Portfolio Optimization and Diversification in China: Policy Implications for Vietnam and other Emerging Markets

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PORTFOLIO OPTIMIZATION & DIVERSIFICATION IN CHINA: POLICY IMPLICATIONS FOR VIETNAM & OTHER EMERGING MARKETS

Abstract

This paper is conducted to examine risk, return and portfolio optimization at the industry level in China over the period 2007-2016. On the ground of the classical Markowitz framework for portfolio optimalisation, the mean-semivariance optimization framework is established for China's stock market at the industry level. Findings from this study indicate that Healthcare sector plays a significant role among ten industries in China on a stand-alone basis. In addition, a significant change of rankings among the sectors in term of risk is found when the mean-semivariance optimization framework is used. We also find that utilising this new framework helps improve the optimal portfolios in relation to performance, measured by Sortino ratio, and diversification. A simulation technique, generally known as resampling method, is also utilised to check the robustness of the estimates. While the use of this resampling method appears not to improve the performance of optimal portfolios compared with the mean-semivariance framework for China, there is a remarkable advance in diversification of the optimal portfolios. Implications for investors and the governments in Vietnam and other emerging markets have emerged from the study.

Keywords: Mean-semivariance, Portfolio Optimization, Resample, China

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1. Introduction

The Chinese stock market is enormous and plays a significant role to its economic growth as well as other global markets. At the beginning of 2016, Shanghai market, one of the largest equity markets in the world, hits US$3.5 trillion in market capitalization (Shanghai stock exchange 2017 Factbook). A large number of listed stocks in Shanghai Stock Exchange (SSE) are from public sector, which is large and represents the whole economy of China. There are also a number of studies which demonstrate a link between the stock market development in China and economic growth (Liu & Sinclair, 2008; Wong & Zhou, 2011). In addition, the fluctuations in the Chinese stock market have increasingly affected developed stock markets, such as those in the US, the UK, Germany, and Japan (Yu, Fang, Sun, & Du, 2018). In a recent study, Fang and Bessler (2018) argued that Chinese market has a powerful impact on most stock markets in Asia since the nation's role has improved through its economy' strong growth as well as financial openness. This market interdependence is improved partly thanks to the financial market reform in China after joining the World Trade Organization in 2001 (He, Chen, Yao, & Ou, 2015).

The Chinese stock market becomes more attractive as an investment opportunity due to the integration of the national economy into the global markets. Currently, foreign investors can even approach both "A-shares" and "B-shares" on the market, where the first category was restricted to local investors only before the reforms in December 2002. Yao, Ma, and He (2014) found that not only the herding behavior at the beginning of the last decade mostly disappeared over time, but also the A-share markets seem to become more and more rational. Carpenter, Lu, and Whitelaw (2015) considered that the level of market efficiency in China converges to the US. This implies that the stock pricing and portfolio construction methodology is also very similar between two markets even though their levels of risk are different.

An application of finance and investment theories in China's financial markets, seeking for profitable opportunities, has emerged. Drew, Naughton, and Veeraraghavan (2003) built a multi-factor model for Chinese stock market but found that the market factors could not separately explain the return's fluctuation. Later, Xu and Zhang (2014) successfully applied the Fama-French three-factors model in the Chinese stock market and argued that the model could explain more than 93 per cent of the Chinese A-share return's movements.

However, investing in an emerging market like China faces a huge systematic downside risk along with attractive returns. A three-week crash of the Chinese stock market in 2015 blew away about 30 per cent of its market shares, which raised a concern about a more serious influence on the world economy than the Greek debt crisis in 2011 (Allen, 2015). A strong negative impact from the crash on several Asian markets was also noted by Fang and Bessler (2018). In addition, Yu et al. (2018) argued that the large magnitude of risk from the Chinese stock market, especially through downside periods, has reduced the benefit of diversification.

Among the most original portfolio construction theories, Markowitz mean-variance portfolio optimization (Markowitz, 1952) is commonly used to instruct investors how they can efficiently allocate their investments. Unfortunately, this famous theory is also known in literature as producing biases because inputs with massive estimation error are used. This weakness puts the theory into a serious trouble since such an error is amplified by the optimization procedure. Consequently, estimates for the outputs, portfolio's optimal weights as well as risk and return from this framework have arguably become less convincing. For example, when an asset's expected return is overestimated, it will be allocated much more risk by the classical mean-variance optimization method than it should be.

Resampling method introduced by Michaud (1989) is an approach that solves the problem. In a simple language, resampling is the process in which repeated samples are drawn from a data set and a given model is then fitted on each sample with the goal of learning more about the fitted model. It is generally considered that resampling is very costly because the method requires the same statistical methods on different subsets of the same data to be performed repeatedly.

Moreover, since investors do not shy away from the extremely positive returns, the variance used in the classical theory leads to another bias and must be replaced by a downside risk measure, such as semivariance.

In this paper, we will construct the portfolio optimization in China, using classical Markowitz mean-variance framework, mean-semivariance framework, and applying Michaud resampling method to the optimization procedure. This paper explores two research questions. First, are the rankings of risk and returns among sectors significantly changed using different risk-return measures? Second, do resampling method and mean-semivariance framework effectively improve the optimization procedure? Doing so will provide evidence to confirm whether or not

Michaud's resampling efficiency method, which is a statistical resampling procedure based on the well-known bootstrapping procedure, can be used to improve the Markowitz optimization technique and address estimation risk.

The rest of this paper is organized as follows. Section 2 provides the selected academic studies on the topic. Section 3 presents the research methodology, including measurements of risk, return, and rankings strategies along with optimization process. Section 4 presents a discussion about the results. Finally, section 5 concludes the paper.

2. Literature review

2.1. Markowitz's mean-variance optimization

Mean-variance optimization, which was initially introduced by Harry Markowitz in 1952, is known as a cornerstone in portfolio selection world. In 1990, Markowitz shared the Nobel Memorial Prize in Economic Sciences with William Sharpe and Merton Miller for their contribution in the financial economics theory. The mean-variance optimization framework uses expected return as a measure for reward and variance as a risk measure, based on historical return, volatility, and covariance matrix. The outputs of this procedure are optimal portfolios with highest return in each level of risk, along with their proposed weight vectors. This theory is successfully tested by a number of empirical studies such as Farrar (1962) and Perold (1984). It is also the background for the famous capital asset pricing model (Sharpe, 1964). Perold (1984) insisted that the Markowitz framework has been widely accepted as a practical method for portfolio construction process. However, the classical mean-variance framework has its own limitations. For example, the assumption of symmetrically and normally distributed returns.

Ongoing studies on downside risk measures have tried to replace variance by a more appropriate risk measures. Value-at-risk (VaR) is one of the candidate which is developed to mean-VaR framework to solve the optimization problem (Campbell, Huisman, & Koedijk, 2001). Conditional Value-at-risk (CVaR) is later proposed due to the fact that VaR does not own the subadditivity property, one of criteria of a coherent risk measure. Recently, Vo et. al. (2018) applied CVaR to seek for the optimal portfolios in the South East Asian region. In addition, Powell et. al. (2018) constructed new metrics named EVaR and ECVaR to measure downside volatility of commodity assets in various economic periods.

2.2. Mean-semivariance optimization framework

Semi-variance has increasingly utilized from studies on downside risk measures (Harlow, 1991; Sortino & Price, 1994; Sortino & Van Der Meer, 1991). In general, it is an asymmetric risk measure, which quantifies the deviations below the mean or a threshold level of return. Estrada (2006) provided an example of using semi-variance and semideviation as the alternatives. In addition, Estrada (2004) argued semivariance is superior to variance for the following three reasons. First, investors only dislike downside movement on the asset returns; they will not feel harmful with upside returns, which are also included in the measurement of the 'variance'. As such, the semi-variance fits investors' demand in analyzing risk. Second, the semi-variance is more statistically helpful than variance when return is asymmetrically distributed, which is often observed in practice. Finally, semi-variance is a measure that combines variance and skewness at the same time; hence, we can use single factor models to estimate the returns.

Mean-semivariance framework is supported by both strong background theory and empirical studies. Markowitz, the father of mean-variance optimization framework, argued that semi-variance appears to generate better optimal portfolios than those based on variance framework and considered that semi-variance is "more plausible than variance as a measure of risk" (Markowitz, 1959, 1991). The mean-semivariance framework attracts academic and empirical studies. Estrada (2002, 2004, 2006, 2007) constructed a series of papers discuss a number of theoretical frameworks on downside risk basis, including mean-semivariance optimization framework. The author also considered that the usual beta can be substituted by 'downside beta' and suggested using the D-CAPM as an alternative of the CAPM. The author also stated that mean-semivariance framework is particularly appropriate for emerging markets (Estrada, 2004). Boasson, Boasson, and Zhou (2011) used monthly data from seven exchange-traded index funds from 2002 to 2007 to construct mean-semivariance efficient frontier and recommended its application in insurance and banking sectors. In addition, Pla-Santamaria and Bravo (2013) utilized daily data of Dow Jones stocks over the period 2005-2009 to prove that the mean-semivariance is empirically more suitable to reflect the downside risks than a classical mean-variance optimization.

With respect to technique issues, although the mean-semivariance framework gains more and more trusts from academic community, it could not be easily developed due to mathematical problems. In 1993, Markowitz solved the mean-semivariance optimization by transforming into quadratic problem using simulated securities (Markowitz, Todd, Xu, & Yamane, 1993). Foo and Eng (2000) calculated these figures based on lower partial moments (LPM) constructed by Harlow and Rao (1989). Estrada (2008) suggested a heuristic approach that creates a symmetric and exogenous semi-covariance matrix to solve the optimization problem.

This paper adopts the method introduced in Ballestero (2005), which uses Sharpe's beta regression equation (Sharpe, 1964) connecting every asset return to the whole market. A semi-variance matrix and a quadric objective function are constructed, however, heuristics are not required. This technique is also used in some empirical studies on mean-semivariance framework (Boasson et al., 2011).

2.3. Resampling methodology

Resampling methodology, which is generally considered as an enhanced mean-variance optimization from Markowitz (1952), was developed by Michaud (1998) on the basis of a simulation framework. A key objective of this method is to limit the effect of input estimation errors on the optimal portfolio weights and, as such, to achieve more robust portfolios through a balanced and diversified asset allocation. The key distinction separating Michaud resampling method from the original Markowitz optimization is that the resampling utilizes the data from a stochastic process rather than from a predetermined data set. This requires various repeats of random sample selection based on Monte Carlo simulation methodology developed by Metropolis and Ulam (1949).

On a theoretical consideration, Michaud's resampling method shows its superior in improving performance of optimal portfolios compared to the classical mean-variance optimization. Markowitz and Usmen (2006) created a simulated battle where a Bayesian player, representing classical mean-variance optimization, was in competition with Resampling player, who follows the method developed by Michaud (1998). The authors found that the Resampling player won ten out of ten times. Harvey, Liechty, and Liechty (2008) added that the Resampling player will show the advantages when the return distribution is not the same as the historical distribution.

On a practical consideration, empirical studies also demonstrated that Michaud's resampling method will improve performance. Using US risk-free asset and 10 global stock index returns, Fletcher and Hillier (2001) suggested that resampling method provides a higher Sharpe performance of optimal portfolios than the traditional mean-variance framework. Cardoso (2015) found a similar result from a number of selected individual stocks in S&P500 where non-normally distributed resampling is captured.

The resampling method owns two valuable features for the long-term investors: diversification and stability (Fernandes & Ornelas, 2009; Kohli, 2005). Using various asset classes from US equity to Euro government bond, Delcourt and Petitjean (2011) found that the resampled optimization will result in a more stable and diversified optimal portfolios. Mansor, Baharum, and Kamil (2006) run the model for Malaysian stock market and found that the method eliminates estimation error when using daily and weekly data. In relation to stability, Asumeng-Denteh (2004) argued that resampling reduces portfolio rebalancing and, as a consequence, transaction costs incurred in trading while keeping the portfolio optimal. Galloppo (2010) proposed other benefits of resampling method beyond the optimization process. When testing these so-called post-modern models including Tracking Error Minimization Model, Mean Absolute Minimization Model, and Shortfall Probability Model, the author found an improvement in the performance thanks to resampling method.

3. Data and methodology

Indices for ten sectors in China are used in this study. These sectors include basic material, consumer goods, consumer services, financials, health-care, industry, oil and gas, technology, telecommunications, and utilities. The data is obtained from Datastream for the period from 2007 to 2016.

3.1. A brief overview of the performance of various stocks from Chinese industries

Various empirical studies have been conducted to examine the correlations among stocks or stock groups including the correlations between stock markets of different regions, different styles or different sectors in China. These studies have provided mixed findings.

For example, in their studies, Guo and Yang (2004) concluded that companies' performances were significantly different within different industries, while there was no noticeable difference about share revenue and risk. Zhang and Ren (2006) considered that the characteristics of industry segment in the Chinese stock markets have fluctuated among various sectors. Findings from this study indicate that the industrial fluctuations, which kept stability in each cycle, had relationship with industrial characteristics. An interesting study comes from Chen and Chen (2007) who examined the trends of the correlation among major industries in the Chinese stock market with some other international stock markets including the stock markets in Hong Kong, the United States and Japan. Based on the findings, the authors concluded that various industries in the Chinese stock markets have had low correlation with the international stock markets as mentioned above. However, the correlation trend among Chinese sectors was generally increasing.

3.2. Estimates of portfolio risk and return

Portfolio return

For each period, individual sector returns are computed from their index levels using log forms. The portfolio expected return is simply the weighted average of these individual sector returns. Write r_p as the expected return of a portfolio with N assets, r_i as the expected return of the asset i^{th} in that portfolio, and ω_i is the weight of the asset i^{th} in that portfolio; the calculation of portfolio expected return is given:

$$r_p = \sum_{i=1}^{N} \omega_i r_i$$

Variance and portfolio variance

Variance of an individual asset is the average of squared differences between observed returns and their mean. It estimates the distance of a set of returns away from the average value.

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(r_i - \bar{r})^2$$

where σ^2 is the variance of return, $\bar{r}$ is the mean return, r_i is the i^{th} return in n observations in the sample set.

A covariance of a pair of assets quantifies the relationship between them. When the return of the first asset tends to increase matching an increase in the second asset's return, the covariance is positive; otherwise, it is negative. When the returns of the two assets move independently, the covariance is approximately zero. Let us denote σ_{xy} as the covariance between asset x and asset y, both assets have n observations, $\overline{x}$ and $\overline{y}$ as mean return of each asset, x_i and y_i as the i^{th} returns of asset x and asset y, the covariance is given as following:

$$\sigma_{xy} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})$$

Furthermore, the portfolio variance measures the dispersion of portfolio returns and its mean value considering the joint effects between constituent assets. It is defined by the following formula:

$$\sigma_P^2 = \sum_{i=1}^{N}\sum_{j=1}^{N}\omega_i\omega_j\,\sigma_{ij}$$

where σ_P^2 is variance of the portfolio with N assets, σ_{ij} is the covariance between the the asset i^{th} and asset j^{th}, ω_i and ω_j are the weights of the asset i^{th} and asset j^{th} in the portfolio.

Semivariance and portfolio semivariance

Semi-variance is determined by weighted average of square deviations from a threshold level used only the observation which is below that level. Through a mean-semivariance efficient frontier construction, Ballestero (2005) proposed a semi-variance matrix computation based on Sharpe's beta (Sharpe, 1964) regression basis. From Ballestero (2005), we apply the following computation in our study.

$\sigma_{semi}^2(<)$ is the below-the-mean semi-variance;

$\sigma_{semi}^2(>)$ is the above-the-mean semi-variance;

ω_j is the weight of the j^{th} asset in the portfolio;

$\bar{r}_j$ is the mean value (or expected value) of the j^{th} asset;

$\tilde{r}_{jt}$ is the return of the j^{th} asset, t^{th} observation;

T is the number of observations in the sample;

N is the number of assets in the portfolio;

$p(t)$ is the probability of occurrence of the event t. When all the observations from 1 to T have equal probability, then $p(t) = \frac{1}{T}$;

The below-the-mean semi-variance is presented as:

$$\sigma^2_{semi}(<) = \sum_{t=1}^{T}\left(\sum_{j=1}^{N}\tilde{r}_{jt}\,\omega_j - \sum_{j=1}^{N}\bar{r}_j\,\omega_j\right)^2 p(t) \tag{1}$$

where the following inequality is satisfied:

$$\sum_{j=1}^{N}\tilde{r}_{jt}\,\omega_j \leq \sum_{j=1}^{N}\bar{r}_j\,\omega_j$$

Assuming the beta regression equation holds, the return for jth asset is given as:

$$\tilde{r}_j = \alpha_j + \beta_j\tilde{r}_m + \tilde{\varepsilon}_j$$

where β_j is the beta of asset j^{th} and the slope of the regression line:

$$\beta_j = \frac{\sigma_{ij}}{\sigma_m^2}$$

We denote; r_m as the market return; and σ_m^2 is the variance of market portfolio. Then:

$$(\tilde{r}_j - \overline{r_j}) = \tilde{\theta}_j + \beta_j(\tilde{r}_m - \bar{r}_m)$$

Adding up the individual assets in the portfolio:

$$\sum_{j=1}^{N}(\tilde{r}_j - \overline{r_j})\omega_j = \tilde{\theta} + (\tilde{r}_m - \bar{r}_m)\sum_{j=1}^{N}\beta_j\omega_j \tag{2}$$

where

$$\tilde{\theta} = \sum_{j=1}^{N}\tilde{\theta}_j\omega_j$$

Replace (1) by (2):

$$\sigma^2_{semi\,(>)} = \sum_{t=1}^{T} \left(\tilde{\theta} + (\tilde{r}_m - \bar{r}_m) \sum_{j}^{n} \beta_j \omega_j \right)^2 p(t)$$

When the number of assets becomes infinity:

$$\lim_{L\to\infty} \sigma^2_{semi\,(>)} = \sum_{i,j} \beta_i \beta_j \omega_i \omega_j \, \sigma^{2\,market}_{\;semi(>)}$$

As definition, $\sigma^2_{semi\,(>)} + \sigma^2_{semi\,(<)} = \sigma^2$, so we can do the limit for downside semi-variance:

$$\lim_{L\to\infty} \sigma^2_{semi\,(<)} = \sum_{i,j} (\sigma_{ij} - \beta_i \beta_j \, \sigma^{2\,market}_{\;semi(>)}) \omega_i \omega_j$$

***Sortino ratio*[1]**

Sortino ratio is a crucial indicator in estimating asset and portfolio performance, first introduced by Frank Sortino in 1980 (Sortino & Hopelain, 1980). Unlike Sharpe ratio, the Sortino ratio uses a downside risk measure as its denominator as follows:

$$Sortino\ ratio = \frac{r_i - r_f}{Downside\ risk}$$

where r_i is the return of an observed asset, r_f is the risk-free rate. In this paper, we calculate Sortino measures for our optimal portfolio using several different frameworks. We use semi-deviation as downside risk. For simplicity, we set the risk-free rate at 4 per cent, captured from a survey for 51 countries in 2013 (Fernandez, Aguirreamalloa, & Linares, 2013).

[1] We would like to particularly thank a reviewer who draws an attention to us that the Sortino ratio is not consistent with the stochastic dominance (SD) result. It is well known that there are some relations between SD and VaR and CVaR (Ma and Wong, 2010), some relations between SD and Omega ratio (Guo, Jiang, and Wong, 2017), Kappa Ratios (Niu, Wong, and Xu, 2017), Farinelli and Tibiletti ratio (Guo, Niu, and Wong, 2019). As a result, other empirical studies may need to consider all these above techniques to ensure that the findings are enhanced and robust. All these references are listed in the reference list of the paper.

3.3. Optimization

Markowitz mean-variance optimization

Since most nations in the world place bans on short selling in financial market, we set a constraint of non-negative weights within an optimal portfolio. In addition, many mutual funds also set their weights higher than a certain level for diversification purpose. For example, each weight must not be lower than five percent. In this paper, we only apply the non-negative-weight constraint since the frontier will be less efficient with additional constraints. Further details on Markowitz mean-variance optimization are discussed in details in Vo et. al (2018).

Mean-semivariance optimization

Optimization in the mean-semivariance framework applies the same principle of original Markowitz mean-variance optimization. That is, investors attempt to minimize the risk for each level of expected return. In this case, the semi-deviation accounts for risk instead of the classical standard deviation.

Although Markowitz denied applying mean-semivariance framework into optimization process due to computational infeasibility in the past, Markowitz admitted that this measure is potential to enhance the quality of an optimal portfolio. The most difficult part in calculation process is the pairwise covariances among the assets in "downside" perspective, which has been solved in the previous section of this paper. The mathematical function and constraints are given as follows:

The Objective:

$$\min \sum_{i=1}^{T} \sum_{j=1}^{T} (\sigma_{ij} - \beta_i \beta_j \sigma^2_{m,semi\,(>)}) \omega_i \omega_j$$

Constraints:

$$\sum_{i=1}^{T} \omega_i r_i = r_0$$

$$\sum_{i=1}^{T} \omega_i = 1$$

$$\omega_i \geq 0 \text{ with } i = 1,\ldots,n$$

where r_i is the return of the i^{th} asset; r_0 is a predetermined portfolio return; ω_i and ω_j are the weight of asset i^{th} and asset j^{th} in the portfolio; σ_{ij} is the covariance between the i^{th} asset and the j^{th} asset; β_i and β_j are the betas of the i^{th} and j^{th} assets; $\sigma^2_{m,semi\,(>)}$ is the above-the-mean semivariance of market portfolio.

Resampling methodology

Since the standard mean-variance optimization utilizes historical parameters to estimate the expected returns, variances, and covariances between assets in the future, it also creates estimation errors, which could be extremely significant. Michaud (1989) argued that this method accidentally does "errors maximization" instead of maximizing return and minimizing risk. The idea of resampling method fights against the error-maximization bias of the mean-variance procedure.

Following Michaud (1989), this paper uses the parametric resampling in order to build the out-of-sample model. We use the Monte Carlo simulation to set 500 resamples of daily returns in the given period. We also assume that the return follows a geometric Brownian motion, then the resamples will follow a multivariate normal distribution with given mean and standard deviation.

4. Results

4.1. Return, risk, and ranking

Table 1 shows the annualized return, standard deviation, and semideviation of each sector in the whole period 2007-2016 in China. Risks and returns for 10 sectors in China are then ranked based on these estimated figures. Two subperiods 2007-2009 and 2010-2016 are also considered and findings are available at the Appendix.

For the period 2007-2009, Healthcare sector is the best industry, which has the highest return and the lowest standard deviation and the lowest semi-deviation. The Telecom sector seems to be the worst sector according to risk while Financials has the worst performance. For the period from 2010 to 2016, Healthcare sector is still the best performance, but the sector lost its minimum risk to Oil&Gas and Consumer Goods sectors.[2] In total, for the extended period from 2007 to 2016,

[2] It is noted that China conducted its extensive economic reforms in the 1970s which led to a dramatic reduction in public expenditures and undermined the public health and health care systems of the country. However, in 2009, the government started recognizing and reversed course again and established several social health insurance schemes. It is reported that China has now expanded social health insurance to the vast majority of its 1.4 billion citizens, but public spending remains low in comparison with the total demand from its people for the services. As

Healthcare sector is the best sector Interestingly, the same results are found in Vietnam and Singapore (Vo et al., 2018). Oil&Gas sector is the worst in term of performance. Technology and Telecom are the most risky sectors in China. All of those analyses are based on a stand-alone basis.

In order to capture the difference in ranking using different risk measures, being standard deviation and semideviation in this paper, we construct a simple index, to be named the Difference Index, which is widely used in previous empirical studies to examine the differenes with regards to ranking of risks when different risk measures are utilised.

$$\text{Difference Index} = \Sigma(\text{Risk ranking standard deviation} - \text{Risk ranking semideviation})^2$$

Table 2 presents Difference Index among 10 sectors using daily, weekly, and monthly data in the period 2007-2016. When the daily data are used, the Basic Materials sector has the same level of risk regardless of standard deviation or semideviation is used. However, the estimates are so different for the Oil & Gas sector. We also observe that when monthly data is used, significant difference in terms of risk is observed when the two risk measures are used. The estimated Difference Index is 24 for the monthly data and 14 for daily data.

a result, the reliance on private financing generates inequalities in access to health care which is getting more popular in China in these days.

Table 1: Annualized average daily returns, standard deviations, semi-deviations and their rankings by sectors in the whole period from 2007 to 2016 in China, in percent.

Sector	Annual return (%)	Ranked by return	Annual standard deviation (%)	Ranked by standard deviation	Annual semi-deviation (%)	Ranked by semi-deviation
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Basic Materials	-1.0	9	35.7	8	26.4	8
Consumer Goods	8.5	2	30.4	3	22.8	4
Consumer Services	4.4	4	33.6	7	25.5	7
Financials	-0.6	8	30.3	2	21.8	1
Healthcare	13.9	1	29.4	1	21.9	2
Industrials	3.7	6	32.0	5	24.0	6
Oil&Gas	-4.1	10	32.1	6	22.7	3
Technology	6.6	3	35.9	9	26.8	9
Telecom	3.7	7	40.6	10	28.3	10
Utilities	4.3	5	31.0	4	23.2	5
Shanghai index*	1.3		28.2		21.3	
Max	13.9		40.6		28.3	
Mean	3.9		33.10		24.34	
Min	-4.1		29.4		21.8	

* Shanghai index is not included in the ranking group and it is presented as a reference benchmark

Table 2: Rankings among sectors using daily, weekly, and monthly data sets in the period of 2007-2016

Sector	Daily data			Weekly data			Monthly data			
	Rank by std dev	Rank by semi-std dev	Difference index	Rank by std dev	Rank by semi-std dev	Difference Index	Rank by std dev	Rank by semi-std dev	Difference Index	**Total**
(1)	(2)	(3)	(4) = $[(2)-(3)]^2$	(5)	(6)	(7) = $[(5)-(6)]^2$	(8)	(9)	(10) = $[(7)-(8)]^2$	**(11)**
Basic Materials	8	8	0	8	8	0	9	10	1	**1**
Consumer Goods	3	4	1	3	3	0	2	5	9	**10**
Consumer Services	7	7	0	7	7	0	7	7	0	**0**
Financials	2	1	1	4	1	9	3	3	0	**10**
Healthcare	1	2	1	1	2	1	1	1	0	**2**
Industrials	5	6	1	6	6	0	6	6	0	**1**
Oil&Gas	6	3	9	5	4	1	4	4	0	**10**
Technology	9	9	0	9	10	1	8	9	1	**2**
Telecom	10	10	0	10	9	1	10	8	4	**5**
Utilities	4	5	1	2	5	9	5	2	9	**19**
Total			**14**			**22**			**24**	**60**

4.2. Efficient frontiers

Mean-variance optimization framework versus mean-semivariance optimization framework

Both mean-variance and mean-semivariance optimization frameworks are plotted using exactly the same data set as presented in Figure 1 below. For each return level, the mean-semivariance framework improves efficient frontiers by reducing semideviations. Interestingly, the mean-semivariance efficient frontiers are longer toward the bottom-left. However, it is noted that it is shorter toward the top- right at the same time. This implies that under the mean-semivariance framework, investors are provided with a wider risk preference option than under the standard mean-variance framework.

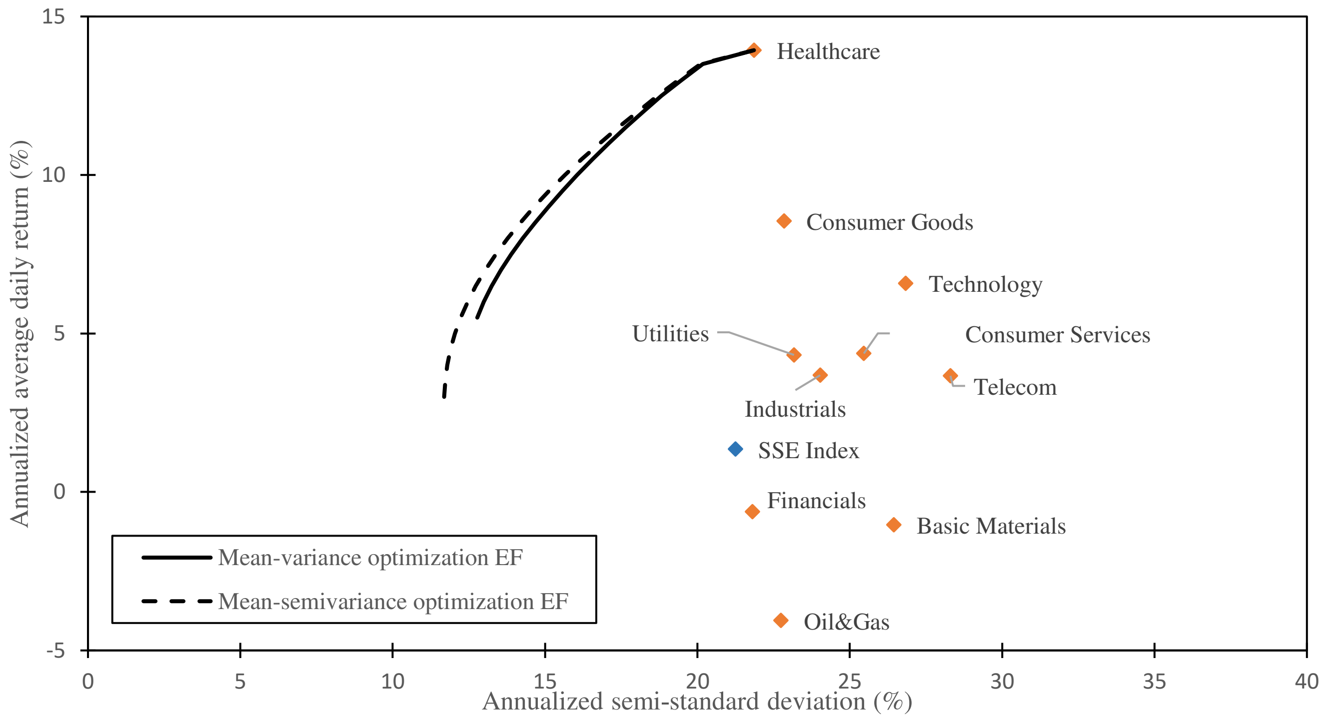


Figure 1: The figure shows the Markowitz efficient frontier as well as mean-semivariance efficient frontier in the period 2007-2016. The annualized average daily returns and annualized semideviations of ten selected sectors along with the SSE Index are presented.

Resampled efficient frontiers

The purpose of resampling method is to reduce error estimation in inputs by running multiple Monte Carlo simulations. For the period of 2007-2016, the annualized return range of optimal portfolios is from 4.6 per cent to approximately 14 per cent. Their semideviations are from 13.2 per cent to 20.7 per cent.

We also run the resampling process using mean-semivariance framework. The mean-semivariance framework significantly improves the optimal portfolio selection when it provides considerably higher return than the mean-variance framework at each level of risk.

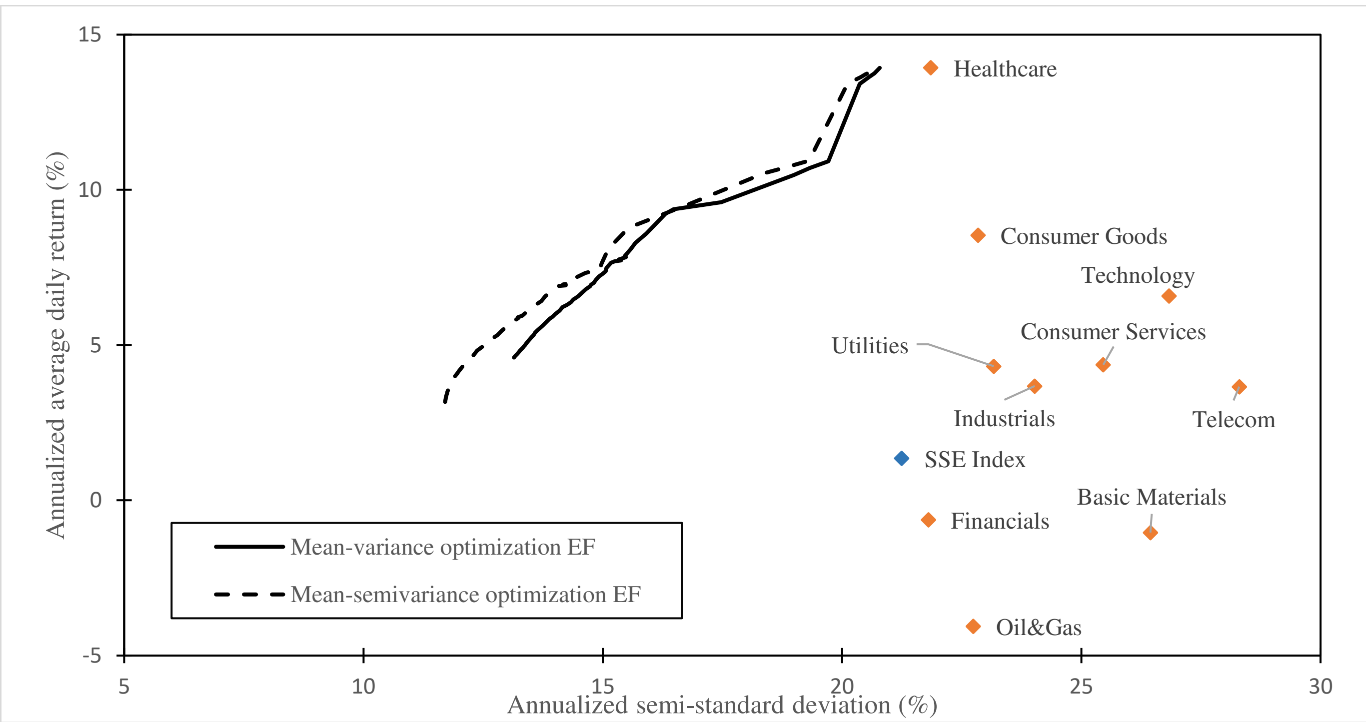


Figure 2: The figure shows the resampled efficient frontier as well as resampled mean-semivariance efficient frontier using 2007-2016 sample. The annualized average daily returns and annualized semideviations of ten selected sectors along with the SSE Index are presented.

Performance comparisons

We calculate Sortino ratios for each optimal portfolio to compare the results from various frameworks. We use the average number of optimal portfolios which offer 5.5 per cent to 13.5 per cent in returns to maintain the comparable comparison across frameworks.

Table 3: The average Sortino ratio under four optimization frameworks:

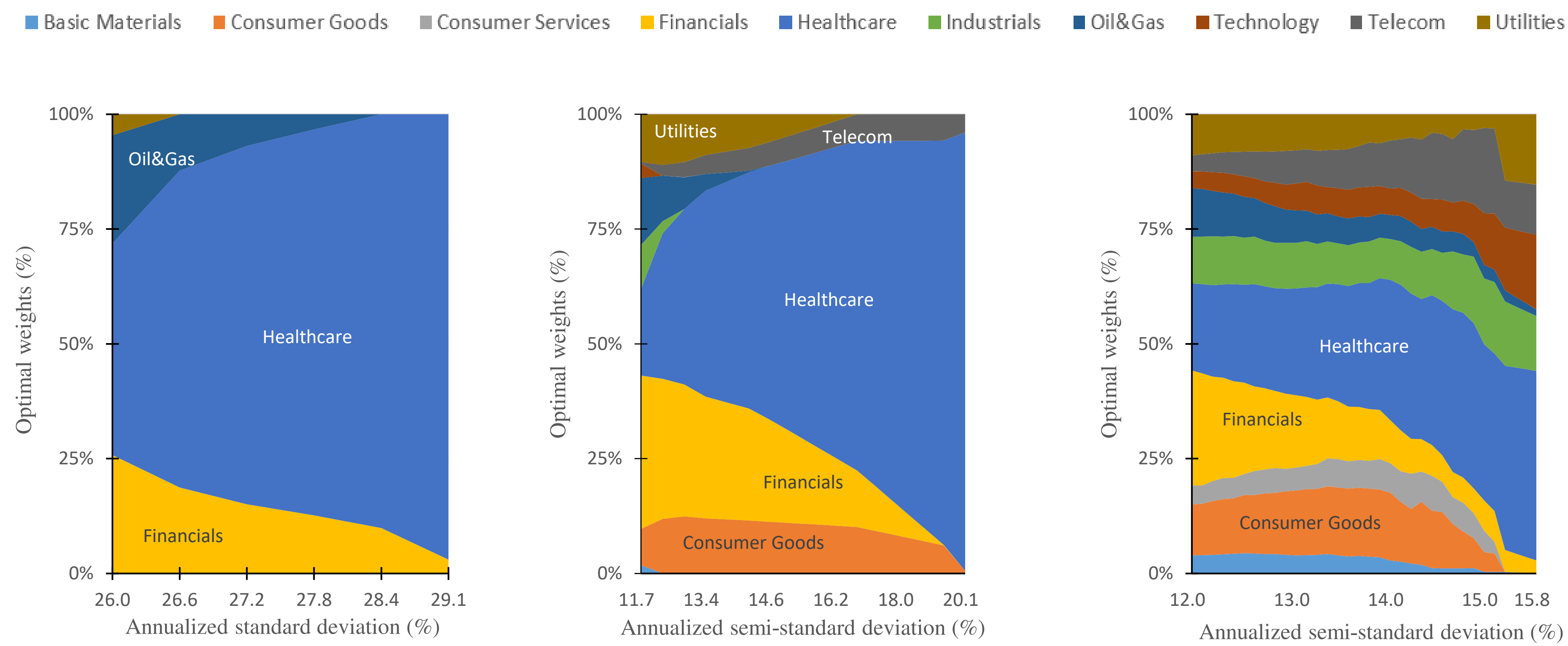
	MVO	Resampled MVO	MSO	Resampled MSO
Average Sortino ratio	33.1	24.9	33.8	25.1

Note: Mean-variance optimization (**MVO**); Resampled mean-variance optimization (**Resampled MVO**); Mean-semivariance optimization (**MSO**); Resampled mean-semivariance optimization (**Resampled MSO**).

Table 3 presents findings to confirm that the mean-semivariance optimization (MSO) brings the highest average Sortino ratio, which implies the improvement of this framework from the classical framework. We also note that resampling method decreases the performance of optimization procedures under both MVO and MSO. For example, the average Sortino ratio of mean-variance optimization decreases from 33.1 to 24.9 after replacing historical inputs by resampling method's inputs.

Diversifications

Figure 3 presents that mean-semivariance efficient frontiers provide better diversification than under the classical mean-variance optimization, especially at the lower return levels. For example, three to four sectors are added in the optimal portfolios using the MVO framework while the number is up to six sectors when the MSO framework is considered. In general, Healthcare sector still contributes the largest weight to the optimal portfolio at most of the risk levels observed. In addition, the resampling method provides notably more diversification than the original method in both MVO and MSO frameworks. Detailed percentage contribution of each sector to the optimal portfolios under various frameworks will be provided upon request.



(a) Optimal weights for each sector by annualized standard deviation, using *traditional mean-variance optimization (MVO)*

(b) Optimal weights for each sector by annualized semideviation, using *mean-semivariance optimization (MSO)*

(c) Optimal weights for each sector by annualized semideviation, using *resampled mean-semivariance optimization (MSO)*

Figure 3: Optimal weights under three framework: (a) traditional mean-variance, (b) mean-semivariance, and (c) resampled mean-semivariance; daily data of ten sectors in China, 2007 to 2016.

5. Conclusions

This paper examines the risk, return and portfolio optimization at the industry level in China over the period 2007-2016. Findings from this study indicate that Healthcare sector is the best sector in terms of risk and return among ten industries in China. This observation implies that the sector was attractive in the past and needs more attention from the Chinese government in the future. In contrast, Telecommunication and Technology appear to be the most risky industries among all other industries in China. In the current stance of the Chinese economy in the World's stage, it appears that the policy addressing fundamental issues of these important industries to attract investors becomes important for a stable development of the Chinese economy.

We find that there is a significant change in risk rankings among the sectors when semideviation is utilised. In this paper, a simple index, the Difference Index, is utilised to capture this movement in ranking. Our findings indicate that a sample using monthly data appears to be mostly affected by the change in the ranking of risks using different risk measures. As a result, various measures of risk should be considered by the investor community for any investment decisions in this financial market.

This paper also constructs mean-semivariance optimization framework for China stock market at the industry level based on the classical Markowitz mean-variance framework. Findings from this study indicate that the new framework, being mean-semivariance optimization framework, the improves the performance of the optimal portfolios, measured by Sortino ratio, and diversification. As a robustness check, a simulation technique using Michaud's resampling method is also utilised. While it appears that the resampling method doest not appear to improve the performance of optimal portfolio, there is a remarkable advance in diversification of the optimal portfolio. As such, it is the claim of this paper that Michaud's resampling method, associated with the mean-semivariance optimization framework, does provide an effective tool for diversification of the optimal portfolio in the context of the Chinese stock market.

On balance, it becomes the responsibility of the investors to consider various measures of risk in order to be well informed before any investment decision is made. For example, empirical findings from this study indicate that using semi-variance or variance may alter the view in relation to a risk level of a particular industry from the Chinese economy. In addition, another contribution of this paper is that the mean-semivariance optimisation framework, which is deviated from a conventional and widely used Markowitz by utilysing semivariance, does improve the diversification of the optimal portfolio from the Chinese stock market.

For the government, empirical findings from this paper present evidence in relation to the level of risk exhbited in each of the 10 industries in the Chinese economy. The Chinese government may consider appropriate measures and policies to ensure that excessively risky industries, in comparison with other industries, should be provided with a transparent framework so that investors can realise the benefits for any decisions they are going to make to invest in these risky industries. These findings are also relevant for governments of other emerging countries, in particular the Vietnamese Government due to the similarities of the economy, the process of economic development, culture and the society.

APPENDICES

Sector (1)	Annual return (%) (2)	Rank by return (3)	Annual standard deviation (%) (4)	Rank by standard deviation (5)	Annual semideviation (%) (6)	Rank by semideviation (7)
Basic Materials	21.5	3	46.2	9	34.5	9
Consumer Goods	23.9	2	40.0	2	30.3	3
Consumer Services	17.9	4	42.2	7	32.2	8
Financials	1.4	10	40.6	4	29.4	2
Healthcare	30.6	1	36.6	1	27.4	1
Industrials	12.9	8	40.4	3	30.6	4
Oil&Gas	6.8	9	45.1	8	31.7	7
Technology	17.3	6	41.7	6	31.3	5
Telecom	14.9	7	50.9	10	36.4	10
Utilities	17.9	5	41.5	5	31.4	6
Shanghai index*	6.3		37.4		28.0	

* Shanghai index is not included in the ranking group on purpose and be presented as a reference benchmark

Appendix 1: This table describes the annual returns, standard deviations, semideviations and their rankings by sectors and Shanghai index in the subperiod 2007-2009. There are 754 daily observations in each sector in the period.

Sector (1)	Annual return (%) (2)	Rank by return (3)	Annual standard deviation (%) (4)	Rank by standard deviation (5)	Annual semideviation (%) (6)	Rank by semi-deviation (7)
Basic Materials	-10.6	10	30.0	8	22.3	8
Consumer Goods	1.9	2	25.1	4	18.9	4
Consumer Services	-1.4	7	29.2	7	22.0	7
Financials	-1.2	6	24.6	2	17.6	1
Healthcare	6.8	1	25.7	5	19.0	5
Industrials	-0.2	4	27.6	6	20.7	6
Oil&Gas	-8.5	9	24.4	1	17.7	2
Technology	1.8	3	33.0	9	24.7	10
Telecom	-0.9	5	35.2	10	24.1	9
Utilities	-1.4	8	25.1	3	18.7	3
Shanghai index*	-0.6		23.2		17.6	

* Shanghai index is not included in the ranking group on purpose and be presented as a reference benchmark

Appendix 2: This table describes the annual returns, standard deviations, semideviations and their rankings by sectors and Shanghai index in the subperiod 2010-2016. There are 1,729 daily observations in each sector in the period.

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