

## Accepted Manuscript

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PII: S2452-3062(17)30068-0  
DOI: [10.1016/j.ecosta.2017.08.001](https://doi.org/10.1016/j.ecosta.2017.08.001)  
Reference: ECOSTA 75



To appear in: *Econometrics and Statistics*

Received date: 1 September 2016  
Revised date: 1 August 2017  
Accepted date: 4 August 2017

Please cite this article as: Sebastian Bayer, Combining Value-at-Risk Forecasts Using Penalized Quantile Regressions, *Econometrics and Statistics* (2017), doi: [10.1016/j.ecosta.2017.08.001](https://doi.org/10.1016/j.ecosta.2017.08.001)

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# Combining Value-at-Risk Forecasts Using Penalized Quantile Regressions

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## Abstract

Penalized quantile regressions are proposed for the combination of Value-at-Risk forecasts. The primary reason for regularization of the quantile regression estimator with the elastic net, lasso and ridge penalties is multicollinearity among the standalone forecasts, which results in poor forecast performance of the non-regularized estimator due to unstable combination weights. This new approach is applied to combining the Value-at-Risk forecasts of a wide range of frequently used risk models for stocks comprising the Dow Jones Industrial Average Index. Within a thorough comparison analysis, the penalized quantile regressions perform better in terms of backtesting and tick losses than the standalone models and several competing forecast combination approaches. This is particularly evident during the global financial crisis of 2007 – 2008.

*Keywords:* Value-at-Risk, Forecast Combination, Quantile Regression, Elastic Net, Regularization  
*JEL:* C51, C52, C53, G32

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## 1. Introduction

Although difficult, it is important to decide between alternative Value-at-Risk (VaR) modeling and forecasting strategies. A poorly selected risk model may have drastic effects on banks and the economy as a whole, as evidenced during the previous financial crisis when many standard approaches predicted inadequately low levels of risk. [Einhorn \(2008\)](#) compares the VaR to “an airbag that works all the time, except when you have a car accident”. The VaR is defined as the worst possible loss over a target horizon that will not be exceeded with a given probability ([Jorion, 2006](#)). Therefore, VaR is a quantile of the distribution of returns over a horizon (usually one or ten days) for a given probability level (typically 1%). A major reason for its popularity is that the [Basel Committee on Banking Supervision \(1996, 2006, 2011\)](#) utilizes the VaR for calculation of the minimum capital requirements which banks need to keep as reserves to cover the market risk of their investments.

Extensive literature exists on how to estimate and predict VaR (see [Kuester et al. \(2006\)](#), [Komunjer \(2013\)](#) and [Nieto and Ruiz \(2016\)](#) for overviews). The primary issue with VaR forecasting, however, is that the models’ performance and reliability in accurately predicting the risk depends heavily on the data. While a parsimonious model might perform well in economically stable periods, it can fail tremendously during a volatile period. Likewise, highly parameterized models might be adequate during periods of high volatility, but can be easily outperformed by simpler approaches in less turbulent times. To date, no unique model or approach dominates throughout the existing VaR forecasting comparisons (see [Kuester et al. \(2006\)](#), [Marinelli et al. \(2007\)](#), [Halbleib and Pohlmeier \(2012\)](#), [Abad and Benito \(2013\)](#), [Boucher et al. \(2014\)](#), [Louzis et al. \(2014\)](#), [Ergen \(2015\)](#), [Nieto and Ruiz \(2016\)](#) and [Bernardi and Catania \(2016\)](#)). The key reasons for this finding are that the applied models are prone to suffer from model misspecification (e.g. through the application of an overly simplistic model) and estimation uncertainty (e.g. they imply a complicated estimation procedure). For a more detailed discussion of the risks and uncertainties involved in VaR forecasting, see [Boucher et al. \(2014\)](#).

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