13 Concluding Remarks

As we discussed in more detail in section 1.2.3, scientific forecasting is the (1) systematic distillation and summary of relevant information about the past and present that (2) by some specific assumption may have something to do with the future. Observed mortality rates in large enough population groups tend to move smoothly over time, and so forecasts a few years ahead are usually easy and accurate by most any sensible method. Attempting to see farther into the future—which is required for important policy purposes—will never be guaranteed because of the required choice of assumptions, but we can improve our distillation of existing information by incorporating more knowledge about the past and present in our forecasting models. We do this in two ways: first, by enabling scholars to include the covariates appropriate to the time-series analysis in each cross section, even if different from the covariates in other cross sections, and by still borrowing strength statistically to improve the estimation of them all; and, second, by incorporating qualitative information known to researchers about common mortality patterns but not explicitly coded in any list of covariates. Both sources of information will certainly increase our ability to systematically distill current mortality patterns, and we hope they will lead to more accurate assessments of the future.

The framework we provide here can be used to improve forecasts beyond those in our empirical analyses. For example, the same ideas can be used to borrow strength between mortality rates for males and females, because we have knowledge about how long each lives, and the relative frequencies of dying from particular causes. Similarly, regions within countries could be used to smooth geographically and to produce finer-grade forecasts. Causes of death do not have the properties of "compositional data," as do election statistics, budget figures, or time-use data (Aitchison, 1986; Katz and King, 1999), in that reducing death from one cause does not necessarily lead to increases in mortality rates from other causes. Thus, unlike these other applications, conditioning on all-cause mortality when predicting cause-specific mortality is not as useful or appropriate as it would be for truly compositional data. However, the mortality rates from different causes do follow relatively common patterns that could be incorporated in our models. This can be done with our technology designed to smooth over geographic regions, with proximity defined by information from studies of comorbidity or epidemiological transition.

Although we have used only mortality data for our running examples in this book and as the testing ground for our methodological studies, the procedures we introduce here may be more widely applicable. The statistical methods we introduce for modeling ignorance in Bayesian analysis, for smoothing based on the expected value of the dependent variable rather than the coefficients, and for connecting all hyperprior parameters to genuine knowledge available to subject matter experts should all extend beyond our application.

For any applications, including mortality, our methods constitute a set of methods rather than just one, as well as a set of tools for constructing new methods and adapting the ones we have derived for new purposes. Throughout, we have attempted to lay bare the choices among assumptions that are required for producing forecasts, and to leave these for the investigator to make and live with rather than for us or our methods to impose on anyone. Our goal has been to provide a way to include more information in forecasts. The quality of any forecasts produced using our methods (and our software) will depend largely on the quality of prior and covariate information included and on assumptions about the future.

Finally, as we emphasized in Chapter 1, no method can ever guarantee that real forecasts will be accurate in any application. Indeed, all good forecasters know perfectly well that unexpected events will sometimes occur and cause forecasts to fail miserably in ways that model-based standard errors and confidence intervals cannot hope to capture. In any one application, some models will be inappropriate; covariates can be picked badly so that they map idiosyncrasies rather than systematic patterns likely to persist; choosing the wrong priors can cause us to propagate errors from neighboring cross sections rather than to borrow statistical strength; and when the priors are not correct or strong enough to compensate, any of the usual problems with regression modeling can cause forecasts using these methods to miss their mark. In our view, the best anyone can do is to (1) gather as much context-specific information as possible, (2) ensure that in-sample modeling and out-of-sample forecasts include as much of this information as possible, (3) verify with numerous and diverse out-of-sample tests when a method and particular set of assumptions works and when it fails, and (4) provide software to make sophisticated methods sufficiently intuitive so that they can be widely used and so researchers can build intuition and expertise in their use. These are the tasks we tried to accomplish in this book.