Journal of Banking & Finance 34 (2010) 267–279

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

Model risk and capital reserves

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ARTICLE INFO

Article history:
Received 24 September 2008
Accepted 24 July 2009
Available online 6 August 2009

JEL classification:
G12
G18

Keywords:
Capital requirements
Model risk
Risk measures
Estimation risk
Misspecification risk
Identification risk

ABSTRACT

We propose a procedure to take model risk into account in the computation of capital reserves. This addresses the need to make the allocation of capital reserves to positions in given markets dependent on the extent to which reliable models are available. The proposed procedure can be used in combination with any of the standard risk measures, such as Value-at-Risk and expected shortfall.

We assume that models are obtained by usual econometric methods, which allows us to distinguish between estimation risk and misspecification risk. We discuss an additional source of risk which we refer to as identification risk. By way of illustration, we carry out calculations for equity and FX data sets. In both markets, estimation risk and misspecification risk together explain about half of the multiplication factors employed by the Bank for International Settlements (BIS).

1. Introduction

Due to the growing complexity of financial markets, financial institutions rely more and more on models to assess the risks to which they are exposed. The accuracy of risk assessment depends crucially on the reliability of these models. In spite of the very substantial efforts made both by practitioners and academics to improve the quality of market models, one needs to recognize that there is no such thing as a perfect model. The hazard of working with a potentially incorrect model is referred to as *model risk*. Methods for the quantification of this type of risk are not nearly as well developed as methods for the quantification of market risk given a model, and the view is widely held that better methods to deal with model risk are essential to improve risk management.[1]

While model risk is present in each market, the significance of its role may be different in different markets, depending on such factors as the amount of experience that has been built up and the complexity of products that are being traded. Additionally, it may be important to distinguish between the various purposes for which models are used, such as pricing, hedging, and the computation of capital reserves. There can be several sources of model risk, including for instance the risk of human error in modeling; various factors, and ways to guard against them, are discussed by Derman (1996).

The main question that we want to answer in this paper is how to incorporate model risk associated to the application of econometric methods into the computation of required levels of capital reserves. While it is of course possible and useful to investigate the effect of parameter variations on risk measures that are computed in a particular parametric framework, as for instance in Bongaerts and Charlier (2009), our aim in this paper is to take model risk explicitly into account as a separate risk factor. The paper is similar in spirit to the work of West (1996), who discusses when and how to adjust critical values for tests of predictive ability in order to take parameter estimation uncertainty into account. Here we adjust levels of risk measures, such as VaR, rather than critical values. There are parallels as well with the work of Brock et al. (2003, 2007) on the role of model risk in policy evaluation. However, the model averaging method proposed by Brock et al.

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[1] For instance, the chief executive of the British Financial Services Authority, Hector Sants, writes in a letter to financial industry CEOs (August 13, 2008; http://www.fsa.gov.uk/pubs/ceo/valuation.pdf): "Few firms have sufficiently developed frameworks for articulating model risk tolerance, and measuring and controlling risks within that tolerance. We believe a better defined and implemented model risk management framework could therefore feed into a better defined and implemented valuation risk management framework".

0378-4266/$ - see front matter
doi:10.1016/j.jbankfin.2009.07.025

(2003) is difficult to use in the applications we have in mind, since it requires specification of a prior over the model space. The dispersion view expounded by Brock et al. (2007) is useful for robustness analysis of policies; risk assessment, however, typically calls for quantification of risk by means of a single number expressing the required capital reserve.

Hull and Suo (2002) quantify model risk by comparing the pricing and hedging performance of a simple model within the context of a more complicated model, which is interpreted as representing the true data generating process. This is a way of judging whether a proposed model simplification is feasible. In this paper we do not assume that we know the true data generating process. Closer to the present paper is the work by Cont (2006), who studies the impact of model risk on pricing. Our paper is different in the sense that we are concerned with risk measures rather than prices; moreover, we discuss a specific procedure to arrive at classes of alternative models, whereas the discussion of Cont (2006) is abstract in this respect. Approaches to the design of policies that are robust with respect to model uncertainty have been developed for instance by Hansen and Sargent (2007) and ElKaroui et al. (1998). Robust hedging strategies can play an important role in mitigation of model risk. Here we assume that the effect of hedging is already incorporated in the definition of a given position.

In this paper, we incorporate model risk into risk measure calculations by constructing classes of models on the basis of standard econometric procedures. We then arrive at adjustments of a nominal risk measure, such as VaR, by computing the worst case across such classes. We distinguish between several stages of modeling which each give rise to different model classes and hence to different adjustments of a chosen risk measure. In this way, we define several components of model risk which we refer to as *estimation risk*, *misspecification risk,* and *identification risk*.

Estimation risk is the risk associated with inaccurate estimation of parameters. This type of model risk has perhaps most frequently been discussed in the literature; see for instance Gibson et al. (1999), Talay and Zheng (2002) and Bossy et al. (2000). Misspecification risk is associated with incorrect model specification. The presence of misspecification risk may be detected by the use of standard econometric methods. Identification risk arises when observationally indistinguishable models have different consequences for capital reserves.

For an example of identification risk, consider the following situation. The value of a mortgage portfolio depends on the delinquency behavior of home owners, which in turn may be influenced by house price appreciation rates. If in the available data set the house price appreciation rate is constant, or nearly so, then on the basis of statistical procedures it is not possible to make statements about the dependence of model parameters on the appreciation rate. Of course, one might construct models under the assumption that parameters do not depend on the house price appreciation rate. However, such models may not provide adequate risk assessment in situations in which the appreciation rate does move considerably.[2]

As noted by Cont (2006), the notion of components of model risk does not come up in an abstract framework, since in such a setting one can work with a class of alternative models which is assumed given and which in principle does not need to have any particular structure. However, in applications we must have a way to construct the class of alternative models, and this may lead to the presence of more structure than can be or needs to be supposed at the abstract level. The situation we consider in this paper is of that type. The distinctions that we construct are meaningful within the context of a given econometric framework; of course, they do depend on the specific framework that is chosen and we do not claim that model risk in general should be or even can be decomposed in such a way.

Currently, no explicit capital requirements are imposed by regulators in connection with model risk, save perhaps risk factors due to human errors which are covered under operational risk. However, the Basel Committee does apply the so called *multiplication factors* which could be motivated in part as a way of taking model risk into account. In our empirical applications, we consider time series data of the S&P 500 index and the USD/GBP exchange rate. We consider two simple models (a Gaussian i.i.d. model and a GARCH(1,1) model) which are estimated on the basis of rolling-window data, and we find that both are rejected when used as nominal models. However, adding misspecification risk and estimation risk at the usual 95% confidence level leads to risk measure levels that pass the standard backtests in all cases we consider. The results can be interpreted in terms of a multiplication factor that should be applied to account for model risk in a given market. Our results for these models indicate that about half of the regulatory capital set by the Basel Committee can be explained by incorporating estimation and misspecification risk, when computing the 1% Value-at-Risk at a 95% confidence level for estimation risk. Of course there are other considerations that may play a role as well in the determination of multiplication factors, such as macroeconomic effects (procyclicality) and the effects on the behavior of regulated institutions; see for instance Heid (2007) and Kaplanski and Levy (2007).

The remainder of the paper is structured as follows. In Section 2 we first present a simple example based on simulated data to illustrate the approach to model risk that we take in this paper. Then, in Section 3, we discuss the formulation of risk measures in an environment in which we work with multiple models that may employ different probability spaces. Our method of quantifying model risk is presented in general terms in Section 4. Then we turn to empirical applications in Section 5. Section 6 concludes.

2. Illustration of model risk

By *market risk* we understand the risk caused by fluctuations in asset prices. Market risk for a given position may be quantified by a risk measure such as Value-at-Risk (VaR) or Expected Shortfall (ES). The purpose of this section is to illustrate in a simple example the possible impact of several forms of model risk on market risk assessment.

Suppose that X_T denotes the current (known) position, and that the future position can be described by a random variable $X_{T+1} = X_T \exp(Y_{T+1})$, where the log return Y_{T+1} follows some unknown distribution conditional upon the information available at time T, represented by a σ-algebra $\mathscr{F}_T$. To form a risk assessment, one could for instance choose to model the distribution of the log return Y_{T+1} as a normal distribution with mean μ and variance σ^2, i.e.,

$$Y_{T+1}|\mathscr{F}_T \sim \mathscr{N}(\mu, \sigma^2) \tag{1}$$

or, equivalently, $Y_{T+1} = \log(X_{T+1}/X_T) = \mu + \sigma\epsilon_{T+1}$ with $\epsilon_{T+1}|\mathscr{F}_T \sim \mathscr{N}(0,1)$. The Value-at-Risk at level p is then given by

$$\mathrm{VaR}_T(X_{T+1} - X_T) = X_T(1 - \exp(z_p\sigma + \mu)) \tag{2}$$

where z_p denotes the pth quantile of the standard normal distribution, and where the index T indicates that the VaR is calculated at time T, given the information $\mathscr{F}_T$. One may also choose an alterna-

[2] This example is modeled on the 2007 subprime mortgage crisis, but is stated in an idealized form to bring out more clearly the notion of identification risk. Whether in the case of the subprime crisis it was really not possible to predict the changes in delinquency behavior on the basis of data is debatable; see for instance Demyanyk and Van Hemert (forthcoming).