國立政治大學國際經營與貿易學研究所

碩士學位論文

投資組合複製模型實證研究－以波羅的海指數為例

Empirical studies of portfolio replication: Baltic Dry Index

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Abstract

In this paper, I apply the economic tracking portfolio (ETP) approach developed by Lamont (2001) to track Baltic Dry Index (BDI). According to previous studies of ETP, such as Christoffersen (2000), Hayes (2001), Junttila (2004) and Raunig (2007), ETP is tested in closed-economy, using domestic equity as base assets. Junttila (2007) extends this approach to forecast the macroeconomic variables by using international equity returns. Our study also utilizes this concept to forecast BDI, control variables ignored here, and investigates the tracking performance based on different data frequency, forecast horizon, and training period. The results show that, no matter what data frequency is, the performance of recursive window is better than that of rolling window. The returns of diversified mining and iron steel contain more information than other industries about BDI. As a whole, the tracking portfolio can capture the trend of BDI, and also can be used as hedging tool by the practitioners.

Key words: Rolling window, Recursive window, Least square, Tracking portfolio, Macroeconomics

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1 Introduction

The relationship between financial markets and macroeconomic variables has been a interested subject in financial economics, and many scholars try to explain it. Generally speaking, the view of financial assets containing information about economic activity has been widely accepted. To understand the relationship that equity prices incorporate expectation about future real economic activity, the fundamental evaluation formula of equity is introduced. Current stock price is the present value, discounted value, of future interest rates, cash flows, dividends, and risk premium, and these four factors are strongly related to macroeconomics. Thus, the fact that stock returns originate from changes in asset prices suggests that returns reflect the revised expectation to future real economic activity.

According to the concept that equity returns could be used to reflect future economy, Lamont (2001) develops the approach of economic tracking portfolio (ETP). ETP is constructed to track future economic variables because asset returns contain information about discount rate and future cash flow, and uses only unexpected returns of base assets. It maximizes unexpected stock returns to revised expectation of target variables through different combinations of equity. There are many ways to utilize ETP. It can be used to estimate the premium, and also can be used as a tool to forecast and hedge economic risks by the estimated portfolio weights. This study focuses on the second way, and applies ETP to verifying the tracking and hedging performance against Baltic Dry Index (BDI).

Price level of raw materials is a leading indicator of judging the economic circumstances of the world. The price fluctuations of raw materials will directly influence the price of intermediate goods, and further impact on the retailing price of final goods. Therefore, the changes in price of raw materials is a kind of economic risks. Baltic Dry Index demonstrates shipping rates of transporting raw material such as coal, iron ore, steel, grains, cement, cement, sand and gravel. These raw materials are transported by three types of vessels [1], Capsize, Panamax, Supermax. Each type of vessels has certain capac-

[1] There are also other types of vessel, but raw materials are mainly carried by these three types.

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ity of deadweight, transporting the raw materials suitable for them, so there are three sub-indices of the ship freight rates. BDI is the weighted average price of them, and daily calculates as the formula[2], $((CapesizeTCavg \times 0.4) + (PanamaxTCavg \times 0.3) + (SupramaxTCavg \times 0.3)) \times 0.10$, where TCavg is time charter average. There are two types of charter contracts in dry bulk transportation, spot charter which carries cargo from load port to discharge port at per day rate or per ton rate depending on market rate, and time charter which charter party pays fee to shipowner for a fixed period at a set daily rate. BDI reflects the price determined by supply and demand in the marine freight market, and the equilibrium price also reflects the demand of the raw materials in the world. Each day, the exporters or importers will ask marine freight companies for the shipping rate of certain route, and BDI is calculated basing on the ship freight rates of each vessel type on different routes around the world. Many practitioners use BDI to decide daily shipping of trades. By observing BDI, the economic trend would also be predictable.

The two factors influencing the equilibrium freight rates of BDI are supply and demand side of shipping service. The demand of raw materials is driven by industrial production. When the demand of commodity increases, the freight rates also rises up. For instance, iron ore and coal can be used for producing steel, and coal is used for generating electricity. In developing countries, these two commodities are required, increasing the shipping volume. Not only the demand side of raw materials will impact on the equilibrium price, but also the supply side of it. The supply side is the total number of dry bulk carriers, fleet supply. Lun and Quaddus (2009) note that marine freight market, new built market, second-hand market, and demolition market relate to the fleet supply. Marine freight market is the equilibrium price of demand and supply on seaborne trade. The freight rates increase or decrease will influence the equilibrium freight rate. The results of Lun and Quaddus (2009) indicate that the increase of seaborne trade and freight rates raise fleet supply, meaning that marine freight firms expand their capacity to meet the increasing demand. New ships will be taken 2 or 3 years to build, and the economic circumstances and condition of raw materials market would be different during this period. The new-built market would not react to the market at the same time, so this market

[2]Source: The Baltic Exchange

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is rather stable. It may not a influential factor of marine freight rates. In second-hand market, due to the building time of new ships, the second-hand ships become substitutes, and the price of this market will also influence the fleet supply. Buying second-hand ships is able to react to the increasing demand more rapidly, and the only difference of second-hand and new-built market is the age of ships. The demolition market, scrap market, is a place which marine freight firms want to prevent them from bankruptcy, scrapping their old ships, and the scrap metal of ships can generate profits. The increasing of scrap metal will also impact on the price of demolition market. All these four markets could influence the supply side, fleet supply, of marine freight market. But the relation between these four markets and fleet supply is also a research restriction of this study, it is hard to take all factors into account. New-built market is rather easy, but second-hand and demolition markets are difficult to be quantified. Starting from 2006, BDI soared into highest point, and many marine freight firms want to benefit from the prospect of increasing seaborne trade, buying many ships to meet the demand. After the ships had been built, financial crisis also happened. Demand side decreased sharply, while supply side increased too much, causing BDI to plunge. This event raises the importance that marine freight rates can also be heavily influenced by supply side, although it is rather stable in short-term. A inclusive way of considering the four markets that could be influential factors of fleet supply, the stocks of marine freight companies are included as explanatory factors of supply side, because marine freight firms are the participants of these four markets.

The main purpose of this study is to test whether the economic tracking portfolio could track BDI through out-of-sample tracking performance, tracking error. If this ETP tracks well, it could be constructed as hedging tool for practitioners to eliminate the economic risk of BDI. The base assets consists of five industries, construction materials, diversified mining, iron and steel, marine freight and logistics, and grains. The data composition of this study resembles Junttila (2007), using international data rather than the data from a closed-economy. Avoiding the problem of overfitting, totally 14 assets are included. The way of in-sample and out-of-sample estimates is similar to that of Hayes (2001), implementing different forecast horizons and training periods to test the stability out-of-sample portfolio weights. The results of in-sample tests show that the returns of diversified mining and iron steel contain the most information about future BDI, and the

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out-of-sample forecasts indicate that the portfolio weights estimated by recursive perform better than those of rolling window. Another outcome confirmed from the in-sample and out-of-sample estimation is that the tracking portfolio performs better in the period of structural break compared to other two sub-samples, but this hedging portfolio could capture BDI on the whole.

The remainder of this paper is set out as follows: Section 2 discusses the previous works on the linkage between asset prices and economic variables, and the empirical researches of ETP. Section 3 defines the methodology of economic tracking portfolio. Section 4 reports the results of in-sample and out-of-sample tests and the analysis. Section 5 contains the conclusion of this study.

2 Literature Review

The approach of economic tracking portfolio is a new concept after many discussions about linking asset returns and macroeconomic variables in financial economics during past years, and many papers studies the directions of this linkage. That is, the asset returns cloud be explained by macroeconomic variables or the asset return would interpret macroeconomic variables.

The first direction can be viewed as regressing asset returns on economic variables. Chen et al. (1986) find that economic variables, such as spread between long and short interest rates, expected and unexpected industrial production and spread between high- and low-grade bonds are significantly influence stock market returns. Ferson and Harvey (1991) note that the stock market premium captures the stock portfolios, and the premium of interest captures the bond returns. Jones et al. (1998) confirm that assets are expected to earn higher returns if they are exposed to the macroeconomic risk that occurred at predictable time. Ferson and Korajczyk (1995) provide the evidence that larger fraction of security returns can be explained by the economic risk variables by testing single- and multiple- beta models. Chan et al. (1998) use multifactor pricing model to examine that, except for default premium and term premium, macroeconomic variables cannot capture

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return comovements. Vassalou (2000) addresses that exchange rate and and foreign inflation can partly interpret the cross-section equity return within countries.

The second direction can be consider as regressing economic variables on asset returns. Harvey (1989) states that bond and stock market both contain the information about economic growth, and the yield curve explain over 30% more than stock market 5%. Estrella and Mishkin (1998) examine the performance of financial variables in predicting U.S. recession, and find that stock prices are helpful in forecasting economic situation one- to - three quarters ahead. Liew and Vassalou (2000), using the data from ten markets, find that the return factors, SMB and HML, can predict future GDP growth.

The key paper of this study is Lamont (2001). Lamont proposes the concept of economic tracking portfolio (ETP), using current asset returns containing information about macroeconomic situations to capture the innovation in expectation about future economic variables. The economic tracking portfolios are constructed for tracking seven macroeconomic variables, including industrial production growth, real consumption growth, real labor income growth, inflation, excess stock returns, excess bond returns, and Treasury bill returns. The explanatory variables consist of 13 base assets, including four bond portfolios, eight stock portfolios, and the market portfolios. He makes an assumption that the expected returns of base assets are linear function of lagged control variables, so nine control variables are included into the economic tracking portfolios. All variables are monthly data and calculated in the form of log return. Regressing 12 months ahead target variables on the current base assets to obtain the portfolio weights, Lamont concludes that the economic tracking portfolio is useful forecasting future economic variables, and raised the important role of control variable in the tracking portfolio.

After that, some financial economists try to verify this approach of economic tracking portfolio. Christoffersen and Slok (2000) apply ETP to testing whether the asset prices contain information about future economic development in transition economies. Using monthly data of Czech Republic, Hungry, Poland, Russia, Slovakia and Slovenia from 1994 to 1999, they find that exchange rates, interest rates and stock prices can predict future movement of economies in these countries. Hayes (2001) employs this methodol-

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ogy to test three macroeconomic variables, inflation, industrial production growth and growth in the volume of retail sales, in U.K. , and wants to see whether ETP is helpful to economic assessment. The in-sample tests show that ETP can predict future target variables, but this tracking portfolios perform poorly on out-of-sample tests. Less rebalancing frequency and restriction of base assets do not improve the poor tracking performance of out-of-sample. Hayes suggests that mapping of asset price fundamentals to macroeconomic variables may be more successful. Junttila (2004) uses the ETP approach to the IT-intensive stock market in Finland. He concludes that base assets indeed contain information about future economic variables, different industrial portfolios holding different information, and says that the role of control variable is not important in a closed-economy context. Raunig (2007) constructs economic tracking portfolios to track future industrial production growth and inflation in Austria, and it turns out that the out-of-sample tests of ETP help forecast industrial production growth, but predict inflation poorly. So far, studies verifying ETP are all implemented in a closed-economy. Junttila (2007) extends ETP approach to international assets, using excess currency returns and excess stock returns of U.S., Italy, France and Germany to track industrial production growth and inflation of each country. Control variables are also included in this paper, but the analysis does not mention the importance of them. He suggests that the problems of previous studies could be using closed-economy data and larger numbers of base assets, so uses international data in his research. And the out-of-sample results indicate that using international data is possible to capture the development of macroeconomies.

3 Methodology

Applying Lamont's (2001) economic tracking portfolio (ETP) model as the theoretical framework, this study investigates the tracking performance of Baltic Dry Index by dynamic portfolio strategy.

Lamont proposes the concept of economic tracking portfolio for replicating economic variables, constructing portfolios of base assets that can forecast target variables.

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First, decompose the target variable to see which components will be track. Any target variable at time $t+k$, y_{t+k}, can be expressed the sum of prior conditional expectation and a one-period forecast error, e_{t+k}:

$$y_{t+k} = E_{t+k-1}[y_{t+k}] + e_{t+k} \tag{1}$$

The conditional expectation at time $t+k-1$ can be substituted for the sum of the conditional expectation at time $t+k-2$ and one-period revision between time $t+k-2$ to $t+k-1$ as below:

$$y_{t+k} = E_{t+k-2}[y_{t+k}] + (E_{t+k-1} - E_{t+k-2})[y_{t+k}] + e_{t+k} \tag{2}$$

We can also do backwardly recursive on right-hand side of Eq. (2), showing that the target variable is the sum of conditional expectation at time $t-1$ and $k+1$ one-period conditional expectation revisions:

$$y_{t+k} = E_{t-1}[y_{t+k}] + \sum_{j=0}^{k}(E_{t+k-j} - E_{t+k+j-1})[y_{t+k}] \Rightarrow y_{t+k} = E_t[y_{t+k}] \tag{3}$$

More general form of the equations derived above as follows:

$$\begin{aligned} y_{t+k} &= E_{t-1}[y_{t+k}] + (E_t - E_{t-1})[y_{t+k}] + \sum_{j=1}^{k}(E_{t+j} - E_{t+j-1})[y_{t+k}] \\ &= E_{t-1}[y_{t+k}] + (E_t - E_{t-1})[y_{t+k}] + \xi_{t,t+k} \end{aligned} \tag{4}$$

where $\xi_{t,t+k} = \sum_{j=1}^{k} e_{t+j} = \sum_{j=1}^{k}(E_{t+j} - E_{t+j-1})[y_{t+k}]$

Apparently, the realization of target variable is the process of conditional expectation revisions, the sum of conditional expectation at time $t-1$, the revision of expectation between time $t-1$ and t, and future expectation revisions.

Economic tracking portfolio is constructed based on unexpected returns of base assets, relating maximally the unexpected returns of portfolio to the unexpected components of

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target variable in future period t+k, y_{t+k}. The tracking portfolio returns is $r_t = bR_{t-1,t}$, where $R_{t-1,t}$ is a $N \times 1$ column vector consists of base assets in period from $t-1$ to t.

The tracking portfolio is structured of unexpected returns on the base assets. Unexpected returns denote actual returns minus expected returns, with notation $\widetilde{R}_{t-1,t} \equiv R_{t-1,t} - E_{t-1}[R_{t-1,t}]$. The unexpected components of future target variable is "news" about y_{t+k}, where y_{t+k} is Baltic Dry Index in period $t+k$. The notation $\Delta E_{t+k} \equiv E_t[y_{t+k}] - E_{t-1}[y_{t+k}]$, called innovation in expectations, represents the news about y_{t+k}.

The portfolio weights are estimated for regression $\Delta E_t[y_{t+k}]$ on $\widetilde{R}_{t-1,t}$, maximizing the correlation between the Baltic Dry Index and fitted value, $\widetilde{r}_{t-1,t}$. Based on the discussion above, the key assumption of this method can be illustrated the projection equation:

$$\Delta E_t[y_{t+k}] = a\widetilde{R}_{t-1,t} + \eta_t \tag{5}$$

where η_t is the tracking error that is orthogonal to the unexpected returns, and $\mathbf{a}$ is a $1 \times N$ row vector representing the portfolio weights. Since changes in equity prices reflect the revisions of future dividends, cashflow, and risk premium, $\mathbf{a}$ should be non-zero. Both left- and right-hand side are mean zero expectational errors, so there is no intercept in Eq. (5).

An ETP applies unexpected returns on base assets to track one-period revisions in expectations of target variable k periods ahead, but this revision of left-hand side in Eq. (5) is unobservable. So we need to drive an alternative that can use y_{t+k} rather than $\Delta E_t[y_{t+k}]$. Substituting Eq. (5) into Eq. (4), this gives:

$$y_{t+k} = E_{t-1}[y_{t+k}] + a\widetilde{R}_{t-1,t} + \eta_t + \xi_{t,t+k} \tag{6}$$

Now, the second assumption is made that the expected returns on base assets at time t can be written as the linear function of control variables:

$$E_{t-1}[R_{t-1,t}] = dZ_{t-1} \tag{7}$$

where Z_{t-1} is a $L \times 1$ column vector of control variables at time $t-1$, d is an $N \times L$ matrix. Then, the unexpected returns on base assets can be represented in another way:

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$$\widetilde{R}_{t-1,t} = R_{t-1,t} - dZ_{t-1} \tag{8}$$

Eq. (8) can be used to replace $E_{t-1}[R_{t-1,t}]$ in Eq. (6):

$$y_{t+k} = E_{t-1}[y_{t+k}] + a(R_{t-1,t} - dZ_{t-1}) + \eta_t + \xi_{t,t+k} \tag{9}$$

Lastly, define the projection equation of the lagged conditional expectation of $[y_{t+k}]$ on lagged control variables:

$$E_{t-1}[y_{t+k}] = fZ_{t-1} + \mu_{t-1} \tag{10}$$

Substituting Eq. (10) into Eq. (9) gives:

$$\begin{aligned} y_{t+k} &= aR_{t-1,t} + fZ_{t-1} - adZ_{t-1} + \mu_{t-1} + \eta_t + \xi_{t,t+k} \\ &= bR_{t-1,t} + cZ_{t-1} + \varepsilon_{t,t+k} \end{aligned} \tag{11}$$

where $b = a$, $c = f - ad$, and $\varepsilon_{t,t+k} = \mu_{t-1} + \eta_t + \xi_{t,t+k}$ orthogonal to both unexpected returns and control variables. This equation is more feasible than Eq. (5). Apply OLS regression to obtain the portfolio weights $\hat{b}$, then produces the unexpected components of ETP that maximally correlated with $\Delta E_t[y_{t+k}]$.

This study investigates the tracking performance of Baltic Dry Index as hedgers, rather than only forecasts the macroeconomic variable as policy makers. This is different from the original concept of economic tracking portfolio. In light of Lamont's (2001), control variables is important to control the tracking effectiveness. Hayes (2001) finds that control variables have little impact on the significance of ETP in some economic variables. And Junttila (2004) concludes that the control variables do not have influence on ETP. The importance of control variables is ambiguous. So I ignore the control variables here, the model estimated in this research as follows:

$$y_{t+k} = wR_{t-1,t} + \varepsilon_{t,t+k} \tag{12}$$

where w is portfolio weights and $\varepsilon_{t,t+k}$ is tracking error. A point should be noticed here is that the tracking portfolio constructed in this study is zero-cost portfolio, meaning that it does not restrict the portfolio weights w. Downing et al. (2012) also adopted

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this strategy and find that if imposing the restriction, long-only portfolio, on portfolio weights, the resulting performance is not nearly as successful in hedging macroeconomic variables.

4 Data

4.1 Variables selection

After data transformation the sample period runs from October 1994 to November 2017, including daily and weekly data. All data are compiled from datastream. The target variable, Baltic Dry Index (BDI), is the change in the log of price index from.

Baltic Dry Index is an index reflecting daily shipping rates of several shipping sizes that transport different dry bulk goods on multiple sea routes across the globe. The main dry bulk goods are iron ore and coal used for producing steel, and there are other raw materials, such as concrete, sands, or grains that are also transported by dry bulk carriers. The data are formed on the basis of their classification given by datastream, including diversified mining, iron and steel, marine freight and logistics, construction materials and grains. The industrial stocks are selected for base assets by market capitalization rankings according to each industry, while the futures traded frequently in the market are chosen as the assets of grains. All the explanatory variables are the log changes in the prices.

This study adapts an international view to traditional ETP using domestic data to forecast macroeconomic variables in a closed economy, and the concept is identical to that of Junttila (2007). Adding more international stocks of industries to the base assets reveals more information of BDI, but also potentially raises the problem of overfitting and poor out-of-sample performance. Basing on market capitalization in each industry, the companies ranked top five are selected for constructing the ETP. With restriction of listing dates, some of these stocks listed later than October 1994, resulting that not every top five company could be included in the base assets. A full list of data is given in Table 1.

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As a result, I perform the analysis by using log returns of fourteen assets, and the regression of this research is conducted on several horizons, that is, $k = 0, 5, 10, 15$,and 20 days and weeks.

4.2 Preliminary analysis

Baltic Dry Index in full sample period, illustrated in Figure 1, represents a structural break from August 2003 to December 2008. During this time period, there is a major change in the economic environment. Avoiding the influence of abnormal period on the data analysis, I split the research period into three sub-samples, October 1994 to August 2003, December 2008 to November 2017 and August 2003 to December 2008. It can also investigate the tracking performance in three sub-samples, especially the period of structural break.

Before the whole sample estimate and out-of-sample test, it is essential to analyze the correlations between the base assets and BDI. Table 2 shows the correlation coefficients of daily and weekly data. In general, no matter what data frequency is, it indicates that the asset returns are weakly correlated with the returns of target variables, but we can also discuss whether this study could be applied by the original framework of economic tracking portfolio.

The concept of ETP using asset returns at time t to predict target variable at time $t + k$ could be observed by correlations on different horizons, namely k. Check the forecasting ability of the base assets on the upper part of Table 3 showing correlation coefficients of daily data on different horizons. AAL correlates strongest with BDI, the coefficient being as strong as 0.0465. Most of asset returns, except those of grains, strongly correlate with BDI in 5 and 10 days, and weakest in 15 days. The correlations of weekly data shown in lower part of Table 3 presents a different outcome, and most of the highest correlation coefficients of each stock are in 0 week. That is, the returns of weekly data could contemporaneously reflect BDI, rather than forecast it in the future, like daily data. Not

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only industries contain different information about future BDI, but also data frequency.

5 Empirical results

5.1 In-sample estimates

Table 4-11, totally eight tables, show the results from the in-sample estimation. The statistical tests in these tables on the tracking ability of different industrial stocks are conducted by six Wald-tests, designed to reveal the information content of different industry. Wald1 tests the hypothesis that the weights of construction materials are jointly zero; Wald2 tests the hypothesis that the weights of diversified mining are jointly zero; Wald3 tests the hypothesis that the weights of iron steels are jointly zero; Wald4 tests the hypothesis that the weights of marine freight and logistics are jointly zero; Wald5 tests the hypothesis that the weights of grains are jointly zero; Wald6 tests the tracking ability of all the fourteen assets together. The estimates of portfolio weights represented in the tables can also confirm the preliminary analysis that the ETP is useful for tracking BDI. I analyze the in-sample estimation according to the Wald-test statistics of industries, checking the tracking ability of the base assets separately and the contents of BDI included in the industries on different forecast horizons and different data frequency.

First, from the results of daily data as shown in Tables 4, 6, 8 and 10, I observe that, in full-sample, the returns of construction materials, diversified mining and iron steel are able to track contemporaneous and future BDI at 10% significance level. The raw materials, main bulk goods transported by bulk carriers which shipping rates are calculated as BDI, are useful for hedging BDI. Compared to full-sample estimation, the portfolio weights of diversified mining, iron steel and grains in sub-sample1 only help forecast BDI in the future, reflecting that the base assets have the forecasting ability in this period. In sub-sample2, only one industry, iron steel, contains information track BDI at 0, 5 and 15 days, meaning that after the financial crisis, from 2007 to 2008, the raw materials cannot explain BDI. But during the period of structural break, sub-sample3, the raw material industries still remains tracking ability, even better than non-structural

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break period. The returns of marine freight freight only have significant effect during this period due to the surplus fleet supply after 2008. In other sub-samples, the returns of marine freight do not influence BDI like the structural break, and the reason may be that the long construction time of new ships cannot contemporaneously reflect marine freight rates. Before the end of financial crisis, 2008, the returns of BDI can be replicated by diversified mining very well, but the tracking effectiveness of this industry disappears after the structural break. On the contrary, before and after the structural break, iron steel can sufficiently predict BDI. It seems that the industrial condition in iron steel is an indicator predicting future BDI under normal economic circumstances. Wald6 indicates that, except for sub-sample2, the tracking portfolios has the ability to track BDI. Another point is that industrial circumstances of real estate industry is also a leading economic indicator, but the returns of construction materials do not significantly play role in sub-sample1 and sub-sample2, like those of marine freight industry. The reason is perhaps that after dot-com bubble and before financial crisis, the world economy was growing up, and real estate indeed plays role on forecasting future economy. The tracking portfolios in full-sample and sub-sample3 can track contemporaneous and future BDI at 0, 5 and 10 days at 5% significance level, while the tracking portfolio in sub-sample1 is able to predict future BDI at 10 and 20 days at 10% significance level.

Second, the results of weekly data are exhibited in Tables 5, 7, 9 and 11. The tracking effectiveness of tracking portfolios on weekly data are different from those of on daily data in sub-sample1 and sub-sample2. In full-sample, the results is similar to those of daily data, and the main industries of bulk goods still can track BDI contemporaneously, at 5% risk level, and the returns of diversified mining has the forecasting ability to track future BDI at 10 and 15 weeks. The returns of two industries in sub-sample1, diversified mining and iron steel, contain the information for forecasting the BDI at 10 and 20 weeks, and one thing can be confirm that the individual industry is able to track future BDI in this period, no matter what data frequency is. The estimation of weekly data in sub-sample2 is similar to that of daily data, only industrial difference. All returns of industries in sub-sample3 significantly track BDI, except for marine freight and grains predicting future BDI, and other industries can track contemporaneous and future BDI at 5, 10 and 15 weeks at 10% risk level. Compare to previous analysis of daily data, iron

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steel industry cannot track BDI very well in sub-sample2. Instead, the returns of diversified mining are able to track BDI in all four periods. Wald6 shows that the tracking portfolios track future BDI well at 10 weeks in full-sample, sub-sample1 and sub-sample3, but for sub-sample2.

According to the results discussed above, the portfolios track BDI very well in full-sample and sub-sample3, the tracking effectiveness during the structural break being better than those of in sub-sample1 and sub-sample2. And the representative industries that contain the most information for track and predict BDI are diversified mining and iron steel, because they are the main materials transported by dry bulk carrier.

5.2 Out-of-sample forecasts

Despite the fact that the tracking portfolio with appropriate properties indeed track BDI in in-sample estimates, it does not provide grounds for the practitioners to hedge BDI. For the sake of robustness, I test the out-of-sample performance of the BDI tracking portfolio. The hedgers would like to see whether the ETP captures BDI in response to the recent changes of base asset returns, suggesting that the revised expectation of investors on the base assets reflects future BDI. It raises two issues that should be taken into account when implementing the out-of-sample forecasts based on the available data: the choice of training period, how much should the past data be used to estimate the portfolio weights; the determination of rebalancing frequency, how often do the portfolio weights be re-estimated.

According to the conventional wisdom of estimation window, most financial practitioners use 5-year window, previous 60 monthly data, in their forecasting and performance analysis. Lamont (2001) notices that 5-year window is not long enough to catch the business cycles, and he suggests that 20-year period is better in tracking target variable in out-of-sample test. Because the sample period is not long enough to compute the out-of-sample portfolio weights and the data frequency does not include monthly data, I do not apply this estimation window. Denoting m as training period used to estimate the

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portfolio weights, I examine the tracking performance of out-of-sample by trying different estimation window in this study, $m = 60, 120, 180$ and 240 on daily data, $m = 40, 60, 800$ and 100 on weekly data.

Another issue of portfolio weights rebalancing refers to reaction speed of true portfolio weights, meaning that reaction time between BDI and the tracking portfolios is unknown, and there is no theoretical basis to tell us how to determine the rebalancing frequency. If the true portfolio weights react to BDI frequently, adjusting the portfolio weights is necessary, capturing the target variable more precisely; if the true portfolio weights react to BDI infrequently, adjusting the portfolio weights would be unnecessary, or the portfolios predict incorrect BDI. So it also need to be tested. I rebalance the portfolios of daily data by daily and weekly frequency, and those of weekly data are rebalanced weekly and monthly.

The out-of-sample tests are conducted by rolling and recursive regressions: $r^{ETP}_{\tau+b} = \hat{w}_\tau R_{\tau+1}$, where τ is the end of day or week, b is the rebalancing frequency, and $\hat{w}_\tau$ is the portfolio weights calculated from Eq. (12) using previous m observations. This process is repeated by daily and weekly rebalancing on daily data, and by weekly and monthly rebalancing on weekly data to obtain $\hat{w}R_{t-1,t}$ which is from a dynamic portfolio strategy.

Running the rolling and recursive regression, I compare the tracking error, defined as $\sigma(r^{ETP}_t - y_{t+k})$, of rolling window with that of recursive window, checking whether the tracking error will decrease when extending the training period. In addition, this study also implements another regression to test the stability of the portfolio weight as follows:

$$
\begin{aligned}
y_{t+k} &= \alpha + \gamma \hat{b}_t R_{t-1,t} + \eta_{t,t+k} \\
&= \alpha + \gamma r^{ETP}_t + \eta_{t,t+k}
\end{aligned}
\tag{13}
$$

The null hypothesis of γ is one. If the tracking portfolio tracks BDI perfectly, no matter using rolling or recursive window, γ would be one. If the tracking performance of the portfolio fully deteriorates, γ would be zero. Because of errors in parameter estimation, this coefficient would be less than one. As long as γ is significantly different from zero

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and positive, the tracking portfolio could track BDI to some extent.

Before the results of sub-samples are discussed, the overall conclusion emerging from these results is that the tracking errors of the ETP decrease over longer training period. The longer the estimation window is, the portfolio would be more precise. And there are not consistent results that longer forecast horizons lead to decreased tracking errors. Besides, smaller tracking error does not completely indicate that the tracking portfolio tracks well, and it also have to make sure γ is significantly positive. The robustness tests of full-sample and sub-sample3 suggest that the ETP performs better in these two sample periods than others, like the outcome of in-sample tests. Overall, the estimates of γ show that the out-of-sample forecast of the tracking performance is very poor, such results being similar to those of Hayes (2001). Many coefficients are negative, implying that this tracking portfolio captures wrong direction of BDI.

In full-sample, the coefficients of daily and weekly data that are significantly positive and insignificantly different from one are estimated on recursive window. Those of daily data are close to one with longer forecast horizon, $k = 20$ being the best. And those of weekly data are $k = 20$ on weekly rebalancing and with $k = 10$ on monthly rebalancing, but there is little difference between 10 and 20 weeks horizons on monthly rebalancing. In sub-sample1, regardless of data frequency, training period, forecast horizon, rolling or recursive window, only one coefficient is significantly positive, but it is too low to track BDI. Others are all significantly different from zero and negative. The tracking portfolio has no tracking power in this period. In sub-sample2, the tracking performance of daily data is worse than that of sub-sample1, none of coefficients being different from zero. There is better tracking performance on weekly data, 10 weeks forecast horizon conducted on recursive window, weekly and monthly rebalancing. In-sub sample3, it seems that the tracking performance of daily data is similar to that of full-sample, and the difference is that rolling window performs better in this period compared to other sub-samples. More coefficients are significantly positive and larger than 0.1. Although the coefficients rebalanced weekly and monthly on recursive window with 5 weeks forecast horizon are different from one, they are larger enough to capture BDI. Finally, regardless of weekly or monthly rebalancing, the γ of weekly data with 20 weeks forecast horizon

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are significantly positive. Furthermore, the coefficients estimated by 100 weeks training period are the largest of the robustness tests in this period.

In addition to the analysis above, we can also observe the figures to check the tracking effectiveness of the BDI tracking portfolio, and the returns and simulated index are illustrated in Figures 12-13. Because the data are too long in each sample period, the figures in appendix only present 100 points start from the first point of estimation window, making the analysis more easily. Each figure I choose the largest γ to show the tracking performance of the ETP. From these figures, three findings are made here. First, the BDI tracking portfolio captures the trend of the target variable, although the γ is very low in sub-sample1 and sub-sample2. And the return of figures, the returns generated from the weekly data are more volatile than those of daily data, but all of them can track BDI. Second, recursive window is better than rolling window in this study. It is different to many previous financial studies suggesting that the rolling window is better than recursive window. Third, rebalancing frequency isn't influence the tracking ability of the BDI tracking portfolio. Irrespective of daily or weekly rebalancing in daily data, and weekly or monthly rebalancing in weekly data, the simulated indices almost overlap the BDI.

6 Conclusions

The relationship between stock market returns and macroeconomic variables have been the main research subject that are discussed in many papers during past years in financial economics. This study utilizes the concept of economic tracking portfolio proposed by Lamont (2001), using international stock returns to forecast future Baltic Dry Index.

In-sample tests, the results being similar to those of Hayes (2001), all portfolio weights are very small, so I analyze the industrial predicting power by Wald tests. The tests show that the BDI tracking portfolio tracks BDI mainly by the returns of two industries, diversified mining and iron steel. It is reasonable, because the industrial circumstances of these two are often used to explain and reflect future economy in the world. And the

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returns of base assets indeed contain the information about future BDI, indicating that the forecasting ability of BDI tracking portfolio exists. The in-sample tests in each sub-samples show that in full-sample and sub-sample3 the BDI tracking portfolio can predict future BDI to some extent. The outcome of out-of-sample forecasts suggest that many coefficients, γ, are negative, wrong direction in tracking the target variable, especially in rolling window. The recursive window is better than rolling window to implement out-of-sample test in full-sample and sub-sample3, except for the results of weekly data in sub-sample3, and the coefficients of γ are larger enough to track BDI. In these two sample periods, the coefficients increase along with longer forecast horizon, proving that the tracking portfolio contain information about future BDI. One thing can be confirmed that in-sample and out-of-sample tests, ETP in full-sample and sub-sample3 has significant effects. On the other hand, the BDI tracking portfolio can track the target variable to some extent during the whole sample period, and have good predicting ability after the financial crisis. And the figures shown in appendix seem to be contradicted to the numbers analysis, the returns of ETP and simulated indices almost perfectly overlapping the BDI. I think the problem is that the value of Baltic Dry Index is very large, and the volatile returns of ETP is hard to be reflected in the simulated indices, making it overlapping target variable.

In order to make this study more persuasive, I also try to add the stocks that do not include in this study to the tracking portfolio, because they listed during the research period. After the economy of Chinese grown up, many international companies of diversified mining and iron steel in China rank top 10 in the world. But none of them include in my BDI tracking portfolio due to listing dates, because they listed later than October 1994. Avoiding adding too many base assets to raise the problem of overfitting, I only add top 3 of each industry, totally 15 stocks, into my portfolio. But the results is quietly worse than those I present here.

From the empirical results, BDI is a very noisy variable, and the critical issue of the economic tracking portfolio is base assets selection. Maybe the futures of exchange rates and interest rates of development countries should be take into account, but it also have to control the quantity of base assets, avoiding overfitting.

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Appendices

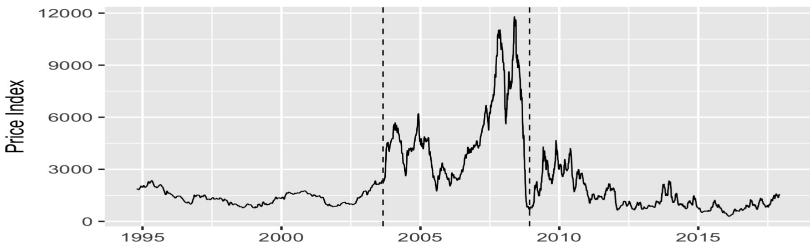

Figure 1: Baltic Dry Index

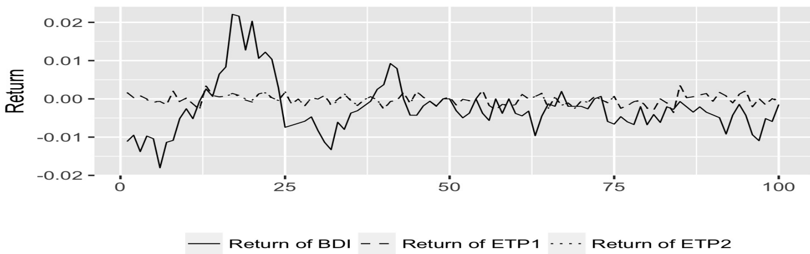

Figure 2: Return of daily data sub-sample1. ETP1 is daily rebalanced and calculated on recursive window with $k = 15$; ETP2 is weekly rebalanced and calculated on recursive window with $k = 15$.

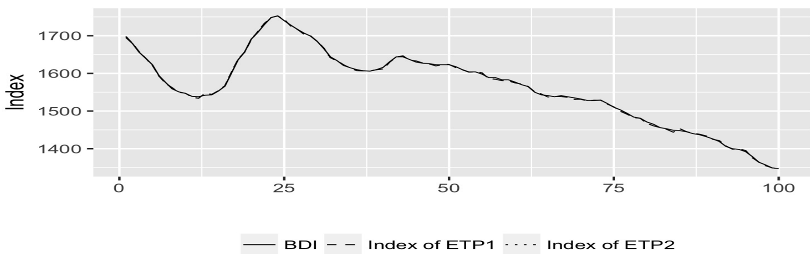

Figure 3: Index of daily data sub-sample1. ETP1 is daily rebalanced and calculated on recursive window with $k = 15$; ETP2 is weekly rebalanced and calculated on recursive window with $k = 15$.

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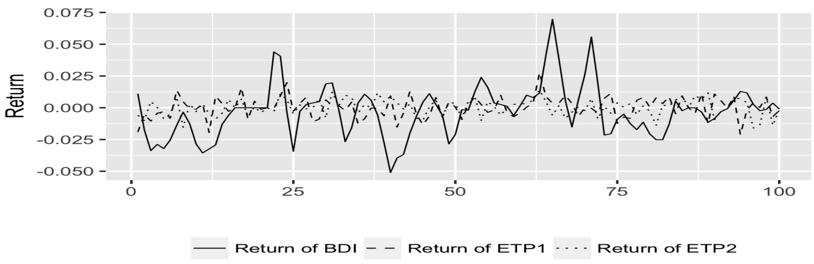

Figure 4: Return of daily data in sub-sample2. ETP1 is daily rebalanced and calculated on rolling window with $k = 0$, $m = 120$; ETP2 is weekly rebalanced and calculated on rolling window with $k = 0$, $m = 120$.

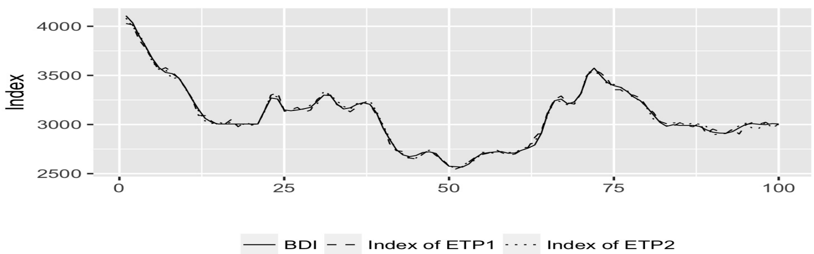

Figure 5: Index of daily data in sub-sample2. ETP1 is daily rebalanced and calculated on rolling window with $k = 0$, $m = 120$; ETP2 is weekly rebalanced and calculated on rolling window with $k = 0$, $m = 120$.

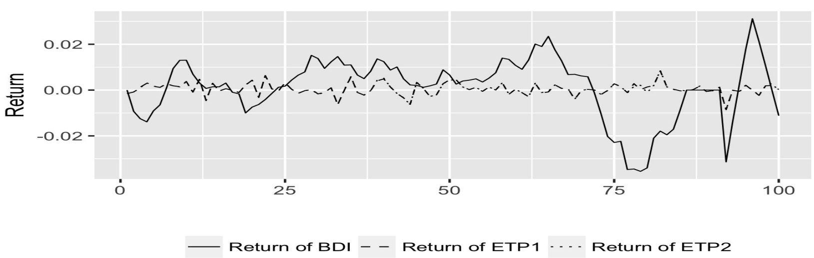

Figure 6: Return of daily data in sub-sample3. ETP1 is daily rebalanced and calculated on recursive window with $k = 5$; ETP2 is weekly rebalanced and calculated on recursive window with $k = 5$.

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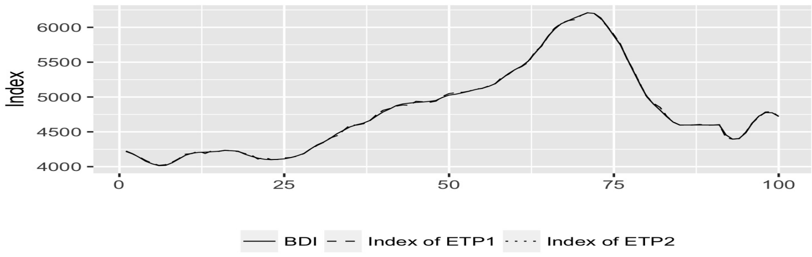

Figure 7: Index of daily data in sub-sample3. ETP1 is daily rebalanced and calculated on recursive window with $k = 5$; ETP2 is weekly rebalanced and calculated on recursive window with $k = 5$.

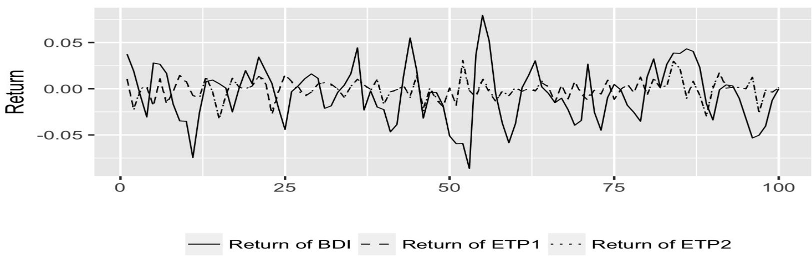

Figure 8: Return of weekly data sub-sample1. ETP1 is weekly rebalanced and calculated on recursive window with $k = 5$; ETP2 is monthly rebalanced and calculated on recursive window with $k = 5$.

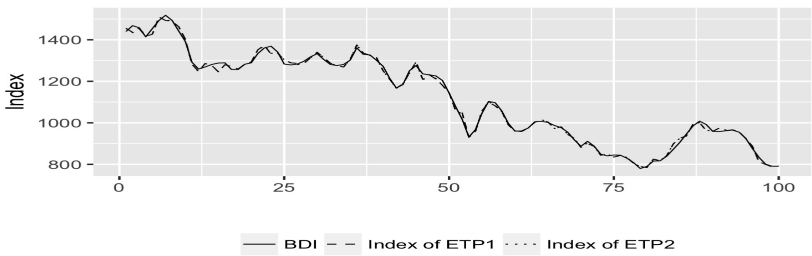

Figure 9: Index of weekly data sub-sample1. ETP1 is weekly rebalanced and calculated on recursive window with $k = 5$; ETP2 is monthly rebalanced and calculated on recursive window with $k = 5$.

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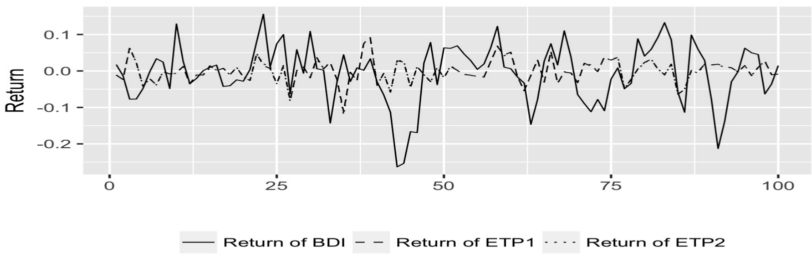

Figure 10: Return of weekly data in sub-sample2. ETP1 is daily rebalanced and calculated on recursive window with $k = 10$; ETP2 is monthly rebalanced and calculated on recursive window with $k = 10$.

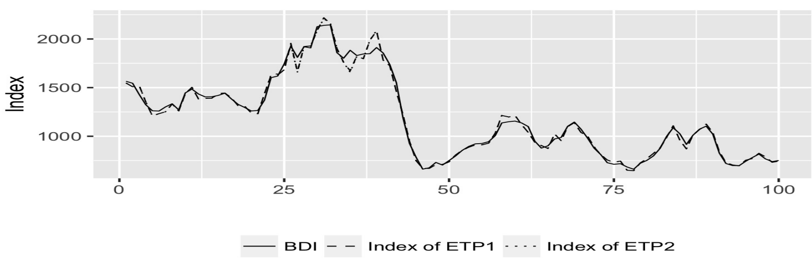

Figure 11: Index of weekly data in sub-sample2. ETP1 is daily rebalanced and calculated on recursive window with $k = 10$; ETP2 is monthly rebalanced and calculated on recursive window with $k = 10$.

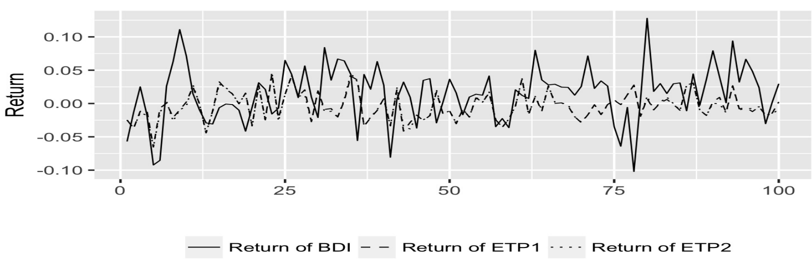

Figure 12: Return of weekly data in sub-sample3. ETP1 is daily rebalanced and calculated on rolling window with $k = 20$, $m = 100$; ETP2 is monthly rebalanced and calculated on rolling window with $k = 20$, $m = 100$.

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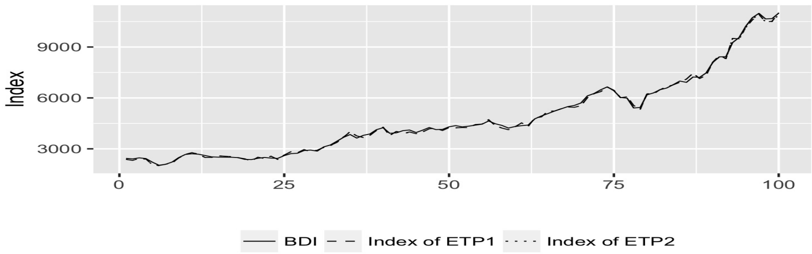

Figure 13: Index of weekly data in sub-sample3. ETP1 is daily rebalanced and calculated on rolling window with $k = 20$, $m = 100$; ETP2 is monthly rebalanced and calculated on rolling window with $k = 20$, $m = 100$.

Table 1: Base Assets

Identifier	**Company Name**	**Industry**
LHN	Lafargeholcim Ltd	Construction Materials
CRH	CRH PLC	Construction Materials
BHP	BHP Billiton Ltd	Diversified Mining
RIO	Rio Tinto Ltd	Diversified Mining
AAL	Anglo American PLC	Diversified Mining
GMEXICOB	Grupo Mexico SAB de CV	Diversified Mining
SVS	Siderurgica Venezolana Sivensa SA	Iron and Steel
VALE3	VALE SA	Iron and Steel
MAERSKb	AP Moeller - Maersk A/S	Marine Freight and Logistics
KNIN	Kuehne und Nagel International AG	Marine Freight and Logistics
BOLL	Bollore SA	Marine Freight and Logistics
Grain	**Exchange**	
Corn	Chicago Board of Trade	
Wheat	Chicago Board of Trade	
Wheat	Kansas City Board of Trade	

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Table 2: Correlation between BDI and base assets

	BDI				
Data Frequency	Daily				
k	0	5	10	15	20
LHN	0.0088	0.0175	0.0126	−0.0124	0.0071
CRH	−0.0211	0.0214	−0.0005	−0.0280	0.0039
BHP	0.0331	0.0272	0.0242	0.0037	0.0122
RIO	0.0438	0.0385	0.0284	0.0103	0.0177
AAL	0.0111	0.0465	0.0306	0.0113	0.0143
GMEXICOB	0.0118	0.0245	0.0258	0.0046	0.0289
SVS	0.0430	0.0258	0.0267	0.0194	0.0100
VALE3	0.0082	0.0448	0.0365	0.0143	0.0211
MAERSKb	0.0166	0.0251	0.0228	−0.0149	0.0152
KNIN	0.0025	0.0234	0.0310	−0.0009	0.0004
BOLL	0.0097	0.0101	0.0000	−0.0148	−0.0027
Corn(CBT)	−0.0004	−0.0004	0.0048	−0.0011	−0.0098
Wheat(CBT)	0.0121	−0.0013	0.0182	0.0043	0.0084
Wheat(KCBT)	0.0142	0.0013	0.0248	0.0011	0.0114
Data Frequency	Weekly				
LHN	0.0255	0.0197	0.0269	−0.0600	0.0512
CRH	−0.0182	0.0359	0.0130	−0.0173	0.0154
BHP	0.1199	0.0484	0.0767	−0.0604	0.0386
RIO	0.1234	0.0487	−0.0196	−0.0182	0.0189
AAL	0.0983	0.0712	0.0388	−0.0650	0.0569
GMEXICOB	0.0562	0.0571	0.0323	0.0188	−0.0208
SVS	0.0773	−0.0267	−0.0050	−0.0286	−0.0110
VALE3	0.0796	0.0869	0.0127	−0.0085	0.0299
MAERSKb	0.0751	0.0451	0.0593	−0.0587	0.0063
KNIN	0.0171	0.0510	0.0469	−0.0005	0.0095
BOLL	0.0424	0.0408	−0.0144	−0.0344	0.0123
Corn(CBT)	0.0218	0.0158	−0.0089	−0.0118	−0.0625
Wheat(CBT)	0.0497	0.0302	0.0090	−0.0189	−0.0160
Wheat(KCBT)	0.0536	0.0439	0.0212	−0.0135	−0.0103

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Table 3: Descriptive statistics of BDI and base assets

Data Frequency			Daily			
	Min.	**1st Qu.**	**Mean**	**3rd Qu.**	**Max.**	**S.D.**
BDI	−0.1207	−0.0073	0.0000	0.0069	0.1366	0.0174
LHN	−0.2007	−0.0092	0.0001	0.0098	0.2131	0.0217
CRH	−0.1809	−0.0093	0.0003	0.0103	0.1410	0.0200
BHP	−0.1408	−0.0098	0.0002	0.0104	0.1146	0.0183
RIO	−0.4194	−0.0100	0.0003	0.0106	0.1435	0.0202
AAL	−0.2260	−0.0127	0.0001	0.0134	0.2053	0.0278
GMEXICOB	−0.1838	−0.0117	0.0006	0.0125	0.1744	0.0249
SVS	−0.6504	0.0000	0.0016	0.0000	0.4050	0.0407
VALE3	−0.2055	−0.0122	0.0005	0.0131	0.2955	0.0270
MAERSKb	−0.1392	−0.0101	0.0003	0.0106	0.2337	0.0209
KNIN	−0.1823	−0.0075	0.0005	0.0081	0.1730	0.0185
BOLL	−0.2224	−0.0073	0.0006	0.0082	0.1087	0.0181
Corn(CBT)	−0.2762	−0.0089	0.0001	0.0091	0.1276	0.0177
Wheat(CBT)	−0.2861	−0.0100	0.0000	0.0096	0.0810	0.0195
Wheat(KCBT)	−0.1259	−0.0100	0.0000	0.0096	0.0810	0.0172
Data Frequency			Weekly			
BDI	−0.5373	−0.0325	−0.0002	0.0298	0.4457	0.0712
LHN	−0.2012	−0.0229	0.0005	0.0236	0.2464	0.0447
CRH	−0.2558	−0.0230	0.0017	0.0279	0.1788	0.0429
BHP	−0.2221	−0.0227	0.0011	0.0255	0.1518	0.0404
RIO	−0.4938	−0.0229	0.0014	0.0279	0.2477	0.0455
AAL	−0.4317	−0.0304	0.0003	0.0342	0.3791	0.0598
GMEXICOB	−0.3337	−0.0274	0.0032	0.0351	0.2598	0.0563
SVS	−0.6504	−0.0248	0.0079	0.0310	0.6931	0.1017
VALE3	−0.2856	−0.0337	0.0023	0.0349	0.3381	0.0603
MAERSKb	−0.2231	−0.0234	0.0013	0.0283	0.2774	0.0452
KNIN	−0.2076	−0.0172	0.0027	0.0215	0.2376	0.0368
BOLL	−0.2237	−0.0175	0.0028	0.0227	0.2022	0.0382
Corn(CBT)	−0.3278	−0.0203	0.0004	0.0211	0.2325	0.0405
Wheat(CBT)	−0.1763	−0.0113	0.0000	0.0105	0.2330	0.0418
Wheat(KCBT)	−0.1709	−0.0244	0.0000	0.0245	0.1687	0.0399

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Table 4: In-sample estimates of daily data in full sample (1994/10/19-2017/11/30)

Data Frequency	Daily				
k	0	5	10	15	20
Portfolio Weights					
LHN	0.0079	−0.0049	−0.0019	−0.0067	−0.0006
CRH	−0.0349***	0.0004	−0.0206	−0.0285**	−0.0046
BHP	0.0034	−0.0086	0.0022	−0.0060	−0.0041
RIO	0.0357**	0.0266*	0.0143	0.0129	0.0141
AAL	0.0006	0.0179*	0.0082	0.0144	0.0012
GMEXICOB	0.0048	0.0021	0.0072	0.0025	0.0173*
SVS	0.0181***	0.0104*	0.0110**	0.0086	0.0039
VALE3	−0.0001	0.0194**	0.0162*	0.0098	0.0077
MAERSKb	0.0121	0.0037	0.0087	−0.0126	0.0088
KNIN	−0.0036	0.0082	0.0228*	0.0057	−0.0073
BOLL	0.006654	−0.0024	−0.0088	−0.0118	−0.0074
Corn(CBT)	−0.0125	−0.0051	−0.0145	−0.0047	−0.0256
Wheat(CBT)	0.0023	−0.0087	−0.0076	0.0139	0.0023
Wheat(KCBT)	0.0194	0.0063	0.0358	−0.0112	0.0208
Mean return (%)	−0.0026	−0.0028	−0.0028	−0.0025	−0.0025
Standard deviation(%)	0.1277	0.1173	0.1159	0.0871	0.0776
Wald 1	7.2720**	0.1720	2.8120	5.9960**	0.1427
	(0.0264)	(0.9176)	(0.2452)	(0.0499)	(0.9311)
Wald 2	11.2500**	8.1320*	3.7290	3.4010	4.3260
	(0.0239)	(0.0868)	(0.4439)	(0.4931)	(0.3637)
Wald 3	10.7700***	7.8980**	7.0200**	3.5210	1.1640
	(0.0046)	(0.0193)	(0.0299)	(0.1720)	(0.5588)
Wald 4	1.3690	0.5384	4.1150	2.1330	1.0370
	(0.7128)	(0.9104)	(0.2493)	(0.5453)	(0.7922)
Wald 5	1.9010	0.4685	3.6040	0.3745	3.2140
	(0.5932)	(0.9258)	(0.3075)	(0.9455)	(0.3598)
Wald 6	32.4700***	27.3300**	26.6500**	14.9800	11.8800
	(0.0034)	(0.0174)	(0.0214)	(0.4517)	(0.6160)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

P-values of wald test are in parentheses.

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Table 5: In-sample estimates of weekly data in full sample (1994/10/19-2017/11/30)

Data Frequency	Weekly				
k	0	5	10	15	20
Portfolio Weights					
LHN	-0.0165	-0.0635	-0.0192	-0.0830	0.0822
CRH	-0.1364^{**}	0.0162	-0.0267	0.0459	-0.0306
BHP	0.0927	-0.0024	0.2895^{***}	-0.1238	0.0589
RIO	0.1063	-0.0110	-0.2421^{***}	0.0948	-0.0439
AAL	0.0381	0.0365	0.0265	-0.0821^{*}	0.0775
GMEXICOB	-0.0014	0.0286	0.0216	0.0783^{*}	-0.0628
SVS	0.0515^{**}	-0.0200	-0.0060	-0.0186	-0.0110
VALE3	0.0246	0.0727^{*}	-0.0154	0.0257	0.0188
MAERSKb	0.0848	0.0164	0.0687	-0.0788	-0.0222
KNIN	-0.0523	0.0497	0.0722	0.0862	-0.0242
BOLL	0.0423	0.0415	-0.0567	-0.0463	0.0028
Corn(CBT)	-0.0314	-0.0226	-0.0488	-0.0030	-0.1426^{**}
Wheat(CBT)	-0.0112	-0.0699	-0.0508	-0.0642	0.0222
Wheat(KCBT)	0.0881	0.1276	0.0881	0.0468	0.0237
Mean return (%)	-0.0153	-0.0017	-0.0209	-0.0207	-0.0260
Standard deviation(%)	1.2899	0.8171	1.0633	0.9083	0.8182
Wald 1	6.8470^{**}	1.1530	0.4626	2.0560	1.8930
	(0.0326)	(0.5619)	(0.7935)	(0.3577)	(0.3880)
Wald 2	13.8200^{***}	1.1180	18.6700^{***}	9.1830^{*}	5.3980
	(0.0079)	(0.8913)	(0.0009)	(0.0567)	(0.2488)
Wald 3	6.9360^{**}	4.1250	0.2249	1.1900	0.4812
	(0.0312)	(0.1271)	(0.8937)	(0.5517)	(0.7861)
Wald 4	3.4980	1.4670	4.0470	3.8890	0.3661
	(0.3211)	(0.6899)	(0.2564)	(0.2736)	(0.9472)
Wald 5	1.7070	1.5920	1.1550	0.4358	5.6810
	(0.6353)	(0.6612)	(0.7638)	(0.9327)	(0.1282)
Wald 6	40.4200^{***}	15.7700	26.7300^{**}	19.2300	15.4300
	(0.0002)	(0.3277)	(0.0209)	(0.1562)	(0.3493)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

P-values of wald test are in parentheses.

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Table 6: In-sample estimates of daily data in sub-sample1 (1994/10/19-2003/08/29)

Data Frequency	Daily				
k	0	5	10	15	20
Portfolio Weights					
LHN	−0.0012	−0.0034	−0.0024	−0.0011	0.0031
CRH	−0.0125	0.0064	0.0008	−0.0047	−0.0192**
BHP	0.0184	0.0050	−0.0086	0.0051	−0.0022
RIO	−0.0022	0.0005	0.0236**	0.0133	−0.0089
AAL	0.0028	0.0044	0.0091	0.0087	0.0023
GMEXICOB	−0.0029	−0.0048	0.0046	0.0113**	0.0157***
SVS	0.0046	0.0082**	0.0080**	0.0040	0.0028
VALE3	0.0005	0.0005	−0.0018	−0.0006	0.0005
MAERSKb	−0.0031	0.0031	−0.0029	−0.0054	0.0037
KNIN	0.0045	−0.0038	−0.0002	−0.0035	0.0053
BOLL	−0.0008	−0.0100	0.0049	−0.0005	−0.0065
Corn(CBT)	−0.0092	−0.0078	−0.0187	−0.0281**	−0.0268**
Wheat(CBT)	0.0024	−0.0085	−0.0168	−0.0069	−0.0028
Wheat(KCBT)	0.0049	0.0042	−0.0022	0.0099	0.0216
Mean return (%)	0.0089	0.0083	0.0085	0.0092	0.0093
Standard deviation(%)	0.0432	0.0510	0.0747	0.0677	0.0717
Wald 1	1.9430	0.7073	0.1503	0.3096	4.3570
	(0.3785)	(0.7021)	(0.9276)	(0.8566)	(0.1132)
Wald 2	3.7620	1.5390	8.1380*	10.1500**	8.4640*
	(0.4392)	(0.8196)	(0.0866)	(0.0380)	(0.0760)
Wald 3	1.5550	4.8800*	4.6540*	1.1300	0.5847
	(0.4595)	(0.0872)	(0.0976)	(0.5685)	(0.7465)
Wald 4	0.5419	2.3490	0.5959	0.8031	1.5700
	(0.9096)	(0.5032)	(0.8974)	(0.8487)	(0.6662)
Wald 5	0.7243	1.5640	9.6660**	7.8980**	6.4190*
	(0.8675)	(0.6675)	(0.0216)	(0.0482)	(0.0929)
Wald 6	8.0240	11.1500	23.9200**	19.5600	21.8900*
	(0.8881)	(0.6745)	(0.0468)	(0.1447)	(0.0810)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

P-values of wald test are in parentheses.

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Table 7: In-sample estimates of weekly data in sub-sample1 (1994/10/19-2003/08/29)

Data Frequency	Weekly				
k	0	5	10	15	20
Portfolio Weights					
LHN	0.0031	0.0244	−0.0287	−0.0101	−0.0045
CRH	0.0062	−0.0374	−0.0233	−0.0634	−0.0284
BHP	0.1037**	−0.0060	−0.0302	−0.0084	−0.0404
RIO	−0.0824	−0.0132	0.0655	0.0535	−0.0186
AAL	0.0318	0.0049	−0.0005	0.0042	0.0707**
GMEXICOB	−0.0251	0.0306	−0.0066	−0.0100	−0.0528**
SVS	0.0251*	−0.0110	−0.0344**	0.0020	−0.0028
VALE3	−0.0042	0.0189	−0.0208	0.0530**	0.0073
MAERSKb	0.0034	−0.0050	0.0659*	−0.0304	−0.0065
KNIN	−0.0280	0.0152	−0.0042	−0.0370	−0.0123
BOLL	−0.0236	0.0126	−0.0082	−0.0141	0.0236
Corn(CBT)	−0.0426	−0.0433	−0.0477	−0.0110	−0.0510
Wheat(CBT)	−0.0265	−0.0221	0.0764	−0.0538	−0.0479
Wheat(KCBT)	0.0626	0.0765	−0.0323	−0.0042	0.0337
Mean return (%)	0.0460	0.0421	0.0325	0.0335	0.0201
Standard deviation(%)	0.5311	0.3680	0.5551	0.5514	0.5627
Wald 1	0.0403	1.1130	1.3150	2.7360	0.5361
	(0.9801)	(0.5733)	(0.5181)	(0.2546)	(0.7649)
Wald 2	6.7280	1.5100	1.6520	1.5920	9.6860**
	(0.1510)	(0.8249)	(0.7995)	(0.8102)	(0.0461)
Wald 3	2.9120	1.1110	6.1090**	4.8610*	0.1186
	(0.2331)	(0.5737)	(0.0472)	(0.0880)	(0.9424)
Wald 4	1.0280	0.2976	3.9110	2.0990	0.6157
	(0.7946)	(0.9605)	(0.2712)	(0.5521)	(0.8928)
Wald 5	5.6810	1.7420	1.5090	2.1430	2.1990
	(0.1282)	(0.6276)	(0.6803)	(0.5433)	(0.5321)
Wald 6	15.4300	6.1740	14.0700	13.6400	13.9300
	(0.3493)	(0.9619)	(0.4448)	(0.4769)	(0.4549)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

P-values of wald test are in parentheses.

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Table 8: In-sample estimates of daily data in sub-sample2 (2008/12/05-2017/11/30)

Data Frequency	Daily				
k	0	5	10	15	20
Portfolio Weights					
LHN	0.0459	−0.0207	0.0142	−0.0077	0.0379
CRH	−0.0288	0.0292	−0.0505*	−0.0375	0.0062
BHP	0.0453	−0.0251	−0.0704	−0.0459	0.0165
RIO	−0.0115	0.0236	0.0469	0.0329	0.0024
AAL	−0.0093	0.0129	0.0065	−0.0014	0.0050
GMEXICOB	0.0013	−0.0374	−0.0371	−0.0474*	−0.0027
SVS	0.0298***	0.0124	0.0065	0.0092	−0.0043
VALE3	0.0013	0.0622***	0.0266	0.0474**	0.0165
MAERSKb	0.0075	−0.0274	0.0104	−0.0233	0.0111
KNIN	−0.0421	0.0375	0.0602	0.0156	−0.0627
BOLL	0.0057	−0.0419	−0.0534	−0.0326	−0.0205
Corn(CBT)	−0.0307	0.0151	−0.0019	0.0147	−0.0401
Wheat(CBT)	0.0291	−0.0448	−0.0138	0.0724	0.0788
Wheat(KCBT)	0.0053	0.0220	0.0526	−0.0859	−0.0741
Mean return (%)	0.0368	0.0341	0.0276	0.0306	0.0306
Standard deviation(%)	0.1703	0.1967	0.1845	0.2015	0.1349
Wald 1	2.0140	1.1470	3.3410	2.3110	1.4560
	(0.3653)	(0.5635)	(0.1882)	(0.3149)	(0.4828)
Wald 2	1.6080	2.4390	4.1490	4.1460	0.5061
	(0.8073)	(0.6555)	(0.3863)	(0.3866)	(0.9729)
Wald 3	7.0930**	8.7550**	1.7210	5.0710*	0.6844
	(0.0288)	(0.0126)	(0.4230)	(0.0792)	(0.7102)
Wald 4	1.0900	3.0520	4.5830	1.7270	2.8980
	(0.7795)	(0.3837)	(0.2050)	(0.6310)	(0.4076)
Wald 5	1.1950	0.7786	1.9510	1.7160	2.6580
	(0.7542)	(0.8546)	(0.5827)	(0.6334)	(0.4475)
Wald 6	12.7200	16.95	14.9200	17.7800	7.8980
	(0.5489)	(0.2587)	(0.3824)	(0.2168)	(0.8946)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

P-values of wald test are in parentheses.

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Table 9: In-sample estimates of weekly data in sub-sample2 (2008/12/05-2017/11/30)

Data Frequency	Weekly				
k	0	5	10	15	20
Portfolio Weights					
LHN	−0.0211	−0.1004	0.0779	−0.1924	0.0564
CRH	−0.1058	0.0386	−0.2147*	0.0152	0.1088
BHP	0.2542	−0.0628	0.7008***	−0.2741	0.0638
RIO	0.0690	−0.0158	−0.4304***	0.1980	−0.0540
AAL	0.0134	0.0910	−0.0122	−0.0922	0.0991
GMEXICOB	−0.0379	−0.0678	0.0921	0.0629	−0.1105
SVS	0.0701*	−0.0508	0.0067	−0.0095	−0.0326
VALE3	0.0852	0.0929	−0.1231	−0.0165	0.0138
MAERSKb	0.1789	−0.0727	0.2702**	0.0889	−0.1027
KNIN	−0.2997*	0.0539	−0.0575	0.2566	0.0232
BOLL	−0.0059	0.1689	−0.0698	−0.1269	0.0467
Corn(CBT)	0.0084	−0.0837	−0.0442	0.0498	−0.3007**
Wheat(CBT)	−0.0373	−0.0653	−0.2732	0.0297	−0.1169
Wheat(KCBT)	0.1035	0.2140	0.2346	−0.0071	0.1859
Mean return (%)	0.1489	0.1473	0.0336	−0.0859	0.0000
Standard deviation(%)	1.8594	1.2477	2.3770	1.4942	1.5931
Wald 1	0.9470	0.4316	2.8670	1.8940	1.3990
	(0.6228)	(0.8059)	(0.2385)	(0.3879)	(0.4968)
Wald 2	4.6200	0.9783	21.4300***	4.8490	1.8660
	(0.3285)	(0.9131)	(0.0003)	(0.3031)	(0.7604)
Wald 3	4.0620	2.4370	1.4730	0.0859	0.6966
	(0.1312)	(0.2957)	(0.4787)	(0.9580)	(0.7059)
Wald 4	3.7390	1.4660	4.2990	3.5670	0.6528
	(0.2911)	(0.6901)	(0.2309)	(0.3122)	(0.8843)
Wald 5	0.4890	1.4360	1.7350	0.4568	7.8990**
	(0.9213)	(0.6972)	(0.6291)	(0.9283)	(0.0481)
Wald 6	19.2400	8.4100	32.3000***	12.6700	14.3900
	(0.1559)	(0.8669)	(0.0036)	(0.5524)	(0.4212)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

P-values of wald test are in parentheses.

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Table 10: In-sample estimates of daily data in sub-sample3 (2003/09/01-2008/12/04)

Data Frequency	Daily				
k	0	5	10	15	20
Portfolio Weights					
LHN	0.0125	0.0116	−0.0174	−0.0100	−0.0575
CRH	−0.0922***	−0.0655**	−0.0098	−0.0264	−0.0001
BHP	−0.0430	−0.0298	0.0469	−0.0323	−0.0057
RIO	0.0953***	0.0701**	0.0086	0.0410	0.0253
AAL	0.0100	0.0357	−0.0110	0.0282	−0.0146
GMEXICOB	0.0191	0.0442*	0.0327	0.0281	0.0535**
SVS	0.0197	0.0095	0.0326**	0.0159	0.0239*
VALE3	−0.0050	−0.0076	0.0531**	−0.0132	0.0021
MAERSKb	0.0517*	0.0388	0.0333	−0.0116	0.0286
KNIN	−0.0018	−0.0033	0.0402	0.0280	0.0121
BOLL	0.0157	0.0726**	0.0015	0.0074	0.0064
Corn(CBT)	−0.0047	−0.0371	−0.0280	0.0050	−0.0129
Wheat(CBT)	−0.0228	0.0327	−0.0010	−0.0087	−0.0524
Wheat(KCBT)	0.0459	−0.0041	0.0591	0.0255	0.1112**
Mean return (%)	−0.0891	−0.0907	−0.0929	−0.0964	−0.1060
Standard deviation(%)	0.2901	0.3240	0.3322	0.1559	0.2267
Wald 1	10.0000***	4.9670*	0.4564	1.0370	2.5620
	(0.0067)	(0.0834)	(0.7960)	(0.5953)	(0.2778)
Wald 2	16.2300***	15.8800***	7.6760	4.3520	6.0340
	(0.0027)	(0.0032)	(0.1042)	(0.3605)	(0.1966)
Wald 3	2.1770	0.6113	10.1100***	1.6650	3.0090
	(0.3367)	(0.7367)	(0.0064)	(0.4350)	(0.2221)
Wald 4	3.8520	8.1220**	3.4440	1.0080	1.3020
	(0.2779)	(0.0436)	(0.3280)	(0.7993)	(0.7287)
Wald 5	0.9563	1.5780	3.8650	0.5911	5.6920
	(0.8118)	(0.6644)	(0.2764)	(0.8985)	(0.1276)
Wald 6	35.4500***	44.2100***	46.2300***	9.8570	21.0400
	(0.00126)	(0.0001)	(0.0002)	(0.7726)	(0.1006)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

P-values of wald test are in parentheses.

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Table 11: In-sample estimates of weekly data in sub-sample3 (2003/09/01-2008/12/04)

Data Frequency	Weekly				
k	0	5	10	15	20
Portfolio Weights					
LHN	−0.0020	−0.5784***	0.0729	0.2635	0.1144
CRH	−0.5256***	0.2369	−0.0354	0.1547	0.1182
BHP	−0.2276	−0.0981	−0.0351	−0.1397	0.0325
RIO	0.4257**	−0.0176	−0.0047	0.2472	0.0083
AAL	0.0661	0.1336	−0.2842	−0.3413*	0.2681
GMEXICOB	0.0756	0.0795	0.1554	0.2893**	−0.1960
SVS	0.0734	0.0934*	0.0611	−0.0752	0.0171
VALE3	−0.0937	0.2271*	0.2292*	0.0449	0.0127
MAERSKb	0.1997	0.0986	−0.0270	−0.3887***	−0.2554*
KNIN	0.1613	0.1465	0.2779*	0.0993	−0.1359
BOLL	0.2871**	0.0637	−0.1844	−0.0758	0.2911*
Corn(CBT)	−0.1319	0.1529	0.1807	−0.0510	−0.0660
Wheat(CBT)	0.0859	−0.1674	−0.3510	−0.2213	0.0003
Wheat(KCBT)	0.0161	0.0994	0.5013*	0.2640	0.0492
Mean return (%)	−0.4002	−0.5257	−0.6664	−0.6911	−0.7747
Standard deviation(%)	2.8456	2.2716	2.1658	2.1985	1.6299
Wald 1	14.7100***	7.6770**	0.1234	3.5520	0.9668
	(0.0006)	(0.0215)	(0.9402)	(0.1693)	(0.6167)
Wald 2	9.6090**	1.6580	4.7130	8.3780*	4.8280
	(0.0476)	(0.7983)	(0.3181)	(0.0787)	(0.3054)
Wald 3	2.3590	5.5550*	3.9870	1.8410	0.0933
	(0.3075)	(0.0622)	(0.1362)	(0.3982)	(0.9544)
Wald 4	8.7420**	1.8480	4.0090	7.4720*	5.7540
	(0.0329)	(0.6044)	(0.2604)	(0.0583)	(0.1242)
Wald 5	1.2640	1.4310	6.4900*	1.4080	0.2865
	(0.7378)	(0.6982)	(0.0901)	(0.7036)	(0.9625)
Wald 6	39.8900***	23.8500**	21.5200*	21.5200*	11.0700
	(0.0003)	(0.0477)	(0.0890)	(0.0891)	(0.6808)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

P-values of wald test are in parentheses.

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Table 12: Out-of-sample tests of daily data in full sample (1994/10/19-2017/11/30)

Data Frequency		Daily				
	m=	60	120	180	240	Recursive
Daily rebalancing						
$k = 0$	γ	-0.0173	0.0435	0.0309	0.0497	0.4005**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0018
	Tracking error	0.0255	0.0190	0.0186	0.0183	0.0178
$k = 5$	γ	0.0191	0.0685**	0.0472	0.0636	0.4892**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0135
	Tracking error	0.0259	0.0190	0.0185	0.0183	0.0178
$k = 10$	γ	-0.0259	-0.0295	0.0129	-0.0159	0.4498**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0027
	Tracking error	0.0226	0.0191	0.0186	0.0185	0.0178
$k = 15$	γ	0.0102	0.1114***	0.0739	0.0652	0.6516***
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.1545
	Tracking error	0.0307	0.0186	0.0183	0.0182	0.0178
$k = 20$	γ	-0.0074	-0.0109	-0.0238	-0.0081	0.6893***
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.1876
	Tracking error	0.0223	0.0191	0.0187	0.0185	0.0178
Weekly rebalancing						
$k = 0$	γ	-0.0108	0.0623*	0.0770*	0.0997**	0.4784**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.1107
	Tracking error	0.0236	0.0190	0.0185	0.0183	0.0178
$k = 5$	γ	0.0123	0.0681**	0.0457	0.0567	0.4985**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0156
	Tracking error	0.0261	0.0189	0.0185	0.0183	0.0178
$k = 10$	γ	-0.0278*	-0.0210	0.0072	-0.0133	0.4828***
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0046
	Tracking error	0.0244	0.0192	0.0186	0.0185	0.0178
$k = 15$	γ	0.0051	0.0560	0.0288	0.0198	0.5463**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0628
	Tracking error	0.0302	0.0187	0.0184	0.0182	0.0178
$k = 20$	γ	-0.0193	-0.0375	-0.0356	-0.0285	0.6248***
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.1107
	Tracking error	0.0238	0.0195	0.0188	0.0185	0.0178

Superscript of the numbers is the null hypothesis of zero: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Table 13: Out-of-sample tests of weekly data in full sample (1994/10/19-2017/11/30)

Data Frequency		Weekly				
	m=	40	60	80	100	Recursive
Weekly rebalancing						
$k = 0$	γ	0.0427	0.0777	0.0100	0.1663**	0.0001
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0944	0.0862	0.0813	0.0793	2.1178
$k = 5$	γ	−0.0229	−0.0500	−0.0381	−0.0834	0.5292**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0769
	Tracking error	0.0961	0.0878	0.0856	0.0830	0.0743
$k = 10$	γ	0.0338	0.0596	0.1194**	0.1289*	0.6197**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.1288
	Tracking error	0.1190	0.0875	0.0829	0.0794	0.0742
$k = 15$	γ	−0.0665**	−0.0829**	−0.1152**	−0.1430**	−0.7273***
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1066	0.0953	0.0892	0.0852	0.0758
$k = 20$	γ	0.1118***	0.0872*	0.0504	0.1359*	0.6240**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.1812
	Tracking error	0.0989	0.0840	0.0817	0.0790	0.0743
Monthly rebalancing						
$k = 0$	γ	0.0590*	0.0545	0.0549	0.1201*	0.1519
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.1741
	Tracking error	0.0950	0.0864	0.0821	0.0800	0.0767
$k = 5$	γ	−0.0340	−0.0609	−0.0626	−0.0784	0.4587*
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0440
	Tracking error	0.0963	0.0888	0.0883	0.0829	0.0744
$k = 10$	γ	0.0433*	0.0747	0.1369**	0.1506**	0.6417**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.1566
	Tracking error	0.1211	0.0872	0.0826	0.0791	0.0742
$k = 15$	γ	−0.0671**	−0.0784*	−0.0906*	−0.1271**	−0.7504***
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1048	0.0943	0.0873	0.0844	0.0758
$k = 20$	γ	0.0951***	0.1026*	0.0866	0.1174	0.6166**
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.1741
	Tracking error	0.0980	0.0832	0.0813	0.0793	0.0743

Superscript of the numbers is the null hypothesis of zero: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Table 14: Out-of-sample tests of daily data in sub-sample1 (1994/10/19-2003/08/29)

Data Frequency		Daily				
	m=	60	120	180	240	Recursive
Daily rebalancing						
$k=0$	γ	-0.0370	0.0050	0.0011	0.0438	-0.0094
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0087	0.0080	0.0078	0.0077	0.0205
$k=5$	γ	0.0138	-0.1195^{*}	-0.2000^{**}	-0.1854^{*}	-0.1957
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0087	0.0082	0.0079	0.0078	0.0076
$k=10$	γ	0.0457	-0.0194	-0.0064	0.0556	0.1840
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0086	0.0081	0.0079	0.0077	0.0076
$k=15$	γ	0.0257	-0.0157	-0.0051	-0.0147	0.1932
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0086	0.0080	0.0079	0.0078	0.0076
$k=20$	γ	0.0068	-0.0062	-0.0018	0.0209	0.1405
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0086	0.0080	0.0078	0.0077	0.0076
Weekly rebalancing						
$k=0$	γ	-0.0523	-0.0108	-0.0020	0.0490	0.0150^{***}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0088	0.0081	0.0079	0.0077	0.0417
$k=5$	γ	0.0084	-0.1524^{**}	-0.2127^{***}	-0.2082^{**}	-0.1847
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0087	0.0082	0.0079	0.0078	0.0076
$k=10$	γ	0.0396	-0.0368	-0.0071	0.0328	0.1661
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0086	0.0081	0.0079	0.0078	0.0076
$k=15$	γ	-0.0034	-0.0221	-0.0206	-0.0174	0.1934
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0086	0.0081	0.0079	0.0078	0.0076
$k=20$	γ	0.0049	-0.0129	0.0080	0.0322	0.1360
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0085	0.0080	0.0078	0.0077	0.0076

Superscript of the numbers is the null hypothesis of zero: * $p<0.1$, ** $p<0.05$, *** $p<0.01$

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Table 15: Out-of-sample tests of weekly data in sub-sample1 (1994/10/19-2003/08/29)

Data Frequency		Weekly				
	m=	40	60	80	100	Recursive
Weekly rebalancing						
$k = 0$	γ	-0.0612	-0.0846	0.0197	0.0500	0.0001
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0405	0.0375	0.0348	0.0342	3.7719
$k = 5$	γ	-0.0068	-0.0330	-0.0719	-0.077	0.1770
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0002
	Tracking error	0.0419	0.0378	0.0361	0.0347	0.0323
$k = 10$	γ	-0.0207	0.0292	-0.0148	-0.0373	-0.2370
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0445	0.0368	0.0356	0.0347	0.0340
$k = 15$	γ	-0.0284	-0.0384	-0.0735	-0.1296	-0.2649^{*}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0439	0.0391	0.0376	0.0365	0.0346
$k = 20$	γ	-0.0471	0.0014	0.0417	0.0373	0.0812
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0422	0.0373	0.0356	0.0346	0.0328
Monthly rebalancing						
$k = 0$	γ	-0.0092	-0.0694	0.0471	0.0672	-0.0098
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0392	0.0373	0.0346	0.0342	0.0478
$k = 5$	γ	-0.0037	-0.0381	-0.0805	-0.0606	0.2242
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0005
	Tracking error	0.0418	0.0380	0.0362	0.0347	0.0322
$k = 10$	γ	-0.0175	0.0423	-0.0167	-0.0378	-0.2175
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0450	0.0366	0.0356	0.0347	0.0339
$k = 15$	γ	-0.0500	-0.0375	-0.0662	-0.1154	-0.2495^{*}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0442	0.0390	0.0377	0.0365	0.0346
$k = 20$	γ	-0.0276	-0.0326	0.0377	0.0163	0.0686
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0413	0.0376	0.0355	0.0348	0.0328

Superscript of the numbers is the null hypothesis of zero: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Table 16: Out-of-sample tests of daily data in sub-sample2 (2008/12/05-2017/11/30)

Data Frequency		Daily				
	m=	60	120	180	240	Recursive
Daily rebalancing						
$k=0$	γ	-0.0121	0.0553	0.0218	0.0146	-0.0851
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0357	0.0234	0.0228	0.0225	0.0225
$k=5$	γ	0.0153	0.0416	0.0253	0.0206	-0.1776
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0366	0.0235	0.0228	0.0225	0.0219
$k=10$	γ	-0.0352	-0.0643	-0.0251	-0.0654	-0.2744
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0293	0.0237	0.0230	0.0228	0.0219
$k=15$	γ	0.0065	0.0005	-0.0304	0.0046	-0.0321
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0458	0.0230	0.0226	0.0223	0.0219
$k=20$	γ	-0.0092	-0.0153	0.0152	-0.0047	-0.1165
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0292	0.0237	0.0231	0.0228	0.0219
Weekly rebalancing						
$k=0$	γ	-0.0139	0.0550	0.0192	0.0261	0.0059
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0332	0.0233	0.0228	0.0225	0.0227
$k=5$	γ	0.0149	0.0658	0.0347	0.0133	-0.1743
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0373	0.0232	0.0228	0.0226	0.0219
$k=10$	γ	-0.0286	-0.0541	-0.0202	-0.0570	-0.2547
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0318	0.0236	0.0230	0.0228	0.0219
$k=15$	γ	0.0050	-0.0192	-0.0359	-0.0117	-0.0357
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0470	0.0234	0.0226	0.0223	0.0219
$k=20$	γ	-0.0055	-0.0154	0.0122	0.0015	-0.1202
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0296	0.0238	0.0231	0.0228	0.0219

Superscript of the numbers is the null hypothesis of zero: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Table 17: Out-of-sample tests of weekly data in sub-sample2 (2008/12/05-2017/11/30)

Data Frequency		Weekly				
	m=	40	60	80	100	Recursive
Weekly rebalancing						
$k=0$	γ	-0.0262	0.0508	0.0419	0.1378	0.0703
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1117	0.1036	0.0957	0.0919	0.0960
$k=5$	γ	-0.0145	-0.0862	-0.0765	-0.0922	-0.1676
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0023
	Tracking error	0.1125	0.1059	0.1050	0.0987	0.0911
$k=10$	γ	0.0799^{*}	0.1780^{**}	0.2413^{***}	0.2716^{**}	0.4950^{***}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1233	0.0990	0.0942	0.0891	0.0853
$k=15$	γ	-0.0533	-0.0988	-0.1390	-0.2623^{**}	-0.6478^{***}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1184	0.1127	0.1025	0.0963	0.0904
$k=20$	γ	0.0708	0.0057	-0.0919	0.0121	0.2141
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1249	0.1028	0.0988	0.0938	0.0870
Monthly rebalancing						
$k=0$	γ	0.0124	0.0411	-0.0133	0.1006	0.0963
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1141	0.1025	0.0966	0.0923	0.0927
$k=5$	γ	-0.0406	-0.0978	-0.0929	-0.0975	-0.1620
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1144	0.1086	0.1112	0.0988	0.0912
$k=10$	γ	0.0612	0.1640^{**}	0.2408^{***}	0.2551^{**}	0.4935^{***}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0021
	Tracking error	0.1276	0.0993	0.0942	0.0895	0.0853
$k=15$	γ	-0.0811	-0.0995	-0.1137	-0.2301^{*}	-0.6480^{***}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1241	0.1126	0.0995	0.0956	0.0904
$k=20$	γ	0.0419	-0.0183	-0.0660	-0.0012	0.2221
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1247	0.1017	0.0984	0.0941	0.0870

Superscript of the numbers is the null hypothesis of zero: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Table 18: Out-of-sample tests of daily data in sub-sample3 (2003/09/01-2008/12/04)

Data Frequency		Daily				
	m=	60	120	180	240	Recursive
Daily rebalancing						
$k = 0$	γ	-0.0178	0.0283	-0.0006	0.0479	-0.0027
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0214	0.0198	0.0195	0.0192	0.0326
$k = 5$	γ	0.0638	0.3032^{***}	0.2189^{**}	0.2800^{**}	0.5216^{***}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0031
	Tracking error	0.0212	0.0191	0.0191	0.0189	0.0186
$k = 10$	γ	0.0362	0.0455	0.0109	-0.0201	0.1705
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0216	0.0196	0.0192	0.0191	0.0187
$k = 15$	γ	0.1091^{**}	0.3873^{***}	0.3235^{***}	0.2844^{**}	0.3639^{*}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0020
	Tracking error	0.0207	0.0189	0.0188	0.0188	0.0186
$k = 20$	γ	0.0061	-0.0037	-0.1477	0.0640	0.3836^{*}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0018
	Tracking error	0.0220	0.0198	0.0195	0.0191	0.0186
Weekly rebalancing						
$k = 0$	γ	0.0581	0.1408^{*}	0.1470^{*}	0.1935^{*}	0.0003
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0211	0.0196	0.0193	0.0191	0.0722
$k = 5$	γ	0.0747	0.2760^{***}	0.1775^{*}	0.2410^{**}	0.4700^{***}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0012
	Tracking error	0.0211	0.0191	0.0191	0.0189	0.0186
$k = 10$	γ	-0.0167	0.0080	-0.0808	-0.1219	0.0166
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.0220	0.0197	0.0194	0.0192	0.0188
$k = 15$	γ	0.0497	0.3018^{***}	0.2379^{**}	0.1930	0.3267
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0011
	Tracking error	0.0212	0.0192	0.0189	0.0189	0.0186
$k = 20$	γ	-0.0546	-0.0980	-0.2114^{**}	-0.0599	0.2534
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0001
	Tracking error	0.0225	0.0201	0.0197	0.0193	0.0187

Superscript of the numbers is the null hypothesis of zero: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Table 19: Out-of-sample tests of weekly data in sub-sample3 (2003/09/01-2008/12/04)

Data Frequency		Weekly				
	m=	40	60	80	100	Recursive
Weekly rebalancing						
$k=0$	γ	0.1264	0.1748	0.1311	0.1487	0.0660
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1031	0.0933	0.0919	0.0909	0.1094
$k=5$	γ	-0.2147^{**}	-0.2166	-0.2074	-0.3352^{*}	-0.0247
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0002
	Tracking error	0.1142	0.1004	0.0963	0.0971	0.0882
$k=10$	γ	-0.0600	-0.3865^{***}	-0.3818^{**}	-0.3833^{**}	-0.4500
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1159	0.1041	0.1001	0.0968	0.0897
$k=15$	γ	-0.2632^{***}	-0.3267^{***}	-0.4303^{***}	-0.3868^{**}	-0.4672^{*}
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1343	0.1126	0.1069	0.1012	0.0908
$k=20$	γ	0.5157^{***}	0.4716^{***}	0.5435^{***}	0.8230^{***}	0.5924^{*}
	p-val(1)	0.0000	0.0030	0.0267	0.4470	0.2073
	Tracking error	0.0837	0.0848	0.0838	0.0812	0.0839
Monthly rebalancing						
$k=0$	γ	0.0352	0.1870	0.1617	0.1707	0.1923
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1086	0.0920	0.0904	0.0895	0.0925
$k=5$	γ	-0.1020	-0.1630	-0.1486	-0.2634	0.1062
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0017
	Tracking error	0.1025	0.0975	0.0944	0.0947	0.0871
$k=10$	γ	-0.0176	-0.4118	-0.3671^{**}	-0.3668^{*}	-0.4840
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1088	0.1012	0.0975	0.0947	0.0893
$k=15$	γ	-0.1859^{**}	-0.2335^{**}	-0.3107^{**}	-0.2460	-0.2538
	p-val(1)	0.0000	0.0000	0.0000	0.0000	0.0000
	Tracking error	0.1299	0.1097	0.1047	0.0986	0.0899
$k=20$	γ	0.5660^{***}	0.5296^{***}	0.6361^{***}	0.8133^{***}	0.6217^{**}
	p-val(1)	0.0000	0.0049	0.0607	0.3973	0.2274
	Tracking error	0.0815	0.0049	0.0824	0.0810	0.0837

Superscript of the numbers is the null hypothesis of zero: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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