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A spatial mean-variance MIP model for energy market risk analysis

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Abstract

The paper presents a short-term market risk model based on the Markowitz mean-variance method for spatial electricity markets. The spatial nature is captured using the correlation of geographically separated markets and the consideration of wheeling administration. The model also includes transaction costs and other practical constraints, resulting in a mixed integer programming (MIP) model. The incorporation of those practical constraints makes the model more attractive than the traditional Markowitz portfolio model with continuity. A case study is used to illustrate the practical application of the model. The results show that the MIP portfolio efficient frontier is neither smooth nor concave. The paper also considers the possible extension of the model to other energy markets, including natural gas and oil markets.

JEL classifications: G12; L71

Keywords: Markowitz; Mean-variance; MIP; Portfolio; Risk

1. Introduction

There have been many studies on risk and portfolio selection based on the Markowitz mean-variance (MV) method (Markowitz, 1952, 1959). Due to its robustness and ease of implementation (i.e. using Quadratic Programming), the MV

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method has also found wide applications in the financial industry worldwide. Despite the fact that semivariance (SV) has been used as a risk measure (e.g., Markowitz, 1959; Porter, 1974), the MV method is still a powerful tool because of its computational advantage. Besides, there is only a minor difference between the efficient frontiers of the MV and SV portfolios (Michaud, 1998). As pointed out by Markowitz, the successful application of the SV method depends on finding the joint probability distribution of a portfolio and this has been a serious computational problem. As a result, only approximate methods are used for estimating the portfolio semivariance (Markowitz et al., 1993; Nawrocki, 1991).

The MV method is not perfect—it cannot take into consideration fixed transaction fees and other fixed costs. As a result, the MV method can only achieve sub-optimal solutions in portfolio selection and risk quantification. Portfolio models based on MV often overstate diversification and the problem is partly induced by ignoring fixed transaction costs. The CAPM (Capital Asset Pricing Model—Sharpe, 1964) and the APT (Arbitrage Pricing Theorem—Ross, 1976) models also have the same problem. Fortunately, there have been attempts to resolve the problem. Proportional transaction costs have been discussed by many authors (e.g. Pogue, 1970; Chen et al., 1971). For portfolio risk analysis considering option pricing and transaction costs, Leland (1985) introduced the notion of a break-even volatility and the idea was furthered by Whalley and Wilmott (1993). However, all these studies do not incorporate integer formulations.

The MIP models are the most appropriate choice for portfolio risk analysis when fixed transaction costs and minimum transaction lots are considered. In fact, there have been a few portfolio studies with MIP formulations. For example, Bertsimas et al. (1999) described an MIP portfolio model based on the maximization of expected returns, Kellerer et al. (2001) discussed an MIP model with fixed transaction costs and the minimum transaction lots. However, no MIP portfolios, with a market risk formulation, have been used for spatial energy markets and this makes our study very meaningful. In the following, we will first focus our portfolio risk study on short-term electricity markets with a special attention paid to a spatial market setting and will discuss the extension of the model to other energy markets.

In regulated power systems, risks are primarily associated with system planning and operation. They include the risk of capacity shortages due to under planning, load uncertainty and system failures (Billinton and Allan, 1996). The risk in power production costing due to load uncertainty and plant availability has also been addressed extensively (Breipohl et al., 1992; Douglas et al., 1998). As deregulation unfolds, power producers are facing more risks than before. To name a few, there can be operating risk, credit risk, market risk, legal risk, etc. A grand unification model including all these risks has yet to be researched.

Producers need to assess different market risks in the deregulated environment. For example, a large power producer in a region may assume an oligopolistic strategy. The producer would face the risk that other producers may not use the same oligopolistic strategy and may be undercut by its opponents. On the other hand, a small producer or a competitive fringe may seldom adopt a gaming strategy (Hogan, 1997) and it may primarily be concerned with the risk associated with