of issues including conscription, officers, the Army, and a military career (Edward A. Suchman, 1950). They were asked a number of questions to which they were to respond with "positive" or "negative" and to report whether or not they strongly held this opinion. A soldier's positive score equaled the number of positive responses while his intensity score equaled the number of opinions held "strongly." The study concluded: "People on both ends of the content scale feel more strongly than people in the middle of the scale" (Suchman, 1950 p. 275).

The first objective of this paper is to explain why rigidity and extremism might be related. Our theoretical analysis begins with a population for which traits relating to extremity of opinions and rigidity of thinking are

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[1] See, for example, Abraham S. Luchins and Edith Hirsch Luchins (1959), William A. Scott (1966), and David H. Jonassen and Barbara L. Grabowski (1993).

[2] For a ranking of U.S. presidents in terms of flexibility, see Gary M. Maranell (1970).

independently distributed. Agents are endowed with some prior set of beliefs on an unknown variable. These beliefs are normally distributed, and the mean and precision (that is, inverse of the variance) are allowed to differ across agents. The distance between the mean of an agent's beliefs and the average mean in the population measures the extremity of an agent's beliefs while an agent's rigidity is measured by the precision of his beliefs (in that higher precision implies less sensitivity to new information). For the initial population, agents' means and precisions are assumed to be independently distributed so that rigidity is just as likely to be found with moderate views as with extreme ones. We then have agents receive a series of public signals about this unknown variable and engage in Bayesian updating. Assuming that the cumulative public signal is sufficiently informative, the cumulative public signal will then, roughly speaking, represent the predominant "opinion" in that most agents' expectations will lie near it. Now consider agents whose prior mean was distant from the cumulative public signal. If endowed with low-precision beliefs, he will adjust his beliefs a lot so that his posterior opinion (that is, mean) is close to the predominant opinion. However, if his prior beliefs had high precision, he will not adjust them very much in which case his posterior opinion remains distant from the predominant opinion in society. Therefore, we find that those agents with posterior means that are extreme relative to the mean of most agents' beliefs will tend to attach relatively high precision to their beliefs. In other words, when agents receive common information, the only way in which an agent can persist with extreme views is *if* he attaches high confidence to them; if he did not, he would have adjusted his beliefs so that they are in line with what most people believe. In this manner, a common societal process—learning in response to publicly available information—induces a positive correlation between extremism and rigidity.

The second objective of this paper is to test this theory. It predicts that those agents who hold relatively extreme views will, on average, modify their views less over time. This hypothesis is tested on members of the U.S. Congress over the period 1950–1990. We do indeed find that the more extreme is a legislator's early voting behavior, which acts as a proxy for his beliefs, the less his voting behavior changes over his time in Congress. This empirical work also serves to provide documentation of the extremism-rigidity relationship beyond casual observation and surveys.

I. A Model of a Heterogeneous Society

Consider a society with a continuum of agents who are uncertain about some common variable denoted $\alpha \in \mathbf{R}$. Agents differ along two dimensions: the rigidity of their thinking and the extremity of their opinions on α. Since we will later assume that agents' beliefs are symmetric and single-peaked, it is natural to use the mean of an agent's probability distribution in making statements regarding the extremity of his opinions. More specifically, though still speaking loosely, an agent's opinions are more extreme if his mean estimate for α is farther away from the mean estimate for the population. Characterizing the dimension of rigidity is a bit trickier as rigidity has a variety of connotations. The particular notion we have in mind is that a more rigid agent is less willing to see the validity of facts as they relate to some unknown. Anecdotally, notoriously rigid agents seem to be very confident that what they believe is true as reflected in their unwillingness to compromise. Such an interpretation is consistent with some psychologists' notion of rigidity (Scott, 1966).

Our approach to capturing the dimensions of extreme views and rigid thinking is based upon the specification that agents' beliefs over α are normally distributed and agents differ in terms of both the mean and precision (that is, the inverse of the variance) of their probability distribution. Agent i's type is then the pair (μ_i, τ_i) where μ_i is the mean of agent i's prior probability distribution on α and τ_i is its precision. μ_i is assumed to be the key determinant of an agent's opinions and will be used in measuring the extremity of an agent's beliefs. τ_i is assumed to be a measure of an agent's rigidity. Since a higher value for τ_i implies more confidence in one's opinion, τ_i would seem to capture some of the elements suggested by notions of rigidity.

Given an agent's type is the mean and precision of his prior distribution, the population of agents is defined over $\mathbf{R} \times \mathbf{R}_+$. We begin by assuming that the population distribution is such that agents' two traits are independently distributed. Let $G(\cdot):\mathbf{R} \rightarrow [0, 1]$ denote the population distribution on the mean and $H(\cdot):\mathbf{R}_+ \rightarrow [0, 1]$ denote the population distribution on the precision. $G(\cdot)$ is assumed to have a density function, $g(\cdot)$, which is almost everywhere twice differentiable. To derive our main result, the following structure is placed upon it.

ASSUMPTION 1: *There exists μ^o such that $g'(\mu) \geq 0$ for all $\mu < \mu^o$ and $g'(\mu) \leq 0$ for all $\mu > \mu^o$.*

ASSUMPTION 2: $[g'(\mu)]^2 - g''(\mu)g(\mu) \geq 0$ *for all* μ.

Assumption 1 states that the population density function on the prior mean is either single-peaked or the set of maxima is an interval. Assumption 2 requires that $\frac{g'(\mu)}{g(\mu)}$ be nonincreasing in μ. Several common probability distribution functions satisfy Assumptions 1 and 2, including the uniform, triangular, and normal. It is also assumed that $H(\cdot)$ has a density function, which we denote $h(\cdot)$. Independence implies that the population distribution on τ, conditional on a value for μ, is the same for all values of μ and is, of course, $H(\cdot)$.

The societal process that lies at the heart of our analysis is the rather routine one of learning. Let n denote the number of signals on α received by agents where $n \geq 1$. All agents receive the same n signals.[3] Each signal has mean α and is normally distributed with precision $r > 0$. Letting $\bar{\alpha}$ be the mean of these n signals, Bayesian updating results in the posterior beliefs of agent i being normally distributed with mean $\hat{\mu}_i$ and precision $\hat{\tau}_i$ where:

$$(1) \qquad \hat{\mu}_i = \frac{\tau_i\mu_i + nr\bar{\alpha}}{\tau_i + nr}, \quad \hat{\tau}_i = \tau_i + nr.$$

Note that $|\hat{\mu}_i - \mu_i| = \left(\frac{nr}{\tau_i + nr}\right)|\bar{\alpha} - \mu_i|$ so that the change in an agent's opinion is decreasing in τ_i. Thus, agents who are more rigid (that is, have a higher value of τ_i) are less responsive to new information, which seems to be a characteristic of rigid types. We will let $\hat{G}(\cdot\,|\bar{\alpha})$ and $\hat{H}(\cdot\,|\bar{\alpha})$ denote the population distribution on the posterior mean and posterior precision conditional on $\bar{\alpha}$, respectively, though we will typically suppress the variable $\bar{\alpha}$. Generally, "^" refers to a variable, distribution, or density function after Bayesian updating on α in response to the public signals.

II. Emergence of a Correlation Between Extreme Views and Rigid Thinking

Initially, the distribution of opinions and rigidities in the population is independent. We now want to show that the process of agents updating their beliefs in response to new information induces a correlation in these traits in that agents who hold relatively extreme beliefs tend to be relatively rigid. In defining "extreme" we will take $\bar{\alpha}$ as an approximate center of mass for the population distribution of the posterior means. Note that this is true if there are sufficiently many signals.[4]

The joint population density function on the prior mean and prior precision is simply $h(\tau)g(\mu)$ since τ and μ are independently distributed. We will let $\hat{k}(\cdot\,,\cdot\,|\bar{\alpha})$ denote the joint population density function on the posterior mean and posterior precision conditional on the signal $\bar{\alpha}$. If $\hat{h}(\cdot\,|\bar{\alpha})$ denotes the population density function on the posterior precision and $\hat{g}(\cdot\,|\hat{\tau}, \bar{\alpha})$ denotes the population density function on the posterior mean, conditional on a value for the posterior precision, it is of course

[3] We conjecture that there would be comparable results if agents receive private signals of α as long as the distribution from which these signals are drawn is independent of an agent's type. However, how those results would be stated is likely to differ. For the sake of keeping agent heterogeneity limited to prior beliefs, we decided to rule out differences in new information.

[4] For all $\epsilon > 0$ and $\delta \in (0, 1)$, there exists N such that if $n > N$ then $\hat{G}(\cdot)$ attaches probability of at least $1 - \delta$ to $\hat{\mu}$ lying in $(\bar{\alpha} - \epsilon, \bar{\alpha} + \epsilon)$.

true that: $\hat{k}(\hat{\mu}, \hat{\tau}) = \hat{h}(\hat{\tau})\hat{g}(\hat{\mu}|\hat{\tau})$ (where $\bar{\alpha}$ is suppressed). Given that $\hat{\tau} = \tau + nr$ and the population density function on τ is $h(\cdot)$ then $\hat{h}(\hat{\tau}) = h(\hat{\tau} - nr)$. Since $\hat{\mu} = \mu + \left(\frac{nr}{\hat{\tau}}\right)(\bar{\alpha} - \mu)$ then, solving for μ, one derives $\mu = \hat{\mu} + \left(\frac{nr}{\hat{\tau} - nr}\right)(\hat{\mu} - \bar{\alpha})$. Using this fact and that $g(\cdot)$ is the population density function on μ, it follows that:

$$(2) \quad \hat{g}(\hat{\mu}|\hat{\tau}) = g\left(\hat{\mu} + \left(\frac{nr}{\hat{\tau} - nr}\right)(\hat{\mu} - \bar{\alpha})\right).$$

Thus, the joint population density function is:

$$(3) \quad \hat{k}(\hat{\mu}, \hat{\tau}) = h(\hat{\tau} - nr) \times g\left(\hat{\mu} + \left(\frac{nr}{\hat{\tau} - nr}\right)(\hat{\mu} - \bar{\alpha})\right).$$

This is the posterior probability density function on agents' types after they have incorporated the information embodied in $\bar{\alpha}$.

The population density function on the posterior precision conditional on a value for the posterior mean is $\hat{h}(\hat{\tau}|\hat{\mu}) = \frac{\hat{k}(\hat{\mu}, \hat{\tau})}{\hat{g}(\hat{\mu})}$ where $\hat{g}(\hat{\mu}) = \int \hat{k}(\hat{\mu}, \hat{\tau})d\hat{\tau}$. In characterizing the posterior relationship between the extremity and rigidity of an agent's beliefs, we will consider the population distribution on the posterior precision conditional on a value for the posterior mean. This distribution is $\hat{H}(\hat{\tau}^o|\hat{\mu}) = \int_0^{\hat{\tau}^o} \hat{h}(\hat{\tau}|\hat{\mu})d\hat{\tau}$. In other words, we consider the frequency of various levels of rigidities for a particular opinion.

The Theorem shows that if the posterior mean $\hat{\mu}'$ is more extreme than the posterior mean $\hat{\mu}''$ then the proportion of agents whose precision is at least some value is greater among those agents with mean $\hat{\mu}'$ than it is among those agents with mean $\hat{\mu}''$; in other words, the conditional distribution on $\hat{\tau}$ shifts in terms of first-order stochastic dominance as $\hat{\mu}$ goes from $\hat{\mu}''$ to $\hat{\mu}'$. Thus, the more extreme is the posterior mean, the greater is the proportion of agents with relatively high levels of rigidity. In stating our main result, let us define: $\bar{\mu} \equiv \max\{\tilde{\mu}|g(\tilde{\mu}) \geq g(\mu)\forall\mu\}$ and $\underline{\mu} \equiv \min\{\tilde{\mu}|g(\tilde{\mu}) \geq g(\mu)\forall\mu\}$.

THEOREM: *If $\hat{\mu}' > \hat{\mu}'' > \max\{\bar{\alpha}, \underline{\mu}\}$ or $\min\{\bar{\alpha}, \bar{\mu}\} > \hat{\mu}'' > \hat{\mu}'$ then $\hat{H}(\hat{\tau}|\hat{\mu}') \leq \hat{H}(\hat{\tau}|\hat{\mu}'')$ for all $\hat{\tau}$.*

PROOF:

$\hat{H}(\hat{\tau}|\hat{\mu}') \leq \hat{H}(\hat{\tau}|\hat{\mu}'')$ for all $\hat{\tau}$ is the definition that $\hat{H}(\cdot|\hat{\mu}')$ stochastically dominates $\hat{H}(\cdot|\hat{\mu}'')$ in the first degree. Let us first consider the case of $\hat{\mu}' > \hat{\mu}'' > \max\{\bar{\alpha}, \underline{\mu}\}$. By Proposition 5 in Paul R. Milgrom (1981), $\hat{H}(\cdot|\hat{\mu}')$ stochastically dominates $\hat{H}(\cdot|\hat{\mu}'')$ in the first degree iff $[\partial\hat{g}(\hat{\mu}|\hat{\tau})/\partial\hat{\tau}]/\hat{g}(\hat{\mu}|\hat{\tau})$ is nondecreasing in $\hat{\mu}$ for all $\hat{\mu} \in [\hat{\mu}'', \hat{\mu}']$, for all $\hat{\tau}$. Since $\hat{g}(\hat{\mu}|\hat{\tau}) = g\left(\hat{\mu} + \left(\frac{nr}{\hat{\tau} - nr}\right)(\hat{\mu} - \bar{\alpha})\right)$ and letting $\phi(\hat{\mu}, \hat{\tau}) \equiv \hat{\mu} + \left(\frac{nr}{\hat{\tau} - nr}\right)(\hat{\mu} - \bar{\alpha})$ then:

$$(4) \quad \frac{\partial \hat{g}(\hat{\mu}|\hat{\tau})}{\partial \hat{\tau}} = -g'(\phi(\hat{\mu}, \hat{\tau})) \times [nr(\hat{\mu} - \bar{\alpha})/(\hat{\tau} - nr)^2].$$

Thus,

$$(5) \quad \frac{\partial[(\partial\hat{g}(\hat{\mu}|\hat{\tau})/\partial\hat{\tau})/\hat{g}(\hat{\mu}|\hat{\tau})]}{\partial\hat{\mu}} = [g(\phi(\hat{\mu}, \hat{\tau}))(\hat{\tau} - nr)^2]^{-2} \times \Big\{-g''(\phi(\hat{\mu}, \hat{\tau})) \times \left(\frac{\hat{\tau}}{\hat{\tau} - nr}\right)nr(\hat{\mu} - \bar{\alpha}) \times g(\phi(\hat{\mu}, \hat{\tau})) - g'(\phi(\hat{\mu}, \hat{\tau}))nrg(\phi(\hat{\mu}, \hat{\tau})) + g'(\phi(\hat{\mu}, \hat{\tau}))nr(\hat{\mu} - \bar{\alpha}) \times g'(\phi(\hat{\mu}, \hat{\tau}))\left(\frac{\hat{\tau}}{\hat{\tau} - nr}\right)\Big\}.$$

From (5) we get:

$$(6)\quad sign\left\{\frac{\partial[(\partial\hat{g}(\hat{\mu}|\hat{\tau})/\partial\hat{\tau})/\hat{g}(\hat{\mu}|\hat{\tau})]}{\partial\hat{\mu}}\right\}$$

$$= sign\left\{\left(\frac{\hat{\tau}}{\hat{\tau}-nr}\right)(\hat{\mu}-\bar{\alpha}) \times [(g'(\phi(\hat{\mu},\hat{\tau})))^2 - g''(\phi(\hat{\mu},\hat{\tau}))g(\phi(\hat{\mu},\hat{\tau}))] - g'(\phi(\hat{\mu},\hat{\tau}))g(\phi(\hat{\mu},\hat{\tau}))\right\}.$$

By Assumption 2, $[g'(\phi(\hat{\mu},\hat{\tau}))]^2 - g''(\phi(\hat{\mu},\hat{\tau}))g(\phi(\hat{\mu},\hat{\tau})) \geq 0$. Since we are presuming that $\hat{\mu} > \max\{\bar{\alpha}, \underline{\mu}\}$ then $\hat{\mu} - \bar{\alpha} > 0$ and thus:

$$(7)\quad \left(\frac{\hat{\tau}}{\hat{\tau}-nr}\right)(\hat{\mu}-\bar{\alpha}) \times [(g'(\phi(\hat{\mu},\hat{\tau})))^2 - g''(\phi(\hat{\mu},\hat{\tau})) \times g(\phi(\hat{\mu},\hat{\tau}))] \geq 0.$$

Hence, the first term in (6) is nonnegative. Next note that it follows from $\hat{\mu} > \bar{\alpha}$ that $\phi(\hat{\mu},\hat{\tau}) > \hat{\mu}$ and since $\hat{\mu} > \max\{\bar{\alpha}, \underline{\mu}\}$ then $\phi(\hat{\mu},\hat{\tau}) > \underline{\mu}$. Therefore, by Assumption 1, $g'(\phi(\hat{\mu},\hat{\tau})) \leq 0$ which implies $-g'(\cdot)g(\cdot) \geq 0$. We conclude that (6) is nonnegative. This proves that $\hat{H}(\,\cdot\,|\hat{\mu}')$ stochastically dominates $\hat{H}(\,\cdot\,|\hat{\mu}'')$ in the first degree when $\hat{\mu}' > \hat{\mu}'' > \max\{\bar{\alpha}, \underline{\mu}\}$.

The case of $\min\{\bar{\alpha}, \bar{\mu}\} > \hat{\mu}'' > \hat{\mu}'$ is similar. Since we want to show that $\hat{H}(\,\cdot\,|\hat{\mu}')$ stochastically dominates $\hat{H}(\,\cdot\,|\hat{\mu}'')$ in the first degree when $\hat{\mu}'' > \hat{\mu}'$, we instead need to show that $[\partial\hat{g}(\hat{\mu}|\hat{\tau})/\partial\hat{\tau}]/\hat{g}(\hat{\mu}|\hat{\tau})$ is nonincreasing in $\hat{\mu}$, for all $\hat{\tau}$. This requires that (6) be nonpositive. Since $\hat{\mu} < \bar{\alpha}$ then the first term of the two terms in (6) is nonpositive. Since $\bar{\mu} > \hat{\mu} > \phi(\hat{\mu},\hat{\tau})$ then, by Assumption 1, $g'(\cdot) \geq 0$, which implies that the second term is nonpositive. Thus, (6) is nonpositive when $\min\{\bar{\alpha}, \bar{\mu}\} > \hat{\mu}$.

COROLLARY: *If $\hat{\mu}' > \hat{\mu}'' > \max\{\bar{\alpha}, \underline{\mu}\}$ or $\min\{\bar{\alpha}, \bar{\mu}\} > \hat{\mu}'' > \hat{\mu}'$ then the average rigidity of an agent with posterior mean $\hat{\mu}'$ exceeds the average rigidity of an agent with posterior mean $\hat{\mu}''$.*

In interpreting the Theorem, it is imagined that the "mainstream" opinion lies between $\min\{\bar{\alpha}, \bar{\mu}\}$ and $\max\{\bar{\alpha}, \underline{\mu}\}$ so that, for example, if $\hat{\mu}' > \hat{\mu}'' > \max\{\bar{\alpha}, \underline{\mu}\}$ then an agent with posterior mean $\hat{\mu}'$ is farther away from the mainstream view than someone with posterior mean $\hat{\mu}''$ and, in this sense, the former agent is more extreme. If $g(\cdot)$ is single-peaked with its peak denoted $\tilde{\mu}$ (so that $\bar{\mu} = \tilde{\mu} = \underline{\mu}$) then the interpretation is that the mainstream opinion lies between $\tilde{\mu}$ and $\bar{\alpha}$, which seems fairly reasonable. Roughly speaking, the Theorem says that the more extreme is an agent's opinion relative to the mainstream opinion, the more likely is he to be relatively rigid. The frequency of highly rigid agents is greatest among those agents with extreme views while the frequency of highly flexible agents is greatest among those agents with moderate views.

We began with a population in which the traits of extreme opinions and rigid thinking were unrelated. An individual with a moderate position was just as likely to be rigid as someone with an extreme position. In the process of agents updating their beliefs in response to publicly available information, a positive correlation emerged between these traits. More extreme views are held by people who tend to be more rigid thinkers. What is going on is really quite straightforward. Among those agents whose prior mean was *ex post* relatively extreme (that is, far from to $\bar{\alpha}$), the more flexible ones adjust their beliefs a lot so that their posterior mean is relatively close to $\bar{\alpha}$. Those agents whose prior mean was relatively close to $\bar{\alpha}$ remain, of course, close to $\bar{\alpha}$ (though how much closer they are to $\bar{\alpha}$ depends on an agent's rigidity). As a result, the only remaining agents with a posterior mean distant from $\bar{\alpha}$ are those who are rigid. In other words, the only way in which an agent can persist holding nonmainstream views after receiving publicly available information is for him to be rigid; if he were flexible then he would have adjusted his beliefs to be more in line with the mainstream.[5]

[5] Our results would seem to hold if we instead allowed agents to assign different precisions to the distribution over the signals on α. In terms of (1), heterogeneity would be in terms of r rather than τ. Agents with a lower r might be interpreted as being "more skeptical" in that they perceive signals as being less informative; for example, they tend to dismiss newspaper reports more easily. This theory would then predict a positive correlation between extremism and skepticism (and more skeptical agents are more rigid). A non-Bayesian variation is to allow agents to differ in terms of confirmatory bias where more severe bias results in more

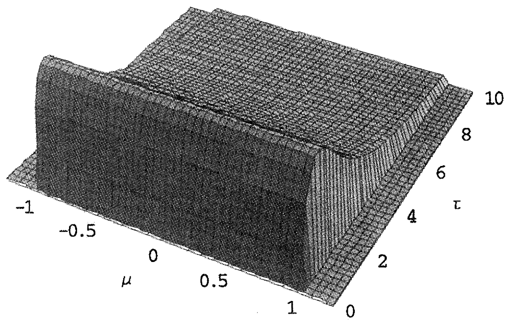

FIGURE 1. JOINT PROBABILITY DENSITY FUNCTION ON AGENTS' PRIOR MEAN AND PRIOR PRECISION

Notes: $G(\cdot)$ is a uniform distribution on $[-1, 1]$ and $H(\cdot)$ is a lognormal distribution with mean 1 and variance 1.

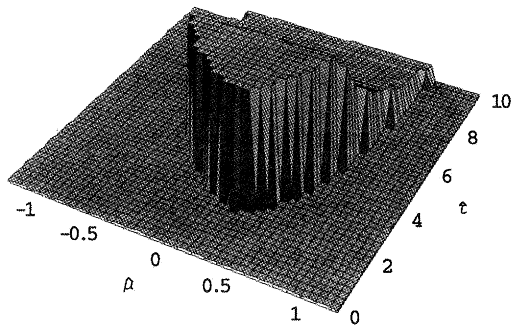

FIGURE 2. JOINT PROBABILITY DENSITY FUNCTION ON AGENTS' POSTERIOR MEAN AND POSTERIOR PRECISION

Notes: $nr = 2$ and $\bar{\alpha} = 0.25$. Joint probability density function on agents' prior mean and prior precision is as specified in Figure 1.

Example: Let $G(\cdot)$ be uniformly distributed over $[-1, 1]$ and $H(\cdot)$ be a lognormal distribution with mean 1 and variance 1. Figure 1 shows the joint probability density function on agents' prior mean and prior precision. For $nr = 2$ and $\bar{\alpha} = 0.25$, Figure 2 shows the joint probability density function on agents' posterior mean and posterior precision. For values of $\hat{\mu}$ near 0.25 (the mean of the signals), the conditional distribution on $\hat{\tau}$ looks somewhat like a lognormal distribution with a lower bound of 2. As we increase $\hat{\mu}$ above 0.25, the lower bound of the support on $\hat{h}(\,\cdot\,|\mu)$ increases implying that more mass is placed on higher values of the posterior precision.

III. Extremism and Rigidity Among Members of Congress

The central prediction of the theory is that more extreme beliefs are positively correlated with more precise beliefs. In this section, we test the theory by examining two time-series implications of this correlation between extremism and precision. First, agents with more extreme beliefs should engage in less adjustment of their beliefs over time. Second, while all agents' beliefs should be converging on the average beliefs in the population, agents with more extreme beliefs should have their beliefs converging slower. These relationships are examined for members of the U.S. Congress over the period 1950–1990. In that beliefs are not observed but behavior is, voting scores will be used as proxies for legislators' beliefs.

The empirical approach is based upon the following general conception of the legislative setting. Each legislator has some prior beliefs on those factors pertinent to how he votes; for example, the efficacy of different policies and the preferences of his constituents. Legislators receive signals that contain information about these various factors and update their beliefs based upon these signals. How much weight they give to these signals depends on the precision of their prior beliefs. These updated beliefs determine a legislator's optimal policy position, and this policy position then determines how he votes when faced with a series of legislative bills.

Voting behavior is measured for its ideological content through the use of ADA scores. Each year, the liberal interest group Americans for Democratic Action (ADA) scores members of the Senate and the House of Representatives on approximately 20 roll-call votes. A legislator's score measures the extent to which his votes matched up with the positions of the ADA. A score of 100 is a perfect match, while a score of zero means a legislator voted contrary to the ADA's positions on all roll calls. The plan is to use extremism and variability in legislators' ADA scores as proxies for extremism and variability in legislators' beliefs. While the ADA has been col-

rigidity (see Matthew Rabin and Joel L. Schrag, 1999). Our argument should result in extremism and confirmatory bias (and thereby rigidity) being positively correlated.

lecting this data only since 1960, Timothy Groseclose et al. (1995) extended the data set back to 1947 using a similar technique to ADA scoring. They also devised an index of real ADA scores that allows ADA scores to be compared across time and between chambers. While ADA scores range from 0 to 100, real ADA scores are not constrained to lie in that interval. Our data set encompasses real annual ADA scores for all members of the Senate and the House of Representatives over 1950–1990.[6]

To summarize our results, the more extreme is a legislator's initial voting record, the lower is the variance in her voting record during her time in Congress. We also find that all legislators' scores converge toward the mean voting score in Congress but that the voting scores of more extreme legislators converge to the mean slower. Prior to presenting the empirical evidence, we first consider the appropriateness of using voting scores as proxies for beliefs by examining the mapping from a legislator's beliefs to his optimal policy position and the mapping from his optimal policy position to his ADA score.

A. *A Theory of Voting Scores*

Mapping from Beliefs to Policy Position.—For the purpose of estimating the relative importance of various factors in senatorial voting, Levitt (1996) specified a simple model of voting behavior which we modify by allowing legislators to be uncertain about those factors. Letting $E_{i,t}[X]$ denote legislator i's expectation of random variable X in period t, legislator i's expected utility in period t is specified to be:

$$-E_{i,t}\left[\frac{1}{2}\sum_{j=1}^{K}\beta^j(V_{i,t}-W_i^j)^2\right]. \tag{8}$$

$V_{i,t}$ is legislator i's policy position and is a choice variable. $W_i^1, \ldots, W_i^K$ are the exogenous factors relevant to legislator i's voting choice where $\beta^j > 0$ and $\sum_{j=1}^{K}\beta^j = 1$. Solving for the policy position that maximizes (8), one derives:

$$V_{i,t}^* = \sum_{j=1}^{K}\beta^j E_{i,t}[W_i^j]. \tag{9}$$

Equation (9) shows how a legislator's policy position depends on his beliefs over the unknown variables.

To ease the notational burden, the ensuing analysis sets $K = 2$, and we refer to those two factors as personal policy preferences (or ideology), which has weight β, and the preferences of constituents, which has weight $1-\beta$. Let W_i^p and W_i^{mv} denote legislator i's personal policy preferences and the preferences of the median voter, respectively. Furthermore, let $\varepsilon_{i,t}^p$ and $\varepsilon_{i,t}^{mv}$ be legislator i's period t signals of his personal policy preferences and the preferences of the median voter, respectively. Assume that $\varepsilon_{i,t}^p \sim N(\mu_{\varepsilon^p}, \sigma_{\varepsilon^p}^2)$ and $\varepsilon_{i,t}^{mv} \sim N(\mu_{\varepsilon^{mv}}, \sigma_{\varepsilon^{mv}}^2)$ and are independently distributed and independently and identically distributed (i.i.d.) over time. Under the assumption that the prior distributions on W_i^p and W_i^{mv} are normally distributed, it follows that:

$$E_{i,t}[W_i^p] = \lambda_{i,t}^p E_{i,t-1}[W_i^p] + (1-\lambda_{i,t}^p)\varepsilon_{i,t}^p \tag{10}$$

and

$$E_{i,t}[W_i^{mv}] = \lambda_{i,t}^{mv} E_{i,t-1}[W_i^{mv}] + (1-\lambda_{i,t}^{mv})\varepsilon_{i,t}^{mv} \tag{11}$$

where $\lambda_{i,t}^p(\lambda_{i,t}^{mv}) \in (0, 1)$ depends on the period t precisions of legislator i associated with his period t beliefs on $W_i^p(W_i^{mv})$ and $\varepsilon_{i,t}^p(\varepsilon_{i,t}^{mv})$. Substituting these expressions into legislator i's optimal policy position:

$$V_{i,t}^* = \beta\{\lambda_{i,t}^p E_{i,t-1}[W_i^p] + (1-\lambda_{i,t}^p)\varepsilon_{i,t}^p\} + (1-\beta)\{\lambda_{i,t}^{mv} E_{i,t-1}[W_i^{mv}] + (1-\lambda_{i,t}^{mv})\varepsilon_{i,t}^{mv}\}. \tag{12}$$

To gain some insight into how these factors

[6] Alternatively, we could have used other voting measures such as scores devised by Americans for Constitutional Action. However, it is likely to have made little difference in that the various scores are highly correlated. For more information about this issue, see Groseclose et al. (1995) and Levitt (1996), who describe the merits and limitations of ADA scores.

influence the variability in a legislator's optimal policy position, we consider the period t variance of legislator i's optimal policy position:

$$\text{(13)}\quad \mathrm{Var}[V_{i,t}^{*}] = \beta^2(1-\lambda_{i,t}^{p})^2\sigma_{\varepsilon^p}^2 + (1-\beta)^2(1-\lambda_{i,t}^{mv})^2\sigma_{\varepsilon^{mv}}^2.$$

Using this model to guide our intuition, our theory predicts that legislators with more extreme beliefs on W_i^p and W_i^{mv} [and thus, by (9), more extreme policy positions] tend to have higher values for $\lambda_{i,t}^{p}$ and $\lambda_{i,t}^{mv}$ and, by (13), lower variance to their policy position. Legislators with more extreme policy positions should then experience less variability in their policy positions. The extent to which this relationship carries over to voting behavior and voting scores is considered next.

Mapping from Policy Position to Voting Score.—In calculating an ADA score, N bills are selected. Associated with each bill is a status quo, which is the policy that remains in place if the bill is defeated. A bill and status quo are represented by a position in the policy space [0, 1] and the selection process is represented by bills and status quos being i.i.d. draws from [0, 1]. In fact, the ADA engages in an intensive selection process but one which we do not attempt to model. Let $K(\cdot):[0, 1] \rightarrow [0, 1]$ denote the cumulative distribution function (c.d.f.) on bills and $L(\cdot):[0, 1] \rightarrow [0, 1]$ denote the c.d.f. on status quos. Assume $K(\cdot)$ and $L(\cdot)$ are twice differentiable. A legislator's optimal policy position is denoted $v \in [0, 1]$ (which we referred to as $V_{i,t}^{*}$ above) while a bill and status quo are denoted b and s, respectively. The assumption is that a legislator with optimal policy position v votes for bill b over status quo s if and only if $|v - b| < |v - s|$.

A legislator's ADA score is the proportion of the N bills for which he voted the same as the ADA. Specifying the policy position of the ADA to be 0, a legislator votes the same as the ADA if and only if $\frac{b+s}{2} < v$. In that a legislator's ADA score is proportional to the sum of N binomial random variables (divided by N), a legislator's expected ADA score is proportional to the probability that $\frac{b+s}{2} < v$, which is $\int_0^1 \int_{2v-s}^1 dK(b)dL(s)$ or:

$$\text{(14)}\quad ADA(v) = \begin{cases} \displaystyle\int_0^{2v} [1 - K(2v - s)]\, dL(s) + [1 - L(2v)] & \text{if } v \in [0, \tfrac{1}{2}] \\ \displaystyle\int_{2v-1}^{1} [1 - K(2v - s)]\, dL(s) & \text{if } v \in [\tfrac{1}{2}, 1]. \end{cases}$$

Taking the first derivative of (14), one finds that ADA(v) is decreasing in v. Since a legislator's ADA score is then a monotonic transformation of his optimal policy position, which is itself a monotonic transformation of his beliefs [see (9)], a legislator's voting score is a suitable proxy for his beliefs. The appropriateness of the variability in ADA scores as a proxy for the variability in beliefs is a bit more problematic. Taking the second derivative of (14), one finds that ADA(v) is generally nonlinear in v. Hence, the sensitivity of a legislator's ADA score to changes in his policy position may depend on where his initial policy position lies. For example, if one assumes that K and L are uniform over [0, 1] then:

$$\text{(15)}\quad ADA(v) = \begin{cases} 1 - 2v^2 & \text{if } v \in [0, \tfrac{1}{2}] \\ 2(1 - v)^2 & \text{if } v \in [\tfrac{1}{2}, 1] \end{cases}$$

so that ADA″(v) $\lesseqgtr 0$ as $v \lesseqgtr$ ½ (see Figure 3). A given change in beliefs (operating through their effect on a legislator's policy position) will result in a smaller variation in the ADA scores of a more extreme legislator and, thereby, result in a lower variance. In this case, the mapping from policy positions to voting scores introduces bias that favors our hypotheses. However, one can specify assumptions on K and L for which the bias works against our hypotheses. Our response is twofold. First, after examining the relationship between extremism and variability

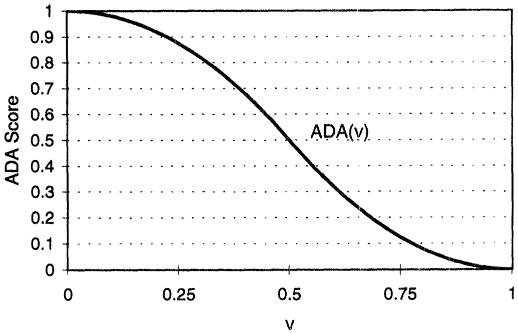

FIGURE 3. ADA SCORING FUNCTION

Note: $K(\cdot)$ and $L(\cdot)$ are uniform distributions on [0, 1].

in ADA scores, we develop and estimate a test for this bias. Second, we estimate an alternative model that is immune to this bias though it less effectively utilizes the information in the data set.

B. *Extremism and Variability in a Legislator's ADA Score*

In that an agent who attaches higher precision to his beliefs is less responsive to new information, agents with more precise beliefs are expected to modify their beliefs less. Given the predicted positive correlation between extremity of beliefs and the level of precision with which those beliefs are held, our first testable hypothesis is: the more extreme is the ideological content of a legislator's voting record, the less that the ideological content of his voting record changes over time. A maintained hypothesis in our analysis is that the process which correlates extremism and rigidity has been operating prior to an individual being elected to Congress so that, if the theory is correct, the predicted correlation between extremism and rigidity exists when a congressional member casts his first legislative vote.[7]

Letting N_i denote the number of ADA scores for legislator i in the sample, our basic approach is to use the first c observations to measure his extremism and the remaining $N_i - c$ observations to measure his variability. More specifically, a legislator's degree of extremism is measured by $|\text{Med(ADA)}_0 - \text{ADA}_{i,0}|$, which is the distance between the average of legislator i's initial c real ADA scores, denoted $\text{ADA}_{i,0}$, and the median average initial c scores for all legislators in the sample, denoted Med(ADA)_0.[8] As a measure of variability, we use the variance of a legislator's score, denoted Var(ADA)_i, over his last $N_i - c$ years in the sample.[9]

For all members of Congress with at least six years in office, Figure 4 plots a legislator's average real ADA score during his first three years in the sample and the variance in that score over all years excluding the first three. To test our first hypothesis, we estimated:

$$(16)\quad \text{Var}(ADA)_i = \alpha_0 + \alpha_1|\text{Med}(ADA)_0 - ADA_{i,0}| + \gamma\mathbf{Z} + \epsilon_i$$

where $\mathbf{Z}$ is a vector of control variables. For Table 1, the sample is limited to legislators with at least six years of tenure and $c = 3$, though results are robust to that specification.[10] Our theory predicts that $\alpha_1 < 0$. Across the various regressions, the estimated value for α_1 is negative and highly statistically significant. There is strong and robust evidence of more extreme legislators having less variability in their ADA scores.

A potential problem with this empirical model is selection bias in that our sample has censored those legislators who die, choose not to run again, or fail to be reelected. It is the last that is a concern in that the voting record of a

[7] If this is not true, our empirical methods remain valid but are less likely to produce evidence in support of the theory.

[8] If a legislator entered Congress after 1946, we use scores from his first c legislative years. If he entered Congress prior to 1947, we use his scores from 1947 to 1947 + $(c - 1)$.

[9] One does not want to use the same sample to calculate measures of extremism and variability. Suppose that each legislator's score is actually an independent draw with the probability distribution being identical across legislators. Now compare two legislators; one who had relatively low scores over his lifetime and one who had both low and high scores. Compared to the latter, the former would have a relatively low average score and a relatively low variance, which is the same prediction as our theory.

[10] Later empirical models will use a legislator's initial ADA score ($c = 1$), though this is not important for results.

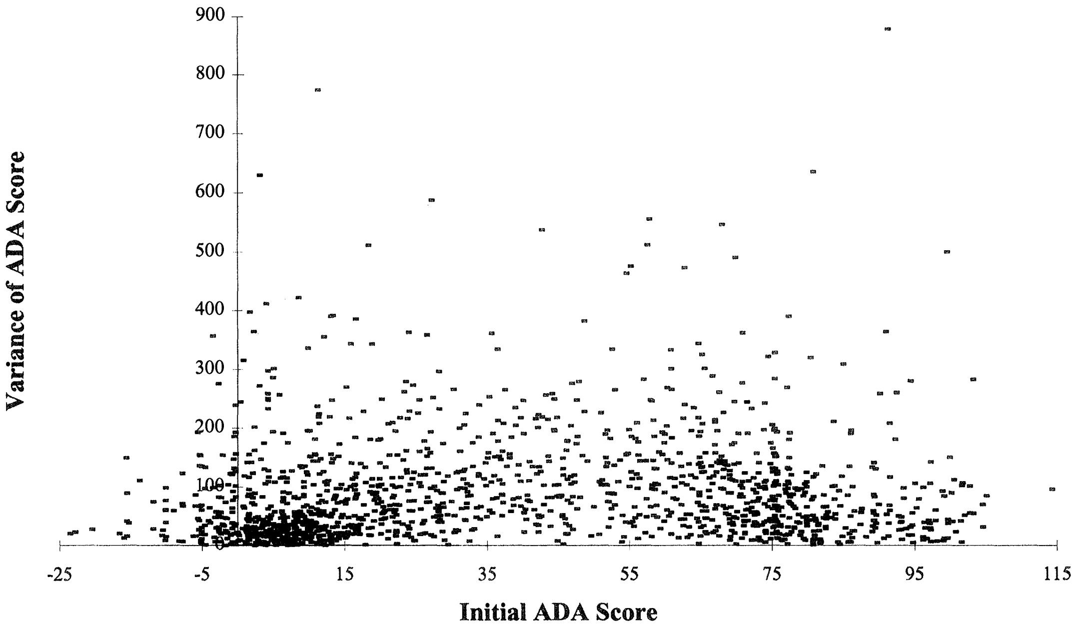

FIGURE 4. LEGISLATORS' INITIAL VOTING RECORD AND VARIABILITY IN VOTING RECORD

Notes: Initial ADA score is the average of a legislator's first three real ADA scores in the sample. Variance of ADA score is the variance of a legislator's real ADA score in the sample excluding the first three observations. Sample includes all legislators with at least six observations.

TABLE 1—ESTIMATED RELATIONSHIP OF INITIAL EXTREMISM ON LIFETIME VARIANCE OF VOTING RECORD
$\text{VAR(ADA)}_i = \alpha_0 + \alpha_1|\text{MED}(ADA)_0 - ADA_{i,0}| + \gamma\mathbf{Z} + \epsilon_i$

Coefficient on:	(1)	(2)	(3)	(4)	(5)
INTERCEPT	105.65	72.74	—	56.16	—
	(4.703)	(1.657)	—	(6.212)	—
ABSOLUTE DEVIATION FROM MEDIAN	−0.525	−0.677	−0.505	−0.420	−0.561
	(0.147)	(0.037)	(0.144)	(0.160)	(0.238)
TENURE	—	2.873	3.598	3.505	3.187
	—	(0.074)	(0.329)	(0.341)	(0.772)
DISTRICT TENURE	—	—	−2.733	—	0.904
	—	—	(1.040)	—	(1.419)
SENATE	—	—	—	16.19	—
	—	—	—	(15.26)	—
SEN*(ABSOLUTE DEVIATION FROM MEDIAN)	—	—	—	−0.686	—
	—	—	—	(0.365)	—
SEN*TENURE	—	—	—	−0.235	—
	—	—	—	(0.827)	—
SEN*(DISTRICT TENURE)	—	—	−4.456	—	—
	—	—	(5.853)	—	—
OBSERVATIONS	1,458	1,458	1,458	1,458	570

Notes: The specifications in the table are variations of the above regression. Columns (1)–(5) include all legislators from 1950–1990 with at least six years of tenure. Column (2) estimates the model employing weighted least squares with weights = 1/TENURE$_i$. Column (3) includes dummy variables for districts. Column (5) includes all legislators with at least six years of tenure from 1970–1990. All standard errors are robust to heteroskedasticity of unknown form and are given in parentheses.

legislator is presumably correlated with the outcome of his bid for reelection. In that selection bias suggests we are giving too much weight to legislators with longer tenure, we have reestimated the model using weighted least squares with a weight of $\frac{1}{Tenure_i}$ where $Tenure_i$ is the number of years legislator i was in office. We have also included it as an independent variable. Note that our Bayesian learning theory predicts that legislators with longer tenure should exhibit less variance due to having accumulated more information over time.

After taking account of tenure, the negative relationship between extremism and variability in voting behavior not only persists but is strengthened [column (2)]. However, contrary to the learning theory, the coefficient on *Tenure* is positive so that legislators with more experience have higher variances. Both results can be explained in light of selection bias. Legislators who are rigid and fail to respond to changes in voter preferences may have lower reelection rates. Long-term surviving legislators may then be those who adjust their voting behavior. In that failure to adjust to voter preferences is likely to be more detrimental to extreme legislators than to moderate ones, selection bias would seem to work against finding evidence to support our theory in that rigid extremists may be censored from our sample.

A key presumption underlying our empirical strategy is that legislators differ only in the mean and precision of their prior beliefs. However, suppose legislators do not have the same probability distribution over signals or, more to the point, this probability distribution is correlated with a legislator's extremism.[11] Of particular concern is that voters' preferences may be more volatile in more moderate districts and, ceteris paribus, more moderate districts have more moderate legislators.[12] While one would expect legislators to adjust their positions in response to changes in voter preferences, as long as they give some weight to their own personal policy preferences such adjustment should be partial, which implies a lower probability of being reelected. Districts with larger changes in voters' preferences are then expected to result in more turnover of legislators. We then include *District Tenure*—the average tenure for legislators in a district—as well as district dummies as explanatory variables. In that this effect should be less severe for senators because of their longer reelection cycle, we also interact *District Tenure* with a dummy variable that takes the value 1 if a legislator is a member of the Senate. Referring to column (3), the negative relationship between extremism and variability persists. As predicted, *District Tenure* is negative and statistically significant, though this does not prove to be robust to restricting the sample to 1970–1990.

Finally, the basic model with tenure (using ordinary least squares) is estimated allowing for differences between the Senate and the House [column (4)]. We fail to reject the null that the coefficients associated with the Senate are jointly zero at the 0.05 level. We also limit the sample to 1970–1990 [column (5)]. In both of these modifications, the negative relationship between variability in ADA scores and extremism and the positive relationship between variability and tenure persist.

C. *Bias from the ADA Scoring Function*

Recall that the mapping from a legislator's policy position to his ADA score may result in his ADA score being more or less sensitive to changes in his policy position, depending on the location of his policy position. In particular, we are most concerned with the possibility exemplified in Figure 3, where ADA scores are less sensitive to changes in a legislator's policy

[11] In terms of (13), the implicit assumption we are making is that $\sigma^2_{\varepsilon^p}$ and $\sigma^2_{\varepsilon^{mv}}$ are independent of $E_{i,t}[W_i^p]$ and $E_{i,t}[W_i^{mv}]$.

[12] Volatility in voters' preferences is a concern only if it is due to changes in the identity of the median voter. One referee put forth the following rationale for why there may be more volatility in more moderate districts. Suppose some districts are strongly liberal (conservative) so that the median voter is always a Democrat (Republican). Other districts are moderate and the median voter may swing between being a Republican and a Democrat. In those districts, legislators tend to be moderate and may experience relatively large changes in their policy positions when the majority party in the district switches.

position when a legislator is more extreme. In this section, we develop and run a test for such bias.

Consider $v \in (0, \frac{1}{2})$ and suppose the change in the policy position, Δv, lies in $(0, \frac{1}{2} - v)$. For the case shown in Figure 3, it follows that

$$(17) \qquad |ADA(v + \Delta v) - ADA(v)| > |ADA(v - \Delta v) - ADA(v)|.$$

This says that the change in the ADA score is larger when the change in policy position makes a legislator more moderate than when it makes him more extreme. The same can be shown for $v \in (\frac{1}{2}, 1)$. If one assumes that the density function on changes in policy positions is symmetric around zero, an ADA function as shown in Figure 3 should result in the average change in the ADA score, conditional on the change moving the ADA score toward the mean score in the population, exceeding the average change in the ADA score, conditional on the change moving the ADA score away from the mean score in the population. If instead ADA(v) is more sensitive to changes in v when v is more extreme (say, it is convex then concave), the opposite relationship would be true. We test for bias by comparing the average change in ADA scores depending on whether the change was a move toward or away from the population mean.[13]

Letting $M(\text{ADA})_t$ denote the mean real ADA score for all legislators in period t, the average value of $|\text{ADA}_{i,t} - \text{ADA}_{i,t-1}|$ is estimated to be 8.90 when $|\text{ADA}_{i,t} - M(\text{ADA})_t| < |\text{ADA}_{i,t-1} - M(\text{ADA})_{t-1}|$ and 9.20 when $|\text{ADA}_{i,t} - M(\text{ADA})_t| > |\text{ADA}_{i,t-1} - M(\text{ADA})_{t-1}|$. These are different at the 0.027 level (using a χ^2 test). Though there is evidence of bias due to the ADA scoring function, the bias is working against finding evidence in support of our hypotheses and thus does not appear to be the source of the negative relationship between extremism and variability found in Table 1.

[13] In our model of ADA scores, ½ actually represents the mean/median of bills and status quos and not the mean/median of the policy position of legislators. Nevertheless, the two variables should be close.

D. *Extremism and the Rate of Convergence of ADA Scores*

A second property of the theory is that as agents repeatedly receive public signals, their beliefs are converging on the cumulative public signal and those agents whose beliefs are more precise find their beliefs converging slower. This logic leads to our second testable hypothesis: the more extreme is a legislator's voting record, the slower his voting record converges to the average voting record.[14] To test this hypothesis, we estimated the following equation:

$$(18) \quad ADA_{i,t} - M(ADA)_t = \sum_{j=1}^{8} \delta_j \rho_j [ADA_{i,t-1} - M(ADA)_{t-1}] + \epsilon_{i,t}$$

where $\text{ADA}_{i,t}$ is the real ADA score of legislator i for year t, $M(\text{ADA})_t$ is the mean real ADA score for all legislators in year t, and δ_j is a dummy variable that takes the value one if and only if legislator i's initial real ADA score was in the jth fractile of all legislators' initial real ADA scores. Fractile 1 includes the 12.5 percent of legislators with the lowest initial scores (most conservative) while fractile 8 includes the 12.5 percent with the highest initial scores (most liberal). The most moderate elements are in fractiles 4 and 5. Our theory predicts: $\rho_1 > \rho_2 > \rho_3 > \rho_4$ and $\rho_5 < \rho_6 < \rho_7 < \rho_8$; that is, the more extreme is a legislator's initial voting score—in terms of the fractile to which it belongs—the slower that his score converges to the average score among contemporaneous legislators.[15]

[14] Our theory predicts full convergence of ADA scores, which we do not expect to happen. We should get a prediction of partial but not full convergence by augmenting the model to allow legislators to learn about an idiosyncratic variable as well as a common variable.

[15] Ralph Braid offered the following alternative model to explain our results in Table 1. Suppose that legislator i votes the same as the ADA with probability ξ_i and legislators differ in terms of this probability. In that the variance of legislator i's ADA score is decreasing in $|\xi_i - \frac{1}{2}|$, this model also predicts the relationship in Table 1. However, it

TABLE 2—ESTIMATED COEFFICIENTS OF CONVERGENCE TO AVERAGE VOTING RECORD
$ADA_{i,t} - M(ADA)_t = \Sigma_{i=1}^{8} \delta_i \rho_j [ADA_{i,t-1} - M(ADA)_{t-1}] + \epsilon_{i,t}$

Coefficient on:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FRACTILE 1	0.922	0.940	0.970	0.974	0.966	0.968	0.943	0.962
	(0.009)	(0.007)	(0.007)	(0.007)	(0.010)	(0.009)	(0.006)	(0.010)
FRACTILE 2	0.958	0.968	0.975	0.981	0.977	0.982	0.963	0.969
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
FRACTILE 3	0.955	0.969	0.960	0.970	0.971	0.981	0.924	0.936
	(0.009)	(0.007)	(0.007)	(0.007)	(0.010)	(0.009)	(0.008)	(0.007)
FRACTILE 4	0.893	0.911	0.920	0.931	0.921	0.934	0.840	0.891
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)	(0.007)
FRACTILE 5	0.791	0.826	0.814	0.849	0.778	0.799	0.821	0.797
	(0.013)	(0.012)	(0.015)	(0.013)	(0.019)	(0.019)	(0.012)	(0.011)
FRACTILE 6	0.862	0.885	0.862	0.888	0.816	0.813	0.879	0.878
	(0.011)	(0.010)	(0.012)	(0.011)	(0.017)	(0.017)	(0.009)	(0.009)
FRACTILE 7	0.916	0.929	0.922	0.937	0.893	0.909	0.928	0.935
	(0.007)	(0.006)	(0.008)	(0.007)	(0.011)	(0.010)	(0.006)	(0.006)
FRACTILE 8	0.947	0.957	0.952	0.965	0.943	0.954	0.951	0.944
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
MIN*FRAC 1	—	—	—	—	—	—	—	−0.085
	—	—	—	—	—	—	—	(0.014)
MIN*FRAC 8	—	—	—	—	—	—	—	−0.433
	—	—	—	—	—	—	—	(0.094)
$\bar{R}^2$	0.85	0.85	0.88	0.88	0.88	0.88	0.85	0.85
OBSERVATIONS	17,630	17,630	12,648	12,648	9,432	9,432	17,383	17,630

Notes: The specifications in the table are variations of the above regression. Column (1) includes all legislators from 1950–1990. Column (2) estimates column (1)'s model using absolute rather than squared deviations. Column (3) includes all legislators with at least six years of tenure from 1950–1990. Column (4) estimates column (3)'s model using absolute rather than squared deviations. Column (5) estimates column (1)'s model from 1970–1990. Column (6) estimates column (5)'s model using absolute rather than squared deviations. Column (7) estimates column (1)'s model excluding conservative Democrats, i.e., Democratic legislators with ADA scores in the most conservative quartile. Column (8) estimates column (1)'s model with dummy variables for minimum (ADA = 0) and maximum (ADA = 100) interacted with the appropriate fractile. All standard errors are robust to heteroskedasticity of unknown form and are given in parentheses.

Table 2 reports various estimations of (18). Summarizing the results, it is generally found that the estimated coefficients for fractiles 2 through 8 are in the predicted order: $\hat{\rho}_2 > \hat{\rho}_3 > \hat{\rho}_4$ and $\hat{\rho}_5 < \hat{\rho}_6 < \hat{\rho}_7 < \hat{\rho}_8$. Examining the liberal side of the spectrum for column (1), the distance between the average voting score and the voting score of those legislators in fractile 5 fell, on average, by 18.9 percent annually while it fell by only 13.8 percent for those in fractile 6, 8.4 percent for those in fractile 7, and 5.3 percent for those in fractile 8. The estimated coefficients for fractiles 5 through 8 are generally significantly different from each another at the 0.01 level. Turning to the conservative side, the evidence is supportive—though not as strong. While the coefficient for fractile 4 is less than that for fractiles 1, 2, and 3 and the differences are significant at the 0.01 level, the coefficients for fractiles 2 and 3 are not significantly different. These results are robust to: (i) excluding legislators with less than six years in Congress [columns (3–4)]; (ii) limiting the sample to the narrower time frame of 1970–1990 [columns (5–6)]; and (iii) reestimating the model using absolute rather than squared deviations so as to reduce the influence of outliers [columns (2), (4), and (6)]. In summary, there is solid confirmation of the prediction that the voting scores of more extreme politicians converge slower to the average score in Congress.[16]

does not predict that ADA scores would be converging at differential rates. Thus, the empirical analysis in this section will allow us to differentiate between this alternative theory and our theory.

[16] An unexplained finding is the difference in the strength of results between liberals and conservatives. This difference may be due to conservatives being a more diverse

An empirical finding inconsistent with the theory is that the estimated coefficient for fractile 1 is less than that for fractile 2 and, for some regressions, the difference is statistically significant. This may be due to a potential source of bias not yet discussed, which is that the distribution of ADA scores is bounded so that the tails are truncated. This could bias our estimates of ρ_1 and ρ_8. A legislator who has the lowest (highest) ADA score cannot get a lower (higher) score even if he became more conservative (liberal), while he would get a higher (lower) score if he became more liberal (conservative). This would bias results in favor of supporting our hypothesis for the empirical model in Table 1, as then those who are very conservative or very liberal have little room to move. On the other hand, it biases against supporting our hypothesis for the empirical model in Table 2. In that case, the increased conservatism (liberalism) would not be picked up so that our estimate of $\rho_1(\rho_8)$ would tend to overestimate the rate of convergence for the most extreme legislators, which works against finding support for our hypotheses. To examine this issue, we reestimated both models after excluding all legislators who had a nominal ADA score of 0 or 100 at any time in their legislative career. The qualitative findings in Tables 1 and 2 persisted.[17]

E. *Extremism and Variability in a Legislator's ADA Rank*

In light of the bias associated with the mapping from a legislator's policy position to his ADA score, we now consider an alternative model that is immune to this bias. The empirical model involves the estimation of the probability that the fractile within which a legislator's ADA score lies switches from year to year and to what extent this probability is related to a legislator's extremism, where extremism is measured by the fractile in which a legislator's initial ADA score lies. This model does not suffer from the above-mentioned bias because such bias is due to ADA scores being a nonlinear function of a legislator's optimal policy position, and this approach uses only ordinal information—the fractile within which a legislator's score lies.

The probability that legislator i's score switches fractiles between periods $t-1$ and t is specified to be:

$$(19)\quad P(switch)_{i,t} = \sum_{i=1}^{4} \rho_i[FRACTILE_{i,0}] + \gamma\mathbf{Z} + \epsilon_{i,t}.$$

If a legislator's initial-year score was in fractile i or $8-i$ (where the population of scores are those for that legislator's initial year) then the variable $FRACTILE_{i,0}$ equals 1 and is 0 otherwise. $\mathbf{Z}$ is a vector of control variables: general economic indicators—last period's unemployment rate ($UNEM_{t-1}$) and inflation rate ($INFLATION_{t-1}$); the number of years the legislator has been in office ($TENURE_{i,t-1}$); whether the legislator is up for reelection (where $ELECTION_{t-1} = 1$ if that is the case); and a time trend. Table 3 shows the probit results.[18] The estimated coefficients are monotonically increasing as the fractile containing a legislator's initial score becomes more moderate. In all regressions, the probability of switching fractiles is higher, the more moderate is a legislator's initial ADA score.

In summing all of the empirical evidence, we find that those members of Congress who are relatively extreme—as measured by the ideological content of their initial voting record—tend to change their voting behavior less over

group in that it includes both Republicans and southern Democrats, which may muddy up results. Excluding those Democrats in fractiles 1 and 2, we reran the model [column (7)]. The results for conservatives are stronger in that the estimated coefficients for fractiles 2, 3, and 4 are all in the correct order and the differences are significant at the 0.01 level.

[17] We also directly tested the hypothesis that truncation is biasing results by adding two independent variables. MIN interacts with FRACTILE 1 and takes the value 1 when the (associated nominal) ADA score equals 0. MAX interacts with FRACTILE 8 and takes the value 1 when the (associated nominal) ADA score equals 100. Both of these variables are negative and significant, which means that the truncated values tend to lower estimates for ρ_1 and ρ_8. Our qualitative findings are strengthened in that the estimate for ρ_1 is no longer significantly higher than that for ρ_2.

[18] Qualitative results are robust to estimating a logit model.

TABLE 3—ESTIMATED COEFFICIENTS IN PROBABILITY OF SWITCHING MODEL (PROBIT) USING INITIAL PERIOD'S MEASURE $P(switch)_{i,t} = \Sigma_{i=1}^{4} \rho_i[FRACTILE_{i,0}] + \gamma\mathbf{Z} + \epsilon_{i,t}$

Coefficient on:	(1)	(2)	(3)	(4)	(5)
FRACTILE 1,8	0.034	0.001	0.190	−0.047	−0.053
	(0.047)	(0.052)	(0.111)	(0.098)	(0.109)
FRACTILE 2,7	0.341	0.302	0.543	0.258	0.222
	(0.047)	(0.052)	(0.112)	(0.098)	(0.110)
FRACTILE 3,6	0.544	0.515	0.695	0.459	0.426
	(0.048)	(0.053)	(0.117)	(0.097)	(0.110)
FRACTILE 4,5	0.591	0.559	0.756	0.503	0.520
	(0.049)	(0.054)	(0.116)	(0.098)	(0.113)
$TENURE_{i,t-1}$	−0.010	−0.010	−0.011	−0.010	−0.007
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)
$UNEM_{t-1}$	−0.026	−0.026	−0.028	−0.026	0.005
	(0.008)	(0.008)	(0.018)	(0.008)	(0.010)
$INFLATION_{t-1}$	0.026	0.029	0.012	0.026	0.020
	(0.004)	(0.004)	(0.008)	(0.004)	(0.005)
$ELECTION_{t-1}$	0.085	0.081	0.107	0.087	−0.018
	(0.020)	(0.023)	(0.047)	(0.020)	(0.027)
$TIME_t$	−0.008	−0.008	−0.010	−0.008	−0.009
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)
Ln *L*	−10,645	−8,659	−1,981	−10,583	−5,898
OBSERVATIONS	15,767	12,826	2,941	15,767	8,697

Notes: The specifications in the table are variations of the above regression. Column (1) includes all legislators with at least six years of experience from 1950–1990. Column (2) estimates column (1)'s model for the House. Column (3) estimates column (1)'s model for the Senate. Column (4) estimates column (1)'s model with district dummy variables. Column (5) estimates column (1)'s model from 1970–1990. All standard errors are given in parentheses.

time. This evidence is consistent with extremists being rigid and moderates being flexible.[19]

IV. Concluding Remarks

This paper makes a case for there being a positive correlation between the traits of extreme opinions and rigid thinking. What are some implications of such a correlation? A standard model would most likely predict that leaders (whether in the context of a country, a firm, or some other form of society) whose views are far from the mainstream would be forced to engage in greater compromise than leaders with more mainstream views. However, our result suggests a quite different prediction. If extreme views are associated with a rigidity in one's thinking then leaders with more extreme views may actually be less willing to compromise and, furthermore, eventual actions may be closer to their ideal point than what would be true for a leader with more moderate views. But why should a society concede to such extreme demands? First, since a relatively rigid agent is less inclined to compromise, he is then more inclined to pursue activities that risk a stalemate. Engaging in potentially costly activities may act as a credible signal of a lack of willingness to compromise. The more flexible members of society may have little choice but to cave in. Second, if there is indeed a positive correlation between extreme views and rigid thinking among society's members, people are likely to infer such an association through their experiences, whether consciously or subconsciously. When a leader comes into power who has held nonmainstream views for a long time, society may recognize that they will either need to do most of the compromising or nothing will get done.

[19] Keith T. Poole and Howard Rosenthal (1984) look at a closely related issue. They do not develop a theory that relates individual traits but do estimate an empirical model using voting data that allows legislators' utility functions to differ in their location—which measures the ideal point, and shape—which measures the intensity of preferences. Using cross-sectional data for the Senate, they found results consistent with ours—in that more extreme legislators have more intense preferences—though it is important to remember that intensity is defined differently from our measure of rigidity. This relationship was not found for the House, though the source of the problem might have been computational (Poole, private communication, September 16, 1995).

While the implications of a positive correlation between extreme views and rigid thinking obviously need to be worked out, the above argument would suggest that there may be some substantive implications generated by it. Hopefully, this paper may spark some ideas as to the social contexts within which it may be quite important and thus worthy of investigation.

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