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## **Human Deviations from Normative Causal Reasoning**

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Humans possess considerable causal knowledge about the world. For example, one might have beliefs about how economic variables affect one another, such as that high interest rates cause small trade deficits and also low amounts of retirement savings. Or, about weather systems: that high amounts of ozone cause low air pressure which in turn causes high humidity. How do people represent and reason with such knowledge? One possibility is that causal knowledge is represented as causal graphs known as *Bayesian networks*, in which variables are depicted as nodes and causal relations as directed edges, as in Fig. 1.



Figure 1

One principle which constrains inferences in Bayesian networks is the *causal Markov condition*. Consider the two particular economies shown in Fig. 2. About the first we know that it has high interest rates but nothing about its trade deficits or retirement savings. About the second we know that it also has small trade deficits. If asked to predict which is more likely to have low retirement savings, we should (according to the causal Markov condition) have no



Figure 2

preference. Because knowledge of interest rates makes trade deficits and retirement savings *conditionally independent*, small trade deficits in the second case provides no additional evidence about retirement savings. In other words, interest rates *screens off* trade deficits from retirement savings. Screening off also applies to variables connected in a causal chain (e.g., the weather variables in Fig. 1).

To test whether people honor the causal Markov condition, in Expt. 1 each S was taught 3 causal networks (the two in Fig. 1 plus a third in which two variables cause a third) in the domains of economics, meteorology, and sociology. They were then presented with pairs of cases (e.g., two economies, as in Fig. 2) and asked which was more likely to have a particular variable (e.g., low retirement saving), or whether they were "equally likely." The proportion of choices in favor of the case with the extra variable (e.g., small trade deficits) is shown in Fig. 3 ("equally likely" responses were coded as 0.5). Whereas screening off predicts choice proportions of 0.5, Fig. 3 indicates that the

extra variable provided evidence for the inference, despite the fact that it was screened off. This result was not merely due to Ss' prior domain knowledge (directly linking, e.g., small trade deficits with low retirement savings), because the senses of variables described as causally related was balanced over Ss (e.g., some Ss learned that high interest rates causes *high* retirement savings).

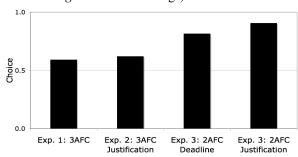


Figure 3

One explanation for these results is that Ss were reasoning "associatively," that is, failing to apply the "rules" of causal inference (Sloman, 1996). Expt. 2 attempted to induce rulebased processing by increasing processing time. Each S learned just one network, was tape recorded, and asked to justify their choices. Surprisingly, the number of screening off errors increased (modestly) relative to Expt. 1 (Fig. 3). Processing effort was manipulated directly in Expt. 3 in which one group responded within a 14s deadline and a second gave recorded justifications. The "equally likely" response alternative was eliminated. Not only did the 2AFC greatly increase the number of screening off errors (Fig. 3), such errors were more common in the justification condition vs. the deadline condition. Again, justified and unspeeded responses produced more screening off errors, not fewer. Such errors have also been found between causally related category features (Rehder & Burnett, 2005).

Why does more processing time produce more errors? One possibility is that Ss had more time to think of (or construct) additional ways in which variables already causally connected might be related (e.g., how small trade deficits might be related to low retirement savings), so that the variables were no longer screened off. The assumption that variables which are causally related in one way are also related in other ways may sometimes be justified. But when it is not, the result will be incorrect inferences between variables that are in fact conditionally independent.

#### References

Rehder, B. & Burnett, R. (2005). Feature inference and the causal structure of categories. *Cog. Psych.*, *50*, 264-314. Sloman, S. A. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin*, *119*, 3-23.