Probabilistic Causality and Explanation in Political Science

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1. Introduction

Most political scientists view explanation, not prediction, as the main goal of social science research (see Achen, 1987). Explanation has been synonymous with causation since the death nearly twenty-five years ago of the deductive-nomological model of explanation associated most closely with Carl Hempel (see Suppe, 1977). One can argue that most, if not all, research projects in political science aim at producing causal knowledge of political phenomena. It is astonishing to discover that despite the ubiquity of causal claims in political science (see Braumoeller and Goertz, 1997), the nature of causal explanation is rarely discussed. In fact, the evolution of techniques for making causal claims has developed in almost total isolation from the philosophical literature on causation (Woodward, 1988). This isolation can be traced to the lingering grip of the deductive-nomological model, which denies the utility or possibility of causal explanation, as well as the divergent research agendas of the two fields. Philosophers are generally interested in providing accounts of singular or “token” causation (Hitchcock, 1993) whereas political scientists, if interested at all, are generally interested in accounts of general or “type” causation (see section two for further explanation).

Relatively recent work in the philosophy of causation, however, should be of interest to political scientists. A handful of philosophers have developed a theory of probabilistic causation that captures the essential elements of the causal claims that quantitative political scientists make. This account is of interest not only for the causal language it provides political scientists, but also for the detail it provides regarding causal structures of which empirical researchers should be aware. While a perfectly valid philosophical analysis, the probabilistic theory does not, due to an inherent circularity, allow causal claims to be tested. The resulting conclusion is that causal relations cannot be reduced to statistical regularities and that causal explanation must therefore deal explicitly with process. Using substantive examples, I argue, however, that the theories investigated by quantitative political scientists are by necessity deductive rather than inductive and hence not as amenable to process explanations as theories in the physical sciences. Some implications for testing follow.

The purposes of this paper are to serve as a primer for political scientists on probabilistic causation and to present an argument regarding the possibility of causal explanation in political science. The plan of the paper is as follows: in section two, I discuss the reasons why a probabilistic analysis of causation is necessary; in section three, I lay out the basics of the probabilistic theory of causation and point out the circularity; in section four, I consider the possibility of causal process explanations in political science; and in section five, I end the paper with a call for eliminative induction and contingent knowledge.

2. <u>Why a Probabilistic Account of Causation is Necessary</u>

Traditional analyses of causation specify causal relations in terms of necessary and sufficient conditions. A general specification of causation in terms of these conditions might be as follows (see Sosa and Tooley, 1993):

(1) *Sufficiency*

C is a cause of **E** if and only if **C** and **E** are actual and **C** is *ceteris paribus* sufficient for **E**.

(2) *Necessity*

C is a cause of **E** if and only if **C** and **E** are actual and **C** is *ceteris paribus* necessary for **E**.

The basic idea of probabilistic causality is that a cause should raise the probability of its effect. A general specification of causation in terms of probability might be:

(3) **C** is a cause of **E** if and only if **E** is more likely in the presence of **C** than in the absence of **C**, *ceteris paribus*.

This account of causation was developed by Reichenbach (1956), Good (1961, 1962), Suppes (1970), Cartwright (1979), Salmon (1998), Humphreys (1989) and Eells (1991). Three issues that traditional analyses cannot accommodate prompted the development of probabilistic analyses of causation. All three issues are inherent to political science research and the social sciences in general. The issues include: one, giving an account of general causation; two, the presence of multiple causes (overdetermination); and three, indeterminism. These issues are troubling because social scientists generally want to make general causal statements, multiple causes are common throughout the social sciences (Humphreys, 1989), and social phenomena are quite likely to be indeterminate. I explain each of these issues below and demonstrate the problems they present for the traditional analyses.

General Causation

Political scientists generally want to make a claim of the form “C causes E.” To be specific, they wish to make claims that are analogous to:

(4) Smoking causes lung cancer

as opposed to claims such as:

(5) Bob’s smoking caused his lung cancer.

Taking an example from the literature of international relations, political scientists wish to make claims similar to:

(6) System uncertainty causes an increase in dispute initiation

and not:

(7) System uncertainty caused a dispute initiation between Israel and Egypt.

A clue to the distinction between statements (4) and (5) and between statements (6) and (7) can be found in the tense of the verb "cause." Singular causal statements such as (5) and (7) address past events and answer the question, "Did X cause Y?" General causal claims, on the other hand, answer the question, "Does X cause Y?" The difference is between a statement that makes a claim that is contingent upon a specific time and place and a claim that is generalized. Political scientists want to make generalized claims about political phenomena and therefore need a theory of causation that can accommodate such claims.

The unique characteristic of general causal statements is that they may true despite numerous examples to the contrary (Cartwright, 1979; Carroll, 1991). Smoking may cause lung cancer even if it did not cause lung cancer in Bob's case or Jane's case or Fred's case. The problems these statements present to a necessary or sufficient analysis are clear. A sufficient condition is of the form:

(8) $S \rightarrow LC$.

That is, smoking is sufficient for lung cancer, which means that everyone who smokes contracts lung cancer. Statement (8) is clearly untrue. Many smokers never contract lung cancer and yet we still believe (4).

Necessary conditions suffer from similar flaws. A necessary condition would take the form:

(9) $LC \rightarrow S$

That is, smoking is necessary for lung cancer, which means that everyone who contracts lung cancer smoked. Statement (9) is also untrue. There exist numerous people with lung cancer who never touched a cigarette and still we believe (4).

Note that general causal statements present no problems for probabilistic analyses of causation. Proponents of these accounts claim only that causes make their effects more likely, not that the causes must always be present when the effects are present (necessary conditions) or that effects must always be present when their causes are present (sufficient conditions). The fact that general causal claims describe relations that do not hold in every instance is easily accommodated by probabilistic accounts because of the very nature of probability. To say that the probability of "heads" when flipping a coin is 50% does not mean that half of every sequence of coin flips should result in "heads." The statement could very well be true even if no sequence (except the infinite sequence) resulted in 50% "heads."

Lewis's (1973) analysis of causation in terms of counterfactuals must also be mentioned. Under Lewis's conception of causation, smoking would be the cause of Bob's lung cancer if it were the case that if Bob had not smoked, then he would not have contracted lung cancer. In logic notation, the counterfactual conditional takes the following form:

(10) $(\exists x)(\sim Sx \rightarrow \sim LCx)$

That is, there exists a person who, if he had not smoked, would not have lung cancer. The difference between (10) and either (8) or (9) should be obvious; (10) makes a singular causal claim as opposed to a general causal claim. Lewis has stated explicitly that his theory should only be applied to singular causal statements. The consequence of this decision is that in order for Lewis's analysis to stand as a general theory of causation, Lewis must deny that general causal statements are anything more than generalizations over singular causal statements (see Carroll, 1991, for one such argument.) I take the position, however, that general causal statements are more than generalizations over singular causal statements and that political scientists actually have an interest in making such statements.

While the above makes clear that traditional analyses cannot accommodate general causal statements, it is less clear whether or not separate theories of singular and general causation are necessary. Good (1961), Sober (1985) and Eells (1991) are among those who believe that separate analyses are necessary. Carrol (1991) and Hitchcock (1995) are among those who believe that one analysis should work for both levels. The issue generally turns on the analysis of examples in which an event occurs "the hard way." A classic example comes from Good (1961): Professor Moriarty is about to push a boulder over a cliff and crush Sherlock Holmes. Moriarty lines up the boulder carefully so as not to miss and is about to push it when Watson arrives on the scene. Not being able to see Holmes, Watson decides to push the boulder over the cliff but in a direction away from where Moriarty was aiming. Holmes, unfortunately, moves in the same direction and is killed.

The issue here is that we want to say that Watson caused Holmes' death, but the fact of the matter is that Watson's pushing the boulder actually decreased the chances of Holmes' death. Examples such as these seem to confound condition (3), the premise that causes should raise the probabilities of their effects. Attempts have been made to address the issue (see Hitchcock, 1995) but most proponents of probabilistic causation are content to ignore the problem as an issue that concerns only the analysis of singular causal statements. As the issue certainly cannot be settled here, I assume that singular and general causal claims need not be explained by the same theory.

Multiple Causes (Overdetermination)

The presence of multiple causes also creates serious problems for the traditional analyses of causation. If these theories cannot accommodate multiple causes they will be useless to social science, where very few social theories can be adequately modeled using simple regression.[1] Multiple regression has been the mainstay of empirical social science and the use of multiple regression implies that multiple causal factors are at work.

An example from Mackie (1974:44) illustrates the problems of overdetermination:

> Lightning strikes a barn in which straw is stored, and a tramp throws a burning cigarette butt into the straw at the same place and at the same time: the straw catches fire.

The necessity analysis of causation requires that a cause be a necessary condition of its effect. Neither the lightning strike nor the cigarette butt in this example is necessary for the fire to start. If lightning had not struck, the cigarette butt would have caused the fire.

If the tramp had not thrown the cigarette, the lightning strike would have caused the fire. The lightning strike and the cigarette butt are certainly not jointly necessary. Either way then, by adhering to the necessity theory of causation, we would have to deny that either the lightning strike or the cigarette butt caused the fire (Sosa and Tooley, 1993).[2]

A similar problem plagues the sufficiency analysis. Let us assume (following Humphreys, 1989) that the basic minimum definition of cause is that **C** is a cause of **E** only if **C**'s existence contributes to **E**'s existence. Let us further assume that either the lightning strike or the cigarette butt is sufficient to start the fire. Given the lightning strike, the cigarette butt contributes nothing to the onset of the fire. Similarly, given the cigarette butt, the lightning strike contributes nothing to the onset of the fire. Neither the lightning strike nor the cigarette butt then contributed to the existence of the fire and therefore neither meets Humphreys's minimum standard. Neither the lightning strike nor the cigarette butt then may be the cause of the fire.

Probabilistic accounts, however, require no "all or nothing" determinations. The lightning strike and the cigarette butt may both raise the probability of the fire and therefore both may be classified as a cause. Thinking about causation in probabilistic fashion allows for talk of "contributing" causes or factors in a way that traditional analyses do not. It is then possible to talk of how much one factor or another contributes to the effect.

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[1] A simple regression has only one independent variable (see Hanushek and Jackson, 1977).
[2] Note that a similar objection would affect the counterfactual analysis.

Indeterminism

Determinism is simply the philosophical position that if an event has happened or will happen, then it was always meant to happen. That is, all actions and reactions in the universe have been predetermined since the dawn of time. The relationship between necessary and sufficient conditions and determinism is easily seen if we rewrite statements (8) and (9) in general terms:

(11) $C \rightarrow E$ Sufficient condition

(12) $E \rightarrow C$ Necessary condition

The sufficient condition translated reads, "If C (the cause) occurs, then E (the effect) occurs." The sufficient condition states that if C occurs, E *must* follow. If the occurrence of E does not always follow C, as would be the case in a nondeterministic world, then there can be no sufficient condition.

A similar argument may be made for necessary conditions. Statement (12) translated reads, "E (the effect) occurs only if C (the cause) occurs." The condition states that if E occurred, then C *must* have occurred. If E can occur by chance, as would be the case in a nondeterministic world, then there exist no necessary conditions. Necessary and sufficient conditions and the analyses that depend upon them (such as Mackie's *inus* conditions) are incompatible with indeterminism.

Whether or not the world is actually indeterministic, we can certainly accept the premise as a working hypothesis. The fact that determinism is under attack in the physical sciences makes determinism in the social sphere even less likely. Paul Humphreys (1989:17) makes the following persuasive argument

> Consider a man who, on a whim, takes an afternoon's motorcycle ride. Descending a hill, a fly strikes him in the

> eye, causing him to lose control. He skids on a patch of loose gravel, is thrown from the machine, and is killed. This sad event, according to the universal determinist, was millions of years beforehand destined to occur at the exact time and place that it did…This claim, when considered in an open-minded way, is incredible.

Humphreys goes on to argue that whatever may actually be true, determinism should not be accorded "high initial probability."

Probabilistic accounts of causation are, by their very nature, compatible with indeterminism. What must be understood is the relation between causation and chance. Under the probabilistic account, causes raise the probabilities of their effects. Whether or not those effects happen, though, is up to chance; the effect or event either occurs or does not occur. The point to remember here is that chance is not a causal power (Humphreys, 1989).

3. Probabilistic Causation

As stated in (3), the general idea behind a probabilistic analysis of causation is quite simple: a cause raises the background probability that an event or effect occurs. The condition is generally formalized in the notation of conditional probability. **C** is a cause of an effect, **E**, if and only if:

(13) $$P(E \mid C) > P(E \mid \sim C)$$

That is, the probability that **E** occurs is greater in the presence of **C** than in the absence of **C**. The canonical example from the philosophical literature is the relationship between lung cancer and smoking. While it is certainly possible to contract lung cancer without smoking, the probability of attracting lung cancer is greater if one smokes. Numerous similar examples may be found throughout political science: higher education increases the probability of voting Democratic, dyadic democracy increases the probability of peace between dyads, and bipolarity increases the probability of stability.

Unfortunately, condition (13) does not suffice as a statement of probabilistic causation. To take another canonical example, a storm is more probable when a barometer is falling than when a barometer is rising. That is, storms and barometers are positively correlated. Under condition (13), we would have to assign the falling barometer the status of cause although falling barometers are clearly not the cause of storms. Condition (13) therefore is too vague and needs to be refined.

The problem with the barometer example is, of course, the problem of spurious correlation, an idea that is familiar to social scientists of all persuasions. The stumbling block is that our intuitions regarding causation in this case do not match the physical correlations that we observe. The goal is to find a sufficient condition that always provides correlations that match our causal intuitions. We know very well that falling barometers do not cause storms and we need a method of calculating the conditional probability that will reflect that fact. If we can find such a condition, we can apply it to situations where our intuitions are not as good. The history of probabilistic causation in philosophy is really the history of attempts to match causal intuitions to correlations. In the discussion that follows, I draw explicitly on the work of Nancy Cartwright (1979) and Ellery Eells (1991) who together have crafted one of the more successful attempts to pin down a theory of probabilistic causation. Their work in turn owes quite a bit to Reichenbach (1956) and Suppes (1970).

In the simplest case of spurious correlation, **C** raises the probability of **E** but **C** is not a cause of **E**. Instead, a third factor, **Z**, is correlated with both **C** and **E** and therefore accounts for the noncausal correlation between **C** and **E**. Looking at the barometer/storm example, it is an approaching cold front that causes both the falling barometer and the storm and thereby generates the spurious correlation. Following Reichenbach (1956), Eells defines the following probabilistic structure which Salmon (1998) termed a "conjunctive fork":

(14) $P(C \mid Z) > P(C \mid \sim Z)$
(15) $P(E \mid Z) > P(E \mid \sim Z)$
(16) $P(E \mid C \,\&\, Z) = P(E \mid \sim C \,\&\, Z)$
(17) $P(E \mid C \& \sim Z) = P(E \mid \sim C \& \sim Z)$

All of which, when taken together, imply:

(18) $P(E \mid C) > P(E \mid \sim C)$

Condition (14) states that **Z** is correlated with **C** (cold fronts and falling barometers are correlated). Condition (15) states that **Z** is also correlated with **E** (cold fronts and storms are correlated). Conditions (16) and (17) state that **Z** "screens off" **C** from **E**. In more familiar terms, (16) and (17) state that by controlling for **Z** (i.e., holding **Z** "fixed"), the spurious correlation between **C** and **E** disappears (when we control for approaching cold fronts, we see that there is no correlation between storms and falling barometers).

Based on the above, we could enhance condition (13) with condition (19):

(19) There exists no **Z** such that its existence being temporally prior to **C** and **E** would cause **C** to be "screened off" from **E**.

The issue, though, is not so simple. So far we have addresses only positive correlation and positive causal relevance (i.e., **C** raises the probability of **E**). The correlations we observe, however, may also be negative or zero. The causal relation between the factors may also be negative (**C** lowers the probability of **E**) or neutral (**C** has no effect on the probability of **E**.)[3] Eells points out that each of these possible correlational states may be combined with each of the states of causal relevance (see Eells, 1991, chapter 2 for examples). Table 1 lists the possible combinations.

Table 1

		Causal Relevance		
		Positive	Neutral	Negative
Observed Correlation	Positive	Match	*Mismatch*	*Mismatch*
	Zero	*Mismatch*	Match	*Mismatch*
	Negative	*Mismatch*	*Mismatch*	Match

Along Table 1's main diagonal, the observed correlations match our causal intuitions and hence there is no problem. The interesting cases are in the off-diagonal cells. Here, the observed correlations do not match our causal intuitions and we observe spurious correlations.[4]

The lesson, Eells concludes, it that positive correlation is neither necessary nor sufficient for positive causal relevance. What can be said about these cases of spurious correlation is that the explanation involves a third factor, **Z**, that is causally relevant to **E** "independently of **C**'s causal role, if any, for **E**" (Eells, 1991). Cartwright (1979) points

[3] Eells also defines "mixed" relevance, which I will ignore in the interest of clarity.
[4] The term "spurious" is usually reserved for positive correlations but the concept can certainly be generalized.

out that Simpson's paradox explains all these examples and that any association between two variables in a given population:

(20) $P(E \mid C) > P(E \mid \sim C)$
(21) $P(E \mid C) = P(E \mid \sim C)$
(22) $P(E \mid C) < P(E \mid \sim C)$

can be reversed in the subpopulations by finding a **Z** that is correlated with both **C** and **E**. She argues that condition (15) holds, but only in situations where all other causal factors are held fixed – a requirement she refers to as "causal homogeneity." Cartwright's account is then:

(23) **C** causes **E** if and only if **C** increases the probability of **E** in every situation which is otherwise causally homogeneous with respect to **E**.

Condition (23) is the starting point for Eells' account of causation. Eells demonstrates that controlling for "causal background contexts" is a sufficient condition for matching our intuitions to the observed correlations. The "causal background context" requirement is precisely the same as Cartwright's requirement of causal homogeneity. Both requirements simply state that all factors that are causally relevant to **E** but are causally independent of **C** must be held fixed.[5] Employing Hitchcock's (1993) notation, Eells's necessary and sufficient condition for positive causal relevance is:

(24) $P(E \mid C \cap Z_i) > P(E \mid \sim C \cap Z_i) \quad \forall Z_i$

where Z_i is a partition of the causal background context. A partition is a mutually exclusive and exhaustive set of factors that are causally relevant to **E**. Using the same notation, we can define negative causal relevance

[5] These factors must be causally independent of **C** because if the factors were intermediate between **C** and **E**, then the relationship between **C** and **E** may not be spurious.

(25) $$P(E \mid C \cap Z_i) < P(E \mid \sim C \cap Z_i) \quad \forall Z_i$$

and causal neutrality

(26) $$P(E \mid C \cap Z_i) = P(E \mid \sim C \cap Z_i) \quad \forall Z_i$$

Conditions (24-26) simply state that in order to affirm the causal relevance of factor **C**, whether positive, negative or neutral, we must control for all other causal factors.

To be causally relevant then according to Eells, **C** must have an effect on **E** "beyond that which is explainable by *other*, independent, causes of **E** that may be correlated with **C**" (Eells, 1991:84).[6] Conditions (24-26) explicitly state that the equality or inequality must hold for all Z_i. The requirement is know as "context-unanimity" and means that a cause must raise or lower or neither raise nor lower the probability of its effect across all elements of the partition **Z** (Hitchcock, 1995). The "context-unanimity" requirement has not been universally accepted. The counterexample comes from Dupre (1984:172):

> Suppose that scientists employed by the tobacco industry were to discover some rare physiological condition the beneficiaries of which were less likely to get lung cancer if they smoked than if they didn't.

The problem presented here is that were we to hold the "rare physiological condition" fixed, as context-unanimity requires, we would find a situation where smoking lowers the probability of lung cancer and thereby violates (24). We would conclude therefore that smoking is not a cause of lung cancer.

Eells is, of course, aware of this argument and answers it by arguing that a probabilistic causal claim may only be made in reference to a particular population. The example Eells uses is that the conditional probability of having a heart attack given 15 years of heavy smoking is likely to be different for 30 years olds and 50 year olds. In order to assess accurately the causal relevance of **C** on **E,** then, we must identify both the causal background context and the relevant population.

The account of probabilistic causation provided above should prove to be somewhat familiar to quantitative political scientists as the account is analogous to regression analysis in statistics. Cartwright (1979:435), in fact, points out that condition (24) is known to statisticians as the partial conditional probability of **E** on **C**, holding Z_i fixed, and as such, forms the basis for regression analyses of causation.[7] The probabilistic account of causation and regression analysis are unfortunately similar in another way as well. Regression analysis requires "proper specification" before the results of the estimation may be believed (Freedman, 1987). There is an inherent circularity here. If we knew the true specification of our model, it is less likely that we would want to estimate the effects, to say nothing of testing those effects. The circularity in regression analysis is not necessarily fatal; there are instances where we might know the true specification and still might want to know the effects. The circularity in conditions (24-26), however, is fatal. *These conditions require that we know all the causal factors affecting **E** (the Z_i) prior to knowing whether or not **C** is causally relevant.* Thus, while the Cartwright-Eells account may be a perfectly valid

[6] Remember that "independent" here mean "causally independent."

philosophical analysis, it is much less useful to the practicing political scientist who is attempting to discern which factors should and should not be included in a causal explanation.

4. Causal Processes

The circularity described above prevents the Cartwright-Eells account from being a reductive analysis of causation, an account that conceives of causality solely in terms of probabilities. The problem is that conditional probabilities cannot fix which factors should be included in a causal explanation. Fixing such an explanation solely in terms of statistical relevance requires full knowledge of the relevant causal factors. Such knowledge is, of course, not to be had.

The general response to the failures of reductive accounts of causation is to suggest that these accounts be bolstered or replaced by explanations of causal process. In reviewing reductive accounts by Good, Reichenbach, and Suppes, Salmon (1998:224) argues:

> It seems to me that the fundamental source of difficulty in all three of the theories I have discussed is that they attempt to carry out the construction of causal relations on the basis of probabilistic relations among discrete events without taking account of the physical connections among them.

"[T]he physical connections among them" refers to the actual processes through which events occur. Richard Miller (1987:139) also argues for process explanations by defining

[7] The main difference between (24) and regression is that (24) requires one to control for all causally relevant factors whereas regression requires one to control for only those factors that are causally relevant *and* correlated with the included factors (see Eells, 1991:85; Hanushek and Jackson, 1977).

a theory as "a description of a repertoire of causal mechanisms, a theoretical explanation, an explanation appealing to instances of such a repertoire." Similar arguments come from David Dessler (1991:345) who, drawing on Harre (1970), states that, "causal explanation shows the *generative* connection between cause and effect…and it is this generative connection that gives the notion of cause meaning beyond that of simple regularity."

Miller and Dessler are both addressing themselves explicitly to social scientists (political scientists, in Dessler's case). The problem, as Miller and Dessler see it, is that social scientists in particular have labored under the deductive-nomological or covering law model of explanation proposed by Hempel and Oppenheim (1948). Explanation according to Hempel and Oppenheim consists solely of statements of conditions and general laws from which one can deduce the event to be explained. In concise notation, an explanation takes the following form:

(27)
$$\frac{\begin{array}{c} C_1, C_2, \ldots, C_k \\ L_1, L_2, \ldots, L_r \end{array}}{E}$$

where the C_i are the antecedent conditions, the L_i are the general laws, and E is the event.[8] Explanation then consists of subsuming the event to be explained under a covering law. "Causal" in this account means only that "any event of a specified kind…is accompanied by another event which in turn has certain specified characteristics."[9]

[8] Hempel (1962) and Salmon (1984) both proposed statistical versions of the D-N model but the extensions are not necessary for the argument here.
[9] Note that covering law models are a kind of sufficiency analysis. If **E** can be deduced from **C** and **L**, then **C** and **L** are sufficient for **E** by definition.

Miller and Dessler's objections are that most explanations in the social sciences and political science, respectively, are of the covering law kind. An explanation of why two states did not escalate a dispute to war would consist of a general law, such as dyadic democracy decreases the likelihood of dispute escalation, and a statement of initial conditions, such as each of the states in the dyad is a democracy. Explanation in this case is basically a "snapshot" of the conditions under which we would expect some event to take place.

Dessler contrasts such explanations with the kind of explanation that one finds when studying thunderstorms.

> The generative process…begins with the cold air mass lifting the warm air with which it collides; the lifting becomes focused in the convective cells…eventually the downdraft spreads through the entire cell, pulling its contents to the ground in a formidable current of wind and rain.

The explanation in this case consists of a statement of the causal process that leads from the collision of two air masses to the advent of the actual thunderstorm. Dessler argues that this form of explanation, one that encompasses causal process, is the kind of explanation for which political scientists should be striving.

The flaw in Dessler's argument is that there is a real difference between the kinds of phenomena that natural scientists are attempting to explain and the kind of phenomena political scientists are attempting to explain. Generating the causal process explanation of thunderstorms was most likely a heavily inductive endeavor. That is not to say that deduction had no part to play in forming the explanation, but only that induction had a much larger part. Thunderstorms occur thousands of times a year. It is easy to be present before a thunderstorm begins and during a thunderstorm. It is relatively easy to send up weather balloons or aircraft or use doppler radar to study and measure the internal structure of the atmosphere before and during thunderstorms. Models were probably generated and updated with an enormous amount of new data numerous times a year. Through this inductive process, a widely accepted causal explanation was generated over time.

Wars, unfortunately, cannot be studied in the same fashion. First, wars occur rarely. Between 1816 and 1980, there were only 118 international wars (Small, 1990). If we counted the wars that have occurred since the end of World War II (a rough date for the advent of modern political science), that number drops to 30. The same access to the phenomena is therefore not possible. Second, whereas measuring the characteristics of thunderstorms is relatively easy, making the same kinds of measurements for wars is quite difficult. Access to the halls of power is extremely limited before and during the event, and memoirs are of dubious value. Most quantitative studies of war must make do with data published long after the event and that was designed for different uses. Third, because of these limitations, the study of war is more deductive than inductive. Deductive explanations are often of the covering law variety as deductions begin with first principles and initial conditions. The steps in a deduction are true by definition and interest focuses on the predictions of the model. The explanation that results is therefore a deductive-nomological explanation. Not surprisingly, then, the same kind of causal process explanation of war has not been forthcoming.

This is not say that political phenomena are rare or that all natural phenomena are easily measured or observed. After all, elections happen frequently (though not as frequently as thunderstorms) and the administration of surveys has achieved a very high level of expertise. (It is telling that Dessler provides no examples of process explanations in political science.) Black holes in space, on the other hand, are difficult to observe, difficult to measure, and are sometimes even difficult to find. Phenomena of all kinds lie on a continuum from easily observed and measured to not easily observed or measured. The claim I am making is that most political phenomena lie toward the unhappy end of that continuum and most natural phenomena do not. The result, then, is that political scientists are faced with making causal claims based mostly on probabilities and observed correlations. How we can test these claims in the face of the circularity described in section three is the subject of the next section.

5. Eliminative Induction

While the deductive nature of political research does not rule out process explanations, it certainly makes such explanations harder to come by. Political scientists are relegated to attempting to fix causal explanations on the basis of statistical relevance where we cannot possibly meet the necessary and sufficient condition for causal explanation (i.e., knowledge of all causally relevant factors). The solution I propose is not a return to qualitative research, (although that is one option), but rather a revival of eliminative induction.

Eliminative induction is a model of scientific progress where science progresses by the "weeding out" of alternative theories. The general idea is that competing theories are eliminated until only one theory remains. In principle, that theory should be the true theory. John Earman (1992) has likened eliminative induction to the classic English detective novel where the brilliant detective eliminates suspects one by one until only the guilty party remains. The important clue in Earman's analogy is that for a piece of evidence to count against one suspect, it must count for another suspect. If all the suspects had access to the candlestick, then the fact that the murder was done with candlestick cannot be evidence. This aspect of eliminative induction, as Vineberg (1996) notes, solves both Hempel's raven paradox[10] and Goodman's "new riddle of induction."[11]

Eliminative induction is not unknown to quantitative political scientists (except perhaps in name). As noted in section three, in attempting to fix a causal explanation in probabilistic terms, we are faced with the same circularity that we face as political scientists in choosing a proper specification. To fix a causal explanation then, we may employ the same techniques that one would apply to choose a regression specification. Taken together, those techniques are an informal application of eliminative induction. Achen (1987:149) argues:

> "Verification," then, consists…in trying out alternative explanations and counterexplanations in an attempt to eliminate all but one of them.

Note that eliminative induction is often used by qualitative political scientists as well and as such, forms a foundation for political methodology.

In order to make eliminative induction work in its pure form, a number of untenable assumptions must be met. First, one must know all possible competing causal explanations. Second, data must be available that can confirm one explanation while

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[10] Hempel's raven paradox states that because $(x)(Raven(x) \supset Black(x))$ is logically equivalent to $(x)(\sim Black(x) \supset \sim Raven(x))$, the generalization that all ravens are black is confirmed by any object that is neither black nor a raven (see Hempel, 1945).

[11] Nelson's "new riddle of induction" involves a new type predicate *grue* where *grue* stands for "examined before time *t* and green or not examined before *t* and blue" and *t* is some time after now. As all observed

disconfirming another explanation. Third, one of the explanations must be true. In actual practice, of course, none of these conditions can be met. It is impossible to know all competing explanations and if we cannot know all competing explanations, we cannot be sure that the true theory is among the ones we do know.

The fact that we cannot meet these assumptions does not diminish the usefulness of eliminative induction. If we cannot deterministically eliminate an explanation, we may be able to eliminate it probabilistically. Enough disconfirming evidence can drive the probability below the point where we would consider the explanation plausible (Earman, 1992). In the same vein, by the time we turn to eliminative induction, we have already performed a more or less informal search of the explanation space. The explanation that eliminative induction produces then will be the most plausible explanation given the current state of knowledge. None of this guarantees that further evidence will not bring a probabilistically eliminated theory back to life or that the original explanation search was too crude (Vineberg, 1996). Either way, however, we should end up with a causal explanation that is better than the one with which we started. Achen (1987:149) continues:

> No sensible social scientist believes any particular specification, coefficient estimate, or standard error…When this sort of data analysis, done several times in different contexts by different investigators, results in a strong and consistent effect according with the qualitative theory, the theory will begin to be believed.

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emeralds are green, and therefore *grue*, the hypothesis that "all emeralds are *grue*" is just as highly confirmed as the hypothesis that "all emeralds are green" (see Nelson, 1965).

6. Conclusion

I have attempted to answer two questions in this paper. The first is how we are to understand causality in the social sciences and the second is how we use that knowledge to fix causal explanations. I have argued that the answer to the first question is "probabilistically" and the answer to the second question is "no." Unlike its traditional counterparts, probabilistic causation accommodates the three desiderata that social scientists look for in a theory of causation: an account of general causation, the presence of multiple causes, and indeterminism. Probabilistic causation provides a language through which social scientists can talk of causal claims. In addition, the probabilistic account, expressed in terms of conditional probability, should feel familiar to quantitative social scientists who are used to regression analysis.

Probabilistic causation, however, provides no means by which social scientists can fix causal explanations. The move from a probabilistic analysis to a process analysis does not solve the dilemma. Unlike theories in the natural sciences, most theories in the social sciences are deductive and therefore do not lend themselves to process explanations. I have argued that one of the ways we can free ourselves from this bind is to embrace eliminative induction and live with the knowledge that we have chosen the best explanation available to us.

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