

Structural versus Parametric Uncertainty

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Abstract

Uncertainty within a model is not the same as uncertainty about the model. Parametric uncertainty concerns unknown values inside a chosen structure; structural uncertainty concerns which structure, mechanism, functional form or model class is appropriate. Reporting only standard errors, confidence intervals or posterior intervals conditional on one model can therefore understate the uncertainty relevant to a scientific claim when multiple structures remain plausible. This article defines structural and parametric uncertainty, explains how they interact, and shows why averaging, calibration or sensitivity analysis cannot make structural uncertainty disappear. Model discrepancy, practical identifiability and alternative plausible structures require separate treatment. INF-004 owns the decision about which rivals remain live; INF-008 owns qualification of the conclusion while that structural plurality persists. The aim is not to produce one universal combined uncertainty number, but to prevent conditional precision from being mistaken for unconditional certainty.

Keywords: structural uncertainty; parametric uncertainty; model uncertainty; model discrepancy; identifiability; uncertainty propagation; sensitivity analysis

1. Conditional precision can hide structural uncertainty

Most statistical intervals are conditional on a model. If the model structure is wrong or one of several plausible structures, a narrow interval around its parameters does not capture the uncertainty that matters to the scientific conclusion. Draper formalised model uncertainty as a distinct component that should be assessed and propagated rather than silently conditioned away [1].

2. Parametric uncertainty

Parametric uncertainty concerns unknown numerical values within a specified structure: rate constants, regression coefficients, elastic moduli, reaction yields or other parameters. It can arise from finite data, measurement noise or incomplete excitation of the system. Standard errors, profile likelihoods, posterior distributions and confidence intervals are examples of tools for characterising this uncertainty under their respective assumptions.

3. Structural uncertainty

Structural uncertainty concerns the form of the model itself: which variables or mechanisms are present, the direction of causal relations, the functional form connecting variables, the error model, boundary conditions or which candidate model class is appropriate. Structural uncertainty can remain even when every model is individually well estimated. INF-004 identifies which rival structures remain live; INF-008 determines how the scientific conclusion must be qualified because of that fact.

4. Practical identifiability is not structural uncertainty

A parameter can be structurally identifiable in a fixed model yet practically unidentifiable from the available data. Raue and colleagues show how profile likelihood can reveal such practical limitations in partially observed dynamical models [2]. This is still uncertainty within a chosen structure. By contrast, structural uncertainty exists when different model structures remain plausible even with ideally estimated parameters.

5. Model discrepancy

Complex models rarely reproduce reality exactly. Kennedy and O'Hagan distinguish uncertainty about calibration parameters from discrepancy between a computer model and the physical system [3]. Treating discrepancy as if it were parameter noise can force parameter estimates to compensate for missing physics and create overconfident predictions. A scientifically defensible analysis therefore states what the model is expected to represent and what residual discrepancy remains outside its parameterisation.

6. Sensitivity analysis and uncertainty propagation

Sensitivity analysis can identify which assumptions or inputs most influence a conclusion and is useful for exploring parametric and structural alternatives. Global sensitivity methods deliberately vary inputs over specified ranges rather than relying on one-at-a-time perturbations [4]. But sensitivity analysis is only as comprehensive as the set of variations considered. It cannot demonstrate robustness to an omitted structure that was never included in the analysis.

7. Combining uncertainty without hiding its source

Model averaging and hierarchical approaches can propagate uncertainty across a specified model set, but the resulting aggregate remains conditional on that set and on the weighting scheme. INF therefore prefers source-resolved reporting when feasible: parameter uncertainty within each model, between-model variation, and plausible structural alternatives that the model set does not represent. A single combined interval can be useful, but it should not erase the distinction between these components.

8. What changes the claim

Structural uncertainty often changes the wording of a justified conclusion more than parametric uncertainty does. If every plausible structure predicts the same qualitative direction, the conclusion may remain robust despite model uncertainty. If sign, mechanism or extrapolation changes across structures, the claim should remain correspondingly conditional. This is the bridge from INF-008 to INF-009, which asks whether a conclusion survives declared model and assumption variation.

9. Minimum reporting discipline

- State the model structure on which parameter uncertainty is conditional.
- Identify materially plausible alternative structures.
- Separate practical parameter non-identifiability from structural ambiguity.
- Represent model discrepancy explicitly when the model is known to be an approximation.
- Report sensitivity to assumptions that could change the scientific conclusion.
- Do not present a narrow conditional interval as the total uncertainty when model structure remains contested.

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Data and materials statement

No new experimental dataset was generated for this article. The article is a methodological analysis based on the cited literature and the frozen ownership architecture of the INF series.