

A Model of Choice for Public Policy

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ABSTRACT

Punctuated equilibrium is supposed to be a viable alternative to incrementalism, and, indeed, the authors of the model have sometimes made such claims. But punctuated equilibrium was developed to explain change in policy subsystems and does not serve as a complete model of policy choice in the same way that incrementalism has served. This article develops a full-blown and viable model of choice for public policy based on disproportionate information processing. Its dynamics are based in the allocation of political attention to policy topics and the manner in which political systems process information. The model leads directly to outcomes that are consistent with punctuated equilibrium and are not generally consistent with incrementalism. Incrementalism, however, may be deduced from the model as a special case. The model is best tested using stochastic process approaches. Incrementalism logically must yield a normal distribution of outcomes, but disproportionate information processing yields leptokurtic outcomes. Adding institutional constraints only makes the stochastic process implications more severe. To support our arguments, we present both static and dynamic simulations of these processes. We also show that these simulations are consistent with observations of U.S. government budgets.

Incrementalism implies that policy choice at a particular time is a marginal adjustment from a previous policy choice. The model has been thoroughly discredited by theoretical, methodological, and empirical critiques, but it survives because no convincing alternative has been offered. It is the purpose of this article to offer such an alternative, one that shows how incrementalism is a special case of a generalized updating model we term *disproportionate information processing*. It is also the foundation for punctuated equilibrium, so it unifies incrementalism and punctuated equilibrium within a single decision-making model. Incrementalism failed because it had no underlying theory of information processing; once one is specified, the rest is easy.

Models of policy choice are best tested using stochastic process methods that focus on full distributions of choices rather than single choices. We examine the stochastic process implications of disproportionate information processing and compare these implications to

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incrementalism, and we present some simulations that indicate how robust these results are. Finally, by comparing the results from our simulations with actual budget distributions, we show that disproportionate information processing is consistent with these distributions but incrementalism is not.

THE INCREMENTAL MODEL

The notion that decision makers make incremental course corrections from the status quo has dominated thinking about policy change since the late 1950s. While the concept is general, it has been applied with particular success in the study of public budgets. Scholars drawing on Lindblom (1959), Wildavsky (1964), and others have argued that annual budget results tend to drift rather than to shift abruptly. Budgets were powerfully affected by the concepts of “base” and “fair share,” which assume that each year’s budget should be based on the previous allocation and that any increment should be shared relatively equally across categories and agencies.

The incremental model as a descriptive model of policy choice has been subject to withering fire on theoretical, methodological, and empirical grounds, all profound criticisms that it did not survive. Critics have noted problems in the models used by Davis, Dempster, and Wildavsky (Gist 1982; Natchez and Bupp 1973), in the measures used (Wanat 1974), in the conceptual clarity of terms (Berry 1990; Hayes 1992), and in the nature of the underlying decision-making model (Padgett 1980, 1981). Others have complained of problems in capturing the complexities with simple theories of budgeting, particularly the incremental model (Kiel and Elliott 1992; Rubin 1988; Schick 1998). While the incremental model was discredited by these critiques, it was never replaced by a viable alternative.

The incrementalists based their approach to budget behavior on models of decision making featuring “considerations of limited rationality in the face of complexity and uncertainty” (Davis, Dempster, and Wildavsky 1974, 421). In that framework, outputs are governed by standard operating procedures, and these SOPs are incremental in nature. Participants have been expected to use incremental decision rules for three reasons. The first involves the relative ease of reversing mistakes following incremental changes. The second concerns the desire of participants to establish stable expectations in a complex and uncertain environment. The third concerns the nature of overlapping, conflicting, and interacting institutions in American politics, which push participants toward compromise (Davis, Dempster, and Wildavsky 1966, 1974; Fenno 1966; Lindblom 1959; Wildavsky 1964).

All of this does a fine job of explaining where the drag comes from—why decision makers might rely on the status quo and adjust policy from that point. *But it does not offer much of a guide concerning how decision makers arrive at these adjustments.* It turns out that this is the Achilles heel of the incremental model. A wrongheaded updating model is why the incremental model is so demonstrably wrong when it comes to empirical testing. It is also the key to developing a decision-making model that avoids the difficulties of the incremental model while allowing that model to be deduced as a special case.

Incrementalism in its pure form implies that a decision path will be a random walk through time. This is the case because today’s decision is an adjustment from yesterday’s. Since we do not know exactly how incremental adjustments are made at any one point in time, we commonly assume that the adjustment is random. The central limit theorem is

a strong buttress for assuming that changes from the status quo are drawn from a normal distribution. Hence we can write (Padgett 1980):

$$P_t = P_{t-1} + \varepsilon_t \quad [1]$$

or

$$P_t - P_{t-1} = \varepsilon_t$$

Policy today (P_t) is policy yesterday (P_{t-1}) plus or minus a random component. This implies directly that any period-to-period policy change is simply a random component. If we sum up all these changes or first differences, then the resulting frequency distribution would be approximately normal. The reason is because of our standard assumptions about the error term of the model and the central limit theorem. If we add up all these error terms, each of which is drawn from an unknown distribution with finite variance, then the sum of these terms will be a normal distribution.

Considerable debate, much of it based on misunderstandings, has characterized the notion of incrementalism. Much of the debate has centered on “how large” a policy change would need to be to qualify as “nonincremental.” Any particular policy change in the eye of one beholder can be trivial; in the eye of another, it can be huge. In the absence of an agreed-upon standard, the question of policy change versus continued policy stability is unanswerable. That argument is needless in the distributional perspective, where any change is judged relative to the overall pattern of policy stability and change. If incrementalism holds, then the distribution of policy changes across time must be normally distributed. If it is not so distributed, incrementalism cannot be the right model for the decision process.

INCREMENTALISM AND UPWARD DRIFT

An important modification of the incrementalist model we call “incrementalism with upward drift.” Government budgets in most developed democracies have moved upward since World War II, a payoff from successful economic management. In such an environment, incrementalist politics of mutual partisan adjustment and successive limited comparisons (Lindblom 1959) is played out within a growing pie. Moreover, many programs are funded by formulas that include the size of the target population or some sort of poverty-level floor. These aspects of program funding can result in growth of budgets as the economy grows.

This suggests that the year-to-year upward drift is proportional to last year’s budget. Economists have faced a somewhat similar problem, the growth of firms over time. If the factors influencing growth were similar for large and small firms, as they would be if a growing economy lifts all boats, then the growth of firms over time would be proportional to the size of the firm. This assumption is enshrined in economics as the Gibrat thesis (Cefis, Ciccarelli, and Orsenigo 2001).

Incrementalism with upward drift would imply a similar thesis with regard to government budgets. The economy would lift all programs, leading to a proportional growth increment rather than the additive growth increment postulated in the pure incremental model of equation 1. If this stronger form of upward drift, the Gibrat thesis, were applied to government budgets, it would imply that the annual percentage change (rather than the annual dollar change) would be constant—up to the random component. In this formulation the annual percentage change in budgetary commitments would follow a random walk, and the annual proportional (or percentage) difference would follow a normal distribution.

Equation 2 says that the policy at time t equals the policy at the earlier time period $t - 1$ plus a component that is proportional to the policy at the earlier time period and a random component:

$$P_t = P_{t-1} + kP_{t-1} + \varepsilon_t \tag{2}$$

(sometimes written as $P_t = [1 + k]P_{t-1} + \varepsilon_t$)

We can express this as

$$P_t - P_{t-1} = kP_{t-1} + \varepsilon_t$$

and

$$(P_t - P_{t-1})/P_{t-1} = k + \omega_t$$

where

$$\omega_t = \varepsilon_t/P_{t-1}$$

This shows that the proportional change—the change in policy positions between time 1 and time 2 divided by the policy position at time 1—is a constant. That is, the proportional (or percentage, if we just multiply by 100) change is a constant, k . This proportional growth increment is constant across time.

The pure incremental model predicts a normal distribution for first differences; the Gibrat model applied to government budgets implies that the percentage change distribution will be normal. The constant, k , just augments each value of the frequency distribution and hence will not affect the shape of the distribution. What we would observe is a location of the center of the distribution at some positive number rather than the 0 predicted by the pure incremental model. Of course, punctuated change can coexist with upward drift. In the United States, the typical program has grown at 4 percent or so since 1947. The Gibrat form of the incremental model, however, predicts that the 4 percent growth is the whole story and that all the other changes would just fall in a normal distribution around this value.

It is critical to understand that a straightforward incremental policy process will invariably lead to an outcome change distribution that is normal. And vice versa: *any normal distribution of policy outcome changes must have been generated by an incremental policy process.* Any time we observe any nonnormal distribution of policy change, we must conclude that incrementalism cannot alone be responsible for policy change. That is why distributional analyses are so critical to policy studies.

EMPIRICAL EVIDENCE ON BUDGET DISTRIBUTIONS

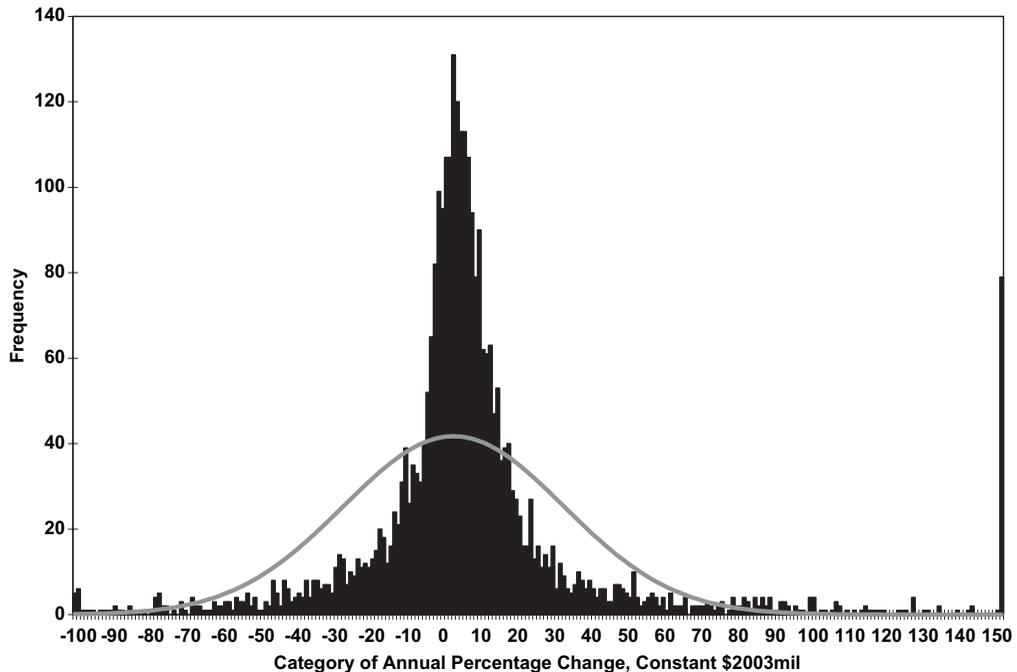
An examination of empirical budget distributions shows that they are never normally distributed. The typical pattern is clearly leptokurtic. Figure 1 shows the classic pattern. It is a pooled frequency distribution of inflation-adjusted annual percentage changes of U.S. Office of Management and Budget subfunctions for 1947 through 2003. Pooling across subcategories is necessary because of the relative short length of the time series.

A normal distribution with standard deviation approximately equal to the standard deviation of the frequency distribution is added to the figure for comparison purposes.¹ It is

1 The standard deviation for the raw distribution is 343; for the pooled distribution it is approximately 35. This is due to the extreme positive values for some categories of expenditure. We have used a standard deviation of 30 to plot the normal distribution on the graph.

Figure 1

Pooled Frequency Distribution of Annual Percentage Changes in U.S. Congressional Budget Authority, Fy1947–2003, in Constant 2003 Million Dollars



clear from this heuristic comparison, and it is clear from more exacting statistical tests, that the distribution is not normal.

This “shape of change” is familiar to many students of public policy (Jones, Sulkin, and Larsen 2003; True, Jones, and Baumgartner 1999). But the distribution of budget changes for the U.S. national government is not unique; other studies have found similar distributions in U.S. municipalities (Jordan 2003), British and German national budgets (Breunig 2003; John and Margetts 2003), Danish local budgets (Mortensen 2003), and Texas school district expenditures (Robinson 2004). The pattern is general, and the implication is clear: public budgeting is not incremental. What is to be explained is the leptokurtic distribution of changes.

Punctuated equilibrium (Baumgartner and Jones 1993) predicts outcomes consistent with budgetary leptokurtosis, with long periods of policy stasis interrupted episodically with bursts of rapid policy change. But punctuated equilibrium is narrower than incrementalism; it is a policy-making model but not fundamentally a decision-making model. In important ways, incrementalism is both, because it predicts a path of policy outcomes (“product incrementalism”) and a decision-making style (“process incrementalism”). However, underlying punctuated equilibrium is a decision-making model, attention-driven choice (Jones 2001; Jones and Baumgartner 2005). Attention at the individual and collective levels governs the shift from stasis to the positive feedback processes that define rapid change. By providing a model of choice that is consistent with both incrementalism and punctuated equilibrium, we hope to put to rest the confusion that has characterized discussions about decision making and public policy.

IMPLICIT INDICATORS AS UPDATING

Two different perspectives have guided studies of information processing in politics. In one, information is viewed as a scarce good, and a decision maker must pay search costs of some form or another to update his or her beliefs about the world (Downs 1957; Krehbiel 1991). Information is supplied only when it is paid for (the search costs). In the second perspective, information is freely supplied, but it is of varying reliability, and the decision maker must prioritize the competing messages. Our model is based in this second perspective, which is more relevant for policy choice. Simon (1996) writes of an “information-rich” world where attention, not information, is the scarce good, and Rick Hall notes that “policy relevant information is abundant, perhaps embarrassingly rich, on Capitol Hill” (1996, 90). The reasons for such information oversupply are twofold. The first is that the incentives for interest groups, think tanks, and administrative agencies are to produce rather than to withhold information; otherwise your competitor will supply the information. So in politics, unlike economics, the incentives are to produce rather than withhold information. Second, Congress has established in the past many agencies whose primary or even sole duty is to produce information—reports, analyses, testimony, and so on.

So in politics a good starting point is to ask how policy makers attend to and prioritize information.² We actually have good theories about what to do if we have lots of noisy information about the state of the world. The simple, basic weighted average is the workhorse in information-rich situations. In educational testing, we weight items by reliability to produce a score, or index, across testing items. The worth of capital markets is assessed by an index of stock prices weighted by market shares. Economies are judged by weighted averages of goods and services. In political science, the positions of legislators are judged by Poole-Rosenthal scores, which are based on roll-call votes weighted by their relevance to an underlying dimensional structure.

In all of these and many more situations a decision maker explicitly forms an index out of numerous, often noisy sources of information and keys future choices to the value of the index. But decision makers invariably are producing implicit indicators on virtually every choice they make. Probably the most vivid description of this process of *implicit index construction* is Doug Arnold’s (1990) description of how legislators estimate the potential preferences, which are preferences that are potentially evoked in an election campaign. Arnold writes that legislators “talk with and listen to their constituents, they read their mail, they watch how issues develop over time, they look for clues about salience and intensity, they consider who might have an incentive to arouse public opinion, they learn from others’ mistakes . . . legislators need only combine estimates from various sources in order to estimate their own constituents’ potential preferences” (1990, 10).

The trick is in the combining. How are these diverse sources combined in a sensible manner to reflect the changing state of the world? Combining messages means both getting the sources right and getting the weights right. Not all sources in Arnold’s potential preference study are equally valid and reliable. If one has good estimates of reliability, then those can serve as weights, but this will not solve the salience problem. An indicator may shift its relevance to political action rapidly in the political fray. Prior to the publishing of photographs of prisoner abuse at Abu Ghraib Prison in Iraq, policy makers had treated this

2 This does not mean that searching is unimportant; clearly at some level it is critical, but search alone does not solve the prioritization problem.

aspect of the occupation as irrelevant, even though there was plenty of information that indicated problems. The vividness of the photographs shifted the salience of this issue.

RATIONAL UPDATING

The best way to update one's beliefs about the world when information is plentiful and sources are fallible is by keying action to an index made up of a weighted combination of indicators, with the weights determined by relevance to the part of the world being monitored and the reliability of the information. We leave the question of how weights are determined aside for the present, but we note that there are standard ways in some circumstances for dealing with them. For example, relevance may be judged through interitem correlations (such as is done in creating standardized tests), and reliability may be judged through repeated measures.

The implicit index model, simply a weighted average of indicators, can be written as

$$L_t = \omega_{1t}I_{1t} + \omega_{2t}I_{2t} + \dots + \omega_{kt}I_{kt} + \gamma_t \quad [3]$$

where

L_t is the value of the index at time t ,

I_{kt} is the k th indicator of the state of the world,

ω_{kt} is the weight for the k th indicator,

and γ_t is a random error component.

If the index is used to update prior beliefs about the world, we can write

$$D_t = kL_t - D_{t-1} + \xi_t$$

$$D_t = k(\omega_{1t}I_{1t} + \omega_{2t}I_{2t} + \dots + \omega_{kt}I_{kt} + \gamma_t) - D_{t-1} + \xi_t$$

or

$$(D_t - D_{t-1}) = k(\omega_{1t}I_{1t} + \omega_{2t}I_{2t} + \dots + \omega_{kt}I_{kt} + \gamma_t) + \xi_t \quad [4]$$

where

D_t is the decision at time t ,

D_{t-1} is the decision at time $t - 1$,

ξ_t is a random component,

and k is just a constant to adjust the units of the index to the units of the decision.

The change from last period's decision is just keyed to the value of the index. That is, a decision maker in a choice situation would examine an index comprising a weighted combination of indicators and update his or her beliefs based on this index. The decision would be a direct consequence of this updating.

STOCHASTIC PROCESS IMPLICATIONS OF THE IMPLICIT INDEX MODEL

What happens if we were to examine a frequency distribution of decision-to-decision first differences where decision makers were using an implicit index model of the form of

equations 3 and 4? We know that a pure incremental model of decision making yields a normal distribution of first differences. In the case of the implicit indicator approach, we know nothing about the particular distributions of underlying indicators, but it would be very difficult to assume that these indicators were normally distributed. Most indicators are probably not normally distributed, since they could indicate the need for policy action due to wars, natural disasters, financial crises, and so forth, none of which is likely to be distributed normally. In the limit, however, a weighted combination of these distributions will be normally distributed, so long as there is a sufficient number of indicators and the weights are not radically different from one another. This is a result of the central limit theorem, which is remarkably robust with respect to the form of the linear combination of the indicators.

As a consequence, the distribution of first differences under conditions of rational updating will be normal. But we note that incremental decision making under the standard assumptions yields a normal distribution. In fact, the standard incremental model has a “hidden assumption” in it: that decision makers update in a fashion consistent with the implicit indicator approach. That is, the incremental model will yield a normal distribution of outcomes only if policy changes are keyed to a sum of external events.³ If incremental decision makers do not update according to an approximation of the implicit indicator approach as laid out here, the distribution of their decisions will not be normal.

It turns out that the central limit theorem is very robust with respect to the number of variables that must be combined into an “index” in order to yield a normal distribution. We may show this by using a simple simulation. We have drawn a sample of 10,000 random digits for five different variables.⁴ These will serve as the indicators of problems facing government. We may think of these as various indicators of an underlying problem. To take one example, we can think of intelligence analysis about the potential threat from a potential enemy abroad. These indicators must be combined in order to make judgments about the necessity of government action.

Some of these indicators may be subject to severe threshold effects—for example, an indicator of the threat from North Korea could increase nonlinearly if a serious attempt at acquiring nuclear arms is discovered. Others may not be. The central limit theorem implies that if we weight and sum enough indicators, regardless of their distributions, so long as the weights are not terribly different from one another, the sum will be normally distributed.

A simple simulation illustrates this property graphically. We have applied five different nonlinear transformations to the five simulated random variables.⁵ Then we summed the five variables and prepared a histogram similar to that diagrammed in figure 1, the budget change histogram. The resulting diagram is presented in figure 2.

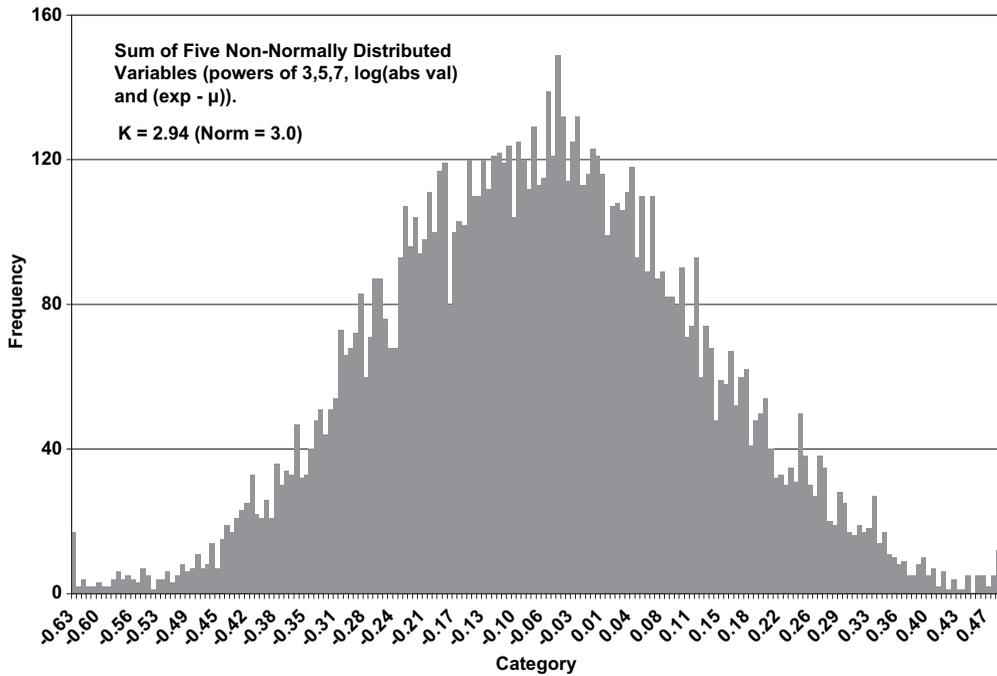
It is evident that the distribution approximates the normal distribution, and statistical tests indicate that it does not differ significantly from the normal. This is in many ways an astounding result, because of the limited number of variables we included and the very nonnormal shapes of each of the underlying indicators. Rational adaptation, in the sense of combining several indicators, each of which may be fallible and skewed itself, will lead over time to a normal distribution of responses to the problems that government faces. In

3 The implicit index is a decision-making interpretation of how the various “causes” of a decision are incorporated into the decision.

4 This was done using a uniform distribution with a mean of 0 and a standard deviation of 1.

5 The transformations were powers of 3, 5, and 7; the log of the absolute value; and the exponential of the variable minus the mean.

Figure 2
Frequency Distribution of the Sum of Five Nonnormally Distributed Random Variables



general, if government makes policy according to equation 3, then the outcomes would be normally distributed.

The fact that U.S. budget authority is definitely not normally distributed tells us something very important. It must mean that adjustments in budgets (that is, changes in budget allocations) are not simple sums of external challenges. That is, policy makers do not just study the various sources of information that they have available to them, combine them in some sort of index, and produce policy keyed to the index. Nor do they incrementally adjust from the last period's change with the adjustment keyed to numerous additive causes, consciously (via index construction) or nonconsciously (because whatever causes updating somehow mimics index construction). If they did that, budget outcomes would be normally distributed. Figure 2 shows that this would be the case even if they were facing a great range of different inputs, each being generated by a widely different process (and even if none of these input series were normal). As long as there were many inputs, the combination of many different ones would lead to a normal distribution of outputs.

Incrementalism is updating from the last period's policy decision. To make sense out of the model, we must assume that the updating is random. Ironically, this randomness occurs only when decision makers key their choices to numerous additive causes. This could occur consciously, because decision makers construct indexes that they act upon, or nonconsciously, because the mechanisms forcing choices mimic the index-construction process. In either case, the process might be characterized as *rational updating*, because index construction is a fully rational process in an information-rich world with fallible

indicators. If a policy distribution is not normal, then we are left with the conclusion that incrementalism with index-type updating cannot have occurred, and the process is something other than fully rational updating. *Only* additive, index-type updating will yield normality.

HEURISTICS, BOUNDED RATIONALITY, AND “INDICATOR LOCK”

Bounded rationality and attention-driven choice imply that people are unlikely to follow an index-construction strategy in dealing with most of the choices they face. Rather, they are more likely to hone in on one aspect of a complex situation and key decisions to that aspect. They “lock on” to one indicator, which serves as a heuristic for future decision making. Common heuristics in politics include the positions of party leaders and interest groups but can also include single-focus indicators summarized by catch phrases such as “the axis of evil” or “health care is a right.” Such symbolism leads us to judge the state of the world by reference to single indicators. Even when decision makers rely on a basket of indicators, it is likely that they shift weights as the context changes, fail to focus on many aspects of the world that may not immediately be relevant but have serious long-term consequences, and otherwise compromise the fully rational model of handling diverse signals in an information-rich world.

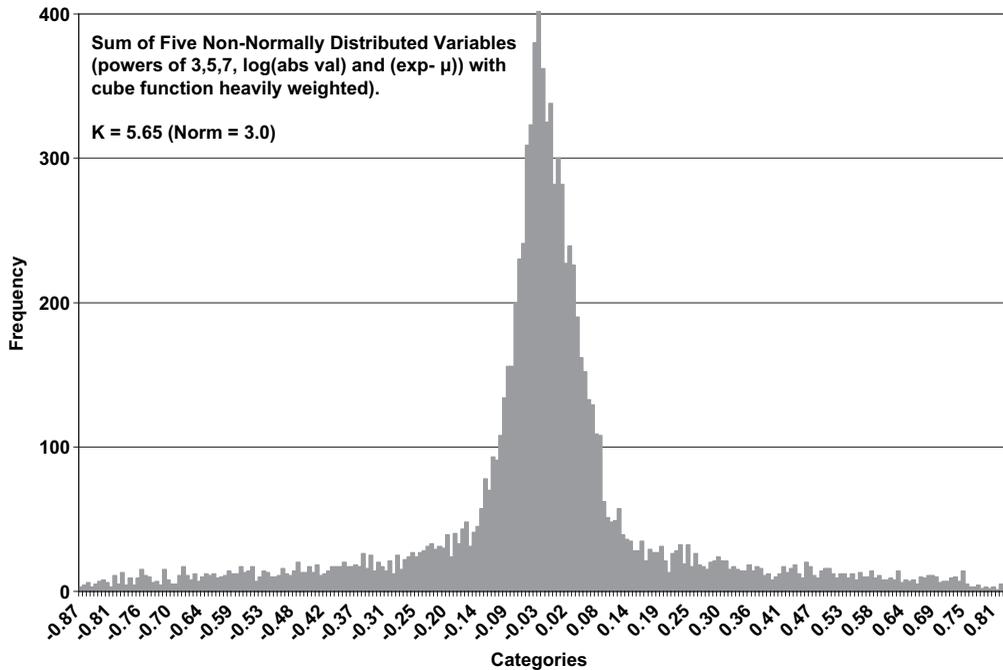
Unlike the balanced, proportional, and indeed rational updating that is a consequence of index construction, this is *disproportionate information processing* (Jones 2001; Jones and Baumgartner 2005). Some aspects of the world are unmonitored, unattended to; other aspects are incorporated into the decision process beyond their intrinsic merit. Decisions of course can be keyed only to those aspects of the world that are monitored. This works fine unless the unmonitored aspects of the world turn out to be relevant to the decision. If they are not incorporated in the decision, then errors in decisions—conceived of as the difference between what a full index would imply for choice and what the incomplete basket of monitored indicators implies—will cumulate over time. Such an error-accumulation model (Larkey 1979) implies disjoint and episodic adjustments in decision making that may or may not be keyed to episodes in the environment.

This is classic bounded rationality in the policy process. Because of the cognitive and emotional constitutions of decision makers, decision making is cybernetic, continually underadjusting and then overcorrecting in an erratic path. Suddenly decision makers recognize that previously ignored facets of the environment are relevant and scramble to incorporate them. Choice is attention driven because unmonitored aspects of reality must be brought into the choice calculus as it becomes impossible to ignore them. Decisions are always “catching up” to reality; generals are always fighting the last war.

The mistake, and maybe the only mistake, of the early incrementalists was the failure to recognize the role that attention plays in information updating. They understood the role of bounded rationality in forcing adjustments from the existing policy choice, but they did not appreciate the full implications of bounded rationality for error accumulation in incremental decision making and the consequent need to update episodically.

Institutions impose error correction by providing incentives to those who make course corrections. The legislator who fails to estimate the “potential preferences” of his or her constituents runs the risk of electoral defeat. The business executive who ignores market trends may watch as the company’s value declines. The worker who shirks risks the loss of a job. The more efficient the mechanisms that enforce error correction, the less erratic the decision path will be.

Figure 3
Frequency Distribution of the Sum of Five Nonnormally Distributed Random Variables with One Disproportionately Weighted



STOCHASTIC PROCESS IMPLICATIONS

What are the distributional implications of attention-driven updating? Indicator lock implies that the weights for the basket of indicators that the decision maker implicitly uses to monitor the world are unequal, probably severely so. In this case, the central limit theorem will not guarantee that the sum of a set of random variables will converge on a normal distribution as the number of indicators in the basket increases.

We may simulate this disproportionate response process in a manner similar to our simulation of proportionate information processing. We again generated 10,000 random numbers each for five separate nonnormally distributed variables. This time, instead of weighting each one equally, we gave one indicator a weight of 0.8, and the rest were weighted at 0.05.⁶ Then we summed the weighted indicators and plotted the results as shown in figure 3.

The distribution is not at all normal. It is leptokurtic, with a kurtosis of 5.65. This distribution cannot have resulted from the nonnormality of indicators; it can only have been generated by the weights. Mathematically, the central limit theorem does not hold when the weights of the summed random variables differ from one another by a large amount. They do not, however, need to be equal; they just cannot be as wildly dissimilar as in our simulation.

⁶ The overweighted indicator was the cube. Overweighting any of the other indicators yields similar results, although the extent of the leptokurtosis changes.

If the weighted indicators were normally distributed, then the weighted series would be closer to normal. But a decision maker relying on a single indicator whose distribution was normal would be just “getting lucky,” because there is no statistical reason (or empirical reason that we can discern) for assuming that an arbitrarily chosen input stream would be normal. If a few indicators are simultaneously monitored, however, the result is a normal distribution of information. In particular, no expectation about the distribution of outputs can be asserted based on the happenstance that an arbitrarily chosen input distribution is normal.⁷

This is important to grasp. Even if each component part of informational input is nonnormally distributed, the full input distribution will be, so long as decision makers monitor a “basket” of indicators. If they produce policy responses that are proportional to the basket of indicators, they will produce normally distributed outputs. If they “panic” in response to one indicator, then the outputs will not be normal. They will be leptokurtic. *Leptokurtic distributions in policy choice are prime indicators of disproportionality in the choice process.*

Moreover, while any particular major change from the status quo can be explained with reference to specific exogenous events, the distinct budgetary leptokurtosis so in evidence cannot be explained with reference to the entire set of exogenous events. This paradox is a direct and unavoidable result of the central limit theorem. Given enough time and a few indicators, normality in outputs will prevail. Policy leptokurtosis is explicable only through a model of choice centering on the internal dynamics of policy making. One cannot find explanations of leptokurtic outputs in the input distributions alone.⁸

UPDATING AND ATTENTION-DRIVEN CHOICE

Decision makers are bombarded with information from many sources, and they may seek out other sources to inform themselves. How do they prioritize the information from these many sources, and how do they combine them in making decisions? How do they update their beliefs about the world and incorporate these new beliefs into decisions? The best way would be to weight the information streams by importance and add them to make an index. If participants in an institution receive information from independent diverse streams and weight and sum these diverse streams in an index, then the resulting distribution would be normal by the central limit theorem, at least in the limit.

Let us now turn to less-than-perfect human systems. If individual decision makers rely on a limited set of indicators to monitor their environments, and update them or include newly salient aspects of the environment in the decision-making calculus episodically, the result will be a flow of “news” (that is, the information flow that the decision maker attends to) that is not normal. If decision makers act on the “news,” rather than a basket of indicators, they will produce a distribution of outcomes that is not normal. Attention-driven choice guarantees nonnormal distributions of policy outputs.

The cognitive architecture of the decision maker imposes a selective bias on the flow of information. Of course, decision makers in politics will not cling forever to bad information, but they undoubtedly believe it far beyond its utility. When the information is

⁷ This assumption is commonly made by researchers studying policy outputs using a regression framework when they uncritically assume that the distribution of “errors” or “disturbances” is normal.

⁸ Attention-driven choice does not imply that decision making is disconnected from the flow of events, and there surely can be circumstances when weights are shifted in a manner that matches event severity. That will not change the powerful stochastic implications of the model, however.

exposed as faulty, the decision maker must shift to a new understanding of the situation. In effect, the decision maker locks choice into a set of facts based in the past and must update in a punctuated manner in the face of change that cannot be ignored. The “news”—that part of the information stream a decision maker attends to and interprets—is leptokurtic.

We have arrived at two very important results. First, pure incremental decision making updated by proportional responses to incoming signals will result in a normal distribution of policy changes. Proportional information processing, when there are multiple, fallible indicators, implies a normal distribution of choices. Updating a choice from a prior standing decision does not change this result. Incrementalism hinges completely on the proportionality assumption, although mostly this has gone unrecognized. As a consequence, proportionate updating in the incremental model is rational adaptation.

Incremental decision making updated by disproportional decision making, however, seems to lead to leptokurtic output distributions. Our model of updating recognizes that decision makers often overweight a single indicator among several. As a decision maker is forced to update using other potential indicators, a pattern of stability and punctuations occurs. This is boundedly rational updating.

We do not have any statistical theorems to justify this claim, but it is strongly suggested by our simulation. Several of the indicators included in the model were upward sloping, approximating threshold effects which suggest response only after a certain level of severity is reached. Others were downward sloping, suggesting a rapid response, then leveling off. In either situation, leptokurtic output distributions resulted from reliance on a single indicator.

We have analyzed decisions on a single policy topic, but a similar model holds among topics. Political leaders typically must juggle numerous policy topics, investing attention in a one-at-a-time manner. This juggling involves overattention to one area as all are changing. The result is an outcome distribution across policy areas that is leptokurtic. The logic is similar whether we focus on choices involved in a single decision or we focus on the panoply of issues that the political system processes.

The converse of these propositions is also true: normal output distributions invariably indicate incremental decision making with proportional updating, and leptokurtic output distributions are characteristic indicators of disproportionality in the choice process. If we observe such output distributions, we can conclude that disproportionate information processing is occurring.

FRICION IN POLITICAL INSTITUTIONS

We have concentrated thus far on human factors in decision making that generally lead to disproportionate information processing. Even without the friction of formal institutional arrangements, policy would be produced disproportionately. Add institutions into the mix, and the disproportionality can be magnified. One advantage of the stochastic approach we employ here is that we can examine theoretically these two sources of disproportionality even though we have no idea of the particular combinations that might emerge in any particular situation.

We need to be somewhat more precise about the idea that decision-making costs lead to institutional friction. The payoff will be a very general framework for studying political, economic, and social change where interactions among actors are structured by institutions. An *institution* may be defined as a set of individuals acting according to common rules

resulting in collective outcomes. Institutional rules are not neutral, in the sense that different rules often lead to different outcomes (Jackson 1990, 2). These aggregations of individuals interacting according to rules react to information from the environment and come to a collective response (even if the collective response is simply the sum of individual actions, as it is for markets and elections and roll-call voting in legislatures).

Decision-making systems impose four kinds of costs in making decisions in response to a changing environment: decision costs, transaction costs, information costs, and cognitive costs. *Decision costs* are costs that actors trying to come to agreement incur. They include bargaining costs and institutionally imposed costs, such as those built into a separation-of-powers governing arrangement (Bish 1973; Buchanan and Tullock 1962). *Transaction costs* are costs that parties incur after they come to agreement (North 1990). In market transactions, these involve such items as the cost of insuring compliance to contractual agreements and other payments to third parties to complete the transaction. It ought to be clear that in advanced democracies decision costs in the policy-making process heavily outweigh transaction costs. Bringing relevant parties to agreement in a system of separated powers (decision costs) generally outweighs the costs of holding hearings, enacting statutes, or changing budgetary allocations once agreement has been reached (transaction costs). In any case, we combine these costs in our analysis, terming them together “decision costs.”

Information costs are search costs—costs of obtaining information relevant to making a decision. These are costs that exist when a person (or an organization) *wants* to make a decision. *Cognitive costs* are costs associated with the limited processing capacity of any social institution made up of human beings. These are costs that occur because people *do not know* they need to make a decision. If one is not attending to a key component of the environment, then he or she cannot decide to incur search or information costs. Information and cognitive costs will be imposed in any decision-making system, but decision and transaction costs are highly sensitive to the particular rules and procedures of institutions. These are pure institutional costs.

Institutional costs in politics may approximate the manner in which friction operates in physical models. How can we assess the level of friction that is present in a decision-making institution? In essence, we will treat the cognitive architectures of decision makers as part of a general “cost structure” that affects the processing of information. That will allow us conceptually to integrate the formal institutional costs with the “cognitive costs” of boundedly rational decision makers.

The manner in which a policy-making system responds to information is critical in assessing policy change. As we have seen, the major problem with the initial incremental model of policy change is that it did not incorporate the flow of information from outside the system. No matter what the external challenge, the system responded incrementally. That is quite unrealistic and leads to models that are easily rejected. If we can understand how decision-making systems respond to information in the absence of any institutionally imposed costs, then that idealized model can serve as a basis of comparison for systems that impose such costs.

A hypothetical fully efficient decision-making institution that imposed no costs would respond seamlessly to the world around it. That is, it would incorporate all relevant aspects of the information it encountered and would “use up” all the information in its decision-making process. The outputs of such a system would perfectly reflect the information flows coming from its environment (Simon 1996). If there were big changes in the environment, the system would respond with big changes. Similarly, small changes would generate only

small changes. The major example of such a cost-free system is the classical model of a competitive economy.

In such a pure system,

$$R = \beta S \quad [5]$$

where

R = response = ΔO = change in output,

S = information (signal),

and β = benefits derived from the information flow (<1).

The system reacts directly to the input flow by changing its output. What happens in real institutions in which decision-making costs are imposed? If costs are assumed to act linearly on the system, then

$$R = \beta S - C \quad [6]$$

where

C = costs.

Our hypothetical system continues to respond directly to the input flow. Now, however, it will not act until it recovers the costs that must be invested in reacting to the flow of information. Where costs are low, signals of low power get reflected into public policy. Where costs are high, only the strongest signals are translated into public policy. But the addition of set decision costs would have no great impact on the classical model; it simply generates a constant subtraction from the reaction of the system to the inputs—the reaction remains proportionate. In any case, set costs are not realistic.

In politics costs are imposed only when actors take the trouble to use the system to block action. For minimal changes, actors who would normally be opposed might not take the trouble. For major changes, they can mobilize and make use of the system to try to block changes, but they can also get on a bandwagon and push for even greater action than the signal might indicate. Costs might be proportionately high for signals of low strength (making the response less than the signal); but they might decline as the signal got stronger (making the response potentially more powerful than the signal). This leads to a model in which costs go down as the strength of the signal increases. While we cannot know exactly the form of the equation translating inputs into outputs, we do know that it is multiplicative rather than additive as in equation 6. The signal and institutional costs interact with each other to magnify the effects of the signal. This severely complicates matters and generally leads to leptokurtic output distributions:

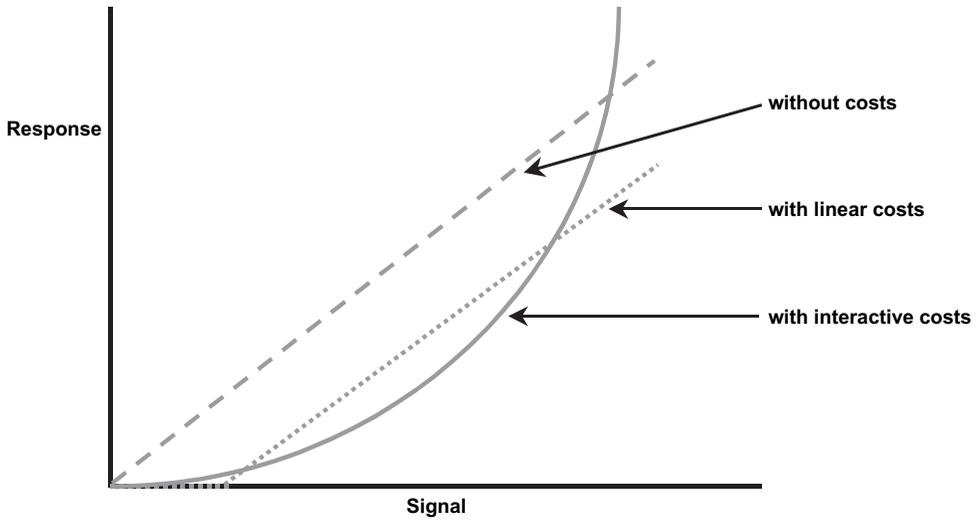
$$R = \beta S \times C \quad [7]$$

In this model, costs interact with the signal.

DISTRIBUTIONS

What would the different types of costs we just described generate in terms of distributions of outputs, when dealing with the same series of inputs? Figure 4 depicts idealized

Figure 4
Information-Processing Policy Systems with Institutional Costs



response functions to input flows for a frictionless cost-free policy system, a system with fixed institutional costs, and an interactive system. The frictionless system is highly sensitive to incoming information. For a hypothetical one-unit change in relevant information, the system responds with a proportional level of outputs. (If $\beta = 1$, then the inputs and the reactions are equal; if $\beta > 1$, outputs are stronger than inputs; if $\beta < 1$, then outputs are less than the inputs. But in any case the reactions are directly proportionate to the size of the input; this is reflected in the straight line going up from the origin along the 45-degree angle; it reflects a hypothetical β of 1.)

Figure 4 shows three curves: the frictionless one just described, one with fixed costs (also a straight line but to the right of the first one), and one with interactive costs (showing responses being very low but curving sharply upward as the size of the signal grows). The system with fixed institutional costs ignores signals of low intensity and then responds proportionally to the strength of the signal after some threshold in signal strength is reached. Like the first one, this model reacts proportionately but systematically at a lower level of response than if there were no decision costs. But let us consider the third line in some detail. This is the one where costs interact with the strength of the signal. In fact, the way we have modeled it here, costs reduce action up to some threshold and then gradually shift so that they amplify rather than reduce the reaction of the system to larger inputs. Such a model will produce virtually no response when signals are low but massive reactions to strong signals; leptokurtosis results from its disproportionality.

COMPLEXITY IN INFORMATION PROCESSING

The preceding discussion reflects the complexity of human decision-making systems. We have here tried to simplify by analyzing institutional costs within a single framework. The key question is how people interacting in political institutions process and respond to signals from the environment. If institutions add friction to informational inputs, then

outputs will not be directly related to inputs. But how will inputs and outputs differ in policy-making systems? We posit that whatever the input flow, the output flow will be both more stable (ignoring many important signals) and more punctuated (reacting strongly to some signals).

Lots of work in political science points toward an information-processing approach with political institutions playing major roles in creating the friction and disjointedness associated with this approach. Institutional analyses show that a “policy core” exists that is not responsive to changes in preferences (for example, through replacement of legislators in elections); but when preferences change enough to move the pivotal legislator’s preferences outside the core, then major punctuations in policy can occur (Hammond and Miller 1987; Krehbiel 1998). Policy process scholars have argued that policy agendas change when attentiveness and mobilization are directed at particular aspects of a complex environment, raising the probability of major policy innovations based on new ideas. Again, stability (when attention is not directed at the issue) and punctuation (when it is) occur in a single process (Baumgartner and Jones 1993). Similarly, in elections, first-past-the-post voting systems and partisan identifications by voters operate together to add great stability to election patterns that are nevertheless occasionally disrupted by realignments. In general, then, institutional decision costs will add to the kurtosis of output distributions.⁹

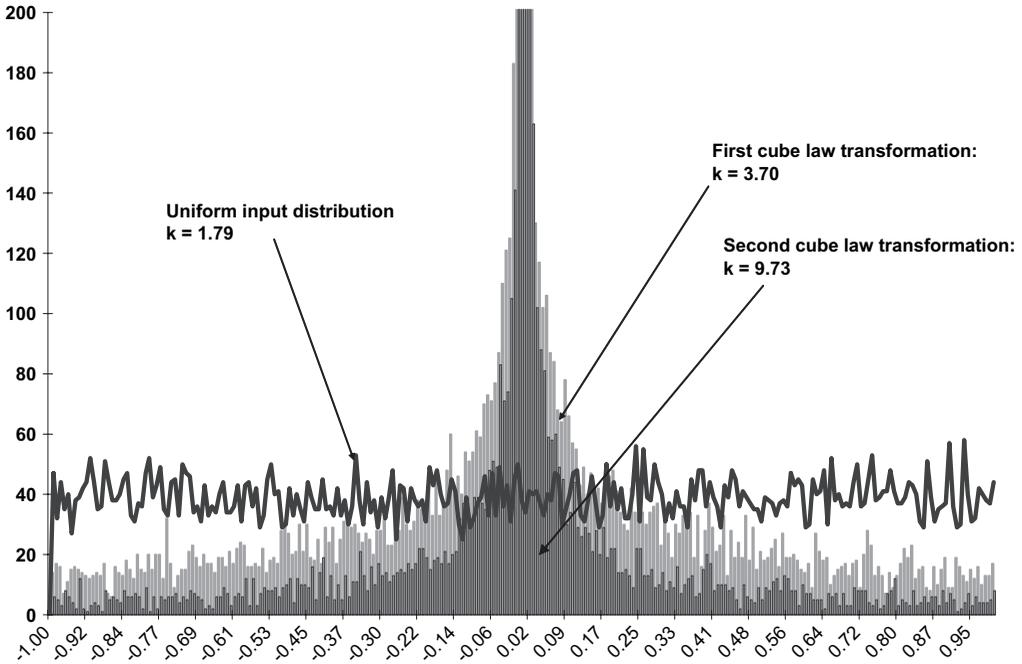
SIMULATING GENERALIZED COST STRUCTURES

We now offer some simulations of the effects of generalized interactive cost structures on the output distributions of decision-making systems. We present the results of two different simulations. The first is a static simulation, in two stages. For the static simulation we think of information processing as occurring in stages, one associated with cognitive costs and one associated with institutional costs. At each stage, costs are assumed to be disproportionate to the size of the input signal. Informational inputs are transformed first because of the inevitable cognitive costs that would be there no matter what the institutional setting. The resulting series is then transformed a second time to simulate the institutional costs that may also be present. For the sake of simplicity, both transformations are identical. This allows us to know whether a simple two-stage transformation can generate leptokurtic output distributions of the form of figure 1. Then we turn to a more complex but more realistic dynamic simulation and ask the same question.

Think of an input stream affecting a policy-making system. We may characterize the input stream as a distribution. Because informational signals stem from numerous diverse sources, it is a reasonable assumption that the underlying (but unobserved) input distribution is normal, as would be the case for the implicit index model. Then the system imposes nonlinear transformations on the input stream, as in figure 4. This simulates the case of delay in responding to input signals at low levels of intensity and then responding with increasing intensity to the signal as it increases. For our static simulations, we use a cubic transformation. The particular form of the transformation is arbitrary, but the general logic is not:

⁹ Institutions can also simplify decisions and overcome information and cognitive costs, leading to less kurtosis in outputs (Robinson 2004). But American national institutions were designed explicitly to impede overreacting and hence should lead to more kurtosis. Federalism, however, ought to operate against kurtosis by undermining veto coalitions (Baumgartner and Jones 1993).

Figure 5
 Frequency Distributions of a Uniform Information Input with Two Cube Law Transformations Applied Sequentially. (The y-axis is truncated to illustrate the differences between the bodies of the distributions.)



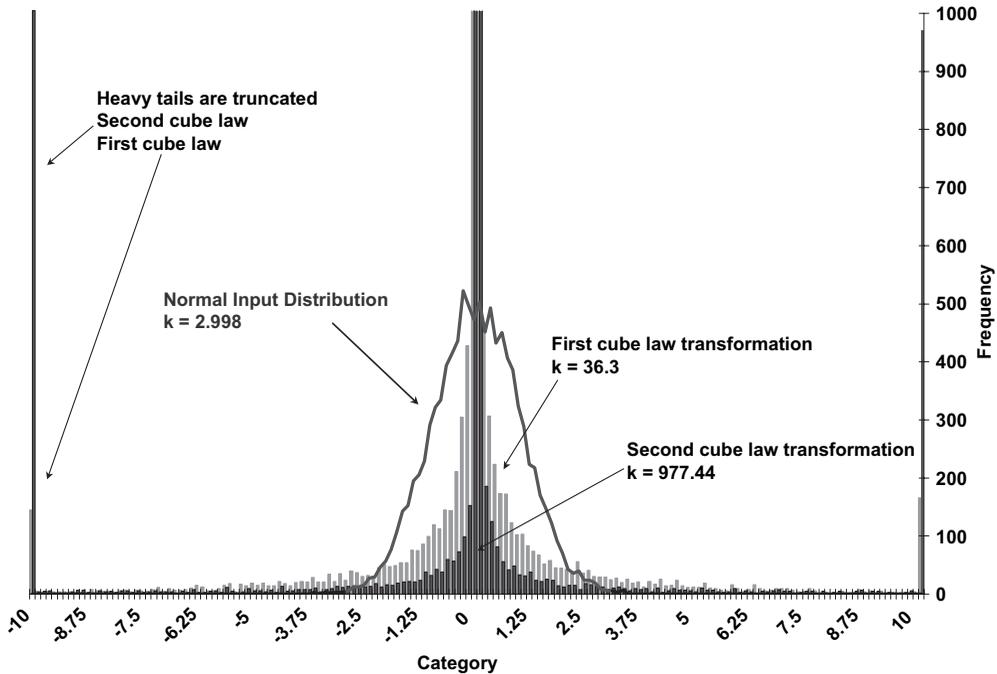
$$R = \beta S^3 \tag{8}$$

Before we simulate the likely situation of a normal input distribution, we present in figure 5 a simulation for the case of a uniform input distribution in order to get a firmer understanding of just what the transformations do. This is a kind of limiting case in which the world has some uncertainty but may be monitored by one indicator, and that indicator is uniform and unchanging. We generated 10,000 random numbers drawn from a uniform distribution with a mean of 0 and a standard deviation of 1. We cubed these numbers once and cubed the resulting numbers once again. Then we made frequency distributions for all three sets of 10,000 numbers. The input series, being uniform random, has a strongly negative kurtosis value (e.g., it is platykurtic rather than leptokurtic). The first cube law transformation yields a kurtosis of 3.70, slightly more than the normal, while the second’s kurtosis is 9.73 and is leptokurtic. Even in a hypothetical uniform world, nonlinear cognitive and institutional costs will yield leptokurtic output distributions.

Now we turn to a more realistic distribution of inputs in a complex world. The central limit theorem and the associated implicit index model dictate that the input distribution would be normal if diverse input streams are combined to yield an index or sum of the indicator values. Figure 6 simulates this situation, again with the two sequential cube transformations. Again the distributions are highly leptokurtic, with the first transformation producing a kurtosis of 36.30, and the second, 977.44. In both of these two important cases for the distribution of information coming into a policy-making system, outputs will be leptokurtic when costs are nonlinear.

Figure 6

Frequency Distributions of a Normal Information Input with Two Cube Law Transformations Applied Sequentially. (The y-axis is truncated to illustrate the differences between the bodies of the distributions.)



Much more important, however, is the fact that the leptokurtosis increases disproportionately as the costs move from cognitive costs alone (the first cube law transformation) to cognitive costs and institutional costs (the second transformation). This happens regardless of the input distribution—the ordering of the distribution by extensiveness of cost imposed leads to a parallel ordering of the magnitude of kurtosis. Remember that an informationally efficient institution (or, for that matter, decision maker) would translate information into policy outputs in a proportional manner. As costs are imposed, either by the cognitive “stickiness” of the decision maker or by the formal “stickiness” of the political institution, the result is increasing kurtosis in the distribution of outputs.

FURTHER OBSERVATIONS ON THE TRANSFORMATIONS

We have reason to expect that cognitive costs will be added in a convex curve relationship like the cube law represents. Attention allocation and the general bias toward the status quo in most systems of decision making work to delay responses; but then internal dynamics can operate to respond increasingly intensely to the stimulus via positive feedback effects. The cube law and other upward-turning, convex curves model this kind of general process. It is also possible that cognitive costs act to cause immediate overreaction and then a dampening down of response. This would be modeled by a concave curve, such as the

Table 1
 Kurtosis Calculations for 10,000 Random Normal Numbers, Transformed Nonlinearly and Subjected to a Second Cube Transformation

Distribution Used for the First Transformation	First Transformation (Cognitive Costs)	Second Transformation (Institutional Costs) (Results from the First Transformation, Cubed)
Power 3 (Cube)	39.304	974.441
Power 5	368.044	5,393.799
Power 7	8,880.357	9,999.961
Exponential	38.239	3,947.561
Logarithm	6.771	133.913
Square Root	2.500	7.534

Note: The table shows kurtosis values of a distribution of data after transforming a Normal random input series once and then twice. The first transformation, designed to simulate possible cognitive costs, multiplies the input series by the factor described in the left-hand column. The second transformation simulates institutional costs, and this does not change; it always cubes the results from the first transformation. For example, the first row shows that when the input series is cubed, the resulting distribution has a kurtosis value of 39. When this series is again cubed in the second transformation, the value is 974. In the second example the first transformation raises the input series to the fifth power, leading to values of 368 after the first transformation and 5,394 after the second. A wide variety of transformations is used to simulate possible cognitive cost structures. All generate high kurtosis scores.

logarithm or a power function under 1.0. But based on our understanding of the structures of American government, we are pretty sure that the institutional costs of the Madisonian variety operate to cause delays in responses. These institutional facets can be overcome, but they generally operate in a single direction: toward more delay. Therefore, we can imagine the two sets of costs in our model to operate differently; we assess that possibility below.

Table 1 reports the results of a few more simulations of the form described above. Here we use a variety of different assumptions about the form of cognitive costs but continue to use a cube law to model institutional costs. That is, we assume that various curves might describe the disproportionality associated with cognitive costs, but only a convex curve such as the cube law can model the operation of American-style institutional decision costs. The first column in the table lists the transformations used to model cognitive costs. The second column reports the results of several transformations representing cognitive costs. All save one—the square root transformation—have kurtosis values considerably in excess of 3.0, the value for the normal distribution. The value for the square root transformation is less than 3, suggesting that cognitive costs can yield distributions that are less punctuated than the normal.

In the third column of table 1, a cube transformation is applied, and all values substantially exceed the normal. This will be true generally of the general class of convex transformations that model institutional decision costs—power functions of values above 1, the exponential, and other such transformations all will lead to kurtosis values above 3.0 for most if not all input distributions.

If we were to monitor a rational-adaptive decision process over time, in which diverse input streams were combined through the implicit index model, we would see a normal distribution of outputs. Proportionate information processing implies a normal distribution and a kurtosis value of 3.0. Cognitive costs move the kurtosis value of outputs away from 3.0 in this manner: If the decision-making process generally encourages delay and overresponse, the kurtosis value will be greater than 3.0; if it encourages overresponse and

then dampening down, the value will be less than 3.0. Because of the manner in which attention must be allocated, we expect that generally the former will be true, but there is no way to be absolutely certain. We can say with certainty, however, that decision-making costs, such as those imposed by formal American governing institutions, will work to increase kurtosis values, because they build in delay. This institutional delay implies that no response occurs for low input values. The accumulated delay, however, has a corollary: overresponse when response finally does occur.

DYNAMIC SIMULATIONS OF INSTITUTIONAL FRICTION

Now we turn to a dynamic simulation of institutional friction. In association with Professor James Stimson of the University of North Carolina, we have designed a computer simulation to study the effects of institutional friction on the distribution of policy outputs.¹⁰ Our theory is dynamic, so the model is similarly dynamic, but it is more complex than the simple transformations we discussed above. We ask the basic question of whether a simple dynamic model of institutional friction can generate leptokurtic output distributions of the form of figure 1. If we can confirm our static simulations with a dynamic one, we will be all the more confident that we are on the right track.

The model examines only the friction component of our theory; it does not incorporate negative or positive feedback effects that can affect the policy process. It has four fundamental components:

a *signal* that is input into a hypothetical policy-making system

a *friction mechanism* that sets a threshold below which the system responds only partially

an *error accumulation* feature that builds up pressure in the environment that may produce subsequent policy action

a *response* that is dictated by the strength of the input signal and institutional friction that has accumulated from previous periods

Basically we draw an input signal from a normal distribution and run it through a system that adds friction. Friction is modeled by a parameter that operates as a threshold. Above the threshold, the signal generates a response equivalent to the strength of the signal—the signal has overcome the friction. Below the threshold, it generates a partial response. Friction is slowing down the response. If the “partial” response is set to 0, then below the threshold we have “gridlock”—no response whatsoever. If the partial response is positive, then the system responds to the input signal with some fraction of the signal strength. The policy-making system has added friction by attenuating the response but not entirely blocking it. The model also has an “error accumulation” feature by which partial responses allow the system to get out of adjustment to its informational environment. That part of the signal that is not responded to accumulates and can affect the policy-making process in the future.

¹⁰ We are deeply indebted to Professor Stimson, who suggested the idea of a dynamic simulation and wrote the code. The code is available from us at <http://www.policyagendas.org>.

The model has two variables, the information signal and the policy response, and it has three parameters that model the institutional friction and govern the policy response. The signal flows through the system, generating a policy output that is dependent on the operation of this simulated institutional system.¹¹ We simulate the input signal at time t by a random draw from the standard normal distribution (that is, with a mean of 0 and a standard deviation of 1). One might think of this as input from an implicit index with “rational adaptation,” so that the simulation will focus on institutional friction alone.

The friction parameter, C , acts as a threshold, and its level can be set by the user of the simulation. Above the value of C , the signal generates a response proportional to the strength of the signal. Below the value of C , the signal generates only a partial response. The extensiveness of the response is governed by the efficiency parameter, λ ; if $\lambda = 1$, then there is essentially no threshold and no institutional friction. The signal passes through the institutional frame unhindered, generating a response proportional to its strength. If $\lambda = 0$, then there is no partial response to the signal, and friction is at its maximum. The λ parameter is also user specified.

If the signal is hindered, that portion of the signal that does not generate a response cumulates and is added to the next period’s signal strength. This simulates the buildup of pressure when problems fester and are only partially addressed. But it is possible that the whole situation will “blow over,” and that happens in the model when an input signal receives a negative sign when the cumulated signal is positive (and vice versa). That is, the model allows accumulated pressures both to build up and to dissipate.

Finally, β , the amplification parameter, is set by the user. β allows for the signal to be magnified or attenuated in the translation process. It is linear only, whereas positive feedback effects might be modeled in a more complex fashion. But at present we simply want to examine whether a simple dynamic friction process can generate leptokurtic outputs.

The simulation relies on repeated random draws that are run through the system. These random draws are the S_t —that is, the hypothetical time series, and t is one million. Results of our hypothetical policy-making system that has run for a million time periods

11 The model may be written as follows:
The variables:

$$R_t = \text{response}$$

$$S_t = \text{input signal}$$

The parameters:

$$C = \text{friction parameter}$$

$$\lambda = \text{efficiency parameter}$$

$$\beta = \text{amplification parameter}$$

$$R_t = \beta S_t \text{ if } S_t + \sum_{0 < k < t} S_k > C; \text{ otherwise } R_t = \lambda \beta S_t$$

where

$$0 < \lambda < 1 \text{ (}\lambda \text{ may vary between 0 and 1),}$$

$$0 < t < k \text{ (the time series goes from period 0 to period } k\text{),}$$

$$\text{and } S_t = N(0,1) \text{ (each input signal is drawn from a standard normal distribution).}$$

are input into a frequency distribution. This allows us to study the shape of the distribution, including its kurtosis. We can then alter the friction and other parameters of the system (there are only three parameters, and each can be adjusted easily by the user) and observe the results. On a portable computer, each simulation takes just a few seconds, even with a million observations.

The primary finding from the simulation is clear and unambiguous: for appreciable friction, output distributions are invariably leptokurtic. Numerous runs of this simulation yield leptokurtic output distributions.¹² A direct comparison between figure 1 and one of our simulations gives some indication of the extent to which we have properly modeled the friction process by our simulation. Figure 7 compares directly a simulation incorporating a great amount of friction with a considerable partial response.¹³ A normal distribution with similar standard deviation is presented for comparative purposes. The similarities between the two are remarkable, with both having strong central peaks and very fat tails. Clearly institutional friction is capable of producing policy output distributions consistent with what we observe empirically. Nevertheless, there are some differences; the simulated graph is not as leptokurtic as the actual data, which have both a more concentrated central peak and fatter tails. In effect, institutional friction (at least the way in which we have modeled it) cannot fully account for budget distributions. This is almost certainly due to the exclusive focus on friction in the model, with no provisions for positive feedback and cascades, and the assumption that cognitive costs are unimportant.

More complete results are presented in figure 8. There we graph the kurtosis of the resulting output series against λ , the parameter that captures partial response, for three levels of the threshold parameter. (Recall that the input series are always the same.) The system works entirely as expected. The stronger the friction, the more punctuated the policy output. Kurtosis is a function of both the threshold C and the extent of partial response—leakage through the threshold. As the threshold increases, kurtosis increases exponentially (note the log scale). When little leakage occurs with a high threshold, kurtosis is exceptionally large—most of the cases represent no change, but a small number of really big punctuations occur. When the leakage around the institutional friction reaches a maximum (at $\lambda = 1$), the level of the threshold is irrelevant, and kurtosis for all values of the threshold equals 3, the value for the normal input distribution. No friction, no leptokurtosis. It is that simple.

In general, the dynamic simulation supports our general argument here that the interaction of cognitive factors with institutional friction invariably leads to a pattern across time of general stability with episodic punctuations. And our simulations allow us to show that with friction set to 0 or leakage set to its maximum, there is no punctuation at all. So we believe there is something important in these parameters that explains the punctuated equilibrium patterns that we observe in the real data.

THE GENERAL PUNCTUATION HYPOTHESIS

The results of our analyses and simulations lead to a testable hypothesis about the interaction of boundedly rational decision makers and the institutions within which they make choices. As all government institutions impose costs, we expect all outputs from

12 This is so for equations in which $C = 1$ and greater. The friction parameter has standard deviation units, so $C = 1$ may be interpreted as a system that responds to about one-third of the signals it receives.

13 $C = 3$; $\lambda = 0.4$; $B = 1$.

Figure 7
Budget Authority (A) and Simulated Institutional Friction Model (B) Note: $C = 3; \lambda = 0.4; \beta = 1$.

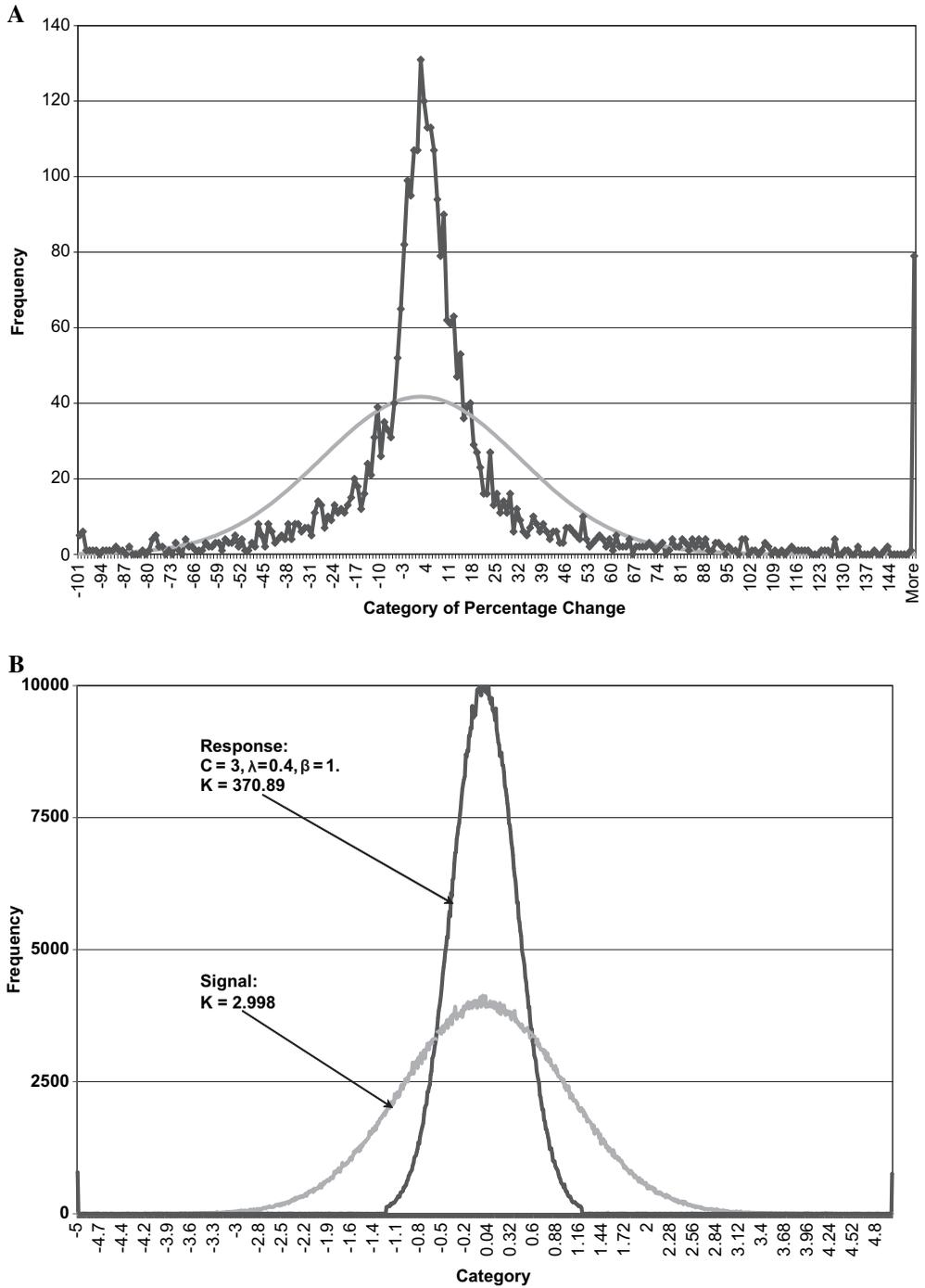
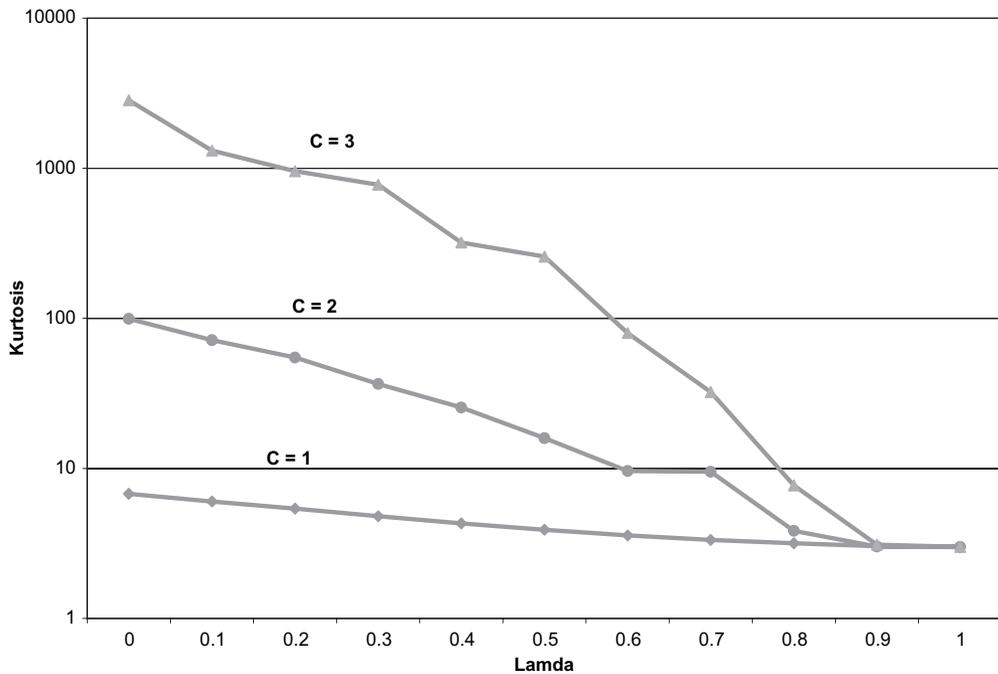


Figure 8
Kurtosis Values as a Function of the Extent of Institutional Friction



them to show positive kurtosis. As decision-making costs increase—that is, as it is more difficult to translate informational inputs into policy outputs—the more leptokurtic the corresponding output distributions. We term this the *general punctuation hypothesis*. We have tested this hypothesis and have found very strong evidence in its support (Jones and Baumgartner in press, ch. 7; Jones, Sulkin, and Larsen 2003). Kurtosis increases as the (implied) institutional friction of the process increases.

CONCLUSIONS

In this article, we have detailed a robust model of choice that incorporates both incrementalism and punctuated equilibrium and have developed a fresh look at policy change using stochastic process methods. Incrementalism and proportional updating to incoming information, which we show here to be equivalent models, invariably yield normal distributions of outcomes. Disproportionate updating results in fat-tailed distributions, basically generated by interdependencies among cases. Our simulations of friction models suggest that adding costs increases the kurtosis of distributions—the extent to which they are punctuated.

The institutional friction model is a policy-making model, basically an extension of our earlier punctuated equilibrium model. Here we have been able to develop a full underlying decision-making model that supports the policy-making model and subsumes under it both the incrementalist and the punctuated equilibrium models.

One irony in our study is that the early incrementalists may have erred partly by not realizing just how right they were. Their model of boundedly rational information updating clearly recognized that policy makers could not make systematically comprehensive adjustments to changing environmental signals. The model that we have proposed here and the empirical results from the U.S. federal budget presented in figure 1 show a tremendous tendency toward incrementalism. The size of the central peak in these distributions is enormous when compared to the normal distribution. This reflects the inability or unwillingness of decision makers to react proportionately to moderate changes in the environment; rather, they tend to underreact to these. What the incrementalists overlooked, and what we add in this approach, is the direct corollary of the disproportionate response that they incorporated in their early models: that information that is ignored will accumulate over time, producing occasional lurches or policy punctuations. These produce the “fat tails” characteristic of the leptokurtic distributions that we have shown empirically and derived through simulations. The incrementalists got it right but told only half the story. A more general approach, presented here, based on disproportionate response to information both demonstrates the importance of the original insights of the incrementalists and makes a more complete and realistic model of the policy process.

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