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An adaptive modeling and asset allocation approach to financial markets based on discrete microstructure model

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ABSTRACT

In previous works, it was verified that the discrete-time microstructure (DTMS) model, which is estimated by training dataset of a financial time series, may be effectively applied to asset allocation control on the following test data. However, if the length of test dataset is too long, prediction capability of the estimated DTMS model may gradually decline due to behavior change of financial market, so that the asset allocation result may become worse on the latter part of test data. To overcome the drawback, this paper presents a semi-on-line adaptive modeling and trading approach to financial time series based on the DTMS model and using a receding horizon optimization procedure. First, a long-interval identification window is selected, and the dataset on the identification window is used to estimate a DTMS model, which will be used to do asset allocation on the following short-term trading interval that is referred to as the trading window. After asset allocation is over on the trading window, the length-fixed identification window is then moved to a new window that includes the previous trading window, and a new DTMS model is estimated by using the dataset on the new identification window. Next, asset allocation continues on the next trading window that follows the previous trading window, and then the modeling and asset allocation process will go on according to the above steps. In order to enhance the flexibility and adaptability of the DTMS model, a comprehensive parameter optimization method is proposed, which incorporates particle swarm optimization (PSO) with Kalman filter and maximum likelihood method for estimating the states and parameters of DTMS model. Based on the adaptive DTMS model estimated on each identification window, an adaptive asset allocation control strategy is designed to achieve optimal control of financial assets. The parameters of the asset allocation controller are optimized by the PSO algorithm on each identification window. Case studies on Hang Seng Index (HSI) of Hong Kong stock exchange and S&P 500 index show that the proposed adaptive modeling and trading strategy can obtain much better asset allocation control performance compared with the parameters-fixed DTMS model.

1. Introduction

Q3 Financial markets generally present strong randomness, nonlinearity and stochastic volatility. Many researches on financial time series have been developed and are mainly to find the feature of some financial time series and to predict buying/selling assets to obtain high returns. Some researches capture the stochastic features of a time series by extracting a set of fuzzy rules or relying on probabilistic reasoning [1,2]. Some mathematical models have been applied to characterize the financial markets and predict their returns [3,4]. For instance, AR (autoregressive) model [5] and its extended models (e.g. ARMA (autoregressive moving-average) model and ARIMA (autoregressive integrated moving-average) model) [6,7] were used to model and predict the returns in econometrics, financial economics and microeconomics. ARCH (autoregressive conditional heteroskedasticity) model [8,9], GARCH (generalized autoregressive conditional heteroskedasticity) model [10,11] and SV (stochastic volatility) model [12], which use different volatility equation to present the time-varying process of the variance of return, were proposed to model the volatility of returns. Neural network models [13,14] were also applied to

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describing the nonlinearity of financial time series because of their good function approximation. However, these models mentioned above mainly focus on modeling the dynamics of asset price or its return itself and especially its conditional variance.

Recently, some economists and physicists have begun to explore the dynamic mechanism of market price-varying processes. In fact, it is necessary to deal with the dynamics of a financial market from microscopic point of view. Some researchers have proposed phenomenological models by identifying different processes influenced by the demand and supply of the market. One of the most interesting of these models is the microstructure model proposed by Bouchaud and Cont [15], which is on the basis of market microstructure theory [16] and presents the relationship between price, excess demand and liquidity of a market. This model provides an abstract description for market price driven by market liquidity and excess demand. However, the two market variables (market liquidity and excess demand) are unobservable and would not be easily measured directly. If the two hidden variables can be estimated from an observable price series, it would help investors make buying or selling decision to obtain higher return. Based on this modeling theory, Iino and Ozaki [17] expanded this model and built three continuous time stochastic differential equations to describe the relationship of market price, excess demand and liquidity, which was called the continuous time microstructure (CTMS) model. Peng et al. [18] improved the diffusion term of price in the continuous model. Its corresponding discrete time microstructure (DTMS) model was proposed by Peng et al. [19] using Euler discretization method. Some improvements of the discrete microstructure model were also presented in [20,21]. The previous works mainly apply Kalman filtering and the maximum likelihood method to estimate the model parameters by training dataset of a financial time series, and then use the identified microstructure model to recursively predict the market excess demand and liquidity and make investment decisions based on the predicted information on the following test data. However, if the length of test dataset is too long, the built model may not characterize the latest data sufficiently, so that the model prediction precision and the model-based asset control performance may gradually decline over time. Therefore, it is important to timely update the model to allow it to describe the dynamics of the changing financial market.

Moving window method is an advisable choice for overcoming the above problem. Peng et al. [22] used moving window technique to build an AR model with time-varying coefficients for fitting finance time series, which improved the ability of predicting the expected return and variance of a portfolio. Gao et al. [23] proposed a windowing-based random weighting method to fit the systematic model errors and the covariance matrices of observation vector in Kalman filtering method, and predicted the state vector within a moving window, which can effectively resist the disturbances of systematic model errors on system state estimation. McAlister et al. [24] used a five-year moving window to examine the impact of a firm's advertising and research-development (R&D) on its systematic risk, and concluded that the two market manifestations lower systematic risk of the firm's stock. The moving window method is an on-line approach.

In this paper, from the viewpoint of improving adaptability of a model and on the basis of the previous works, we design two moving windows: a long-interval identification window on which the dataset is used to estimate a DTMS model, and a short-interval trading window on which the dataset is used to do asset allocation on the basis of the estimated DTMS model. After asset allocation is over on the trading window, the length-fixed identification window is then moved to a new window that contains the previous trading window, and then a new DTMS model is estimated by using the updated dataset. Next, asset allocation is continued on the next trading window that follows the previous trading window as well as the new identification window. Thus, the modeling process will be repeated for the updated dataset, and a set of DTMS model will be built over time and their parameters will be optimized successively. These models with time-varying parameters are referred to as the adaptive DTMS (ADTMS) models. Furthermore, asset allocation process will be carried out successively according to the above steps. The modeling and trading process is a receding horizon optimization procedure [25,26] and is also a semi-on-line adaptive approach. For each ADTMS model in the adaptive modeling process, the parameters and the initial value of conditional mean, conditional variance and state variables are all estimated by a hybrid algorithm proposed in this paper, which incorporates PSO (particle swarm optimization algorithm) [27], the Kalman filter and the maximum likelihood method. This estimation method is very flexible and can automatically search for the optimal parameters within the setting span. Furthermore, a modeling evaluation approach is reported based on the feature of the estimated market excess demand and liquidity, which may eliminate some unreasonable modeling results to ensure the acquired model more appropriate for characterizing financial time series.

The purpose of building a financial model is to obtain more effective information of financial markets and to predict the market price better and to achieve the optimal asset allocation. Theoretically and practically, asset allocation is a very interesting issue for investors. One of key problems is still to forecast the returns. Markowitz's mean-variance theory is a well known portfolio method, and it achieves asset allocation by maximizing investment return and minimizing investment risk [22,28–30]. The prediction of return on assets may be gotten based on the AR [22,31], ARCH, GARCH and SV model [10,11]. In general, the predictive error of asset price is close to a white noise with zero mean due to the randomness of financial markets. Usually, it is not easy to acquire satisfactory dynamic allocation results based on the predicted price. Dourra and Siy [32], Sevastianov and Dymova [33] and Michalak [34] applied a fuzzy logic technique to construct an experts trading knowledge base and carry out the assets allocation. From the estimated DTMS model, one can obtain information about future market trend provided by the directly-immeasurable excess demand, which shows much better stability than the market trend information obtained from the prediction of price itself, so the assets allocation based on the predicted excess demand may acquire higher profits. Peng et al. [19] achieved the effective assets allocation based on the identified excess demand. In this paper, based on the prediction of the excess demand obtained from the proposed ADTMS model that is estimated on each identification window, an adaptive dynamic asset allocation strategy, which optimizes the allocation threshold parameters by PSO algorithm on each identification window and controls the proportion of buying/selling assets on the trading window, is applied to enhance investment returns.

Finally, some examples utilizing the adaptive modeling and dynamic asset allocation strategy for real financial data, such as Hong Kong stock exchange and S&P 500 index, are studied. Comparing with the previous method, the proposed adaptive modeling and asset allocation method may make the updated model over time capture the dynamics of stock prices better, and may also make the new model-based asset control obtain higher profit.

2. Market microstructure models

Market microstructure model is proposed by Bouchaud and Cont [15] based on market microstructure theory [16]. It is one of phenomenological models and may capture the dynamics of a financial time series by representing the relationship between price, excess demand and market liquidity in a financial market.