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# Big-Data Technology in Finance: Quality of Stock-Trading Information in Vietnamese Stock Market

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***Abstract***

*Quantitative finance is a field of applied research where the data is important information investors' profitability and financial risk of financial assets in the processes of decision-making. And financial institutions and securities have applied big-data technologies in stock market to exploit useful information for investors using mobile stock-trading apps. The standardization of database from the raw data of companies' financial statements, statistical reports and stock-trading data support to enhance data mining analysis by predictive patterns with high feasibility for useful information for investors' decision-making. And quantitative tools of predictive patterns for financial advanced indexes test expected market return and favourable market timing for buying or selling stocks in stages of market cycle and prediction of market risk before market-trend crash. On the development of securities' mobile stock-trading apps, the addition of new advanced indexes increases the quality of stock-trading information in Vietnamese stock market generally, seeks competitive advantages of market segments for securities particularly when they change big-data technology in mobile stock-trading apps. This contribution has a better using FinTech combined with stock-trading algorithms to provide more useful and confident information of optimal profitability and financial risk management that individual and institutional investors catch up the trend of big-data technology.*

***Keywords:*** *Big Data, Data Structure, Raw Data, Stock-Trading, Technical Analysis*

## INTRODUCTION

Information of stock-trading in finance in the period 2005-2015 was only a discipline of small-data, and the scarcity of data-access source in analysing yields of profitability and financial risks is obvious with basic information of transaction about on stock prices: open, high, low, close and volumes for each trading day. More and more type data exceed the data storage requirements, the increase in the daily transactive data with numerous companies listed in stock market has significantly affected the information accessibility to analyse investment analysis and risk management. Therefore, the goal of this study is to standardize big data in finance from corporate financial statements in data structure and trading data from stock market for the exploitation of useful information for investors [20].

On the competitiveness of Vietnamese securities' companies, the basic tools in mobile stock-trading apps in analysing the financial information of corporate financial statements and trading information in stock market have been outdated, compared to recent applied research, in which basic financial indexes, daily transaction and trading figures of prices and volumes only shows basic information for investors. Because of basic financial tools such as $EPS$, $P/E$, $ROA$, $ROE$, $P/B$, $Beta$ and others in their mobile stock-trading apps, the market segments of advanced financial tools in forecasting expected stock return and financial risk have not still been exploited for the Vietnamese securities' companies in attracting more individual investors [29]. The investors' satisfaction is based on the relationship between the perceived usefulness and the perceived ease of use in mobile stock-trading apps, but its quality of trading information in supporting effective investment and risk controls is unexploited so that investors expect optimal profitability in stock market.

The development of Vietnamese stock-trading consultants in recent years has still been developing stronger than using basic financial tools in mobile stock-trading apps, because of the weakness in exploiting useful information that investors only pay more attention to favourable market timing for buying or selling stocks on daily transactions. Although securities' mobile stock-trading apps still support some indicators of market timing, it is lack of advanced financial tools to explain how to reach expected stock return as well as risk threshold for

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holding stocks, especially market risk or systematic risk in stock market. So, the analysis of big data strongly affects investors' decision-making in stock-trading processes, the enhancement of securities' mobile stock-trading apps is higher feasible.

The construction of advanced financial tools in mobile stock-trading apps can be useful in decision making for a wide range of stock-market participants, as well as for financial institutions in the commercialization of mobile stock-trading apps which risk assessment of stock-trading information is a key point in big-data analysis. By synergizing predictive modelling and user-specific insights, this comprehensive system contributes to enhancing stock-trading precision and user empowerment [23]

In the context of this research, the authors suggest two objectives for the development of securities' mobile stock-trading apps in big data analysis, applied in Vietnamese stock market that participants pay attention to advanced financial tools in the decision making of stock-trading processes. For solving this problem of stock-trading apps enhancement, two main objectives are planned as follows:

**Objective 1:** Standardization of financial database for supporting basic and advanced financial indexes and charts.

The quality of trading information that investors pay more attention to is data access with high confidence, and the standardization of financial database is essential to design financial indexes and key figures at basic level and advanced level. In many mobile stock-trading apps, exploited information from the database includes basic indexes such as $EPS$, $P/E$, $ROA$, $ROE$, $P/B$, $Beta$ and others; daily market transaction of prices and volumes in types of charts and figures; corporate news; and basic indicator for buying or selling without the illustration of indexes and figures. This is an unexploited point in their mobile stock-trading apps which advanced tools is a key to attract more participants. Therefore, the standardization of financial database is derived from two three sources of financial statements, shareholders' information, and stock-trading data. The assessment of big-data analysis such as the analysis of expected market return, market risk, and market timing for buying and selling stocks is key advanced tools of mobile stock-trading apps. To solve the problem, the storage of raw-data is processed feasibly before the steps of big-data analysis for advanced tools.

The standardization of database helps data mining in two levels:

(i) Data mining at firm-level. Business cycle affects investors' decision making. In the growth stage of revenue and gross profit, the accumulation of capital assets usually exists in medium term or long term, rather than short term so that the measurement of advanced financial indexes for giving charts is essential in investment decision making of equity ownership in medium or long terms.

(ii) Data mining at industrial-level. The analysis of corporate competitive advantages help to remove the weakness of in that the firm-level revenue and gross-profit growth is higher than the industrial-level revenue and gross-profit growth and this help investors to remove corporates that have lower firm-level revenue and gross-profit growth than industrial-level one.

Moreover, data mining from raw data is from a prerequisite for the data quality testing [13]. In some recent studies, algorithms with complicated indexes such as variable of stock market volatility from daily unstructured data exchanged for quarterly or yearly data [19, 26], variable of risk-taking $Zscore$ in unstructured data [8, 32], latent variable in principal factor analysis $PCA$ in unstructured data [24] and others require automatic-programming techniques by statistical software for finding useful information of investment decision making in types of financial models.

**Objective 2:** Development of statistical algorithms and predictive patterns for giving advanced tools in decision-making of stock-trading processes.

The prediction of stock prices is a main subject of participants in stock market which stock expected return and financial are two keywords in decision-making of stock-trading processes. Basic financial indexes have still unsolved these problems in prediction, then the development of statistical algorithms or predictive patterns is essential. In the context, we provide two new indexes: equilibrium price $P_e$ to predict expected market price and expected market return $E(R_m)$ to determine favourable market timing in decision-making of stock-trading processes [2].

Because the responses of financial statements and statistical reports are slower than the responses of stock-trading information, the new designment of equilibrium price $P_e$ and expected market return $E(R_m)$ helps investors predict market risk before the market crash. The combination of market index and its equilibrium price indicates that favourable market timing for buying and selling stocks rely on market cycle: recovery, uptrend, and downtrend. In each stage of market cycle, profitability and market risk is different.

The quality of stock-trading information that investors pay more attention to is data access with high confidence, the standardization of financial database and the designment of advanced tools are the main task of this research. On two mentioned-above objectives, the contents of this papers are shown as follows: literature of big data and information quality of stock-trading, methodology of database standardization and advanced tools of stock-trading prediction, discussion and conclusion.

## LITERATURE OF BIG DATA AND QUALITY OF STOCK-TRADING INFORMATION

Digitization and transformation of information is the discipline of big-data analytics. On the strong development in data digitization, software and data processing have created major changes in the applied search for finding investment opportunities in stock market. The challenge for financial institutions in general and securities companies in particular exploits the useful information from raw data (financial statements, statistical reports, or market trading data) to help investors' success in reaching optimal profitability and risk controls. The big-data technology in finance have opened the era of data mining in the management of financial activities [10, 20, 22, 34, 35, 37].

### Big Data In Finance

According to a recent study of Fang & Zhang [20], the rise of daily data has changed dramatically in stock market, in investment analysis and portfolio management. And the increase in wide range of financial data to form big data, which participants, companies, and institutions have been exploited in a way of predictable patterns, the specialization of programming techniques to manage various data fields in big data to give useful financial information with high usability.

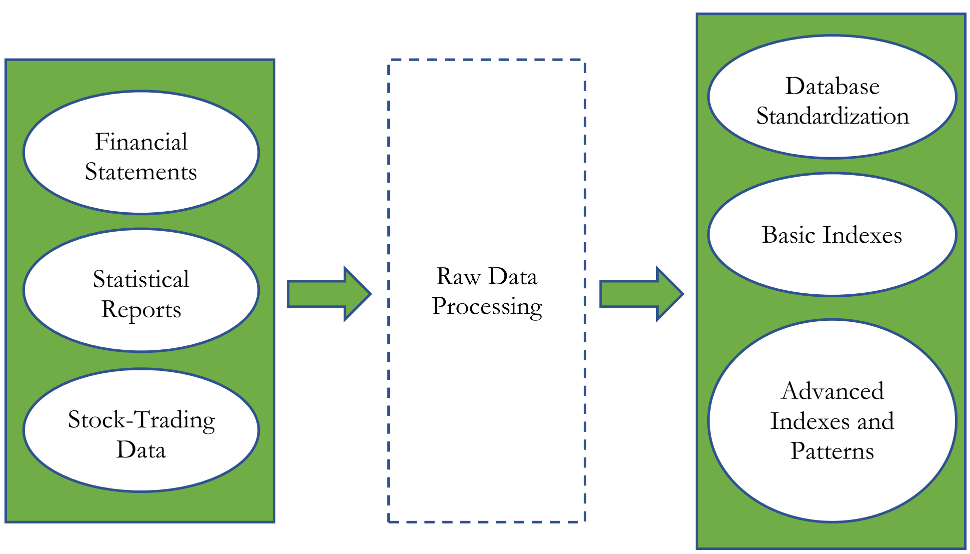


**Figure 1.** Basic Management System of Big Data in Finance

Quarterly and annual information access of financial statements is a slower response to the daily information access of market prices, so that financial analysts and institutions make a connection between the data of financial statements and the stock-trading data for accessing their information by basic financial indexes such as the price-to-earnings $P/E$ ratios, the price-to-book ratio $P/B$; or patterns for capital asset pricing CAPM such as the three-factor CAPM financial models [17], the five-factor CAPM [18]. Despite the development of information technology, all available information is always hidden in its market price [16], so the transformation of data visualization and predictive analysis on stock-trading data is crucial for financial analysts and institutions in stock market. For instance, a company's market price increase is often faster response than financial information of good business performance that the company announces.

In Figure 1, a basic process of big-data management in finance is divided into three steps: inputs of raw data (financial statements, statistical reports, stock-trading data); raw data processing; outputs (database standardization, basic indexes, advanced indexes and patterns). On the development of predictive patterns in stock market, basic functions of traditional indexes such as $EPS$, $P/E$, $P/B$, $ROE$, $ROA$, $D/E$ and others in mobile stock-trading apps are exposed some following limitations:

## Basic Financial Indexes

Basic financial indexes are usually designed in mobile stock-trading apps to provide small information of company's performance, basic figures and charts from stock-trading. These tools are not enough to assess the quality of stock-trading information because of the following limitations:

## Earnings Per Share EPS

Earnings per share $EPS$ is defined as net income per share that the company earned at the end of a reporting term [25, 33]. The formula of earnings per share is determined as follows:

$$EPS = \frac{EAT}{Q_O}, \tag{1}$$

where EAT is earnings after tax and Q_O is total outstanding stocks. For example, earnings per share of VNM in the lastest 4 quarters Q3/2023-Q2/2024 is 4,682.74 VND/share, that is, a VNM stock gets profits that could be divided for shareholders is 4,682.74 VND.

In term of financial meaning, the EPS index reflects a relationship between company's net income and outstanding stocks and this information provides the capacity of receiving dividend from net income, but the EPS index is always stochastic over time because of company's business cycle and stock split.

## Price-Earnings Ratio P/E

Price-earnings ratio $P/E$ is defined as the ratio of market price and earnings per share [25; 4]. Logically, investors look at this $P/E$ index for the greater productivity of buying stocks when it is low [1]. The formula of price-earnings ratio is determined by:

$$P/E = \frac{P_m}{EPS}, \tag{2}$$

in which P_m is market price and EPS is earnings per share. For example, price-earnings ratio of VNM in Q2/2024 is P⁄E=65,500⁄4,682.74≈14, that is, it takes over 14 years to pay back for holding long-term stocks.

In term of financial meaning, the P⁄E index reflects a relationship between stock price and earnings per share that a company earns. However, stock-price fluctuations also depend on market cycle, different from earnings per share affected by company business cycle. The P⁄E index could be confident if the stage of market cycle and business cycle is at the recovery stage.

### Price-to-Book Value Ratio $\mathbf{P/B}$

Price-to-book value ratio P/B is defined as a comparative ratio between market value and book value [6, 12]. A high P/B index is a factor of investors' confidence in its prospects [12]. The formula of price-to-book value ratio is determined as follows:

$$P/B = \frac{P_m}{B}, \tag{3}$$

in which $P_m$ is market price and $B$ is book value per share. For example, price-to-book value ratio of VNM in Q2/2024 is $P/B = 65{,}500/18{,}343 \approx 3.57$, that is, market value of VNM is valued at 3.57 times its book value.

In term of financial meaning, the $P/B$ index reflects a comparative ratio between the market value and the book value for equity ownership. However, stock price fluctuations still depend on market cycle and market timing, while book value is affected by business cycle and debt-equity ratio for effective financial leverage.

### Return on Equity ROE

Return on equity $ROE$ is defined as a measure of a company's equity performance, dividing net income by equity [4]. The exploitation of the $ROE$ index usually combines with others for stock evaluation. For instance, Wilcox [36] used two indexes of price-earnings ratio $P/E$ and return on equity $ROE$ for stock evaluation. The formula of return on equity is determined as follows:

$$ROE = \frac{EAT}{E}, \tag{4}$$

in which $EAT$ is earnings after tax, $E$ is equity. For example, return on equity of VNM in Q2/2024 is $ROE = 2{,}696/38{,}337 \approx 0.07$, that is, VNM's company earns 0.07 VND of profit one VND of equity.

In term of financial meaning, the $ROE$ index reflects a relationship between net income and equity, providing information of financial performance. However, the $ROE$ index is not mentioned to stock-trading information for a favourable market timing in the process of decision making.

#### *2.2.5. Return on Assets $ROA$*

Return on assets $ROA$ is defined as a measure of a company's total-assets performance, dividing net income by total assets [30]. And the basic formula of return on assets is determined as follows:

$$ROA = \frac{EAT}{TA}, \tag{5a}$$

in which $EAT$ is earnings after tax and $TA$ is total assets. For example, return on assets of VNM in Q2/2024 is $ROA = 2{,}696/54{,}194 \approx 0.05$, that is, VNM's company earns 0.05 VND of profit on one VND of assets. Moreover, the $ROA$ index is considered as a measure of a company's total-assets performance with financial leverage, determined as follows [9]:

$$ROA = \frac{EAT + IntEx}{TA}, \tag{5b}$$

where $IntEx$ is interest expense.

In term of financial meaning, the $ROA$ index reflects a relationship between a net income and total assets, providing information of assets' efficiency. However, the $ROA$ index is not mentioned to stock-trading information for a favourable market timing in the process of decision making.

#### *2.2.6. Debt-Equity Ratio $\mathbf{D/E}$*

Debt-to-equity ratio $D/E$ is defined as a comparative ratio used to assess a company's leverage, dividing total debt by total equity [9]. The $D/E$ index is used in the DuPont analysis. The formula of debt-equity ratio is determined as follows:

$$D/E = \frac{D}{E}, \tag{6}$$

in which $D$ is total debt and $E$ is total equity. For example, debt-equity ratio of VNM in Q2/2024 is $D/E = 15{,}857/38{,}337 \approx 0.41$, that is, one VND of equity is financed, VNM borrows 0.41 VND of debt.

In term of financial meaning, the $D/E$ index reflects a relationship between total debt and total equity, providing information of a company's financial leverage. However, the $D/E$ index is not mentioned to stock-trading information for a favourable market timing in the process of decision making.

Although the 06 mentioned-above indexes provide some part of financial information, the quality stock-trading information in the process of decision making seek investors' profitability and their risk controls that they pay more attention to. Because Fama [16] indicates that all company's information is reflected into its stock price, data mining of stock-trading is a key factor to derive advanced indexes and predictive patterns.

## CAPM and Market Beta

On the measurement of expected market return, capital asset pricing model CAPM is a typical model to reflect a relationship between stock expected return $E(R_i)$ and stock beta $\hat{b}_i$ by security market line $SML$ in Figure 2. The classification of risk-less interest rate $R_f$ and risk market return $R_m$ is a strong point of the one-factor CAPM, where the government regulatory tool of riskless interest rate $R_f$ controls the volatility of returns $R_i$ in stock market, that an increase in interest rate $R_f$ leads to a decrease in expected market return $E(R_m)$. After Covid-19, CAPM has still not explained the problem that an increase in interest rate $R_f$ led to an increase in expected market return $E(R_m)$ and this broke out a heart of CAPM [2]. In some reviews of CAPM, Black et al. [11] examined the sensitivity of security market line $SML$ between the expected returns and betas in multi-stages of market cycle, Baker & Wurgler [7], Antoniou et al. [3], and Apergis & Rehman [5] measured market sensitivity based on optimistic and pessimistic conditions, Doukas & Han [15] measured beta according to varying-time data.

According to Anh & Khanh [2], internal market risk is divided into types: market risk under cash inflows into stock market that stock prices are valued higher as usual, and market risk under cash outflows that stock prices are valued lower as usual. Market beta is only confident in capital asset pricing when market cycle and business cycle are at the recovery stage. Therefore, data mining of stock-trading in the process of decision making rely on two factors of expected market return and favourable market timing for buying or selling normal stocks.

## One-Factor CAPM and Stock Beta

One-Factor CAPM is based on the classification of riskless interest rate and risk return to estimate stock beta, which is defined as a stock premium risk to reflect a relationship between stock return $R_i$ and market return $R_m$, determined by the following equation:

$$E(R_i) - R_f = \hat{a}_i + \left[E(R_m) - R_f\right] \times \hat{b}_i, \tag{7}$$

where $R_i$ the stock return or portfolio return, $R_m$ is market return or market return, $R_f$ is riskless interest rate to represent a regulatory tool of central bank, $\hat{b}_i$ is slope coefficient or stock beta to represent a stock premium risk, and $\hat{a}_i$ is intercept coefficient or excess return out of market return. For example, interest rate of government bond on average term of 10 years in the Jan-2024 issue is $R_f = 3.97\%$, stock beta based on stock-trading data of VNM and VN-INDEX from Oct-2005 to Aug-2024 is estimated $\hat{b}_i = 0.726$, and VNM excess return $\hat{a}_i \approx 0$. With VN-INDEX expected market return $E(R_m) = 13.7\%$, expected stock return of VNM is derived from equation (7):

$$E(R_i) - 3.97\% = 0 + [13.7\% - 3.97\%] \times 0.726 = 10.15\%$$

## Security Market Line SML and Long-Term Market Timing

Stock beta $\hat{b}_i$ reflects a relationship between stock return $R_i$ and market return $R_m$, the estimation of expected market return $E(R_m)$ and the prediction of market timing for buying and selling market portfolio is two key factors in the success of decision making which Vietnamese individual investors do not pay more attention to it.

Figure 1 reflects a relationship between stocks' beta and expected stock returns, where stocks A and B have lower risk returns than market return and stock betas of A and B is lower than $SML$; stocks C and D have higher risk returns than market risk and stock betas of C and D is greater than $SML$. Although the stock beta is an advanced index shown in mobile stock-trading apps, investors' knowledges of stock betas and market risk is still a distance for their success of decision making.

In term of financial meaning, stock beta $\hat{b}_i$ reflects long-term market timing, providing information of long-term market timing for buying stocks when the combination of betas and expected returns is below the $SML$, or selling stocks when the one is above the $SML$. However, the explanation of market trend crash is not still found on the $SML$ to find out internal market risk [2]. So, the development of other advanced tools in securities' mobile stock-trading apps is essential to the process of decision making.

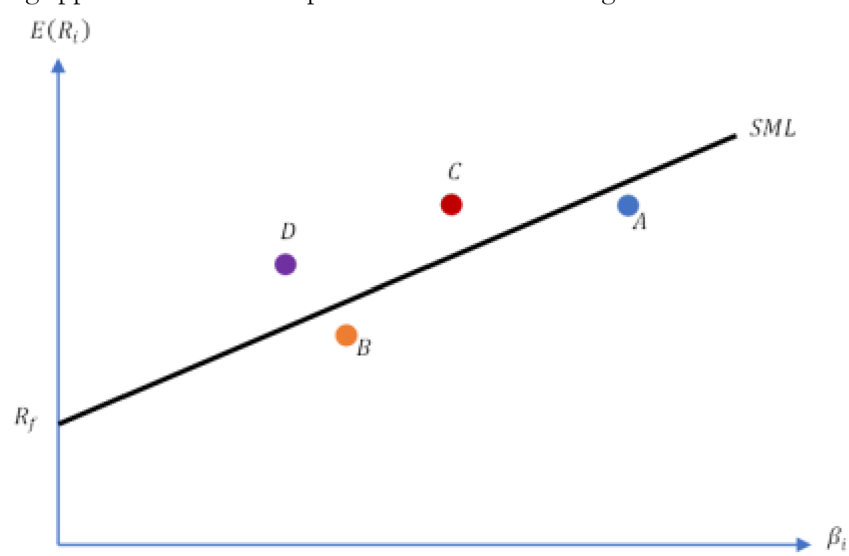


**Figure 2.** Security Market Line $SML$

## METHODOLOGY

The standardization of database from raw-data (financial statements, statistical report, stock-trading data and others) is very important to estimate basic and advanced indexes throughout predictive patterns. So, data mining and applications for decision-making is outlined in the process of big-data analysis.

## Data Mining and Applications

The term "Data Mining" refers to the research of advanced science and technology for data exploration to discover unknown or predictive patterns with high confidence. Using technology to exploit big-data including information systems, machine learning, artificial intelligence, data engineering, and knowledge discovery are just a few disciplines of data mining [14, 21, 27, 31]. Generally, data mining, so-called discovery of data or knowledge is defined as the process of analysing big data from various perspectives and summarizing them into useful information. Technically, data mining is the process of finding patterns on big-data for advanced indexes. And the accessibility of these useful information makes financial multi-applications [14, 21], such as the prediction of expected market return, the determination of favourable market timing, the risk management of portfolio, the location of stages in market cycle and business cycle.

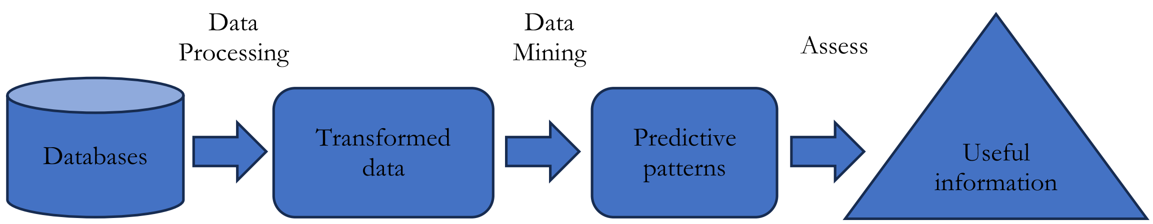


**Figure 3.** Big Data Decision System in the Stock Market [14]

In Figure 3, there are three main steps to find out useful knowledge from big data:

(i) Data processing: In the initial step of database standardization, where raw data is updated continuously into various data fields before converting the research data, where data structure is basically designed on three types: cross-sectional data, time-series data, and panel data.

(ii) Data mining: The data mining is often hidden in big-data analysis throughout the predictive patterns before providing useful information for decision making.

(iii) Assessing of useful information for decision making, where optimal profitability and risk management is the heart of big-data decision system.

## Data Structure

The designation of database is based on the type of data structure, which is convenient for data mining. In academic research and applications, data structure is typically found on three basic types of cross-sectional data, time series, and panel data, which are shown in Table 1.

Normally, these data structures are used in academic research, rather than applications, therefore database standardization needs to be flexible or exchangeable to connect with Table 2 in applied patterns.

**Table 1. Structure of panel data**

| Id | Time (quarterly/year) | Variable 1 | … | Variable k |
|---|---|---|---|---|
| 1 | T1 | | | |
| 2 | T1 | | | |
| … | … | | | |
| n | T1 | | | |
| 1 | T2 | | | |
| 2 | T2 | | | |
| … | … | | | |
| n | T2 | | | |
| … | … | | | |
| 1 | Tm | | | |
| 2 | Tm | | | |
| … | … | | | |
| n | Tm | | | |

Most of stock-trading data is biased to data structure in Table 2, to support the analysis of portfolio, such as one-factor CAPM; three-factor CAPM [17]; five-factor CAPM [18], or mean-variance model [28].

**Table 2. Stock-trading structure of a portfolio**

| Time (daily) | Stock 1 | Stock 2 | … | Stock k |
|---|---|---|---|---|
| T1 | | | | |
| T1 | | | | |
| … | | | | |
| T1 | | | | |
| T2 | | | | |
| T2 | | | | |
| … | | | | |
| T2 | | | | |
| … | | | | |
| Tm | | | | |
| Tm | | | | |
| … | | | | |
| Tm | | | | |

## Classification of Variables

The classification of variables is based on predictive patterns, where research variables are derived from raw variables, known as observational variables in data processing. And data processing is complicated, automatic programming techniques is supported to find out proxy variables or latent variables in data processing. There are two groups of research variables:

- Research variables are estimated from raw variables. In this group, data processing techniques are quite simple because basic algorithms are used in quantitative methods to estimate research variables.

- Research variables are estimated from proxy variables or latent variables. In this group, data processing techniques are complex because they use advanced algorithms in quantitative methods to estimate latent variables or representative variables into study variables of financial models.

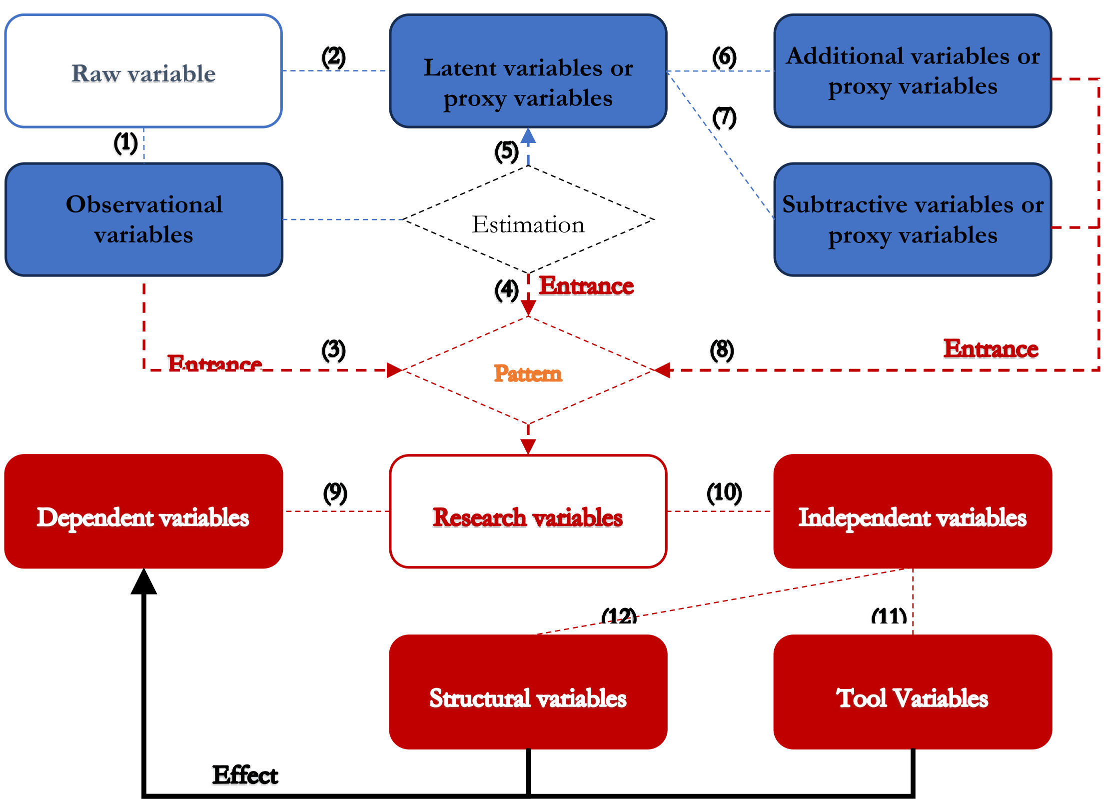

**Figure 4.** Variable classification tree in financial patterns

## Technology of Data Mining and Summary of Financial Indexes

## Technology of Data Mining

The key point of database standardization needs the designation of a program of data mining for users (analysts, researchers) to provide confident database source, easily to use them in predictive patterns. In the context of this research, the authors design a data-mining program in Excel VBA to provide tools of raw-data processing, basic data-mining and automatic-programming functions to estimate basic and advanced indexes. This is named "Pro-Data" that the users perform three basic steps of raw-data processing:

Step 1: Download the .csv file from the database on the website: vietstock.vn

Step 2: Select the raw variable of the financial statement in the .csv file

Step 3: run the program "Prodata.xlsm" to exchange the raw variables in these .csv files to the control panel structure.

In addition, estimating proxy variables or latent variables, this research designs visual automatic-programming functions, such as proxy variables to analyse the market stock volatility, expected market return, latent variables for principal component analysis PCA with flexibility compared to SPSS and Stata in financial algorithms of stock-trading to support predictive patterns.

## Summary of Financial Indexes

After database standardization of Table 1 and Table 2, financial indexes are typically estimated in Table 3.

**Table 3. Summary of financial indexes**

| | Financial Indexes | Symbol | Financial Statements | Market Trading |
|---|---|---|---|---|
| **1** | Return on Equity | $ROE$ | x | |
| **2** | Returns on assets | $ROA$ | x | |
| **3** | Selling profit | $ROS$ | x | |
| **4** | Dividend per share | $EPS$ | x | |
| **5** | Price-to-earnings ratio | $P/E$ | x | x |
| **6** | Price-to-book ratio | $P/B$ | x | x |
| **7** | Single-Factor CAPM | $E(R_m) - R_f$ | | x |
| **8** | Three-Factor CAPM | | x | x |
| **9** | CAPM Five Factors | | x | x |
| **10** | Average Variance Model | | | x |
| **11** | Discount model - dividend | | x | x |
| **12** | Stock market volatility | | | x |
| **13** | Expected market returns | $E(R_m)$ | | x |
| **14** | Taking bank risks | $Z_{score}$ | x | x |

## Supply-Demand Stock-Trading and New Advanced Indexes

The stock-trading of supply and demand is much referred to investment analysis and portfolio management, but it is rarely paid attention to market cycle to explore attributes of long-term supply-demand stock-trading, divided into groups of distributions: (i) cash inflows with high market-price distribution and (ii) cash outflows with attractive market-price distribution.

The exploration of supply-demand stock-trading based on two distributions help to set up the formulation of market transaction in the context that "investors' profits are formed from controls of abortive investors' money pockets to success investors' money pockets". The failure or success of investors rely on stages of market cycle.

## Classification of Stages in Market Cycle

The designation of profitability and risk controls is in accordance with three stages of uptrend, downtrend, and recovery in market cycle. Finding out market opportunities for minimization of investors' risk is classified in Table 4.

**Table 4. Classification of expected market return and financial risk in stages of market cycle**

| | | Uptrend | Downtrend | Recovery |
|---|---|---|---|---|
| 1 | Expected yield | High profit margins | Low profit margins | Stable profit margin |
| 2 | Financial risk | Market risk when stock prices are priced higher the condition of cash inflows<br>Scarcity of diversified risk of stocks | Market risk when stock prices are priced more attractive than the condition of cash outflows<br>Market risk combined with diversified risk of stocks | Scarcity of market risk<br>Diversified risk of stocks |

## Rule of Supply-Demand Stock-Trading

The movement of supply and demand in stock market is based on the sharp fluctuation of equilibrium price, which is defined as an accumulated stock-trading break-even price, determined as follows:

$$P_e = \frac{\sum P_m Q_m}{\sum Q_m}, \quad (8)$$

in which $P_e$ is equilibrium price between stock supply and cash demand, accumulated from the first-trading day to current-trading day, $P_m$ is daily market price, and $Q_m$ is daily volume. For example, the VN-INDEX represents market portfolio in Hochiminh Stock Exchange. However, the fluctuation of market index $P_m$ is hard to predict so that it needs to be exchanged into other attributes of equilibrium price, speculative price, distribution price and others to explain key stages of market cycle or market trend.

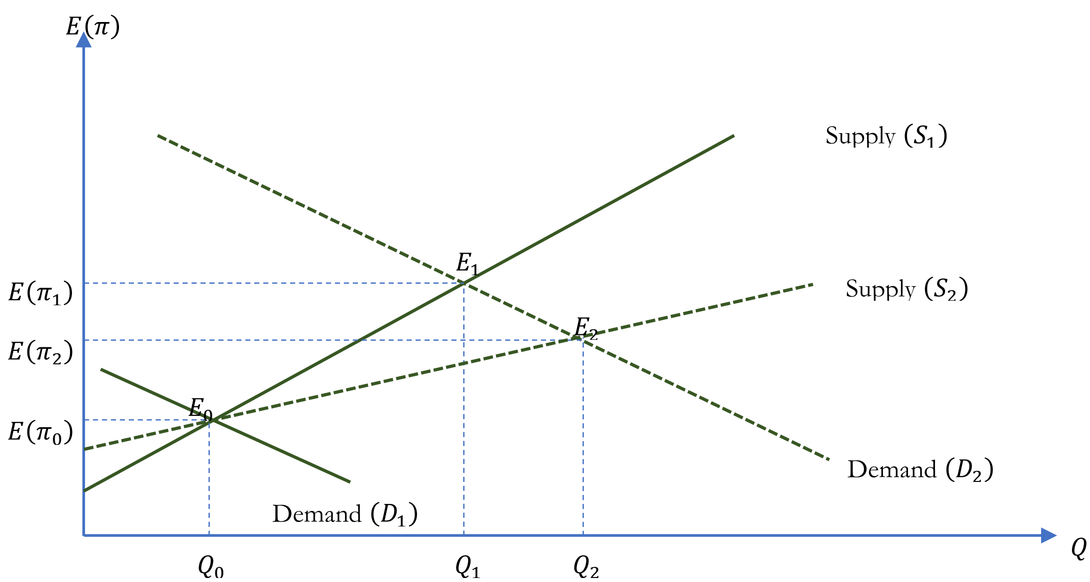


**Figure 5.** The rule of stock supply cash demand [2].

In generalization, the Figure 5 describes some rule of stock supply and cash demand based on a relationship between expected market profit $E(\pi)$ and stock volume $Q$ to find out three stages of market cycle. In recovery stage of market cycle, expected market profit reaches at $E(\pi_0)$ with equilibrium point $E_0$, which the controllability of stocks is good in long-term after market trend is crashed. In uptrend stage of market cycle, expected market profit reaches at $E(\pi_1)$ with equilibrium point $E_1$, which propensity of stocks increase lightly and market peaks could happen several times in this stage. In downtrend stage of market cycle, expected market profit reaches at $E(\pi_2)$ with equilibrium point $E_2$, which uncontrollability of stocks is investors' pessimistic behaviours or exceed leverage under worse economic activities, so that companies' capital is usually restructured in this stage.

### A Model of Expected Market Return and Market Timing

Based on assumptions about the rule of stock supply and cash demand in stock market, combined with a relationship of fluctuation between market-price differential $dP_m$ and equilibrium-price differential $dP_e$, a model of expected market return and market timing is proposed as follows:

Expected market return in stable state $E(R_m)'$:

$$dP_m = a_e + E(R_m)' \times dP_e, \quad (9a)$$

in which $a_e$ is the adjustment of differential between market price and equilibrium price.

Expected market return in current stage $E(R_m)$:

$$dP_m = E(R_m) \times dP_e, \quad (9b)$$

Combining equations (9a) and (9b) determines the appropriate market timing:

- Conditions for buying stocks when the expected market return in stable state is higher than the expected market return in current state: $E(R_m)' > E(R_m)$; or

- Conditions for selling stocks when the expected market return in stable state is lower than the expected market return in current state: $E(R_m)' < E(R_m)$.

- Conditions for selling controlling stocks when both the expected market return in stable state and the expected market return in current state are low.

The development of advanced indexes in Section 3.6 is a new look of methodology for supporting the process of decision making [2]. Most of financial tools in securities' mobile stock-trading apps have still exploited this key point efficiently.

## RESEARCH FINDINGS

In this section, we provide some research findings of advanced indexed by predictive pattens for the enhancement and addition into mobile stock-trading apps. In the context, the data of VN-INDEX is collected from the source https://s.cafef.vn/du-lieu-download.chn to find out some useful information.

### Optimal Market Price and Market Distribution

In the context of this research, we use the differential of VN-INDEX equilibrium price to describe the rule of market distribution, shown in Figure 5.

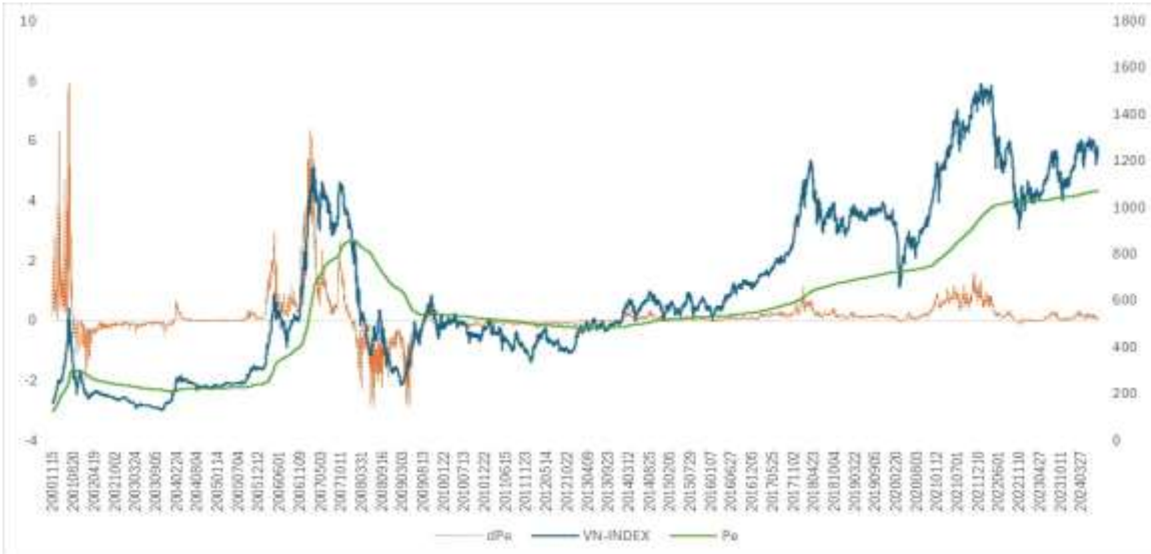


**Figure 6.** The distribution of VN-INDEX

Figure 6 shows that uptrend stages happen when market price $P_m$ is higher than equilibrium price $P_e$ and reach optimal profitability with the strong fluctuation of $dP_e$ or market price $P_m$ is much higher than equilibrium price $P_e$ to form the area of high market-price distribution; and downtrend stages when market price $P_m$ is lower than equilibrium price $P_e$ and reach optimal profitability with the strong fluctuation of $dP_e$ or market price $P_m$ is much lower than equilibrium price $P_e$ to form the area of attractive market-price distribution; and recovery stages happen when the $dP_e$ is smoothed and market price $P_m$ is close to equilibrium price $P_e$. Different from the control area or market adjustment, the fluctuation of $dP_e$ is relative with small market peak and market price $P_m$ is also close to equilibrium price $P_e$.

## Expected Market Return and Favourable Market Timing

Figure 7 describes expected market return and market timing of VN-INDEX from 03/2015 to 08/2024, where market index $P_m$ is in the right vertical axis, expected market return in stable state $E(R_m)'$ and expected market return in current state $E(R_m)$ are in the left vertical axis, to reflect favourable market timing: buying areas are 03/2020, 10/2022, and 10/2023. Besides, the Figure 6 also predicts market risk crash when the expected market return is fallen sharply before market index decreases dramatically at the area of 1528 points in November 2021.


**Figure 7.** Expected market return and market timing of VN-INDEX

## DISCUSSION AND CONCLUSION

This study describes big data technology in exploiting useful information to find out market opportunities for individual investors or institutions and support quantitative tools throughout advanced indexes of expected market return and market timing. For solving this problem, database standardization is essential to securities or institution in big-data analysis to provide useful information in the process of decision making.

Despite the limitations of basic financial indexes and traditional patterns, the big-data technology in stock market makes competitive advances of securities that have rarely paid attention to. And this is unexploited market segment to attract more investors.

The research provides some basic data-mining in raw-data processing by automatic-programming techniques and designation of advanced indexes for further research with higher practical patterns in investment analysis and portfolio management.

### Conflicts of Interest

The Authors declare no conflicts of interest.

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