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A Multiple-Goal Investment Strategy for Sovereign Wealth Funds: An Application to China*

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Abstract
This paper develops a multiple-goal investment strategy for sovereign wealth funds. In our investment strategy, we embed the Black-Litterman (B-L) model into the mean variance mental accounting (MVMA) approach. The B-L method provides a means of modeling return expectations, and the MVMA framework allows the derivation of the optimal asset allocation from a global investment perspective, in a response to a specific macroeconomic environment.

1. Introduction

Sovereign wealth funds (SWFs), or the state wealth management agencies that manage foreign assets of the state with a relatively longer investment horizon, have emerged as prominent institutional investors in global capital markets in recent years. The number and size of SWFs have experienced rapid growth since the turn of the century, particularly China's SWFs. The first Chinese SWF, China Investment Corporation (CIC) was

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established in September 2007, with capital of US$ 200 billion. China had concluded that its stock of foreign exchange reserves had greatly exceeded the prudent level, and CIC was founded to invest the excess reserves to earn higher returns. The external assets under CIC management stood at US$ 482 billion at the end of 2012.

The government has multiple objectives, such as short-term macro-stabilization and long-term wealth maximization. For example, during the 2008–09 global financial crisis, many countries had their SWFs play the shock-absorbing role of recapitalizing systemically important banks that were in financial distress. Given a government's multiple goals, it could either establish a specialized SWF for each goal or mandate its SWF with multiple goals. Chile has founded two SWFs: a Social and Economic Stabilization Fund and a Pension Reserve Fund. The Government Pension Fund Global of Norway performs three functions: a stabilization fund, a savings fund, and a pension reserve fund.

The contributions of this paper are (a) to formulate a multiple-goal investment framework for SWFs by embedding the Black-Litterman (B-L) model (Black and Litterman 1992) for forecasting expected rates of return into the mean variance mental accounting (MVMA) framework introduced by Das et al. (2010); and (b) to apply this new proposed investment strategy to the case of China.

2. Stylized facts about SWFs and China's economy

2.1 Overview of sovereign wealth funds

SWFs can be classified in terms of two criteria. According to their source of funding, SWFs can be grouped as commodity-based and non-commodity SWFs. Commodity-based SWFs are funded mainly from oil exports, gas, and other important minerals (e.g., the Gulf Cooperation Council,[1] Norway, Russia, and Chile), and non-commodity SWFs are funded by the transfer of assets from both official foreign reserves and government budget surpluses (e.g., China and other Asian countries). Table 1 shows the profile of commodity-based SWFs, including fund name, the year founded, current SWF asset size, and information of rating transparency, while Table 2 displays non-commodity-based SWFs, according to SWF rankings in the website of the SWF Institute.

As can be seen from Table 1, 50 percent of commodity-based SWFs have been established since 2000. Currently, Kuwait, Norway, Saudi Arabia, and United Arab Emirates–Abu Dhabi have SWF asset holdings exceeding US$ 100 billion, among which the Norwegian Government Pension Fund Global is the largest fund, holding US$ 715.90 billion. The Linaburg-Maduell Transparency Index, created by Carl Linaburg and Michael Maduell

1 The Gulf Cooperation Council includes six Middle Eastern countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates.

Table 1. Commodity-based sovereign wealth funnds (SWFs)

Country	Fund name	Year founded	Current asset size by billion USD	Linaburg-Maduell Transparency Index
Algeria	Revenue Regulation Fund	2000	56.70	1
Azerbaijan	State Oil Fund	1999	32.70	10
Botswana	Pula Fund	1994	6.90	6
Brunei	Brunei Investment Agency	1983	30.00	1
Canada	Alberta's Heritage Fund	1976	16.40	9
Chile	Social and Economic Stabilization Fund	2007	15.00	10
	Pension Reserve Fund	2006	5.90	10
East Timor	Timor-Leste Petroleum Fund	2005	11.80	8
Iran	National Development Fund of Iran	2011	42.00	5
Kazakhstan	Kazakhstan National Fund	2000	61.80	8
Kuwait	Kuwait Investment Authority	1953	342.00	6
Libya	Libyan Investment Authority	2006	65.00	1
Mexico	Oil Revenues Stabilization Fund of Mexico	2000	6.00	n/a
Norway	Government Pension Fund—Global	1990	715.90	10
Oman	State General Reserve Fund	1980	8.20	1
Qatar	Qatar Investment Authority	2005	115.00	5
Russia	National Welfare Fund	2008	175.50	5
Saudi Arabia	SAMA Foreign Holdings	n/a	532.80	4
	Public Investment Fund	2008	5.30	4
UAE-Abu Dhabi	Abu Dhabi Investment Authority	1976	627.00	5
	International Petroleum Investment Company	1984	65.30	9
	Mubadala Development Company	2002	53.10	10
UAE-Dubai	Investment Corporation of Dubai	2006	70.00	4
US-Alaska	Alaska Permanent Fund	1976	45.00	10
US-Texas	Texas Permanent School Fund	1854	25.50	9
US-Wyoming	Permanent Wyoming Mineral Trust Fund	1974	5.60	9

Source: *Originally from SWF rankings on the Web site of www.Swfinstitute.org and the authors' compilation.*

Note: *This table depicts the profile of commodity-based SWFs selected based on their data availability, in which the listed SWFs are the funds whose asset sizes have exceeded USD 5 billion. Current asset size is the size updated in March 2013. The Linaburg-Maduell Transparency Index, developed at the SWF Institute, is a method of rating transparency with regard to SWFs, where the minimum score is 1, and a minimum rating of 8 is recommended to claim adequate transparency.*

at the SWF Institute, rates the transparency of SWFs. The index was developed by introducing ten essential principles that describe SWF transparency to the public and assigning one point to each principle; the minimum score is one, and a minimum rating of eight is recommended to claim adequate transparency. More than 50 percent of commodity-based SWFs score less than eight, indicating that they have inadequate transparency. All SWFs of the developed economies in Table 1 gain a rating of more than eight, indicating their transparent information disclosure. The public accountability and transparency of SWFs are the prerequisites for sound SWF management and good corporate governance.

The other important standard of transparency of SWFs refers to the Generally Accepted Principles and Practices, also known as the "Santiago Principles", a set of principles guiding all the activities of SWFs, presented by the International Working Group of Sovereign Wealth Funds in September 2008 (IWG 2008).

As we can see from Table 2, nearly 60 percent of non-commodity SWFs have been founded since 2000. China, China–Hong Kong, and Singapore have current SWF asset holdings surpassing US$ 100 billion. Among these, China's SAFE Investment Company

Table 2. Non-commodity SWFs

Country	Fund name	Year founded	Current asset size by billion USD	Linaburg-Maduell Transparency Index
Australia	Australian Future Fund	2006	83.00	10
Bahrain	Mumtalakat Holding Company	2006	7.10	9
Brazil	Sovereign Fund of Brazil	2008	5.30	9
China	SAFE Investment Company	1997	567.90	4
	China Investment Corporation	2007	482.00	7
	National Social Security Fund	2000	160.60	5
China-Hong Kong	Hong Kong Monetary Authority Investment Portfolio	1993	298.70	8
France	Strategic Investment Fund	2008	25.50	9
Ireland	National Pensions Reserve Fund	2001	19.40	10
Malaysia	Khazanah Nasional	1993	39.10	5
New Zealand	New Zealand Superannuation Fund	2003	16.60	10
Peru	Fiscal Stabilization Fund	1999	7.10	n/a
Russia	Russian Direct Investment Fund	2011	11.50	n/a
Singapore	Government of Singapore Investment Corporation	1981	247.50	6
	Temasek Holdings	1974	157.50	10
South Korea	Korea Investment Corporation	2005	56.60	9
US-New Mexico	New Mexico State Investment Council	1958	16.30	9

Source: *Originally from SWF rankings on the Web site of www.Swfinstitute.org and the authors' compilation.*

Note: *This table describes the profile of non-commodity SWFs selected based on their data availability, in which the listed SWFs are the funds whose asset sizes have exceeded USD 5 billion. Current asset size is the size updated in March 2013. The Linaburg-Maduell Transparency Index, developed at the SWF Institute, is a method of rating transparency with regard to SWFs, where the minimum score is 1, and a minimum rating of 8 is recommended to claim adequate transparency.*

holds US$ 567.90 billion, taking the lead in the non-commodity SWFs. With regard to the transparency issue, almost 60 percent of non-commodity SWFs score more than eight, showing adequate transparency.

Alternatively, according to their distinct mandates and policy objectives, SWFs can be categorized into four types: stabilization funds, saving funds, pension reserve funds, and reserve investment funds[2] (IMF 2012). Table 3 shows the objectives of the four types of SWFs and their observed asset allocations at the end of 2010, based on publicly available data for 30 selected SWFs that meet the definition outlined in the Santiago Principles.

As shown in Table 3, there are four asset types usually used for SWF investment: cash, fixed income, equities, and alternative assets. The former two belong to the category of safe assets, and the latter two are considered risky assets. On the whole, stabilization funds invest their wealth mainly in safe assets, including 91 percent in fixed income and 5 percent in cash, whereas the other three funds are largely risky investors (i.e., more than

2 IMF (2012) lists the countries owning SWFs and their corresponding fund types. Stabilization funds are those in Azerbaijan, Bahrain, Botswana, Chile, Kiribati, Mexico, Oman, Russia, Timor-Leste, and Trinidad and Tobago. Saving funds are those in Abu Dhabi, Alberta (Canada), Alaska (United States), Bahrain, Brunei, Kazakhstan, Kuwait, Malaysia, Norway, Qatar, Russia, and Singapore. Pension reserve funds are those in Australia, Chile, Ireland, and New Zealand. Reserve investment funds are those in China, Korea, and Singapore.

Table 3. Objectives of SWFs by type and their observed asset allocations

	Stabilization funds	Saving funds	Pension reserve funds	Reserve investment funds
Objective	**Insulate government budgets and economies from commodity price volatility and external shocks**	**Share cross-generational wealth by transfering non-renewable assets into a diversified portfolio of foreign financial assets to provide for future generations**	**Meet future pension liabilities on the governments' balance sheets**	**Reduce reserve holding costs and pursue higher returns**
Cash	5%	4%	9%	3%
Fixed Income	91%	26%	19%	25%
Equities	4%	55%	39%	66%
Alternative Asset	0%	15%	33%	6%
Safe Assets	96%	30%	28%	28%
Risky Assets	4%	70%	72%	72%
Total	100%	100%	100%	100%

Source: *Originally in Box 3.1 from IMF (2012) and the authors' compilation.*

Note: *This table shows objectives of SWFs by type and their observed asset allocations at the end of 2010 according to the IMF (2012), in which safe assets include cash and fixed income, and risky assets comprise equities and alternative assets.*

70 percent of their wealth is invested in risky assets, with the remainder in safe assets). The observed investment patterns show that the four types of SWFs are heterogeneous towards risk preference and tolerance, based on their different macroeconomic objectives. Thus, with the exception of stabilization funds, most SWFs act as investors in a long-term investment horizon and have limited liquidity needs.

The recent financial crisis has given SWFs an opportunity to play the role of providing financial stability by injecting their significant capital into systemically important Western banks that were financially distressed due to market stress in 2007–08. Table 4 displays a series of capital injections from a number of SWFs to Western banks during the period from May 2007 to July 2008.

2.2 China's economy

Figure 1 shows China's total foreign reserves and the total reserves/GDP ratio from 2001 to 2011. The size of total foreign reserves augmented from US$ 216 billion at the end of 2001 to US$ 3,203 billion at the end of 2011, indicating huge current account surpluses and foreign direct investment during this period. At the same time, the total reserves to GDP ratio gradually increased, peaking at 48.40 percent in 2009, and then declining slightly to 43.76 percent in 2011.

In spite of China's huge economic achievement during the last decade, there are large risks facing China's economy (see Woo 2008; Yueh 2011; Wang and Woo 2011; Woo 2012; Woo et al. 2012). For example, the current underdevelopment of China's financial

Table 4. Important capital injections from SWFs into banks during the 2007–08 financial crisis

Foreign bank	Date[a]	SWF	Value (U.S.$ billion)	Stake (%)	Deal features
Blackstone (U.S.)	May-07	China Investment Corporation	3	9.9	Nonvoting units in limited partership; 10% ceiling; 3-year lock-in and >3-year divestiture period
Barclays (UK)	Jun-07	Qatar Investment Authority	3.5	6.42	Common stock by exercising presold rights issues
	Jul-07	Temasek	n/a	2.6	Common stock
Standard Chartered (UK)	Aug-07	Temasek	n/a	11	Common stock
Citigroup (U.S.)	Nov-07	Abu Dhabi Investment Authority	7.5	n/a	4.9% convertible units at 11% interest
	Nov-07	Kuwait Investment Authority	3	n/a	2% optional convertible preferred stock; 9% dividend
	Jan-08	Government of Singapore Investment Corporation	6.88	n/a	3.7% optional convertible preferred stock; 7% dividend; noncallable prior to year 7; 20% conversion premium; 6-month lockup
UBS Switzerland	Dec-07	Government of Singapore Investment Corporation	n/a	n/a	Convertible debt securities at 9% interest; must be converted into shares within 2 years
Morgan Stanley (U.S.)	Dec-07	China Investment Corporation	5	n/a	Convertible units at 9% interest
Merrill Lynch	Dec-07	Temasek	4.4	9.4	Mandatory convertible preferred stock; 9% interest; option to buy additional U.S. $600 million worth of stock
	Jan-08	Kuwait Investment Authority	2	3.3	Mandatory convertible preferred shares; 9% interest
	Jan-08	Korean Investment Corporation	2	3.3	n/a
	Feb-08	Temasek	0.6	1.23	Common stock
	Jul-08	Temasek	0.9	n/a	Common stock

Source: *Originally from Table 1 in Pistor (2009) and the authors' sifting by eliminating transactions both between governments and banks and between other financial institutions and banks.*

Note: [a]*Organized by first date involving a transaction with the bank in question.*

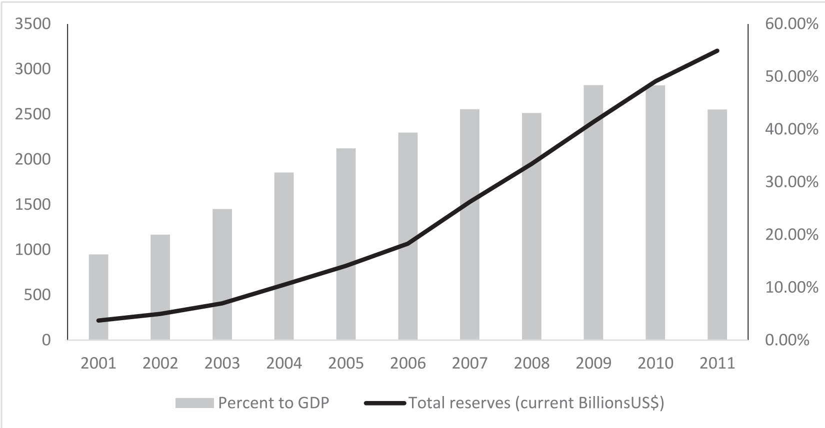
system may suffer from potentially uninsured risks.[3] Another risk is that the rapidly aging population is a potential funding crisis for China's National Social Security Fund.

3. The multiple-goal SWF investment framework

In this section, we propose a multiple-goal investment framework for China's SWF to formulate strategic asset allocation and thus to construct the benchmark portfolio, by embedding the Black-Litterman model (1992) of forecasting expected rates of return into

3 See Woo et al. (2014) for a comprehensive agenda for financial sector reform to prevent and manage financial crises.

Figure 1. China's total foreign reserves and the total reserves/GDP ratio



Source: *Source: World Bank Database: World Development Indicators (WDI) 2013.*

the MVMA framework by Das et al. (2010). We first delineate the MVMA framework to show the multiple-goal investment mechanism, then use the B-L model as a means to form forward-looking return forecasts, and finally derive the multiple-goal investment strategy for China's SWF.

3.1 The MVMA optimization

In our model setting, the problem faced by the sovereign wealth managers is to select portfolio weights $\mathbf{w} = [w_1, \ldots, w_n]'$ for N assets, in which the assets have an expected return vector $\boldsymbol{\mu} \in R^n$ and a return covariance matrix $\sum \in R^{n \times n}$. The standard MV problem is a trade-off between the portfolio return and its variance:

$$\max_{\mathbf{w}} \mathbf{w}'\boldsymbol{\mu} - \frac{\gamma}{2}\mathbf{w}'\sum\mathbf{w}, \tag{1}$$

subject to the full-investment constraint

$$\mathbf{w}'\mathbf{1} = 1, \tag{2}$$

where $\mathbf{1} = [1, 1, \ldots, 1]' \in R^n$, and γ is the risk aversion coefficient, which balances the trade-offs in the mean-variance space.

Based on equations (1) and (2), and using the Lagrange-multiplier method, the solution to optimal portfolio weights in closed form is[4]

$$\mathbf{w}(\gamma) = \frac{1}{\gamma}\sum^{-1}\left[\boldsymbol{\mu} - \left(\frac{\mathbf{1}'\sum^{-1}\boldsymbol{\mu} - \gamma}{\mathbf{1}'\sum^{-1}\mathbf{1}}\right)1\right] \in R^{n}. \tag{3}$$

Given the expected return vector $\boldsymbol{\mu}$ and the covariance matrix $\sum$, equation (3) shows that the optimal portfolio weights $\mathbf{w}$ are a function of the risk aversion coefficientγ. According to this solution, the wealth managers can specify γ by choosing distinct values for $\gamma > 0$, and then solve the problem (equation (1)) in terms of solution (3). With a collection of different risk-aversion values in hand, they can maximize mean-variance utility to find corresponding points on the efficient frontier.

Meanwhile, wealth managers in behavioral portfolio theory take their overall portfolio as collections of mental accounting (MA) sub-portfolios, in which each sub-portfolio (i.e., each mental account) is mapped onto a goal. Following Das et al. (2010), we assume that the sovereign wealth managers always have difficulty in stating their precise risk-aversion coefficient (γ), but are comfortable stating the threshold levels for each mental account (goal) and their corresponding maximum probabilities of failing to reach them. As a result, the MA problem indicates that the sovereign wealth managers consider a threshold level of return H for portfolio$p$ in a certain mental account, and regard the maximum probability of the portfolio failing to reach portfolio return $r(p)$ as α. Thus, they have

$$\text{Prob}[r(p) \leq H] \leq \alpha. \tag{4}$$

Portfolio returns are assumed to be normally distributed. In terms of value at risk (VaR), inequality (4) implies the following inequality:

$$H \leq \mathbf{w}'\boldsymbol{\mu} + \Phi^{-1}(\alpha)\left[\mathbf{w}'\sum\mathbf{w}\right]^{1/2}, \tag{5}$$

where $\Phi(\bullet)$ is the cumulative standard normal distribution function.

Ultimately, the wealth managers in the MVMA framework act as if they have different risk preferences in each of the mental accounts. Thus, solving the MA problem is equivalent to solving a standard MV problem with a specific “implied” risk-aversion coefficient. The wealth managers’ aim is to derive optimal portfolio weights from equation (3) subject to constraint (5). Optimization cannot be achieved unless constraint (5) is an equality. In

4 The detailed derivation of this solution can be found in the Appendix of Das et al. (2010).

consequence, the solution to the wealth managers' implied risk aversion γ is formulated by the following equation:

$$H = \mathbf{w}(\gamma)'\boldsymbol{\mu} + \Phi^{-1}(\alpha)\left[\mathbf{w}'(\gamma)\sum\mathbf{w}\right]^{1/2}, \tag{6}$$

where the solution of $\mathbf{w}(\gamma)$ is provided from equation (3). Plugging equation (3) into equation (6), it is straightforward to find the solution to equation (6), based on which one can obtain different values of the risk preference γ.

As a result, the MVMA framework suggests that the portfolio optimization problem for the wealth managers is specified by a threshold level of return H and a probability value α. When the managers specify their MA preferences for each sub-portfolio through the parameter pair(H, α) they implicitly denote what their risk preferences (γ) are over the given portfolio choice set$(\boldsymbol{\mu}, \sum)$. With the risk aversion coefficient (γ), the wealth managers can derive their optimal portfolio weights.

Because SWFs are unleveraged positions, however, we need to resort to quadratic programming (QP) optimizers to derive optimal portfolio weights under short-selling constraints. Following Das et al. (2010), the sovereign wealth managers can use VaR as their risk management framework, which can be expressed by the MVMA problem as

$$\text{Solve}_{\gamma}\,\mathbf{w}(\gamma)'\boldsymbol{\mu} + \Phi^{-1}(\alpha)\sqrt{\mathbf{w}(\gamma)'\sum\mathbf{w}(\gamma)} = H, \tag{7}$$

where $\mathbf{w}(\gamma)$ is the first order condition to the following MV problem:

$$\max_{w}\, w'\boldsymbol{\mu} - \frac{\gamma}{2}w'\sum w, \tag{8}$$

subject to the full invested constraint and short-selling constraints

$$\mathbf{w}'\mathbf{1} = 1,\ \ \mathbf{w} \geq 0 \text{ and } \mathbf{w} \leq 1. \tag{9}$$

According to equations (7)–(9), for each sub-portfolio, each VaR constraint which is specified by a threshold level H and a probability value α in the MA problem corresponds to a particular implied coefficient of risk aversion γ in the MV problem. Thus, the wealth managers solve the nonlinear equation (7) based on a specified γ (i.e., a specified sub-portfolio) and thus derive the optimal portfolio weights by solving the QP in equations (8) and (9). For the specified γ or sub-portfolio, the managers need to check whether the solution $\mathbf{w}(\gamma)$ can make equation (7) hold. If not, they must change γ accordingly and then solve the QP until equation (7) holds.

3.2 The Black-Litterman model

We use the model in Black and Litterman (1992) to generate our input forecast (i.e., the expected returns). The B-L model uses the equilibrium returns as the starting point for its estimation. Equilibrium returns are inferred from the market capitalization weights, using a "reverse optimization process." Black and Litterman (1992) argue that this process, based on market capitalization weights, can derive consensus excess returns, which are consistent with the tangency portfolio of the capital asset pricing model. With the market forces of supply and demand in equilibrium, the weight allocation across the investment universe is expected to be optimal and the optimal weight can therefore act as the basis for asset allocation.

In the B-L model, given the risk aversion coefficient δ that indicates the level of risk against returns of the market portfolio, the historical variance covariance matrix $\sum$, and the vector of market capitalization weights $\mathbf{w}_M$, the reverse optimization process can provide the vector of implied equilibrium returns $\boldsymbol{\mu}_M$ in excess of the risk-free rate as

$$\boldsymbol{\mu}_M = \delta \sum \mathbf{w}_M. \tag{10}$$

If the wealth managers do not agree with the implied equilibrium excess returns, they can introduce their own views. Specifically, they may take the implied equilibrium returns as the prior distribution and regard the corresponding forecasted returns as forward-looking views-based returns, to form the posterior B-L returns. For example, assume there are k views, which can be either relative or absolute and are represented in $k \times 1$ the vector $\mathbf{Q}$. The $k \times n$ matrix $\mathbf{P}$ is then used to define these views: $\mathbf{Q} = \mathbf{P} \cdot \mathbf{r}_a$. The first view is represented as a linear combination of expected returns denoted by the first row of $\mathbf{P}$. A confidence level is associated with each of the views implied by $\mathbf{Q}$. Thus, the investor's beliefs can be described by a normal view distribution: $\mathbf{P} \cdot \mathbf{r}_a \sim N(\mathbf{Q}, \boldsymbol{\Omega})$, where $\boldsymbol{\Omega}$ is a $k \times k$ diagonal covariance matrix. In the same vein, the confidence in the equilibrium model and the derived implied returns can be defined. Consequently, we obtain the prior equilibrium distribution: $\mathbf{r}_a \sim N(\boldsymbol{\mu}_M, \tau \sum)$, where τ is a known quantity indicating the uncertainty level to scale the historical covariance matrix $\sum$.

Following the Bayesian estimation method, the wealth managers can generate the posterior B-L returns as follows:

$$E(\mathbf{r}_{BL}) = \left[\left(\tau \sum \right)^{-1} + \mathbf{P}'\boldsymbol{\Omega}\mathbf{P} \right]^{-1} \times \left[\left(\tau \sum \right)^{-1} \boldsymbol{\mu}_M + \mathbf{P}'\boldsymbol{\Omega}\mathbf{Q} \right]. \tag{11}$$

As a result, with the implied equilibrium excess returns $\boldsymbol{\mu}_M$ and the B-L excess returns $E(\mathbf{r}_{BL})$ in hand, we can obtain the implied equilibrium total returns $\boldsymbol{\mu}_M^T$ and the B-L total returns $E(\mathbf{r}_{BL}^T)$ by adding to each of them the risk-free rate.

Table 5. Objective, risk tolerance, and investment horizon of the three sub-portfolios

Sub-portfolio	Policy objective	Risk tolerance	Investment horizon
Precautionary	Provide contingent liquidity supports as a means of self-insurance to cushion the possible negative effects caused by commodity price volatility or systemic risks	Lower	Short
Investment	Invest in a medium-term goal to fund contingent domestic liabilities	Modest	Medium
Bequest	Transfer national wealth from now to the future and benefit next generations	Higher	Long

Note: *This table shows the profile of the designed three sub-portfolios for our multiple-objective SWF investment policy.*

3.3 The multiple-goal investment strategy

Embedding the B-L model into the MVMA framework, our multiple-goal investment strategy for SWFs in the world can be accomplished through three steps. First, to meet various macroeconomic policies such as providing liquidity support and transferring wealth across generations, sovereign wealth managers take their portfolios as a collection of three sub-portfolios. Table 5 displays the profile of our designed three sub-portfolios, including their policy objectives, risk tolerance, and investment horizon.

The first is a "precautionary sub-portfolio", where the managers specify higher risk-aversion coefficients, showing lower risk tolerance; they invest in a short investment horizon for providing contingent liquidity support to both internal and external banking sectors to cushion against the possible negative effects triggered by traditional financial crises or "twin crises". The second is an "investment sub-portfolio", in which the managers specify medium risk-aversion parameters, implying modest risk tolerance; they invest in a medium-term investment horizon for funding contingent domestic liabilities (e.g., contingent pension payment). The third is a "bequest sub-portfolio", in which the managers with lower risk-aversion parameters invest in a long-term investment horizon, attempting to transfer such national wealth from now to the future and thus to benefit subsequent generations. As a result, according to different types of funds, the managers can construct their distinct aggregate portfolios by allocating their total investable wealth across the three sub-portfolios in a variety of proportions. Generally, for a conservative SWF (e.g. stabilization fund), most of the total investable wealth (more than 50 percent) should be allocated to the precautionary sub-portfolio, and the remainder into the other two, aiming mainly to meet large liquidity needs; for a progressive SWF (e.g., saving fund, pension reserve fund, or reserve investment fund), on the other hand, most of the wealth should be allocated to the bequest sub-portfolio, and the remainder into the other two, due to their limited liquidity needs.

Before entering into their three sub-portfolios, the managers first choose their investment classes out of the available investment universe. They derive the implied equilibrium total return $\boldsymbol{\mu}_M^T$ in light of market capitalization weights, and the B-L total returns $E(\mathbf{r}_{BL}^T)$ in light of their forward-looking investment views. Finally, using $\boldsymbol{\mu}_M^T$ and $E(\mathbf{r}_{BL}^T)$, respectively, the managers figure out the two sub-groups of optimal asset allocation for the three sub-portfolios by solving equations (7)–(9), and construct their specified aggregate portfolios based on their overall policy objectives.

4. An empirical study of China's case

4.1 Selection of our asset classes

Before delivering our empirical study, we first investigate the global investment patterns of China's SWFs in recent years, and then identify the recent trends of consumption of the resource commodities that are vital for China's economic growth, based on both of which we formulate the selected asset classes.

4.1.1 The recent investment patterns of China's SWFs Among the listed China's SWFs in terms of Table 2, only CIC publishes its overall investment patterns, as a result of which, we use the published investment patterns of CIC as a benchmark for formulation of our asset classes. According to the CIC's latest annual report (2012), its invested asset classes covers the four asset types: cash, fixed-income securities, equities, and alternative assets. Among those, as of the end of 2012, CIC holds 22.9 percent of its total investment in safe assets, including 3.8 percent in cash and 19.1 in fixed-income securities; and 77.1 percent in risky assets, consisting of 32 percent in public equities and 45.1 percent in alternative assets. Within the fixed-income securities, CIC holds sovereign bonds of advanced and emerging economies, corporate bonds, and inflation-indexed bonds; within its equities and alternative assets, it has been the trend that CIC implements the long-term investments by hedge funds or private equities mainly in energy, mining, real estate, and infrastructure sectors. For example, in 2012, CIC invested £276 million in Thames Water in return for an 8.68 percent stake, and £450 million in Heathrow Airport Holdings Ltd for a 10 percent stake.

4.1.2 The recent trends of China's commodity consumption Due to the rapid development of China's economy, China has become a major consumer of a broad range of primary commodities such as oil, gas, metals, and other raw materials. For example, McKay, Sheng and Song (2010) suggest that China's recent growth hinges heavily on the use of natural resources. Roache (2012) implies that during the year 2010, China's consumption accounts for 20 percent non-renewable energy resources, 23 percent agricultural raw material, and 40 percent metals of the world's total consumption, respectively. Roache also indicates that China's share of the global base metal trade has increased dramatically from around 8 percent to 30 percent during the decade from 2001 to 2010. Roberts and Rush (2012) argue that China's exports from the manufacturing sector can be taken as a significant determinant of China's raw material demand. That is to say, as long as the export demand continues, China's raw material demand will not stop even though the prices of raw materials increase to a higher level. Thus, based on its current structure of economic growth, China has been playing the role of a leading importer in the international commodity market.

4.1.3 Selection of asset classes Based on both the recent investment behavior of CIC and the recent trends of resource commodity consumption in China, we consider 18 asset classes as our investment opportunity set. Among those, ten asset classes are safe assets, consisting of five developed countries' long-term government bonds, U.S. agencies, U.S. corporate bonds, U.S. asset-backed securities (ABS), U.S. inflation-linked securities, and U.S. 3-month treasury bills (T-bills). The other eight asset classes are risky assets, including the equities of the four emerging economies (i.e., Brazil, Russia, India, and South Africa), and four alternative assets. For equities, we choose the equity markets from these countries for the reason that the BRICS countries as a group are expected to be a powerful economic bloc with a huge potential of future economic growth (Cheng et al. 2007). For alternative assets, we use the four equity-based indices as the proxies of the corresponding alternative asset classes invested by hedge funds or private equities, due to the fact that it is difficult to measure the market capitalizations of both hedge funds and private equities.

4.2 Data and implementation

We use 18 indices, which include bonds, equities, and alternative assets, to simulate a variety of market risk factors in view of the long-term investment horizon. For the bonds, we use the long-term government bond indices of five developed economies (U.S., UK, Germany, Canada, and Australia), one U.S. corporate bond index, one U.S. agency bond index, one U.S. ABS index, one U.S. inflation-linked security index, and one 3-month U.S. T-bill index, all of which are from Bank of America Merrill Lynch. For the equities, MSCI Brazil, MSCI Russia, MSCI India, and MSCI South Africa indices are used as the proxies for these four-country equity markets. For the four alternative assets, the four MSCI world indices in energy, materials, real estate, and infrastructure, which are the four equity-based indices across 24 developed markets (DM) countries,[5] are used as the proxies of China's SWF global investment in the corresponding alternative assets. Monthly total return indices of all selected asset classes are used over the sample period from January 1999 to January 2013, with a total of 169 observations. Based on a U.S.-dollar denomination, all total return indices are calculated in a log-return style. The 3-month U.S. T-bill is taken as the risk-free rate.

Table 6 displays the descriptive statistics of the selected asset classes. For all government bonds, the Canada government bond outperforms both the German and the UK government bonds, compared with their mean returns and standard deviations. The German

5 According to the MSCI Web site, DM countries include: Australia, Austria, Belgium, Canada, Denmark, Finland, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK, and the United States.

Table 6. Descriptive statistics

Name	Market	Instrument type	Mean	Std deviation
US GVT	USA	Long-term Bonds	4.90%	3.17%
UK GVT	UK	Long-term Bonds	5.29%	9.11%
GERMAN GVT	Germany	Long-term Bonds	5.43%	10.81%
CANADA GVT	Canada	Long-term Bonds	8.33%	8.77%
AUSTRALIA GVT	Australia	Long-term Bonds	10.02%	12.79%
US CORP	USA	Corporate	6.46%	5.60%
US AGENCIES	USA	Agencies	4.94%	2.78%
US ABS	USA	Asset Backed Securities	4.55%	2.43%
US INFL LKD	USA	Inflation-linked Securities	7.64%	6.03%
US TBILL3M	USA	Cash Equivalents	2.49%	0.62%
MSCI BRAZIL	Brazil	Equities	16.60%	38.18%
MSCI RUSSIA	Russia	Equities	21.85%	42.96%
MSCI INDIA	India	Equities	14.55%	33.58%
MSCI SOUTH AFRICA	South Africa	Equities	14.99%	27.95%
DM ENERGY	Developed Markets	Alternatives	9.17%	22.30%
DM MATERALS	Developed Markets	Alternatives	8.80%	24.99%
DM REAL ESTATE	Developed Markets	Alternatives	8.03%	22.24%
DM INFRASTRUCTURE	Developed Markets	Alternatives	1.49%	15.47%

Note: *This table shows descriptive statistics of all considered asset classes. Our calculations use monthly data. The mean and standard deviations are reported annually.*

government bond has a slightly higher return than the U.S. government bond, but has a relatively higher standard deviation. The Australia government bond has the best mean return with the highest standard deviation, and the U.S. government bond has the lowest standard deviation. For all equities, the equity markets of all four emerging economies can generate higher mean returns but also have high volatilities, among which Russia is the most unstable market in the all asset classes. For all alternative assets, the infrastructure sector across the 24 developed economies provides the surprisingly lowest mean return (i.e., 1.49 percent in annual return out of all selected asset classes). A 3-month U.S. T-bill delivers the lowest standard deviation.

Now, we formulate the B-L returns based on our naive investment views. First, by the “reverse optimization process”, we derive our implied equilibrium excess returns as a benchmark, based on which the wealth managers then form their forward-looking investment views. Here we make three simple assumptions for the future: (1) assets in the infrastructure sector will perform better than before, particularly compared with those in energy and material sectors, due to the popularity of infrastructure equity investments; (2) German government bonds will perform the same as Australian government bonds; and (3) U.S. inflation-linked securities will outperform U.S. 3-month T-bills better than the difference between their equilibrium returns. As a result, taking equilibrium total returns as a benchmark, the managers form the four investment views: (1) DM energy will outperform DM infrastructure by only 2.0 percent; (2) DM materials will also outperform DM infrastructure by only 2.0 percent; (3) There will be no difference in the performance between German and Australia government bonds; and (4) U.S. inflation-linked securities will outperform U.S. 3-month T-bills by 5.0 percent. All views’ confidence levels are assigned to 50 percent.

Table 7. Market weights and return estimates

Name	Market weights	Equilibrium returns	The B-L returns
US GVT	28.17%	2.45%	3.23%
UK GVT	3.75%	5.01%	6.26%
GERMAN GVT	4.08%	5.78%	7.37%
CANADA GVT	1.15%	5.73%	5.95%
AUSTRALIA GVT	0.82%	7.63%	8.29%
US CORP	18.36%	4.02%	5.17%
US AGENCIES	2.77%	2.69%	3.36%
US ABS	0.79%	2.90%	3.34%
USINFLLKD	3.80%	3.72%	5.59%
US TBILL3M	0.67%	2.48%	2.47%
MSCI BRAZIL	1.72%	17.69%	15.17%
MSCI RUSSIA	0.94%	17.47%	15.82%
MSCI INDIA	0.89%	12.87%	12.00%
MSCI SOUTH AFRICA	1.02%	13.43%	12.30%
DM ENERGY	11.44%	12.19%	11.33%
DM MATERALS	6.92%	13.74%	12.11%
DM REAL ESTATE	3.54%	11.78%	11.44%
DM INFRASTRUCTURE	9.16%	8.49%	8.48%

Source: *Market capitalization data of all safe assets are from BIS Securities Statistics on the BIS official Web site. The data of all risky assets are from the MSCI official Web site.*

Note: *Market weights are obtained by using market capitalization data of all asset classes. Equilibrium total returns and the B-L total returns are derived by adding the risk-free rate to equilibrium excess return and the B-L excess returns, respectively.*

Table 7 illustrates the market weights of all the asset classes and their two estimates (i.e., equilibrium total returns and the B-L total returns). With regard to market weights, U.S. government bonds have the largest market capitalization of all the selected asset classes; U.S. corporate bonds and DM energy have the second and the third largest, respectively; and the U.S. 3-month T-bill has the least market capitalization. Due to the former two views that favor DM infrastructure, all the returns within the risky assets have decreased slightly; whereas due to the latter two views that favor German government bonds and U.S. inflation-linked securities, all the returns within the safe assets have increased slightly, except U.S. 3-month T-bills.

Using equilibrium and the B-L total return, we enter into the MVMA framework to carry out our multiple-objective investment policy for China's SWFs. By solving equations (3)–(5), we derive the two sets of optimal asset allocation for the asset classes considered. According to each of these sets of optimal asset allocation, we construct our three sub-portfolios (i.e., the precautionary, the investment, and the bequest sub-portfolios) by specifying three distinct risk-aversion parameters from high to low, to accomplish our various macroeconomic policy objectives. We also construct a specified aggregate portfolio by allocating the total investable wealth into the three sub-portfolios in a 20:20:60 division across the three sub-portfolios (20 percent of the total investable wealth into the precautionary sub-portfolio, 20 percent into the investment one, and 60 percent into the bequest one), due to the fact that China's SWFs as reserve investment fund have a relatively higher risk tolerance. We then examine the MA problem for all portfolios by

Table 8. Optimal portfolio weights for the three sub-portfolios and the one aggregate portfolio (equilibrium returns)

Risk aversion:	Υ = 13.273	Υ = 5.682	Υ = 2.536	20:20:60 mix
Asset classes	**Precautionary sub-portfolio**	**Investment sub-portfolio**	**Bequest sub-portfolio**	**Aggregate portfolio**
US GVT	11.26%	19.83%	0.01%	6.22%
UK GVT	1.83%	3.20%	0.03%	1.02%
GERMAN GVT	1.87%	6.68%	7.52%	6.22%
CANADA GVT	0.45%	1.20%	0.01%	0.34%
AUSTRALIA GVT	1.05%	1.27%	5.63%	3.84%
US CORP	9.88%	21.72%	0.02%	6.33%
US AGENCIES	1.08%	0.30%	0.01%	0.28%
US ABS	2.41%	0.08%	0.01%	0.50%
US INFL LKD	1.77%	6.50%	0.02%	1.66%
US TBILL3M	51.31%	0.05%	0.01%	10.27%
MSCI BRAZIL	0.74%	2.08%	9.29%	6.14%
MSCI RUSSIA	0.38%	1.15%	3.49%	2.40%
MSCI INDIA	0.35%	0.85%	2.15%	1.53%
MSCI SOUTH AFRICA	0.59%	1.26%	4.86%	3.29%
DM ENERGY	5.53%	12.69%	26.75%	19.69%
DM MATERALS	3.19%	7.14%	18.07%	12.91%
DM REAL ESTATE	1.69%	4.05%	15.94%	10.71%
DM INFRASTRUCTURE	4.64%	9.96%	6.21%	6.64%
Safe Assets	82.89%	60.81%	13.25%	36.69%
Risky Assets	17.11%	39.19%	86.75%	63.31%
Total Weights	100%	100%	100%	100%
Expected Returns	4.44%	7.02%	12.20%	9.61%
Std. Dev.	3.86%	8.93%	19.98%	14.55%

Note: *The portfolio weights for all portfolios are obtained using the solutions in equations (3)–(5) based on the equilibrium returns. The expected returns and standard deviations of all portfolios are presented at the bottom of the table.*

working out the VaR constraint—that is, equation (3), in which we can map various threshold levels of returns into the maximum probabilities of not reaching them.

4.3 Main results

4.3.1 The optimal portfolio weights based on the two return estimates Table 8 displays the optimal portfolio weights for the three sub-portfolios and the one aggregate portfolio under equilibrium total returns, and Table 9 shows those under the B-L returns. We use the range of risk aversion coefficient from 0 to 20 to show the degree of risk aversion for investors, in line with Aït-Sahalia and Brandt (2001).

In terms of Table 8, for the precautionary sub-portfolio, with the highest risk-aversion value out of the three sub-portfolios (i.e., $\gamma = 13.273$) its expected return reaches 4.44 percent, with standard deviation of 3.86 percent; as a result of which, this sub-portfolio holds 82.89 percent in safe assets, including 51.31 percent in 3-month T-bills and 31.59 percent in other bonds; and 17.11 percent in risky assets (2.05 percent in emerging market equities and 15.05 percent in alternative assets). For the investment sub-portfolio with $\gamma = 5.682$, the largest holding would be U.S. corporate bonds (21.72 percent) and the second largest would be U.S. government bonds (19.83 percent). Because of its medium-risk attitude, this portfolio holds 60.81 percent in safe assets and 39.19 percent in risky assets. For the

Table 9. Optimal portfolio weights for the three sub-portfolios and the one aggregate portfolio (the B-L returns)

Risk aversion:	Υ = 13.273	Υ = 5.682	Υ = 2.536	20:20:60 mix
Asset classes	**Precautionary sub-portfolio**	**Investment sub-portfolio**	**Bequest sub-portfolio**	**Aggregate portfolio**
US GVT	12.23%	0.00%	0.00%	2.45%
UK GVT	1.96%	0.01%	0.00%	0.39%
GERMAN GVT	6.01%	35.72%	0.00%	8.35%
CANADA GVT	0.03%	0.00%	0.00%	0.01%
AUSTRALIA GVT	0.01%	0.03%	0.00%	0.01%
US CORP	9.24%	0.01%	0.00%	1.85%
US AGENCIES	1.64%	0.00%	0.00%	0.33%
US ABS	1.42%	0.00%	0.00%	0.28%
USINFLLKD	41.06%	25.46%	0.00%	13.31%
US TBILL3M	10.90%	0.00%	0.00%	2.18%
MSCI BRAZIL	0.36%	3.77%	21.76%	13.88%
MSCI RUSSIA	0.19%	4.95%	17.98%	11.82%
MSCI INDIA	0.34%	1.31%	0.38%	0.56%
MSCI SOUTH AFRICA	0.02%	0.42%	6.42%	3.94%
DM ENERGY	5.54%	13.43%	19.78%	15.66%
DM MATERALS	0.02%	0.02%	0.00%	0.01%
DM REAL ESTATE	1.19%	13.59%	33.67%	23.16%
DM INFRASTRUCTURE	7.83%	1.27%	0.00%	1.82%
Safe Assets	84.50%	61.25%	0.00%	29.15%
Risky Assets	15.50%	38.75%	100.00%	70.85%
Total Weights	100%	100%	100%	100%
Expected Returns	5.67%	8.81%	13.07%	10.74%
Std. Dev.	4.92%	11.43%	25.58%	18.62%

Note: *The portfolio weights for all portfolios are obtained using the solutions in equations (3)–(5) based on the B-L returns. The expected returns and standard deviations of all portfolios are presented at the bottom of the table.*

bequest sub-portfolio with $\gamma = 2.536$, the largest holding would be DM energy (26.75 percent) and the second largest would be DM materials (18.07 percent). As a result of its having the lowest risk aversion out of the three, this portfolio holds 13.25 percent in safe assets and 86.75 percent in risky assets (most in alternative assets). Our specified aggregate portfolio shows the relatively higher risk tolerance, holding 63.31 percent in risky assets and 36.69 percent in safe assets.

After forming the investment views, Table 9 illustrates the shifts of optimal weights between the selected asset classes and changes in both returns and standard deviations for each portfolio. For example, because of the one view favoring U.S. inflation-linked securities, within the precautionary sub-portfolio, (1) most holdings in Table 9 have shifted significantly from U.S. 3-month T-bills to U.S. inflation-linked securities, compared with Table 8; and (2) although holdings in safe assets from Table 9 are slightly more than those from Table 8, both the return and the standard deviation in this sub-portfolio from Table 9 have slightly increased, compared with those from Table 8. The same two changes happen also in the investment sub-portfolio, by comparing the two tables. In the bequest sub-portfolio, however, due to the severe no short-sale binding, this sub-portfolio in Table 9 holds 100 percent in risky assets, most of which focuses on DM real estate, DM energy, and Brazil and Russia equities, causing the relatively higher standard deviation

Table 10. Threshold return levels and corresponding maximum probabilities of not reaching them (equilibrium returns)

Risk aversion:	Y = 13.273	Y = 5.682	Y = 2.536	20:20:60 mix
Threshold return level	**Precautionary sub-portfolio**	**Investment sub-portfolio**	**Bequest sub-portfolio**	**Aggregate portfolio**
−10.00%	0.01%	2.83%	13.33%	8.89%
−5.00%	0.72%	8.91%	19.47%	15.77%
0.00%	12.50°%	21.59%	27.07%	25.45%
5.00%	55.77°%	41.05%	35.93%	37.57%
10.00%	92.51%	63.07%	45.62%	51.07%
Expected Returns	4.44°%	7.02%	12.20%	9.61%
Std. Dev.	3.86%	8.93%	19.98%	14.55%

Note: *The results are computed using equation (3) based on the equilibrium returns after obtaining portfolio returns and standard deviations for each portfolio.*

Table 11. Threshold return levels and corresponding maximum probabilities of not reaching them (the B-L returns)

Risk aversion:	Y = 13.273	Y = 5.682	Y = 2.536	20:20:60 mix
Threshold return level	**Precautionary sub-portfolio**	**Investment sub-portfolio**	**Bequest sub-portfolio**	**Aggregate portfolio**
−10.00%	0.07%	4.99%	18.36%	13.27%
−5.00%	1.51%	11.35%	24.00%	19.90%
0.00%	12.46%	22.04%	30.47%	28.20%
5.00%	44.58%	36.94%	37.62%	37.89%
10.00%	81.06%	54.15%	45.22%	48.41%
Expected Returns	5.67%	8.81%	13.07%	10.74%
Std. Dev.	4.92%	11.43%	25.58%	18.62%

Note: *The results are computed using equation (3) based on the B-L returns after obtaining portfolio returns and standard deviations for each portfolio.*

(25.58 percent). As a result, the return in the aggregate portfolio from Table 9 is slightly more than that from Table 8, but the standard deviation is relatively higher than that from Table 8.

4.3.2 The MA problems based on the two return estimates Table 10 describes the threshold levels of return and the corresponding maximum probabilities of not reaching them for the three sub-portfolios and the one aggregate portfolios under equilibrium total returns, and Table 11 depicts those under the B-L returns. According to Table 10, within the precautionary sub-portfolio, the wealth managers care most about the maximum probability of the negative return (0.00 percent), which is 12.50 percent, the lowest value compared with those within the other two sub-portfolios; whereas within the bequest sub-portfolio, the managers focus most on the maximum probability of return level of 10.00 percent, which is 45.62 percent, also the lowest value compared with those within the other two sub-portfolios.

Table 11 displays the return levels and their corresponding maximum probabilities of failing to reach them for each portfolio after adding the investment views. Comparing Table 10 with Table 11, we can observe that, for the positive return levels (i.e., 5.00 percent and 10.00 percent), the maximum probabilities within the precautionary and investment sub-portfolios from Table 11 are less than their corresponding probabilities from Table 10; whereas for the negative return levels (i.e., –5.00 percent and –10.00 percent) the opposite is true. In addition, comparing the maximum probabilities within the bequest sub-portfolio from Table 11 with those from Table 10, it seems that adding the specified four views does not decrease the probabilities on the whole, because of the high standard deviation (i.e., 25.58 percent) in this sub-portfolio based on the B-L return estimates.

5. Concluding remarks

In this paper, we propose a multiple-goal investment framework for SWFs. We use this framework to design three sub-portfolios (precautionary, investment, and bequest sub-portfolios) to meet the China's three main policy objectives. We selected 18 asset classes to show the usefulness of this framework for China's sovereign wealth managers. For example, China's Reserve Investment Fund, which has a relatively long investment horizon (and thus tends to invest more in risky assets) allocates more than 50 percent of its total investible wealth into the bequest sub-portfolio to earn higher returns.

We plan to start constructing portfolios for China's SWFs and follow their performance over time. We intend to compare the performance of our computed portfolios with the actual performance of China's SWFs, and to report our findings in a follow-up paper.

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