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Comment: Assessing the Science Behind Graphical Modelling Techniques

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These papers, labelled here CW (Cox and Wermuth) and SDLC (Spiegelhalter, Dawid, Lauritzen and Cowell), are welcome reviews of extensive collaborations. CW are the more limited of the pair in their aims, making a few points convincingly, most notably (1) that covariance-based regression models are conceptually distinct from the simultaneous causal models of econometrics, even when both varieties are expressed through identical linear equations, and (2) that models with covariance matrices corresponding to restricted graphical structures often give good fits to empirical matrices. The SDLC paper by contrast is a tour de force that aims to leave no relevant topic unmentioned.

Both sets of authors intend their formal models and computations to speak to issues of scientific knowledge and science-based decision making, and in particular both are concerned about the informal scientific understanding that motivates their formal models. CW are reluctant to use the term "causal," viewing it as too ambiguous, but the authors substitute nonspecific language such as "appropriate subject matter considerations." SDLC, in contrast, discuss "influence" and "relevance" that take "account of one's understanding of causal structure." The difference appears to be that CW wish to hold to the idea that informal prior knowl-

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