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Maslow Portfolio Selection for Individuals with Low Financial Sustainability

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Abstract: In this paper, we extend Maslow's need hierarchy theory and the two-level optimization approach by developing the framework of the Maslow portfolio selection model (MPSM) by solving the two optimization problems to meet the need of individuals with low financial sustainability who prefer to satisfy their lower-level (safety) need first, and, thereafter, look for higher-level (self-actualization) need to maximize the optimal return. We illustrate our proposed model with real American stock data from the S&P index and conduct the out-of-sample analysis to compare the performance of our proposed Variance-CVaR (conditional value-at-risk) MPSM with both traditional mean-variance and mean-CVaR models. Our empirical analysis shows that our proposed Variance-CVaR MPSM is not only sustainable, but also obtains the best out-of-sample performance in the sense that the optimal portfolios obtained by using our proposed Variance-CVaR MPSM obtain the highest cumulative returns in the out-of-sample period among the models used in our paper. We note that our proposed model is not only suitable to individuals with low financial sustainability, but also suitable to institutions or investors with high financial sustainability.

Keywords: portfolio selection; need hierarchy theory; two-level optimization; variance; coherent risk measures

JEL Classification: G11; C61; C44

1. Introduction

There is an increasing number of organizations, especially governments, who take financial sustainability into account. Traditionally, financial sustainability can be defined as the ability of government to finance the provision of public services at present without compromising the ability to do so in the future [1–3]. In the latest decade, empirical research has been conducted on the financial sustainability of Microfinance institutions [4–6]. Nurmakhanova et al. [7] claim that sustainable Microfinance institutions are the ones that operate profitably and do not require subsidies to succeed. They show that focusing on financial sustainability does not necessarily hurt the depth and breadth of outreach (social mission).

However, financial sustainability is ignored by conventional portfolio selection models. The mean-risk model is the most widely used framework in the portfolio selection. In the pioneer work of the mean-variance (MV) model, Markowitz [8] uses the variance of a portfolio return as risk function. As a measure of dispersion about the expected mean, variance is desirable risk measure for investors to evaluate their risk, especially for individuals with low financial sustainability. However, variance has a serious shortcoming that it equally penalizes returns on both sides of the distribution, limiting its application to jointly elliptical distributions [9]. To circumvent the limitation, Artzner et al. [10] introduce the coherent risk measure via an axiomatic method and discuss that a good risk measure should satisfy monotonicity, translation invariance, positive homogeneity, and subadditivity.

Recently, the seemingly large daily price movements in high-tech stocks have further generated investigation into the market risk. Extreme price movements in the financial markets are rare, but extraordinarily important for investors and financial institutions with both high and low financial sustainability. Value-at-Risk (VaR) [11] is one well-known tool to take care of the left tails of distributions (extremely unfavorable outcomes). Nonetheless, VaR is not a coherent risk measure. To overcome this limitation, conditional VaR (CVaR) becomes popular because CVaR possesses some attractive theoretical properties including being coherent, consistent with second-order stochastic dominance [12], and easy to operate [13]. Dobrovolskiene and Tamosiuniene [14] develop a sustainability-oriented model of financial resource allocation in a project portfolio by integrating a composite sustainability index of a project into Markowitz's classical mean-variance model.

Investors could consider different kinds of risk in the portfolio selection according to different sustainability. This idea is consistent with the need hierarchy theory proposed in [15]. De Brouwer [16] offers an alternative formulation of the behavioural portfolio theory via the theory of needs, and Colson et al. [17] develop the approach for the two-level optimization estimation. In this paper, we extend their theories by developing the framework of the Maslow portfolio selection model (MPSM) and solving the two optimization problems to meet the need of individuals with low financial sustainability who prefer to satisfy their lower-level (safety) need first, and thereafter, look for higher-level (self-actualization) need to maximize the optimal return. In addition, we develop a special MPSM call Variance-CVaR MPSM.

In order to check whether our proposed model is superior to the traditional MV model in [8] and the mean-CVaR (M-CVaR) model in [13], we illustrate our proposed model with real American stock data from the S&P index and conduct the out-of-sample analysis to compare the performance of our proposed Variance-CVaR MPSM with both MV and M-CVaR models. Our empirical analysis shows that our proposed Variance-CVaR MPSM is not only sustainable, but also obtains the best out-of-sample performance in the sense that the optimal portfolios obtained by using our proposed Variance-CVaR MPSM obtain the highest cumulative returns in the out-of-sample period among the models used in our paper.

Our findings support our conjecture that individuals with low financial sustainability who prefer to satisfy their lower-level (safety) needs first, and, thereafter, look for higher-level (self-actualization) needs do prefer our proposed models to both MV and M-CVaR models. We also find that institutions or investors with high financial sustainability who prefer to look for higher-level (self-actualization) needs first, and, thereafter, satisfy their lower-level (safety) needs also prefer our proposed models to both MV and M-CVaR models in our illustration.

The rest of the paper is organized as follows. In Section 2, we do a quick review on the coherent risk measure. The Variance-Coherent Maslow portfolio selection model are proposed in Section 3. Empirical study on the American stock market is carried out in Section 4. Section 5 draws inferences and conclusions from the findings in this paper.

2. Coherent Risk Measures

Artzner et al. [10] define the coherent risk measure as follows:

Definition 1. *A risk measure $\rho : \mathcal{L}_\infty \to \mathbb{R}$ is called* ***coherent*** *if it satisfies the following four axioms:*

1. **Monotonicity:** *for all $X, Y \in \mathcal{L}_\infty$ with $X \le Y$, $\rho(Y) \le \rho(X)$;*
2. **Translation invariance:** *for all $X \in \mathcal{L}_\infty$ and $\alpha \in \mathbb{R}$, $\rho(X + \alpha) = \rho(X) - \alpha$;*
3. **Positive homogeneity:** *for all $X \in \mathcal{L}_\infty$ and $\lambda \ge 0$, $\rho(\lambda X) = \lambda\rho(X)$; and*

4. **Subadditivity:** *for all* $X, Y \in \mathcal{L}_\infty$, $\rho(X+Y) \leq \rho(X) + \rho(Y)$.

Applying the Separation Theorem for convex sets, we obtain the following general representation for all coherent risk measures in "generalized scenarios":

Proposition 1. *A risk measure* $\rho : \mathcal{L}_\infty \to \mathbb{R}$ *is called* ***coherent*** *if and only if there exists a family* $\mathcal{P}$ *of probability measures on the set of states of nature such that*

$$\rho(X) = \sup_{\mathbb{P} \in \mathcal{P}} \left\{ E_{\mathbb{P}}(-X) \right\} . \tag{1}$$

Using Definition 1 for the coherent risk measure, some specific risk measures have been proposed [18,19]. One of the popular measures is the conditional value-at-risk (CVaR) developed in [13,20]. To be specific, for any $\alpha \in (0, 1]$, we have

$$CVaR_\alpha(X) = \inf_{t \in \mathbb{R}} \{t + \frac{1}{1-\alpha} E[-X - t]_+\}. \tag{2}$$

This coherent risk measure not only has a clear interpretation, but also obtains some good properties. For example, the ranking of assets by using the mean return and CVaR is equivalent to that by using the second-order stochastic dominance [12]. Furthermore, CVaR is the best convex approximation to VaR [21]. In this paper, in order to describe investors' subjective risk preference better, we propose to use the **spectral risk measure**, which is defined as follows:

Definition 2. *A* **spectral risk measure** $\rho_\phi : \mathcal{L}_\infty \to \mathbb{R}$ *is defined as*

$$\rho_\phi(X) = -\int_0^1 \phi(p) F_X^{-1}(p) dp, \tag{3}$$

in which $\phi : [0, 1] \to [0, 1]$ *is called a* **spectral function** *satisfying*

1. $\phi(p) \geq 0$ *for all* $p \in (0, 1]$;
2. $\phi(p_1) \geq \phi(p_2)$ *for all* $p_1, p_2 \in (0, 1]$ *with* $p_1 < p_2$; *and*
3. $\int_0^1 \phi(p) dp = 1$.

3. Variance-Coherent Maslow Portfolio Selection Model

In this section, we first recall the framework of the Maslow portfolio selection model, and, thereafter, set the specific model with coherent risk measures. Assume that there are n risky assets $S = (s_1, ...; s_n)'$ whose random returns are denoted by $R = (R_1, ...; R_n)'$ with mean $\mu = (\mu_1, ...; \mu_n)'$ and covariance matrix $\Sigma = (\sigma_{ij})_{n \times n}$. Denote the portfolio held by an investor as $x = (x_1, ...; x_n)'$ with $\sum_{i=1}^n x_i = 1$, and the random return rate of her/his portfolio is $\sum_{i=1}^n R_i x_i$ with mean $\sum_{i=1}^n \mu_i x_i$ and variance $x'\Sigma x$.

3.1. Framework of MPSM

According to the hierarchy theory proposed in [15], the safety and self-actualization needed are closely related to investment activity such that investors would like to ensure the safety of their initial wealth first, and, thereafter, gain as much profit as possible. Maslow suggests that the safety needs (lower-level needs) must be fulfilled before the individuals desire for self-actualization needs (higher-level needs). This hierarchy can be modelled by using the two-level optimization in [17], in which one optimization problem is embedded within another optimization problem.

In this paper, we extend the theory developed in [15] and the two-level optimization approach developed in [17] to obtain the framework of MPSM by solving the following two optimization problems to meet the need of individuals with low financial sustainability who prefer to satisfy their lower-level (safety) need first, and, thereafter, look for higher-level (self-actualization) need:

$$\begin{aligned} \textbf{upper-level:} \quad & \max \quad \sum_{i=1}^{n} \mu_i x_i, && (4)\\ & \text{s.t.} \quad r_u(x) \le L, && (5)\\ & \qquad r_l(x) \le f^* + \delta, && (6)\\ & \qquad \sum_{i=1}^{n} x_i = 1, && (7)\\ & \qquad x_i \ge 0,\ i = 1, \cdots, n, && (8) \end{aligned}$$

where f^* is the optimal value obtained from solving the following optimization problem:

$$\begin{aligned} \textbf{lower-level:} \quad & \min \quad r_l(y), && (9)\\ & \text{s.t.} \quad \sum_{i=1}^{n} \mu_i y_i \ge G, && (10)\\ & \qquad \sum_{i=1}^{n} y_i = 1, && (11)\\ & \qquad y_i \ge 0,\ i = 1, \cdots, n. && (12) \end{aligned}$$

Here, two risk measures, $r_l(x)$ and $r_u(x)$, depend on portfolio composition x and describe the risks corresponding to the lower-level (safety) needs and higher-level (self-actualization) needs, and the two preset parameters, G and L, are the minimum return and maximum loss investors could accept, respectively. Short-selling is restricted in the MPSM to stabilize the portfolio problem [22].

Constraint (6) links the lower-level (safety) needs to the higher-level (self-actualization) needs by f^*. δ is viewed as a tolerance parameter for the safety requirement. The greater the δ, the lower the requirement for safety. Constraint (6) is designed to fit the needs of individuals with low financial sustainability who prefer to satisfy their lower-level (safety) needs first, and thereafter, look for higher-level (self-actualization) needs.

Remark 1. *The two-level optimization problem stated in (4)–(12) can be viewed as the $\delta-$constraint method for solving bi-objective programming [23].*

Remark 2. *Since Equations in (4)–(12) do not give any restriction on the forms of both $r_l(x)$ and $r_u(x)$, investors have all the freedom and flexibility to construct different MPSMs.*

3.2. Variance-Coherent MPSM

Since our proposed model allows investors to have all the freedom and flexibility to construct different MPSMs, in this section, we propose the following particular MPSM: when setting $r_l(x)$ and $r_u(x)$ as variance and coherent risk measures, respectively, we obtain the concrete portfolio selection model, which is called Variance-Coherent MPSM under the framework of MPSM as stated in the following:

$$\begin{aligned}
\textbf{higher-level:} \quad \max \quad & \sum_{i=1}^{n} \mu_i x_i, && (13)\\
\text{s.t.} \quad & \rho(x) \le L, && (14)\\
& x'\Sigma x \le f^* + \delta, && (15)\\
& \sum_{i=1}^{n} x_i = 1, && (16)\\
& x_i \ge 0,\ i = 1, \cdots, n, && (17)
\end{aligned}$$

where f^* is the optimal value obtained from solving the following optimization problem:

$$\begin{aligned}
\textbf{lower-level:} \quad \min \quad & y'\Sigma y, && (18)\\
\text{s.t.} \quad & \sum_{i=1}^{n} \mu_i y_i \ge G, && (19)\\
& \sum_{i=1}^{n} y_i = 1, && (20)\\
& y_i \ge 0,\ i = 1, \cdots, n. && (21)
\end{aligned}$$

There are several reasons we set the two risk functions in the above. Firstly, when pursuing higher-level needs, investors would like to use more advanced risk control methods or financial instruments as shown from Equations (13) to (17). Secondly, variance and coherent risk measures are good alternatives for investors to meet different levels of needs. On one hand, variance measures the overall volatility, and, thus, it helps to ensure the safety of the initial wealth. On the other hand, coherent risk measures depict the tail risks so as to provide investors more chance to obtain high payoffs. Thirdly, from the viewpoint of empirical comparability, setting $r_l(x)$ and $r_u(x)$ as variance and coherent risk measures makes it easier for academics and practitioners to compare our proposed model with the classical models in [8,13] through empirical analyses since they are closely related. To some extent, this chronological order provides us a criterion for choosing risk functions corresponding to different levels of needs.

4. Empirical Analyses

To illustrate the effectiveness of our proposed model stated in Equations (13)–(21) of Section 3.2, we investigate the superiority of using our proposed Variance-Coherent MPSM empirically. Here, we take the coherent risk measure as CVaR; that is to say, the spectral function is taken as $\phi(p) = \frac{1}{1-\alpha} 1_{\{0 \le p \le 1-\alpha\}}$. This investigation is based on the historical data of stocks from all components of the S&P 500 Index in the American stock market.

For comparison purposes, we also analyse the performance of a few other closely related models, including the classical MV and M-CVaR models in [8,13]. In essence, they depict both investors' safety needs and self-actualization needs. For convenience, we use "MV", "M-CVaR", "Maslow (0.008)", and "Maslow (0.010)" to stand for the optimal portfolios obtained under the classical MV model, M-CVaR model and our proposed model (13)–(21) with $\delta = 0.008$ and $\delta = 0.010$, respectively.

4.1. Data

To ensure decentralization, we choose 30 stocks classified into different industries from the components of the S&P 500 Index. The stocks shown in Table 1 are chosen because they have either the 30 highest market capitalizations or the 30 largest trading volumes, and, thus, they are the leading stocks in the corresponding industries.

Historical weekly returns of the aforementioned 30 stocks in six years, from 6 October 2011 to 5 October 2017, are downloaded from the Yahoo Finance (http://finance.yahoo.com/) to form the data set. Moreover, the data from 6 October 2011 to October 5 2016 are used to obtain the optimal portfolios, and the remaining data are used for evaluating the out-of-sample performance.

Table 1. Stock pool (in alphabetical order).

No.	Name	No.	Name	No.	Name
1	AAPL	11	DUK	21	MCD
2	AEP	12	F	22	MDT
3	AIG	13	FDX	23	MSFT
4	AMGN	14	GE	24	NKE
5	AXP	15	HD	25	PG
6	BA	16	HON	26	SLB
7	BAC	17	INTC	27	T
8	CAT	18	JNJ	28	UNH
9	CMCSA	19	JPM	29	WMT
10	CVX	20	KO	30	XOM

Note: These 30 stocks are numbered in alphabetical order. They are the leading ones in their corresponding industries. The time period is from 6 October 2011 to 5 October 2017.

4.2. The Characteristics of the Optimal Portfolios

In this section, we look into the characteristics of the optimal portfolios obtained by using different portfolio selection models. In this experiment, we set $\alpha = 0.95$. According to the features of historical data, we set $G = 0.001$ and $L = 0.05$. The optimal portfolios under the Variance-CVaR MPSM are obtained by following the steps described in Section 3. We summarize the characteristics of individual stocks in Table 2, including the sample mean and risk (variance and $\mathrm{CVaR}_{0.95}$).

One can easily observe from the fifth column of Table 2 that the optimal portfolios obtained under the MV (safety needs) model are of the most diversification while the optimal portfolios displayed in the last column that are obtained under the M-CVaR (self-actualization needs) model are of the most concentration because there is only one asset in each portfolio under this category. Nonetheless, the optimal portfolios corresponding to our proposed Variance-CVaR MPSM (13)–(21) strike a balance between the most diversification and the most concentration that the optimal portfolios are diversified but not the most diversified and not the most concentrated. In addition, with the increase of the tolerance parameter δ for the safety requirement, the optimal portfolio derived from our proposed model becomes more concentrated.

All the above empirical results are in agreement with the motivations of the portfolio selection models. The well-diversified portfolios are robust with respect to the collapse of any stock, and, thus, being safe to some extent. The concentrated portfolios (Column 8) including only stocks with the largest means gain the higher returns during the formation period. The compromising portfolios derived from our new Variance-CVaR MPSM not only contain the assets with larger means to get higher returns at one hand, but also allocate the wealth to several other stocks to enhance the diversification and robustness of the portfolios on the other hand.

Table 2. The characteristics of the stocks and the optimal portfolios under different models.

No.	Mean	Variance	$CVaR_{0.95}$	MV	Maslow (0.008)	Maslow (0.010)	M-CVaR
1	0.00404	0.00151	0.07937	0.04441	0	0	0
2	0.00292	0.00050	0.04568	0	0	0	0
3	0.00478	0.00120	0.07103	0	0	0	0
4	0.00506	0.00098	0.05577	0	0.03968	0	0
5	0.00203	0.00081	0.06450	0.01195	0	0	0
6	0.00390	0.00092	0.06374	0	0	0	0
7	0.00493	0.00186	0.08423	0	0	0	0
8	0.00178	0.00123	0.07027	0	0	0	0
9	0.00497	0.00072	0.04690	0	0.18695	0.09400	0
10	0.00146	0.00089	0.06205	0	0	0	0
11	0.00204	0.00045	0.04590	0.20159	0	0	0
12	0.00184	0.00131	0.07279	0	0	0	0
13	0.00399	0.00093	0.06051	0	0	0	0
14	0.00327	0.00076	0.05318	0	0	0	0
15	0.00585	0.00067	0.04747	0	0.59555	0.81397	1.00000
16	0.00406	0.00067	0.05145	0	0	0	0
17	0.00317	0.00095	0.06752	0	0	0	0
18	0.00319	0.00033	0.03577	0.16204	0	0	0
19	0.00414	0.00109	0.07121	0	0	0	0
20	0.00170	0.00044	0.04402	0	0	0	0
21	0.00183	0.00041	0.04445	0.17576	0	0	0
22	0.00440	0.00054	0.04456	0.03585	0	0	0
23	0.00409	0.00104	0.07210	0	0	0	0
24	0.00398	0.00087	0.05899	0	0	0	0
25	0.00211	0.00037	0.04206	0.14469	0	0	0
26	0.00205	0.00130	0.07410	0	0	0	0
27	0.00244	0.00046	0.04281	0.07682	0	0	0
28	0.00496	0.00076	0.05413	0.03914	0.17783	0.09203	0
29	0.00171	0.00055	0.05434	0.09760	0	0	0
30	0.00147	0.00057	0.05289	0.01016	0	0	0

Note: MV, M-CVaR, Maslow (0.008), and Maslow (0.010) stand for the optimal portfolios obtained under the MV model, M-CVaR model, and as our proposed model (13)–(21) with $\delta = 0.008$ and $\delta = 0.010$, respectively.

4.3. Out-of-Sample Performance

During the formation period, one could conclude that the optimal portfolios obtained under the MV (safety needs) model are of the most diversification while the optimal portfolios obtained under the M-CVaR (self-actualization needs) model are of the most concentration. However, the optimal portfolios obtained from our proposed Variance-CVaR MPSMs are neither of the most diversification nor of the most concentration. Could this be used to infer that the performance of our proposed Variance-CVaR MPSMs is not good? We say that this is not true. Whether the performance of the optimal portfolios is good or not does not depend on their performance of the portfolios in the formation period (since one cannot make any cent from the formation period) but depends on their performance on the testing period (that one can make profit in the testing period). This argument is consistent with DeMiguel et al. [24], who suggest that the out-of-sample performance is one of the most optimal ways to compare different investment strategies.

Thus, in this section, we carry out the out-of-sample analysis to evaluate the practical usefulness of different portfolio selection models. To do so, we investigate the payoffs of different optimal portfolios by using their cumulative returns and exhibit the results in Figure 1, which enable us to examine the evolution of the actual out-of-sample returns over time. Obviously, for a given time, the higher the cumulative return, the better the optimal portfolio or the corresponding portfolio selection model.

From Figure 1, one can tell that the cumulative returns of the safety strategy are always the lowest. On the other hand, the out-of-sample performance of the "most promising" strategy (M-CVaR) is barely satisfactory because this strategy suffers from the maximum losses at the very beginning, and thus, obtains the minimum gains during the final period. Nonetheless, the two optimal portfolios determined by our proposed Variance-CVaR MPSM outperform the two strategies above significantly, which can be easily observed from the curves in Figure 1 corresponding to Maslow (0.008) and Maslow (0.010). This shows that our proposed Variance-CVaR MPSM is not only sustainable, but also obtains the best performance among the four models in our analysis.

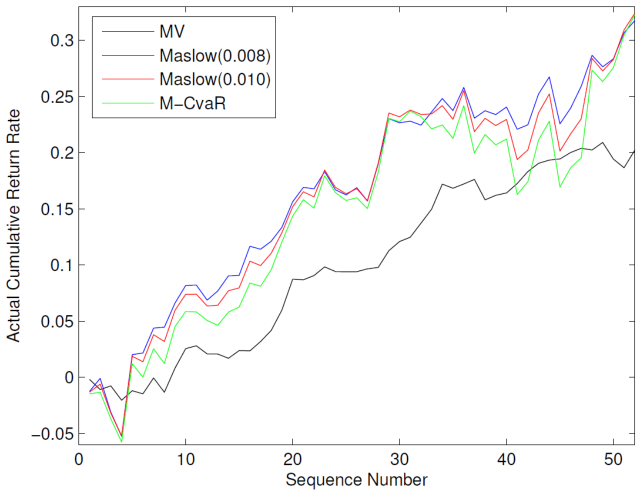

Figure 1. The cumulative return rates of the optimal portfolios got under different portfolio selection models. Note: MV, M-CVaR, Maslow (0.008) and Maslow (0.010) stand for the optimal portfolios obtained under the MV model, M-CVaR model, as well as our proposed model (13)–(21) with $\delta = 0.008$ and $\delta = 0.010$, respectively.

4.4. Further Discussion on the Results and Methods

To examine whether our proposed model outperforms the most commonly-used classical MV (safety needs) model developed in [8] and the M-CVaR (self-actualization needs) model developed in [13], we illustrate our proposed model with real American stock data from the S&P index and conduct the out-of-sample analysis to compare the performance of our proposed Variance-CVaR MPSM with both MV and M-CVaR models. Our empirical analysis shows that our proposed Variance-CVaR MPSM is not only sustainable, but also obtains the best out-of-sample performance in the sense that the optimal portfolios obtained by using our proposed Variance-CVaR MPSM obtain the highest cumulative returns in the out-of-sample period among the models used in our paper.

We note that our proposed model is mainly designed for individuals with low financial sustainability who prefer to satisfy their lower-level (safety) needs first, and, thereafter, look for higher-level (self-actualization) needs. One may believe that our proposed model is not suitable for investors with high financial sustainability. We argue that this is not true. Firstly, there are still some institutions or investors with high financial sustainability who still prefer to satisfy their lower-level (safety) needs first, and, thereafter, look for higher-level (self-actualization) needs. Our models are still suitable for these types of institutions or investors with high financial sustainability. Secondly, even for institutions or investors with high financial sustainability who prefer to look for higher-level (self-actualization) needs first, and, thereafter, satisfy their lower-level (safety) needs, our proposed models could still be suitable for them because our empirical study does find that our proposed Variance-CVaR MPSM obtains the highest cumulative returns in the out-of-sample period among the models used in our paper. Thus, we can claim that our proposed model is not only suitable for institutions or investors with high financial sustainability who still prefer to satisfy their lower-level (safety) needs first, and, thereafter, look for higher-level (self-actualization) needs, but is also suitable for institutions or investors with high financial sustainability who prefer to look for higher-level (self-actualization) needs first, and thereafter, satisfy their lower-level (safety) needs.

Nonetheless, our proposed model is designed for individuals with low financial sustainability who prefer to satisfy their lower-level (safety) needs first, and, thereafter, look for higher-level (self-actualization) needs, not for institutions or investors with high financial sustainability who prefer to look for higher-level (self-actualization) needs first, and, thereafter, satisfy their lower-level (safety) needs. One could easily modify our proposed model to obtain the model suitable for institutions or investors with high financial sustainability who prefer to look for higher-level (self-actualization) needs first, and, thereafter, satisfy their lower-level (safety) needs.

Many studies, for example, Michaud [25], have found the traditional estimation of the MV-optimized model in [8] does more harm than good for high dimensional big data. To circumvent the limitation, Bai et al. [26] develop the bootstrap-corrected estimation that could analytically circumvent the limitation and is proportionally consistent with the theoretical return parameter. Leung et al. [27] derive explicit formulas for the estimator of the optimal portfolio return. Bai et al. [28] prove that the traditional estimate for the optimal return of self-financing portfolios always over-estimates from its theoretic value. To circumvent the problem, they develop a bootstrap estimate for the optimal return of self-financing portfolios and prove that this estimate is consistent with its counterpart parameter. Bai et al. [28] further develop the spectrally-corrected estimation to improve the estimation further. Extension of our paper could incorporate both the MPSM approach developed in our paper and the bootstrap-corrected estimation or the spectrally-corrected estimation to meet the needs of individuals with low financial sustainability who prefer to satisfy their lower-level (safety) needs first, and, thereafter, look for higher-level (self-actualization) need for high-dimensional big data.

Investigating whether international diversification and home bias inertia are substitutes or complements for Americans, Abid et al. [29,30] conclude that the US investors have a ‘home bias’ if they prefer less risk and to be ’internationally diversified’ if they prefer higher risk. Hoang et al. [31] conclude that gold is good for the diversification of stock portfolios but not for bond portfolios in the Paris gold market. On the other hand, studying the role of gold quoted on the Shanghai Gold Exchange in the diversification of Chinese portfolios, Hoang et al. [32] show that, in general, risk-averse investors prefer not to include gold while risk-seeking investors prefer to include it in their stock-bond portfolios, especially in crisis periods. They also find that risk-seekers prefer including gold in an equal-weighted portfolio while risk-averters prefer including gold in efficient portfolios. Studying the performance in the Hong Kong residential property market, Qiao and Wong [33] conclude that risk averters prefer to invest in smaller property while Tsang et al. [34] conclude that, regardless of whether the buyers eschew risk, embrace risk or are indifferent to it, they prefer to invest in smaller property. On the other hand, to study the performance of a portfolio of US/UK equities, bonds, gold, and housing, Bouri et al. [35] conclude that wine is the best investment among all individual assets under their study, and, in general, investors prefer to invest in with-wine portfolios than without-wine portfolios to gain higher expected utility. It will be interesting to readdress all the above issues and other important issues in finance and economics by using the theory developed in our paper, in order to check whether investors’ preferences change when they adopt our proposed model.

5. Conclusions

In this paper, we extend the need hierarchy theory developed in [15] and the two-level optimization approach developed by Colson et al. in [17] to obtain the framework of the Maslow portfolio selection (Variance-CVaR MPSM) model by solving the two optimization problems to meet the need of individuals with low financial sustainability who prefer to satisfy their lower-level (safety) needs first, and, thereafter, look for higher-level (self-actualization) needs. Investors with low financial sustainability pay more attention to the safety of their financial investment. Investors are more concerned about the basic or lower level needing to be satisfied first, and, thereafter, care about their upper level needs to gain a higher return. In particular, investors like to use diversified strategy to obtain an efficient instrument to manage risk so that they could make the risk level affordable.

To do so, we first solve the optimization problem to minimize the risk first, and, thereafter, solve the optimization problem to maximize the optimal return.

Further study includes the extension of our new portfolio selection model to the multi-period case because investors tend to adjust their investment strategies with the emergence of new information, especially for the investors with strong financial sustainability to adopt long-term investment. In this paper, we use variance or CVaR as risk. Extensions could use other risk measures to represent risk, including the Sharpe Ratio in [36], mixed Sharpe ratio in [37], mean-variance-ratio in [38], Omega ratio in [39], Kappa Ratios in [40], and Farinelli and Tibiletti ratio in [41] to represent risk.

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