CHARLES UNIVERSITY
FACULTY OF SOCIAL SCIENCES
Institute of Economic Studies

Analysis of Exchange-Traded Funds Pricing Deviations and Tracking Errors: Evidence from U.S. Market

Bachelor's thesis

Author: Martin Panáček
Study program: Economics and Finance
Supervisor: Mgr. Petr Polák, Msc. Ph.D.
Year of defense: 2022

Declaration of Authorship

The author hereby declares that he or she compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain any other academic title.

The author grants to Charles University permission to reproduce and to distribute copies of this thesis in whole or in part and agrees with the thesis being used for study and scientific purposes.

Prague, January 4, 2022

Martin Panacek

Abstract

In this thesis, we present an analysis of pricing deviations and tracking errors of ETFs with regard to their focus. We deploy several panel data models estimated on a sample of 12 U.S. iShares ETFs divideded into three categories: broad market ETFs, dividend ETFs and sector specific ETFs and examine if the pricing deviations and tracking errors differs between the groups. We suggest, that dividend and sector specific ETFs tend to have bigger pricing deviations and tracking errors, however, we attribute it mainly to the higher expense ratios associated with them, rather than because of their focus.

JEL Classification	G10, G15, G23
Keywords	Exchange-Traded Funds, Pricing Deviations, Tracking Errors

Title	Analysis of Exchange-Traded Funds Pricing Deviations and Tracking Errors: Evidence from U.S. Market

Author's e-mail	`martin.panacek@icloud.com`
Supervisor's e-mail	`polakpet@gmail.com`

Abstrakt

V této práci prezentujeme analýzu cenových odchylek a sledovacích chyb ETF fondů v závislosti na jejich zaměření. Využíváme několik modelů panelových dat estimovaných na vzorku 12 iShares ETF fondů z trhů v USA rozdělených do tří kategorií: obecné ETF, dividendové ETF a sektorově zaměřené ETF. Docházíme k závěru že dividendové a sektorově zaměřené fondy mají větší cenové odchylky a sledovací chyby, nicméně připisujeme to zejména vyšším poměrovým ukazatelům nákladům které tyto fondy mají, místo jejich zaměření.

Klasifikace JEL	G10, G15, G23
Klíčová slova	ETF Fondy, Cenové odchylky, sledovací hyby
Název práce	Analýza cenových odchylek a sledovacích chyb ETF fondů: Případ amerického trhu
E-mail autora	`martin.panacek@icloud.com`
E-mail vedoucího práce	`polakpet@gmail.com`

Acknowledgments

The author would like to thank Mgr. Petr Polák, Msc. Ph.D. for supervising the thesis, valuable comments and advices. The author would also like to thank his friends and family and express appreciation for their support.

Typeset in FSV LaTeX template with great thanks to prof. Zuzana Havrankova and prof. Tomas Havranek of Institute of Economic Studies, Faculty of Social Sciences, Charles University.

Bibliographic Record

Panáček, Martin: *Analysis of Exchange-Traded Funds Pricing Deviations and Tracking Errors: Evidence from U.S. Market.* Bachelor's thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies, Prague. 2022, pages 52. Advisor: Mgr. Petr Polák, Msc. Ph.D.

Contents

List of Tables

List of Figures

Acronyms

AP Authorised Participant

AUM Assets Under Management

CEF Closed-Ended Mutual Fund

DIA SPDR Dow Jones Industrial Average ETF Trust

ETC Exchange Traded Commodity

ETF Exchange Traded Fund

ETN Exchange Traded Note

NAV Net Asset Value

OEF Open-Ended Mutual Fund

PD Pricing Deivation

QQQ Invesco QQQ Trust

SPY Standard & Poors Depository Receipts

TE Tracking Error

WEBS World Equity Benchmark Series

Chapter 1

Introduction

Exchange-Traded Fund, or by its often-used acronym - ETF, is an investment vehicle, originally designed to replicate the performance of a broad market index, like open-ended index mutual funds (OEFs) aim to do. However, there are significant differences in the way these two instruments work. In author's opinion, the most significant difference is that while shares of OEFs are traded once a day, directly with the fund company (e.g., Vanguard) at an end-of-day Net Asset Value (NAV), ETF shares are always purchased and sold on a stock exchange. This implies a different mechanism of creation and redemption of the shares. In addition, ETFs can also be traded at margin and sold short, which makes them useful for hedging and various trading strategies. There are also differences in settlement periods, tax treatment and a few more aspects. Detailed description of how ETFs work, together with its history, can be found in several books and articles, (e.g. Ferri 2008; Abner 2016; Lettau & Madhavan 2018). We will discuss the important aspects and differences in detail later. ETFs become very popular in the last two decades, arguably because of allowing investors to hold wide and diversified basket of stocks or even other assets, without them needing to individually pick and buy them. Such popularity resulted in ETF assets globally amounting to approximately 7.7 billion USD in 2020 (statista.com 2021) and also in great attention of researchers.

The objective of this thesis is, following the work of e.g, Engle & Sarkar (2006) or DeFusco *et al.* (2009) or Dorocáková (2017) to analyse our hypothesis, that dividend ETFs and sector-specific ETFs tend to have higher pricing deviations and tracking errors than ETFs following general market indices like S&P 500 or Dow Jones Industrial Average. To analyse our hypothesis, we build several panel data models, which we estimate on a sample of 12 U.S. iShares

ETFs. We arrive to conclusion, that even though dividend and sector-specific ETFs tend to have bigger pricing deviations (in absolute values) than ETFs following general market indices, the reason for this is mainly due to the higher expense ratios associated with them.

The remainder of the thesis is structured as follows: Chapter 2 presents the literature review and hypotheses. Chapter 3 presents short overview of history, together with ETF architecture and lists some basic properties and metrics related to ETF which we use in the analysis. Chapter 4 presents the methodology and results of models we use to analyze our hypotheses. Chapter 5 summarizes our findings.

Chapter 2

Literature Review & Hypotheses

2.1 Literature Review

While ETF is a relatively new financial product, because of its popularity, it already gained attention of researchers. Looking at the existing literature, researchers are currently mainly interested in the following topics:

- Analysis of pricing deviation and liquidity
- Comparison of Exchange-Traded Funds with Open-Ended Index Mutual Funds
- Tax Efficiency of ETFs
- Trading strategies using ETFs
- Smart Beta ETFs and actively managed ETFs

As was already mentioned, the ability to trade at premium (discount) is one of the significant differences between ETFs and OEFs and as such it has become one of the most frequently analyzed topics. DeFusco *et al.* (2009) examines the pricing deviation of SPY, QQQ and DIA – the three most liquid funds at that time and find that it is predictable and non-zero, with the drivers of its size being the price discovery process and accumulation and distribution of dividends paid by the underlying stocks. Engle & Sarkar (2006) studies 21 U.S. domestic and 16 international (MSCI) ETFs and shows that premiums (discounts) are usually small and short lasting for domestic ETFs, but higher and persistent for international funds. This is supported by results of Delcoure & Zhong (2007) showing that iShares country ETFs trade at economically significant premiums

10-50% of the time. Suggested factors affecting the premium size and duration are institutional ownership, exchange rate volatility, bid-ask spread, trading volume and correlation with U.S. market. Ackert & Tian (2008) arrive to similar results and find a relationship between the premiums and market liquidity. This relationship is discussed in detail by Madhavan & Sobczyk (2016). Other studies, such as Dorocáková (2017) suggests the fund size as a factor affecting the tracking error.

As ETFs and OEFs are both designed to do the same thing – replicate return of some index, it is natural to compare their performance and study the aspects in which they differ. Elton *et al.* (2002) examine the performance of SPY during 1993-1998 and find that, on average SPY underperforms the S&P 500 index by 28.4 basis points a year. This underperformance is explained by two reasons. The first, rather obvious one is the yearly expense ratio charged by the fund, which was 18.45 basis points at that time. The second reason, accounting for the remaining 9.95 basis points is the fact, that for SPY, the dividends received from the underlying stocks are distributed quarterly and being held at a non-interest-bearing account until paid out. It should be noted, that while the latter was true for SPY at that time, there are different options how to structure an ETF nowadays, including the possibility of dividends being reinvested into the index by the fund straight away. Besides that, they compare SPY underperformance with the Vanguard 500 index OEF total annual fees ratio, which was approximately 18 basis points for individual investors at that time. If we disregard the dividend reinvestment (as this issue can be overcome), we can conclude that the performance was almost identical. Poterba & Shoven (2002) arrive at similar conclusion by comparing the pre-tax and after-tax returns of SPY and Vanguard 500 fund during 1994-2000 and finding that returns were very similar, with returns of the Vanguard 500 Index fund being slightly higher.

Such similarity poses a question: Why these two instruments coexist together? Existing research suggests that the reason for this may be the clientele effect. Based on comparison of aggregate flows into ETFs and OEFs tracking different underlying indices, Agapova (2011) suggests that these two investment vehicles are substitutes, but not perfect substitutes because of the differences in liquidity and tax treatment. Besides that, she finds that on average, ETFs have smaller tracking errors and are more effective in returns after fees. Huang & Guedj (2009) present similar results with suggestion that ETFs may be better suited for narrower and less liquid indices where OEF structure is not cost effective.

As ETFs also have some common features with CEFs, mainly the ability to be traded continuously throughout the day, it is also intuitive to compare performance of these two investment vehicles. Harper & Madura (2006) examines a sample of country CEFs and country ETFs between 1996 and 2001 and find that ETFs exhibit higher mean and risk-adjusted returns, suggesting that an investment strategy using passive ETFs may be superior to a strategy utilizing actively-managed CEFs.

This brings us to another frequently analyzed topic also related to ETFs: Are actively managed funds able to outperform the market? This question is not solely attributable to ETFs, but as the expansion of ETFs in the recent years is arguably a factor which made passive investment strategies popular, passive ETFs are often being used as a benchmark for actively managed funds. In general, most studies and analysis are in favor of passive investing suggesting that only a very small portion of active funds can beat their benchmarks. Such statement is supported, for example, by results of Rompotis (2009), suggesting that active ETFs underperform not only the market indices, but also their passive ETF counterparts. Moreover, Moraes (2021) estimates, that 95% of the actively managed funds fail to generate value to the investors (using several combination of ETFs as a benchmark).

2.2 Hypothesis

Based on what we just presented, we develop the following hypotheses, which we will analyze in this thesis:

Hypothesis 1: Dividend (income) ETFs tend to have bigger pricing deviations than ETFs following general market indices.

Hypothesis 2: Sector-specific ETFs tend to have bigger pricing deviations than ETFs following general market indices.

Hypothesis 3: Dividend (income) ETFs tend to have bigger tracking errors than ETFs following general market indices.

Hypothesis 4: Sector-specific ETFs tend to have bigger tracking errors than ETFs following general market indices.

Chapter 3

History, Mechanics and Basic Properties of ETFs

3.1 History of ETFs

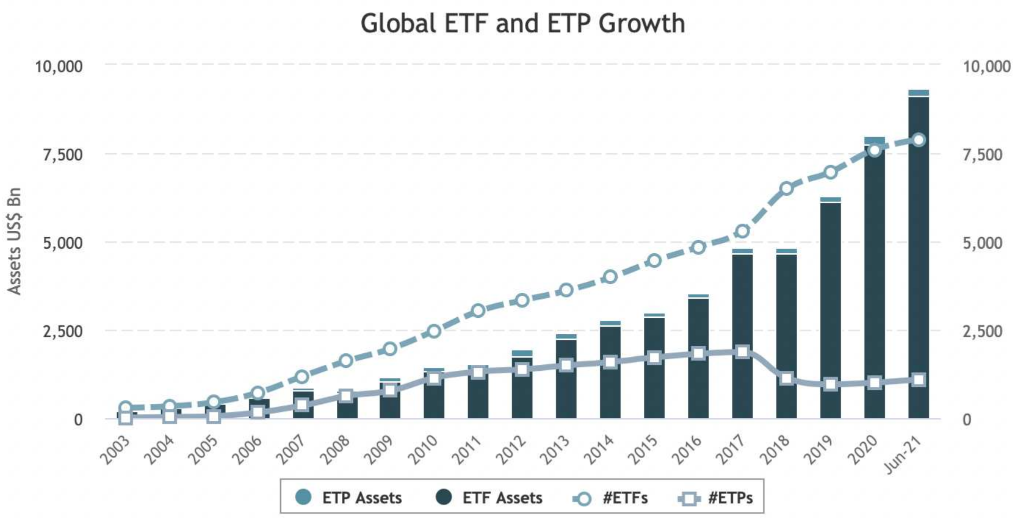
In January 1993, State Street Global Advisors launched the first ETF - Standard & Poor's Depositary Receipts (SPY), which aims to track the S&P 500 index. With the unit price set to trade at approximately one tenth of the index value, it enabled a wide range of subjects from individual investors to institutional investors and hedge funds to hold and trade wide and diversified basket of stocks without need to actively manage it and at a price which all of them could afford. This resulted in big popularity, SPY gained around 500 million USD assets under management (AUM) in its first year and with over 380 billion USD AUM (as of July 2021), it is still the biggest ETF on the market (etf.com 2021).

After 3 years, in 1996 Morgan Stanley, together with Barclays Global Investors created World Equity Benchmark Shares (WEBS) – a series of thirteen ETFs tracking individual equity markets around the world (e.g., United Kingdom, Germany, South Korea). Later, in 2000, WEBS were renamed as iShares MSCI (msci.com 2000), which is still active by now.

Since then, the number of ETFs available and its variety started to grow faster, as illustrated by Figure 3.1. During the last two decades, several new types of ETFs were invented. Nowadays, besides equity, ETFs can also track prices of other asset classes like commodities, fixed income instruments or currencies and they can be also sold short. Some of the latest innovations in the ETF world are actively managed ETFs and smart beta ETFs,designed with aim to outperform the index by weighting the securities with use of other factors than market capitalization, e.g., momentum or volatility and actively managed ETFs, which is, however, a goal that only a few actively managed funds able to accomplish in general. As we already have discussed in the literature review, most of the studies are in favor of passive investing. To illustrate this, in 2019, 71% of U.S. large cap actively managed fund underperformed the S&P 500 index and if we extend the time span to 2016-2020, this percentage rises to 81% of such funds (fool.com 2022).

In short, there is now an ETF for almost any asset class, market index and purpose one can imagine. Such variability, together with other advantages, which will be discussed later contributed to its popularity, which resulted in assets managed by ETFs globally amounting to approximately 7.74 billion USD in 2020 (statista.com 2021)

Figure 3.1: ETF Assets Globally



Source: etfgi.com, accessed Jul 27, 2021

3.2 ETF Architecture

As it was already mentioned, ETF is essentially a mutual fund, which is traded like a stock. Even though ETFs were originally designed to replicate stock indices performance, nowadays ETFs also able to follow returns of various assets. Based on the underlying instruments, we can divide the ETFs into the following categories:

- **Stock Index ETFs** — is the first and still heavily dominant category aiming to track a stock index (either a market index or a custom-build index).

- **Commodity ETFs** — Sometimes also referred to as Exchange-Traded Commodities (ETCs) are ETFs aiming to track returns of commodities such as precious metals (e.g. gold, silver) or fuels (e.g. oil, gas) either individually or in a basket.

- **Bond ETFs** — Sometimes also referred to as Exchange-Traded Notes (ETNs) are ETFs tracking returns of bonds and other debt instruments.

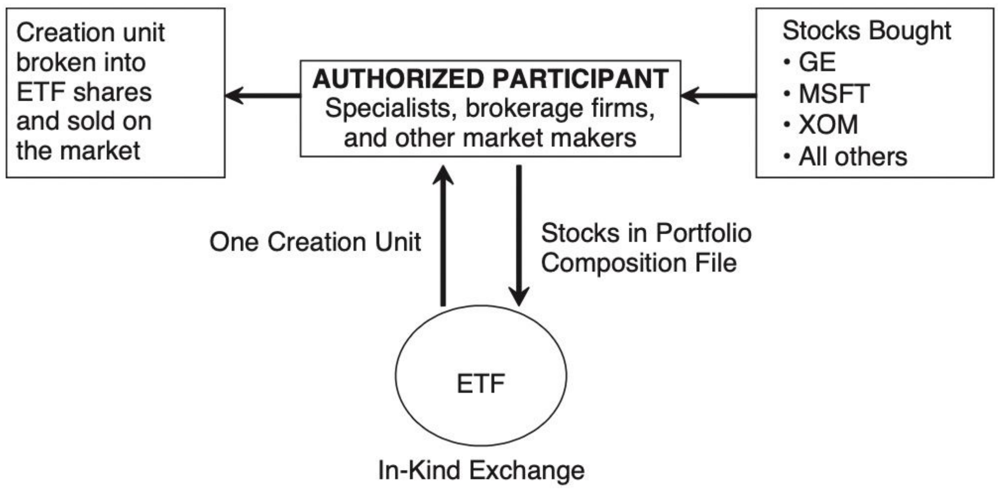
- **Currency ETFs** — are ETFs investing in individual or multiple currencies earning profits from the changes of foreign exchange spot rates and the interest rates of the currencies.

This list is probably not complete, as there are also other assets that are being or can be invested into with an ETF-structure instrument, for example cryptocurrencies and other crypto assets. We can also categorize ETFs based on how the managers of the fund treat dividends (and other income). Such income can be either periodically distributed to the investors (Distributing ETFs) or directly reinvested back into the underlying instruments (Reinvesting ETFs). ETFs can also utilize different investing strategies. Most of the ETFs on the market passively invest into a predefined index. However, in the recent years, ETFs also become able to weight the current positions based on factors other than market capitalization, such as volatility, momentum, dividend distribution or financial fundamentals and metrics (so-called Smart Beta ETF). There are also some completely actively managed ETFs on the market. Lastly, ETFs can be also levered or even inverse.

In the remainder of this subsection, we describe the mechanism allowing ETFs to track the returns of the underlying assets and being directly traded on the stock exchange. The fund can either directly own all or just a representative sample of the underlying securities (Physical Replication) or use, usually collateralized, swap contracts instead (Synthetic Replication). For this to be possible, a special mechanism for creation and redemption of shares, as shown in Figure 3.2 and Figure 3.3, needs to be implemented. An ETF manager cooperates with a limited number of large financial institutions called Authorized Participants (APs). These institutions act as an intermediary between the fund managers and markets.

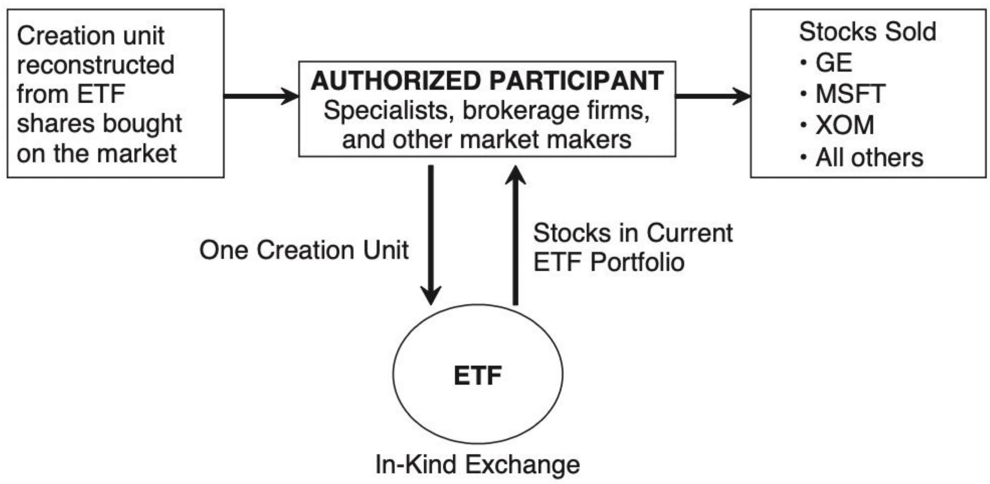
When new ETF shares needs to be created, APs buys or borrows a basket of securities corresponding to the tracked index and exchange it with the fund manager for an ETF creation unit. This unit is then split into individual ETF shares, which are sold on the stock exchange. Similarly, when ETF shares needs to be redeemed, APs buys the ETF shares, exchanges them with the fund manager for the corresponding securities, which are then sold or returned.

Figure 3.2: ETF Shares Creation



Source: Ferri (2008)

Figure 3.3: ETF Shares Redemption



Source: Ferri (2008)

Another important role of APs is to keep the price of ETF shares close to its NAV. Since ETFs are traded continuously throughout the day at stock exchanges, their price is resulting from the realized trades which may result in ETF being traded at premium or discount. Because of their ability to exchange the ETF shares for the corresponding basket of securities, APs perform arbitrage, whenever they see a profit opportunity. When the price of ETF exceeds the NAV, APs obtains the underlying securities and exchange it for the creation unit, which is then sold on the market as illustrated by Figure 3.2. When the price is lower than the NAV, APs buys the ETF shares and exchange it for the basket on securities which is then sold as illustrated Figure 3.3. This is repeated until there is no or little (not big enough to cover the costs of the trade) profit opportunity. As there are enough APs for the market to be competitive and the costs of the trades are relatively small in comparison to the profits resulting from the arbitrage, ETF prices and its NAV are usually very close to each other (but not perfectly).

3.3 Basic Properties

In this section, we present certain common notions together with properties and metrics which we will further analyze later. First, we define **return over a period** **(R)** as

$$R = \frac{P_1 - P_0}{P_0}$$

where P_0 and P_1 are prices (or values) of an asset on the beginning and end of the period, respectively.

Before we can introduce the pricing deviation, we need to define the **Net Asset Value of an ETF** **(NAV_{ETF})**, which is determined by the following equation:

$$NAV_{ETF} = \frac{As_{ETF} - Li_{ETF}}{Sh_{ETF}}$$

where As_{ETF} and Li_{ETF} are the assets and liabilities of an ETF; Sh_{ETF} is the number of shares outstanding.

Expense ratio **(ER_{ETF})** represents the cost efficiency of an ETF. It is defined as:

$$ER_{ETF} = \frac{OE_{ETF}}{\overline{NAV}_{ETF}}$$

where OE_{ETF} are the annual operating costs incurred by the ETF (including the management fees) and $\overline{NAV}_{ETF}$ is the average daily NAV of an ETF in a given year.

There are several ways how to define **Pricing Deviation (PD)**. (DeFusco et al., 2009) define it as a difference between the ETF price and the theoretical price of corresponding part of related index[1]. While this is an interesting approach, it is not suitable for our analysis as we will also use ETFs following custom indices, where the theoretical price is not published. We will stick to the definition used by (Engle and Sarkar, 2006) which is as follows:

$$PD_{ETF} = \frac{P_{ETF} - NAV_{ETF}}{P_{ETF}}$$

where P_{ETF} is the close price of an ETF.

Tracking error (TE) represents how closely can the ETF track the return of the underlying index. We define it as:

$$TE_{ETF} = R_{ETF} - R_{NAV}$$

where R_{ETF} is the return on the ETF calculated using the adjusted close prices (to account for dividend distributions, stock splits, etc...) and R_{NAV} is the return on the NAV of the ETF.

[1]Market index ETFs are usually priced as a fraction of the underlying index (e.g., 1/100 of S&P 500, 1/40 of Dow Jones Industrial Average, etc...).

Chapter 4

Empirical Analysis

In this section, we present the data, econometric methods, and models we use to analyze our hypothesis together with commented estimation results. Usually, analyzing stocks and other instruments focus on portfolio and performance analysis, which includes calculating standard deviations of returns, comparing several performance metrics, computing optimal portfolios, or developing trading strategies. This area of analysis is also applicable to the ETFs, such portfolio models are presented, for example by (Kenneth *et al.* 2013; Puelz *et al.* 2015). Rather than analyzing the ETFs from a portfolio perspective, in this thesis, we focus on analyzing how ETFs perform at their fundamental task, which is tracking the prices and returns of their underlying assets, following the work of (Engle & Sarkar 2006; Delcoure & Zhong 2007; Dorocáková 2017).

4.1 Data Description & Summary Statistics

For our analysis, we will be using data related to 12 U.S. iShares ETFs during 2015 - 2019. Historical prices and trading volumes are downloaded from Yahoo Finance[1] , remaining data are taken from the US iShares website[2]. We split the analyzed ETFs into three categories based on their focus: ETFs following some general market index; dividend (Income) ETFs and ETFs following some sector-specific index. List of the analyzed ETFs is presented in Table 4.1

iShares funds were selected because of data availability and convenience of its format. We selected the dividend ones from their catalogue, and haphazardly chose some from the biggest ETFs in the other categories. Unless stated

[1]https://finance.yahoo.com

[2]https://www.ishares.com/us/products/etf-investments

otherwise, we will use the closing prices as our NAVs data are also calculated at the end of trading day.

Table 4.1: Overview of analyzed ETFs

Category	Ticker	Name	ER(%)	Net Assets (USD)
Broad				
	IVV	Core SP 500	0.03	321,153,441,939.97
	IWM	Russell 2000	0.19	74,039,501,898.00
	ITOT	Core SP Total U.S. Stock Market	0.03	45,734,974,027.72
	IYY	Dow Jones U.S.	0.20	1,815,975,238.66
Dividend				
	DGRO	Core Dividend Growth	0.08	21,360,033,970.71
	PFF	Preferred and Income Securities	0.46	20,542,896,421.29
	DVY	Select Dividend	0.38	18,758,530,485.80
	HDV	Core High Dividend	0.08	7,477,142,683.91
Sector				
	IBB	Biotechnology	0.45	10,547,524,467.93
	SOXX	Semiconductor	0.43	8,302,814,720.23
	IYG	U.S. Financial Services	0.41	2,719,560,220.70
	IYE	U.S. Energy	0.41	2,464,792,180.82

Source: Data downloaded from iShares website as of Nov 3, 2021

Before we proceed further to the analysis, we present some of the aforementioned properties and metrics calculated individually for each ETF and as a summary both on the group level and for the whole dataset.

4.1.1 Pricing Deviation

The summary statistics and variances of pricing deviation are presented in Table 4.2, Table 4.3 shows the summary statistics and variances of the pricing deviation in absolute value. As we are dealing with very small numbers, in both cases, the numbers are multiplied by 10^6 for better readability and manipulation with the data.

We can see that the dividend group of ETFs exhibits notably higher values, which might be a sign that our hypothesis of this group having higher pricing deviations than other groups could be true. On the other hand, in case of sector specific ETFs, we can see that even though maximum and minimum values are similar to the dividend group, means, medians and variances are much closer to the general market group and the overall averages. This applies both to the nominal and absolute values. It is also worth mentioning, that on the individual level, the highest absolute value of minimum and maximum, together with highest variance is exhibited by PFF, which also has the highest expense ratio from the analyzed ETFs (0.46%). Mean and medium of the absolute value of pricing deviation of PFF are also the highest. We can also notice similar pattern in opposite direction. IVV, which has, together with ITOT, the lowest expense ratio in the dataset (0.03%) exhibits the lowest variance and second lowest maximum value. Variance of ITOT is also one of the lowest. This might indicate some relationship between the premiums and expense ratios.

Table 4.2: Summary Statistics of Pricing Deviations

Category	Ticker	Min	Mean	Median	Max	Variance
Broad		-3,057.801	53.233	75.19	3,182.755	0.216
	IVV	-1,452.10	34.928	45.774	1,557.851	0.089
	IWM	-1,900.429	9.141	11.867	1,654.204	0.245
	IYY	-3,057.801	-49.72	-51.824	3,182.775	0.357
	ITOT	-2,369.487	218.586	249.097	1,641.675	0.135
Dividend		-5,034.648	154.325	143.204	6,563.191	0.58
	DGRO	-2,447.839	428.704	441.85	2,553.175	0.283
	PFF	-5,034.648	137.044	351.405	6,563.191	1.725
	DVY	-1,035.169	-4.092	-0.716	1,986.727	0.102
	HDV	-1,751.067	55.645	47.368	3,044.786	0.103
Sector		-5,503.792	-17.499	-18.141	5,379.506	0.254
	IBB	-4,192.648	-10.398	-29.679	5,379.506	0.465
	SOXX	-5,503.792	-26.834	-36.042	2,407.92	0.232
	IYG	-1,459.738	7.806	8.227	1,693.597	0.123
	IYE	-2,736.759	-40.569	-28.396	1,554.981	0.197
Total		-5,503.792	63.353	67.546	6,563.191	0.355

Source: Author's calculation

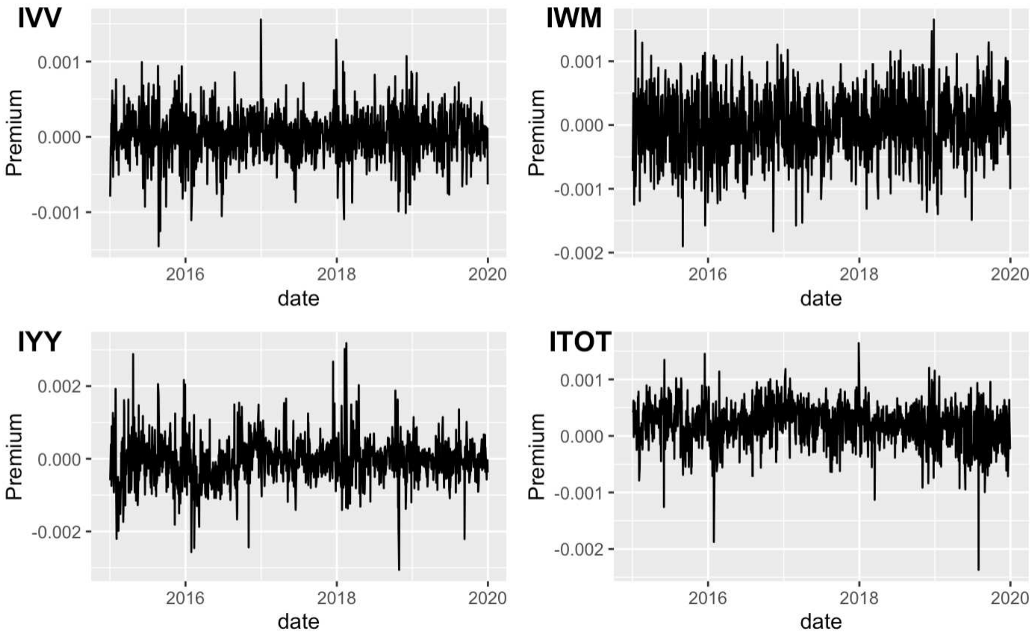
Table 4.3: Summary Statistics of Pricing Deviations in Absolute Values

Category	Ticker	Min	Mean	Median	Max	Variance
Broad		0.189	348.515	266.564	3,182.755	0.098
	IVV	0.19	222.371	165.094	1,557.851	0.04
	IWM	2.041	393.679	337.407	1,900.429	0.09
	IYY	1.048	428.46	291.464	3,182.775	0.176
	ITOT	0.23	349.561	311.096	2,369.487	0.061
Dividend		0.261	528.511	344.836	6,563.191	0.325
	DGRO	0.835	551.072	475.472	2,553.175	0.163
	PFF	6.096	1077.923	956.478	6,563.191	0.581
	DVY	0.261	246.521	199.693	1,986.727	0.041
	HDV	0.375	238.529	193.623	3,044.786	0.049
Sector		0	364.923	291.554	5,503.792	0.122
	IBB	0.621	486.591	396.544	5,379.506	0.228
	SOXX	0.033	344.694	272.024	5,503.792	0.114
	IYG	1.38	270.582	228.279	1,693.597	0.05
	IYE	0	357.827	308.87	2,736.759	0.071
Total		0	413.983	298.196	6,563.191	0.188

Source: Author's calculation

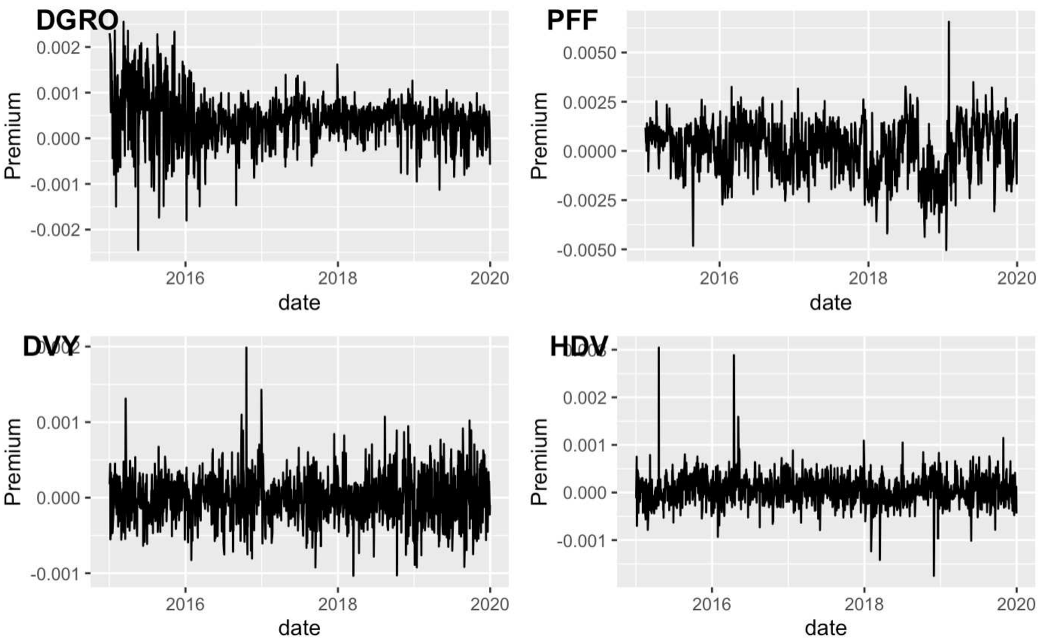
We also provide graphical representation of the pricing deviations in the different ETF groups in Figure 4.1, Figure 4.2 and Figure 4.3 for the broad market group, dividend group and sector-specific group, respectively. The graphs are in line with the calculated summary statistics, the values and amplitudes of the pricing deviations are highest in the dividend group, followed by the sector specific group. Moreover, If we look at the form of the curves, we do not see any significant time trends and we find only a few outliers within the individual time series.

Figure 4.1: Premiums in the Broad Market Group



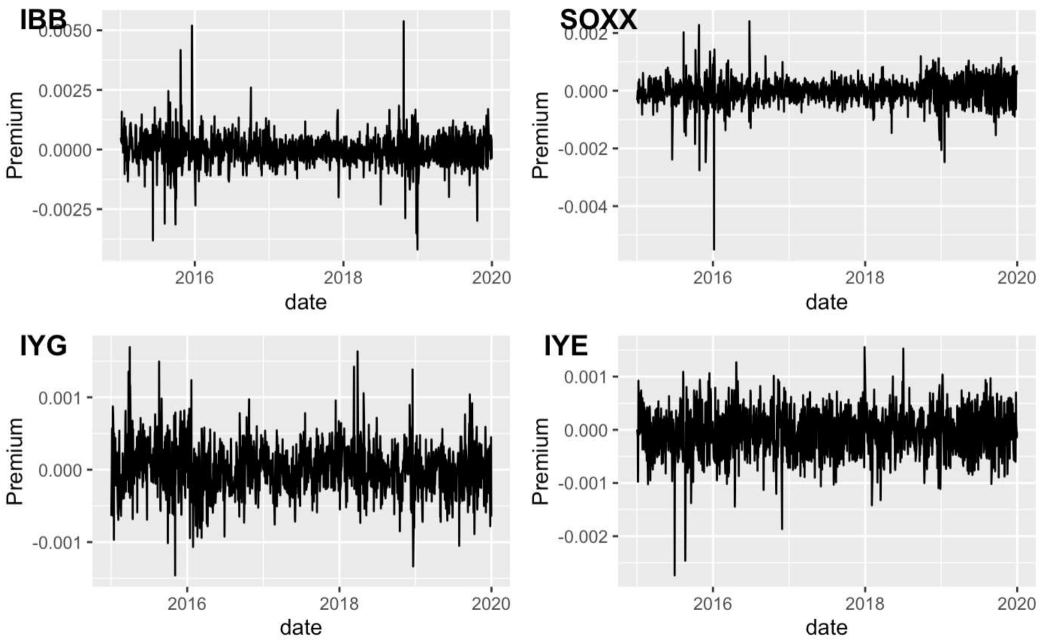
Source: Author's Calculation

Figure 4.2: Premiums in the Dividend Group



Source: Author's Calculation

Figure 4.3: Premiums in the Sector-Specific Group



Source: Author's Calculation

4.1.2 Tracking Error

As in the case of pricing deviation, we present the summary statistics and variances of the tracking error in nominal and absolute values in in Table 4.4, Table 4.5, respectively. Values are again multiplied by 10^6 for the same reasons. Except for the median of the absolute value, which is the highest for the sector specific ETFs, means, medians and variances are again highest in the dividend group. Like in the case of pricing deviation, ETFs with lowest expense ratios (IVV and ITOT) exhibits the lowest variances both for the nominal and absolute value of the tracking error. Similarly, tracking errors of ETFs with highest expense ratios (e.g., PFF, IYE) tend to have higher variances, however, we can also notice, that variance of IBB, which has the second highest expense ratio, is below the overall average.

Table 4.4: Summary Statistics of Tracking Errors

Category	Ticker	Min	Mean	Median	Max	Variance
Broad		-4,271.135	69.143	7.511	7,464.009	0.688
	IVV	-2,295.87	77.561	7.161	6,404.065	0.563
	IWM	-2,668.44	52.406	-12.629	5,714.921	0.658
	IYY	-4,271.135	71.425	11.737	7,464.009	0.944
	ITOT	-2,573.752	75.179	13.362	6,377.818	0.589
Dividend		-4,635.237	144.188	16.806	10,549.981	1.481
	DGRO	-3,613.141	86.202	11.536	6,978.695	0.965
	PFF	-4,635.237	223.227	81.591	8,906.164	2.267
	DVY	-1,893.723	129.553	10.026	10,411.204	1.294
	HDV	-3,139.953	137.769	10.86	10,549.981	1.393
Sector		-6,432.725	62.564	8.483	40,798.935	1.097
	IBB	-6,006.189	6.989	-10.924	5,327.618	0.921
	SOXX	-6,432.725	47.45	20.511	5,742.548	0.607
	IYG	-2,156.15	58.615	1.659	5,356.972	0.462
	IYE	-2,652.252	137.205	17.553	40,798.935	2.393
Total		-6,432.725	91.965	11.414	40,798.93	1.09

Source: Author's calculation

Table 4.5: Summary Statistics of Tracking Errors in Absolute Values

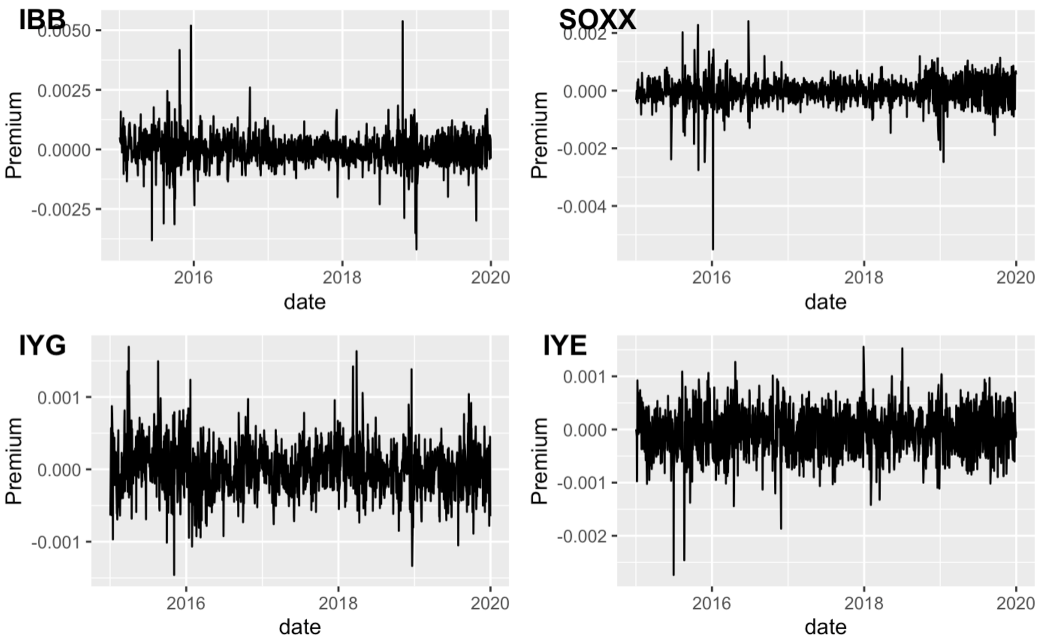
Category	Ticker	Min	Mean	Median	Max	Variance
Broad		0.271	500.096	327.144	7,464.009	0.442
	IVV	0.43	378.123	239.769	6,404.065	0.426
	IWM	0.92	571.317	432.625	5,714.921	0.334
	IYY	0.271	616.233	404.284	7,464.009	0.569
	ITOT	0.328	434.71	282.507	6,377.818	0.405
Dividend		0.11	630.647	331.967	10,549.981	1.104
	DGRO	0.324	543.188	309.546	6,978.695	0.678
	PFF	2.681	1084.125	787.479	8,906.164	1.141
	DVY	0.11	449.301	248.288	10,411.204	1.109
	HDV	0.42	445.974	243.862	10,549.981	1.213
Sector		0.244	550.357	369.512	40,798.935	0.798
	IBB	0.244	679.416	519.86	6,006.189	0.459
	SOXX	0.93	512.298	356.148	6,432.725	0.346
	IYG	0.297	412.068	290.712	5,356.972	0.295
	IYE	1.837	597.647	392.492	40,798.935	2.053
Total		0.11	560.367	343.009	40,798.935	0.784

Source: Author's calculation

As we did in case of pricing deviations, here we also present the graphical representation of tracking errors in the different ETF groups in Figure 4.4, Figure 4.5 and Figure 4.6 for the broad market group, dividend group and sector-specific group, respectively. Similarly to pricing deviations, graphs are mostly in line with what we conclude from the summary statistics. We see that the values and amplitudes are the biggest for the ETFs in the dividend group, followed by the sector-specific group (except for the outlier at the end of IYE series).

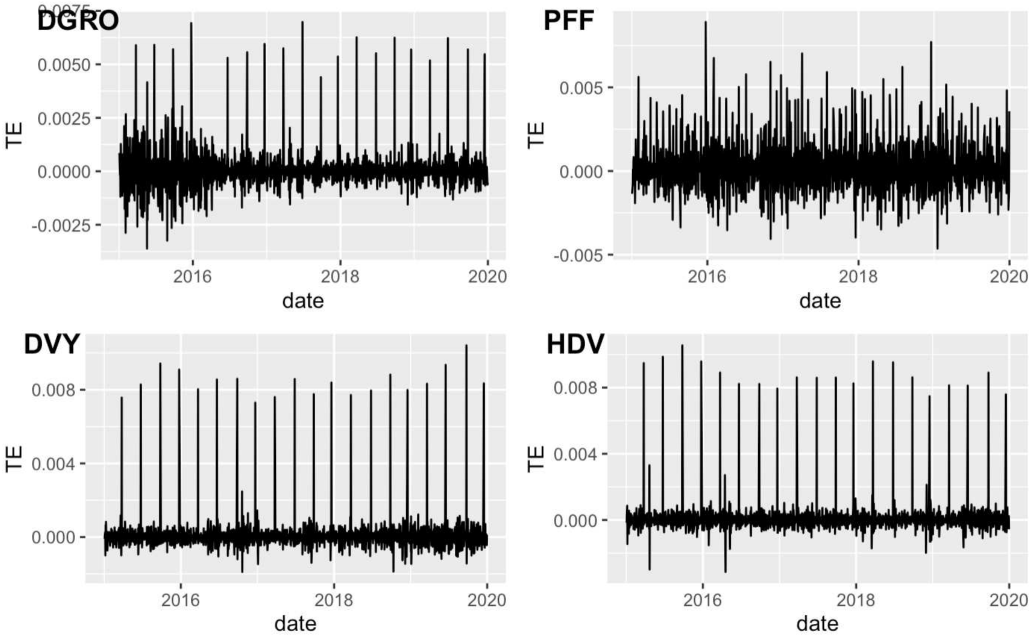
Looking at the curves for the individual time series, we see, that in most of the time, the series behaves regularly, without increasing or decreasing variance, however, we see much more outliers than in the case of pricing deviation, which may cause problems during the analysis. Moreover, outside the broad market group, these outliers seam to appear somehow periodically, especially for dividend group, which may be caused either by receiving the dividends by the funds or by paying them out to shareholders. This may cause another problem in the analysis; however it also partially supports our hypotheses that dividend ETFs tend to have bigger tracking errors.

Figure 4.4: Tracking Errors in the Broad Market Group



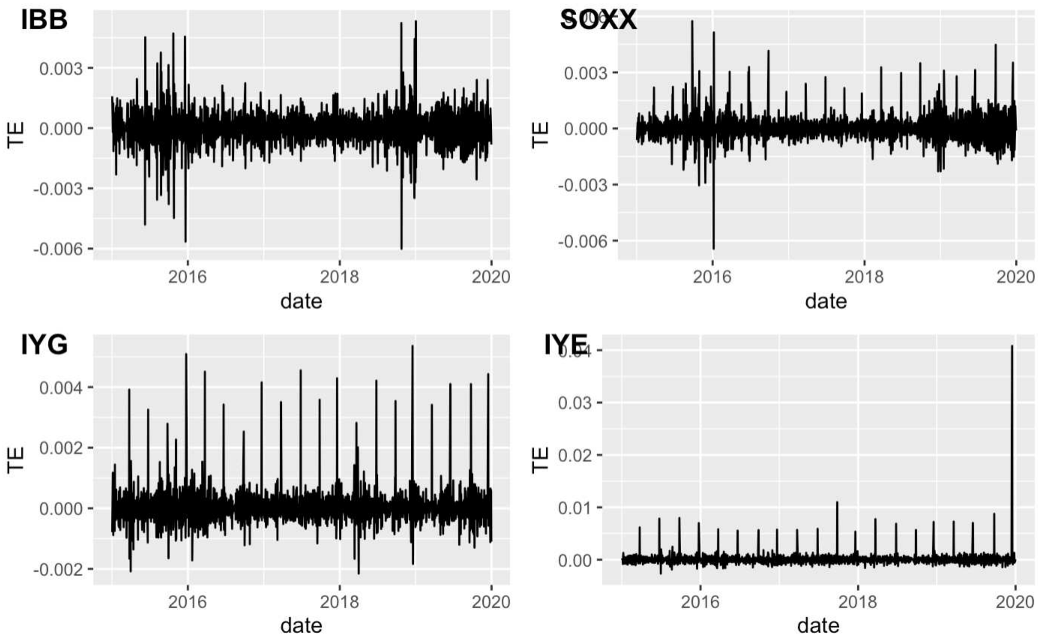
Source: Author's Calculation

Figure 4.5: Tracking Errors in the Dividend Group



Source: Author's Calculation

Figure 4.6: Tracking Errors in the Sector-Specific Group



Source: Author's Calculation

4.2 Models

4.2.1 Pricing Deviation

To analyze the relationship between the pricing deviation and the class of the ETF, we build a panel data model which will be estimated by the least squares regression. We start with two baseline models represented by the following equations:

$$PD_{i,t} = NAV_{i,t} + ER_i + Div_i + Spec_i + a_i + u_{i,t} \tag{PD Baseline}$$

$$|PD_{i,t}| = NAV_{i,t} + ER_i + Div_i + Spec_i + a_i + u_{i,t} \tag{absPD Baseline}$$

where $PD_{i,t}$ is the pricing deviation, $NAV_{i,t}$ is the net asset value, ER_i[3] is the expense ratio , Div_i is a dummy variable which takes value of 1 for dividend ETFs and 0 otherwise and $Spec_i$ is a dummy variable which takes value of 1 for sector specific ETFs and 0 otherwise. a_i is the unobserved effect and $u_{i,t}$ is the idiosyncratic error.

As we utilize dummy variables, within the least squares framework, we can use either Pooled OLS or a Random Effect Model as in Fixed effects model, the dummy variables of our interest would be differenced away. We choose the Random effect model. This model comes with some rather strong theoretical assumptions, on which fulfilments we should shortly comment.

For the model to be consistent it assumes a random sample selection, which in the purest form is hardly achievable as we would need to be selecting from the whole population of ETFs, however, except for the fact that we chose the iShares ETFs for good data availability and conveniency of the format, the sample was selected at least haphazardly. Next assumption is that there are no perfect linear relationships between the explanatory variables, which looking at the summary statistics and graphical representation of the data is not something we expect to be violated. Lastly, we need the expected value of the unobserved effect given all explanatory variables to be constant, which is something we can never be sure of and because of the specification of the model,

[3] As of Nov 3,2021 (Date when the dataset was downloaded).

we are not able to compare it to Fixed Effects Model using a Hausman test. However, we do not expect the unobserved effect to be significantly correlated with the explanatory variables.

More, for large sample inference, we need the variance of the unobserved effect given all explanatory variables to be constant and the idiosyncratic errors for the individual observations to be uncorrelated. Again, this is something we can not be sure of, but we do not see any significant reasons why this should be violated. Lastly, if the tests report autocorrelation or heteroscedasticity in the model, we will adjust it accordingly.

Results of the models estimated with daily and weekly data are presented in Table 4.6. In general, we do not arrive at anything satisfactory, both models in both data frequencies have extremely low R-squared. Moreover, using the Durbin-Watson and Breusch-Pagan tests, we detect autocorrelation and heteroscedasticity in the models. Therefore, we need to adjust the model to address these issues.

Table 4.6: Estimation Results of Baseline PD Models

	PD Baseline daily	PD Baseline weekly	absPD Baseline daily	absPD Baseline weekly
Intercept	3.93e-05	6.75e-05	2.90e-04**	3.59e-04***
	(7.23e-05)	(9.08e-05)	(1.24e-04)	(1.37e-04)
NAV	5.63e-07**	-3.05e-07	-4.27e-07***	-8.11e-07**
	(2.26e-07)	(4.40e-07)	(1.53e-07)	(3.58e-07)
ER	-5.04e-04*	-5.87e-04*	9.93e-04*	1.13e-03**
	(2.97e-04)	(3.16e-04)	(5.49e-04)	(5.79e-04)
Div	2.07e-04**	2.06e-04**	1.59e-05	-2.89e-05
	(9.11e-05)	(9.91e-05)	(1.67e-04)	(1.77e-04)
$Spec$	1.01e-04	1.84e-04	-3.05e-04	-3.73e-04
	(1.22e-04)	(1.30e-04)	(2.27e-04)	(2.40e-04)
Observations	15,096	3,132	15,096	3,132
R^2	0.001	0.002	0.001	0.005
Adjusted R^2	0.0003	0.001	0.001	0.004
F Statistic	9.018*	7.391	11.876**	16.967***
Note:	*p<0.1; **p<0.05; ***p<0.01			

For the model with nominal value of pricing deviation, we have only limited possibilities to transform the data. However, we reached some improvements by adding lags of the dependent variable and removing NAV from the equation. Using weekly data, we estimate the following model:

$$\begin{aligned} PD_{i,t} = PD_{i,t-1} + PD_{i,t-2} + PD_{i,t-3} \\ + ER_i + Div_i + Spec_i + a_i + u_{i,t} \end{aligned} \tag{PD 1}$$

Results of the estimation are shown in Table 4.7. Even though heteroscedasticity is still detected, autocorrelation is no longer present, R-squared of the model is reasonable (0.06) and our variables of interest shows at least some significance. With use of cluster robust standard errors, all three lags of pricing deviation are significant with positive sign at 95% confidence level. The dummy variables for the dividend and sector specific group are significant at 90% confidence level and shows positive signs. As the pricing deviation can be both positive and negative, this does not tell us anything about its size, however it indicates that there might be some relationship between the pricing deviation and the group in which the ETF belongs.

Table 4.7: Estimation Results of Updated PD Model

	PD 1 weekly	PD 1 HSC weekly
Intercept	1.83e-05	1.83e-05
	(2.27e-05)	(4.46e-05)
ER	-3.84e-04***	-3.84e-04
	(1.03e-04)	(2.41e-04)
Div	1.49e-04***	1.49e-04*
	(3.15e-05)	(7.90e-05)
$Spec$	1.25e-04***	1.25e-04*
	(4.24e-05)	(7.54e-05)
PD_{t-1}	1.23e-01***	1.23e-01**
	(1.79e-02)	(4.95e-02)
PD_{t-2}	1.18e-01***	1.18e-01***
	(1.79e-02)	(1.11e-02)
PD_{t-3}	6.65e-02***	6.65e-02***
	(1.79e-02)	(1.71e-02)
Observations	3.117	3.117
R^2	.061	.061
Adjusted R^2	.059	.059
F Statistic	200.951***	200.951***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Now we move to the absolute value model. Apart from adding lags of the pricing deviation into the equation, this model also allows us to transform it. So, we create a new variable, which we will use as the dependent variable by applying the following transformation to the pricing deviation:

$$PDtrans_{i,t} = \log\left(10^8 \times |PD_{i,t}|\right) \qquad \text{(PD Transformation)}$$

To be able to perform this transformation, we must remove one set of observations from the dataset, as one of the ETFs have exactly zero pricing deviation at one data point. As in the case of nominal value model, we also add 3 lags of the dependent variable and create the following three models:

$$\begin{aligned} PDtrans_{i,t} = PDtrans_{i,t-1} + PDtrans_{i,t-2} + PDtrans_{i,t-3} \\ + NAV_{i,t} + ER_i + Div_i + Spec_i + a_i + u_{i,t} \end{aligned} \tag{PDtrans 1}$$

$$\begin{aligned} PDtrans_{i,t} = PDtrans_{i,t-1} + PDtrans_{i,t-2} + PDtrans_{i,t-3} \\ + ER_i + Div_i + Spec_i + a_i + u_{i,t} \end{aligned} \tag{PDtrans 2}$$

$$\begin{aligned} PDtrans_{i,t} = PDtrans_{i,t-1} + PDtrans_{i,t-2} + PDtrans_{i,t-3} \\ + Div_i + Spec_i + a_i + u_{i,t} \end{aligned} \tag{PDtrans 3}$$

Because of the heteroscedasticity and autocorrelation, we only use the weekly data to estimate these models; results of the estimation are presented in Table 4.8. For the Model (PDtrans 1) we get R-squared of 0.098 and Adjusted R-squared of 0.096. As a result of the Durbin-Watson test (p-value 0.96) we do not find autocorrelation in the model. Running the Breusch-Pagan test results in p-value of 0.08, which allows us to reject heteroscedasticity in the model, however, we are close to the turning point at 95% confidence level.

If we directly proceed to interpretation of the model without any further adjustment, we see that all variables are highly significant (at least 99% confidence level). All three lags of the dependent variable have positive coefficients (0.09, 0.1, 0.08, respectively), which indicate some persistence in size of the pricing deviation for individual ETFs. The coefficient for NAV is negative (0.002), however, in comparison to other coefficients, its absolute value is small. This is reasonable, as the price and NAV of the ETF are usually extremely close and pricing deviation is calculated in percentages of the price, thus NAV is not expected to affect PD much.

With the value of 1.38, the expense ratio seems to affect the pricing deviation the most among the explanatory variables. The positive sign is in line with what we noticed in the summary statistics where we suggested that ETFs with higher ER could have higher PD. The dummy variables for the dividend and sector specific group are both negative (0.16 and 0.47, respectively) which does not correspond with our expectations. Possible explanation for this is that even though the ETFs from the dividend and sector specific group have higher pricing deviation than the ones in the general group, the reason for it would be that these ETFs also tend to have higher expense ratios. If we were to use the heteroscedasticity cluster robust standard errors (due to the not so convincing p-value of the Breusch-Pagan test), ER and DIV would become insignificant and SPEC remains significant only at 90% confidence level.

As we have discussed, NAV should not play a significant role. Results of the estimated Model (PDtrans 2), where this variable is removed from the equation are presented in Table 4.8. R-squared and adjusted R-squared are slightly lower than for Model (PDtrans 1) at 0.088 and 0.086, respectively. For the Durbin-Watson test, we get a p-value of 0.62 and for the Breusch-Pagan tests, we get a p-value of 0.50, which allows us to reject autocorrelation and heteroscedasticity in the model. For the remaining explanatory variables, signs and sizes of the coefficients remains very similar to those estimated in Model (PDtrans 1), except for DIV, where the (absolute) value is twice bigger, however, the variable is now insignificant. Interpretation of the results would also be the same.

In Model (PDtrans 3) we remove from the equation all except the lags of the dependent variable and the group dummy variables. Results of the estimation are shown in table Table 4.8. This model has the lowest R-squared and adjusted R-squared from our three models, at 0.071 and 0.069, respectively. The resulting p-values for the Durbin-Watson and Breusch-Pagan tests are 0.69 and 0.57 so we are again able to reject autocorrelation and heteroscedasticity in the model. Again, all the lags of dependent variables are highly significant, this time with slightly higher coefficients (0.12, 0.14, 0.12). However, now the coefficient for the dividend group turned positive (0.14). Coefficient for the sector specific group remained insignificant for this model. This could be a sign that our interpretation of previous models that rather than the group dummies, the expense ratio might be the factor that drives the size of pricing deviation.

In the light of our findings, we build one more model, where we keep only the lags of the dependent variable and the expense ratio. The resulting model equation is as follows:

$$PDtrans_{i,t} = PDtrans_{i,t-1} + PDtrans_{i,t-2} + PDtrans_{i,t-3} + ER_i + a_i + u_{i,t} \qquad \text{(PDtrans 4)}$$

This model is again estimated with the weekly data, results are presented in table x. This time the R-squared and adjusted R-squared are 0.75 and 0.74, respectively, which is higher than for Model (PDtrans 3). Durbin-Watson and Breusch-Pagan tests report p-values of 0.69 and 0.55, so again, we can reject autocorrelation and heteroscedasticity in the model. As in the previous cases, all the lags are highly significant with positive signs (0.12, 0.13, 0.11). Expense ratio is also highly significant with a positive sign (0.58).

Table 4.8: Estimation Results of Transformed PD Model

	PD trans 1 weekly	PD trans 2 weekly	PD trans 3 weekly	PD trans 4 weekly
Intercept	7.363***	6.730***	6.333***	6.298***
	(0.288)	(0.268)	(0.263)	(0.264)
ER	1.380***	1.422***	0.582***	
	(0.188)	(0.188)	(0.121)	
Div	−0.163***	−0.038		0.144***
	(0.059)	(0.055)		(0.050)
$Spec$	−0.467***	−0.425***		0.017
	(0.076)	(0.076)		(0.049)
PD_{t-1}	0.091***	0.103***	0.119***	0.123***
	(0.018)	(0.018)	(0.018)	(0.018)
PD_{t-2}	0.106***	0.118***	0.134***	0.138***
	(0.018)	(0.018)	(0.018)	(0.018)
PD_{t-3}	0.085***	0.096***	0.111***	0.115***
	(0.018)	(0.018)	(0.018)	(0.018)
Observations	3.117	3.117	3.117	3.117
R^2	.098	.088	.075	.071
Adjusted R^2	.096	.086	.074	.069
F Statistic	336.304***	298.934***	251.829***	237.666***
Note:	*p<0.1; **p<0.05; ***p<0.01			

To summarize all together, based on the outcomes of our models, we were able to find some factors explaining movements in the pricing deviation of the ETFs from our dataset. Regarding our original hypotheses, results are slightly ambiguous. Looking at the values and positive signs of the estimated dummy variables coefficients in Model (PDtrans 3) we would be able to accept hypothesis 1 that ETFs in the dividend group have bigger pricing deviation than those following general market indices. For the sector specific ETFs, we are not able to conclude anything about hypothesis 2 as the coefficient is both insignificant and small compared to others in the model. However, based on our findings in the summary statistics section, we also added other expense ratio to our models as an explanatory factor, which turned out to be the most influential factor driving the size of the pricing deviation, based on the positive sign and relative size of the coefficient of the variable ER estimated in Model (PDtrans 1) and Model (PDtrans 2). In Model (PDtrans 2) we even see that coefficient for DIV becomes insignificant while coefficient for SPEC remains significant but turns negative.

This together leads us to conclusion, that even though dividend and sector specific ETFs tend to have bigger pricing deviations, it appears, that it mostly explained by the higher expense ratio associated with them rather than by the group belonging. Moreover, this conclusion is also supported by comparison of Model (PDtrans 3) and Model (PDtrans 4), where, besides the lags of the dependent variable, we only kept the group dummy variables or the expense ratio, respectively, as the explanatory variable. Model 4 containing the expense ratio has a slightly higher R-squared than Model 3 which contains the group variables, meaning it explains the variance in the pricing deviation slightly better. Also, in both Model (PDtrans 3) and Model (PDtrans 4), coefficients for the lags of dependent variable are almost identical, but the coefficient for expense ratio is much bigger than the dummy variables coefficient, suggesting its bigger influence. The results are obviously potentially limited by validity of the assumptions we could have not directly tested or controlled for, however, as we have deployed several models which are, in context what we already said, shoving similar results, the results exhibit at least some robustness.

4.2.2 Tracking Error

For analysis of the tracking error, we proceed the same way as in the case of pricing deviation. Again, we build two baseline panel data models and estimate them using the least squares regression. The model equations are as follows:

$$TE_{i,t} = NAV_{i,t} + ER_i + Div_i + Spec_i + a_i + u_{i,t} \tag{TE Baseline}$$

$$\begin{aligned} |TE_{i,t}| = NAV_{i,t} + ER_i + Div_i + Spec_i \\ + a_i + u_{i,t} \end{aligned} \tag{TE Baseline Abs}$$

Where $TE_{i,t}$ is the tracking error, $NAV_{i,t}$ is the net asset value, ER_i[4] is the expense ratio , Div_i is a dummy variable which takes value of 1 for dividend

[4]As of Nov 3,2021 (Date when the dataset was downloaded).

ETFs and 0 otherwise and $Spec_i$ is a dummy variable which takes value of 1 for sector specific ETFs and 0 otherwise, a_i is the unobserved effect and $u_{i,t}$ is the idiosyncratic error. Again, we use the Random Effects model for the same reasons as for pricing deviation. The discussion about the theoretical assumptions of the model and their validity would be also analogous.

Results of the estimated baseline models can be found in Table 4.9. As in the case of pricing deviation, estimation of these baseline models does not yield interesting results. Again, R-squared is low in both cases regardless of using daily or weekly data and we find autocorrelation and heteroscedasticity in the models, so we have to update the models and transform the data.

Table 4.9: Estimation Results of Baseline TE Models

	TE baseline daily	TE baseline weekly	absTE baseline daily	absTE baseline weekly
Intercept	6.71e-05*	6.75e-05	4.67e-04***	6.10e-04***
	(4.01e-05)	(9.08e-05)	(9.95e-05)	(1.24e-04)
NAV	−1.06e-07	−3.05e-07	−6.38e-07*	−1.69e-06***
	(2.23e-07)	(4.40e-07)	(3.32e-07)	(5.67e-07)
ER	1.36e-04	−-5.87e-04*	1.01e-03**	1.09e-03**
	(1.23e-04)	(3.16e-04)	(4.02e-04)	(4.48e-04)
Div	4.93e-05	2.06e-04**	−4.94e-05	−1.37e-04
	(3.94e-05)	(9.91e-05)	(1.24e-04)	(1.40e-04)
$Spec$	−5.18e-05	1.84e-04	−2.82e-04*	−3.51e-04*
	(5.07e-05)	(1.30e-04)	(1.66e-04)	(1.85e-04)
Observations	15,096	3,132	15,096	3,132
R^2	0.001	0.002	0.001	0.005
Adjusted R^2	0.0003	0.001	0.001	0.004
F Statistic	9.018*	7.391	11.876**	16.967***

Note: *p<0.1; **p<0.05; ***p<0.01

For the model with nominal value of the tracking error, the only possibilities we have are adding lags of the dependent variable and adding or removing the explanatory variables. After trying some variations, we end up with the following model:

$$
\begin{aligned}
TE_{i,t} = TE_{i,t-1} + TE_{i,t-2} + TE_{i,t-3} \\
+ ER_i + Div_i + Spec_i + a_i + u_{i,t}
\end{aligned}
\tag{TE 1}
$$

This time, we estimate it with both daily and weekly data. In both cases, we reject autocorrelation in the model with resulting p-values of Durbin-Watson test being 0.53 and 0.51 for daily and weekly data, respectively. However, Breusch-Pagan test detects heteroscedasticity in the model regardless of the data used, so we deploy heteroscedasticity cluster robust standard errors before we proceed to interpret the results of the estimation, which are shown in Table 4.10.

For the daily data, the resulting R-squared and adjusted R-squared are 0.047 and 0.046, respectively. For the lags of dependent variable, coefficients are significant and exhibit negative signs (-0.21, -0.08, -0.04). We also find the dividend group dummy variable to be significant, the coefficient has a positive sign (7.4e-5), however its size is relatively small when compared to the coefficients for the lags. Remaining explanatory variables are insignificant.

For the weekly data, the situation is different. Both group dummy variables are highly significant, with positive coefficients; 1.38e-4 for the dividend group and 1.20e-4 for the sector specific group. First lag of the dependent variable and expense ratio are insignificant, the second and third lags are significant only at 90% confidence level, with the coefficient for the second lag being positive (2.91e-2) and coefficient for the third lag being negative (2.80e-2). However, the model estimated on weekly data has a significant drawback, which is low R-squared (0.006). In general, with use of the nominal value model, we find some indications of relationships which could be useful for making predictions, however, as the tracking error can go both positive and negative way, the results are hard to interpret.

Table 4.10: Estimation Results of Adjusted TE Model

	TE 1 daily	TE 1 HSC daily	TE 1 weekly	TE 1 HSC weekly
Intercept	7.09e-05***	7.09e-05***	−8.70e-05**	−8.70e-05***
	(1.67e-05)	(1.73e-05)	(3.52e-05)	(1.42e-05)
ER	1.87e-04**	1.87e-04	5.64e-06	5.64e-06
	(7.50e-05)	(1.27e-04)	(1.58e-04)	(5.96e-05)
Div	7.39e-05***	7.39e-05**	1.38e-04***	1.38e-04***
	(2.28e-05)	(2.67e-05)	(4.83e-05)	(1.67e-05)
$Spec$	−6.70e-05**	−6.70e-05	1.20e-04*	1.20e-04*
	(3.10e-05)	(5.50e-05)	(6.55e-05)	(2.89e-05)
TE_{-1}	−2.14e-01***	−2.14e-01***	−1.24e-02	−1.24e-02
	(8.14e-03)	(4.79e-02)	(1.79e-02)	(1.21e-02)
TE_{-2}	−7.79e-02***	−7.79e-02**	2.91e-02	2.91e-02*
	(8.30e-03)	(2.45e-02)	(1.79e-02)	(1.56e-02)
TE_{-3}	−3.81e-02***	−3.81e-02*	−2.90e-02	−2.90e-02*
	(8.14e-03)	(1.58e-02)	(1.79e-02)	(1.50e-02)
Observations	15,093	15,093	3,129	3,129
R^2	0.047	0.047	0.006	0.006
Adjusted R^2	0.046	0.046	0.004	0.004
F Statistic	737.311***	737.311***	17.930***	17.930***
Note:	*p<0.1; **p<0.05; ***p<0.01			

For easier interpretation, and more flexibility with the transformations, we move to the absolute value model. We proceed similar way as we did in the case of modeling the pricing deviation; we create a new dependent variable which is as follows:

$$TEtrans_{i,t} = \log\left(10^7 \times |TE_{i,t}|\right) \qquad \text{(TE Transformation)}$$

With use of this dependent variable, we introduce the following model:

$$TEtrans_{i,t} = TEtrans_{i,t-1} + TEtrans_{i,t-2} + TEtrans_{i,t-3} + NAV_{i,t} + ER_i + Div_i + Spec_i + a_i + u_{i,t} \tag{TEtrans 1}$$

We again estimate the model with both daily and weekly data and, again using the Durbin-Watson (p-values of 0.62 and 0.54 for daily and weekly data, respectively) and Breusch-Pagan (p-values of 0.15 and 0.95 for daily and weekly data, respectively) tests, we reject autocorrelation and heteroscedasticity being present in either version of the model, so we can proceed directly to interpret the results.

The results of the model estimated using daily data are presented in Table 4.11. Looking at the results, we directly see that this model performs better than the one with nominal value of the tracking error. Resulting R-squared and adjusted R-squared are 0.075 and 0.074 respectively, all lags of the dependent variable together with all explanatory variables are highly significant. The coefficients for all three lags are positive (0.16, 0.04, 0.06) indicating some persistence in the size of the tracking error according to the model. Like in pricing deviation models, the expense ratio has noticeably higher coefficient then the other explanatory variables, with a positive value of 1.41 and the coefficients for the group dummy variables have negative sign but are much smaller. We also suggest analogous explanation that the dividend and sector specific ETFs tend to have bigger tracking errors because of higher expense ratio associated with them, which corresponds to what we see in the summary statistics. Because of the size of the coefficient, NAV appears not to have any significant influence. Estimating the same model with weekly data, yields very similar results, only with slight changes to the coefficient values and lower R-squared. Size of the coefficients remain unchanged. Such results can also be found in Table 4.11.

Table 4.11: Estimation Results of Model TEtrans 1

	TEtrans 1 daily	TEtrans 1 weekly
Intercept	5.882^{***}	6.360^{***}
	(0.102)	(0.238)
$TEtrans_{-1}$	0.157^{***}	0.062^{***}
	(0.008)	(0.018)
$TEtrans_{-2}$	0.045^{***}	0.073^{***}
	(0.008)	(0.018)
$TEtrans_{-3}$	0.059^{***}	0.065^{***}
	(0.008)	(0.018)
NAV	-0.001^{***}	-0.001^{***}
	(0.0002)	(0.0004)
ER	1.409^{***}	1.492^{***}
	(0.091)	(0.204)
Div	-0.228^{***}	-0.205^{***}
	(0.029)	(0.064)
$Spec$	-0.389^{***}	-0.411^{***}
	(0.037)	(0.082)
Observations	15,093	3,129
R^2	0.075	0.050
Adjusted R^2	0.074	0.048
F Statistic	$1{,}217.369^{***}$	165.806^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01	

Lastly, we create models focusing on the dummy variables and expense ratio separately. The model equations are as follows:

$$TEtrans_{i,t} = TEtrans_{i,t-1} + TEtrans_{i,t-2} + TEtrans_{i,t-3} + ER_i + a_i + u_{i,t} \qquad \text{(TEtrans Model 2)}$$

$$TEtrans_{i,t} = TEtrans_{i,t-1} + TEtrans_{i,t-2} + TEtrans_{i,t-3} \\ + Div_i + Spec_i + a_i + u_{i,t} \qquad \text{(TEtrans Model 3)}$$

The results of the Model (TEtrans Model 2) estimated both on daily and weekly data again shows significance of the expense ratio. The R-squared is 0.064 and 0.40; the adjusted R-squared is 0.064 and 0.39, respectively and running the Durbin-Watson and Breusch-Pagan tests yields rejecting heteroscedasticity and autocorrelation in the model for both data frequencies. The coefficient for ER is highly significant, positive, and almost the same in both cases (0.76 and 0.78, respectively). The lags of the dependent variable are also all highly significant in both cases, showing almost identical values, except for the first lag, where the coefficient is notably higher for the model estimated using daily data.

Finally, we estimate Model (TEtrans Model 3), focusing only on the group dummy variables. Again, we use both daily and weekly data for the estimation, however, now only the daily data version yields interesting results. For the daily data, the resulting R-squared is 0.055, and based on the resulting p-values of the tests, we can again reject both heteroscedasticity and autocorrelation, however, we are close to the turning point in case of heteroscedasticity. If we directly proceed to the interpretation of the models without any adjustments, we see that all lags of the dependent variable, together with the dummy variables are significant. DIV and SPEC are both positive with values of 0.054 and 0.081 respectively. If we use the heteroscedasticity cluster robust errors, both group dummy variables become insignificant. For the weekly data, we get R-squared of 0.03 with the only the lags of the dependent variable being significant. All estimation results related to Model (TEtrans Model 2) and Model (TEtrans Model 3) are shown in table Table 4.12.

Table 4.12: Estimation Results of Models TEtrans 2 and TEtrans 3

	TEtrans 2 daily	TEtrans 2 weekly	TEtrans 3 daily	TEtrans 3 weekly
Intercept	5.437***	5.953***	5.341***	5.846***
	(0.094)	(0.223)	(0.095)	(0.224)
$absTEtrans_{-1}$	0.169***	0.073***	0.180***	0.084***
	(0.008)	(0.018)	(0.008)	(0.018)
$absTEtrans_{-2}$	0.055***	0.084***	0.065***	0.095***
	(0.008)	(0.018)	(0.008)	(0.018)
$absTEtrans_{-3}$	0.070***	0.077***	0.081***	0.087***
	(0.008)	(0.018)	(0.008)	(0.018)
ER	0.758***	0.782***		
	(0.059)	(0.132)		
Div			0.054**	0.070
			(0.024)	(0.054)
$Spec$			0.081***	0.078
			(0.024)	(0.054)
Observations	15,093	3,129	15,093	3,129
R^2	0.064	0.040	0.055	0.030
Adjusted R^2	0.064	0.039	0.055	0.029
F Statistic	1,038.505***	131.415***	877.718***	97.676***
Note:	*p<0.1; **p<0.05; ***p<0.01			

Overall, the results of the tracking error models lead us to similar conclusions as in the case of pricing deviation. Looking at the results of model x where we focus only at the group dummy variables, we could be accepting hypothesis 3 and hypothesis 4, but based on the results of models also including the expense ratio as an explanatory factor, we conclude that the bigger tracking errors of ETFs from the dividend and sector specific groups appears to be caused by the higher expense ratios associated with them. Again, if we compare the model x and model x, we see that the model containing the expense ratio explains the variation in the tracking error better (because of its higher R-squared). Again, the results are potentially limited by validity of the assumptions we could have not directly tested or controlled for. As for the pricing deviation, the fact that we have used multiple models mainly reporting similar results shows some robustness of our analysis.

Chapter 5

Conclusion

In this thesis, we attempted to analyze the drivers of pricing deviations and tracking errors of U.S. market Exchange-Traded Funds, with special interest in the relationship of these metrics to the focus of the ETF. In the last two decades, ETFs become very popular as an investment instrument allowing investors to hold an diversified basket of securities without the need of picking and buying them individually and also being able to trade them like a stock anytime the markets are open. This lead to significant growth of ETFs globally, both in terms of asset value and variety, which also resulted in increased attention of researchers.

Based on the existing research, such as the work of Engle & Sarkar (2006) or DeFusco *et al.* (2009) or Dorocáková (2017), who analyze the reasons of pricing deviations and tracking errors and factors affecting its size, we developed a hypothesis that ETFs focused on dividend stock and ETFs focused on specific sectors tend to have bigger pricing deviations than those following some general market indices like S&P 500 or Dow Jones Industrial Average.

Our goal was to empirically estimate relationship between ETF being dividend or sector oriented and its pricing deviation and tracking error. For this, we built several panel data least squares regression models estimated on a sample of 12 U.S. iShares ETFs utilizing dummy variables denoting if the ETF is focused on the broad markets, dividend stocks or sector specific stocks, together with other factors such as expense ratios and net asset values of the ETFs.

The results of our analysis are slightly ambiguous. Even though results of models containing only the dummy variables and lags of the dependent variable shows that to some significance, dividend and sector-specific ETFs do tend to have bigger pricing deviations and tracking errors (both in absolute values), after adding other explanatory variables into the models, the estimated coefficients for dummy variables often become very small in compared with the coefficients for other explanatory variables. It these models, it appears that the factor affecting the pricing deviations and tracking errors the most, is the expense ratio the most, is the expense ratio of the fund. This brings us to a conclusion, that although the dividend and sector-specific ETFs tend to have higher pricing deviations and tracking errors, the reason for that is mainly the fact, that such ETFs often also have higher expense ratios associated with them. Because of this, we also estimated models where the expense ratio is, besides the lags of dependent variables, the only explanatory variable for the pricing deviations and tracking errors. We found out, that the models containing only the expense ratios not only explains bigger portion of the variation in pricing deviation and tracking errors than the models containing only the dummy variables, but also, the coefficients for the expense ratios are relatively much higher than those for the dummy variables, which supports our claim.

Regarding the possible extensions of our work, we see some space for improvements especially in more advanced methodology and also analysing other factors affecting the pricing deviations and tracking errors. For example, we suggest to use a dataset containing individual dividend and other income flows into ETFs and their distributions to the shareholder or to use more advanced data models. However, such datasets may be hard to obtain.

Bibliography

Abner, D. J. (2016): *The ETF handbook: how to value and trade exchange-traded funds.* Hoboken, N.J.: John Wiley & Sons.

Ackert, L. F. & Y. S. Tian (2008): "Arbitrage, Liquidity, and the Valuation of Exchange Traded Funds." *Financial Markets, Institutions & Instruments* **17(5)**: pp. 331–362.

Agapova, A. (2011): "Conventional mutual index funds versus exchange traded funds." *Journal of Financial Markets* **14(2)**: pp. 323–343.

DeFusco, R. A., S. I. Ivanov, & G. V. Karels (2009): "The exchange traded funds' pricing deviation: analysis and forecasts." *Journal of Economics and Finance* **35(2)**: pp. 181–197.

Delcoure, N. & M. Zhong (2007): "On the premiums of iShares." *Journal of Empirical Finance* **134(1)**: pp. 168–195.

Dorocáková, M. (2017): "Comparison of ETF's perfomance related to tracking error." *Journal of Iternational Studies* **10(4)**: pp. 154–165.

Elton, E. J., M. J. Gruber, G. Comer, & K. Li (2002): "Spiders: Where Are the Bugs?" *Journal of Business* **75(3)**: pp. 453–472.

Engle, R. F. & D. Sarkar (2006): "Premiums-Discounts and Exchange Traded Funds." *The Journal of Derivatives* **13(4)**: pp. 27–45.

etf.com (2021): "ETF Finder." *Website*, https://www.etf.com/etfanalytics/etf-finder; acessed Jul 19, 2021.

Ferri, R. A. (2008): *The ETF book: all you need to know about exchange-traded funds.* Hoboken, N.J.: John Wiley & Sons.

FOOL.COM (2022): "What You Need to Know About Active vs. Passive Investing." *Website*, https://www.fool.com/investing/how-to-invest/active-vs-passive-investing/; acessed Jan 3, 2022.

HARPER, J. T. & J. MADURA (2006): "Performance comparison between exchange-traded funds and closed-end country funds." *Journal of International Financial Markets, Institutions and Money* **16(2)**: pp. 104–122.

HUANG, J. C. & I. GUEDJ (2009): "Are ETFs Replacing Index Mutual Funds." *AFA 2009 san francisco meetings paper*, SSRN Electronic Journal.

KENNETH, L. K. K., K. K. LAI, & K. HE (2013): "Modeling Exchange Traded Funds Portfolio Using Optimization Model." *Conference paper*, 2013 Sixth International Conference on Business Intelligence and Financial Engineering.

LETTAU, M. & A. MADHAVAN (2018): "Exchange-Traded Funds 101 for Economists." *Journal of Economic Perspectives* **32(1)**: pp. 135–154.

MADHAVAN, A. & A. SOBCZYK (2016): "Price Dynamics and Liquidity of Exchange-Traded Funds." *Journal of Investment Management* **14(5)**: pp. 86–102.

MORAES, F. (2021): "Unskilled fund managers: Replicating active fund performance with few ETFs." *International Review of Financial Analysis* **78**.

MSCI.COM (2000): "US Exchange Traded Funds Based on MSCI Indices Launched by Barclays Global Investors." *Website*, https://www.msci.com/eqb/pressreleases/archive/pr000519.html; acessed Jul 19, 2021.

POTERBA, J. M. & J. B. SHOVEN (2002): "Exchange-Traded Funds: A New Investment Option for Taxable Investors." *American Economic Review* **92(2)**: pp. 422–427.

PUELZ, D., C. M. CARVALHO, & R. P. HAHN (2015): "Optimal ETF Selection for Passive Investing." *arxiv.org* .

ROMPOTIS, G. G. (2009): "Active vs. Passive Management: New Evidence from Exchange Traded Funds." *SSRN Electronic Journal* .

STATISTA.COM (2021): "Development of assets of global exchange traded funds (ETFs) from 2003 to 2020." *Website*, https://www.statista.com/statistics/224579/worldwide-etf-assets-under-management-since-1997/; acessed Jul 19, 2021.

Appendix A

Dataset & R code

Dataset and R code used for the analysis are available upon request.