Evaluating the Tracking Performance and Tracking Error of New Zealand Exchange Traded Funds[†]

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Abstract

This study examines the tracking performance and tracking error of New Zealand Exchange Traded Funds (ETFs). We document that New Zealand ETFs do not replicate their corresponding indexes perfectly. At the daily frequency, we observe that the ETFs have substantially different exposures to their underlying indexes from what they should be, which is confirmed by cointegration analysis. At the monthly frequency, tracking performance improves, but still shows significant differences between the ETF and its underlying index. When we examine the tracking errors of the ETFs, we observe that these are substantial, and that there is considerable variation in tracking error. Regression analysis shows that both characteristics of the ETF and the constituents of the index the ETF tracks, as well as the volatility of the underlying benchmark are determinants of the tracking error of the ETFs.

JEL Codes: G11; G23.

Keywords: Exchange Traded Funds; New Zealand; Tracking error; Performance.

1. Introduction

In 1993, the first ETF which tracks the S&P 500 index was launched, and was called the S&P Depository Receipts (SPDR). Since then, the global ETF market has grown dramatically. Although a standard ETF consists of a basket of financial assets such as common stocks, the trading mechanism of an ETF is different from its underlying assets. ETFs usually track a particular index, and are publicly traded on stock exchanges. ETFs are hybrid investment vehicles sharing properties of exchange-listed corporate securities and open-ended mutual funds (Bernstein, 2002). In other words, ETFs enable investors to buy a single ETF share which provides them with exposure to a basket of securities, and trade it on secondary markets during trading hours.

Prior literature has documented that ETFs are attractive due to low costs, potential tax efficiencies, and stock-like features. Bansal and Somani (2002), and McGuire and Helmrich (2008) argue that ETFs are attractive to investors because of increased cost efficiency compared with mutual funds, easy trading during the trading hours, and their ability to offer creative investment solutions. Poterba and Shoven (2002) argue that ETFs are prototypes for the future evolution of the mutual fund industry. In addition they argue that ETFs are more "tax efficient" than traditional equity mutual funds. Moreover, Bowman (2012) notes that since most ETFs are passive investments, they differ from mutual funds in terms of transparency, i.e. investors know what stocks are held by ETFs, but do not know this for a mutual fund. Many of the newer ETFs are based on specialized indexes, including indexes that are designed specifically for a particular ETF.[1] Originally marketed as opportunities for retail investors to

[1]For instance the VXX is an ETF that tracks a constant maturity index based on VIX futures (see e.g. Whaley, 2013).

participate in a tradable portfolio or basket products, today ETFs are held in increasing amounts by institutional investors (including mutual funds) and other investors as part of sophisticated trading and hedging strategies. This is because of the flexibility that ETFs offer, where investors can short sell ETFs, write options on them, and set market, limit, and stop-loss orders. In addition, ETFs can be created on various assets (stocks, commodities, etc.) and can allow for leveraged or inverse exposures to the underlying index. Given the attractive properties of ETFs, many studies have focused on the investment efficiency of ETFs, focusing on performance, tracking error and explaining tracking error. However, to date, no study has focused on the New Zealand ETF market. This study aims to fill this gap.

In this paper, we examine the tracking performance (i.e. how well ETFs can replicate their respective benchmarks) and tracking error (i.e. what drives deviations from the benchmark) for the three main New Zealand focused ETFs, the NZ Top 50 (FNZ), the NZ Top 10 (TNZ), and the NZ Mid Cap (MDZ).[2] Consistent with prior literature, our analysis shows that the three New Zealand ETFs do not replicate the performance of their corresponding index perfectly. At the daily frequency, we observe that the ETFs have substantially different exposures to their underlying indexes from what they should be. Cointegration analysis confirms this finding and shows that there is considerable persistence in price deviations of the ETF from its benchmark. This implies that the New Zealand ETFs may not be appropriate vehicles for very active trading strategies (such as day or high frequency trading). At the monthly frequency, tracking performance improves, but still shows significant differences between the ETF and its underlying. When we examine the tracking errors of the ETFs, we observe that these are

[2]Smartshares recently changed the names of their ETFs. The NZ Top 50 was previously called the SmartFONZ and tracks the S&P/NZX50 Portfolio Index; the NZ Top 10 was called the SmartTENZ and tracks the S&P/NZX10 Index; and the NZ Mid Cap was previously called the SmartMIDZ and tracks the S&P/NZX MidCap Index.

substantial, and larger than compared with ETFs from other markets. Regression analysis shows that both characteristics of the ETF and the constituents of the index the ETF tracks (such as its bid-ask spread and trading volume), as well as the volatility of the underlying benchmark are determinants of the tracking error of the ETFs.

Overall, our results should be of relevance to New Zealand market participants. With the ETF market in New Zealand growing over time, and the ETFs considered in this study being an option for KiwiSaver investment, investors in these ETFs should have an interest in understanding the properties we document in this study. The fact that tracking errors are substantially larger than for ETFs in other markets should be of concern to investors. The results may also be of interest to the ETF provider, and may provide some guidance on where improvements in terms of tracking performance and tracking error may be possible.

The remainder of this paper is organized as follows. Section 2 includes the literature review. The methodologies and data are described in Sections 3 and 4, respectively. Section 5 presents the empirical results. Section 6 concludes the paper.

2. Literature Review

Prior literature has extensively studied the ETF market around the world, and has documented that the majority of ETFs have considerable tracking errors, and most of them underperform their underlying index. Several factors, such as exchange rate movements, have been proposed to explain the existence of tracking error. For example, Rompotis (2006) examines the performance of global ETFs listed on the Swiss stock exchange, and finds that these ETFs underperform their benchmark, do not replicate their benchmarks accurately, and performance is negatively related to management fees, while tracking error is positively related to management fees. Harper, Madura, and Schnusenberg (2006) compare the risk and return performance of ETFs to closed-end funds in US, and reach three main conclusions. First, ETFs generate higher returns than closed-end funds due to their lower expense ratios. Second, ETFs have higher Sharpe ratios than closed-end funds. Third, the passive investment strategy is superior to the active one. Blitz, Huij and Swinkels (2010) find that European ETFs underperform their benchmark by 50 to 150 basis points p.a. and suggest that the ETFs' expense ratios and dividend taxes can explain the underperformance.

The ETF market in emerging markets also received considerable attention. For instance, Shin and Soydemir (2010) study the tracking error performance of Asian ETFs. They argue that the Asian ETF market is less efficient in disseminating information, resulting in greater tracking error. Jiang, Guo and Lan (2010) investigate the price efficiency of the Shanghai 50 ETF in China, and find that this ETF and the underlying index are cointegrated. They also find that the ETF price is not close to its underlying index in the second half of 2007 due to Chinese stock market financial turbulence. Baş and Sarıoğlu (2015) focus on Turkish ETFs and find that tracking errors are significantly different from zero. Employing similar measures of tracking error, Chu (2011) finds significant tracking errors for ETFs traded in Hong Kong. He finds that tracking error is positively related to expense ratio, and negatively related to assets under management.

Another line of research focuses on the role of ETFs in market completion and price efficiency. For example, Wang, Hussain, and Ahmed (2010) study Chinese gold ETFs and show that the launch of gold ETFs significantly improves China's ability to deal with issues such as diversification, inflation protection and currency hedging. Rompotis (2011) examines weak-form efficiency of the Swiss ETF market, and finds that this ETF market is weak-form efficient. Agapova (2011) examines the substitutability of conventional index mutual funds and ETFs, and shows that conventional index funds and ETFs are indeed substitutes, although not perfect ones. She suggests that ETFs offer new features that conventional index cannot, and explains the coexistence of both index funds and ETFs by a clientele effect. Hilliard (2014) analyses ETF premiums and discounts and shows a high degree of efficiency of the ETF arbitrage pricing mechanism. International equity and bond ETFs face more barriers to arbitrage, which results in higher long-term premiums and lower speeds of adjustment.

Previous literature also focuses on the link between ETFs and other financial assets. Corbet and Twomey (2014) investigate how US ETFs influence commodity market volatility, and document significant differences in the volatility of large and small commodity markets after the introduction of ETFs. Their results show that large commodity markets are directly influenced by large holdings of ETFs, whereas small commodity markets benefit from the investment in ETFs. Pan and Li (2016) examine the tracking error performance of gold ETFs in China and document that the tracking errors of these ETFs are generally lower than those of equity-based ETFs. Nguyen and Phengpis (2009) examine the opening of ETF markets in a multimarket trading environment in the US, and find that the American Stock Exchange is the most costly, which is consistent with market power hypothesis.

Several studies have examined liquidity issues around ETFs and their underlying assets. Chau, Deesomsak and Lau (2011) investigate the feedback trading of US ETFs and find that the level of feedback trading tends to increase when investors are optimistic, and that the influence of sentiment on feedback trading varies across market regimes. Caginalp, Desantis and Sayrak (2014) investigate the price dynamics of US equity ETFs and find that highly liquid ETFs can deviate from the daily net asset value. They show that traders are not only aware of the under-reaction of others, but also self-optimize by anticipating others' reaction. Marshall, Nguyen and Visaltanachoti (2013) analyse the trading conditions for S&P 500 ETFs, when mispricing allows arbitrage opportunities to be created. The authors argue that although these ETFs are not perfect substitutes, investors view them as close substitutes to the underlying indexes. Spreads increase just before arbitrage opportunities, consistent with a decrease in liquidity.

Predictability of returns and volatility of ETFs has also been examined intensively. Yang, Cabrera and Wang (2009) find evidence of daily return predictability for 18 international stock index ETFs. DeFusco, Ivanov and Karels (2011) find that the price deviation between the Spider, Diamond, and Cubes and their underlying indexes are predictable and nonzero. Krause and Tse (2012) examine the spillover effect of volatility and returns between Canadian and US industry ETFs. They find that information is impounded more rapidly in US ETFs and that price discovery flows consistently from the US to Canada. At the volatility level spillovers are largely bi-directional. Negative US return spillover and asymmetric volatility creates bi-directional volatility feedback effects.

Although there is a large volume of literature focusing on ETFs in the US and other markets, to date there is no research that focuses on the New Zealand market. Studies that have focused on the global ETF market also have not included New Zealand-based ETFs in their samples. In this study we intend to fill this gap by focusing on New Zealand ETFs and capturing and modelling their tracking performance and tracking errors.

3. Methodology

In this section, we detail the methodology we employ to measure the tracking performance and tracking error of New Zealand listed ETFs.

3.1 Tracking Performance

We employ two approaches to measure the tracking performance of the New Zealand-based ETFs. First, we conduct a regression analysis (CAPM), where we compare the excess returns on the ETF to the excess returns on its benchmark, i.e.,

$$(r_t^{ETF} - r_t^f) = \alpha + \beta(r_t^{IND} - r_t^f) + \varepsilon_t, \tag{1}$$

where r_t^{ETF} is the return on the ETF, r_t^f is the return on the 90-day bank bill rate, and r_t^{IND} is the return on the index that the ETF tracks. The intercept, α, captures the out- or underperformance of the ETF relative to the index, while β captures the exposure of the ETF to the movements in the index. If the ETF tracks the benchmark well, we would expect α = 0, and β = 1. In addition to these measures, we can also assess the R^2 of the regression. If the fund replicates the index well, we would expect the R^2 to be close to one.

A second way of assessing the tracking performance of the ETF is to assess whether the (log) price series of the ETF and its benchmark are cointegrated. We assess the cointegration between the ETF and its index by following the Engle and Granger (1987), and Johansen (1988) procedure. For the Engle and Granger (1987) procedure we conduct a regression of the log prices of the ETF on the log prices of its index, i.e.,

$$p_t^{ETF} = \gamma + \delta p_t^{IND} + \eta_t, \tag{2}$$

where p_t^{ETF} is the log price of the ETF at time t, and p_t^{IND} is the log price of the index it tracks. The coefficient δ captures the long-run relation between the ETF and the index and is expected to be equal to 1 if the ETF tracks the index perfectly. The intercept, γ, captures any persistent deviations between the ETF and the index, which can be due to the fact that the ETF may trade at a different price level/multiple than the index.

One of the features of cointegration is that price levels (or logs of prices) typically are non-stationary. However, cointegration implies that a linear combination of non-stationary variables becomes stationary. A formal test for this is provided by Johansen (1988), who suggests that trace statistics can be computed for the long-run coefficient matrix.

If prices are cointegrated, then the Engle-Granger representation theorem states that returns on both the ETF and the index can be modelled using an error correction model (ECM). Specifically, we estimate the following ECM,

$$r_t^{ETF} = \mu + \lambda \pi p_{t-1} + \varphi(L) r_t^{ETF} + \theta(L) r_t^{IND} + \nu_t, \tag{3}$$

where πp_{t-1} is the error correction term obtained from the Johansen procedure, and $\varphi(L)$ and $\theta(L)$ is a polynomial in the lag operator, L, where $L > 0$. The coefficient, λ, captures the speed of adjustment coefficient and measures the speed by which the ETF error-corrects to imbalances in the long-run relation between the ETF and its index. From λ, we can compute the half-life of the ETF-index price difference, which is given by $\frac{\ln 2}{|\lambda|}$.

3.2 Tracking Error

The deviation between the ETF and its underlying index is known as the tracking error (TE). Prior literature has found that in most financial markets, ETFs fail to replicate their underlying index accurately (e.g. Rompotis, 2006). In this section, three approaches are discussed to measure tracking error. The first measure is based on the absolute differences between the returns on the ETF and its underlying index, i.e.,

$$TE_1 = \frac{\sum_{t=1}^{T} | r_t^{ETF} - r_t^{IND} |}{T} , \tag{4}$$

where T is the window that the tracking error is measured over.

The second metric is based on the standard deviation of the differences between the return on the ETF and its underlying index, i.e.,

$$TE_2 = \sqrt{\frac{\sum_{t=1}^{T} [(r_t^{ETF} - r_t^{IND})\overline{(r_t^{ETF} - r_t^{IND})}]}{T}} . \tag{5}$$

The third metric we can use is the standard error of the residuals of a linear regression of ETF returns on their corresponding underlying index returns, i.e.,

$$r_t^{ETF} = \alpha + \beta r_t^{IND} + \varepsilon_t, \tag{6}$$

where $TE_3 = S.E.(\varepsilon_t)$.

The various measures of tracking error detailed above can be used to assess how well the ETFs track their underlying indices. If there are deviations of the ETF from its underlying index, it will be interesting to see what drives those deviations, and what explains the observed tracking error. As mentioned by Shin and Soydemir (2010), many factors can affect and predict the tracking error, including total expense ratio, daily volatility, trading volume, etc. Qadan and Yagil (2012) investigate tracking ability of US ETFs and find that tracking error is correlated with daily volatility of US ETFs, as well as trading volume. Elia (2012) assesses the determinants of the tracking errors of European ETFs, and finds that total expense ratio and tax regime are significant factors to explain the tracking error of European ETFs. Following these studies, we assess what drives the tracking error of the New Zealand ETFs. In contrast to previous studies, which focus on cross-sectional determinants of tracking error, we focus on what affects the time variation in tracking error, since we only evaluate three ETFs. We examine the relation between the tracking error of each ETF by estimating the following regression

$$TE_t = \alpha_1 + \alpha_2 ETF\%Spread_t + \alpha_3 ETF\,Vol_t + \alpha_4 IND\%Spread_t + \alpha_5 IND\,Vol_t + \alpha_6 Volatility + \varepsilon_t, \tag{7}$$

where TE_t denotes the tracking error, $ETF\%Spread_t$ is the average percentage spread of the ETF, computed as $\frac{(Ask_t - Bid_t)}{(Ask_t + Bid_t)/2}$, over month t, $ETFVol_t$ is the log of the volume traded in the ETF over month t, $IND\%Spread_t$ is the average percentage spread of the stocks in the representative index over month t, $INDVol_t$ is the log of the volume traded in the constituents of the index over month t, and $Volatility_t$ is the volatility of the index that the ETF tracks and is computed as the standard deviation of daily returns over month t.

We include percentage spread of the ETF as the tracking error may be affected by the cost of trading in the ETF. If the cost of trading is very high, liquidity in the ETF will be very low and thus the market price of the ETF may not always reflect the value of the underlying index. Similarly, we include the log of the volume traded in the ETF over month t (both spread and volume were also included by Shin and Soydemir (2010) in their regressions to explain tracking error). This also is a proxy for liquidity of the ETF, and we expect that if volume is very low, the ETF may track its respective index less well. Likewise we include the percentage spread and the traded volume in the constituents of the respective indexes.[3] We use these measures as proxies for the liquidity of the stocks in the underlying indexes, and expect that if liquidity is low, the ETF may track its respective index less well. Finally, we include the volatility of the indexes in the regressions as indexes may be harder to track in times of high market turbulence (see also Rompotis, 2006).

[3]Since we do not have historical data on the constituents of the indexes, we construct our own by ranking all NZ stocks based on their annual market values. Once the constituent stocks are selected, we compute the index % spread and trading volume using the market value as weights. Thus, the index % spread and trading volume are the value-weighted average of individual % spread and trading volume of constituent stocks, if the data is available. For the FNZ, we impose a cap of 5% on the weight of each stock included in the S&P/NZX50 Portfolio index. No cap is imposed when constructing the other two indexes (S&P/NZX10 and MidCap).

4. Data

Daily and monthly total return data of the three New Zealand focused ETFs and their underlying indexes are obtained from DataStream. Specifically, we obtain data on the FNZ, which is the ETF that tracks the S&P/NZX 50 Portfolio Index; the TNZ, which tracks the S&P/NZX 10 Index; and the MDZ, which tracks the S&P/NZX Mid Cap Index.[4] As of July 2016, these ETFs had approximately NZD 212, 78 and 70 million in assets under management, respectively. Our sample period is from 11 June 1996 to 30 June 2016. In addition, we obtain data on daily volume and end-of-day bid-ask spreads of the ETF and of the stocks listed on the NZX from DataStream.

INSERT TABLE 1 ABOUT HERE

Table 1 presents summary statistics of daily and monthly returns for the three ETFs and their underlying indexes in Panels A and B, respectively. Average daily returns are small as expected and similar for the ETFs and their respective index. However, when we compare the standard deviation of the ETFs vis-à-vis their respective index, we note that the volatilities of the ETFs are substantially larger, an observation that is in line with Rompotis (2006) who considers a sample of 32 global ETFs. For most series skewness is negative, and kurtosis well exceeds the value of 3, showing that most series have fat tails. This negative skewness and fat tails is a common observation in financial time series. Although the average returns are small, the minimum and maximum values are large. In case of the FNZ and MDZ, we observe that these

[4] The FNZ was introduced on 10 December 2004; the TNZ was introduced on 11 June 1996; and the MDZ was introduced on 16 June 1997.

values are more extreme for the ETF than for the respective index, in line with the observation of a higher standard deviation for these series.

For the monthly series, reported in Panel B, we observe that the statistical properties of the ETFs are much more in line with their underlying index. We observe that the standard deviations of the ETFs are close to the standard deviations of the respective indexes, and again all series display negative skewness and kurtosis in excess of three.

Comparing the summary statistics of the daily data with those of the monthly data suggests that, most likely, the tracking performance of the ETFs will be better at the monthly frequency (as properties of the ETF and their benchmark are much more in line with each other). One of the reasons for the deviating properties at the daily frequency could be due to the potentially low liquidity of the ETFs. This could lead to relatively wide bid-ask spreads on the ETFs and could cause market microstructure noise (such as the bid-ask bounce) to affect the price series of the ETFs.

INSERT FIGURE 1 HERE

To provide a visual representation of the dynamics of the ETF versus its underlying benchmark, we provide a time series plot of the FNZ versus the S&P/NZX50 Portfolio Index in Figure 1. We note that the ETF trades at a value that is 1/1,000th of the index value and thus present the values of the ETF on the left vertical axis and the value of the index on the right vertical axis. Visually, the ETF tracks the index well. We do observe that at times there are some small spikes in the ETF away from the index, which confirms the observed higher volatility in the

FNZ compared with the S&P/NZX 50 Portfolio Index. In addition, we do, at times, observe small but persistent deviations in the ETF from the index, which could result in tracking error.

5. Empirical results

5.1 Tracking Performance of ETFs

We start our analysis by focussing on the tracking performance of the ETFs, i.e., we focus on whether the ETFs replicate their respective indexes well. As detailed in Section 3, we do this by running CAPM regressions of the excess returns of the ETF on the excess returns of the index. In Table 2, we report the results for these regressions both using daily (Panel A) and monthly (Panel B) data. From Panel A, we observe that α is insignificant for all ETFs, showing that none of the ETFs either out- or underperform their respective indexes. When we consider the β for the three ETFs, we observe that all of these deviate substantially from one, and in all cases the slope is significantly different from one, suggesting that these indexes do not track their benchmarks one-to-one, but actually have a substantially lower exposure to their benchmarks. Finally, the R^2's of these regressions are quite low ranging from 10.16% to 33.05%. This suggests that most of the variation of the ETF is not explained by the variation in the index. Hence, based on these CAPM regressions, we conclude that the daily tracking performance of these ETFs is not very good. A potential reason for this might be the low liquidity in these products and the effect of market microstructure noise – an issue that we explore in Section 5.2.

In Panel B, we report the tracking performance based on the CAPM using monthly data. When we consider the α, we note that these are negative in all three cases and significantly so for the TNZ and MDZ, suggesting that these ETFs significantly underperform their respective indexes.

The slope coefficients, β, for the three ETFs are now much closer to one, although we still observe that these β's are significantly different from one (for the FNZ the significance is only at the 10% level). The observation, though, that all these slope coefficients are significantly different from one is interesting and may be a consequence of a possible cash drag (where the ETF provider retains and accumulates cash in an account to meet its semi-annual dividend payments). Finally, we observe that there is a substantial improvement in the R^2 of the regressions which range from 75.68% to 87.11%.

INSERT TABLE 2 HERE

The second step in the analysis of tracking performance of ETFs is a cointegration analysis. In Table 2, we report the results for the cointegration analysis, where we report the results for the daily (monthly) data in Panel A (Panel B). The first two columns of these panels show the intercept and slope coefficients of the linear regression of the log prices of the ETF on the log prices of the indexes. The intercept in this case, captures the multiple at which the ETF trades. For the FNZ and TNZ this is 1/1,000, which is approximately equal to the intercepts (i.e. $e^{-6.8405} \approx 0.001$). For the MDZ this is 1/1,500. Of more interest is the slope coefficient, δ, which, if the ETF follows the index well, should be equal to 1. In all cases, we observe that the coefficient is close to one, but statistical tests show that the δ's are significantly different from 1. The next column shows the Johansen Trace statistic, as a formal test for cointegration among the series. In all three cases, the Trace statistic is larger than its critical value indicating that the series are indeed cointegrated, and thus that there is a long-run equilibrium between the ETF and the index it tracks. The last column shows the speed of adjustment coefficient of the error correction model, λ, which shows the degree to which the prices of the ETFs error correct to the price difference that occurs between the ETF and its respective benchmark. All these coefficients are negative suggesting that when a positive (negative) gap occurs between the ETF and its index, the value of the ETF will decline (increase) to close the price gap. We see that the speed of adjustment coefficient is most negative for the FNZ, suggesting that this ETF error corrects strongest to price differences. To provide an economic interpretation for this coefficient, we can use this coefficient to compute the half-life. This half-life is given as $t_{half} = \ln 2/|\lambda|$. For the FNZ this is equal to 4.43, so it takes about 4.5 days to close half of the price deviation. Thus mispricings of the FNZ relative to the S&P/NZX 50 Portfolio index tend to persist for quite some time. For the TNZ and MDZ these half-lifes are 6.8 and 9.9 days, respectively.

In Panel B, we report the results for the cointegration analysis using the monthly data. Overall, the results for these data are broadly in line with those of the daily data, which is to be expected because cointegration analysis assesses long-run equilibria and is therefore not much affected by the sampling frequency. The only thing we notice is that we lose a considerable amount of statistical power in this analysis, where in the case of the FNZ and TNZ we can no longer reject the null hypothesis of $\delta = 1$, we observe a considerable drop in the Trace statistic and we find that the speed of adjustment coefficients are no longer significant.

INSERT FIGURE 2 HERE

To give some visual representation of the price deviations that can occur between the ETF and its respective index, we provide a time series plot of the log price difference between the FNZ and the S&P/NZX 50 Portfolio index in Figure 2. The figure demonstrates that price deviations can be large (up to 8% in magnitude), and quite persistent over time. From the graph, we can observe that the price deviations were, on average, just after the inception date of the FNZ, and we also notice that the magnitude of the price deviations has decreased over time. This suggests some improvement in the tracking performance of the FNZ.

5.2 Tracking Error of NZ ETFs

The previous section has provided us with some indication about the tracking performance of the three main New Zealand ETFs. In this section, we examine the tracking error and discuss what factors contribute to explaining the tracking error of the ETFs. Since tracking errors are based on measures of deviation, such as standard deviations or absolute differences, the analysis in this section is based on the daily data only, and we use daily data to calculate monthly measures of tracking error.

In Table 3, we report summary statistics on the three measures of tracking error detailed in Section 3. We find some variation in the different measures of tracking error. Specifically, we observe that TE_1, on average, has the lowest value across the three ETFs. TE_1 is highest for the FNZ and lowest for MDZ, likewise TE_2 is highest for FNZ. However, TE_3, which is based on the residuals of the regression of ETF returns on benchmark returns is highest for TNZ. All TE series display a high positive skewness and excess kurtosis, suggesting that the distribution has a fat tail to the right. The maximum value confirms that the tracking errors can be very large at times, going up to 13% for the MDZ based on TE_1.

Although the average tracking errors are mostly below 1% (in the range of 0.65% to 0.94%), they are substantially larger than those for ETFs in other markets. For instance, Frino and Gallagher (2001) show that the tracking error of US ETFs is about 0.039% to 0.11% per month during the period 1994-1998. Frino and Gallagher (2002) document that the tracking error of Australian ETFs is about 0.074% to 0.224% per month. Chu (2011) finds a daily tracking error of Hong Kong ETFs ranging from 0.28% to 2.17%. For emerging markets, Rompotis (2014) finds that ETFs have an average tracking error ranging from 0.3% to 0.5% per day.

INSERT TABLE 3 HERE

To visualize the tracking error, we provide a time series plot for TE_1 (i.e. we compute the daily absolute return difference between the ETF and its index) for the FNZ in Figure 3. Overall, we observe that there is substantial variation in the tracking error, being over 8% in the earlier part of the sample. The figure shows that there is a downward trend in the variation of the tracking error over time.

INSERT FIGURE 3 HERE

To examine what determines the tracking error for the three New Zealand-based ETFs, we run regressions of daily and monthly tracking error on various variables as highlighted in Equation (7). We add variables in three steps, i.e. we first add the variables that consider properties of the ETF, subsequently we add variables that capture characteristics of the stock in the index that the ETF tracks and finally add the volatility of the index that the ETF tracks.

INSERT TABLE 4 HERE

Table 4 shows the results for the daily tracking error measures on the FNZ. The first column shows the results for the regression that considers the characteristics of the ETF. Overall, we observe that characteristics of the ETFs are related to the tracking error, where the %Spread has a positive impact on the tracking error, and the ETF traded volume has a negative impact. These results hold for all three measures of tracking error, and suggest that illiquidity of the ETF contributes to the tracking error (e.g. due to staleness of prices or large price movements due to large spreads). In the second column, we add the characteristics of the constituents of the index, which are the weighted average %Spread and traded volume. Similar to the ETF characteristics, we observe that the percentage spread has a positive impact on the tracking error measures, whereas traded volume has a negative impact. This suggests that illiquidity in the stock in the underlying index of the ETF also affect tracking error. However, in contrast to the characteristics of the ETF, which directly affect the price of the ETF, the illiquidity in the underlying stocks relates to frictions/costs in replicating the index. Finally, we add the volatility of the index in the regression. We observe that index volatility has a positive and significant impact on the tracking error measures, suggesting that the tracking error is larger during times of high volatility. This can be due either to increased difficulty or costs of matching the ETF with the underlying. For the other variables, the main results mostly maintain, except for the %Spread of the index, which becomes insignificant after the inclusion of index volatility.

INSERT TABLES 5 AND 6 HERE

In Tables 5 and 6, we report the results for the daily tracking error measures for the TNZ and MDZ, respectively. For the TNZ, we observe that characteristics of the ETF significantly affect the tracking error measures (%Spread having a positive impact and traded volume a negative impact). For the characteristics of the stock in the underlying index, we observe that mostly the %Spread has an impact on the tracking error performance, which reflects the cost of trading. The traded volume is insignificant in the full specification, suggesting that illiquidity is not much of an issue for this ETF. Volatility of the index is again a strong determinant of tracking error. For the MDZ, in Table 6, the results are very similar to those presented for the TNZ, with %Spread (traded volume) of the ETF having a positive (negative) impact, the %Spread of the constituents having an impact, and index volatility being a strong determinant of tracking error.

INSERT TABLES 7 TO 9 HERE

In Tables 7 to 9, we present the results for the same regressions, now based on monthly data. In contrast to the daily regressions, we observe that monthly tracking error for the ETFs is not affected by the %Spread of the ETF. This confirms that the positive relation between the tracking error and the %Spread that we observed at the daily frequency relates to market microstructure issues, such as the bid-ask bounce. We find some mixed evidence on the impact of trading volume in the ETF on the tracking error. For the FNZ and MDZ we observe a negative relation between trading volume and the tracking error, in line with the results observed in the daily regression. However, for the TNZ, we observe some positive relations. This finding could be explained by a price pressure effect, where large volume in the ETF can push prices away from fundamentals (i.e. index values). For the characteristics of the constituents of the index, we find some evidence in line with the results from the daily analysis, i.e. %Spread has a positive impact on tracking errors, while traded volume has a negative impact. However, these results in general are weaker than those at the daily level. Finally, we observe that volatility of the underlying index remains a strong determinant of tracking error.

Overall, the regressions on the determinants of tracking error show that the ETFs have greater difficulty in managing tracking error in times of high volatility. However, the regression strongly suggests that the illiquidity in the ETFs, which results in relatively wide bid-ask spreads and low volume are a key determinant of the tracking error (especially at the daily level). To improve tracking error performance, the ETF provider could focus on ways to improve the liquidity of the ETFs. One possible way to achieve this could be to have a reverse split of the ETFs or reduce tick size (e.g. Anderson, 2013), so that they trade at larger prices as this could potentially lower the percentage spread of the ETFs and attract more liquidity to the ETFs.

6. Conclusions

This study examines how well these ETFs can replicate the performance of their underlying indexes, and what are the determinants of the tracking errors of New Zealand ETFs. We show that the New Zealand ETFs do not replicate the performance of their corresponding index perfectly. Both at the daily and monthly frequencies, we observe significant differences between the ETF and its underlying index. The tracking errors of the ETFs are substantial, and larger than those of ETFs in other markets. Regression analysis shows that both characteristics of the ETF and the constituents of the index the ETF tracks, as well as the volatility of the underlying benchmark are determinants of the tracking error of the ETFs.

Overall, our results have implications for both investors and the ETF provider. Investors should be concerned with the relatively large tracking errors as these can result in a performance of the ETF that deviates from index that the investor is seeking exposure to. The research presented in this paper will assist them in better understanding the products they invest in. In addition, the fact that daily tracking performance is very poor suggests that these ETFs are not vehicles for very active trading (e.g. day trading or high-frequency trading). For the ETF provider, our results may provide some guidance on where improvements in terms of tracking performance and tracking error may be possible. In fact, Smartshares has already put some measures into place in an attempt to reduce tracking error. Specifically, Smartshares, very recently, introduced dedicated market making in its ETFs to improve liquidity and decrease spreads.

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Table 1: Descriptive Statistics of NZ ETF Returns

This table presents descriptive statistics of daily (Panel A) and monthly returns (Panel B) for three New Zealand ETFs and their underlying indexes. The first two columns relate to Smartfonz (FNZ) and the S&P/NZX 50 Portfolio Index (NZX50P) for the period 10 December 2004 to 30 June 2016. The third and fourth relate to Smarttenz (TNZ) and the S&P/NZX 10 Index (NZX10) for the period 11 June 1996 to 30 June 2016. The last two columns relate to Smartmidz (Code: MDZ) and the S&P/NZX Midcap Index (NZXMid) for the period 16 June 1997 to 30 June 2016.

Panel A: Daily Data						
	R_{FNZ}	R_{NZX50P}	R_{TNZ}	R_{NZX10}	R_{MDZ}	R_{NZXMid}
Mean	0.03%	0.03%	0.02%	0.01%	0.03%	0.04%
Std. Dev	1.10%	0.65%	1.13%	0.98%	0.92%	0.66%
Kurtosis	0.01	-0.49	-0.37	-0.70	-0.41	-0.96
Skewness	11.41	9.91	13.83	19.96	14.33	17.59
Max	9.15%	5.81%	10.27%	10.63%	8.89%	6.21%
Min	-6.95%	-5.22%	-12.67%	-15.45%	-9.53%	-8.60%
Nobs	2,898	2,898	5,043	5,043	4,787	4,787
Panel B: Monthly Data						
Mean	0.53%	0.67%	0.39%	0.58%	0.53%	0.82%
Std. Dev	3.63%	3.38%	4.42%	4.34%	3.66%	3.60%
Kurtosis	-0.78	-0.82	-0.61	-0.85	-0.35	-0.35
Skewness	4.92	4.61	5.29	4.94	3.76	3.98
Max	-13.44%	-11.20%	-20.77%	-19.67%	-10.75%	-10.51%
Min	0.51%	1.25%	0.80%	1.09%	0.68%	1.26%
Nobs	8.33%	9.11%	14.49%	9.64%	10.54%	11.58%

Table 2: Tracking Performance

This table reports results on the tracking performance of the three New Zealand focused ETFs (FNZ, TNZ, MDZ). Panel A (B) reports results for the daily (monthly) data. The first part in each panel shows the results of the regression $(r_t^{ETF} - r_t^f) = \alpha + \beta(r_t^{IND} - r_t^f) + \varepsilon_t$, where r_t^{ETF} is the return on the ETF, r_t^{IND} is the return on its underlying index, and r_t^f is the risk free rate (90 day bank bill rate) on day t. We report coefficients along with Newey-West corrected t-statistics in parentheses. The t-statistics of the test on the null hypothesis whether β equals to one is also included. We further report an F-statistic testing whether jointly $\alpha = 0$ and $\beta = 1$. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.

The second part in each panel shows the results of assessing the cointegration between the log prices of each ETF and its underlying index. There are two steps. First, the regression is estimated as $p_t^{ETF} = \gamma + \delta p_t^{IND} + \eta_t$, where p_t^{ETF} and p_t^{IND} denote the log prices of the ETF and its index on day t, respectively. T-statistics are in parenthesis. The t-statistics of the test on the null hypothesis whether δ equals to one is also included. Second, the error correction model (ECM) is estimated based on the residuals from the above regression. The speed-of-adjustment coefficient estimate, λ, is also shown in the table. We also include the results from the Johansen Cointegration Test using Trace test on the hypothesis whether there is at most one cointegrating vector between two log prices. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.

Panel A: Daily Data				
CAPM regression:				
ETF	α (x100)	β Null Hypothesis: ($\beta = 0$, $\beta = 1$)	F-Stat [$\alpha = 0$, $\beta = 1$]	R^2
FNZ	0.0073	0.5498***	58.68***	0.1034
	(0.37)	(13.20, -10.80)		
TNZ	0.015	0.6788***	102.98***	0.3453
	(1.16)	(30.23, -14.35)		
MDZ	0.0073	0.4667***	85.57***	0.1120
	(0.56)	(10.99, -12.56)		
Cointegration Analysis:				
ETF	γ	δ Null Hypothesis: ($\delta = 0$, $\delta = 1$)	Trace Statistics	λ
FNZ	-6.8405***	0.9922***	132.28***	-0.1563***
	(-562.87)	(598.36, -4.70)		(-11.00)
TNZ	-6.8762***	0.9956***	130.57***	-0.1028***
	(-708.79)	(712.14, -3.14)		(-9.47)
MDZ	-7.3463***	1.0553***	133.84***	-0.0770***
	(-783.24)	(872.13, 45.69)		(10.69)
Panel B: Monthly Data				
CAPM regression:				
ETF	α (x100)	β Null Hypothesis: ($\beta = 0$, $\beta = 1$)	F-Stat [$\alpha = 0$, $\beta = 1$]	R^2
FNZ	-0.0921	0.9348***	2.76*	0.7568
	(-0.97)	(16.39, -1.14)		
TNZ	-0.1604**	0.9499***	4.22**	0.8711
	(-2.39)	(28.91, -1.52)		
MDZ	-0.2365***	0.9396***	14.45***	0.8514
	(-3.44)	(37.19, -2.39)		
Cointegration Analysis:				
ETF	γ	δ Null Hypothesis: ($\delta = 0$, $\delta = 1$)	Trace Statistics	λ
FNZ	-6.8810***	0.9975***	20.76***	-0.2364
	(-123.56)	(131.34, -0.33)		(-0.99)
TNZ	-6.0919***	0.9991***	23.87***	-0.3610
	(-156.48)	(157.23, -0.14)		(-1.21)
MDZ	-7.3025***	1.0495***	21.18***	-0.1482
	(-182.25)	(203.11, 9.59)		(-0.94)

Table 3: Tracking Error

This table presents the descriptive statistics of three measures of the tracking errors of three New Zealand ETFs in our sample. The statistics are shown for the daily and monthly data in Panel A and Panel B, respectively. They are Smartfonz (FNZ) between 10th December 2004 and 30th June 2016, Smarttenz (TNZ) between 11th June 1996 2004 and 30th June 2016, and Smartmidz (MDZ) between 16th June 1997 and 30th June 2016. TE_1 measures the absolute difference between the ETF returns and the corresponding index returns. TE_2 is calculated as the standard deviation of the difference between the ETF returns and the returns of underlying market indexes over the previous month. TE1 is calculated as the residuals of regression as: $R^{ETF}{}_t = \alpha + \beta * R^{Ind}{}_t + \varepsilon_t$.

Panel A: Daily Data								
ETF	Variable	Mean	Std. Dev.	Skewness	Kurtosis	Min.	Median	Max.
FNZ	TE_1	0.7090%	0.8212%	3.13	18.06	0.0006%	0.4650%	8.9493%
	TE_2	0.9404%	0.5408%	1.44	5.04	0.2589%	0.7476%	3.1464%
	TE_3	0.8916%	0.5404%	1.46	5.17	0.2573%	0.7116%	3.0563%
TNZ	TE_1	0.6973%	0.6747%	2.77	18.84	0.0000%	0.5194%	8.6289%
	TE_2	0.8814%	0.4010%	2.08	10.15	0.2809%	0.7910%	3.4872%
	TE_3	0.8267%	0.3889%	2.09	10.33	0.2432%	0.7270%	3.2344%
MDZ	TE_1	0.6451%	0.6789%	3.58	36.05	0.0005%	0.4514%	13.1095%
	TE_2	0.8503%	0.3874%	2.21	12.14	0.2233%	0.7719%	3.5096%
	TE_3	0.7780%	0.3704%	1.81	8.46	0.1659%	0.7034%	3.0267%
Panel B: Monthly Data								
ETF	Variable	Mean	Std. Dev.	Skewness	Kurtosis	Min.	Median	Max.
FNZ	TE_1	1.2657%	1.2860%	2.62	13.01	0.0058%	0.8463%	8.1244%
	TE_2	1.6863%	0.6780%	0.82	2.72	0.5710%	1.5942%	3.1474%
	TE_3	1.6807%	0.6713%	0.80	2.75	0.5491%	1.5895%	3.1316%
TNZ	TE_1	1.2009%	1.0745%	2.07	9.79	0.0272%	0.9678%	7.8169%
	TE_2	1.5270%	0.5543%	0.79	2.38	0.8393%	1.3016%	2.8274%
	TE_3	1.5092%	0.5645%	0.83	2.60	0.8224%	1.3183%	2.9691%
MDZ	TE_1	1.1267%	0.9210%	1.63	6.96	0.0006%	0.9032%	5.8981%
	TE_2	1.3716%	0.3851%	0.95	3.67	0.6592%	1.3496%	2.3629%
	TE_3	1.3531%	0.3863%	0.96	3.77	0.6762%	1.3397%	2.3744%

Table 4: Determinants of Daily Tracking Error of FNZ

This table shows the results of regression of three measures of tracking error. The dependent variable is one of the three tracking error measures, TE_1, TE_2, or TE_3. The independent variables include: the percentage spread of ETF (ETF %Spread), the natural logarithm of ETF daily volume (ETF Volume), the market-capitalization weighted average of percentage spreads of the constituent stocks in S&P/NZX50 Portfolio Index (Index %Spread), the natural logarithm of market-capitalization weighted average of daily volumes of the constituent stocks in S&P/NZX50 Portfolio Index (Index Trading Volume), and the volatility of index returns (computed as standard deviation of index returns over previous 10 trading days). T-statistics with the Newey-West correction are shown in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.

	Model-1	Model-2	Model-3
Panel A: TE1			
Intercept	0.0091***	0.0131***	0.0103***
	(14.28)	(10.85)	(8.44)
ETF %Spread	0.3912***	0.3777***	0.3453***
	(10.24)	(9.68)	(8.64)
ETF Volume	-0.0030***	-0.0026***	-0.0023***
	(-7.62)	(-6.47)	(-5.63)
Index %Spread		0.1020**	-0.0474
		(2.43)	(-1.19)
Index Volume		-0.0011***	-0.0009***
		(-4.30)	(-3.84)
Volatility of Index Return			0.5337***
			(5.29)
R^2	17.64%	18.63%	21.38%
Panel B: TE2			
Intercept	0.0135***	0.0204***	0.0169***
	(23.19)	(18.29)	(14.44)
ETF %Spread	0.1742***	0.1528***	0.1133***
	(10.95)	(9.79)	(7.42)
ETF Trading Volume	-0.0036***	-0.0030***	-0.0026***
	(-11.66)	(-9.73)	(-8.73)
VW Average Index %Spread		0.1325***	-0.0496
		(2.43)	(-1.38)
VW Average Index Trading Volume		-0.0018**	-0.0016***
		(-8.34)	(-7.94)
Volatility of Index Return			0.6471***
			(7.97)
R^2	19.47%	26.22%	36.32%
Panel C: TE3			
Intercept	0.0130***	0.0042***	0.0165***
	(22.03)	(3.92)	(13.94)
ETF %Spread	0.1789***	0.0698***	0.1224***
	(11.16)	(5.29)	(7.81)
ETF Trading Volume	-0.0036***	-0.0010***	-0.0027***
	(-11.53)	(-6.22)	(-8.78)
VW Average Index %Spread		0.1036***	-0.0576
		(3.12)	(-1.60)
VW Average Index Trading Volume			-0.0015***
			(-7.51)
Volatility of Index Return		0.4481***	0.5977***
		(3.54)	(7.28)
R^2	19.94%	25.66%	34.55%

Table 5: Determinants of Daily Tracking Error of TNZ

This table shows the results of regression of three measures of tracking error. The dependent variable is one of the three tracking error measures, TE_1, TE_2, or TE_3. The independent variables include: the percentage spread of ETF (ETF %Spread), the natural logarithm of ETF daily volume (ETF Volume), the market-capitalization weighted average of percentage spreads of the constituent stocks in S&P/NZX50 Portfolio Index (Index %Spread), the natural logarithm of market-capitalization weighted average of daily volumes of the constituent stocks in S&P/NZX50 Portfolio Index (Index Trading Volume), and the volatility of index returns (computed as standard deviation of index returns over previous 10 trading days). T-statistics with the Newey-West correction are shown in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.

	Model-1	Model-2	Model-3
Panel A: TE1			
Intercept	0.0081***	0.0078***	0.0050***
	(23.23)	(12.84)	(4.32)
ETF %Spread	0.21193***	0.1969***	0.1561***
	(8.65)	(8.06)	(5.86)
ETF Trading Volume	-0.0015***	-0.0015***	-0.0015***
	(-7.55)	(-7.88)	(-8.10)
VW Average Index %Spread		0.0527***	0.0297***
		(4.50)	(3.63)
VW Average Index Trading Volume		-0.0002	0.0000
		(-1.57)	(0.72)
Volatility of Index Return			0.3085***
			(2.93)
R^2	6.65%	7.94%	11.39%
Panel B: TE2			
Intercept	0.0092***	0.0093***	0.0056***
	(29.66)	(19.30)	(4.40)
ETF %Spread	0.1132***	0.0995***	0.0444***
	(8.74)	(7.73)	(2.94)
ETF Trading Volume	-0.0007***	-0.0008***	-0.0008***
	(-4.63)	(-5.34)	(-6.24)
VW Average Index %Spread		0.0474***	0.0161**
		(4.33)	(2.47)
VW Average Index Trading Volume		-0.0002**	0.0000
		(-2.56)	(0.82)
Volatility of Index Return			0.4215***
			(3.51)
R^2	5.258%	9.29%	29.21%
Panel C: TE3			
Intercept	0.0083***	0.0088***	0.0051***
	(28.37)	(18.60)	(4.37)
ETF %Spread	0.1223***	0.1073***	0.0532***
	(9.09)	(8.02)	(3.71)
ETF Trading Volume	-0.0005***	-0.0006***	-0.0006***
	(-3.59)	(-4.46)	(-5.27)
VW Average Index %Spread		0.0482***	0.0174***
		(4.61)	(2.79)
VW Average Index Trading Volume		-0.0003***	0.0000
		(-3.52)	(0.04)
Volatility of Index Return			0.4146***
			(3.83)
R^2	6.59%	11.08%	31.25%

Table 6: Determinants of Daily Tracking Error of MDZ

This table shows the results of regression of three measures of tracking error. The dependent variable is one of the three tracking error measures, TE_1, TE_2, or TE_3. The independent variables include: the percentage spread of ETF (ETF %Spread), the natural logarithm of ETF daily volume (ETF Volume), the market-capitalization weighted average of percentage spreads of the constituent stocks in S&P/NZX50 Portfolio Index (Index %Spread), the natural logarithm of market-capitalization weighted average of daily volumes of the constituent stocks in S&P/NZX50 Portfolio Index (Index Trading Volume), and the volatility of index returns (computed as standard deviation of index returns over previous 10 trading days). T-statistics with the Newey-West correction are shown in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.

	Model-1	Model-2	Model-3
Panel A: TE1			
Intercept	0.0072***	0.0051***	0.0035**
	(27.41)	(3.17)	(2.43)
ETF %Spread	0.3266***	0.3144***	0.2909***
	(5.58)	(5.50)	(5.69)
ETF Trading Volume	-0.0014***	-0.0013***	-0.0013***
	(-5.55)	(-5.25)	(-5.23)
VW Average Index %Spread		0.1541***	0.0821***
		(3.90)	(2.75)
VW Average Index Trading Volume		0.0001	0.0000
		(0.02)	(0.24)
Volatility of Index Return			0.4357***
			(3.98)
R^2	7.79%	9.49%	12.79%
Panel B: TE2			
Intercept	0.0091***	0.0059***	0.0042***
	(40.17)	(4.51)	(3.92)
ETF %Spread	0.1078***	0.0940***	0.0698***
	(5.72)	(5.55)	(5.29)
ETF Trading Volume	-0.0012***	-0.0011***	-0.0010***
	(-6.85)	(-6.78)	(-6.22)
VW Average Index %Spread		0.1776***	0.1036***
		(3.80)	(3.12)
VW Average Index Trading Volume		0.0001	0.0002
		(0.82)	(1.23)
Volatility of Index Return			0.4481***
			(3.54)
R^2	4.62%	12.80%	25.66%
Panel C: TE3			
Intercept	0.0083**	0.0052***	0.0035***
	(31.81)	(4.15)	(3.57)
ETF %Spread	0.1099***	0.0968***	0.0717***
	(6.47)	(6.28)	(6.33)
ETF Trading Volume	-0.0011***	-0.0010***	-0.0010***
	(-6.72)	(-6.62)	(-6.74)
VW Average Index %Spread		0.1676***	0.0911***
		(3.95)	(3.24)
VW Average Index Trading Volume		0.0002	0.0002
		(0.96)	(1.45)
Volatility of Index Return			0.4636***
			(5.34)
R^2	4.93%	12.77%	27.61%

Table 7: Determinants of Monthly Tracking Error of FNZ

This table shows the results of regression of three measures of tracking error. The dependent variable is one of the three tracking error measures, TE_1, TE_2, or TE_3. The independent variables include: the percentage spread of ETF (ETF %Spread), the natural logarithm of ETF daily volume (ETF Volume), the market-capitalization weighted average of percentage spreads of the constituent stocks in S&P/NZX50 Portfolio Index (Index %Spread), the natural logarithm of market-capitalization weighted average of daily volumes of the constituent stocks in S&P/NZX50 Portfolio Index (Index Trading Volume), and the volatility of index returns (computed as standard deviation of index returns over previous 10 trading days). T-statistics with the Newey-West correction are shown in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.

	Model-1	Model-2	Model-3
Panel A: TE1			
Intercept	0.0527***	0.0634***	0.0547***
	(3.44)	(3.58)	(2.86)
ETF %Spread	0.3437	0.3118	0.2964
	(1.37)	(1.19)	(0.95)
ETF Trading Volume	-0.0060***	-0.0064***	-0.0058*
	(-3.11)	(-2.63)	(-1.83)
VW Average Index %Spread		0.7877	0.6682
		(1.47)	(1.37)
VW Average Index Trading Volume		-0.0018	-0.0016
		(-1.15)	(-0.99)
Volatility of Index Return			0.1714*
			(1.70)
R^2	13.98%	19.43%	20.39%
Panel B: TE2			
Intercept	0.0375***	0.0518***	0.0399***
	(4.22)	(4.71)	(3.81)
ETF %Spread	0.1624	0.1618	0.0430
	(1.40)	(1.40)	(0.76)
ETF Trading Volume	-0.0030**	-0.0004	-0.0007
	(-2.37)	(-0.34)	(-0.79)
VW Average Index %Spread		0.3727*	0.1315
		(1.67)	(1.29)
VW Average Index Trading Volume		-0.0046***	-0.0039***
		(-3.56)	(-3.70)
Volatility of Index Return			0.3930***
			(5.44)
R^2	8.21%	26.22%	64.73%
Panel C: TE3			
Intercept	0.0037***	0.0506***	0.0388***
	(4.19)	(4.59)	(1.26)
ETF %Spread	0.1565	0.1567	0.0380
	(1.37)	(1.37)	(0.68)
ETF Trading Volume	-0.0029**	-0.0003	-0.0006
	(-2.30)	(-0.28)	(-0.73)
VW Average Index %Spread		0.3572	0.1165
		(1.65)	(1.23)
VW Average Index Trading Volume		-0.0045***	-0.0038***
		(-3.46)	(-3.52)
Volatility of Index Return			0.3925***
			(5.42)
R^2	7.72%	25.16%	64.33%

Table 8: Determinants of Monthly Tracking Error of TNZ

This table shows the results of regression of three measures of tracking error. The dependent variable is one of the three tracking error measures, TE_1, TE_2, or TE_3. The independent variables include: the percentage spread of ETF (ETF %Spread), the natural logarithm of ETF daily volume (ETF Volume), the market-capitalization weighted average of percentage spreads of the constituent stocks in S&P/NZX50 Portfolio Index (Index %Spread), the natural logarithm of market-capitalization weighted average of daily volumes of the constituent stocks in S&P/NZX50 Portfolio Index (Index Trading Volume), and the volatility of index returns (computed as standard deviation of index returns over previous 10 trading days). T-statistics with the Newey-West correction are shown in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.

	Model-1	Model-2	Model-3
Panel A: TE1			
Intercept	0.0083	0.0044	0.0065
	(1.30)	(0.80)	(0.82)
ETF %Spread	-0.0338	-0.078**	-0.0806**
	(-0.88)	(-2.10)	(-1.99)
ETF Trading Volume	0.0013	-0.0001	-0.0002
	(0.63)	(-0.08)	(-0.10)
VW Average Index %Spread		0.26***	-0.0361
		(5.55)	(-0.70)
VW Average Index Trading Volume		-0.0359	-0.0003
		(-0.69)	(-0.30)
Volatility of Index Return			0.2528***
			(5.08)
R^2	6.65%	14.09%	14.13%
Panel B: TE2			
Intercept	0.0056	0.0207***	0.0106
	(1.26)	(2.89)	(1.33)
ETF %Spread	0.0121	-0.0247	-0.0308
	(0.41)	(-0.84)	(-1.10)
ETF Trading Volume	0.0031**	0.0027*	0.0009
	(2.13)	(1.96)	(0.81)
VW Average Index %Spread		0.0714*	0.0254
		(1.85)	(0.70)
VW Average Index Trading Volume		-0.0021**	-0.0007
		(-2.58)	(-0.63)
Volatility of Index Return			0.1663***
			(3.23)
R^2	4.69%	18.98%	33.34%
Panel C: TE3			
Intercept	0.0050	0.0209***	0.0113
	(1.12)	(2.92)	(1.40)
ETF %Spread	0.016	-0.0216	-0.0275
	(0.54)	(-0.73)	(-0.96)
ETF Trading Volume	0.0032**	0.0028**	0.0011
	(2.25)	(2.09)	(0.98)
VW Average Index %Spread		0.0649*	0.0212
		(1.66)	(0.57)
VW Average Index Trading Volume		-0.0022***	-0.0008
		(-2.61)	(-0.76)
Volatility of Index Return			0.1582***
			(3.17)
R^2	3.46%	19.6%	32.18%

Table 9: Determinants of Monthly Tracking Error of MDZ

This table shows the results of regression of three measures of tracking error. The dependent variable is one of the three tracking error measures, TE_1, TE_2, or TE_3. The independent variables include: the percentage spread of ETF (ETF %Spread), the natural logarithm of ETF daily volume (ETF Volume), the market-capitalization weighted average of percentage spreads of the constituent stocks in S&P/NZX50 Portfolio Index (Index %Spread), the natural logarithm of market-capitalization weighted average of daily volumes of the constituent stocks in S&P/NZX50 Portfolio Index (Index Trading Volume), and the volatility of index returns (computed as standard deviation of index returns over previous 10 trading days). T-statistics with the Newey-West correction are shown in parenthesis. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.

	Model-1	Model-2	Model-3
Panel A: TE1			
Intercept	0.020***	0.0413**	0.0289*
	(3.23)	(2.45)	(1.85)
ETF %Spread	0.2741	0.2442	0.2642
	(1.55)	(1.39)	(1.53)
ETF Trading Volume	-0.0019	-0.0017	-0.0019
	(-1.58)	(-1.43)	(-1.39)
VW Average Index %Spread		0.0891	0.0479
		(1.24)	(0.85)
VW Average Index Trading Volume		-0.0025	-0.0015
		(-1.65)	(-0.97)
Volatility of Index Return			0.1325**
			(1.95)
R^2	8.24%	10.13%	12.66%
Panel B: TE2			
Intercept	0.0307***	0.024***	0.0189**
	(8.17)	(2.63)	(2.22)
ETF %Spread	0.0031	-0.0216	-0.0230
	(0.06)	(-0.50)	(-0.70)
ETF Trading Volume	-0.0032***	-0.0027***	-0.0025***
	(-4.90)	(-4.56)	(-5.33)
VW Average Index %Spread		0.1213	0.1000*
		(1.49)	(1.86)
VW Average Index Trading Volume		0.0002	0.0003
		(0.23)	(0.37)
Volatility of Index Return			0.1285***
			(2.69)
R^2	23.5%	29.72%	40.23%
Panel C: TE3			
Intercept	0.0308***	0.0237***	0.0187**
	(8.23)	(2.63)	(2.26)
ETF %Spread	0.0025	-0.0218	-0.0232
	(0.05)	(-0.50)	(-0.69)
ETF Trading Volume	-0.0032***	-0.0028***	-0.0026***
	(-5.01)	(-4.69)	(-5.54)
VW Average Index %Spread		0.1209	0.1001*
		(1.45)	(1.78)
VW Average Index Trading Volume		0.0003	0.0004
		(0.29)	(0.44)
Volatility of Index Return			0.1249***
			(2.54)
R^2	2.41%	12.77%	36.73%

Figure 1: Time Series of Prices of FNZ and S&P/NZX50 Portfolio Index

The solid line represents the daily price of the Smartfonz (FNZ). The dashed line is the daily S&P/NZX50 Portfolio Index. The sample period is between 10th December 2004 and 30th June 2016.

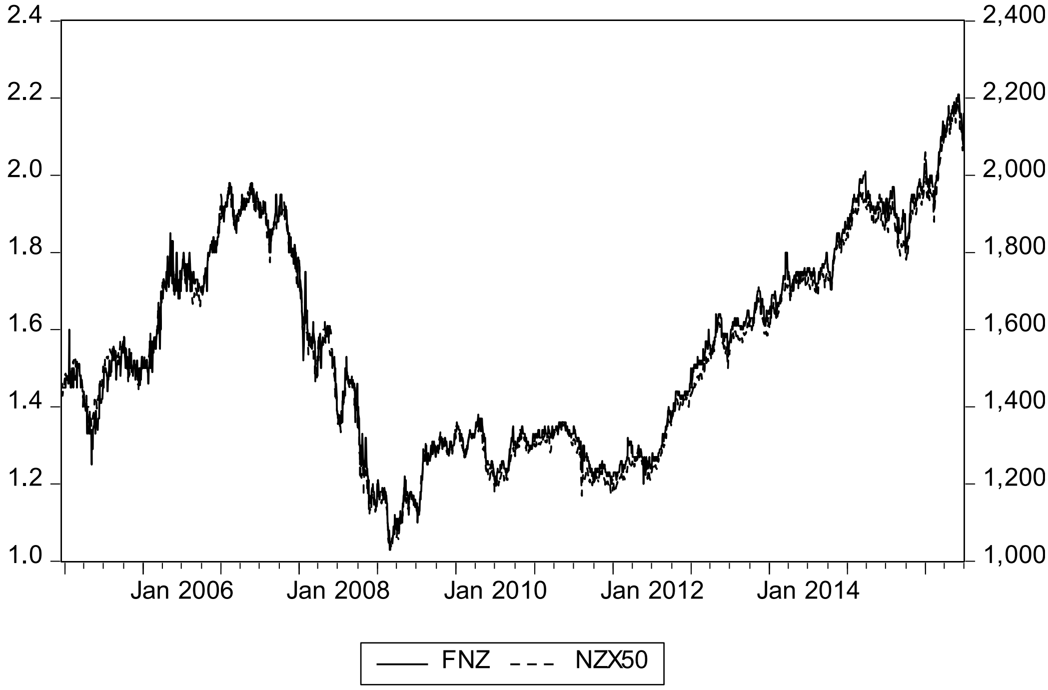

Figure 2: Time Series of Price Difference between FNZ and S&P/NZX50 Portfolio Index

This figure plots the time series of the estimate of daily price difference between the Smartfonz and S&P/NZX50 Portfolio Index. Price differences are calculated using the logarithms of prices collected, and thus reflect percentage differences. The sample period is between 10th December 2004 and 30th June 2016.

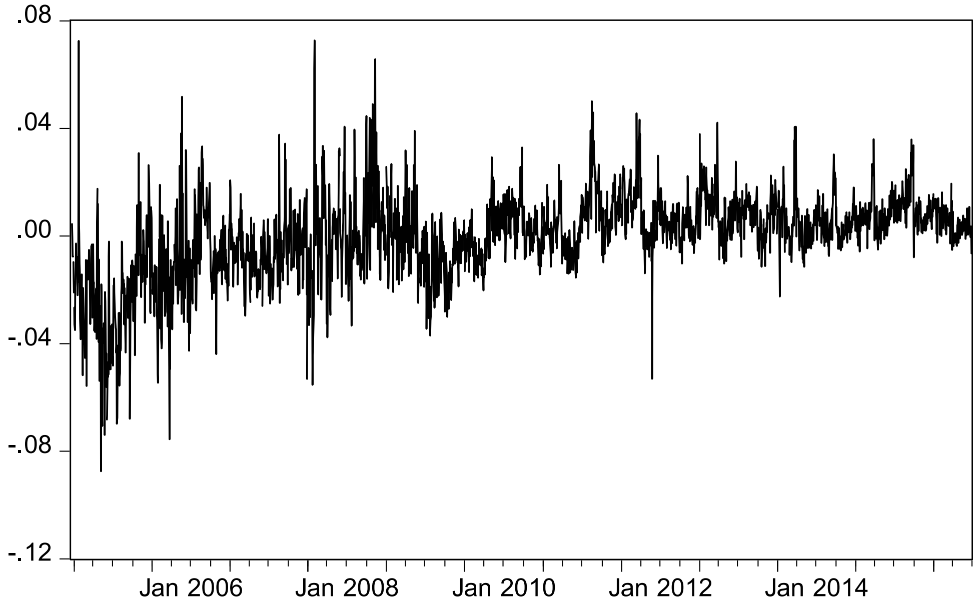

Figure 3: Time Series of Tracking Error of FNZ

This figure plots the time series of the estimate of daily tracking error of the Smartfonz (FNZ) with its underlying index of S&P/NZX50 Portfolio Index. Tracking error is computed as the absolute value of return difference between FNZ and S&P/NZX50 Portfolio Index. The sample period is between 10th December 2004 and 30th June 2016.