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Evolution of Asset Pricing Models: From Traditional Methods to Machine Learning Applications

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Abstract:

This paper examines the development of asset pricing models following chronological order. Beginning with traditional methods, this paper introduces the historical background of the Capital Asset Pricing Model (CAPM) as well as the strengths and weaknesses of the application of this model in the real world. To enhance the predictiveness of CAPM and improve this over-simplified model, researchers have come up with the FAMA-French Model with multiple factors. These models incorporate more factors when predicting returns of assets, but they are still based on linear relationships. With the growing volatility of the financial market, the financial industry requires more complicated models to capture more nuanced trends. With such a need, the researchers apply the most advanced machine learning technique to the asset pricing process, using models such as neural networks, random forest, and gradient boosting to enhance the predictiveness of asset pricing models. However, these advanced methods also bring issues such as overfitting and interpretability to investors. By tracing the development of asset pricing methodologies, this paper offers insights into the ongoing refinement of financial models and points out potential future research direction.

Keywords: Asset Pricing; CAPM; Fama-French Model; Machine Learning.

1. Introduction

In the 1960s, people witnessed a period of rapid growth in the financial market. The Western world seemed to break away from the doom of World War II. Both Europe and the United States experienced robust economic growth, generating fortunes for institutional and individual investors. With such fortunes under control, investors proactively sought opportunities to capture more profits with money on hand. It was under such confidence and blooms that the foundational theory of the Capital Asset Pricing Model (CAPM) shed light on the method of achieving excessive returns. The birth of CAPM was a milestone in financial history, as it was the first model to measure the relationship between an asset's expected return and its systematic risk. By applying CAPM, investors could understand and evaluate how assets are priced in an equilibrium market, which helped them make more rational investing decisions [1]. This paper, following chronological order, starts by introducing CAPM with its corresponding application as well as relative strengths and weaknesses. It then introduces the FAMA-French Model with emphasis specifically on the Three-Factor Model and Five-Factor Model. After discussing the limitations of these muti-factor models, the paper reaches the modern era in which it starts the conversation regarding the application of the machine learning model in asset pricing. The machine learning models bring in better predictiveness but, at the same time, more complexity as well. Specifically, this paper will introduce three applications of machine learning methods in asset pricing, namely random forest, gradient boosting, and neural networks. Eventually, this paper sheds some light on the future direction of research as well as the future development of asset pricing methods. This paper offers a unique perspective of examining the development of asset pricing methodology from a chronological and historical perspective. While mathematicians and researchers devote time and effort to developing new mathematical models, it is crucial to understand the historical and practical context that supports those technical functions. In the end, the goal of mathematical functions is to support applications in the real world, and by examining the development of those functions, people gain a more profound perspective when deciding the correct direction for future development.

2. Traditional Method of Asset Pricing

Introduced independently by Treynor et al, CAPM states that the expected return of assets equals the risk-free rate plus the product of the asset's beta and market risk premium, where beta measures the sensitivity of that asset relative to the movement of the market. Even though this model came out in the 1960s and various more advanced models were developed later, the application of CAPM is still rather common these days. Perhaps the most widely application is the estimate of firms' cost of equity despite the debates regarding the accuracy of CAPM's pricing capability in real-world settings [2]. One of the reasons behind the widespread use of an inaccurate model is the simplicity of CAPM, as it demonstrates a direct way of understanding the return based on its risk. However, such simplicity and straightforwardness rely on unrealistic assumptions [3]. One such assumption is that all assets are accessible to the public, while in reality, there are hidden information and unpublicized assets, and investors might not get access to all assets. Therefore, the so-called optimal market portfolio does not exist [3]. To deal with the over-simplification of relying solely on the beta, in 1992 Eugene Fama and Kenneth French developed the Fama-French Three-Factor Model as an extension to CAPM. The Fama-French Three-Factor Model represents an update to CAPM. The Fama-French Three-Factor Model not only considers the implication of the market risk premium but also includes two more factors, namely Small Minus Big (SMB), which accounts for the size risk, and High Minus Low (HML), which accounts for the value risk. The model states that the expected return (E[R]) equals the risk-free rate plus the summation of three products. The first product is beta one (B1) times market risk premium. The second product is beta two (B2) multiplied by SMB. The third product is beta three (B3) times HML. B1, B2, and B3 are factor coefficients that measure the sensitivity of the specific asset to each factor. In particular, the SMB factor originates from the historical trend that small-cap stocks tend to outperform large-cap stocks, and the HML factor represents the fact that high market-to-book ratio (M/B) companies tend to outperform companies with low M/B ratios. The Fama-French Three-Factor Model is an empirical asset pricing model that works backward. By backward indicates, the empirical asset pricing model considers given stock returns and builds a model to fit those patterns [4]. As an empirical asset pricing model and an updated version of CAPM, the Fama-French Three-Factor Model outperforms CAPM when using data in both the United States and Indian capital markets for backtesting [5]. However, this model is still relatively simple and straightforward and may not explain all changes in returns of certain assets. For example, a key factor that this model ignores is momentum, which refers to the trend that stocks that performed well in the past will continue to perform well in the future. As a result, in 1997, Carhart introduced a four-factor model by adding the momentum factor in addition to the Fama-French Three-Factor Model [4].

Ever since Fame and French came up with the Three-Factor Model as well as Carhart's Four-Factor Model, the research for a better pricing model continued, and in 2015, Fama and French developed a better model on top of the Three-Factor Model. They used the dividend discount model to substantiate the addition of two more factors, profitability and investment, which eventually became the Five-Factor Model [4]. This new model is based on empirical tests indicating that the Three-Factor Model cannot fully explain variations in the cross-section of equity returns. Later, evidence suggests that the variations in equity returns arise from profitability and investment choices that are not included in the Three-Factor Model [6]. With such

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significant evidence comes the Five-Factor-Model, which follows a similar structure as the Three-Factor-Model. The only difference is that this improved version considers profitability and investment factors. For profitability, Fama and French use the Robust-Minus-Weak factor (RMW), which accounts for the difference in return between companies with high operating profitability and those with low profitability. The idea behind this is that companies with high profitability tend to generate higher returns. As for investment, Fama and French incorporate a factor named Conservative-Minus-Aggressive (CMA), which is calculated by the difference in returns between firms with low asset growth (conservative) and firms with high asset growth (aggressive). This factor represents the trend in which companies with more conservative investment styles will outperform those with more aggressive investment styles in the long run. Although an improved model beyond the Three-Factor Model, the Five-Factor Model still has weaknesses. Firstly, like many asset pricing models, the five-factor model has difficulty exploring the reason explaining the average returns of small stocks [6]. Secondly, the addition of the two new factors in the model seems to undermine the effect of the HML factor in some emerging markets [6]. Furthermore, the relevance of certain factors varies by region. For example, the profitability and investment factors have a pronounced effect in North America, Europe, and the Asia-Pacific regions, yet they have little impact on average equity returns in the Japanese market [6]. As a result, many research studies have been conducted with respect to specific markets to improve the Five-Factor Model.

From CAPM to the Five-Factor Model, the development of the asset pricing model represents a building-block process in which later researchers test the inaccuracy or insufficiency of the works of prior researchers and build on top of those works. CAPM lays the foundation of using linear regressions to predict the returns and Fama and French later found that, on average, 70 percent of the variations of the returns can be explained by CAPM. In comparison, the rest 30 percent is subject to other factors, such as the company's investment style, profitability status, undervaluation, and market capitalization [7]. With these in mind, Fama and French developed their models to better explain the expected returns of assets. These factors are then reflected in the Three-Factor and Five-Factor Model later [7]. As a result of the unique characteristics of asset pricing in fragile economies, particularly emerging markets with heightened volatility, low liquidity, and deviations from a normal distribution, ongoing testing of this model is necessary to enhance its effectiveness and accuracy in explaining asset returns [7].

3. Machine Learning as a New Method

As an advanced method of asset pricing, the application of machine learning in the finance industry began in the 1990s with a focus on applying neural networks in the decision-making process [8]. Those early models were relatively simple and suffered from computational limits. Also, in the 1990s, several studies explored the potential application of machine learning in banking to improve lending decisions and credit risk management [8]. More recent finance research has continued to focus on prediction but with a shift toward deep learning and other advanced machine learning methods [8]. These new applications include investigating the factors behind firm risks, optimizing option hedging, modeling investor sentiment, forecasting stock returns, and analyzing stock price movements using order book data [8].

In recent years, the machine learning model has gained increasing popularity in asset pricing for several reasons, which make this method advantageous compared with the traditional method. The first advantage of the machine learning model is its ability to handle nonlinear relationships. Traditional methods, such as CAPM and Fama French, assume a linear relationship between factors and returns. However, in the real world, financial data tends to display a much more complex trend of nonlinear relationships. Nonlinear modeling plays a crucial role not only in the stock market but also in other areas such as default risk modeling. This gives an edge to machine learning methods that are naturally well-suited for accommodating these nonlinearities [9]. Another advantage of the machine learning method is its feature selection capability. Compared with the traditional method in which researchers need to manually select factors, the machine learning method automatically selects the most predictive features under the limitations of certain hyperparameters. This not only discovers hidden patterns but also has shown to be the neat way of dealing with large numbers of factors. Besides, the machine learning method can incorporate various types of inputs. While the traditional method typically uses numerical, categorical, binary values as inputs, machine learning is capable of taking into account news sentiment, social media sentiments, topology, satellite images, or even traffic web. These features are capable of predicting future returns in the stock market or other asset classes, even though they have long been ignored by traditional asset pricing models.

Despite the various advantages, the machine learning method does have disadvantages as well. As the machine learning model presents a better way of modeling nonlinear relationships, it also brings up new concerns regarding interpretability. To provide an economic interpretation of a model's predictive success, it is crucial to assess how different variables contribute to the predictions. While examining the gradient can offer insights, it only provides a local evaluation of variable influence at specific points in the data rather than the extent of variable contributions throughout the whole time series [9]. This lack of explainability makes it difficult for investors, asset managers, or regulators to understand how the model generates such returns. At the same time, the lack of transparency also poses a potential threat to regulatory needs in the financial market. Another disadvantage is associated with overfitting. Financial data is notoriously noisy, and many empirical applications of machine learning methods overlook the importance of hyperparameter tuning, which then leads to overfitting to historical data [10]. This can lead to an over-optimistic prediction when backtesting but generalize poorly to future predictions.

The machine learning method is widely used in asset pricing these days. Particularly, three common applications are random forest, gradient boosting, and neural network. Random forest is an ensemble method that constructs multiple decision trees, each trained on a randomly selected portion of the data and features. The overall prediction is made by averaging the results of all the trees in the case of regression problems or choosing the most common prediction in classification tasks. This approach is beneficial because it can handle different types of input features such as traditional financial indicators and market sentiment indicators. While traditional models struggle to capture factors such as interactions among firms, random forests can capture those features and group stocks into homogeneous groups [11]. Another general application category of machine learning methods is gradient boosting. Gradient boosting tree algorithms are greedy methods that start by pre-processing the data using a technique called sample and feature bagging. Unlike the CAPM, which uses a single model, gradient boosting trains multiple simple models known as weak base learners (typically basic regression trees). These base learners are combined, often by averaging, to make the final asset price prediction [12]. This approach is often applied to estimate risk-adjusted return in which investors pick a certain level of risk and then optimizing its portfolio. Finally, neural network is a different category that is widely used these days in asset pricing. Neural networks are models that feature human neurons. These neurons are connected by mechanisms that assign weight to every input value [13]. They generally consist multiple layers that take input values and then produce output predictions. This approach is practical when dealing with nonlinear relationships, which fits the complicacy of the financial market. Neural networks do not have a standard formula and can adapt to the fast-changing environment of the financial market. This approach has been proven to perform well when dealing with noisy data, making it more suitable for modeling the market [13]. A typical application of neural networks in asset pricing is in pricing financial derivatives, where the models can learn from numerous simulated market scenarios. Neural networks are also used in high-frequency trading, as they can handle a significant amount of real-time market data within seconds. In summary, these techniques have advanced to the asset pricing world, offering more nuanced insights and adaptability to real-time data in this increasingly fast-changing market. It is reasonable to expect the evolution of these models in the future and continued enhancement of predictiveness.

4. Conclusion

This paper introduces various asset pricing models from a chronological perspective and tells a coherent story regarding the strengths and weaknesses of each model and how these features contribute to the development of a more advanced model from a chronological perspective. The traditional models, including CAPM and the multi-factor model, are relatively simple, which makes it easy to understand the correlation between factors and returns from investors' perspective. However, they tend to fall short when capturing the complex nonlinear relationship in financial data. With this in mind, researchers apply the machine learning method to asset pricing, and by integrating the theory of neural networks, random forests, and gradient boosting, researchers develop more complicated models that accommodate nonlinear dynamics and handle various types of data input. However, with the development of advanced machine learning models come potential issues regarding overfitting, interpretability, and regulatory transparency. Referring to the history of the development of asset pricing models, researchers often tend to preserve the strengths of the previous models and tackle the limitations of those models. Therefore, one potential future improvement of machine learning models is to find the balance between predictiveness and interpretability, potentially setting more limitations to hyperparameters to keep the model relatively straightforward. Another potential development is to combine traditional economic theory with machine learning techniques. By adding economic theory as another parameter or hyperparameter to the machine learning model (that is, to train the model with economic theory as the underlying foundation), researchers can potentially develop a more predictive model that fits better to the financial market.

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