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Model risk of risk models☆

Jon Danielsson[a], Kevin R. James[b], Marcela Valenzuela[c], Ilknur Zer[d,*]

[a] Department of Finance and The Systemic Risk Centre, London School of Economics, Houghton St., London WC2A 2AE, UK
[b] The Financial Markets Group and The Systemic Risk Centre, London School of Economics, Houghton St., London WC2A 2AE, UK
[c] University of Chile (DII), Beauchef 851, Santiago, Chile
[d] Federal Reserve Board, USA

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ABSTRACT

This paper evaluates the model risk of models used for forecasting systemic and market risk. Model risk, which is the potential for different models to provide inconsistent outcomes, is shown to be increasing with market uncertainty. During calm periods, the underlying risk forecast models produce similar risk readings; hence, model risk is typically negligible. However, the disagreement between the various candidate models increases significantly during market distress, further frustrating the reliability of risk readings. Finally, particular conclusions on the underlying reasons for the high model risk and the implications for practitioners and policy makers are discussed.

1. Introduction

Following the 2008 crisis, risk forecasting has emerged as a key public concern. Statistical risk measures are set to play a much more fundamental role in policy and decision making within financial institutions than before the crisis. Hence, an understanding of the model risk of risk forecast models—that is, the potential for different underlying risk forecast models to provide inconsistent outcomes—is of considerable interest to both policymakers and practitioners. The empirical study of such risk for macroprudential and internal management purposes constitutes the main motivation of this paper.

Why does model risk matter? Risk models play a fundamental role in the regulatory process and are directly embedded within the Basel regulations and therefore used to determine bank capital. While their use for macroprudential purposes is not as clear, there are a number of proposals from the academic and public sectors for using these models for setting bank capital and surcharges to meet systemic risk. Hence, the output of these models has a real economic impact. For these reasons, it is important to understand

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* Corresponding author at: Federal Reserve Board, 20th Street and Constitution Avenue N.W., Washington, DC 20551, USA. Tel.: +1 202 384 4868.

E-mail addresses: j.danielsson@lse.ac.uk (J. Danielsson), k.james1@lse.ac.uk (K.R. James), mvalenzuela@dii.uchile.cl (M. Valenzuela), ilknur.zerboudet@frb.gov (I. Zer).

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to what extent decision makers can rely on risk models and when their use is not advisable.

We start by proposing a general framework for quantifying model risk. To this end, we focus on the level of disagreement amongst the candidate models and propose a new method we term *risk ratio*. This entails applying a range of common risk forecast methodologies to the problem of forecasting risk, and calculating the ratio of the maximum to the minimum risk forecasts. This provides a succinct way of capturing model risk because if the underlying models have passed some model evaluation criteria used by the authorities and financial institutions, they can be considered reputable risk forecasting candidates. If risk is forecasted by a number of equally good models, the risk ratio should be close to 1. If the risk ratio is very different from 1, then it captures the degree to which different models disagree, providing a measure of model risk.

We first focus our attention on the five most commonly used risk forecast models: historical simulation, exponentially weighted moving average, normal GARCH, Student-*t* GARCH, and extreme value theory. In addition, we include six hybrid models identified in the literature as high quality: both extreme value theory and historical simulation applied to GARCH filtered data under the assumptions of normal, Student-*t*, and skewed-*t* error term distributions. While it would be straightforward to expand the universe of models if another prominent candidate emerges, it will not materially affect the results since any additional model can only increase model risk.

We first apply the risk ratio methodology on market risk measures. Value-at-Risk (VaR) has been the main building block of market risk regulations since its first incorporation into the Basel Accords in 1996; hence, the model risk of VaR is our starting point. In addition, we consider the model risk of expected shortfall (ES), since the Basel committee (2013, 2014) has proposed replacing VaR with ES in market risk regulations.

We then propose a general setup for the classification of systemic risk models (SRMs), providing a lens through which to analyze the most common market data based systemic risk models. The prominent marginal expected shortfall (MES) (Acharya et al., 2010), conditional value at risk (CoVaR) (Adrian and Brunnermeier, 2011), SRISK (Brownlees and Engle, 2015; Acharya et al., 2012), Co-Risk (IMF, 2009), and BIS's Shapley value method (Tarashev et al., 2010) all fall under our classification setup. While intended for different purposes, these measures and market risk regulation techniques are closely related; both elementally depend on VaR, suggesting that the model risk of VaR is likely to pass through to market data based SRMs. One could apply the risk ratio approach to the various market data based SRMs, but given their common ancestry, we expect the results to be fundamentally the same, and in the interest of brevity we focus on two SRMs: MES and CoVaR.

The data set consists of large financial institutions traded on the NYSE, AMEX, and NASDAQ from the banking, insurance, real estate, and trading sectors over a sample period spanning 1970–2012. We find that on average, model risk is quite low, indicating that in typical situations decision makers do not have to be too concerned about model choice or model risk. However, the situation changes when looking at individual stocks and periods of stress in financial markets. Model risk is significantly higher when an individual stock is subject to idiosyncratic shocks or when financial markets are stressed. The average maximum 99% VaR risk ratio across the whole sample is 9.23, and in the most extreme case it reaches 55.32, during the 1987 crash. None of the models *systematically* gives the lowest or highest forecasts, and the large risk ratios are not driven by the inclusion of a particular model.

The empirical results are a cause for concern, as the degree of model risk documented here frustrates internal risk management as well as macro-prudential and micro-prudential policy. For this reason, our results should be of considerable value to policymakers and risk managers alike, who will get a better understanding of the reliability of risk models and how to understand the problem of conflicting measurements of the same underlying risk. Ultimately, a better understanding of model risk should lead to more robust policymaking and asset allocation.

We suspect the problem of model risk arises for two reasons. The first is the low frequency of actual financial crises. Developing a model to capture risk during crises is quite challenging, since the actual events of interest have almost never happened during the observation period. Such modeling requires strong assumptions about the stochastic processes governing market prices that are likely to fail when the economy enters a crisis.

Second, common statistical models assume risk is exogenous—extreme events arrive to the markets from outside, like an asteroid would, and the behavior of market participants has nothing to do with the crisis. However, as argued by Danielsson and Shin (2003) and Brunnermeir and Sannikov (2014), risk is really endogenous, created by the interaction between market participants and by their desire to bypass risk control systems. As both risk takers and regulators learn over time, we can also expect price dynamics to change, further frustrating statistical modeling.

It is important to recognize that the output of risk forecast models is used as an input into expensive decisions, be they portfolio allocations or the amount of capital held. Hence, the minimum acceptable criterion for a risk model should not be to weakly beat noise, but the quality of the risk forecasts should be sufficiently high so the cost of type I and type II errors are minimized, as argued by Danielsson et al. (2016).

Furthermore, most successful market risk methodologies, including all of those discussed here, were originally designed for the day-to-day management of market risk in financial institutions. In our view, one should be careful when using the same statistical toolkit for the more demanding job of systemic and tail risk identification.

The outline of the rest of the paper is as follows. Section 2 gives the details of the model risk analysis conducted. Section 3 presents the empirical findings for market regulatory models. Section 4 provides a classification system for systemic risk methodologies and examines the model risk of market data based systemic risk models. Section 5 features a discussion of our main findings. Section 6 concludes.

2. Model risk analysis

Broadly speaking, model risk relates to the uncertainty created by not knowing the data generating process. That high level definition does not provide guidance on how to assess model risk, and any test for model risk will be context dependent.

Within the finance literature, Green and Figlewski (1999), Cont (2006) and Hull and Suo (2002) underline three different sources of model risk. First, there is uncertainty on the choice of the model itself. Second, the underlying theoretical model could be misspecified. Third, some of the input parameters in the underlying model could be unobservable and hence may require assumptions for empirical implementation. For Gibson (2000), model risk is defined as uncertainty over the risk factor distribution, whereas Alexander and Sarabia (2012) distinguish two sources of model risk: inappropriate assumptions about the form of the statistical model, and parameter uncertainty (i.e., estimation error in the parameters of the chosen model). Finally, Hendricks (1996), Glasserman and Xu (2013) and Boucher et al. (2014) define model risk as inaccuracy in