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How Does the Buffett Indicator Work in China?

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By

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Abstract

This study investigates whether the Buffett indicator can be used to make investment decisions in China. The investigation has two approaches. First, this study determines the scaling relationship between the Buffett Indicator and the GDP in China. Previous research and findings in this research regarding the scaling relationship can help international investors when comparing China with a different country as potential investment opportunities. Second, this study also examines whether the Buffett Indicator, the P/E ratio and composite models including the Buffett Indicator can be used as tools for international investors in predicting the Shanghai Index and making investment decisions for the Chinese stock market. The analysis is based on Chinese data from the World Bank, the National Bureau of Statistics of China, the Federal Reserve and the Yahoo Finance. This study finds that there is a sublinear relationship between the Buffett indicator and GDP in China and that the composite models which include the Buffett Indicator perform better to forecast the stock market in China than other indicators.

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Through this research paper, I have learned a lot about the Buffett Indicator and the Chinese stock market. It helped me analyze how financial indicators can be used to evaluate stock markets. I hope this research paper can also help international researchers and investors who plan to get involved in the Chinese stock market.

Introduction

Warren Buffett put forward the Buffett Indicator in an interview with *Fortune* magazine in 2001, and he recognized the Buffett Indicator as a trustworthy indicator of the American stock market (Buffett & Loomis, 2001). The Buffett Indicator has become one of the most popular long-term stock indicators. For instance, if you Google the Buffett Indicator, you can find about 440,000 results (Hamtil, 2016). In recent years, the Buffett Indicator has many representative articles.

The Buffett Indicator is the proportion of total stock market capitalization to the Gross Domestic Product (GDP) of a nation (Jones, 2016). It is a signal for when investors should buy or sell stocks. Total stock market capitalization measures the price of stocks in the market. The GDP of a country is the total value of all goods and services produced by that country in a year. If the Buffett Indicator is 115% or more, it is overvalued. If the Buffett Indicator is below 50%, it is undervalued. If the Buffett Indicator is 75% to 90%, it is about right ("How Warren…", 2017).

There were two big bubbles in China from 2003 to 2017. The first bubble is from October 2006 to January 2009 because of the subprime mortgage crisis. The second is from May 2014 to July 2015 (Liu, Han & Wang, 2016). These two bubbles made the market capitalization in China increase dramatically in 2007 and 2015. Because of the economic recession in China, the market capitalization of China in 2008 decreased a lot, which makes the data of market capitalization in 2007 look even more abnormal. There was also an economic recession in the United States in 2008, and the U.S. stock decreased 25% in May 2015 to February 2016 (McBride, 2018).

The economic environment in China is complex. In the article "The World Bank in China overview", China has changed to a more market-based economy from a centrally planned economy on account of market reforms in 1978, and Chinese society and economy have grown rapidly in the last 40 years. The Chinese government plays a significant part in the Chinese economy. The

Chinese government made “Five-Year Plans” since 1953 to guide the development of its economy and society. The yearly growth objective of the 13th Five-Year scheme (2016-2020) is 6.5%, which shows " rebalancing of the economy ". This proposal reflects that China concentrates on its growth's quality and keeps the purpose of reaching a "moderately prosperous society.” The Chinese government always repairs the economy when there are economic issues in China. For example, the Chinese government had a strong impact on the Chinese economy during the economic recession in 2008. The financial crisis in September 2008 started to significantly influence the business in China in November 2008. Economic growth fell to 6.6% in the first quarter of 2009. Export and import development were negative. A lot of companies shut down or reduced output. The Chinese government quickly made an evaluation of the crisis. In November 2008, it decisively implemented a "positive fiscal policy", supplemented by a sound monetary policy, to stimulate the economy through the central government's investment of 4 trillion yuan (595.6 billion current US$) (Wong, 2010).

Many studies confirm that the Buffett Indicator is likely to continue to be welcomed by the world's investment community. The application of the Buffett Indicator for multinational investment might need more study to grow and to improve upon the utilization of the Buffett Indicator. Since Chang and Pak do not use China in their study, this study expands the research of Chang and Pak to examine whether the BI can be used by international investors to compare the stock market in China and the stock market in another country. To further explore the Buffett Indicator, this study also tests if the Buffett Indicator and composite models that include the Buffett Indicator can be used as tools for international investors in predicting the Shanghai Index and making investment decisions for the Chinese stock market, and compares them with other models that include the P/E ratio. This study builds 4 models to test the utilization of the Buffett Indicator.

The first model is a moving average about the return of the Shanghai Index. The second model uses only the Buffett indicator as an independent variable. The third model employs the P/E ratio. The fourth model takes 4 different forms as following. Firstly, this study builds a composite model including the Buffett Indicator, Population of China, the GDP and the P/E ratio to predict the return of the Shanghai Index. Secondly, this research builds a composite model including the Buffett Indicator, Population of China, and the GDP. Thirdly, this study builds a composite model including the P/E ratio, Population of China, and the GDP. Fourthly, this study builds a composite model including the Buffett Indicator, P/E ratio, and Population of China to predict the return of the Shanghai Index. I tested these models by using the root mean square error (RMSE), mean absolute deviation (MAD), mean squared error (MSE), mean absolute percentage error (MAPE), and mean percentage error (MPE). The importance of this study is testing whether the Buffett Indicator can be used as a tool for international investors to operate in the stock market of China, and compare it with other models, similar to what was done in researches for the United States' stock market. I also tested whether the Buffett Indicator performs better than other models out of the sample.

Literature Review

Moving average, as a computation model, is used to investigate information through generating a sequence of distinct subsets of information. The applications of moving average are extensive. Chan (2013) uses the moving average to predict US inflation, and the author concludes that these “moving average stochastic volatility models” offer better forecasting performance than the normal variants with exclusively random volatility. Yuristia et al. (2019) apply the moving average model to predict the price, and they summarize that the moving average model is the most suitable model to predict the Cassava Price in Indonesia. The significance of moving averages in the stock market cannot be overlooked. Many studies discuss the application of the moving average to predict the stock market (Kannan et al., 2010; Yu, 2002; McMillan et al., 2000). Some researches prove the success of the moving average to predict the future stock price. For example, Wei et al. (2014) used a hybrid forecasting model which includes a moving average model and a linear model to predict the stock price, and they conclude that this proposed model performs better than other models.

The price-to-earnings ratio (P/E ratio) is used to evaluate the performance of an enterprise, which is current share price divided by per-share earnings. Investors think that the P/E ratio is a significant indicator for the finance world because it offers methods to conclude whether a stock is underestimated or overestimated. Danielson and Dowdell (2001) regard the P/E ratio as a qualified model to predict stock return. Shen (2000) tests the historical relation between performance of the stock market and price-earnings ratios and finds a substantial historical proof that in the long and short session, the high P/E ratios were related to disappointing stock market performance. Penman and Zhang (2002) discover that the P/E ratio is different from a line which is fitted to maintainable “earnings scores”.

Many papers have tried to analyze international investment by using the Buffett Indicator in some other countries. For example, Siblis Research (2016) uses the monthly data of 28 countries. Through this research, the authors find that the relationship between the Buffett Indicator and the return of the equity investment preforms negatively. Consequently, authors believe that a relatively low or high Buffett Indicator should be considered in a context of national internal economic environment. In their research, Chang and Pak (2018) conclude that in a group of 13 countries which have a strong super-linear scaling relationship between the Buffett Indicator and GDP, when comparing the stock market of two countries in this group, it is better to choose a nation that has a higher GDP than a nation that has a lower GDP. Their study includes the Buffett indicator information and the relationship between Buffett Indicator and GDP for multiple countries, but not China.

Economic researchers try to build composite models to predict the stock market more precisely. Jones (2019) talks about a multi-variable foresting model based on the MV/GDP metric This author compares the CAPE, Tobin's q and the MV/GDP, which is the Buffett Indicator, and concludes that the Buffet Indicator is a superlative valuation method of the stock market. This author combines the Buffett indicator and Demographic Variables to a demographically adjusted (DAMA) Composite model, and the author finds that this model works more effectively to predict the real market capitalization. Leigh et al. (2005) set up a composite model about information of previous price behavior, interest rate change and volume increase, and authors find that this model is easy to understand and effective to predict the stock price.

Demographic factors are important to consider when investors predict the stock price and they are also the most reliable factors to add into the composite model (Jones, 2019). The estimated rise of the number of people increases risks to financial and macroeconomic stability as well as to the impacts of financial shocks (Young, 2002). The age distribution of the population has a strong impact on the financial market because its influence on the demand of investment funds and the saving rate (Bosworth et al., 2004). Based on 60 years of data and a number of country samples, it suggests that a strong relation will appear between demographic factors as well as both market capitalization and GDP growth (Arnott & Chaves, 2012).

Data and Methods

Part 1

The Buffett Indicator is a proportion of market capitalization to GDP for an individual country. The Buffett Indicator for China is available from the Federal Reserve website from 1996 to 2017 and this study obtains the GDP (current US$) from 1996 to 2017 from the World Bank website. In this part, this study uses the GDP as the independent variable, and the Buffett Indicator as the dependent variable.

The research of Chang and Pak (2018) is followed by this study to find out the scaling relation between the Buffett Indicator and the GDP. The Buffett Indicator is tested as a function of the GDP of China by using an elementary power function.

$$Y = aG^{b} \tag{1}$$

where a is a constant, G is nation's GDP, Y is the Buffett Indicator. The scaling relationship between G and Y is determined by the exponent b. By using the natural logarithm, the equation (1) can be written as:

$$lnY = lna + blnG + \varepsilon \tag{2}$$

In Bettencourt 's study (2013), equation (2) was used to examine the relation between population capacity of urban center and socio-economic action measures. That study talks about that relation is superlinear while b >1, relation is linear while b = 1, and relation is sublinear while b < 1. This research uses the null and alternative hypotheses of as follows:

H_0: $\beta_1 \geq 1$ (there is a superlinear relationship)

H_1: $\beta_1 < 1$ (there is not a superlinear relationship)

Based on Chang and Pak's research, countries, such as Germany, Australia and South Korea, have a superlinear relationship between the Buffett Indicator and GDP. This research expects that there is a sublinear relationship between the Buffett Indicator and GDP in China, because China is more similar to countries that has sublinear relationship between the Buffett Indicator and GDP in Chang and Pak's research. According to Chang and Pak's research, if there is a superlinear relationship between the Buffett Indicator and GDP in a country, investors can compare this country by comparing the size of GDP with another country which also has a superlinear relationship between the Buffett Indicator and GDP to make investment decisions in the international stock market. If there is a sublinear relationship between the Buffett Indicator and GDP in both two countries, people cannot use this method to make investment decisions.

Part 2

The first part of this study determined the scaling relationship between the Buffett Indicator and the GDP in China. Part 2 explores the Buffett Indicator by building 4 models. The data of Part 2 are collected from the Federal Reserve website, the World Bank website, Yahoo Finance and the National Bureau of Statistics of China. The monthly data for the Shanghai Index is available. However, since the Buffett indicator, the GDP, the P/E ratio and the Population are annual data, to expand the research sample and to increase the accuracy of this research, this study adjusts annual data to monthly data by using the $g_m = [(\frac{Xm}{Xm-1})^{12} – 1] \cdot 100$.

The monthly Shanghai Index from January 1992 to December 2017 is collected from the Yahoo Finance. From Appendix 1, Descriptive Statistics of the return of Shanghai Index, this study summarizes that the mean of the return of Shanghai Index is 1.6746, the minimum is -31.1530 and the maximum is 177.2262. The Buffett Indicator from 1996 to 2017 is collected from the Federal Reserve as "Stock Market Capitalization to GDP for China". Since the Buffett Indicator presented by the Federal Reserve is annual, this study uses the formula mentioned before to convert it into monthly data. This study can conclude that the maximum of the Buffett indicator of this period is

78.4485, and the minimum is 9.7561 based on the Appendix 2, which is Descriptive Statistics of the Buffett Indicator. P/E ratio from 1993 to 2017 and Population from 1996 to 2017 are collected from the National Bureau of Statistics of China. Because they are annual data, P/E ratio and Population are also transferred to monthly data. Appendix 3 presents descriptive Statistics of the P/E ratio and Appendix 4 presents descriptive statistics of the Population. The maximum of the P/E ratio is 5,954.7651, and the maximum of the population is 1,390,080,000 for these time periods. This study collects the GDP from 1996 to 2017 from the World Bank. Appendix 5, Descriptive Statistics of the GDP, shows that the mean of GDP in this time period is $ 4,754,615,061,357.3.

According to the Zar (1968),

$$Y= \beta_0+ \beta_1 X \tag{3}$$

a simple linear regression model is insufficient to describe the relation between the dependent variable and the independent variable. Taking logarithms of the independent variable is suggested. After taking the logarithm of the equation (3), the equation (4) is written as:

$$Y= \beta_0+ \alpha W \tag{4}$$

where W= log X. To make the data better fit to this research, and to make the data stationary, this study takes the natural logarithm of the independent variables. In addition, this research uses the return of the Shanghai index, which is converted from the Shanghai Index by using Return $= (\frac{Yt-Yt-1}{Yt-1}) \cdot 100$, instead of the Shanghai Index to make data stationary.

Investors use the historical data to forecast the Financial stock market (Kannan et al., 2010). To increase preciseness and the accuracy of this study, this research uses 12-month moving average to predict the return of Shanghai Index in model 1, and uses the data 12 months ago to forecast the return of Shanghai Index in models 2, 3 and 4, for example, this study uses the Buffett Indicator in September 1996 to forecast the return of Shanghai Index in September 1997.

Many researchers use the RMSE to assess the models (Lord et al., 2010; Sharma et al., 2005; Hooper et al.,2008). RMSE is commonly applied in model evaluation studies to examine the model-performance error (Chai & Draxler, 2014). This study calculates the RMSE to evaluate 4 models, and to find which indicator is more suitable to predict the Chinese stock market. To increase the accuracy of evaluation, this research also uses MAD, MSE, MAPE, and MPE to test results. The formulas of these models are shown in the Appendix 6. The in-sample forecast accuracy comparison among the models in this study is based on R square.

In Model 1, this study attempts to predict the return of the Shanghai Index through 12-month moving average of the return of the Shanghai Index from January 1993 to December 2017. The Shanghai Stock Exchange Composite Index is formed by all B-shares and A-shares that was operated by the Shanghai Stock Exchange, which effectively represents the Chinese Stock and is the biggest exchange in China (Zhang & Li, 2008). In this study, this research compares the actual return of the Shanghai Index and the predicted values of model 1. To examine the accuracy of our prediction, after running the regression, the RMSE, MAD, MSE, MAPE, and MPE are used.

In Model 2, this study forecasts the return of the Shanghai Index by using the Buffett Indicator. The regression analysis is applied to a simple linear regression model, which is

$$Y_t = a\, X_{t-12} + b \tag{5}$$

where Y_t is the return of the Shanghai Index, X_{t-12} is the natural logarithm of the Buffett Indicator 12 months ago, and b is a constant. This study compared the actual value from January 2016 to December 2017 with the predictable value of model 2. This research uses the RMSE, MAD, MSE, MAPE, and MPE between observed value and the predictable Shanghai index to test the model 2.

In Model 3, this study uses the P/E ratio to predict return of the Shanghai Index from January 2016 to December 2017. The simple linear regression formula is as following,

$$Yt = a X_{t-12} + b \quad (6)$$

where Y_t is the return of the Shanghai Index, X_{t-12} is the natural logarithm of the monthly P/E ratio 12 months ago, and b is a constant. This study runs the regression of Model 3 to find the RMSE, MAD, MSE, MAPE, and MPE to judge whether the model 3 is a good method to forecast the return of the Shanghai Index.

In Model 4, this study attempts to forecast the return of the Shanghai Index by building 4 composite models. First, this study builds a composite model including the Buffett Indicator, Population of China, the GDP and the P/E ratio to predict the return of the Shanghai Index from January 2016 to December 2017. The formula for composite model is:

$$Y_t = a X1_{t-12} + b X2_{t-12} + cX3_{t-12} + d X4_{t-12} \quad (7)$$

where Y_t is the return of the Shanghai Index, $X1_{t-12}$ is the natural logarithm of the P/E ratio 12 months ago, $X2_{t-12}$ is the natural logarithm of the Buffett Indicator 12 months ago, $X3_{t-12}$ is the natural logarithm of the Population 12 months ago and $X4_{t-12}$ is the natural logarithm of the GDP 12 months ago. After running regression, this study finds the RMSE, MAD, MSE, MAPE, and MPE between the observed value and the predictable value. Second, this research builds a composite model including the Buffett Indicator, Population of China, and the GDP to predict the return of the Shanghai Index from January 2016 to December 2017. The formula for composite model is:

$$Y_t = a X1_{t-12} + b X2_{t-12} + cX3_{t-12} \quad (8)$$

where Y_t is the return of the Shanghai Index, $X1_{t-12}$ is the natural logarithm of the Buffett Indicator 12 months ago, $X2_{t-12}$ is the natural logarithm of the Population 12 months ago and $X3_{t-12}$ is the natural logarithm of the GDP 12 months ago. After running the regression, this study finds the RMSE, MAD, MSE, MAPE, and MPE between the observed value and the predictable value.

Third, this study builds a composite model including the P/E ratio, Population of China, and the GDP to predict the return of the Shanghai Index from January 2016 to December 2017. The formula for composite model is:

$$Y_t = a\,X1_{t-12} + b\,X2_{\,t-12} + cX3_{\,t-12} \tag{9}$$

where Y_t is the return of the Shanghai Index, $X1_{t-12}$ is the natural logarithm of the P/E ratio12 months ago, $X2_{\,t-12}$ is the natural logarithm of the Population 12 month ago and $X3_{\,t-12}$ is the natural logarithm of the GDP 12 months ago. After running the regression, this study finds the RMSE, MAD, MSE, MAPE, and MPE between the observed value and the predictable value. Fourth, this study builds a composite model including the Buffett Indicator, P/E ratio and Population of China to predict the return of the Shanghai Index from January 2016 to December 2017. The formula for composite model is:

$$Y_t = a\,X1_{t-12} + b\,X2_{\,t-12} + cX3_{\,t-12} \tag{10}$$

where Y_t is the return of the Shanghai Index, $X1_{t-12}$ is the natural logarithm of the P/E ratio 12 months ago, $X2_{\,t-12}$ is the natural logarithm of the Buffett Indicator and $X3_{\,t-12}$ is the natural logarithm of the Population 12 months ago. After running regression, this study finds the RMSE, MAD, MSE, MAPE, and MPE between the observed value and the predictable value.

Analysis of Result and Discussion

Part 1

Following Chang and Pak's model, this study employs the GDP in China from 1996 to 2017 as G, the Buffett Indicator from 1996 to 2017 as Y. After running the regression, this study finds the coefficient of the Ln G is 0.4362

According to the regression, this study rejects the H_0. Hence, there is a liner relationship but not a superlinear relationship between lnY and ln G of China from 1996 to 2017. According to Chang and Pak's research, since the b is less than 1, it shows that the Buffett Indicator as a function of GDP of China between 1996 to 2017 presents a sublinear relation.

In Chang and Pak's research, the authors argue that while investors compare two countries' investment, if the b of two countries are both more than 1, which means that there is a superlinear relationship between the Buffett Indicator and GDP in both two countries, investors can make decisions from comparing the size of the GDP; as the b of two countries are both less than 1, which means that there is a sublinear relationship between the Buffett Indicator and GDP in both two countries, the size of GDP has nothing to do in decision making; if one country has b more than 1, but the other has b less than 1, "both respective values of the Buffett Indicator and GDP matter in investment analysis" (Chang & Pak, 2018).

This research has determined that there is sublinear relationship for China from Chinese data from 1996 to 2017. This research also suggest if investors compare China with a country whose b is also less than 1, investors cannot make decisions from comparing the size of the GDP of these two countries, and if investors compare China with a country whose b is more than 1, investors need to consider both the Buffett Indicator and the GDP to make decisions.

According to these findings, this study finds that using Chang and Pak's simple power function based on the GDP and the Buffett Indicator is not enough for investors to make decisions to invest in China. This research suggests that improved international investment analysis methods based on GDP need to be considered.

Part 2

The following table shows the results of the R square, RMSE, MAD, MSE, MAPE, and MPE in the four models which are built for determining better methods to predict the return of the Shanghai Index. To find better models to predict the return of the Shanghai index, this study presents the results in the following table. Lower absolute values of RMSE, MAD, MSE, MAPE and MPE values are better.

	R Square	**MAD**	**MSE**	**RMSE**	**MAPE**	**MPE**
Model 1	0.1081	6.7427	139.1979	11.7982	1.4776	0.9559
Model 2	0.1335	3.3928	32.9913	5.7438	0.9755	0.8681
Model 3	0.6402	3.3833	33.7382	5.8085	1.2892	1.2204
Model 4						
composite model (P/E, BI, Population, GDP)	0.0407	3.4605	34.6491	5.8863	1.5080	-0.8488
composite model (BI, Population, GDP)	0.0323	3.3608	32.9495	5.7402	1.2652	1.2386
composite model (P/E, Population, GDP)	0.0029	3.3249	32.5207	5.7027	1.1084	1.1084
composite model (P/E, BI, Population)	0.0392	3.3600	34.2710	5.8541	1.5180	1.3868

Table 1 Results of the R square, RMSE, MAD, MSE, MAPE, and MPE in 4 models

This table shows that R square of Model 3, which uses the P/E ratio 12 months ago to predict the return of the Shanghai Index, has a better in-sample forecast accuracy performance. The lower R square means that there are some other factors not considered in these models.

For the MAD results, this study finds that composite models have better performance. The composite model including the P/E ratio, Population and GDP using data 12 months ago has the lowest MAD, which is 3.3249. The composite model including the BI, Population and GDP using data 12 months ago and the composite model including the P/E ratio, BI and Population using data 12 months ago also perform well, and these two models have similar MAD with the composite model including the P/E ratio, Population and GDP.

For the MSE results, the composite model including the P/E ratio, Population, and GDP using data 12 months ago receives the lowest MSE, which is 32.5207. The composite model including the BI, Population and GDP using data 12 months ago, and the model 3, which uses the P/E ratio to predict the return of the Shanghai Index using data 12 months ago, also have better performance. These two models have similar MSE with the composite model including the P/E ratio, Population and GDP. The MSE of composite model including the BI, Population and GDP using data 12 months ago is 32.9495. The MSE of model 3, which uses the P/E ratio to predict the return of the Shanghai Index using data 12 months ago, is 33.7382.

For the RMSE results, the lowest RMSE is 5.7027, which is in the composite model including the P/E ratio, Population and GDP using data 12 months ago. The composite model including the BI, Population, and GDP also performs well, and the RMSE of it is 5.7402. Another model that performs well is model 2, which forecasts the return of the Shanghai Index by using the BI using data 12 months ago.

For the MAPE results, the lowest MAPE is 0.9755, which is in the model 2 that forecasts the return of the Shanghai Index by using the BI using data 12 months ago.

For the MPE results, the composite model including the P/E ratio, BI, Population and GDP using data 12 months ago perform well. The results of MPE show that the composite models including the P/E ratio, BI, Population and GDP perform better than other models.

This study finds that for different measures, the best model to predict the Shanghai Index is different. However, the composite models which include the Buffett Indicator generally perform better than other models.

Conclusion

This study uses two parts to examine if the Buffett Indicator perform effectively in the stock market of China. In the first part, this research follows Chang and Pak's research to determine the scaling relationship between the Buffett Indicator and GDP in China to help international investors when comparing China with a different country as potential investment opportunities. However, this research has determined that there is sublinear relationship for China based on Chinese data from 1992 to 2017, which proves that investors cannot make decisions according to the size of GDP when comparing China with another country. In the second part, this study tests whether the moving average, the Buffett Indicator, the P/E ratio and composite models including the Buffett Indicator can be used as tools for international investors in predicting the Shanghai Index and making investment decisions for the stock market in China. Part 2 proves that the Buffett indicator is effective in the stock market of China similar to in the stock market of the United States, and the composite models which include the Buffett Indicator perform better to predict the return of the Shanghai Index.

There are some limitations of this research. Because of the complexity of the Chinese economy and the policy changing, the amount of data for the economic indicators is limited, and most data are not monthly data. The insufficient data and converted monthly data may influence the accuracy of the research. This study highly recommends the researchers to further explore more data to advance composite models which include the Buffett Indicator to predict the Chinese Stock market.

Works Cited

Arnott, R. D., & Chaves, D. B. (2012). Demographic changes, financial markets, and the economy. *Financial Analysts Journal*, 68(1), 23-46.

Bosworth, B., Bryant, R., & Burtless, G. (2004). The impact of aging on financial markets and the economy: A survey. Available at SSRN 1147668.

Buffett, W., & Loomis, C. (2001, December 10). Warren Buffett on the stock market. *Fortune Magazine*. Retrieve from http://archive.fortune.com/magazines/fortune/fortune_archive/2001/12/10/314691/index.htm.

Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)?. *Geoscientific Model Development Discussions*, 7, 1525-1534.

Chan, J. C. (2013). Moving average stochastic volatility models with application to inflation forecast. *Journal of Econometrics*, 176(2), 162-172.

Chang, Y. S., & Pak, D. H. (2018). Warren Buffett Value Indicator vs. GDP Size─ Is the Relationship Superlinear?. *International Journal of Economics and Business Research*, 15(2).

Danielson, M. G., & Dowdell, T. D. (2001). The return-stages valuation model and the expectations within a firm's P/B and P/E ratios. *Financial Management*, 93-124.

GDP (current US$). (n.d.). World Bank. Retrieved from. https://databank.worldbank.org/data/reports.aspx?source=2&series=NY.GDP.MKTP.CD&country=USA,CHN#.

Hamtil, L. (2016, February 18). Applying the ‘Buffett indicator’ to other countries, *Fortune Financial*. Retrieved from https://www.fortunefinancialadvisors.com/blog/applying-the-buffett-indicator-to-other-countries/.

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic journal of business research methods*, 6(1), 53-60.

How Warren Buffett's favorite stock-market gauge can help investors make smarter decisions. (2017, December 11). *Business Insider.* Retrieved from https://www.businessinsider.com/what-is-the-warren-buffett-indicator-2017-12.

Jones, C. (2016, June 21). One of Warren Buffett’s favorite metrics says stocks are way too expensive, *Forbes.* Retrieved from https://www.forbes.com/sites/chuckjones/2016/06/21/warren-buffetts-gdp-to-market-cap-ratio-signaling-low-returns/#380616c32841.

Jones, S. (2019). Macro vs. Micro Earnings,'Macro-Earnings Negativity', and an Introduction to a Composite Valuation Model. Micro Earnings, *'Macro-Earnings Negativity', and an Introduction to a Composite Valuation Model (February 13, 2019).*

Kannan, K. S., Sekar, P. S., Sathik, M. M., & Arumugam, P. (2010, March). Financial stock market forecast using data mining techniques. In *Proceedings of the International Multiconference of Engineers and computer scientists* (Vol. 1, p. 4).

Leigh, W., Hightower, R., & Modani, N. (2005). Forecasting the New York stock exchange composite index with past price and interest rate on condition of volume spike. *Expert Systems with Applications*, 28(1), 1-8.

Liu, Z., Han, D, & Wang, S. (2016, December 8). Bursting bubbles in China's stock market. *East Asia Forum*. Retrieved from https://www.eastasiaforum.org/2016/12/08/bursting-bubbles-in-chinas-stock-market.

Lord, R., Koekkoek, R., & Dijk, D. V. (2010). A comparison of biased simulation schemes for stochastic volatility models. *Quantitative Finance*, 10(2), 177-194.

McBride, S. (2018, October 24). U.S. stocks are nowhere near a bubble today. *Forbes*. Retrieved from https://www.forbes.com/sites/stephenmcbride1/2018/10/24/us-stocks-are-nowhere-near-a-bubble-today/#5512070812c3.

McMillan, D., Speight, A., & Apgwilym, O. (2000). Forecasting UK stock market volatility. *Applied Financial Economics*, 10(4), 435-448.

National data. (n.d.). National Bureau of Statistics of China. Retrieved from http://data.stats.gov.cn/english/easyquery.htm?cn=C01

Penman, S. H., & Zhang, X. J. (2002). Modeling sustainable earnings and P/E ratios with financial statement analysis. *E Ratios with Financial Statement Analysis (June 1, 2002).*

Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W. R. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of Business Research*, 58(7), 935-943.

Shen, P. (2000). The P/E ratio and stock market performance. *Economic review-Federal reserve bank of Kansas city*, 85(4), 23-36.

Siblis Research. (2016). Global market cap to GNI/GDP ratio for 28 countries. Retrieved from http://siblisresearch.com/data/market-cap-to-gdp-ratios.

SSE Composite Index. (n.d.). Yahoo Finance. Retrieved from https://finance.yahoo.com/quote/000001.SS/history?period1=661496400&period2=1573707600&interval=1mo&filter=history&frequency=1mo.

Stock Market Capitalization to GDP for China. (n.d.). Federal Reserve. Retrieved from https://fred.stlouisfed.org/series/DDDM01CNA156NWDB.

The World Bank in China overview. (n.d.). World Bank. Retrieved from https://www.worldbank.org/en/country/china/overview.

Wei, L. Y., Cheng, C. H., & Wu, H. H. (2014). A hybrid ANFIS based on n-period moving average model to forecast TAIEX stock. *Applied Soft Computing*, 19, 86-92.

Wong, J. (2010). China's economy 2008 and outlook for 2009: Crisis of a sharp slowdown. In *China and the Global Economic Crisis* (pp. 11-23).

Young, G. (2002). The implications of an ageing population for the UK economy.

Yu, J. (2002). Forecasting volatility in the New Zealand stock market. *Applied Financial Economics*, 12(3), 193-202.

Yuristia, R., Apriyanto, D., & Sukiyono, K. (2019). The Best Forecasting Model For Cassava Price. *AGRITROPICA: Journal of Agricultural Sciences*, 2(2).

Zar, J. H. (1968). Calculation and miscalculation of the allometric equation as a model in biological data. *BioScience*, 18(12), 1118-1120.

Zhang, B., & Li, X. (2008). The asymmetric behaviour of stock returns and volatilities: evidence from Chinese stock market. *Applied Economics Letters*, 15(12), 959-962.

Appendix 1 Descriptive Statistics of the return of Shanghai Index

The return of Shanghai Index	
Mean	1.67459708
Standard Error	0.92084243
Median	0.62576132
Mode	#N/A
Standard Deviation	16.2392332
Sample Variance	263.712696
Kurtosis	58.0860003
Skewness	6.01099228
Range	208.379126
Minimum	-31.152949
Maximum	177.226177
Sum	520.799692
Count	311
Largest (1)	177.226177
Smallest (1)	-31.152949

Appendix 2 Descriptive Statistics of the Buffett Indicator

The Buffett Indicator	
Mean	42.4994026
Standard Error	1.13201358
Median	41.0103539
Mode	#N/A
Standard Deviation	17.9701585
Sample Variance	322.926595
Kurtosis	-1.0457625
Skewness	0.19462768
Range	68.6923845
Minimum	9.75611554
Maximum	78.4485
Sum	10709.8495
Count	252
Largest (1)	78.4485
Smallest (1)	9.75611554

Appendix 3 Descriptive Statistics of the P/E ratio

The P/E ratio	
Mean	1955.70642
Standard Error	59.1023818
Median	1744.80804
Mode	#N/A
Standard Deviation	1003.00068
Sample Variance	1006010.36
Kurtosis	1.3378783
Skewness	1.02858115
Range	5620.84512
Minimum	333.920013
Maximum	5954.76514
Sum	563243.45
Count	288
Largest (1)	5954.76514
Smallest (1)	333.920013

Appendix 4 Descriptive Statistics of the Population

Population (10,000 persons)	
Mean	131440.045
Standard Error	286.68891
Median	131788.06
Mode	#N/A
Standard Deviation	4560.06627
Sample Variance	20794204.4
Kurtosis	-1.0295138
Skewness	-0.2003056
Range	16619
Minimum	122389
Maximum	139008
Sum	33254331.4
Count	253
Largest (1)	139008
Smallest (1)	122389

Appendix 5 Descriptive Statistics of the GDP

GDP	
Mean	4.7546E+12
Standard Error	2.3801E+11
Median	3.1259E+12
Mode	#N/A
Standard Deviation	3.7858E+12
Sample Variance	1.4332E+25
Kurtosis	-1.1754538
Skewness	0.61835848
Range	1.128E+13
Minimum	8.6375E+11
Maximum	1.2143E+13
Sum	1.2029E+15
Count	253
Largest (1)	1.2143E+13
Smallest (1)	8.6375E+11

Appendix 6 formulas of RMSE, MAPE, MSE, MAD, MPE

RMSE = $\sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}{n}}$

MAPE = $\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$

MSE = $\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$

MAD = $\frac{1}{n}\sum_{i=1}^{n}|x_i - m(X)|$

MPE = $\frac{100\%}{n}\sum_{t=1}^{n}\frac{a_t - f_t}{a_t}$