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Dependence in Mortality and Longevity Modelling: From Multi-Population Factors to Competing Risks

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Abstract

Mortality and longevity models increasingly require explicit treatment of dependence. Populations exposed to related medical, economic and epidemiological conditions cannot be assumed to evolve independently, while multiple causes of death and policyholder decrements may also share common latent influences. This note reviews two distinct dependence problems: coherence across populations and dependence among competing risks. It explains why these problems should not be conflated, summarizes the role of common-factor mortality models and copula-based competing-risk models, and identifies validation principles for actuarial and demographic forecasting. Particular emphasis is placed on preserving interpretability, avoiding unsupported individual-level causal claims from aggregate data, and evaluating forecasts through mortality rates and downstream life-table quantities.

Keywords: mortality; longevity; multi-population models; competing risks; copulas; coherent forecasting

1. Dependence is structural in mortality applications

Mortality is often modelled as a collection of age-specific rates evolving over time. The classical Lee-Carter model provides a parsimonious decomposition of log mortality into an age profile, an age-specific sensitivity and a time index (Lee & Carter, 1992). When one population is analysed in isolation, the model can be effective for long-run extrapolation. However, related populations frequently share medical innovations, economic conditions, public-health interventions and epidemic shocks. Forecasting them independently can imply implausible long-run divergence.

A second and conceptually different dependence problem arises when mortality is decomposed by cause or when actuarial contracts involve multiple decrements such as death, disability and withdrawal. Here the question is not simply whether two populations share a trend. It concerns how multiple risks are jointly represented and how marginal or crude decrement rates relate to an underlying multivariate structure.

2. Multi-population coherence

Li and Lee (2005) extended the Lee-Carter logic by introducing a common mortality factor for a group of populations together with population-specific deviations. The main motivation was coherence: closely related populations should not be forecast to diverge without bound merely because separate time-series extrapolations happen to have different drifts. Subsequent multi-population approaches have explored common factors, product-ratio structures, cointegration and other mechanisms for sharing information across populations.

Coherence should nevertheless be treated as an empirical and substantive constraint rather than a mechanical objective. Populations can differ persistently because of health systems, behaviour, socioeconomic composition or shocks. A useful model therefore separates common long-run movement from local departures and tests whether the departures are plausibly stationary or mean reverting. Enchev et al. (2017) emphasize the value of a common framework for comparing multi-population models rather than relying on a single specification.

3. Competing risks and copula dependence

Competing-risk settings require different reasoning. In a multiple-decrement model, an individual may be exposed to several failure types but only one event is ultimately observed first. Dependence among latent failure times cannot generally be recovered from observed cause-specific outcomes without additional assumptions. Copula models provide one way to impose and study such assumptions. Kaishev et al. (2007) developed a framework for joint competing-risk survival times using copulas, illustrating how dependence can be incorporated into actuarial multiple-decrement modelling.

The distinction between population-level co-movement and individual-level latent dependence is essential. Aggregate cause-of-death rates that move together over calendar time do not, by themselves, identify the dependence among latent individual failure times. Studies using aggregate mortality panels should therefore describe their dependence layer as dependence among observed or latent aggregate innovations unless the data and assumptions genuinely support individual competing-risk interpretation. This wording is not a minor semantic issue; it determines what conclusions the model can support.

4. Forecast evaluation beyond rate fit

Mortality models are often compared using error measures on log rates, but actuarial and demographic decisions depend on transformed quantities such as survival probabilities, life expectancy, annuity values and capital requirements. A small difference in rate error at old ages may have a different practical meaning from the same error at young ages. Evaluation should therefore be multi-level: rate-level accuracy, age-pattern stability, coherence across populations or causes, and downstream life-table accuracy.

Forecast uncertainty also matters. Stochastic mortality models should communicate predictive intervals or simulation distributions, especially for long horizons. For joint or cause-specific models, simulation should preserve accounting constraints where they exist. For example, cause-specific components should remain compatible with all-cause mortality if the model is designed to decompose the total.

5. Research priorities

Several research directions are particularly promising. Dynamic factor structures can be combined with richer dependence models when Gaussian dependence is inadequate. Bayesian and state-space formulations can represent parameter uncertainty and gradual structural change. Machine-learning models can contribute nonlinear flexibility, but they should preserve actuarial identities and remain interpretable enough for validation. Finally, model-selection studies should report not only which method wins on average but also where it fails by age, sex, population and forecast horizon.

Mortality and longevity research benefits from dependence modelling when the dependence concept is matched to the data-generating question. Multi-population coherence, cause-specific co-movement and competing-risk dependence are related topics, but they are not interchangeable. Clear separation of these concepts is a prerequisite for credible forecasting and actuarial interpretation.

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