Empirical studies of portfolio replication: Baltic Dry Index

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Introduction

- The view of financial assets containing information about economic activity has been widely accepted.
- The fundamental evaluation formula of equity is introduced to understand the relationship between financial assets and economy.
- Current stock price is the present value of future interest rates, cash flow, dividends, and premiums, and these four factors are strongly related to macroeconomics.
- The fact that Stock returns originate from changes in asset prices suggests that returns reflect the revised expectation to future real economic activity.
- This study applies the approach of economic tracking portfolio (ETP) proposed by Lamont (2001) 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.

Introduction (Cont.)

- BDI demonstrates shipping rates of transporting raw materials, such as coal, iron ore, steel, grains, cement, sand, and gravel. Four types of vessel transport these raw materials, Capsize, Panamax, Supermax and Handymax.
- BDI is daily calculated basing on the ship freight rates of each vessel type on different routes around the world, weighted of sub-indices of four types of vessel.
- The price index determined by supply and demand in the marine freight market, and the equilibrium also reflects the demand of raw materials.
- The main purpose of this study is to test whether ETP could track BDI through out-of-sample tracking performance, tracking error.

Introduction (Cont.)

- The data composition resembles Junttila (2007), using international data rather than the data from a closed-economy.
- The stocks of five industries are chosen as base assets, construction materials, diversified mining, iron and steel, marine freight and logistics, and grains.
- The way of in-sample and out-of-sample tests is similar to Hayes (2001), implementing different forecast horizons and training periods to test the stability of ETP.
- In-sample estimates show that the the equity returns of diversified mining and iron steel contain more information about BDI.
- Out-of-sample tests show that the portfolio weights estimated by recursive window is better than those estimated by rolling window, and tracking performance is better in the period structural break than other two sub-samples.

Literature Review

- Lamont (2001)
  - ETP uses current assets returns containing information about future macroeconomic situations to capture the innovation in expectation about future economic variables.
  - Target variables: industrial production growth, real consumption growth, real labor income growth, inflation, excess stock returns, excess bond returns, and Treasury bill returns.
  - Base assets: four bond portfolios, eight stock portfolios, and the market portfolios.
  - He makes an assumption that the returns of base assets are linear function of lagged control variables, so nine control variables are included.
  - All data are the form of long return.
  - Lamont concludes that ETP is useful to track macroeconomic variables, and raises the importance of control variable.

Literature Review (Cont.)

- Christoffersen and Slok (2000)
  - Applies ETP to tests wither the asset prices contain information about future economic development in transition economies.
  - Uses 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 economies in these countries.
- Hayes (2001)
  - He employs ETP to verifying the macroeconomic variables in U.K., and wants to see wether ETP is helpful to forecast economy.
  - Target variables: inflation, industrial production growth, and growth in volume of retail sales.
  - The in-sample tests show that ETP an predict future target variables, but this tracking portfolios perform poorly in out-of-sample tests.
  - Less rebalancing frequency and restriction of base assets do not improve the poor racking performance of out-of-sample.

Literature Review (Cont.)

- Junttila (2004)
  - He uses ETP approach to the IT-intensive stock market in Finland.
  - Junttila concludes that base assets indeed contain information about future economic variables, different industrial portfolios holding different information.
  - The role of control variable is not important in a closed-economy.
- Raunig (2007)
  - Constructs ETP to track future production growth and inflation in Austria.
  - It turns out that the out-of-sample tests of ETP help forecast industrial production growth, but predict inflation poorly.

Literature Review (Cont.)

- Junttila (2007)
  - He extends ETP approach to international assets, using excess currency returns and excess stock returns of U.S, Italy, 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.
  - The problem of previous studies cloud be using closed-economy data and larger numbers of base assets.
  - The results of out-of-sample indicate that using international data is possible to capture the development of macroeconomies.
  - The role of control variable is not important in a closed-economy.

- Apply Lamont's (2001) economic tracking portfolio (ETP) model as the theoretical framework to investigate the tracking performance of Baltic Dry Index tracking portfolio.
- First, decompose the target variable to see which components will be track.

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

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

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

- Backwardly recursive of right-hand side of Eq. (2) shows that the target variable is the sum of conditional expectational expectation at time $t-1$ and $k+1$ one-period conditional expectation revisions:

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

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

- ETP is constructed based on unexpected returns of base assets, relating maximally unexpected returns of portfolio to unexpected components of target variable in future period 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.
- Notation of unexpected returns $\widetilde{R}_{t-1,t} \equiv R_{t-1,t} - E_{t-1}[R_{t-1,t}]$.
- The unexpected components of future target variable is "news" about y_{t+k} with 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, $\widetilde{r}_{t-1,t}$.

- Key assumption of this method can be illustrated the projection model:

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

where η_t is the tracking error that is orthogonal to the unexpected returns, and **a** is a $1 \times N$ row vector representing the portfolio weights.

- The revision of left-hand side in Eq. (5) is unobservable, so we need to derive an alternative that uses y_{t+k} rather than $\Delta E_t[y_{t+k}]$. Substituting Eq. (5) into Eq. (4), this gives:

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

Methodology (Cont.)

- The second assumption is made that the expected returns of 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:

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

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

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

Methodology (Cont.)

- 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. Apply OLS regression to obtain the portfolio weights $\hat{b}$, then produces the unexpected components of ETP that maximally correlated with $\Delta E_t[y_{t+k}]$

Methodology (Cont.)

- This study investigates the tracking performance of Baltic Dry Index as hedgers, rather than only forecasts the macroeconomic variable as policy makers.
- Lamont (2001) suggests that 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.

Data - Variables Selection

- Data runs from October, 1994 to November, 2017, including daily and weekly data. All data are compiled from datastream.
- Baltic Dry Index is the change in the log of price index form.
- The main dry bulk goods are iron ore and coal used for producing steel, and other raw materials, such as concrete, sands, or grains.
- 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 ranking 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.

Data - Variables Selection (Cont.)

- The concept of this study is identical to Junttila (2007), using international equity returns to forecast macroeconomic variable.
- Adding more international stocks to the base assets reveal more information about BDI, but is also raises the problem of overfitting.
- Basing on market capitalization in each industry, the companies ranked top five are selected.
- With restriction of public offering dates, some of these stocks listed later than October, 1994, resulting that not every top five company could be included in the base assets.
- 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, $k = 0, 5, 10, 15, and 20$ days and weeks.

Data - Variables Selection (Cont.)

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	

Data - Preliminary analysis

- 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.
- Table 2 indicates that the asset returns are weakly correlated with the returns of BDI, but we can also discuss whether this study could be applied by ETP.

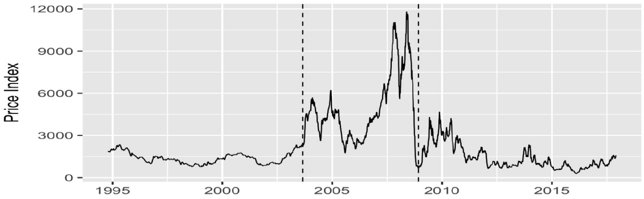

Figure 1: Baltic Dry Index

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

- The statistical tests in Tables 4-11 on tracking ability of different industrial stocks are conducted by six Wald-tests, designed to reveal the information content of different industries.
- The hypothesis of each Wald-test examines that the portfolio weights of industry are jointly zero, Wald1: construction materials, Wald2: diversified mining, Wald3: iron and steels, Wald4: marine freight and logistics, Wald5: grains. Wald6 tests the tracking ability of five industries.

Empirical Results - In-sample estimates (Cont.)

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
Wald1 (Construction Materials)	7.2720**	0.1720	2.8120	5.9960**	0.1427
	(0.0264)	(0.9176)	(0.2452)	(0.0499)	(0.9311)
Wald2 (Diversified Mining)	11.2500**	8.1320*	3.7290	3.4010	4.3260
	(0.0239)	(0.0868)	(0.4439)	(0.4931)	(0.3637)
Wald3 (Iron and Steel)	10.7700***	7.8980**	7.0200**	3.5210	1.1640
	(0.0046)	(0.0193)	(0.0299)	(0.1720)	(0.5588)
Wald4 (Marine Freight and Logistics)	1.3690	0.5384	4.1150	2.1330	1.0370
	(0.7128)	(0.9104)	(0.2493)	(0.5453)	(0.7922)
Wald5 (Grains)	1.9010	0.4685	3.6040	0.3745	3.2140
	(0.5932)	(0.9258)	(0.3075)	(0.9455)	(0.3598)
Wald6 (All Industries)	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.

Empirical Results - In-sample estimates (Cont.)

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
Wald1 (Construction Materials)	1.9430	0.7073	0.1503	0.3096	4.3570
	(0.3785)	(0.7021)	(0.9276)	(0.8566)	(0.1132)
Wald2 (Diversified Mining)	3.7620	1.5390	8.1380*	10.1500**	8.4640*
	(0.4392)	(0.8196)	(0.0866)	(0.0380)	(0.0760)
Wald3 (Iron and Steel)	1.5550	4.8800*	4.6540*	1.1300	0.5847
	(0.4595)	(0.0872)	(0.0976)	(0.5685)	(0.7465)
Wald4 (Marine Freight and Logistics)	0.5419	2.3490	0.5959	0.8031	1.5700
	(0.9096)	(0.5032)	(0.8974)	(0.8487)	(0.6662)
Wald5 (Grains)	0.7243	1.5640	9.6660**	7.8980**	6.4190*
	(0.8675)	(0.6675)	(0.0216)	(0.0482)	(0.0929)
Wald6 (All Industries)	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.

Empirical Results - In-sample estimates (Cont.)

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
Wald1 (Construction Materials)	2.0140	1.1470	3.3410	2.3110	1.4560
	(0.3653)	(0.5635)	(0.1882)	(0.3149)	(0.4828)
Wald2 (Diversified Mining)	1.6080	2.4390	4.1490	4.1460	0.5061
	(0.8073)	(0.6555)	(0.3863)	(0.3866)	(0.9729)
Wald3 (Iron and Steel)	7.0930**	8.7550**	1.7210	5.0710*	0.6844
	(0.0288)	(0.0126)	(0.4230)	(0.0792)	(0.7102)
Wald4 (Marine Freight and Logistics)	1.0900	3.0520	4.5830	1.7270	2.8980
	(0.7795)	(0.3837)	(0.2050)	(0.6310)	(0.4076)
Wald5 (Grains)	1.1950	0.7786	1.9510	1.7160	2.6580
	(0.7542)	(0.8546)	(0.5827)	(0.6334)	(0.4475)
Wald6 (All Industries)	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.

Empirical Results - In-sample estimates (Cont.)

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
Wald1 (Construction Materials)	10.0000***	4.9670*	0.4564	1.0370	2.5620
	(0.0067)	(0.0834)	(0.7960)	(0.5953)	(0.2778)
Wald2 (Diversified Mining)	16.2300***	15.8800***	7.6760	4.3520	6.0340
	(0.0027)	(0.0032)	(0.1042)	(0.3605)	(0.1966)
Wald3 (Iron and Steel)	2.1770	0.6113	10.1100***	1.6650	3.0090
	(0.3367)	(0.7367)	(0.0064)	(0.4350)	(0.2221)
Wald4 (Marine Freight and Logistics)	3.8520	8.1220**	3.4440	1.0080	1.3020
	(0.2779)	(0.0436)	(0.3280)	(0.7993)	(0.7287)
Wald5 (Grains)	0.9563	1.5780	3.8650	0.5911	5.6920
	(0.8118)	(0.6644)	(0.2764)	(0.8985)	(0.1276)
Wald6 (All Industries)	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.

Empirical Results - In-sample estimates (Cont.)

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
Wald1 (Construction Materials)	6.8470**	1.1530	0.4626	2.0560	1.8930
	(0.0326)	(0.5619)	(0.7935)	(0.3577)	(0.3880)
Wald2 (Diversified Mining)	13.8200***	1.1180	18.6700***	9.1830*	5.3980
	(0.0079)	(0.8913)	(0.0009)	(0.0567)	(0.2488)
Wald3 (Iron and Steel)	6.9360**	4.1250	0.2249	1.1900	0.4812
	(0.0312)	(0.1271)	(0.8937)	(0.5517)	(0.7861)
Wald4 (Marine Freight and Logistics)	3.4980	1.4670	4.0470	3.8890	0.3661
	(0.3211)	(0.6899)	(0.2564)	(0.2736)	(0.9472)
Wald5 (Grains)	1.7070	1.5920	1.1550	0.4358	5.6810
	(0.6353)	(0.6612)	(0.7638)	(0.9327)	(0.1282)
Wald6 (All Industries)	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.

Empirical Results - In-sample estimates (Cont.)

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
Wald1 (Construction Materials)	0.0403	1.1130	1.3150	2.7360	0.5361
	(0.9801)	(0.5733)	(0.5181)	(0.2546)	(0.7649)
Wald2 (Diversified Mining)	6.7280	1.5100	1.6520	1.5920	9.6860**
	(0.1510)	(0.8249)	(0.7995)	(0.8102)	(0.0461)
Wald3 (Iron and Steel)	2.9120	1.1110	6.1090**	4.8610*	0.1186
	(0.2331)	(0.5737)	(0.0472)	(0.0880)	(0.9424)
Wald4 (Marine Freight and Logistics)	1.0280	0.2976	3.9110	2.0990	0.6157
	(0.7946)	(0.9605)	(0.2712)	(0.5521)	(0.8928)
Wald5 (Grains)	5.6810	1.7420	1.5090	2.1430	2.1990
	(0.1282)	(0.6276)	(0.6803)	(0.5433)	(0.5321)
Wald6 (All Industries)	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.

Empirical Results - In-sample estimates (Cont.)

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
Wald1 (Construction Materials)	0.9470	0.4316	2.8670	1.8940	1.3990
	(0.6228)	(0.8059)	(0.2385)	(0.3879)	(0.4968)
Wald2 (Diversified Mining)	4.6200	0.9783	21.4300***	4.8490	1.8660
	(0.3285)	(0.9131)	(0.0003)	(0.3031)	(0.7604)
Wald3 (Iron and Steel)	4.0620	2.4370	1.4730	0.0859	0.6966
	(0.1312)	(0.2957)	(0.4787)	(0.9580)	(0.7059)
Wald4 (Marine Freight and Logistics)	3.7390	1.4660	4.2990	3.5670	0.6528
	(0.2911)	(0.6901)	(0.2309)	(0.3122)	(0.8843)
Wald5 (Grains)	0.4890	1.4360	1.7350	0.4568	7.8990**
	(0.9213)	(0.6972)	(0.6291)	(0.9283)	(0.0481)
Wald6 (All Industries)	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.

Empirical Results - In-sample estimates (Cont.)

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
Wald1 (Construction Materials)	14.7100***	7.6770**	0.1234	3.5520	0.9668
	(0.0006)	(0.0215)	(0.9402)	(0.1693)	(0.6167)
Wald2 (Diversified Mining)	9.6090**	1.6580	4.7130	8.3780*	4.8280
	(0.0476)	(0.7983)	(0.3181)	(0.0787)	(0.3054)
Wald3 (Iron and Steel)	2.3590	5.5550*	3.9870	1.8410	0.0933
	(0.3075)	(0.0622)	(0.1362)	(0.3982)	(0.9544)
Wald4 (Marine Freight and Logistics)	8.7420**	1.8480	4.0090	7.4720*	5.7540
	(0.0329)	(0.6044)	(0.2604)	(0.0583)	(0.1242)
Wald5 (Grains)	1.2640	1.4310	6.4900*	1.4080	0.2865
	(0.7378)	(0.6982)	(0.0901)	(0.7036)	(0.9625)
Wald6 (All Industries)	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.

Empirical Results - Out-of-sample forecasts

- In-sample tests do not provide grounds for the practitioners to hedge BDI. For the sake of robustness, out-of-sample forecasts are required.
- The hedgers would like to see wether the ETP captures BDI in response to the recent changes of base assets 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: the choice of training period, and the determination of rebalancing frequency.
- Conventional wisdom of estimation window on financial studies, most scholars use past 60 monthly data to analyze tracking performance.
- Lamont (2001) suggests that 20-year period is better in tracking target variable in out-of-sample test, because 5-year period is not long enough to catch business cycle.

Empirical Results - Out-of-sample forecasts (Cont.)

- The data of this study is not long enough and the data frequency does not include monthly data.
- Denoting m as training period, the portfolio weights are estimated by different estimation window, $m = 60, 120, 180, 240$ on daily data, and $m = 40, 60, 80, 100$ on weekly data.
- There is no theoretical basis to tell us how to determine the rebalancing frequency, so it also need to be tested.
- In this study, the portfolio of daily data are daily and weekly rebalanced, and that of weekly data are weekly and monthly rebalanced.
- Out-of-sample test regression: $r_{\tau+b}^{ETP} = \hat{w}_\tau R_{\tau+1}$, tracking error: $\sigma(r_t^{ETP} - y_{t+k})$.

Empirical Results - Out-of-sample forecasts (Cont.)

- Another regression to test the stability of the portfolio weights:

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

- The overall conclusion emerging from these results is that the tracking errors of ETP decrease over longer training period.
- There are no consistent results that longer forecast horizon lead to decreased tracking errors.

Empirical Results - Out-of-sample forecasts (Cont.)

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

Empirical Results - Out-of-sample forecasts (Cont.)

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: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Empirical Results - Out-of-sample forecasts (Cont.)

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

Empirical Results - Out-of-sample forecasts (Cont.)

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

Empirical Results - Out-of-sample forecasts (Cont.)

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: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

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

Empirical Results - Out-of-sample forecasts (Cont.)

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

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

Empirical Results - Out-of-sample forecasts (Cont.)

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: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Empirical Results - Out-of-sample forecasts (Cont.)

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

Empirical Results - Out-of-sample forecasts (Cont.)

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

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

Empirical Results - Out-of-sample forecasts (Cont.)

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

Empirical Results - Out-of-sample forecasts (Cont.)

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

Empirical Results - Out-of-sample forecasts (Cont.)

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

Empirical Results - Out-of-sample forecasts (Cont.)

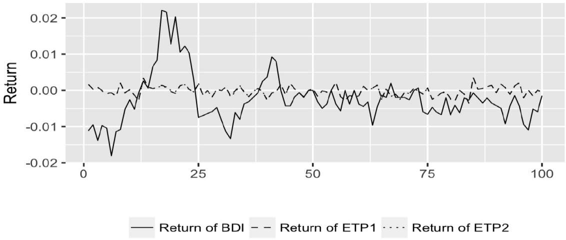

Figure 2: Return of daily data sub-sample1. ETP1 is daily rebalanced and calculated on recursive window with $k = 15$; ETP2 is weekly rebalanced and calculated on recursive window with $k = 15$.

Empirical Results - Out-of-sample forecasts (Cont.)

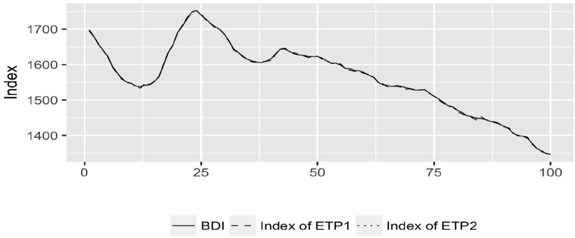

Figure 3: Index of daily data sub-sample1. ETP1 is daily rebalanced and calculated on recursive window with $k = 15$; ETP2 is weekly rebalanced and calculated on recursive window with $k = 15$.

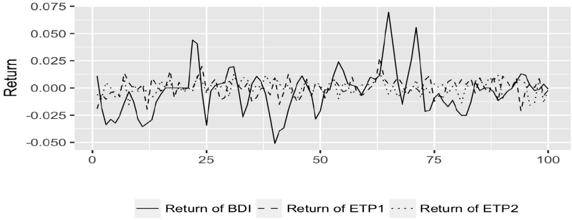

Figure 4: Return of daily data in sub-sample2. ETP1 is daily rebalanced and calculated on rolling window with $k = 0$, $m = 120$; ETP2 is weekly rebalanced and calculated on rolling window with $k = 0$, $m = 120$.

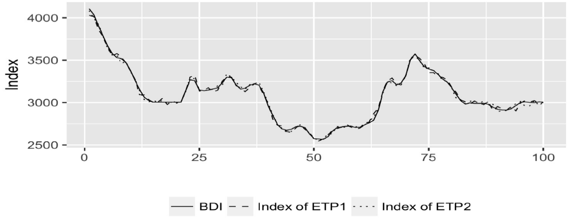

Figure 5: Index of daily data in sub-sample2. ETP1 is daily rebalanced and calculated on rolling window with $k = 0$, $m = 120$; ETP2 is weekly rebalanced and calculated on rolling window with $k = 0$, $m = 120$.

Empirical Results - Out-of-sample forecasts (Cont.)

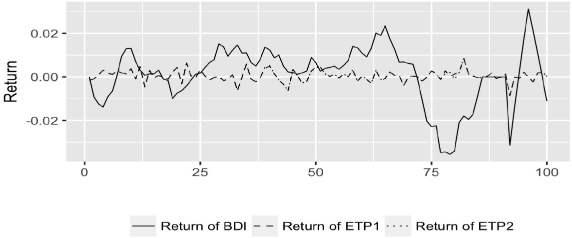

Figure 6: Return of daily data in sub-sample3. ETP1 is daily rebalanced and calculated on recursive window with $k = 5$; ETP2 is weekly rebalanced and calculated on recursive window with $k = 5$.

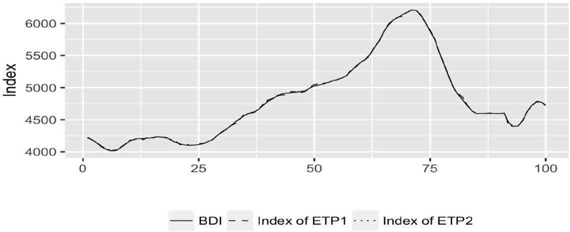

Figure 7: Index of daily data in sub-sample3. ETP1 is daily rebalanced and calculated on recursive window with $k = 5$; ETP2 is weekly rebalanced and calculated on recursive window with $k = 5$.

Empirical Results - Out-of-sample forecasts (Cont.)

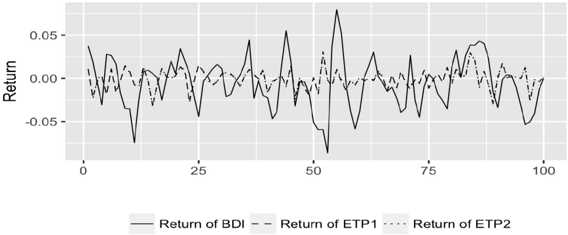

Figure 8: Return of weekly data sub-sample1. ETP1 is weekly rebalanced and calculated on recursive window with $k = 5$; ETP2 is monthly rebalanced and calculated on recursive window with $k = 5$.

Empirical Results - Out-of-sample forecasts (Cont.)

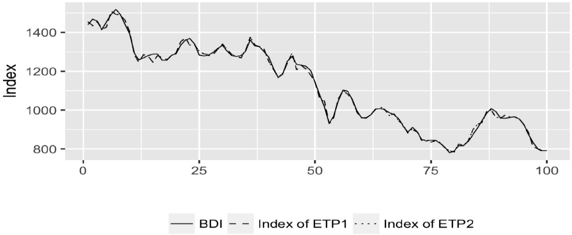

Figure 9: Index of weekly data sub-sample1. ETP1 is weekly rebalanced and calculated on recursive window with $k = 5$; ETP2 is monthly rebalanced and calculated on recursive window with $k = 5$.

Empirical Results - Out-of-sample forecasts (Cont.)

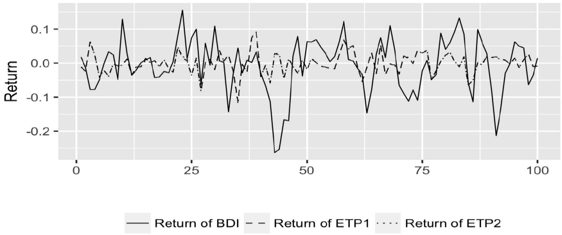

Figure 10: Return of weekly data in sub-sample2. ETP1 is daily rebalanced and calculated on recursive window with $k = 10$; ETP2 is monthly rebalanced and calculated on recursive window with $k = 10$.

Empirical Results - Out-of-sample forecasts (Cont.)

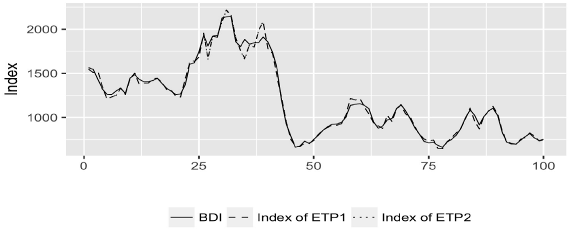

Figure 11: Index of weekly data in sub-sample2. ETP1 is daily rebalanced and calculated on recursive window with $k = 10$; ETP2 is monthly rebalanced and calculated on recursive window with $k = 10$.

Empirical Results - Out-of-sample forecasts (Cont.)

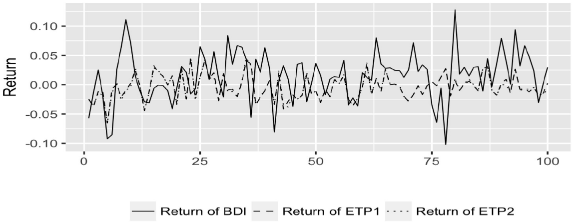

Figure 12: Return of weekly data in sub-sample3. ETP1 is daily rebalanced and calculated on rolling window with $k = 20$, $m = 100$; ETP2 is monthly rebalanced and calculated on rolling window with $k = 20$, $m = 100$.

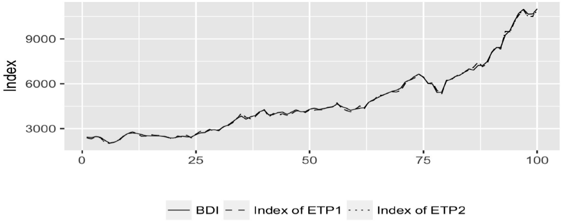

Figure 13: Index of weekly data in sub-sample3. ETP1 is daily rebalanced and calculated on rolling window with $k = 20$, $m = 100$; ETP2 is monthly rebalanced and calculated on rolling window with $k = 20$, $m = 100$.

Conclusions

- In-sample estimates
  - 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.
  - BDI is mainly explained by the returns of two industries, diversified mining and and iron steel.
  - The returns of base assets indeed contain the information about future BDI, indicating the forecasting ability of BDI tracking portfolio exists.
  - Full-sample and sub-sample3 show that BDI tracking portfolio can predict future BDI to some extent.
- Out-of-sample forecasts
  - Many coefficients, γ, are negative, wrong direction in tracking the target variable, especially in rolling window.
  - Recursive window is better that rolling window to implementing out-of-sample test in full-sample and sub-sample3, and the coefficients are larger enough to track BDI.

Conclusions (Cont.)

- Out-of-sample forecasts
  - In full-sample and sub-sample3 the coefficients increase along with longer forecast horizon, proving that the tracking portfolio contain information about future BDI.
  - From the analysis of in-sample and out-of-sample test, ETP in full-sample and sub-sample3 have significant effects.
- The returns ETP and simulated indices
  - The figures seem to be contracted to the numbers analysis, the returns of ETP and simulated indices almost perfectly overlapping BDI.
  - The problem is that the vale of BDI is very large, and the volatile returns of ETP is hard to be reflected in the simulated index.

Conclusions (Cont.)

- I also try to add the stocks that do not include in this study because they are published during the research period.
- Avoiding 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.
- BDI is a very noisy variable, and the critical issue of ETP is base assets selection. Maybe the futures of exchange rates and interest rates should be taken into account, but the problem overfitting also need to be concerned.