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Dependence Modelling Across Finance, Insurance and Demography: A Unified Research Agenda

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Abstract

Dependence is a central feature of risk systems because adverse outcomes rarely occur in isolation. Financial losses co-move during market stress, insurance claims may share latent drivers, mortality improvements may evolve coherently across populations, and demographic outcomes may be linked through common economic and social mechanisms. This short communication develops a unified research agenda for dependence modelling across finance, insurance and demography. It argues that the most useful models should separate marginal behaviour from dependence where appropriate, allow dependence to vary over time and across regimes, distinguish central association from tail dependence, and evaluate models with out-of-sample as well as in-sample criteria. The note also highlights the need for interpretable and reproducible workflows. The objective is not to prescribe a single model class, but to identify principles that permit meaningful comparison across application domains and that can guide methodological contributions to dependence-based risk research.

Keywords: dependence modelling; copulas; systemic risk; actuarial science; mortality; demography; forecasting

1. Introduction

A large class of quantitative problems can be described as questions about joint behaviour rather than isolated marginal behaviour. In finance, a portfolio can appear diversified when correlations are estimated during normal periods yet become highly concentrated when losses occur simultaneously. In insurance, claim counts, severities, policyholder behaviours and catastrophe losses may share common drivers. In mortality and demography, national populations and causes of death often display common trends, while idiosyncratic components remain relevant for forecasting. These examples differ in subject matter but share a statistical problem: the dependence structure may be as important as the marginal distributions themselves.

Copula theory offers one formal route for separating marginal distributions from dependence, following the logic of Sklar's theorem. Modern dependence modelling extends far beyond static bivariate copulas, however. Time-varying copulas, vine constructions, factor models, dynamic correlations, tail-dependence measures and machine-learning approaches all attempt to represent dimensions of joint behaviour that simple linear correlation may miss (Joe, 2014; McNeil et al., 2015; Patton, 2006). The central challenge is therefore not merely to select a flexible model, but to ensure that flexibility corresponds to the scientific question being asked.

2. Four principles for cross-domain dependence research

A first principle is to distinguish marginal risk from dependence risk. A joint model can be misleading if improved fit is driven by better marginal distributions while the dependence layer contributes little. Conversely, a simple marginal specification may obscure a useful dependence signal. Sequential estimation, joint likelihood approaches and diagnostic checks should therefore report the contribution of each layer separately whenever possible.

A second principle is that dependence should not automatically be assumed constant. Financial dependence often strengthens in stressed markets, while demographic and actuarial relationships can shift gradually as medical technology, policy and population composition change. Conditional copulas and dynamic correlation models demonstrate how dependence parameters can respond to past information (Engle, 2002; Patton, 2006). Researchers should justify whether variation is modelled as smooth, autoregressive, covariate-driven or regime-dependent rather than choosing a dynamic form solely because it is technically available.

A third principle is to distinguish average association from tail behaviour. Kendall's tau and Spearman's rho summarize broad concordance, but they do not fully describe the probability of joint extremes. Tail dependence has direct relevance to portfolio drawdowns, solvency stress and systemic events. The financial literature has long shown that conventional dependence measures can understate the behaviour of joint extremes (Poon et al., 2004). Similar caution is appropriate in insurance and demographic applications when rare but consequential joint outcomes matter.

A fourth principle is to evaluate dependence models using the decisions or forecasts they are intended to support. A model selected by in-sample likelihood may not be the best model for one-step-ahead density forecasting, extreme-quantile prediction, reserve aggregation or life-expectancy forecasting. Model comparison should therefore connect statistical fit to the target quantity. Proper scoring rules and out-of-sample loss comparisons provide a disciplined framework for this purpose (Diebold & Mariano, 1995; Gneiting & Raftery, 2007).

3. Domain-specific questions within a common framework

In financial applications, dependence models are often used for portfolio risk, Value-at-Risk, Expected Shortfall, systemic risk and stress testing. The relevant dependence may be asymmetric: downside co-movement can be substantially different from upside co-movement. In this setting, model validation should include stress subsamples and tail-oriented diagnostics rather than only full-sample average fit.

In insurance and actuarial science, dependence can arise between frequencies and severities, among lines of business, across policyholder states, or among competing decrement processes. Copula methods are attractive because they can encode nonlinear association while preserving distinct marginal models. Yet discrete and mixed outcomes require particular care because identification and likelihood construction can differ from the continuous case. The goal should be to preserve actuarial interpretability, especially when outputs feed reserving, capital allocation or solvency calculations.

In mortality and demography, coherence is a central concern. Closely related populations should not generally be forecast as if they evolved independently forever. Multi-population mortality work shows the value of common-factor structures that prevent implausible divergence (Li & Lee, 2005). Dependence also matters across causes of death and competing risks, although aggregate cause-specific data should not be interpreted as directly revealing individual latent lifetimes. The scientific meaning of dependence must therefore be stated explicitly.

4. A research agenda

Future contributions can advance the field in at least five directions. First, dependence measures should become more target-specific, distinguishing ordinary association, lower-tail dependence, upper-tail dependence, extremal co-movement and conditional dependence. Second, dynamic models should be evaluated for stability as well as flexibility; highly adaptive specifications can overfit short samples. Third, forecasting studies should report genuine out-of-sample performance and, where relevant, predictive distributions rather than only point estimates. Fourth, cross-domain studies should make clear which aspects of the methodology are transferable and which depend on institutional features of finance, insurance or demography. Fifth, reproducibility should be treated as part of model validation, with code, data provenance, parameter settings and random seeds documented whenever licensing permits.

A journal spanning finance, insurance and demography can be useful precisely because these disciplines often solve related statistical problems with different terminology. Comparing these approaches can reveal both hidden commonalities and domain-specific constraints.

5. Conclusion

Dependence modelling is most valuable when it clarifies joint risk rather than merely adding mathematical complexity. Across finance, insurance and demography, the strongest research designs are likely to combine interpretable marginal models, a dependence structure justified by the application, explicit attention to tail and temporal behaviour, and validation against the intended forecast or decision target. A unified research agenda should therefore emphasize comparability, transparency and out-of-sample evidence while remaining open to multiple modelling traditions.

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Copula-Based Tail Dependence for Financial and Insurance Risk: A Practical Methodological Note

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Abstract
Tail dependence describes the propensity of variables to experience extreme outcomes together and is therefore directly relevant to portfolio losses, insurance aggregation and stress testing. This methodological note summarizes a practical workflow for copula-based tail-dependence analysis. It emphasizes the distinction between correlation and tail association, the importance of filtering marginal dynamics before estimating dependence, the consequences of copula-family choice, and the need to validate models under both ordinary and stressed conditions. Particular attention is given to the Gaussian, Student-t and Archimedean copula families, to empirical tail diagnostics, and to the interpretation of upper- and lower-tail dependence. The note concludes with a compact reporting checklist intended to improve comparability and reproducibility in applied studies.

Keywords: copula; tail dependence; Value-at-Risk; Expected Shortfall; insurance losses; stress testing

1. Why tail dependence matters
Risk aggregation is most consequential when multiple positions or claims deteriorate at the same time. Linear correlation provides a useful first-order summary of association, but it does not determine joint tail probabilities. Two joint distributions can have similar correlation yet imply materially different probabilities of simultaneous extreme losses. For applications such as solvency assessment, portfolio stress testing and catastrophe aggregation, this distinction is substantive rather than cosmetic (McNeil et al., 2015; Poon et al., 2004).

Copulas provide a convenient decomposition of a multivariate distribution into marginal distributions and a dependence function. This allows a researcher to model heavy tails, skewness or discreteness in the margins while separately selecting a dependence family. The practical benefit is modularity; the practical danger is that a poor marginal model can contaminate the estimated dependence structure.

2. From raw data to pseudo-observations
A defensible workflow begins with the margins. For financial returns, conditional means and volatilities may require ARMA-GARCH-type filtering before dependence is estimated on standardized residuals. For insurance data, the appropriate marginal model depends on whether the outcomes are continuous severities, counts, zero-inflated variables or mixed frequency-severity objects. Residual diagnostics should be reported because remaining serial dependence or heteroskedasticity can be incorrectly absorbed by the copula.

After marginal fitting, observations are transformed to approximately uniform pseudo-observations. Parametric probability integral transforms, empirical ranks or semiparametric approaches may be used. The choice affects finite-sample properties, so it should be documented. Researchers should inspect rank plots and basic concordance measures before estimating complex copulas; sophisticated models cannot repair data problems that are already visible at this stage.

3. Copula families and tail implications

The Gaussian copula is computationally convenient and often useful as a benchmark, but it has zero asymptotic upper- and lower-tail dependence when correlation is below one. The Student-t copula can generate symmetric tail dependence and is therefore a common alternative for heavy-tailed financial co-movement. Archimedean families provide other patterns: Clayton copulas emphasize lower-tail dependence, Gumbel copulas emphasize upper-tail dependence, and rotated versions can represent different directional structures. Vine copulas extend the toolkit to higher dimensions by combining bivariate building blocks (Joe, 2014).

Family choice should follow the empirical question. In equity-loss applications, lower-tail association may be central; in insurance severity applications, upper-tail co-movement can be the main concern. A single scalar dependence parameter should not be interpreted as an all-purpose measure of joint risk. If asymmetry is theoretically plausible, it should be tested or visualized rather than ruled out by construction. Patton's (2006) conditional-copula framework illustrates how asymmetric dependence can vary with information over time.

4. Estimation, selection and validation

Maximum likelihood and inference-functions-for-margins approaches are common estimation strategies. Model selection can use likelihood-based criteria, but AIC or BIC alone should not determine the final specification when the model is intended for tail-risk decisions. Tail-weighted goodness-of-fit diagnostics, probability integral transform checks, exceedance frequencies and stress-sample validation can provide additional evidence.

For a portfolio application, one useful test is to propagate the fitted joint distribution into Value-at-Risk or Expected Shortfall forecasts and evaluate their realized performance. For insurance aggregation, one can compare predictive aggregate-loss distributions, extreme quantiles and capital estimates. The statistical object being evaluated should correspond to the operational purpose of the model. A copula with excellent global fit but poor tail calibration may be unsuitable for a tail-risk task.

5. Reporting checklist and conclusion

Applied tail-dependence studies should report at least the marginal models, transformation to uniforms, copula families considered, estimation method, dependence and tail-dependence estimates, sample period, treatment of serial dependence, selection criteria, stress-period diagnostics and out-of-sample evaluation. Code and random seeds should be archived when simulation is used.

The central message is straightforward: copulas are not automatically tail models. Tail behaviour is a property of the selected family and parameters, and its relevance must be validated against the risk question. A transparent benchmark-to-complexity progression - for example Gaussian, Student-t, asymmetric Archimedean and then vine or dynamic alternatives - often yields more interpretable evidence than immediately adopting the most flexible specification.

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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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Dynamic Dependence Forecasting: Time-Varying Copulas, Rolling Estimation and Forecast Evaluation

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Abstract

Dependence is often treated as a static nuisance parameter even when the application is explicitly predictive. This note considers dependence as a forecast target. It compares three broad approaches - rolling estimation, dynamic conditional correlation, and conditional or time-varying copulas - and discusses when each approach is informative. The note emphasizes the separation of marginal dynamics from dependence dynamics, the choice of forecast horizon, the risk of overfitting highly adaptive models, and the importance of out-of-sample evaluation. It also outlines a simple validation architecture based on rolling-origin forecasts, benchmark models, predictive loss functions and stress-period diagnostics. The objective is to provide a practical framework for empirical studies that claim to forecast dependence rather than merely estimate historical association.

Keywords: dynamic dependence; conditional copula; DCC; forecasting; model comparison; rolling windows

1. Dependence as a forecast object

Many empirical studies estimate a dependence parameter from a historical sample and then use that estimate as if it were stable over the forecast horizon. This can be adequate when dependence evolves slowly, but it is questionable when joint behaviour changes with volatility, liquidity, macroeconomic conditions or other state variables. A forecasting study should therefore ask explicitly whether the dependence measure itself is expected to change and, if so, at what frequency.

Financial econometrics provides several mature frameworks. Engle's (2002) dynamic conditional correlation model treats correlations as evolving conditional moments. Conditional-copula models allow the copula parameter, and potentially the copula family, to depend on lagged information (Patton, 2006). Rolling-window estimation offers a simpler nonparametric form of adaptation by repeatedly re-estimating a static model on recent data.

2. Rolling estimation versus parametric dynamics

Rolling windows are transparent and easy to audit. Their main tuning parameter is the window length. Short windows react quickly but produce noisy estimates; long windows are stable but may adapt too slowly. Researchers should therefore treat window length as a modelling choice, not an implementation detail. Sensitivity analysis across plausible windows is often more informative than selecting one window ex post because it produced the strongest result.

Parametric dynamic models can use information more efficiently by imposing a recursive structure. DCC models update conditional correlations from standardized shocks and past conditional correlations. Conditional copulas similarly update dependence parameters through functions of past probability integral transforms or other state variables. These approaches can generate smoother forecasts and can be estimated jointly with likelihood methods, but misspecification of the updating rule may create persistent forecast errors.

3. Marginal filtering and identification

Dynamic dependence estimation is inseparable from marginal modelling. If volatility clustering remains in the residuals, a time-varying copula may appear to detect changing dependence when it is actually absorbing unmodelled marginal scale dynamics. The forecasting pipeline should therefore diagnose each margin first and then check transformed residuals for approximate uniformity and serial independence.

The same principle applies outside finance. In insurance, seasonal claim intensity or exposure changes should be handled before dependence is interpreted. In mortality, age-period structure and long-run trend should be represented before the residual dependence across populations or causes is modelled. A dynamic dependence parameter is meaningful only relative to the marginal structure it complements.

4. Designing a genuine out-of-sample experiment

A credible dependence-forecasting exercise should specify an estimation window, forecast origin, horizon, update frequency and benchmark before examining the results. Rolling-origin evaluation is particularly useful because it mimics the information set available in real time. Benchmarks should include a constant-dependence model and, where relevant, a simple rolling measure. Complex models should demonstrate incremental forecast value relative to these baselines.

Evaluation depends on the predicted object. If the model produces a full joint predictive density, proper scoring rules are appropriate (Gneiting & Raftery, 2007). If the target is a risk measure, backtests of Value-at-Risk or Expected Shortfall may be more directly relevant. If the target is a dependence statistic, forecast loss can be constructed around realized proxies, but measurement error in those proxies must be acknowledged. Diebold-Mariano-style comparisons can be useful when a stable loss differential is available (Diebold & Mariano, 1995).

5. Stress periods, stability and conclusion

Average out-of-sample performance can conceal important state dependence. A model may perform similarly to a benchmark during ordinary periods but materially better or worse during crises. Stress-period diagnostics should therefore be pre-specified where possible and should not replace full-sample evaluation. Parameter stability, convergence failures and sensitivity to initial conditions should also be reported, because a model that forecasts well only after frequent manual intervention is difficult to reproduce.

Dynamic dependence models are most persuasive when they beat simple benchmarks on a clearly defined forecast target and remain interpretable under stress. The appropriate level of complexity depends on data frequency, sample size and decision horizon. Forecasting dependence is a distinct task from estimating dependence, and empirical papers should be designed accordingly.

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Reproducibility and Model Validation in Dependence-Based Risk Research: A Practical Framework

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Abstract

Dependence-based risk models are often computationally intensive and sensitive to preprocessing, marginal specifications, optimization choices, simulation settings and forecast design. Reproducibility is therefore not an accessory to validation but a condition for meaningful evaluation. This note proposes a practical framework for reproducible dependence research in finance, insurance and demography. The framework covers data provenance, deterministic preprocessing, separation of estimation and evaluation samples, versioned code, random-seed control, parameter disclosure, benchmark specification, robustness analysis and preservation of computational outputs. It also distinguishes reproducibility from replication and argues that journals can improve the reliability of computational research by requiring concise, proportionate transparency statements rather than imposing a single software or repository standard.

Keywords: reproducibility; model validation; open science; risk modelling; forecasting; computational research

1. Why reproducibility matters for dependence models

Modern dependence studies may combine several layers: data cleaning, marginal models, probability integral transforms, copula selection, numerical optimization, simulation, rolling forecasts and downstream risk calculations. Two researchers using the same conceptual method can obtain different results because of seemingly minor implementation choices. Reproducibility is therefore a practical part of model validation, particularly when a paper's contribution depends on computation rather than a closed-form theorem.

Peng (2011) described reproducibility as a minimum standard for computational science when full independent replication is not feasible. Later work emphasized the need to disclose code, computational environments and workflow information where possible (Stodden et al., 2016). Open-science standards likewise encourage transparent reporting without assuming that all data can always be made public (Nosek et al., 2015).

2. A minimum reproducibility record

A dependence-modelling paper should preserve a minimum reproducibility record. First, data provenance should identify the source, access date, sample restrictions and any transformations. Second, preprocessing should be deterministic where feasible and documented sufficiently to reconstruct the analysis sample. Third, software versions and key package versions should be recorded. Fourth, random seeds should be fixed and disclosed for simulations, bootstraps or stochastic optimization. Fifth, model settings - including copula families, window lengths, optimization bounds, convergence tolerances and forecast horizons - should be stated explicitly.

The record does not need to be cumbersome. A machine-readable configuration file, a concise README and a small number of well-named scripts can be more useful than hundreds of undocumented files. The objective is to allow another researcher, or the original author months later, to understand exactly how the reported tables and figures were generated.

3. Validation should be separated from model construction

Reproducibility and validation reinforce each other when the workflow separates model development from evaluation. In-sample diagnostics are useful for detecting misspecification, but they cannot by themselves establish forecast value. A transparent workflow should identify training, validation and test periods, or explain the rolling-origin design used for time series. Benchmark models should be specified before results are interpreted.

Forecast evaluation should also match the prediction target. Density forecasts can be assessed with proper scoring rules (Gneiting & Raftery, 2007). Point or risk forecasts can be compared using target-specific losses and formal predictive-accuracy tests where their assumptions are reasonable (Diebold & Mariano, 1995). Dependence models should additionally be checked for numerical stability, sensitivity to starting values and failed fits, because silently dropping difficult windows can bias reported performance.

4. Robustness without specification mining

Robustness analysis is valuable when it tests a small set of scientifically motivated alternatives: different marginal distributions, dependence families, window lengths, sample endpoints or stress definitions. It becomes less informative when hundreds of specifications are searched and only favourable results are reported. A reproducible paper should make the model universe visible enough for readers to distinguish robustness from specification mining.

Pre-specified benchmark sets, complete result tables and machine-readable outputs can help. When a large model search is itself part of the method, the selection rule should be algorithmic and applied inside the out-of-sample loop rather than using future information. This is especially important for automated copula selection, machine-learning risk models and mortality model-selection systems.

5. Journal-level practice and conclusion

Journals can support reproducibility with proportionate requirements. A short data-availability statement, code-availability statement, conflict-of-interest declaration, funding statement and AI-use disclosure create a useful baseline. When data are proprietary or restricted, authors can still share synthetic examples, code templates and metadata describing the inaccessible inputs. The FAIR principles provide a useful aspiration for making digital research objects findable, accessible, interoperable and reusable when legal and ethical constraints permit (Wilkinson et al., 2016).

Reproducibility does not guarantee correctness, and a reproducible error remains an error. Its value is that it makes the analytical chain inspectable. In dependence-based risk research, where results may be sensitive to marginal assumptions, numerical optimization and simulation, that inspectability is a core component of scientific credibility.

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