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Indonesian Exchange Traded Fund Performance

Radityo Fajar Arianto[1], Hendrawan Supratikno[2], Gracia Shinta S. Ugut[3], Edison Hulu[4]
[1,2,3,4]*Universitas Pelita Harapan, Indonesia*
radityo.arianto@uph.edu, hendrasupra@yahoo.com, edison.hulu@lecturer.uph.edu, gracia.ugut@uph.edu

Abstract

This study aims to examine the effect of index volatility, changes in market capitalization, volume, momentum and liquidity on the difference between net asset value (NAV) return with the benchmark indexreturn of ETFs in Indonesia individually. The sample from this study amounted to 19 ETFs with purposive sampling method for the period 1 January – 30 June 2020. The analytical tool used was multiple regression with time series data. The results of this study include that the volatility of the benchmark index is a significant factor for the six sample ETFs. Meanwhile, changes in market capitalization are not a significant factor affecting tracking error.

Keywords
index return, volatility, market capitalization, liquidity, tracking error

I. Introduction

Exchange Traded Fund (ETF) or in Indonesia called mutual fund ETF is a form of innovation in the financial sector. ETF products have many similarities with mutual funds, but ETFs have similarities with stocks in terms of how they trade in the capital market. The types of ETFs include commodity ETFs, currency ETFs, bonds or fixed income ETFs, *leveraged* ETFs, *inverse* ETFs and stock ETFs whose price movements refer to certain indexes. The purpose of this study is to find out the performance of stock ETFs that refer to certain indexes in Indonesia. Furthermore, the type of ETF that is the subject of this study is a stock ETF that refers to a certain index.

ETFs were first created in Indonesia in 2007. *ETFs* have grown relatively slowly with only 13 *ETF* products listed on the Indonesia Stock Exchange until 2017. Developed countries have a very fast rate of *ETF* development. The literature investigating the history and behavior of *ETFs* in Indonesia is very limited. Most of the research was conducted in developed countries, such as the United States (Olienyk et al., 1999); (Frino & Gallagher, 2001), Japan, Hong Kong (Jares & Lavin, 2004), Switzerland (Milonas & Rompotis, 2006), Australia (Frino & Gallagher, 2002); (Gallagher & Segara, 2006), and Germany (GG Rompotis, 2012); (Chovancova & Arendas, 2015).

Research on ETFs in developing countries such as China was written by Ackert & Tian (2008) and Jiang et al. (2010). Purohit & Malhotra (2015) wrote about ETFs in India. ETFs in developed countries are compared to developing countries so that their growth and evolution can be seen more clearly.

The purpose of this study is to analyze the difference between the net asset *return* (NAV) of ETF and *return* index that is the reference. Net asset value (NAV) is the market value of ETF less the ETF's operating costs per unit. *Return* NAV is obtained from the difference between today's NAV and the previous day, and divided by the previous day. Meanwhile, the *return* index is the difference between today's index value and the previous day's index value, divided by the previous day's index value.

An ETF is said to be good if the ETF actually has a price movement that is very similar to the price movement of reference index. Or in other words, there is no significant difference between NAB *returns* and the reference index *returns*. ETF performance can be measured by how far the difference in *return* between NAV and the reference index. The lower difference, the better ETF.

Differences in returns can occur due to several reasons, including dividend payments, *creation and redemption* mechanisms, tax effects and stock turnover which are constituents of an index that is the reference. The process of continuous *creation and redemption* usually results in costs that are ultimately charged to investors and can reduce the NAV of an ETF.

II. Review of Literature

ETFs are Mutual Funds in the form of Collective Investment Contracts whose participation units are traded on the Stock Exchange, so that ETFs are a combination of the elements of mutual funds in terms of fund management, with the mechanism of shares in terms of buying and selling transactions. (https://www.idx.co.id/produk/exchange-traded-fund-etf/)

An ETF is defined as an investment engine created to replicate the performance of a particular index (Lettau & Madhavan, 2018). *ETFs* globally have grown in size, diversity and market significance. *ETF* assets globally have exceeded the number of hedge funds in 2015, which was around three trillion US dollars. *ETFs* have become an attractive investment tool for both institutional and retail investors (Madhavan, 2016). The point of view of an investor when viewed from the classical theory (utility theory) will have investment desires based on two things, namely, portfolio and profitability (Aminatuzzahra, in Baihaqqy, 2020).

The process of creating and redeeming an ETF can be seen in the image below. (Deville, 2008)

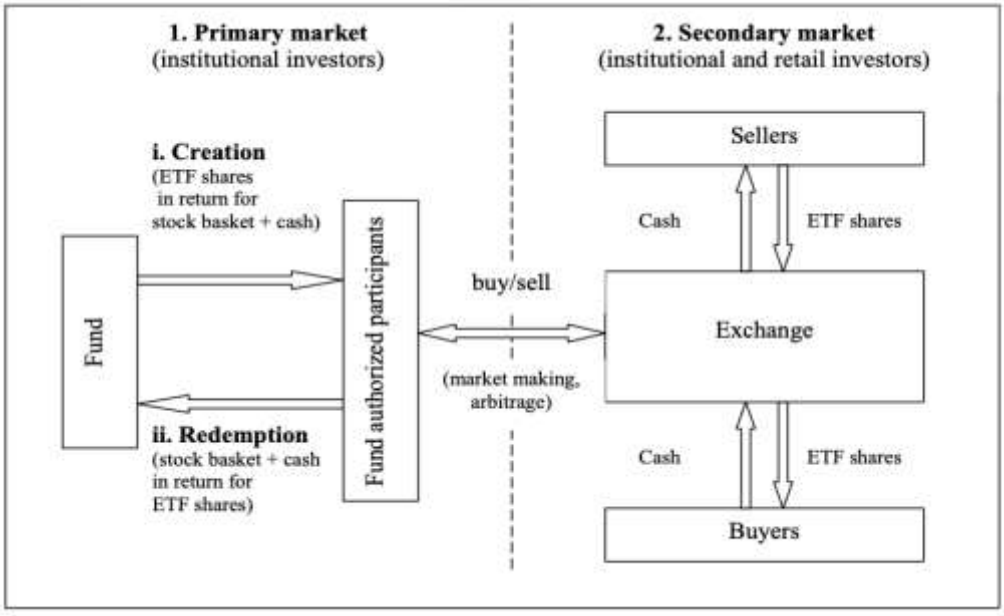

Figure 1. *Primary and Secondary ETF Market Structure* (Deville, 2008)

The initial process involves two parties, namely participant dealers and fund managers. Participating dealers will submit assets in the form of shares or cash equivalents to the fund manager as collateral. The fund manager will then issue/create the ETF and give it to the participating dealers. This process occurs in the primary market and price that occurs is called NAV (net asset value).

Dealers/authorized participants then sell the ETF to other investors in the secondary market during trading hours on the exchange at market prices according to supply and demand. When an investor sells an ETF held in secondary or primary market, *the dealer/authorized participant* will act as a liquidity provider to buy the ETF to be sold. *Participant dealers* will issue buying and selling prices known as market prices or *quoted market prices*.

Gallagher and Segara (2006) and Hassine and Roncalli (2013) describe three benchmark replication techniques that an ETF *fund* manager can follow. The first is a full replication strategy. The fund manager will create a stock portfolio that is exactly same as the reference index, both the stock constituents and percentage. The second is tiered sampling where a fund manager will create a portfolio through sampling from the constituents of reference index stock. The third is optimization in which *fund* managers take stocks whose price movements are similar to constituent stocks in an index. (Gallagher & Segara, 2006); (Hassine & Roncalli, 2013).

Several factors can cause NAB *ETF* returns to deviate from the basic return index. This deviation needs to be measured to see how much deviation the NAB*ETF* returns from the basic index. The larger deviation, the lower performance of ETF. Investment managers usually have internal policies to intervene and make adjustments to keep deviations at a certain level. One tool is to measure *tracking errors* and keep them as low as possible.

Milonas and Rompotis (2006) and Gallagher and Segara (2006) present a way to estimate *tracking error* by using the absolute mean difference, standard error of regression analysis and standard deviation of the difference in returns. Several factors can affect *tracking errors*. (Milonas & Rompotis, 2006)(Gallagher & Segara, 2006)

Deviation of NAV returns with index returns can be caused by several factors such as costs and expenditures of funds, imperfect correlation between assets in portfolios and indexes, rounding of the number of shares in the portfolio assigned to investment managers, into trading units (*rounding lots*). Frino and Gallagher (2001), Kostovetsky (2003), and Milonas and Rompotis (2006) mention expenditures, cash flows of funds, dividends, and changes in index composition as factors that drive the *Tracking Error* of index funds. Rompotis (2006) discusses the ratio of annual expenditures including all costs to manage *ETFs*, market capitalization, daily trading price volatility of *ETFs*, log transformed average daily trading volume, and daily earnings on exchange rates as factors for predicting the average *tracking error* (Frino & Gallagher, 2001) (Kostovetsky, 2003) (Milonas, 2006) & Rompotis, 2006)

Rompotis (2006) empirically investigated the performance of the most traded and sizeable *ETFs* listed on the AMEX and NASDAQ exchanges and found that, on average, managers adopted somewhat conservative investment policies as indicated by the inferiority of beta coefficient relative to unity and concluded that *ETF* performance moved closer to the underlying index. (Rompotis, 2006)

Chu (2011) found that Hong Kong *ETF tracking error* was negatively related to the size of *ETF* but showed a positive relationship to the respective cost ratios. Consequently, the study concluded that it is riskier to replicate the performance of underlying security due to the large *tracking error* compared to *ETFs* in other countries such as US and Australia. (Chu, 2011)

Rompotis (2012) found that German *ETFs* did not adopt a full replication strategy, volatility was positively related to *tracking error*, volatility premium, intraday and *tracking error* were positively influenced by risk, *premium and spread*.

Blitz and Huij (2012) studied the performance of *ETFs* exposed to emerging market equities. The study concludes that *ETFs* that use statistical index replication experience high *tracking errors*, especially when the *cross-sectional* dispersion of stock returns is high. (Blitz & Huij, 2012)

Shanmugham and Zabiulla (2012) show that *Tracking Error* is found to be high in a *bearish* market compared to a *bullish* market. Kanuri and McCleod (2015) evaluated the performance and benefits of diversifying international *ETFs* for US investors during and after the financial crisis. Kanuri and McCleod (2015) found that U.S. *ETFs* has the lowest *Tracking Error* during the entire period. Most *ETFs* passively track *benchmarks* and do nothing positive. Previous research has questioned the benefits of diversifying international investment during times of financial hardship. The study found that international *ETFs* relied heavily on major US indices during the period of our analysis, and therefore, offered limited diversification benefits to US investors. (Shanmugham & Zabiulla, 2012)

Rompotis (2012) investigated the performance and trading characteristics of 43 German Exchange Traded Funds (*ETFs*) traded on the XTRA market. The investigation period was from 2003 to 2005. The findings indicate that this *ETF* did not adopt a full replication strategy. *ETFs* are riskier than the underlying index and have significant *Tracking Errors*. *ETF* returns are negatively associated with *Tracking Error* but positively associated with risk. Return volatility is positively correlated with *tracking error*, premium and intraday volatility. This finding means that the higher magnitude of these variables, the higher risk of *ETFs*. (Rompotis, 2012)

Svetina (2010) studied ETF performance mostly below its reference index. ETF returns are very similar to index funds. The formation of new *ETF* reduces the inflow of incumbent index funds and reduces the market share of incumbent *ETF*. (Svetina, 2010)

Hypothesis: Does volatility, volatility of the reference index, liquidity, volume, market capitalization, momentum affect the difference between NABETF returns and the return of *reference index*?

III. Research Methods

3.1 Return NAV and Return Index

NAV is determined by the market value of securities held less all costs of managing the fund. The model in this study is to measure relationship between the return on net asset value (NAV) and the return of reference index. This study uses a multiple regression model to determine relationship between the return movement of NAV and the return of reference index. The regression equation is as follows:

$$NR_{i,t} = \alpha_i + \beta_i IRI_{i,t} + \varepsilon_{i,t(v,x)} \quad (1)$$

Where:

$NR_{i,t}$ = the *return of the Net Asset Value ETF$_i$ on day t*

α_i = *excess return of ETF can earn above its respective benchmark*

β_i = market *or systematic risk*

$IR_{i,t}$ = the *daily return benchmark index i on day t*

$\varepsilon_{i,t(v,x)}$ = standard *errors of the regression of ETFi on day t for TE1*

Equation (1) indicates that standard error regression can be used to calculate *the tracking error. Tracking Errors* can be caused by several factors. From previous research, traceability errors can be caused by costs, cash flows, dividends, and index composition. (Frino & Gallagher, 2001) (Kostovetsky, 2003) (Milonas & Rompotis, 2006).

This study uses daily NAV to measure *ETF* returns on certain dates. *ETF* returns are calculated by measuring the change in NAV from time t compared to the previous period, t-1, as the proportion of NAV at t-1. The following is the formula for calculating *ETF* returns and benchmark stock index below (Shin & Soydemir, 2010). For the daily return of *ETFi* on day t, the formula is Equation (2):

$$NR_{i,t} = Ln(\frac{NAV_{i,t}}{NAV_{i,t-1}}) \quad (1)$$

Where:

$NR_{i,t}$ = *the return of ETF i's on day t*

$NAV_{i,t}$ = the *Net Asset Value* of *ETFi*'s on day *t*

$NAV_{i,t-1}$ = the *Net Asset Value* of *ETFi*'s on day *t-1*

The return index will be calculated in the same way. For the daily *return* of Stock Index *i* in days, the formula is equation (3):

$$IR_{i,t} = Ln(\frac{Index_{i,t}}{Index_{i,t-1}}) \quad (1)$$

$IR_{i,t}$ = the return of Stock Index *i*'s on day *t*

$Index_{i,t}$ = the benchmark of Stock Index *i*'s on day *t*

$Index_{i,t-1}$ = the benchmark of Stock Index *i*'s on day *t-1*

The result of the above calculation is a collection of daily *return* data NRi, t and IRi, t. With the availability of two data sets, namely $NR_{i,t}$ and $IR_{i,t}$, this study tries to apply a regression model to estimate the return $NR_{i,t}$ described by $IR_{i,t}$. Regression models can be built to explain relationship between *NRi, t* and $IR_{i,t}$ as in equation (1)

Vardarajh, Fabozzi and Jones (2004) discuss several factors that can affect stock portfolio *tracking errors*. They include the number of shares in the portfolio and the market capitalization of portfolio. They also consider differences in style relative to benchmark index, sectoral deviation of the benchmark index, the volatility of benchmark index, and portfolio beta. Other important topics discussed in their study are the components of *tracking errors*, their marginal contribution to *tracking errors* and the reliability of *tracking error* predictions. (Vardharaj et al., 2004)

Tracking Errors can also come from liquidity costs such as *bid/ask spreads.* Dividend policy in the time of receiving dividends for reinvestment purposes and high costs can also be other factors that affect traceability errors (Gallagher & Segara, 2006).

This study selected several factors such as daily volatility, volatility of the reference index, log transformed daily trading volume, changes in market value, return and momentum index which are in line with previous research (Vardharaj et al., 2004) (Gallagher & Segara, 2006) (Shin & Soydemir, 2010).

This study builds a multiple regression model using factors that may have a significant impact on tracking errors. The formula is as follows:

$$TE = \beta_0 + \beta_1 . DVolatility_{i,t} + \beta_2 . DIVolatility_{i,t} + \beta_3 . LnVolume_{i,t} + \beta_4 . LnMarketcap_{i,t} + + \beta_5 . LnMomentumIndex_{i,t} + \beta_6 . CompositeReturn_{i,t} + \varepsilon_{i,t} \quad (4)$$

Where:

TE = *Tracking Errorbased on the difference between NAV and Index*

$\beta_{0,1,\ldots,n}$ = *coefficient of regression*

$DVolatility_{i,t}$ = *daily volatility of market price ofETFi* at day *t (Shin and Soyidemir, 2010)*

$DIVolatility_{i,t}$ =*daily volatility of the benchmark indexi* at day *t (Vardharaj et.al. 2004)*

(Drenovak, 2014) (Kuok and Chu, 2017)

$LnVolume_{i,t}$ = *natural logarithm volumeETFi* at day *t (Shin and Soydemir, 2010)*

$LnMarketcap_{i,t}$ = *The changes in market capitalization of ETF i at time t*

$LnMomentumIndex_{i,t}$ = the *changes in momentum of benchmark index*

Composite Return = *the return of composite index on day t*

$\varepsilon_{i,t}$ = *error term regression analysis*

Elton et al. (2002) explain that *ETF* management costs play a very important role in influencing *ETF* traceability. Milonas & Rompotis (2006) discussed the influence of *management fee* on the movement of *ETF* returns. They used a daily *ETF* return percentage because *NAV* data were not available in the Swiss *ETF* industry at the time. They use published *management fee* ratios as a proxy for *ETF fees*.

The purpose of regression model is to estimate the expected *tracking error* of known management costs. The greater management cost, the greater expected *tracking error*. Other studies also include management costs as an explanatory factor that can affect *tracking errors* (Chu, 2011) (Shin & Soydemir, 2010). Unfortunately in Indonesia, only a few ETFs publish the *expense ratio*.

Another factor that can affect *tracking errors* is the daily volatility of *ETF* prices. Daily volatility can be described as the daily market price volatility of *ETFs* and can be symbolized as D Volatility (Shin & Soydemir, 2010).

The formula for calculating *D Volatility* is as follows:

$$DVolatility_{i,t} = \frac{P_{i,t\ High} - P_{i,t\ Low}}{P_{i,t\ Closed}} x100 \quad (1)$$

Where:

$DVolatility$ = the daily volatility of the market price

$P_{t\ High}$ = The highest price of the *ETF* at time *t.*

$P_{t\ Low}$ = The lowest price of the *ETF* at time *t.*

$P_{t\ Closed}$ = The closing price of the *ETF* at time *t.*

Shin and Soydemir (2010) argue that investors can use daily market value volatility to have a better understanding of how changes in the daily market price of *ETFs* can affect their *tracking errors*. (Shin & Soydemir, 2010)

Frino and Gallagher (2002) conducted research in Australia and found that the volatility of reference index is one of the determinants of traceability errors. According to Frino and Gallagher (2002), *tracking error* is also explained by the market *bid/ask spread*, exogenous liquidity shocks experienced by funds and index replication technique adopted.

Using the single index market model (SMM) Sharpe (1963), Vardaraj et.al. (2004) argue that *tracking error* increases with market volatility. By substituting *benchmark* index for the market index in the equation, they show that if the volatility of *benchmark* index increases it can increase *tracking error* (Vardharaj et al., 2004). Using the formula of Shin and Soydemir (2010) to calculate the daily volatility of *ETF* prices, this study replaces *ETF* prices with a *benchmar*k index to measure the volatility of index. The formula is as follows:

$$DIVolatility_{i,t} = \frac{Index_{i,t\ high} - Index_{i,t\ low}}{Index_{i,t\ closed}}\ x\ 100 \qquad (1)$$

Where:

$DIVolatility_{i,t}$ = percentage daily volatility of the benchmark index *i* at day *t*

$Index_{i,t\ high}$ = the highest value of benchmark index *i* at day *t*

$Index_{i,t\ low}$ = the lowest value of benchmark index *i* at day *t*

$Index_{i,t\ closed}$ = the closed value of benchmark index *i* at day *t*

Another factor that may influence traceability is the number of shares in the portfolio in this case the *ETF*. If the *ETF* acquires all the shares in the *benchmar*k and uses a full replication strategy in creating a portfolio with same weight as the *benchmark* index, then we can expect *tracking error* to be zero. The difference between *ETF* returns and *benchmark* index returns is still due to the presence of *front load fees*, *management fees* and custodial bank *fees* even though an *ETF* uses a full replication strategy. If a full replication strategy still creates fewer *tracking errors*, other strategies such as multilevel sampling and synthesis sampling will create larger *tracking errors*.

Based on a study conducted by Vardharaj et.al. (2004), they argue that *ETF* managers can reduce traceability errors by accommodating more shares to be included in portfolio building with the same weight. From their observations, *tracking error* decreases exponentially as more different stocks are added to the portfolio. *Tracking Error* shows the stability of movement when the number of constituent shares is about 50 shares in one portfolio. Usually, *tracking error* will be below 2% when more shares are added above 50 constituent shares in one portfolio. (Vardharaj et al., 2004)

Dividends can affect *ETF* performance as well as *tracking errors*. This may happen because there is often a time lag when dividends are paid to the *ETF*. In contrast to common stocks, *ETFs* cannot reinvest the dividend. (Shin & Soydemir, 2010). Unfortunately, dividend data in most *ETFs* in Indonesia is not published in a transparent manner.

Milona and Rompotis (2006) discuss several factors that generally affect *ETF* trading volume. These factors are *ETF* volatility, number of trades and *lagged return* from dividends. Elton et al. (2002) argue that there is a relationship between volume measures and market volatility and arbitrage opportunities. The buying and selling activity will determine the volume configuration. This implies that there is a positive correlation between *ETF* returns and number of trades. *ETF* returns from the previous day may have

an effect on today's volume size. This applies to both short and long term investors. It is expected that there is a positive relationship between *ETF flagged return* and *ETF* volume. (Milonas & Rompotis, 2006)

Chu (2011) investigated the effect of Hong Kong *ETF* market size on the magnitude of *ETF tracking errors*. They argue that the size of *ETF* has an inverse relationship with *tracking errors*. The size of *ETF* comes from the market capitalization of *ETF*. The larger size, the smaller *tracking error*. (Chu, 2011)

The research period is from 01 June 2019 - 01 July 2020. This period was chosen to collect more *ETF* data so that the study can have a general picture of *ETF* performance in Indonesia, especially in Q1 and Q2 2020 where the COVID-19 pandemic hit. Indonesia at an early stage.

The fastest growth in Indonesian *ETFs* occurred during the 2018-2019 period. Several new *ETFs* were launched in 2018 and early 2019. During this time, 24 new *ETFs* were launched. That made the number of *ETFs* jump from 14 to 38 *ETFs* within two years.

The selection of period with two considerations, first has a population of at least 30 *ETFs*, and could cover at least two quarters of 2020 at the start of COVID-19 pandemic that hit Indonesia. The final total sample in this study is 19 *ETFs* for the research period January 1 - June 30, 2020 which have complete data.

The population is all ETFs listed on Indonesia Stock Exchange. Sampling was done by using a purposive sample due to limited data and limited time. The sampled ETFs totaled 35 ETFs since their inception until the last ETF in the effective trading period on 01 Jan 2020.

IV. Results and Discussion

Indonesia has 41 *ETFs* listed on Indonesia Stock Exchange as of April 20, 2020. Three *ETFs* are bond ETFs. Other *ETFs* have shares as the main underlying asset of at least 80% and a maximum of 20% in the domestic money market and safe deposits as regulated by Financial Services Authority (OJK). Data can be downloaded from https://www.idx.co.id/data-pasar/data-exchange-traded-fund-*ETF*/.

ETF issuance per year in Indonesia can be seen in the following figure:

Figure 2. *Indonesia Number of ETFs Issued Per Year*

PT. Indo premier Sekuritas is the most active in being a participating dealer not only for PT. Indo Premier Investment Management, but also for other investment managers in Indonesia. The market share controlled is 97% in the *ETF* industry as of November 2019. Total *Assets under Management* Indonesia *ETF* as of November 2019 is Rp. 15 trillion, of which Rp. 10 trillion controlled by PT. Indo Premier Investment Management.

There are 18 investment managers making ETFs in Indonesia as of December 31, 2019. Where PT. Indo Premier Investment Management became the company that issued the most ETFs with a total of 11 products, followed by PT. Pinnacle Persada Investama and PT. Batavia Prosperindo Asset Management with seven and three ETFs, respectively.

The number of ETFs per Investment Manager is presented below. PT. Indo Premier Investment Management leads with 28% total ETFs, followed by PT. Pinnacle Persada Investama and PT. Batavia Prosperindo Asset Management. In fourth place there are three Investment Managers, namely PT Bahana TCW Investment Management, PT. Sinar Mas Asset Management, and PT. BNI Asset Management.

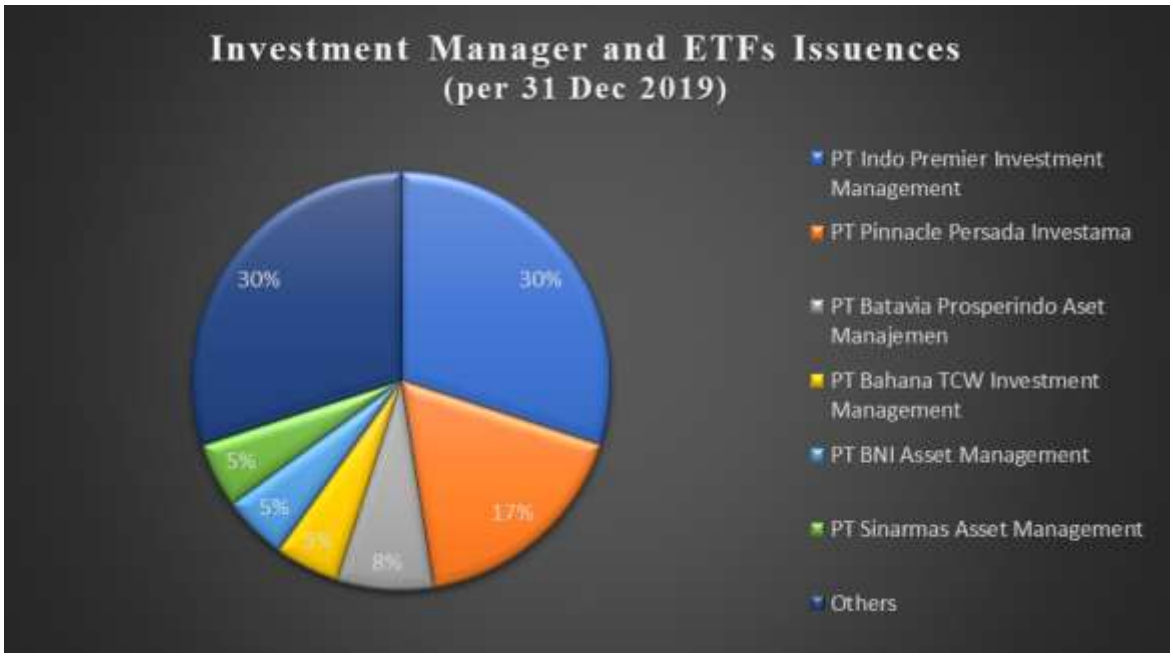

Figure 3. *Investment Manager and ETF Issuance*

There are 37 ETFs traded as of January 2, 2020. Two of the 37 ETFs are bond ETFs issued from the population. The remaining 35 ETFs are stock-based ETFs. Seven of the 35 ETFs are not index-based stock ETFs and are excluded from the population. The rest are 28 index-based equity ETFs, so that 28 ETFs are the target population in this study. Seven of the 28 ETFs do not have publicly available data, such as trading volume and market capitalization data. Researchers took seven ETFs that had incomplete data from the observation period from January 2, 2020 to July 1, 2020. Two of the remaining 21 ETFs had low-quality data and became outliers. It is also taken from the sample. And the remaining 19 ETFs were sampled in this study.

Researchers try to see and analyze the difference between *NAV* returns and *benchmark* index returns. Regression model as below:

Table 1. Regression Result TE

Ranking	Ticker	Obs.	α_i	β_i	Prob. (F-statistic)	Adjusted *R-squared*	|Mean Error|	| Std. Dev.Error|
1	XSBC	123	-1.4189 (0.0000) (0.0000)	0.9747 (0.0000) (0.0000)	0.0000	0.9999	0.0013	0.0014
2	XPFT	123	-1.6194 (0.0000)	0.9731 (0.0000)	0.0000	0.9998	0.0017	0.0016
3	XPID	123	0.1526 (0.0000)	0.9746 (0.0000)	0.0000	0.9998	0.0017	0.0015
4	XISR	123	0.1675 (0.0000) (0.0000)	0.9747 (0.0000) (0.0000)	0.0000	0.9998	0.0018	0.0016
5	XMIG	123	0.1942 (0.0000)	0.9620 (0.0000)	0.0000	0.9998	0.0018	0.0016
6	XBNI	123	-1.5973 (0.0000)	0.9686 (0.0000)	0.0000	0.9997	0.0020	0.0018
7	XPTD	123	0.0358 (0.0022)	0.9908 (0.0000)	0.0000	0.9996	0.0025	0.0023
8	RLQ45X	123	0.3040 (0.0000)	0.9614 (0.0000)	0.0000	0.9996	0.0027	0.0020
9	XIHD	123	0.2382 (0.0000)	0.9630 (0.0000)	0.0000	0.9995	0.0027	0.0022
10	XIIT	123	0.2828 (0.0000)	0.9594 (0.0000)	0.0000	0.9995	0.0028	0.0020
11	XPMI	123	-1.7074 (0.0000)	0.9673 (0.0000)	0.0000	0.9995	0.0029	0.0019
12	XIJI	123	0.0089 (0.5582)	1.0002 (0.0000)	0.0000	0.9993	0.0029	0.0021
13	XIPI	123	0.1456 (0.0000)	0.9722 (0.0000)	0.0000	0.9989	0.0040	0.0035
14	XPCR	123	-0.2998 (0.0000)	1.0392 (0.0000)	0.0000	0.9985	0.0053	0.0042
15	XMTS	123	0.5655 (0.0000)	0.9646 (0.0000)	0.0000	0.9976	0.0056	0.0041
16	XAQA	123	0.1076 (0.0144)	0.9786 (0.0000)	0.0000	0.9947	0.0099	0.0067
17	XISC	123	0.4718 (0.0000)	1.0218 (0.0000)	0.0000	0.9946	0.0123	0.0086
18	XIIF	123	-2.6331 (0.0000)	1.2555 (0.0000)	0.0000	0.9843	0.0195	0.0164
19	XIIC	123	-2.8810 (0.0000)	1.2945 (0.0000)	0.0000	0.6839	0.0693	0.0375

Note: number in bracket are prob. t statistics level of significant

Of the 19 ETFs, all of them show that differences in NAV returns are significantly affected by differences in index returns. From Adjusted R-squared value, it can be concluded that the regression model is very strong, 18 ETFs have a value of 0.99 and only one ETF has a value of 0.68, namely XIIC. *The mean absolute error* ranges from 0.0013 to 0.069. Where XSBC has the best performance, while XIIC has the lowest performance.

$$TE1 = \beta_0 + \beta_1.DVolatility_{i,t} + \beta_2.DIVolatility_{i,t} + \beta_3.LnVolume_{i,t} + \beta_4.LnMarketcap_{i,t} + + \beta_5.LnMomentumIndex_{i,t} + \beta_6.CompositeReturn_{i,t} + \beta_7.Age_{i,t} + \varepsilon_{i,t} \quad (4)$$

Table 2. Regression Determinants Factors for TE

No	Ticker	Coefficient and Probability	C	DVolatility	DIVolatility	LnVolume	LnMarket Cap	LnMomIndex	Return Composite	Ln(Age)	Prob(F-statistic)	Adjusted R-squared
			β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7		
1	RLQ45	Coefficient	0.0043	0.0100	0.0008	0.0000	-0.0062	-0.0004	0.0080	-0.0014	0.1734	0.0290
		Prob.	0.9344	0.0921	0.8656	0.9149	0.3705	0.9220	0.3827	0.8194		
2	XAQA	Coefficient	-0.0445	0.0147	0.0357	-0.0001	0.0047	-0.0116	0.0361	0.0018	0.0000	0.3242
		Prob.	0.0000	0.5553	0.0000	0.6237	0.6432	0.2724	0.0001	0.0565		
3	XBNI	Coefficient	-0.0061	-0.0005	0.0062	0.0000	0.0003	-0.0074	-0.0014	0.0012	0.2315	0.0206
		Prob.	0.4066	0.9434	0.0988	0.7923	0.9134	0.1325	0.7011	0.2581		
4	XIHD	Coefficient	-0.0065	0.0192	0.0042	0.0000	-0.0011	-0.0086	-0.0006	0.0012	0.0135	0.0904
		Prob.	0.3378	0.0142	0.3138	0.8856	0.7516	0.1242	0.9093	0.1428		
5	XIIC	Coefficient	-0.5760	-0.0955	0.1594	0.0002	-0.0025	-0.0209	0.0685	0.0652	0.0000	0.2463
		Prob.	0.0222	0.2145	0.0000	0.6057	0.8617	0.6799	0.0448	0.0414		
6	XIIF	Coefficient	-0.0697	0.1745	0.0372	0.0001	0.0466	0.0051	0.0044	0.0092	0.0005	0.1540
		Prob.	0.7005	0.0003	0.2502	0.7457	0.0669	0.8977	0.9087	0.6936		
7	XIIT	Coefficient	0.0011	0.0087	0.0030	0.0000	0.0022	-0.0034	-0.0043	0.0004	0.0844	0.0481
		Prob.	0.9726	0.1835	0.5867	0.2651	0.7346	0.4559	0.6246	0.9122		
8	XIJI	Coefficient	-0.0630	-0.0099	0.0020	0.0000	-0.0019	-0.0019	0.0034	0.0077	0.3393	0.0086
		Prob.	0.0268	0.1554	0.5225	0.8179	0.5276	0.7017	0.3589	0.0348		
9	XIPI	Coefficient	-0.0007	0.0006	0.0096	0.0000	0.0014	-0.0067	-0.0030	0.0007	0.2031	0.0245
		Prob.	0.9257	0.9309	0.0302	0.6218	0.6383	0.2819	0.5607	0.4549		
10	XISC	Coefficient	-0.0283	0.0292	0.0877	0.0002	0.0164	-0.0772	0.0575	-0.0038	0.0000	0.3790
		Prob.	0.7709	0.2333	0.0000	0.1849	0.3744	0.0007	0.0152	0.7693		
11	XISR	Coefficient	-0.0150	-0.0014	0.0042	0.0000	0.0085	-0.0055	-0.0124	0.0036	0.3271	0.0099
		Prob.	0.5024	0.8157	0.3203	0.8700	0.0905	0.2352	0.0642	0.2146		
12	XMIG	Coefficient	0.0029	-0.0116	0.0128	0.0001	0.0008	-0.0079	-0.0028	0.0000	0.0165	0.0860
		Prob.	0.5721	0.3408	0.0021	0.4638	0.8635	0.1393	0.5520	0.9823		
13	XMTS	Coefficient	-0.0447	0.1234	0.0418	0.0000	-0.0178	-0.0202	0.0377	0.0013	0.0000	0.2472
		Prob.	0.0282	0.1604	0.0001	0.9798	0.0608	0.1839	0.0019	0.6292		
14	XPCR	Coefficient	-0.0389	0.0173	0.0538	0.0004	-0.0056	-0.0242	0.0432	-0.0007	0.0000	0.3975
		Prob.	0.0001	0.7534	0.0000	0.5924	0.6213	0.0390	0.0000	0.2946		
15	XPFT	Coefficient	-0.0108	0.0090	-0.0262	-0.0002	-0.0011	-0.0083	0.0009	0.0016	0.0324	0.0710
		Prob.	0.0739	0.6013	0.7058	0.0028	0.6432	0.0470	0.7979	0.0401		
16	XPID	Coefficient	0.0105	0.0113	0.0119	0.0000	-0.0005	-0.0057	-0.0012	-0.0014	0.0046	0.1125
		Prob.	0.2527	0.0125	0.0004	0.8664	0.8614	0.1990	0.7404	0.2712		
17	XPMI	Coefficient	0.0022	0.0109	0.0004	0.0000	0.0029	-0.0048	-0.0064	0.0008	0.2806	0.0148
		Prob.	0.7230	0.1397	0.9309	0.5841	0.5132	0.3471	0.2273	0.1410		
18	XPTD	Coefficient	-0.0100	0.0016	0.0067	0.0000	0.0017	-0.0062	0.0035	0.0012	0.0021	0.1280
		Prob.	0.0224	0.7691	0.1829	0.6117	0.6320	0.1605	0.3220	0.0074		
19	XSBC	Coefficient	-0.0032	-0.0038	0.0111	0.0000	-0.0027	-0.0060	-0.0007	0.0007	0.0085	0.1001
		Prob.	0.6234	0.6022	0.0014	0.6773	0.4220	0.2051	0.8493	0.4569		

From the table above, the volatility of benchmark index becomes a significant factor for the 9 *ETFs* of sample. The coefficient on the volatility index shows a positive association. That is, the higher volatility of benchmark index, the higher error. The next factor is composite index return which is a significant factor for the five *ETFs* from the sample. It also has a positive relationship between the return of index and error. The larger return index, the higher ETF error.

In this study, the age of *ETF* is also included in the model whether the *ETF* will have a smaller error if it is more mature. The expectation of relationship between the dependent and independent variables is negative. The age of *ETF* was a significant factor for the four *ETFs* of sample. However, the relationship shows a positive relationship between age and error. This may be due to the observation period in the first and second quarters of 2020. As we all know, the world, including Indonesia, is affected by COVID-19 pandemic which has an impact on business, economy, finance and trade. The worst economic impact of the pandemic occurred in the second quarter of 2020 including the decline in the value of investment assets. So that as the first quarter and second quarter of 2020 progress, the greater *absolute error* between *NAV* return and index return.

V. Conclusion

From the analysis above, the author concludes that:

1. The value of constant which is a significant factor for the six ETFs of sample.
2. ETF price volatility is a significant factor for the three ETFs.
3. The volatility of benchmark index is a significant factor for the nine ETFs from the sample.
4. Volume changes are a significant factor for only one ETF.
5. Changes in market capitalization are not significant for all ETFs from the sample.
6. The Momentum Index is a significant factor for the three ETFs.
7. Return of the composite index is a significant factor for the five ETFs.
8. The age of ETF is a significant factor for the four ETFs.
9. The movement of benchmark index significantly affects the return movement of all ETFs.
10. Of the 19 samples studied based on the tracking error of each ETF, the best three ETF performances are XSBC, XPFT and XPID. Meanwhile, the ETFs with the worst performance were XIIC, XIIF and XISC.

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