6.6 Conclusions

Past efforts to establish a theoretical connection between statistical associations (or collapsibility) and confounding have been unsuccessful for three reasons. First, the lack of mathematical language for expressing claims about causal relationships and effect bias has made it difficult to assess the disparity between the requirement of effect unbiasedness (Definition 6.2.1) and statistical criteria purporting to capture unbiasedness.²⁵ Second, the need to exclude barren proxies (Figure 6.3) from consideration has somehow escaped the attention of researchers. Finally, the distinction between stable and incidental unbiasedness has not received the attention it deserves and, as we observed in Example 6.3.3, no connection can be formed between associational criteria (or collapsibility) and confounding without a commitment to the notion of stability. Such commitment rests critically on the conception of a causal model as an assembly of autonomous mechanisms that may vary independently of one another (Aldrich 1989). It is only in anticipation of such independent variations that we are not content with incidental unbiasedness but rather seek conditions of stable unbiasedness. The mathematical formalization of this conception has led to related notions of DAG-isomorph (Pearl 1988b, p. 128) stability (Pearl and Verma 1991), and faithfulness (Spirtes et al. 1993), which assist in the elucidation of causal diagrams from sparse statistical associations (see Chapter 2). The same conception has evidently been shared by authors who aspired to connect associational criteria with confounding.

The advent of structural model analysis, assisted by graphical methods, offers a mathematical framework in which considerations of confounding can be formulated and managed more effectively. Using this framework, this chapter explicates the criterion of stable unbiasedness and shows that this criterion (i) has implicitly been the target of many

²⁵The majority of papers on collapsibility (e.g. Bishop, 1971; Whittemore 1978; Wermuth 1987; Becher 1992; Geng 1992) motivate the topic by citing Simpson's paradox and the dangers of obtaining confounded effect estimates. Of these, only a handful pursue the study of confounding or effect estimates; most prefer to analyze the more manageable phenomenon of collapsibility as a stand-alone target. Some go as far as naming collapsibility "nonconfoundedness" (Grayson 1987; Steyer et al. 1997).

investigations in epidemiology and biostatistics, and (ii) can be given operational statistical tests similar to those invoked in testing collapsibility. We further show (Section 6.5.3) that the structural framework overcomes basic cognitive and methodological barriers that have made confounding one of the most confused topics in the literature. It is therefore natural to predict that this framework will become the primary mathematical basis for future studies of confounding.

Acknowledgment

Sections 6.2–6.3 began as a commentary on Sander Greenland's 1997 manuscript entitled "Causation, Confounding, and Collapsibility." Greenland's paper was motivated by considerations similar to those exposed in this chapter, and it was based on a counterfactual-exchangeability approach that he and James Robins introduced to epidemiology in the mid-1980s. I have since joined Sander and Jamie as co-author on "Causation, Confounding, and Collapsibility" [Greenland et al., 1999b]. However, space limitations and other constraints did not permit the ideas presented in this chapter to be fully expressed in our joint paper.

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