The Journal of Prediction Markets 2021 Vol 15 No 1 pp 67-96

TRACKING ERRORS AND THEIR DETERMINANTS: EVIDENCE FROM JAPAN-LISTED EXCHANGE-TRADED FUNDS

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ABSTRACT

The purposes of this study are to compare the tracking error between 53 sampled physical and 15 over-the-counter (OTC) swap-type exchange-traded funds (ETFs) on the Tokyo Stock Exchange, and to contribute to a better understanding of the impact of selected determinants on the daily tracking error. The sample synthetic ETFs are found having higher tracking error than the sampled physical ETFs. The synthetic-type ETF managers may be difficult in using derivatives to replicate the benchmark performance. A panel regression model with cross-section fixed effects indicates the tracking error of the sampled physical ETFs is negatively related to size but positively related to expense ratio, dividend yield, trading volumes, market risk, and number of constituents in the target indexes. The results conform with the hypotheses that the expense, delay in receiving dividends, the trading cost and the market risk may erode the tracking ability; on the other hand, the economies of scale will improve the tracking ability. This study may help to raise a broader discussion of potential tracking error determinants and to provide new insights.

JEL Codes: G15, G20, G23

Keywords: exchange-traded fund, tracking error, panel regression model, fixed-effects estimation.

1 INTRODUCTION

The first exchange-traded fund (ETF) appeared in Canada in 1989, with the creation of the Toronto 35 Index Participation Fund. The first ETF in the United States (U.S.) appeared in 1992, namely, Standard & Poor's 500 Depositary

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Receipts (SPDR), which was designed to mimic the S&P 500 index passively. In Europe, Morgan Stanley took advantage of a less restrictive regulatory environment in Luxembourg and in 1993 created Optimized Portfolios as Listed Securities (OPALS), which is an ETF listed on the Luxembourg Stock Exchange to reflect different Morgan Stanley Capital International (MSCI) indexes. Japan followed suit on May 29, 1995 when its first ETF, the Nikkei 300, was launched. ETFs are passively managed funds aimed at closely tracking the performance of indicators, which are commonly real observable stock market indexes or investment companies' tailor-made indexes. ETFs have various benefits. They are easily understandable, because information on the indicator is reported daily by the news media and other organizations, enabling price movements and changes in profit/loss to be grasped easily. In addition, ETFs facilitate diversified investment, since there are rich varieties of ETFs that track foreign stocks, real estate investment trusts, and commodity indexes in addition to Japanese stocks. Furthermore, ETFs have low initial investment cost, possibly an amount of several thousand or tens of thousands of yen. Moreover, ETFs have significantly lower management costs than actively managed mutual funds do, since there is no subscription fee for ETFs. Additionally, ETFs do not have to handle open-end-fund redemptions for cash that create additional clerical and trading expenses. The average management cost across the ETFs in Japan is between 0.1% and 1% of the amount invested. ETFs have become increasingly popular, because they represent portfolios of securities designed to track the performance of indexes and offer an efficient way for investors to obtain cost-effective exposure. ETFs are also eligible for short selling in some markets, which provides investment opportunities when investors foresee a bear market in the near future. In fact, ETFs are easier to short than stocks are, because they are exempted from the uptick rule. Portfolio managers can use ETFs as investment tools to help execute dynamic trading strategies and individual investors can use ETFs to participate in foreign stock markets to diversify their investments. Miffre (2006) empirically demonstrates that country-specific ETFs can enhance global asset allocation strategies at a low cost, with a low level of tracking error, and in a tax-efficient manner. The ETF industry in the U.S. experienced rapid growth in the decade after the turn of the millennium, with a 5-year average annual growth rate of 33% (Schuster, 2008). ETFs have grown from a small, niche index-tracking product to become one of the most successful innovations in the history of investment (Charupat & Miu, 2013).

ETFs are playing an increasingly important role in Japan. The number of ETFs listed on Tokyo Stock Exchange (TSE) increased from 18 in 2007 to 207 in March 2017. However, compared with other developed financial markets, the Japan-listed ETF segment is still in its emerging stages. Among these 207 ETFs, most (192) are physical ETFs, which directly buy all of the assets needed to replicate the composition and weighting of their indicators or which buy a portion of the assets needed to replicate the composition along with other assets that have a high degree of correlation with the underlying indicator. The other 15 are over-the-counter (OTC) swap-type ETFs. They resemble the synthetic ETFs in other markets and utilize a management method of aligning the fluctuation rate of the net assets per unit with that of an underlying indicator by concluding a total return swap agreement, which exchanges the returns of the underlying indicator between the ETF issuer and primarily financial institutions.

Tracking error can accumulate over time and significantly affect long-term performance. The aim of an ETF is to track an indicator, such as a stock price index, like the Tokyo Stock Price Index or Nikkei 225, or commodity prices. However, not all ETFs track the indicator with an equal level of accuracy. The performance of an ETF is not guaranteed to be identical to its underlying tracking index. A stock index represents only a calculation derived from a portfolio of stocks and is not subject to the market frictions that an ETF has. If an ETF is not able to perfectly replicate or if it even underperforms the return of an indicator, it is regarded as unable to meet its investment objectives. Persistent underperforming of the indicator may trigger redemption of ETF units. Since the ETFs are traded easily in the stock market, the redemption process will become a market force and move ETF prices. Moreover, the tracking performance is specific for ETFs and may be considered an extra cost of trading and handling ETFs. Therefore, the differences in the performance and deviations from expected performance are of considerable economic interest.

The aim of this study is threefold. The first objective is to explore the possible tracking error of ETFs listed on the TSE using four different models. This may provide further evidence of whether Japan-listed ETFs are traded at their fundamental values. The physical ETFs are replicated by holding all securities of the underlying index; while OTC swap-type ETFs rely on derivatives such as swaps and futures. The swap-type ETFs would argue that they can perfectly mimic the underlying index and consequently deliver the smaller tracking error. The second objective of this article is to compare the tracking ability between these two groups of ETFs. The third objective is to present novel evidence of the rational determinants that may explain the observed tracking error of physical ETFs by constructing a multifactor panel regression model based on a set of operating factors. There is a paucity of research on Japan-listed ETFs and the analysis of ETF tracking error remains a widely misunderstood and frustrating process for investors.

This study highlights the challenges of fund managers who seek to trace markets at a relatively lower cost by arranging a swap agreement rather than physically holding stocks. There is a lack of comprehensive and general study of the tracking error of Japan-listed ETFs and research on potential key determinants still appears to be in its inception. Thus, this study aims to fill this gap in the literature.

The remainder of this paper is organized as follows. Section 2 presents a literature review and the hypotheses. Section 3 describes the data. Section 4 presents the research methodology for assessing tracking performance and the panel data model to determine the impact of determinants on tracking performance. The results of ETFs' tracking performance and the impact of determinants are discussed in Section 5. Section 6 concludes.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Roll (1992) suggests that the level of tracking error may be an important criterion for assessing ETF performance. Pope and Yadav (1994) agree, and argue that tracking error is crucial in structuring and managing ETFs. Tracking error represents the difference between the performance of an ETF and that of its target index. Most recent studies document the inability of ETFs to track their underlying indexes. Elton, Gruber, Comer, and Li (2002) find that SPDR underperforms the S&P index, primarily because of the loss of income caused by holding the dividends received from underlying shares in cash. Cheng, Fund, and Tse (2008) find that the Hong Kong market climate may cause the iShares FTSE/Xinhua China 25 Index ETF returns and S&P500 Index Fund returns to deviate from their underlying indicators. Aber, Li, and Can (2009) find that four actively traded iShares ETFs in the U.S. are unable to track their underlying indexes to a certain extent. Blitz and Huij (2012) report that the tracking error of ETFs in emerging markets is substantially higher than the previously reported levels for developed markets' ETFs. Drenovak, Urosevic, and Jelic (2014) find that Eurozone sovereign debt ETFs have substantially higher tracking error than those reported for U.S. Treasury bond ETFs.

In the very beginning, ETFs replicate the index by holding all securities of the underlying index. Quite recently, ETFs relying on derivatives such as swaps and futures are being traded since 2001. As to the influence of synthetic ETFs, a debate has started. Meinhardt, Mueller, and Schoene (2015) compare the tracking errors of full replication and synthetic ETFs for the German market but they do not find any difference in tracking errors between these two groups of ETFs.

In addition, some prior studies investigate what factors explain the pricing performance or tracking ability of ETFs. Delcoure and Zhong (2007) find that the premiums of iShares are significantly correlated with exchange rate volatility, political and financial crises, institutional ownership, bid–ask spread, and trading volume, and are conditionally correlated between the U.S. market and the home market. Madura and Ngo (2008) find that size, trading volume, and momentum are effective indicators of an ETF's pricing performance. One of the widely recognized factors that affect tracking error is the ETF's expense ratio. Rompotis (2009) finds a positive correlation between tracking ability and expense ratio, which does not contradict the commonly held belief that expenses usually erode ability. Shin and Soydemir (2010) report that expense ratio, dividend, change in exchange rate, and spread in trading prices are sources of tracking ability of foreign equity ETFs. Rompotis (2011) shows that the expenses charged by the ETFs along with the age and risk of ETFs are some of the determinants of the persistence in tracking error. DeFusco, Ivanov, and

Karls (2011) find that the accumulation of dividends by ETFs is one of the determinants of price deviation, which is another measure of tracking inability. Blitz, Huij, and Swinkels (2012) find that fund expense and dividend withholding tax may explain the performance difference and time variations in fund performance. Qadan and Yagil (2012) find that the tracking ability of ETFs is lower in highly volatile periods, which could provide an indication of the factors underlying the tracking error. Drenovak et al. (2014) also show the volatility and duration of underlying indexes; replication method, expense ratio, and size of ETFs are the determinants of tracking performance. Osterhoff and Kaserer (2016) extend the literature by corroborating that the liquidity of individual stocks in the underlying portfolio has an impact on tracking error.

Each of the factors that may affect tracking error is discussed in detail below.

2.1 EXPENSE

One widely recognized factor affecting tracking error is the expense ratio, which is expense scaled by the size of the ETF. It represents the explicit costs of managing an ETF. ETFs have the advantage or selling point of lower management fees than index mutual funds, since ETFs' issuers do not need to provide transfer agency service. Although the expense ratio of ETFs is relatively lower than the mutual funds, it erodes the tracking ability of an ETF and leads to expectations that it should not mimic the performance of the underlying target index. Frino and Gallagher (2001) document that tracking error is positively related to expenses, which indicates that a higher expense ratio results in higher tracking error, i.e. worse tracking ability. The positive relationship between tracking error and expense ratio is supported by some other studies (Rompotis, 2009, 2011; Shin & Soydemir, 2010; Agapova, 2011; Elia, 2012; Blitz et al. (2012); Meinhardt, Mueller, & Schoene, 2015; Osterhoff & Kaserer, 2016). Drenovak et al. (2014) observe a negative relationship between expense ratio and tracking error of European bond ETFs but do not explain the negativity of the relationship. Charupat and Miu (2013) indicate that higher the expense ratio of an ETF is, the more it can be expected to underperform the underlying index. Since a positive relationship is observed in most studies, this study hypothesizes a positive relationship between the size of tracking error (worse tracking ability) and the expense ratio.

2.2 SIZE

Size, measured by the amount of total assets of ETFs, is hypothesized as one of the factors of tracking error. Size is expected to be negatively related to tracking error, because larger ETFs may face lower transaction costs owing to economies of scale (Shin & Soydemir, 2010). Transaction costs are the explicit costs of trading activities in stock markets, including brokerage fees and stamp duties, which can influence an ETF's ability to replicate index performance. Indexes are computed based on an assumption of costless transactions, but in reality, funds are required to trade in financial markets, and explicit transaction costs are incurred. These explicit transaction costs can erode ETF returns and lead to tracking error.

2.3 DIVIDEND AND CASH HOLDING

Frino and Gallagher (2001) and Frino, Gallagher, Neubert, and Oetomo (2004) identify dividend payment as a factor that may also have an impact on tracking error. When the listed stocks that an index is comprised of pay dividends, the index immediately assumes that the dividends are reinvested in the stocks on the ex-dividend day. However, in reality, fund managers have to wait to receive dividends before they are able to reinvest, and their reinvestment activities incur transaction costs that are not considered in the computation of market indexes. These delays in receiving dividends and costs incurred in reinvestment may erode ETFs' ability to replicate index performance. Elton et al. (2002) show that one of the main causes of tracking error is delayed reinvestment of cash dividends. Blitz et al. (2012) and Blitz and Huij (2012) find that dividend taxes explain tracking ability and ETFs' expected returns, respectively. DeFusco et al. (2011) find that the accumulation of dividends by ETFs is one of the factors of tracking error measured by pricing deviation. The higher is the dividend yield, the longer is the time delay in receiving it, the higher is the return of the underlying index, and the more negative is the impact on the ETF return. There is a possible positive relationship between this factor and tracking error, since dividends are regarded as forfeited portfolio returns unless they are reinvested immediately.

2.4 TRADING VOLUME

Regarding the effect of market liquidity on tracking ability, two widely accepted proxies in previous research are trading volume and bid–ask price spread. The trading volume of ETFs is hypothesized to be one of the factors of tracking ability. Higher trading volume leads to greater cash inflows, which is induced by different investor beliefs about an investment's fundamental value. Trading volume may be used as a proxy of the difference in investor beliefs. Difference in investor beliefs may lead to difference between the ETF price and its fundamental values, and thus, a positive relationship between trading volume and tracking ability is hypothesized. Although the outcome that trading volume positively affects tracking ability may not be intuitive, Rompotis (2006) finds a significant positive relationship between trading volume and tracking error.

2.5 RISK

The riskier the market is, more difficult it is for an ETF to replicate the market performance, leading to higher tracking error. Thus, market risk is expected to have a positive relationship with tracking error. Previous studies also show a positive relationship between market volatility and tracking error (Qadan & Yagil, 2012; Drenovak et al., 2014).

2.6 NUMBER OF CONSTITUENT STOCKS

DeFusco et al. (2011) hypothesize that besides the size of the index, the way the index is formed might be another factor of price deviation, which is a measure of tracking inability. Since the exact structure of a part of indexes is proprietary, ETF managers may know only the number of constituent companies in the index and have to guess the exact proportions of its constituents. The number of constituent stocks in the index can be considered one of the factors of tracking error. More stocks in the index make it more difficult for the ETF managers to track the index, and thus, a positive relationship between the number of stocks in the index and tracking error is hypothesized.

2.7 HYPOTHESES

Based on the findings of the literature, we test the following hypotheses in this study.

H1: The synthetic OTC-swap type ETFs have lower tracking errors.

H2: ETF tracking error is positively associated with the expense ratio, dividend yield, trading volume of an ETF; however, negatively associated with the size of an ETF.

H3: ETF tracking error is positively associated with the risk and the number of constituents of target indexes.

3 DATA AND SAMPLE DESCRIPTIVE STATISTICS

The ETFs listed on the TSE are classified into the following 11 categories: Japanese Equity Index (market), Japanese Equity Index (size), Japanese Equity Index (sector), Japanese Equity Index (theme), Enhanced Index, Leveraged/Inverse Index, Real Estate, Foreign Equity Index, Foreign Bond Index, Commodity/Commodity Index, and Commodity/Commodity Index (ETC). According to periodic reports published by Japan Exchange Group (JPX), the top 20 ETFs listed on the TSE in terms of largest trading volume are almost all in the categories of Japanese Equity Index (market) and Leveraged/Inverse Index. Thus, this study selects the ETFs in these two categories in the sample. All of them are physical ETFs. OTC swap-type ETFs that are not in these two categories are also included in the sample for a comparison. However, the impact of determinants on the tracking ability of these ETFs is not investigated in this study.

Except for annual expense ratios, all data are collected on a daily basis for the period January 1, 2010–December 31, 2016. The daily ETF prices, dividend yields, and trading volumes of the sample ETFs, from their date of inception to 31 December 2016, are obtained from DATASTREAM of Thomson Financial Limited, and are checked against the returns supplied directly by investment managers. Financial data, including fund size and expenses over the period 2015–2016, were compiled from the annual reports published by JPX.

Table 1 presents the profile of the sampled ETFs, including name of fund, benchmark index being traced, and date of inception. The study is free of survivorship bias.

Table 1. Overview of ETFs in Observed Sample

Fund	Fund Name	Code	Index Being Traced (Indicator)	Listing Date
(a) Japanese Equity Index (Market)				
1	Daiwa ETF-TOPIX	1305	TOPIX	Jul. 13, 2001
2	TOPIX Exchange Traded Fund	1306	TOPIX	Jul. 13, 2001
3	Listed Index Fund TOPIX	1308	TOPIX	Jan. 9, 2002
4	MAXIS TOPIX ETF	1348	TOPIX	May 15, 2009
5	One ETF TOPIX	1473	TOPIX	Sep. 7, 2015
6	iShares TOPIX ETF	1475	TOPIX	Oct. 20, 2015
7	Daiwa ETF - Nikkei 225	1320	Nikkei 225	Jul. 13, 2001
8	Nikkei 225 Exchange Traded Fund	1321	Nikkei 225	Jul. 13, 2001
9	iShares Nikkei 225 ETF	1329	Nikkei 225	Sep. 5, 2001
10	Listed Index Fund 225	1330	Nikkei 225	Jul. 13, 2001
11	MAXIS NIKKEI225 ETF	1346	Nikkei 225	Feb. 25, 2009
12	Listed Index Fund Nikkei 225 (Mini)	1578	Nikkei 225	Mar. 25, 2013
13	One ETF Nikkei225	1369	Nikkei 225	Jan. 15, 2015
14	SMAM NIKKEI225 ETF	1397	Nikkei 225	Mar. 25, 2015
15	NEXT FUNDS JPX-Nikkei Index 400 Exchange Traded Fund	1591	JPX-Nikkei Index 400	Jan. 28, 2014
16	Listed Index Fund JPX-Nikkei 400	1592	JPX-Nikkei Index 400	Jan. 28, 2014
17	MAXIS JPX-Nikkei Index 400 ETF	1593	JPX-Nikkei Index 400	Feb. 6, 2014
18	Daiwa ETF JPX-Nikkei 400	1599	JPX-Nikkei Index 400	Mar. 27, 2014
19	iShares JPX-Nikkei 400 ETF	1364	JPX-Nikkei Index 400	Dec. 2, 2014
20	One ETF JPX-Nikkei400	1474	JPX-Nikkei Index 400	Sep. 7, 2015
21	Nikkei 300 Stock Index Listed Fund	1319	Nikkei 300	May 29, 1995
22	TSE Mothers Core ETF	1563	TSE Mothers Core Index	Nov. 29, 2011

(*Continued*)

Table 1. (*Continued*)

Fund	Fund Name	Code	Index Being Traced (Indicator)	Listing Date
23	JASDAQ-TOP20 ETF	1551	JASDAQ-TOP20	Dec. 3, 2010
24	Listed Index Fund S&P Japan Emerging Equity 100	1314	S&P Japan Emerging Equity 100	Mar. 11, 2008
(b) Leveraged / Inverse Index				
25	TOPIX Bull 2x ETF	1568	TOPIX Leveraged (2x) Index	Apr. 5, 2012
26	Daiwa ETF Japan TOPIX Leveraged (2x) Index	1367	TOPIX Leveraged (2x) Index	Jan. 6, 2015
27	TOPIX Bear -1x ETF	1569	TOPIX Inverse (-1x) Index	Apr. 5, 2012
28	Daiwa ETF Japan TOPIX Inverse (-1x) Index	1457	TOPIX Inverse (-1x) Index	Apr. 27, 2015
29	TOPIX Bear -2x ETF	1356	TOPIX Double Inverse (-2x) Index	May. 29, 2014
30	Daiwa ETF Japan TOPIX Double Inverse (-2x) Index	1368	TOPIX Double Inverse (-2x) Index	Jan. 6, 2015
31	China H-share Bull 2x ETF	1572	HSCEI Leveraged Index	Dec. 6, 2012
32	China H-share Bear -1x ETF	1573	HSCEI Short Index	Dec. 6, 2012
33	NEXT FUNDS Nikkei 225 Leveraged Index Exchange Traded Fund	1570	Nikkei 225 Leveraged Index	Apr. 12, 2012
34	Nikkei 225 Bull 2x ETF	1579	Nikkei 225 Leveraged Index	May. 9, 2013
35	Listed Index Fund Nikkei Leveraged Index	1358	Nikkei 225 Leveraged Index	Aug. 26, 2014
36	Daiwa ETF Japan Nikkei225 Leveraged Index	1365	Nikkei 225 Leveraged Index	Jan. 6, 2015
37	Rakuten ETF-Nikkei 225 Leveraged Index	1458	Nikkei 225 Leveraged Index	Jul. 15, 2015
38	NEXT FUNDS Nikkei 225 Inverse Index Exchange Traded Fund	1571	Nikkei 225 Leveraged Index	Apr. 12, 2012
39	Nikkei 225 Bear -1x ETF	1580	Nikkei 225 Leveraged Index	May. 9, 2013
40	Daiwa ETF Japan Nikkei225 Inverse Index	1456	Nikkei 225 Leveraged Index	Apr. 27, 2015
41	NEXT FUNDS Nikkei 225 Double Inverse Index Exchange Traded Fund	1357	Nikkei 225 Double Inverse Index	Jul. 16, 2014
42	Nikkei225 Bear -2x ETF	1360	Nikkei 225 Double Inverse Index	Nov. 11, 2014
43	Daiwa ETF Japan Nikkei225 Double Inverse Index	1366	Nikkei 225 Double Inverse Index	Jan. 6, 2015
44	Rakuten ETF-Nikkei 225 Double Inverse Index	1459	Nikkei 225 Double Inverse Index	Jul. 15, 2015

(*Continued*)

Table 1. (*Continued*)

Fund	Fund Name	Code	Index Being Traced (Indicator)	Listing Date
45	Daiwa ETF Japan JPX-Nikkei 400 Leveraged (2x) Index	1464	JPX-Nikkei 400 Leveraged (2x) Index	Aug. 24, 2015
46	JPX-Nikkei 400 Bull 2x Leveraged ETF	1467	JPX-Nikkei 400 Leveraged (2x) Index	Aug. 24, 2015
47	NEXT FUNDS JPX-Nikkei 400 Leveraged Index Exchange Traded Fund	1470	JPX-Nikkei 400 Leveraged (2x) Index	Aug. 24, 2015
48	Daiwa ETF Japan JPX-Nikkei 400 Inverse (-1x) Index	1465	JPX-Nikkei 400 Inverse (-1x) Index	Aug. 24, 2015
49	JPX-Nikkei 400 Bear -1x Inverse ETF	1468	JPX-Nikkei 400 Inverse (-1x) Index	Aug. 24, 2015
50	NEXT FUNDS JPX-Nikkei 400 Inverse Index Exchange Traded Fund	1471	JPX-Nikkei 400 Inverse (-1x) Index	Aug. 24, 2015
51	Daiwa ETF Japan JPX-Nikkei 400 Double Inverse (-2x) Index	1466	JPX-Nikkei 400 Double Inverse (-2x) Index	Aug. 24, 2015
52	JPX-Nikkei 400 Bear -2x Double Inverse ETF	1469	JPX-Nikkei 400 Double Inverse (-2x) Index	Aug. 24, 2015
53	NEXT FUNDS JPX-Nikkei 400 Double Inverse Index Exchange Traded Fund	1472	JPX-Nikkei 400 Double Inverse (-2x) Index	Aug. 24, 2015
(c) OTC Swap-Type				
54	S&P GSCI Energy & Metals Capped Component 35/20THEAM Easy UCITS ETF Class A USD Unit	1327	S&P GSCI Energy & Metals Capped Component35/20 Total Return Index	Oct. 22, 2008
55	ETFS All Commodities	1684	Bloomberg Commodity Index	Mar. 19, 2010
56	ETFS Energy	1685	Bloomberg Energy Subindex	Mar. 19, 2010
57	ETFS Industrial Metals	1686	Bloomberg Industrial Metals Subindex	Mar. 19, 2010
58	ETFS Agriculture	1687	Bloomberg Agriculture Subindex	Mar. 19, 2010
59	ETFS Grains	1688	Bloomberg Grains Subindex	Mar. 19, 2010
60	ETFS Natural Gas	1689	Bloomberg Natural Gas Subindex	Mar. 19, 2010
61	ETFS WTI Crude Oil	1690	Bloomberg Crude Oil Subindex	Mar. 19, 2010
62	ETFS Gasoline	1691	Bloomberg Unleaded Gasoline Subindex	Mar. 19, 2010
63	ETFS Aluminium	1692	Bloomberg Aluminium Subindex	Mar. 19, 2010

Table 1. (*Continued*)

Fund	Fund Name	Code	Index Being Traced (Indicator)	Listing Date
64	ETFS Copper	1693	Bloomberg Copper Subindex	Mar. 19, 2010
65	ETFS Nickel	1694	Bloomberg Nickel Subindex	Mar. 19, 2010
66	ETFS Wheat	1695	Bloomberg Wheat Subindex	Mar. 19, 2010
67	ETFS Corn	1696	Bloomberg Corn Subindex	Mar. 19, 2010
68	ETFS Soybeans	1697	Bloomberg Soybeans Subindex	Mar. 19, 2010

4 METHODOLOGY

4.1 DETERMINING TRACKING ERROR

Pope and Yadav (1994) suggest three different definitions of tracking error to measure the tracking ability of index mutual funds, all of which measure the tracking error of ETFs similarly. The first definition of tracking error (TE_1) is the absolute difference in returns between the fund and the index. This definition provides a measure of the extent to which the return on an ETF_i $(R_{i,t})$ differs from that on the underlying target index $(R_{b,t})$ over sample period n, and regards any deviation in returns regardless of overperformance or underperformance as tracking error. This definition of tracking error is calculated as follows:

$$TE_1 = \frac{\sum_{t=1}^{n} \left| e_{i,t} \right|}{n} \tag{1}$$

where $R_{i,t}$ is the return on ETF_i, $R_{b,t}$ is the return on the underlying target index, and $e_{i,t} = R_{i,t} - R_{b,t}$ is known as the active returns.

The second way to measure tracking error (TE_2) is to compute the standard deviation of the differences between the returns on the ETF and the benchmark indexes, and is calculated as follows:

$$TE_2 = \sqrt{\frac{1}{n-1} \sum_{t=1}^{n} (e_{i,t} - \bar{e}_i)^2} \tag{2}$$

Using standard deviation to measure the tracking error requires the assumption of serially uncorrelated return differences, $e_{i,t}$. Although TE_2 describes variability in active returns, it provides no information on an ETF's underperformance or overperformance of the benchmark index. Thus, as a performance measure, TE_2 is more appropriate for index funds like ETFs than for actively managed mutual funds. The other shortcoming of TE_2 is that if a fund consistently underperforms or overperforms the target index by the same magnitude, the tracking error measured by the standard deviation may lead to a result of zero.

The third way to estimate tracking error (TE_3) is to find the standard error of regression (SER) in the following ordinary least square (OLS) regression, which is an unbiased estimator of the standard deviation of the residuals (ε_i):

$$R_{i,t} = \alpha + \beta \cdot R_{b,t} + \varepsilon_t \tag{3}$$

If an ETF can trace the underlying benchmark index perfectly and uses identical weights to those used in the underlying index, then the value of α in regression model (3) should not be statistically different from zero, the value of β should not be statistically different from one, and R-squared should be close to one. The deviation from the index contributes to the higher standard error of the OLS model. However, Pope and Yadav (1994) point out two problems underlying the use of this measure. First, if β does not exactly equal one, this measure may result in a value different from $TE_{2,i}$ and second, this approach may overestimate tracking error if the relationship in the abovementioned OLS model is not linear.

Cresson, Cudd, and Lipscomb (2002) add a fourth method of estimating tracking error (TE_4), by using the value of the R-squared of the OLS regression defined in equation (3). The authors suggest that using the R-squared as the measure of tracking error also indicates the degree to which the ETF mimics the respective benchmark index, and that therefore, it is a more straightforward measure. However, this measure has the opposite measurement direction to the other three and thus, cannot be compared directly with them.

4.2 DETERMINANTS OF TRACKING ERROR

The literature describes a wide array of factors that may affect the tracking ability of ETFs. To determine whether tracking error is associated with these selected operating characteristics, the tracking error of ETFs is regressed for selected ETF operating characteristics. The dataset is a panel with 53 cross-sections, that is, physical ETFs; and two time periods, 2015 and 2016, when the data of selected determinants are available and the ETFs have been traded for a whole year. The use of the panel data model, rather than cross-sectional or time series models, is chosen because panel data can account for individual differences or heterogeneity. Furthermore, a panel dataset can cover a sufficiently long period, thereby allowing dynamic factors to be studied. Since the number of cross-sections in this study is fairly large, it is not appropriate to use the techniques of seemingly unrelated regressions or include a set of dummy variables for the cross-sections in the model. A panel regression model with fixed-effects estimators may be adapted to panel data with a large number of cross-sections. The fixed-effects estimation in this study is as follows:

$$\tilde{y}_{it} = \beta_1 \tilde{x}_{1it} + \beta_2 \tilde{x}_{2it} + \ldots + \tilde{\varepsilon}_{it} \tag{4}$$

where the "tilde" notation $\tilde{y}_{it} = y_{it} - \bar{y}_i$ indicates that the variables deviate from the mean. The adoption of different portfolio strategies may affect the replication performance of ETFs. A complete panel regression model with fixed effects to control for ETF-inherent characteristics is performed. The model with the proposed factors to explain tracking error is then expressed as follows:

$$\tilde{TE}_{i,t} = \beta_0 + \beta_1 \cdot \tilde{TER}_{i,t} + \beta_2 \cdot \tilde{SIZE}_{i,t} + \beta_3 \cdot \tilde{DIV}_{i,t} + \beta_4 \cdot \tilde{VOL}_{i,t} + \beta_5 \cdot \tilde{RISK}_{i,t}$$

$$+ \beta_6 \cdot \tilde{NUMBER}_{i,t} + \tilde{\varepsilon}_{i,t} \tag{5}$$

where $\widetilde{TER}_{i,t} = TER_{i,t} - \overline{TER}_i$, $\widetilde{SIZE}_{i,t} = SIZE_{i,t} - \overline{SIZE}_i$, $\widetilde{DIV}_{i,t}$

$= DIV_{i,t} - \overline{DIV}_i$, $\widetilde{VOL}_{i,t} = VOL_{i,t} - \overline{VOL}_i$, $\widetilde{RISK}_{i,t} = RISK_{i,t} - \overline{RISK}_i$, $\widetilde{NUMBER}_{i,t}$

$= NUMBER_{i,t} - \overline{NUMBER}_i$.

The independent variables in panel regression (5) include the (1) *TER*: the annual total expense ratio that is charged by the ETF's issuer and scaled to the ETF's size; (2) *SIZE*: the natural logarithm of ETF total assets whose original value is in million JPY; (3) *DIV*: dividend yield, which is measured as a ratio of average dividend and average trading price of the ETF; (4) *VOL*: the natural logarithm of the average daily trading volume; (5) *RISK*: the market risk measured by the coefficient of variation of daily market index, which is the ratio of average standard deviation of daily index to its average; and (7) *NUMBER*: the number of constituents in the underlying index. To overcome the problem of multicollinearity among the regressors and to find the explanatory power of individual factors, the tracking error is regressed on each independent variable individually.

We can also include squared terms of the independent variables to identify a potential nonlinear relationship between tracking error and regressors. The model can be presented as follows:

$$\begin{aligned} \tilde{TE}_{i,t} = {} & \beta_0 + \beta_1 \cdot \tilde{TER}_{i,t} + \beta_2 \cdot \tilde{TER}^2_{i,t} + \beta_3 \cdot \tilde{SIZE}_{i,t} + \beta_4 \cdot \tilde{SIZE}^2_{i,t} + \beta_5 \cdot \tilde{DIV}_{i,t} \\ & + \beta_6 \cdot \tilde{DIV}^2_{i,t} + \beta_7 \cdot \tilde{VOL}_{i,t} + \beta_8 \cdot \tilde{VOL}^2_{i,t} + \beta_9 \cdot \tilde{RISK}_{i,t} + \beta_{10} \cdot \tilde{RISK}^2_{i,t} \\ & + \beta_{11} \cdot \tilde{NUMBER}_{i,t} + \beta_{12} \cdot \tilde{NUMBER}^2_{i,t} + \tilde{\varepsilon}_{i,t} \end{aligned} \tag{6}$$

For models (5) and (6), the heteroscedasticity, time-series autocorrelation, and cross-sectional dependence between panels are tested; positive results for all tests are obtained. We also apply robust standard error suggested by Driscoll and Kraay (1998), which is a computation method that generates heteroscedasticity and autocorrelation-consistent standard error to ensure valid statistical inference of models (5) and (6).

5 RESULTS

5.1 TRACKING ERROR OF ETFS

Table 2 reports the tracking error of the ETFs included in this study for the entire sample period available. Based on the first definition of tracking error (TE_1), the daily tracking error averages range from 0.1106% to 3.4690% across ETFs. The tracking error based on the second definition, the standard deviation of the return differences (TE_2), ranges from 0.1745% to 5.4322%. Based on the third definition of tracking error (TE_3), the daily tracking error of each ETF computed by finding the standard error of regression of the CAPM model defined in equation (3) ranges between 0.1701% and 4.7687%. These results indicate that the sampled ETFs listed on the TSE fall well short of perfectly tracking the underlying indexes, and seem to have difficulty in achieving index returns. From the viewpoint of investors, the ETFs do not provide fully efficient tracking of the underlying indexes. In addition, the daily tracking error of the sampled ETFs documented in this study are comparatively higher than those documented in the U.S. (0.039% to 0.110% per month) (Blume & Edelen, 2004) and in Australia (0.074% to 0.224% per month) (Frino & Gallagher, 2002). The tracking error reflects the inherent frictions that ETF managers face, such as administrative expenses, transaction costs, commissions, underinvested dividends, and delays in the adjustments of ETF portfolios to match changes in constituent stocks in indexes.

The eighth column of Table 2 presents the mean differences between the sample ETFs' returns and their benchmarks. Among them, 45 are positive and 23 are negative. This result shows that the majority of Japan-listed ETFs may provide higher return than their benchmarks. This finding does not support hypothesis *H1* and is surprising, because there is a general view that on average, ETFs tend to underperform their paper-based benchmark indexes.

The tracking error of all ETFs, based on the magnitude of the R-square of the CAPM model (TE_4), is reported in Table 2. The α values are very close to zero for the majority of the sample. The overperformance or underperformance indicated by the α values is statistically insignificant in all cases. All β coefficients are less than one, which indicates that all ETFs' have less movement in their prices than their tracking indexes do. The R-squared for the entire sample ranges from a low of 0.0000 to a high of 0.9916. The values of the R-squared reported in this study differ from those documented in Frino and Gallagher (2001; 2002), which range from 0.997 to 1.000 in the U.S. and from 0.993 to 1.000 in Australia. However, both of those previous studies are based on monthly returns. Our results once again demonstrate the difference in measuring the tracking error of ETFs using daily versus monthly return figures. A fairer comparison would be to use the daily tracking error employing the R-squared of S&P 500 index funds documented in Cresson et al. (2002), who find values ranging from 0.9052 to 0.9609. However, the values of the R-squared documented in this study are still substantially below those documented in the U.S. and Australia. The substantially higher tracking error in Japan-listed ETFs may reflect the higher cost of trading the underlying portfolios of stocks in Japan or the higher cost of trading overseas stocks for Japan-listed ETF managers.

Previous studies have found that swap-type ETFs usually have better tracking performance than do their counterparts adopting a physical replication method. The TSE even claims that OTC swap-type ETFs do not experience tracking error, although they do involve credit risk for the counterparty to the swap agreement. However, the results presented in panel (c) of Table 2 indicate that the OTC swap-type ETFs have higher tracking error. The findings in this study do not seem to support this claim.

Table 3 reports the results of sample ETFs' daily tracking error over the last 4 years in the studied time period. The annual averages of the tracking error of all sample ETFs are presented first and those of individual ETF next. The annual averages of the tracking error measured by different definitions is highest in 2013, decreases in 2014 and 2015, and increases in 2016.

The results presented in Table 2 indicate that the OTC swap-type ETFs have higher tracking error, which contradicts the claims of the TSE. A pooled-variance t-test is performed to test the claim that OTC swap-type ETFs have significantly higher tracking error than physical-type ETFs do. The results are presented in panel A of Table 4. The test statistics support the claim at both the 5% and 1% levels of significance. The reason that OTC swap-type or synthetic ETFs have higher tracking error is easy to understand. This ETF type may not find derivatives that exactly match the stocks included in their benchmark indexes, meaning that their performances may not trace the performances of their benchmark indexes perfectly.

Panel B of Table 4 presents the results of the pool-variance t-test of the claim that the physical-type ETFs have significantly higher mean α and β values obtained from the CAPM model (model (3)). The test results support the claim that the physical-type ETFs have significant higher mean α and β values than do the counterpart OTC swap-type ETFs. A larger negative value of mean α of the OTC swap-type ETFs could be explained by the inferior performance of swap-type ETF managers in using swaps or derivatives to replicate the performance of the benchmark indexes. The mean β value of the physical-type ETFs is closer to 1 than is that of the OTC swap-type ETFs. This is not surprising, because the physical-type ETFs hold stocks rather than trade derivatives to replicate the market performance.

Table 2. Daily Tracking Error of Sample ETFs over the Observed Time Period

		Absolute Difference in Returns					Return Differences			CAPM					Average of
ETF Number	*N*	Mean (TE_1)	Std. Dev.	Min.	Max		Std. Dev. (TE_2)	Mean		S.E. of Reg. (TE_3)	α	β	R^2 (TE_4)		TE_1, TE_2, TE_3
(a) Japanese Equity Index (Market)															
1	1955	0.1258	0.1559	0.0000	2.0845		0.2003	0.0021		0.1989	0.0000	0.9807	0.9748		0.1750
2	1955	0.1329	0.1884	0.0000	2.9413		0.2305	0.0010		0.2306	0.0000	0.9977	0.9675		0.1980
3	1955	0.1314	0.1693	0.0000	2.1873		0.2143	0.0017		0.2136	0.0000	0.9850	0.9713		0.1864
4	1955	0.1408	0.3036	0.0000	8.2271		0.3346	0.0010		0.3320	0.0000	0.9660	0.9309		0.2691
5	474	0.7251	0.8100	0.0000	5.4355		1.0877	0.0028		0.9840	0.0001	0.6657	0.4710		0.9323
6	443	0.1190	0.1597	0.0000	1.7461		0.1992	0.0019		0.1982	0.0000	0.9834	0.9782		0.1721
7	1955	0.1432	0.1813	0.0000	2.1962		0.2310	0.0017		0.2269	0.0000	0.9677	0.9709		0.2004
8	1955	0.1436	0.1914	0.0000	3.3401		0.2393	0.0013		0.2325	0.0000	0.9579	0.9689		0.2051
9	1955	0.1732	0.2161	0.0000	2.5094		0.2770	0.0016		0.2713	0.0000	0.9586	0.9581		0.2405
10	1955	0.1106	0.1349	0.0000	1.7014		0.1745	0.0011		0.1701	0.0000	0.9709	0.9835		0.1517
11	1955	0.1430	0.1820	0.0000	2.8051		0.2314	0.0013		0.2256	0.0000	0.9616	0.9709		0.2000
12	1114	0.5982	0.7166	0.0000	6.4941		0.9337	–0.0001		0.8960	0.0000	0.8123	0.6195		0.8093
13	641	0.1923	0.2184	0.0000	1.7134		0.2911	0.0021		0.2875	0.0000	0.9658	0.9553		0.2570
14	592	0.7958	0.9491	0.0000	9.3967		1.2390	0.0027		1.1760	0.0000	0.7209	0.4278		1.0703
15	893	0.1383	0.1679	0.0000	2.0549		0.2176	0.0001		0.2105	0.0000	0.9572	0.9720		0.1888
16	893	0.1602	0.1915	0.0000	1.6585		0.2498	0.0011		0.2375	0.0000	0.9398	0.9633		0.2158
17	886	0.1274	0.1537	0.0000	1.2194		0.1997	0.0026		0.1918	0.0000	0.9563	0.9761		0.1730
18	851	0.2178	0.3243	0.0000	3.3085		0.3907	0.0016		0.3818	0.0000	0.9347	0.9077		0.3301
19	673	0.1310	0.1466	0.0000	1.2670		0.1967	0.0019		0.1942	0.0000	0.9763	0.9784		0.1740

20	474	0.9179	1.0780	0.0000	8.9718		1.4165	−0.0002		1.1926	0.0001	0.4598	0.2307		1.1757
21	1955	1.0768	1.1681	0.0000	11.0553		1.5889	0.0044		1.5165	0.0001	0.6242	0.2134		1.3941
22	1458	0.9140	1.0651	0.0000	16.3536		1.4037	0.0005		1.3988	0.0000	0.9447	0.6923		1.2388
23	1715	0.8014	0.8641	0.0000	9.4465		1.1787	−0.0004		1.1489	0.0000	0.8956	0.7963		1.0430
24	1838	1.5706	1.6845	0.0000	12.8299		2.3034	−0.0019		1.6986	0.0005	−0.0096	0.0001		1.8575
(b) Leveraged / Inverse Index															
25	1366	0.1844	0.2160	0.0000	2.3365		0.2841	0.0053		0.2837	0.0000	0.9936	0.9878		0.2507
26	648	0.1763	0.2143	0.0000	2.1925		0.2775	0.0072		0.2768	0.0000	0.9917	0.9891		0.2435
27	1366	0.1498	0.1458	0.0000	1.3736		0.2087	−0.0114		0.2088	−0.0001	0.9978	0.9740		0.1891
28	569	0.4905	0.5855	0.0000	5.2278		0.7640	−0.0138		0.7192	−0.0001	0.8122	0.7092		0.6579
29	806	0.2136	0.2875	0.0000	3.5034		0.3576	−0.0211		0.3561	−0.0002	0.9862	0.9804		0.3091
30	648	0.2081	0.2328	0.0000	2.1854		0.3115	−0.0233		0.3117	−0.0002	0.9995	0.9864		0.2771
31	1191	1.5332	1.5057	0.0000	10.3880		2.1490	0.0361		2.1019	0.0003	0.8316	0.5300		1.9280
32	1191	0.9381	0.8831	0.0000	8.5797		1.2885	0.0233		1.2334	0.0001	0.7207	0.3807		1.1533
33	1361	0.2270	0.3174	0.0000	3.3999		0.3902	0.0051		0.3861	0.0000	0.9791	0.9798		0.3344
34	1081	0.1730	0.2488	0.0000	3.4899		0.3031	0.0044		0.2985	0.0000	0.9810	0.9885		0.2582
35	743	0.3179	0.5162	0.0000	4.6049		0.6063	0.0077		0.5704	0.0001	0.9244	0.9515		0.4982
36	648	0.1830	0.2692	0.0000	3.3495		0.3255	0.0056		0.3215	0.0000	0.9809	0.9860		0.2767
37	512	0.1902	0.2243	0.0000	2.2621		0.2940	0.0094		0.2937	0.0000	0.9933	0.9900		0.2593
38	1361	0.1609	0.1824	0.0000	1.8615		0.2431	−0.0097		0.2410	−0.0001	0.9763	0.9684		0.2150
39	1081	0.1338	0.1652	0.0000	2.1352		0.2124	−0.0103		0.2112	−0.0001	0.9833	0.9771		0.1858
40	569	0.1865	0.2026	0.0000	1.5226		0.2752	−0.0113		0.2716	−0.0001	0.9675	0.9629		0.2444
41	772	0.2218	0.3281	0.0000	4.0759		0.3956	−0.0211		0.3893	−0.0002	0.9736	0.9787		0.3355
42	688	0.1769	0.2018	0.0000	2.1174		0.2677	−0.0212		0.2651	−0.0002	0.9859	0.9904		0.2366

(Continued)

Table 2. (*Continued*)

(b) (*Continued*)															
43	648	0.1980	0.2166	0.0000	2.0983		0.2928	–0.0211		0.2892	–0.0002	0.9828	0.9887		0.2600
44	512	0.1641	0.2156	0.0000	2.1154		0.2701	–0.0230		0.2687	–0.0002	0.9899	0.9916		0.2343
45	484	0.2194	0.2360	0.0000	2.2338		0.3222	0.0095		0.3137	0.0000	0.9740	0.9878		0.2851
46	484	0.2826	0.3238	0.0000	3.1077		0.4299	0.0078		0.4069	0.0000	0.9516	0.9787		0.3731
47	484	0.2124	0.2945	0.0000	2.7370		0.3631	0.0097		0.3595	0.0000	0.9813	0.9843		0.3117
48	484	0.4046	0.4732	0.0000	3.1450		0.6227	–0.0140		0.5987	–0.0002	0.8803	0.8197		0.5420
49	484	0.7544	0.7762	0.0000	5.0052		1.0829	–0.0132		1.0106	–0.0002	0.7295	0.5228		0.9493
50	484	0.7479	0.8280	0.0000	6.1527		1.1162	–0.0132		1.0198	–0.0002	0.6850	0.4869		0.9613
51	484	0.2582	0.2609	0.0000	1.9785		0.3663	–0.0263		0.3541	–0.0002	0.9673	0.9844		0.3262
52	484	0.2419	0.2482	0.0000	2.0335		0.3457	–0.0277		0.3440	–0.0002	0.9871	0.9859		0.3105
53	484	0.3838	0.5782	0.0000	6.0612		0.6937	–0.0277		0.6765	–0.0003	0.9462	0.9431		0.5847
(c) *OTC Swap-type*															
54	1955	1.1854	1.0905	0.0000	10.0631		1.6109	0.0160		1.3353	–0.0001	0.0505	0.0013		1.3772
55	1900	1.1236	2.2631	0.0000	28.7408		2.5268	–0.0001		2.3569	–0.0002	–0.0407	0.0002		2.0024
56	1900	1.9075	3.1880	0.0000	46.2500		3.7154	0.0044		3.3763	–0.0006	0.0140	0.0000		2.9997
57	1900	1.4676	3.1984	0.0000	45.8083		3.5191	0.0148		3.2957	0.0000	0.0035	0.0000		2.7608
58	1900	1.5812	1.9826	0.0000	18.4919		2.5362	0.0049		2.3416	0.0000	0.1105	0.0027		2.1530
59	1900	1.8002	2.1534	0.0000	19.1542		2.8070	0.0077		2.5525	0.0000	0.1239	0.0042		2.3866
60	1900	3.4690	4.1796	0.0000	31.7375		5.4322	0.0131		4.7687	–0.0011	–0.0820	0.0017		4.5567
61	1900	2.1610	2.6012	0.0000	22.8279		3.3821	0.0051		2.8578	–0.0005	0.0953	0.0044		2.8003
62	1900	2.0387	3.2158	0.0000	33.4097		3.8078	–0.0029		3.3734	–0.0002	0.0253	0.0002		3.0733
63	1900	1.3308	2.3303	0.0000	27.9754		2.6837	0.0058		2.3856	–0.0002	–0.0205	0.0001		2.1333

64	1900	1.8454	3.2641	0.0000	80.7828		3.7499	0.0035		2.4906	–0.0001	–0.0019	0.0000		2.6953
65	1900	2.1328	3.3554	0.0000	30.0966		3.9762	0.0040		3.5313	–0.0004	0.0273	0.0002		3.2134
66	1900	1.9575	1.7560	0.0000	19.2868		2.6301	0.0058		1.9884	–0.0003	0.0667	0.0038		2.1920
67	1900	1.8194	1.6959	0.0000	12.9948		2.4875	0.0066		2.0400	0.0000	0.1375	0.0123		2.1157
68	1900	1.8228	2.9032	0.0000	30.5046		3.4282	0.0066		3.1875	0.0002	0.0212	0.0001		2.8128

Note: Tracking errors are expressed in percentage terms from the inception of ETFs to December 31 2016 using daily data. *N* represents the number of observations for each ETF used in this study. TE_1 is obtained from the average absolute difference between the returns on ETFs and the returns on their benchmark indices (indicators); TE_2 is obtained from the standard deviation of difference between returns on ETFs and the returns on their benchmark indices (indicators); TE_3 is the standard error of regression in the CAPM model of ETF returns on the returns of their benchmark indices; and TE_4 is the R-squared of CAPM model.

Table 3. Annualized Average Daily Tracking Error of Sample ETFs over the Observed Time Period

		TE_1				TE_2				TE_3			
ETF	***N***	**2013**	**2014**	**2015**	**2016**	**2013**	**2014**	**2015**	**2016**	**2013**	**2014**	**2015**	**2016**
ANNUAL AVERAGE													
		1.0115	0.7639	0.7154	0.8059	1.7851	1.3658	1.1707	1.3445	1.5266	1.2314	1.0268	1.2471
(a) Japanese Equity Index (Market)													
1	1955	0.1219	0.1022	0.0957	0.1113	0.1711	0.1656	0.1503	0.2025	0.1713	0.1662	0.1506	0.2027
2	1955	0.1574	0.1034	0.1034	0.1253	0.3301	0.1716	0.1632	0.2111	0.3273	0.1719	0.1638	0.2115
3	1955	0.1395	0.0910	0.1007	0.1156	0.2502	0.1590	0.1511	0.2035	0.2504	0.1586	0.1505	0.2036
4	1955	0.1440	0.0937	0.1064	0.1131	0.2120	0.1462	0.1624	0.1892	0.2118	0.1464	0.1607	0.1869
5	474	—	—	0.7723	0.8093	—	—	1.1101	1.2096	—	—	0.8988	1.1222
6	443	—	—	0.1440	0.1293	—	—	0.2103	0.2198	—	—	0.2068	0.2189
7	1955	0.2090	0.0882	0.1074	0.0983	0.3328	0.1539	0.1639	0.1705	0.3300	0.1509	0.1592	0.1692
8	1955	0.1947	0.0954	0.1051	0.1038	0.3058	0.1504	0.1567	0.1729	0.3045	0.1448	0.1486	0.1704
9	1955	0.2383	0.1346	0.1267	0.1152	0.3471	0.1911	0.2385	0.1776	0.3330	0.1858	0.2273	0.1758
10	1955	0.1306	0.0874	0.0950	0.0981	0.1875	0.1480	0.1551	0.1687	0.1711	0.1453	0.1528	0.1685
11	1955	0.2055	0.0817	0.1111	0.1106	0.3350	0.1248	0.1731	0.1720	0.3325	0.1222	0.1653	0.1656
12	1114	0.8731	0.5871	0.6004	0.4813	1.1898	0.9073	1.0389	0.7115	1.1293	0.8484	0.9998	0.7059
13	641	—	—	0.1781	0.2008	—	—	0.2479	0.3152	—	—	0.2406	0.3139
14	592	—	—	0.9000	0.8091	—	—	1.4806	1.2093	—	—	1.3750	1.1680
15	893	—	0.1913	0.1269	0.1226	—	0.2912	0.1918	0.1856	—	0.2832	0.1759	0.1807
16	893	—	0.2349	0.1321	0.1512	—	0.3491	0.2069	0.2200	—	0.3205	0.1996	0.2092
17	886	—	0.1716	0.1119	0.1228	—	0.2541	0.1833	0.1858	—	0.2447	0.1720	0.1780
18	851	—	0.3950	0.1258	0.2029	—	0.6850	0.1720	0.2902	—	0.6505	0.1637	0.2865

19	673	—	0.0912	0.1165	0.1579	—	0.1149	0.1730	0.2355	—	0.1144	0.1686	0.2339
20	474	—	—	0.8879	1.0854	—	—	1.3087	1.6642	—	—	1.0327	1.4177
21	1955	1.0532	0.8059	0.9513	1.3174	1.4721	1.2122	1.4299	1.9958	1.4043	1.1196	1.3957	1.9864
22	1458	1.2351	0.9036	0.5443	0.7823	1.7531	1.6939	0.7346	1.0198	1.7501	1.6997	0.7196	1.0012
23	1715	1.2935	0.7340	0.6545	0.8552	1.8798	0.9808	0.9110	1.1717	1.8719	0.8966	0.7736	1.1199
24	1838	2.4922	1.8659	1.2999	1.9640	3.4110	2.4662	1.8307	2.7922	2.5103	1.7044	1.3351	2.1305
(b) Leveraged / Inverse Index													
25	1366	0.2119	0.1463	0.1802	0.1992	0.3136	0.2350	0.2705	0.3046	0.3133	0.2354	0.2713	0.3045
26	648	—	—	0.1783	0.2010	—	—	0.2734	0.3125	—	—	0.2727	0.3118
27	1366	0.1659	0.1560	0.1357	0.1503	0.2444	0.2046	0.1933	0.1956	0.2434	0.2052	0.1936	0.1957
28	569	—	—	0.5480	0.5923	—	—	0.7952	0.8941	—	—	0.7359	0.8449
29	806	—	0.2183	0.2409	0.2147	—	0.3753	0.4248	0.3239	—	0.3705	0.4220	0.3243
30	648	—	—	0.2196	0.2188	—	—	0.3252	0.3263	—	—	0.3249	0.3268
31	1191	1.5191	1.4449	1.8674	1.5371	2.1064	2.0262	2.5972	2.1352	2.0797	1.9324	2.5226	2.1277
32	1191	1.1119	0.8646	1.0561	0.8658	1.5873	1.1409	1.4089	1.1669	1.5595	1.0407	1.3425	1.1192
33	1361	0.3945	0.1601	0.2284	0.1640	0.6158	0.2406	0.4340	0.2508	0.6132	0.2365	0.4214	0.2485
34	1081	0.2370	0.1352	0.1980	0.1749	0.3795	0.2095	0.4044	0.2571	0.3546	0.2053	0.3976	0.2576
35	743	—	0.5280	0.4350	0.2249	—	0.9375	0.7818	0.3424	—	0.8347	0.7318	0.3128
36	648	—	—	0.2164	0.1753	—	—	0.4248	0.2591	—	—	0.4135	0.2580
37	512	—	—	0.2388	0.2026	—	—	0.3820	0.2937	—	—	0.3678	0.2940
38	1361	0.2413	0.1368	0.1682	0.1146	0.3453	0.1833	0.2916	0.1537	0.3451	0.1745	0.2829	0.1538
39	1081	0.1160	0.1058	0.1818	0.1300	0.1597	0.1482	0.3195	0.1806	0.1583	0.1476	0.3124	0.1810
40	569	—	—	0.2572	0.1555	—	—	0.3705	0.2280	—	—	0.3607	0.2265
41	772	—	0.2055	0.2808	0.2073	—	0.2803	0.5032	0.3920	—	0.2762	0.4727	0.3926

(*Continued*)

Table 3. (*Continued*)

(b) (*Continued*)																
42	688		—	0.2422	0.1989	0.1793		—	0.3371	0.2953	0.2682		—	0.3396	0.2875	0.2673
43	648		—	—	0.2229	0.2019		—	—	0.3275	0.2923		—	—	0.3141	0.2919
44	512		—	—	0.2197	0.1650		—	—	0.3597	0.2584		—	—	0.3418	0.2589
45	484		—	—	0.2544	0.2328		—	—	0.3652	0.3394		—	—	0.3430	0.3332
46	484		—	—	0.2581	0.3176		—	—	0.3709	0.4890		—	—	0.3259	0.4647
47	484		—	—	0.3059	0.2171		—	—	0.5621	0.3301		—	—	0.5518	0.3281
48	484		—	—	0.5559	0.4574		—	—	0.8094	0.6670		—	—	0.7401	0.6502
49	484		—	—	0.8766	0.8049		—	—	1.2996	1.1218		—	—	1.1219	0.6502
50	484		—	—	0.6952	0.8772		—	—	1.0233	1.2981		—	—	0.9153	1.1905
51	484		—	—	0.2961	0.2636		—	—	0.4286	0.3694		—	—	0.3653	0.3642
52	484		—	—	0.2889	0.2311		—	—	0.3819	0.3372		—	—	0.3673	0.3377
53	484		—	—	0.6116	0.3295		—	—	0.9908	0.6592		—	—	0.9695	0.6458
(c) *OTC Swap-Type*																
54	1955		0.9439	0.9305	1.4655	1.5214		1.1805	1.2849	1.8753	2.2233		1.0686	1.1444	1.4054	1.9314
55	1900		0.8172	0.9965	1.0026	1.1766		2.0150	3.2728	2.2014	2.6424		1.9565	3.2037	1.9114	2.4277
56	1900		1.4431	1.4819	2.2140	3.7460		3.0032	4.4226	3.6885	6.1766		2.8101	4.3234	3.1822	5.6683
57	1900		1.6021	0.9565	1.3404	1.5704		4.1723	2.5193	4.4464	4.2960		4.0195	2.4334	4.1691	4.2145
58	1900		1.4150	1.2587	1.3409	1.9723		2.0957	2.0279	2.3014	3.7971		1.9645	1.8561	2.0632	3.7239
59	1900		1.4932	1.7578	1.7206	2.0355		2.2815	2.7669	3.0065	3.6162		2.1117	2.5563	2.7364	3.4636
60	1900		3.1137	3.3673	3.9144	3.7370		4.5779	4.9790	6.2411	7.0598		4.0241	3.8545	5.5749	6.6361
61	1900		1.9678	1.7187	3.0749	2.7828		4.0034	3.6929	4.1982	3.6450		3.8514	3.4902	3.1707	2.8501
62	1900		1.2043	1.4863	2.9614	4.1425		2.4332	3.5372	5.3107	6.3079		2.0880	3.2773	4.5790	5.9587

63	1900		1.1433	0.9132	1.0569	1.6541		2.3571	1.4111	2.0764	4.1217		2.0869	0.9123	1.5558	4.0491
64	1900		2.1617	1.4212	1.6325	2.4188		7.2111	2.6098	2.6347	4.0882		2.3003	2.4312	2.1530	3.8846
65	1900		1.4633	2.3836	2.0215	2.8286		2.8372	5.4851	3.7720	5.5569		2.5026	5.3251	3.2354	5.1614
66	1900		1.6392	1.7694	1.9618	1.6880		2.2182	2.2452	2.4914	2.2000		1.8263	1.5974	1.7353	1.6471
67	1900		2.0198	1.6528	1.5551	1.5538		2.9213	2.3012	2.1450	2.1446		2.4672	1.7007	1.7019	1.8437
68	1900		2.5121	1.8429	1.4702	1.9857		4.8125	3.5864	3.0582	4.0095		4.6411	3.2672	2.8224	3.7552

Note: Annualized tracking errors are expressed in percentage terms 2013 to 2016 using daily data. *N* represents the number of observations for each ETF used in this study. TE_1 is obtained from the average absolute difference between the returns on ETFs and the returns on their benchmark indices (indicators); TE_2 is obtained from the standard deviation of difference between returns on ETFs and the returns on their benchmark indices (indicators); and TE_3 is the standard error of regression in the CAPM model of ETF returns on the returns of their benchmark indices.

Table 4. T-test of the Difference between Tracking Errors of Physical and OTC Swap-type ETFs

	Physical ETFs			OTC Swap-Type ETFs		t-statistics	p-value
	Mean	Std. Dev.		Mean	Std. Dev.		
Panel A							
TE_1	0.3672	0.3543		1.8428	0.5548	–12.4502**	0.0000
TE_2	0.5639	0.5102		3.2195	0.9014	–14.7783**	0.0000
TE_3	0.5320	0.4534		2.7921	0.8275	–13.9479**	0.0000

Note: Panel A presents the results of pooled-variance t-test of the evidence that the mean tracking error of OTC Swap-Type ETFs (n = 15) is significantly higher than that of physical ETFs (n = 53) in the sample. Statistical significance of the difference at 5% significance level and 1% significance level is denoted by * (5%) and ** (1%) respectively.

$$H_0 : \mu_{TE_{i,Physical}} = \mu_{TE_{i,OTC\,Swap-Type}}$$

$$H_1 : \mu_{TE_{i,Physical}} < \mu_{TE_{i,OTC\,Swap-Type}}$$

	Physical ETFs			OTC Swap-Type ETFs			
	Mean	Std. Dev.		Mean	Std. Dev.	t-statistics	p-value
Panel B							
Alpha	–0.00003	0.00013		–0.00023	0.00032	3.6478**	0.0003
Beta	0.90050	0.1718		0.03537	0.06246	19.0603**	0.0000

Note: Panel B presents the results of pooled-variance t-test of the evidence that the mean alpha and beta of OTC Swap-Type ETFs (n = 15) is significantly lower than that of physical ETFs (n = 53) in the sample. Statistical significance of the difference at 5% significance level and 1% significance level is denoted by * (5%) and ** (1%) respectively.

$$H_0 : \mu_{ALPHA_{i,Physical}} = \mu_{ALPHA_{i,OTC\,Swap-Type}}$$

$$H_1 : \mu_{ALPHA_{i,Physical}} > \mu_{ALPHA_{i,OTC\,Swap-Type}}$$

$$H_0 : \mu_{BETA_{i,Physical}} = \mu_{BETA_{i,OTC\,Swap-Type}}$$

$$H_1 : \mu_{BETA_{i,Physical}} > \mu_{BETA_{i,OTC\,Swap-Type}}$$

5.2 DETERMINANTS OF TRACKING ERROR

Table 5 presents the results of the panel regression model number (5) with fixed-effects estimation for 53 physical ETFs over the period 2015–2016. The results indicate that tracking error is significantly influenced by each factor individually except for dividend yields and the number of constituents of the target indexes. The results also exhibit expected signs and clearly verify our hypotheses *H2* and *H3*. The results exhibit positive coefficients of expense ratio regardless of which measure of tracking error is used, and indicate that the transaction cost of underlying stocks in the target indexes has a positive measurable effect on the tracking ability of ETFs. A negative coefficient of size is obtained regardless of which measure of tracking error is used, indicating that larger funds produce smaller tracking error. This finding confirms our expectation that larger funds should have lower transaction costs in trading stocks, owing to the economies of scale involved, and this produces lower tracking error for larger index funds. One of the sources of tracking error is the impossibility of an ETF manager being able to perfectly allocate the corresponding capital among the index constituents owing to the indivisibility of individual stocks, which results in remaining cash or investing stocks that

Table 5. Individual Factor Influencing Different Tracking Error and Results for Panel Regression Model (5)

Variable	TE_1	TE_2	TE_3
$\widetilde{TER}$	0.1399* (1.8571)	0.2008* (1.8617)	0.2670* (1.9989)
$\widetilde{SIZE}$	–0.0923* (–2.2565)	–0.1326* (–2.2723)	–0.1278* (–2.4814)
$\widetilde{DIV}$	2.5943 (0.3132)	3.6392 (0.3078)	8.1807 (0.7843)
$\widetilde{VOL}$	0.1591** (5.2737)	0.2265** (5.2586)	0.2082** (5.4792)
$\widetilde{RISK}$	0.0284** (2.6729)	0.0399* (2.6243)	0.0444** (3.3127)
$\widetilde{NUMBER}$	0.0000 (1.8030)	0.0001 (1.8198)	0.0000 (1.7077)
Constant	0.9880** (4.2671)	1.4265** (4.3156)	1.1280** (3.8682)
Adj. R^2	0.4065	0.4022	0.4117
F-statistics	12.9893**	12.7766**	13.2494**

Note: The table presents the results of panel regression model (5) with fixed effects estimation for 53 physical ETFs over the period 2015–2016. The coefficients of scaled expense ratio, natural logarithm of size (size is measured in million JPY), dividend yield, natural logarithm of trading volume, market risk, and number of constituent stocks are shown. The respective t-statistics are in the parentheses. Furthermore, the adjusted R^2 and F-statistics for testing the overall significance of the model are stated. Statistical significance of regression coefficient being different from zero at 5% significance level and 1% significance level is denoted by * (5%) and ** (1%) respectively.

do not perfectly replicate the index weights. However, this impossibility may become small for ETFs with large assets under management. The regression coefficients of other operating characteristics also have signs in accordance with our expectations. Dividend yield is found to have a positive but insignificant impact on tracking error, which supports the theory that delays in receiving dividends and costs incurred in reinvestment may erode ETFs' ability to replicate index performance. Larger trading volume reflects that a larger difference in investor opinions about the market drives the ETFs' return away from that of the target indexes. The positive sign of the regression coefficient of market risk shows that higher risk in the market may make it more difficult for ETFs to replicate performance, leading to greater tracking error. Although the factor of number of constituents in the target index is not significant, it positively affects the tracking error and supports our hypothesis that more securities in the target indexes make it more difficult for ETFs to trace their benchmarks.

The results for the squared variables reported in table 6 suggest that the relationship between tracking error and each of size, trading volume, and the number of constituents is significantly nonlinear in nature. The significant nonlinear relationship between tracking error and size exhibits a concave shape, which implies a declining impact of this factor on ETFs' tracking inability. Once the size of the ETF reaches a certain level, the advantage of economies of scale diminish. On the other hand, both the significant nonlinear relationship between the tracking error and trading volume, and number of constituents exhibit a convex shape, which indicates there is an increasing impact of these factors on the tracking inability.

6 CONCLUSION

ETFs have grown in popularity since their first introduction to Japan in 1995. This study provides a comprehensive study on the tracking ability of the Japan-listed ETFs that are in the categories of Japanese Equity Index (market), Leveraged/Inverse Index and OTC swap ETFs.

We find that the tracking error of the sampled ETFs using daily figures is comparatively higher than those in the U.S. and Australia, and that the majority of the samples underperform the underlying indexes. This result implies that ETF managers in Japan have more difficulties in replicating the performance of the underlying indexes and the respective ETF investors may face additional risks as a result. The study's other implication is that the magnitude of tracking error increases when daily data are employed. The study also computes the tracking error of OTC swap-type (synthetic) ETFs as a comparison, although they are not quite active in the Japanese market, and finds that they are significantly higher than those of physical ETFs. This comparison implies that synthetic-type ETF managers have difficulty in finding the appropriate derivatives to replicate the performance of the target indexes.

Table 6. Individual Factor Influencing Tracking Error TE_1 and Results for Panel Regression Model (6)

Variable	TE_1	TE_2	TE_3
$\widetilde{TER}$	1.5231* (1.9812)	1.8606 (1.9123)	2.2210* (2.2921)
$\widetilde{TER^2}$	1.4912 (1.8958)	1.7276 (1.7356)	2.2986* (2.3185)
$\widetilde{SIZE}$	–0.1929 (–1.6466)	–0.3902* (–2.5505)	–0.3479* (–2.3305)
$\widetilde{SIZE}^2$	–0.0118* (–2.1801)	–0.0199** (–2.8152)	–0.0188** (–2.7228)
$\widetilde{DIV}$	1.8638 (0.0998)	7.1783 (0.2178)	4.5857 (0.1811)
$\widetilde{DIV}^2$	807.4540 (0.7266)	953.1389 (0.4590)	926.6586 (0.6081)
$\widetilde{VOL}$	0.4376** (4.4616)	0.7958** (5.9239)	0.6008** (4.7550)
$\widetilde{VOL}^2$	0.0164** (3.7135)	0.0293** (4.8157)	0.0218** (3.8267)
$\widetilde{RISK}$	0.0406 (1.6268)	0.0597 (1.5677)	0.0287 (0.8747)
$\widetilde{RISK}^2$	0.0013 (1.8189)	0.0028* (2.2947)	0.0013 (1.3613)
$\widetilde{NUMBER}$	0.0021** (6.0618)	0.0026** (5.6372)	0.0026** (5.8299)
$\widetilde{NUMBER^2}$	0.0000** (5.9228)	0.0000** (5.5552)	0.0000** (5.7029)
Constant	3.3877** (5.0189)	5.0462** (5.5447)	3.9066** (4.5089)
Adj. R^2	0.5369	0.6217	0.5276
F-statistics	11.1452**	15.3846**	10.7731**

Note: The table presents the results of panel regression model (6) with fixed effects estimation for 53 physical ETFs over the period 2015–2016. The coefficients of scaled expense ratio, natural logarithm of size (size is measured in million JPY), dividend yield, natural logarithm of trading volume, market risk, and number of constituent stocks are shown. The respective t-statistics are in the parentheses. Furthermore, the adjusted R^2 and F-statistics for testing the overall significance of the model are stated. Statistical significance of regression coefficient being different from zero at 5% significance level and 1% significance level is denoted by * (5%) and ** (1%) respectively.

This study also attempts to establish the determinants of the tracking error of the sampled physical ETFs, that is, the ETFs in the categories of Japanese Equity Index (market) and Leveraged/Inverse Index. As postulated, the tracking error is negatively related to size, but positively related to expense ratio, dividend yield, trading volume, market risk, and number of constituents of the target indexes. The results conform to our hypotheses. The findings indicate that expenses erode the ETFs' tracking ability, that large ETFs should have lower trading cost owing to economies of scale, and thereby lower tracking error, that delays in receiving dividends and the cost incurred increase tracking error, and that higher risk in the market and more securities included as constituents of the target index may make it more difficult for ETF managers to replicate benchmark performances. The nonlinearity analysis shows that the relationship between tracking error and size is significantly nonlinear and exhibits a concave shape, while the relationship between tracking error and each of trading volume and number of constituents is also significantly nonlinear but exhibits a convex shape.

Research on some of the test determinants has just commenced. It was our aim to raise a broader discussion of potential tracking error determinants and to provide some insights. This study raises the issue of whether ETFs are good alternatives to actively managed funds or retailed passively managed funds, and suggests that it is not sensible for investors to rush into investing in ETFs, even though their popularity has been increasing for several years. Future studies could focus on determining the impact of economic climates on tracking ability and the determinants of economic climates.

Practically, we also find that the ETFs traded on the TSE provide little detail regarding tracking error targets and target index replication methods in their prospectuses or factsheets. Recent regulators' calls for better disclosure and transparency on the tracking performance seem to be promised.

BIBLIOGRAPHY

Aber, JW, D Li, and L Can (2009). Price Volatility and Tracking Ability of ETFs. Journal of Asset Management, 10, 210–221.

Blitz, D., Huij, J. (2012) Evaluating the Performance of Global Emerging Markets Equity Exchange-traded Funds, *Emerging Markets Review*, 13, 149–158.

Blitz, D., and J. Huij (2012). Evaluating the Performance of Global Emerging Markets Equity Exchange Traded Funds, Emerging Markets Review, 13, 149–158.

Blitz, D, J Huij, and L Swinkels (2012). The Performance of European Index Funds and Exchange-Traded Funds, European Financial Management, 18, 649–662.

Blume, M. and Edelen, R. (2004) S&P 500 indexers, trading error, and liquidity: a complex answer to profiting, *Journal of Portfolio Management*, 30: 37–46.

Charupat, N., and P. Miu (2013). Recent developments in exchange-traded fund literature: Pricing efficiency, tracking ability, and effects on underlying securities, Managerial Finance, 39, 427–443.

Cheng, LTW, HG Fung, and Y Tse (2008). China's Exchange Traded Fund: Is There a Trading Place Bias? Review of Pacific Basin Financial Markets and Policies, 11, 61–74.

Cresson, J., Cudd, R. and Lipscomb, T. (2002) The Early Attraction of S&P Index Funds: Is Perfect Tracking Performance an Illusion? *Managerial Finance*, **28**, 1–8.

DeFusco, RA, SI Ivanov, and GV Karels (2011). The Exchange Traded Funds' Pricing Deviation: Analysis and Forecasts, Journal of Economics and Finance, 35, 181–197.

Delcoure, N., and Zhong, M. (2007) On the Premiums of iShares, Journal of Empirical Finance, 14, 168–195.

Drenovak, M., B. Urosevic, and R. Jelic (2014). European Bond ETFs: Tracking Errors and the Sovereign Debt Crisis, European Financial Management, 20, 958–994.

Driscoll, J., and Kraay, A. C., 1998, Consistent covariance matrix estimation with spatially dependent data, Review of Economics and Statistics, 80(4): 549–560.

Elia, M. (2012). Tracking Error of Traditional and Synthetic European Exchange-Traded Funds. University ofTurin, working paper. http://dx.doi .org/10.2139/ssrn.2084929

Elton, E. J., Gruber, M. J., Comer, G., and Li, K. (2002) Spiders: Where are the Bugs? Journal of Business, 75, 453–472.

Frino, A., Gallagher, D. R., Neubert, A. S., and Oetomo, T. N. (2004) Index Design and Implications for Index Tracking, Journal of Portfolio Management, 30(2): 89–95.

Frino, A. and Gallagher, D. R. (2001) Tracking S&P 500 index funds. Journal of Portfolio Management 28 (1): 44–55.

Madura, J., & Ngo, T. (2008) Clustered Synergies in the Takeover Market, Journal of Financial Research, 31, 333–356.

Meinhardt, C. and Mueller, S. and Schoene, S. (2015) Physical and Synthetic Exchange Traded Funds: the Good, the Bad or the Ugly? Journal of Investing, Summer 2015, Vol. 24, No. 2, pp. 35–44

Miffre, J (2006). Country-specific ETFs: An Efficient Approach to Global Asset Allocation. EDHEC Business School Working Paper.

Osterhoff, F. and C. Kaserer (2016). Determinants of Tracking Error in German ETFs – the Role of Market Liquidity, Managerial Finance, 42, 417–437.

Pope, P. and P. Yadav, (1994). Discovering Errors in Tracking Error, Journal of Portfolio Management, 20, 27–32.

Qadan, M and J Yagil (2012). On the Dynamics of Tracking Indices by Exchange Traded Funds in the Presence of High Volatility, Managerial Finance, 38, 804–832.

Roll, R. (1992). A Mean/Variance Analysis of Tracking Error, Journal of Portfolio Management, 18, 13–22.

Rompotis, G (2009). Interfamily Competition on Index Tracking: The Case of the Vanguard ETFs and Index Funds, Journal of Asset Management, 10, 263–278.

Rompotis, G. (2011). Predictable Patterns in ETFs' Return and Tracking Error, Studies in Economics and Finance, 28, 14–35.

Shin, S and G Soydemir (2010). Exchange-Traded Funds, Persistence in Tracking Errors and Information Dissemination, Journal of Multinational Financial Management, 20, 214–234.