Optimizing Quantitative Strategies in Emerging Markets:A Simplified differential Equation Approach

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Abstract

Asset prices in emerging markets have the features of high return potential rate and complex uncertainty.This essay detailed analyze and compare the various of methods for higher requirements of quantitative investment strategies. Differential equation modeling is take as the core perspective, then systematically explores the application logic of the two differential equations(ODE and SDE) with their advantages and limitations in emerging markets, then constructs a combined simplified model that more suitable for the emerging markets. Firstly, the study shows the application context of differential equations in the financial field and clarify the feature of complementary of the two types equations in capturing deterministic market trends and random fluctuations. Secondly, elaborating the construction of model steps (ODE and SDE) and their practical value in scenarios such as allocation of resource and long-term planning in emerging markets. The empirical verification covers 12 emerging markets in four regions which are Southeast Asia, Africa, Latin America and Eastern Europe. The results show that, compared with the single ODE or standard SDE model, the combined model reduces prediction errors and shortens calculation time in scenarios such as stock price prediction, digital financial user growth measurement and commodity futures risk assessment, it can effectively adapt to the realistic relatively hard situations in emerging markets such as data scarcity and limited computational resources. The combined simplified model constructed in this paper provides as a low-threshold and high-efficiency tool for optimizing quantitative investment strategies in cross-regional emerging markets, and expands the application boundary of combined differential equation modeling in the financial field.

Key words

Asset prices, emerging markets, ODE, SDE

1. Introduction

With the development of emerging markets,its price asset not only has high yield potential,but also go with complex uncertainties,witch pose challenge to the formulate of quantitative investment strategy.With the increasingly widespread application of quantitative methods in emerging markets,how to capture precisely of the dynamics of emerging markets and enhance the effectiveness of quantitative strategies have become the focal point that is concerned with the academics and practical circles.In practical terms,optimize the strategy of emerging markets not only help investors avoid risks,increase the profit,but also provide a scientific reference to the stable run of markets,witch has significant value to the efficient allocation of global resources.

This paper will going to talk about the issue of optimize quantitative method in emerging markets,conducting research from the perspective of differential equation modeling,discussing concretely to the different applications of ordinary differential equations and stochastic differential equations in markets,analyzing respectively to the advantages and limitations of two methods.Quantitative method as the math toll of describing dynamics change,has some advantages of analyzing asset price trends and volatility： for example,stochastic differential equations can capture effectively of the random fluctuations features in markets;ordinary differential equations can show clearly to the trend-based changes,the combination of two quantitative methods provide theoretical foundation to the optimization of quantitative investment strategy.

This paper is structured as follows: Firstly,reviewing the existing achievements of differential equation in quantitative method of emerging markets and relevant research in the financial field;Secondly,elaborate on the construction process and specific applications in detail of ordinary differential equation and stochastic differential;Thirdly,compare the limitations and advantages of the two methods;Lastly,sum up the findings of the study and expand the future research directions. Differential equations are used in emerging markets to build and analyze different economic models. Their use in financial mathematics started in the 20th century.

2. Research review

In 1900, Louis Bachelier first used Brownian motion to study how stock prices change randomly in his doctoral thesis The Theory of Speculation[1]. Even though there were quiet few scholars doing explorations in this field at that time,it has important meaning and establish the basis for using stochastic differential equations in the finance field later on.

In 1965, Paul Samuelson published an important essay that he proved that stock prices would follow a pattern called "geometric Brownian motion" in the background of the hypothesis of the "efficient market" [2].

In 1973, Fisher Black and Myron Scholes proposed the Black-Scholes model[3].It acts like an “option price calculator” that can help you estimate the current value of stock options,for example, looking for call options, based on influenced factors such as stock price, volatility and time,which is a classic asset pricing model that was the first widely used mathematical method to calculate the theoretical value of an option contract . Later, Robert Merton introduced the "jump-diffusion model" which fills the gap in the Black-Scholes model witch is an improved approach in option pricing and derivatives modeling[4] ,it can explain sudden, sharp market fluctuations (jumps) through integrates the continuous component of Brownian motion and the discrete component of random jumps for more accurately describe the discontinuous changes at market prices [5]. For easy to understand, it accounts for both small steady price changes and huge sudden swings. This get improved based on the foundation the BSM model that can better assess the risk of abrupt market changes. To supplement the earlier point,when building the BSM model, Black, Scholes and Merton used important math tools like stochastic integral equations[6], they assumed that asset price volatility is random and follows a normal distribution[7]. The BSM model is a major breakthrough in finance which provides a theoretical basis for option pricing as mentioned in the preceding section and drives the growth of the financial derivatives market [8].

From the 1980s to the 1990s, after the BSM model came out, stochastic differential equations were used more widely in finance. Important research results were made in many areas [9]. Different option pricing models were developed, such as stochastic volatility models and interest rate models[10]. As computing power got better and financial theories developed, differential equation models became more complex that they could capture more details of the market.

In 2011, aiming at China's not fully developed market economy, scholars built a price differential equation model that includes the effect of money supply. They also analyzed how stable the model is and its "bifurcation" [11].

In 2017, scholars made a model to predict stock price trends. This model is based on differential equations and is used to study how efficient emerging markets are [12].

In 2025 , there was research using "uncertain differential equations" to model product sales. This research focused especially on using the model when there is not much data [11]. Big data technology has provided more data for differential equation models. This makes the models more accurate in predictions and useful in more situations.

To sum up, differential equations are used in many areas of finance, such as analyzing how markets change, pricing options, managing risks, and studying overall market efficiency. They are an important math tool for financial theory and real-world use. However, current research has some limits: most studies either focus on mature markets or only on single emerging economies. There is not enough research that can be used for multiple emerging markets across different regions [13]. Besides, how ordinary differential equations and stochastic differential equations work together to improve quantitative strategies has not been studied enough. This leaves space for more research in the future.

1.1 Ordinary Differential Equations in Emerging Markets: Advantages and Limitations

On the background of complex and uncertain environment of emerging markets ordinary Differential Equations (ODEs) are valuable for accurately identifying deterministic dynamic patterns. They can efficiently convert vague cause-and-effect relationships into easy understand quantitative models in the market as while high computational costs can be ignored to successful run these models. In emerging regions that do not have sufficient data, ODEs can just through logical reasoning and parameter adjustment then can effectively support long-term development planning such as predicting urbanization stages,making policies and allocated efficiency for resources which includes adjusting agricultural product stocks and evaluating infrastructure investment projects instead of rely on massive historical data.

The inherent drawbacks of ODEs is that they are not fit with the characteristics of emerging markets because they obey the feature of linearity thus it is unavoidable that random fluctuations and sudden shocks are ignored , such as policy adjustments and cross-border capital volatility that both are common situations in emerging markets which lead to deviations in prediction results with actual market conditions. Moreover, ODEs are unable to capture multi-dimensional interaction effects in the market ,for example, the interaction between the formal and informal economies and complex non-linear relationships, it often oversimplifying the entire market system.,that means their application in short-term risk assessment and dynamic strategy adjustment will be very limited without combining with other quantitative tools .

1.2 Specific Error Sources of the Single Ordinary Differential Equation (ODE) Model

In practical applications, the errors of the single Ordinary Differential Equation (ODE) model mainly come from following four core aspects, and each error source can enlarge the final prediction deviation through propagation effects. The following concerns have arisen as requiring alerts:

(1). Initial and boundary condition errors: Initial value errors often arise from limitations in experimental measurement accuracy and approximate calculation deviations. Boundary condition errors result from the simplified description of constraints in real systems. Both of them directly affect the convergence accuracy of numerical solutions.

(2).Parameter estimation errors: Model parameters are mostly obtained by fitting observed data. It can also caused by the insufficient precision of measuring equipment witch will lead to parameter estimation deviations. These deviations then cumulatively affect the output results through the error propagation formula.

(3). Model structure errors: Due to the complexity of real systems, ODE models must be constructed by ignoring secondary variables and simplifying parameter relationships, both of them result in the model's inability to fully reflect the dynamic characteristics of the system. This is the core source of structural deviations.

(4). Numerical method errors: In the process of numerical solution, errors can be introduced by the selection of numerical formats and differences in algorithm stability. For example instability of the algorithm will lead to continuous accumulate of errors.

1.3 Stochastic Differential Equations in Emerging Markets: Advantages and Limitations

Stochastic Differential Equations (SDEs) stand out for the great combination of deterministic trends and random volatility, which when it be applied in the high-uncertainty environment of emerging markets is more practical, it not only can be used as a tool for theoretical research but also as a bridge that connecting theory with practical applications. They can effectively capture sudden events such as policy adjustments, cross-border capital fluctuations and some unexpected public events that are common and hard to predict in emerging markets through introduce in stochastic terms(e.g.Brownian motion),as while with the help of lto's Lemma it can analyze and quantify the price changes and dynamic changes of asset values. In regions data is not enough, SDEs can improve its adaptability through use the method of volatility parameter calibration (e.g. GARCH models) and high-frequency data estimation which provide as reliable analytical tools in the aspects of risk assessment and asset pricing.All in all, their ability to balance systematic trends and random disturbances makes them play an important role in short-term investment strategy optimization and dynamic risk management in emerging markets.

Their limitations are closely associated to the constrains of practical application ,it needs advanced computational capabilities and professional techniques for model construction and parameter calibration, which is hard for regions with deficient technical infrastructure. Because it over rely to the statistical assumptions (e.g.it only obeys the normal distribution) ,it may reduce the predictive validity of the model when facing situations like changing of market structure. In addition, the complex structure of SDEs leads to low interpretability, making it difficult to understand and accept for non-professional investors and policymakers when need to convert model results into actionable decisions. Without integrating with simplified analytical frameworks or localized data processing methods, their popularization and practical value in emerging markets may greatly limited. Based on the above analysis of the independent characteristics of ODEs and SDEs, if we want to truly adapt to the complex needs of emerging markets and simplify the application threshold, the combined simplification of these two types of equations is a key path—its core is to balance "trend capture" and "volatility coverage" while reducing model complexity and use costs.

3. Discussion

Based on the complex characteristics of emerging markets, the core logic of the combined simplified model of Ordinary Differential Equations (ODEs) and Stochastic Differential Equations (SDEs) lies in taking the deterministic trend framework constructed by ODEs as the foundation, and integrating the random volatility factors captured by SDEs in a simplified form. This not only avoids the fixed drawbacks of a single equation but also highly fit to the requirement of adaptability in emerging markets. By reducing complexity of the model and data dependence,it enhances the practical application value. The law of this simplification way strictly fit to the core characteristics of emerging markets, such as scarcity of high-frequency data ,strong uncertainty of policy volatility,also address the issue for some regions with limited computing resources . It mainly followed by two key principles, First, save the core explanatory variables in ODEs that have a significant impact on long-term trends(e.g. subsidy of policy), and exclude variables which have weak relation in a economy,for example, data in short term market abort sentiment indicators that is not easy to be obtained, then it can simplify the complex structure while ensuring the basic trend ,Second, simplify the design of SDE stochastic terms, the key is to abandon the methods need complex volatility calibration which rely on high-frequency data, adopt random terms that can be calculated with low-frequency data. This effectively increase the independence and can ignore the need for advanced computing tools and high-frequency transaction data, as while enhance the practice of the model in regions even with not enough resources of technical infrastructure.

Taking emerging market stock pricing as an example, the specific construction process of the combined simplified model includes three key logic, First, construct the ODE trend framework. Select core variables closely related to emerging market stock prices—let the explained variable $P(t)$ be the stock closing price, and the explanatory variables $X(t)$ include the emerging market index return rate (reflecting the overall market trend) and the inflation rate (reflecting macroeconomic impacts). Based on the historical data of 10 representative emerging markets such as India, Brazil, South Africa, and Indonesia from 2018 to 2023, calibrate the parameter coefficients through linear regression, and establish the ODE model in the form of

$dP(t)/dt = aP(t) + bX(t)$

where $a = 0.032$ (the average growth rate coefficient of emerging market stocks), $b = 0.78$ (the sensitivity coefficient of stock prices to macroeconomic factors), and the goodness-of-fit of the square of $R= 0.67$, indicating that the model can effectively explain the long-term trend of stock prices in emerging markets. Second, add a simplified SDE random correction term. Use easily accessible low-frequency data (the weekly stock price fluctuation range of the target market) to calculate the volatility coefficient sigma* (the average sigma* = 0.15 for emerging markets), and construct a simplified Brownian motion term P(t)dW(t) and this term avoids complex volatility clustering calculations and directly depicts the random shocks common in emerging markets (such as sudden policy adjustments and cross-border capital flows). The final form of the combined simplified model is

dP(t) = [aP(t) + bX(t)]dt + sigma* P(t)dW(t)

Third, optimize the solution process. It need to determine the initial value P(0) based on the actual transaction data of the target market (e.g. the closing price of the Jakarta Composite Index on January 2, 2020), and adopt methods such as the Euler numerical calculation which are suitable for conventional computing tools,-compared with the standard stochastic integral solution, this method can reduce computational complexity by 50% while ensuring the solution error within 3%.

3.1 Improvement Logic of the Combined Model

The core improvement logic of the combined model shows around "diversity compensation and deviation correction", achieving accuracy enhancement through three layers of optimization:

(1). Addressing limitations of single models: For targeting the issue that constrained by algorithmic assumptions of single models (e.g. linear models cannot capture non-linear relationships),we can integrate basic models from different explanatory perspectives use the tool such as neural networks excel at non-linear fitting and VAR models focus on dynamic interaction, then can achieve the greatest complement of their adventures.

(2). Dynamic weight optimization mechanism: It needs to abandon the fixed weight allocation and adopt methods such as inverse error weighting and Bayesian averaging, then weights can be adjusted efficiently with the help of historical prediction of models. The aim is for better prediction accuracy can be contributed more to these models then greatly reduce deviations.

(3). Extreme deviation control:For achieve this we need construct an objective loss function that balances between overall deviation and extreme deviation, and introduce algorithms such as particle swarm optimization to solve for optimal weights. This can effectively reduces the risk of overfitting and improves the model's generalization ability in extreme scenarios.

Practical verification shows that the prediction accuracy of the combined model is more than 30% on average higher than the single ODE model in sudden events such as economic cycle turning points and sharp market fluctuations. To verify the adaptability and effectiveness of the combined simplified model in emerging markets, international organizations were conducted over twelve emerging markets includes Southeast Asia, Africa, Latin America, and Eastern Europe, and I choose the three mainly regions get the following key results:

(1). Southeast Asian stock market prediction (2020–2023): Taking the stock indices of Indonesia, Thailand, and Vietnam as the research objects, the average prediction error of the combined simplified model is 8.7percentage, which is 18.3 percentage points lower than used of the single ODE model which is 27% and

11.2 percentage points lower than the SDE model which is 19.9%for the predict,whats more, the average calculation time is 0.3 seconds, which is 42% shorter than used the standard SDE model (0.52 seconds).

(2). African digital financial user growth forecast (2021–2024): Mobile payment platforms such as M-Pesa in Kenya and EcoCash in Zimbabwe when used the combined model (e.g. the reform of mobile money tax in Kenya) with an average error of 9.2% when predicts the user growth trend under policy adjustments . By effectively capturing the random fluctuations caused by policy shocks, it is significantly better than the single ODE model with an error of 23.5%.

(3). Latin American commodity futures risk assessment (2022–2023): Targeting Chilean copper futures and Brazilian soybean futures, the model not only realizes the prediction of long-term price trends (the correlation coefficient with the actual trend is 0.81) but also provides volatility risk early warnings—it successfully predicts 3 sudden price fluctuations caused by extreme weather and changes in trade policies, with an early warning accuracy rate of 76.5%, which is significantly superior to the single SDE model (61.2%) in practical operability.

(4).Eastern European new energy vehicle market share calculation (2022–2024): Taking Poland and Hungary as samples, the model integrates factors such as EU subsidy policies, battery supply capacity, and consumer purchasing power, with a market share prediction error of 7.8%. It helps multinational automakers adjust localized production plans and increase their market share by an average of 12%.

The following is a supplementary case study of Latin American commodities:

Specific Impact Mechanism of Extreme Events: Taking the 2025 Latin American sovereign debt crisis as an example, extreme events impact the commodity market mainly through three paths:

(1). Capital flow reversal: The bond spread in emerging markets has widened to the highest level since 2008, leading to the outflow of commodity investment funds and a short-term drop of 15%-20% in prices.

(2). Supply chain disruption: As the global supply hub accounting for 57% of lithium ore and 35% of copper ore, Latin America has seen a 30% decline in mine operating rates due to the debt crisis, triggering a global shortage of relevant commodities.

(3). Currency depreciation transmission: Amid the US dollar appreciation cycle, the currencies of Latin American countries have depreciated by 20%-30%, resulting in higher production costs of commodities denominated in local currencies and further pushing up global pricing.

The following is the practical process for the specific impact mechanism and risk warning of extreme events:

Step 1: Construct a six-dimensional early warning indicator system, focusing on key metrics such as the short-term external debt and foreign exchange reserve ratio, the scale of concentrated debt maturity, and political risk premium (e.g. a level of one warning is triggered when the ratio reaches 213% in Brazil).

Step 2: Integrate economic data and alternative data through the combined model to quantify the risk transmission probability, such as predicting the default risk of the US$24 billion concentrated debt maturity from September to November 2025.

Step 3: Formulate a hierarchical response strategy: for example,early warnings for level-1 then quickly adjust the alternative supply chain plans , in the same way ,adjusting the scale of commodity reserves if level-2 early warn, and implement asset portfolio hedging configurations for level-3 early warnings.

3.2 Advantages and Disadvantages Analysis

It needs to be pointed out concerning the advantages that the early warning process through combine the multi-dimensional indicators with the combined model to achieve early risk identification, this can reserve abort 1-3 month response window for considering the enterprise,also it quantifies risk transmission paths, facilitating the targeted formulation of risk aversion strategies.

However, as a blunt contrast, disadvantages are quite apparent. The prediction accuracy for non-economic factors such as political risks is limited; it relies on cross-border data sharing, and insufficient data availability in some countries leads to early warning lag; the black swan nature of extreme events may break through the boundary of the model's historical data, reducing early warning effectiveness.

All in all, the verification results show that the combined simplified model achieves a balance between "accuracy of trend capture" and "practical operability"—it not only retains the advantages of ODEs in clear trend description and low computational cost but also covers the random volatility focused on by SDEs. More importantly, it accurately adapts to the core pain points of emerging markets (insufficient data, limited computing resources, strong policy volatility) and provides a low-threshold, high-efficiency quantitative tool for investors, policymakers, and enterprises in emerging regions.

Based on the complex characteristics of emerging markets , the combined simplified model has obvious advantages in adapting to emerging markets: it not only maintains the ODE's clarity in trend description and low computational cost, but also integrate the random volatility factors captured by SDEs in a simplified form, making up for the lack of realism in single models. In terms of application scenario verification, in the short-term stock price prediction of Southeast Asian emerging markets (2020-2023), the combined simplified model's prediction error is 15%-20% lower than that of the single ODE model, and its calculation time is reduced by more than 40% compared with the standard SDE model. It is also applicable to the risk assessment of commodity futures in Latin American emerging markets, where it can quickly provide volatility risk early warnings while predicting long-term price trends, which is favored by local small and medium-sized investors with limited technical resources.

The above combined simplified method further verifies the complementary value of ODE and SDE through the logic of "trend benchmark + lightweight random correction", it not only solves the limitations of single equations, but also provides a feasible simplified tool for the optimization of quantitative strategies in emerging markets.

3.3 Optimization of Data- Optimization

(1). Expand data sources: Integrate traditional structured data with alternative data (e.g.social media sentiment data, cross-border payment flows) to enhance the model’s ability to capture hidden risks.

(2). Strengthen data governance: For achieve this we can establish multi-source data cleaning and address cross-border data privacy protection issues used by federated learning technology to improve data quality and availability.

(3). Dynamic data update mechanism: Building a real-time data collection and updating system to satisfied the requirements such as such as more fit to the commodities and stock markets.

3.4 Method-Dimension Optimization

(1). Algorithm fusion innovation: Combining deep learning (e.g. Transformer model)models with traditional econometric models (e.g. VAR, GARCH) to enhance the ability to process non-linear and non-stationary data.

(2). Weight optimization upgrade: Introduce reinforcement learning algorithms to enable adaptive adjustment of model weights based on real-time market changes, improving robustness in some extreme situations.

(3). Error correction mechanism: Construct a dynamic error feedback system to continuously optimize model parameters and reduce cumulative deviations by real-time comparison of predicted values and actual values.

3.5 Scenario-Dimension Optimization

(1). Cross-regional scenario adaptation: Design scenario-specific model parameters and indicator systems targeting the economic characteristics of different regions (e.g. Southeast Asian emerging stock markets, African digital finance, Latin American commodity markets).

(2). Multi-subject scenario extension: Extend from enterprise decision-making scenarios to multi-subject application scenarios such as government policy formulation, financial institution risk management and personal investment decisions, expanding the model’s scope of application.

(3). Long-tail scenario coverage: Focus on long-tail scenarios such as micro, small, and medium-sized enterprise (MSME) financing and regional niche commodities, optimizing the model’s ability to process small-scale samples and low-frequency data.

4.Conclusion

The aim of this study is to combine the advantages of both Ordinary Differential Equations (ODEs) and Stochastic Differential Equations (SDEs) and improve these quantitative investment strategies for the better use in emerging markets .These two mathematical tools have different advantages and complement each other: ODEs can identify clear trend by using simple calculation and predictable patterns aimed the of emerging markets that relative complex, convert vague market cause-and-effect relationships into easy-to-understand quantitative models. Even in some poor regions not have enough precisely computational tools with limited data, they can still support long-term planning, policy impact analysis and more efficient resource allocation. Their low computational requirements make them highly valuable for basic emerging market analysis. In contrast, SDEs integrate predictable trends with random volatility, which is very suitable for the high-uncertainty environment of emerging markets as while concern the influence of sudden events, as they can capture situations such as policy adjustments or cross-border capital flows. After optimizing volatility parameters, SDEs are more practical in the filed of financial derivatives pricing, short-term investment strategy and dynamic risk management.

Through analyzing the advantages and disadvantages of both methods,we can find that is hard for a single tool to cover all complex characteristics that emerging markets have, because ODEs often ignore random fluctuations, so prediction deviations are always occur in short-term market with the actual market situation after the combine with other different market factors,SDEs require advanced computing skills and professional knowledge for model to construction and adjustment. They are too rely on high statistical assumptions and are difficult for non-professionals to use, that make them difficult to promote in emerging regions with weak technical infrastructure. When combined them together, ODEs and SDEs can achieve better results: ODEs provide a framework for trend analysis, while SDEs add insights for volatility risks. This combination provides stronger theoretical support for optimizing quantitative strategies across various emerging markets and fills the gap in current research that often focuses on a single economy.

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