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Value-at-Risk forecasts by a spatiotemporal model in Chinese stock market

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HIGHLIGHTS

- We model spatial dependence and serial correlation in stock returns.
- We use a spatiotemporal model with time-varying spatial weight matrices.
- Behavioral factors based on firm characteristics are relevant for stock returns.
- Different Value-at-Risk (VaR) models are used and compared to each other.

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ABSTRACT

This paper generalizes a recently proposed spatial autoregressive model and introduces a spatiotemporal model for forecasting stock returns. We support the view that stock returns are affected not only by the absolute values of factors such as firm size, book-to-market ratio and momentum but also by the relative values of factors like trading volume ranking and market capitalization ranking in each period. This article studies a new method for constructing stocks' reference groups; the method is called quartile method. Applying the method empirically to the Shanghai Stock Exchange 50 Index, we compare the daily volatility forecasting performance and the out-of-sample forecasting performance of Value-at-Risk (VaR) estimated by different models. The empirical results show that the spatiotemporal model performs surprisingly well in terms of capturing spatial dependences among individual stocks, and it produces more accurate VaR forecasts than the other three models introduced in the previous literature. Moreover, the findings indicate that both allowing for serial correlation in the disturbances and using time-varying spatial weight matrices can greatly improve the predictive accuracy of a spatial autoregressive model.

1. Introduction

The specification and estimation of dynamic spatial panel data models, which can address spatial dependence among the observations at each point in time and serial correlations between the observations on each spatial unit over time, have been extensively studied in the existing literature [1–5]. However, due to the difficulties in defining contiguity in the context of financial markets, overall, the applications of a dynamic model in space and time in the fields of finance and economics are not very popular.

Some important recent contributions include that of Fernandez [6], who derived a spatial version of the capital asset pricing model (CAPM) using Spearman's correlation coefficients of the financial indicators to define spatial weight matrix.

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Badinger and Egger [7] discussed the specification and estimation method of a spatial autoregressive (SAR, hereafter) model with spatial regressive disturbances and heteroskedastic innovations, allowing for arbitrary but finite-order spatial lags in both the dependent variable and the disturbances. Indeed, a SAR model with multiple spatial lags has been both specified and estimated in numerous studies [8–11]. As referred in Ref. [11], multiple spatial weight matrices may capture the contiguity of spatial units in various dimensions. One such example is Zhu et al. [12], who explored the potential differences in regional housing prices among 20 cities in the US using a dynamic spatial panel data model with GARCH terms. Note that in their paper, two spatial weight matrices are specified: one based on geographical contiguity and the other based on economic similarity. Besides, Amaral et al. [13] used a spatial probit model to study the effect of contagion between banking systems in different countries; they then compared their results under two methods of constructing the spatial weight matrices.

In addition, motivated by the framework of the SAR model proposed by Ref. [7], Arnold et al. [14] introduced a simplified SAR model for stock returns, which incorporates three types of spatial dependences (i.e., global dependences, dependences inside branches and regional dependences). When empirically applied to Stoxx 50 returns, the model performs superior to both the one-factor model and the sample covariance-matrix method in terms of producing more reliable VaR forecasts. Later, the model was partly extended in the following two studies. One further study is Wied [15] who proposed a new formal CUSUM-type statistical test accounting for possible structural break points for the constancy of spatial dependence parameters over time. The motivation for using the change point test arises from the fact that the empirical findings of Arnold et al. [14], which show the increasing spatial dependences during the global financial crisis (GFC, hereafter), demonstrate that the spatial dependence parameters may be not constant over time. By applying the proposed model to Stoxx 50 returns, the paper concludes that combining the SAR model with structural break point tests may lead to superior risk forecasts in portfolio management. Conversely, Schmitt et al. [16] extended the SAR model for stock returns by applying a GARCH fit and local normalization to modify the fluctuating volatilities and the time series of changing trends. The empirical results indicate that their SAR model provides the best estimation of risk measures in the context of portfolio optimization.

Two common features of these spatial models are the specification of the regression model and the estimation method. First, in the context of the specification of the regression model, they consider a SAR model that includes no explanatory variables and assume that although the error terms are cross-sectional independent, they may be serially correlated. As noted by Arnold et al. [14], this assumption on error terms is reasonable given that they assume that the total amount of spatial dependence is captured by the three types of spatial dependences and consider a time component in the model. Second, they all adopt the generalized method of moments (GMM) estimation method suggested by Ref. [17] because the spatial dependence parameters and variance parameters can be easily and consistently estimated via such method.

This paper is related to contributions by the above-mentioned studies. However, this article is different in the following three aspects.

First, there is substantial empirical evidence that stock returns are correlated to both market risk factors and factors that are based on firm-level characteristics like firm size, book-to-market ratio and momentum. For example, the classical capital asset pricing model (CAPM) developed by Sharpe [18] and Lintner [19] shows that stock returns can be determined by the market risk factors. Subsequent work by Fama and French [20] demonstrated that the cross-sectional variations in average equity returns can be better explained by a combination of risk factors such as market risk, firm-level market capitalizations and book-to-market effects than by the one-factor model. Moreover, numerous studies indicate that stock returns may be affected by industry factors, trading volumes, investors' trading behaviors and so on [21–23]. Thus, we generalize the SAR model by adding reasonable exogenous explanatory variables to the regression model. We not only use traditional factors such as market factor, size factor, book-to-market ratio factor and momentum factor as the independent variables but also introduce some behavior explanatory variables. The definition method of the behavior explanatory variables that we provide is new and introduces the concepts of a reference group (indicators that an investor compares when trading individual stocks). In spite of its ambiguity, the reference group has become an increasingly popular concept that has attracted the attention of many researchers in various fields [24–26]. We support the view that stock returns depend not only on the absolute values of factors such as firm size, book-to-market ratio and momentum at the firm level but also on the relative values of factors like ranking of firms' trading volumes, ranking of firms' market capitalizations, ranking of firms inside branches, etc. In other words, it is reference group or these rankings which form investors' trading behaviors that will result in discrepancy between current and desired stock returns. Following this line of thought, the relative values of stocks' reference groups should also be considered when studying stock returns. Moreover, it is reasonable to assume that investors' reference groups change over time, even from morning to evening. Thus, the reference group will be constructed on each trading day. However, the importance of this variable is generally ignored by most of the previous literature. This paper aims to highlight the variable's importance.

Second, numerous researchers have presented evidence that stock returns are serially correlated and in recent years investors have been able to exploit this dependence to obtain abnormally positive expected returns. For instance, DeMiguel et al. [27] studied whether investors can take advantage of stock return's serial dependence to select portfolios of risky assets that perform well out-of-sample using a vector autoregressive (VAR) model to capture serial correlations in stock returns. The empirical results show that both arbitrage and mean–variance portfolios based on the proposed model outperform the traditional portfolios. A natural starting point for such a consideration is momentum because it is a simple strategy and investors may often regard past returns as a key signal of trading. For example, Jegadeesh and Titman [28] documented that the momentum effect exists in asset returns and that the strategy to buy stocks that have performed well in the past and to sell stocks that have performed poorly in the past can produce significant positive returns at the 3- to 12-month