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"Adversarial Density Forecast for Macro-financial Risks"

Abstract: Forecasting macroeconomic risks, and especially tail risks, requires capturing complex distributional dynamics but is constrained by the limited sample sizes typical of macro-financial time series. While parametric benchmarks like skew-t regressions offer stability at the cost of shape rigidity, flexible nonparametric methods often suffer from finite-sample overfitting and tail miscalibration. This paper proposes a Penalized ConditionalWasserstein Generative Adversarial Networks (PcWGAN) for density forecasting. We formalize the estimator as a penalized sieve minimizer of the conditional Wasserstein-1 distance, augmented by moment-quantile penalties. Theoretically, we establish that this penalization acts as a Tikhonov regularizer that restricts the estimator to a "moment tube" with reduced metric entropy, thereby tightening finite-sample oracle risk bounds without altering the asymptotic consistency target. To address the slow convergence rates typical of nonparametric sieves, we implement a second-stage anchored monotone rescaling with interleaved cross-fitting. We show that this semiparametric calibration improves tail reliability without materially distorting the global shape learned in the first stage. Monte Carlo experiments indicate that penalization stabilizes adversarial learning in small samples, and that calibration delivers additional gains in tail coverage and scoring relative to the uncalibrated distribution; under bimodal misspecification it also performs well against parametric benchmarks. In an empirical application to the U.S. Outlook-at-Risk, the proposed approach combines flexible distributional learning with improved tail reliability required for policy analysis, supporting risk measurement in macro-financial settings.