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MASTER'S THESIS

ANALYSIS OF TRACKING ERROR FACTORS BETWEEN MAJOR WORLD INDICES AND TRACKING ETFS

Ljubljana, September 2020 ALEN ROŽAC

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INTRODUCTION

Exchange-traded funds (ETFs) are investment instruments which have been gaining significant momentum and popularity in the recent years. This thesis presents and explores these instruments, and touches on the instruments in close proximity to ETFs. ETFs are a part of a wider group labelled as exchange-traded products (ETPs). Some of these products may or may not be classified as derivatives – ETFs are usually not. Their specific classification depends on how the product is defined and structured. As is the case with most financial instruments, these products too exhibit certain characteristics which can be analyzed in an analytical framework deriving from theory. These frameworks can differ based on product choice and research objective. This thesis is focused on an analysis of tracking performance of ETFs that track the movement of a market index (e.g. S&P 500). In this particular case, the research objective is focused on the performance of tracking ETFs (also called *trackers*) that try to replicate the movement of a specified market index. The final objective is to provide an insight into the efficiency of major markets in a comparative perspective on a global level between eastern and western markets.

This thesis is divided into 3 parts. After a brief introduction to the topic of ETFs, the first part focuses on a general introduction to exchange-traded products in the beginning and on a more in-depth definition of exchange-traded funds in the following chapters. The section also explores how an ETF functions, their market position and market size, and the evolution of the legal framework it was established in. Because there are actually many different kinds of ETFs, a section is also devoted to the typology of ETFs. The theoretical part concludes with quantitative properties of ETFs – namely, the expense ratio and the tracking error – which is also a focus point for the empirical part of the thesis. The concluding topic of tracking errors from part 1 is expanded in the empirical part.

The second part focuses on the actual topic of research of this thesis. In essence, the thesis explores *how well* exchange-traded funds track major (local) market indices (e.g. the S&P 500). The undertaken approach, as evident from the empirical part, is oriented towards a comparison of the tracking performance between western (US and EU) and eastern (JP, HK, CN and SG) markets. Additionally, the empirical part performs a factor analysis with the aim of exploring consistency of factors that contribute to the tracking error between major world indices. After the definition of the research topic, 4 hypotheses are listed and defined in order to better understand the applied methodology. Next, the actual observed ETFs and the data source is provided and accompanied by plots of ETF and index pair time series, followed by a descriptive analysis thereof. The empirical part is concluded with a definition of the econometric method that produces final results.

Lastly, the final chapter presents the results. This includes an interpretation of econometric tests and regression analysis results for the two models as defined in the methodological part. Finally, proposed hypotheses are interpreted on a case-by-case basis.

1 EXCHANGE-TRADED FUNDS

Innovations in financial markets have led to the introduction of new types of financial products and financial services. One of these are ETFs which are more available, more transparent, and in general, as they are based on equities, quicker to acquire, liquidate and trade when compared to other existing alternatives – e.g. mutual funds. These market innovations have proposed a structural move from mutual funds to new investment instruments that offer a wider range of exposures from which investors can practically “pick” from as they are easy to acquire and come with relatively low costs. If an “average” ETF could be defined, it would most probably be a passive index tracking fund (also known as a *tracker*) that aims to replicate a selected market index (e.g. the S&P 500 index) as this kind of an ETF is the least complicated and the most popular kind of an ETF (State Street Global Advisors, LLC, 2014).

The briefly described qualities of these products provide a major case for their rise in popularity in both retail and institutional investors’ choices. In addition to that, actively managed funds have recently been on the losing side of the coin when compared to index funds (trackers) and other passive ETFs in terms of flows of funds in and out of these instruments (Gittlesohn, 2019). This is further explored in section 1.2.2. This chapter offers a description of the instrument (the ETF) and the market it is placed on in order to provide an insight into the mechanics and other basics of the instrument. In addition to that, the following sections of this chapter provide a more thorough analysis of these instruments is presented through a historical, legal, and market perspectives.

1.1 General description of the instrument

As a part of the exchange-traded products instrument class (ETPs), ETFs are investment funds that are traded on a stock exchange – just like stocks. The actual instrument is a *fund* that is divided into *shares*. The shares are placed on an exchange where they can easily be bought or sold by investors. Other common types of exchange traded products are briefly expanded on in section 1.1.1.

ETFs are usually a part of a separate entity subject to a board of trustees and other key service providers. However, since there are a few different types of legal frameworks they can operate in, ETFs can also be organized in several different ways (more on this topic in section 1.2.3). In general, an ETF is registered as an *open-end management company* that enjoys tax benefits by avoiding double taxation due to meeting certain tax requirements that enable it to operate as a so-called *pass-through entity.* As it has already been mentioned, current ETF landscape is quite versatile, although historically, ETFs started off as rather plain index funds (Levitt, 2016).

ETFs are easy to acquire, and they can be bought just like equity shares (stocks). Shares of ETFs can be bought from different brokers and/or investment companies. These include brokers who offer market access and companies such as Vanguard, Fidelity, and Charles Schwab to name a few. In addition to offering brokerage services, it is often the case that these investment companies themselves provide management services and are on the creative side of the market as they also manage their own ETFs. Historically speaking, it used to be the case that ETFs that are managed by an investment firm which mainly offers brokerage services (and market access services in general) had been participating in a so-called "fee war". It is often the case that they therefore offer exposure to their own products free of transaction fees. These firms offset the negative impact of a zero fee by focusing on better fee structures on other products and usually creatively structure their fees in a way that rewards their managers for good performance. However, this practice has been so popular that it has expanded even to brokerage firms which do not manage and offer their own ETFs. These firms can offer zero fees by entering into agreements with bigger investment firms (Rosenberg, 2020).

In popular culture, ETFs are viewed as instruments that can be acquired quickly and easily due to their relatively uncomplicated acquisition process. Comparing the cost of entry to stocks, an ETF may even be a cheaper option for market exposure nowadays as management fees have been lowered to practically zero. On one hand, this has been the case in recent years due to recognition of ETFs as index mutual funds rather than as day-trading tools (Rekenthaler, 2019). On the other hand, Vanguard points towards millennials as one of the major retail ETF investor groups due to the inclination that millennials may view themselves as *self-directed investors*. Vanguard reports that the median age of their investors is at only 36 years (De Luca & Young, 2019).[1]

The other often-noted upside of ETFs is a wide range of available products and exposures that is for some retail investors an interesting speculation idea as it provides an easy and relatively cheap way to a more exotic type of investment strategy. The final *price* does still depend on the exchange, the provider and the legal system the instrument is placed in. To give a few examples, retail investors have the ability to buy shares of exotic ETFs. These would include actively managed ETFs that have a less orthodox objective – i.e. different risk functions and different market scope definitions. Some historical examples of exotic ETFs even include alpha-seeking ETFs that allocate their funds based on insider trading information. Other choices that are interesting for different investors include the ability to "track" a given niche market. For instance, there are ETFs that track companies which are

[1] Only counting accounts with >75% ETF exposure.

invested into developing artificial intelligence (QQQ, VGT, IYW, FTEC) [2] and robotics (ROBO, BOTZ, ARKQ, ROBT); there are even biotech ETFs (IBB, XBI, SBIO, BIB), consumer electronics ETFs, etc. Note that some articles listing "exotic" ETFs may actually point towards exchange-traded notes and/or other exchange-traded products and not only ETFs (Wigglesworth, 2018).

1.1.1 ETF as an exchange-traded product (ETP)

Exchange-traded funds are a part of a wider group of instruments known as exchange-traded products (ETPs). This wider group of investment instruments is signified by both the replication of an underlying security or market segment, and the ability of being traded on an exchange – like a security. This group of instruments includes (Nasdaq Inc., 2020):

1. *Exchange-traded funds (ETFs)* – the *biggest* and the most popular exchange-traded product. This instrument is the main topic of this thesis and will be further described in other sections.

2. *Exchange-traded notes (ETNs)* – securitized financial derivatives (unsecured) which can be traded on an exchange. These instruments offer exposures to primary markets which are only available to authorized participants (Borsa Italiana, 2020b). A good example of an ETN is the *iPath S&P 500 VIX Short-Term Futures ETN* which offers exposure that is based on the movement of the VIX index *(CBOE volatility index).*

3. *Exchange-traded commodities (ETCs)* – operate and are constructed in a similar fashion as ETNs but differ in the underlying marketplace. ETCs are practically secured ETNs with exposure to commodities (e.g. gold, coffee, corn, oil etc.). ETCs can actually even track indices linked to homogenous baskets of goods (e.g. agricultural products, metals etc.). These instruments offer relatively cheap exposure to commodity markets and are quite popular on the European market (Borsa Italiana, 2020a).

Also worth mentioning are closed-end funds, exchange-traded derivative contracts, and synthetic ETFs. Closed-end funds function similarly to ETFs but differ in the way they raise capital to enter the market and are often considered as a type of an exchange-traded product. Exchange-traded derivative contracts are standardized derivatives traded on an exchange. Synthetic ETFs have been introduced in Europe in 2001 and are signified by their replication method that is based on synthetic replication that constructs a position from derivatives

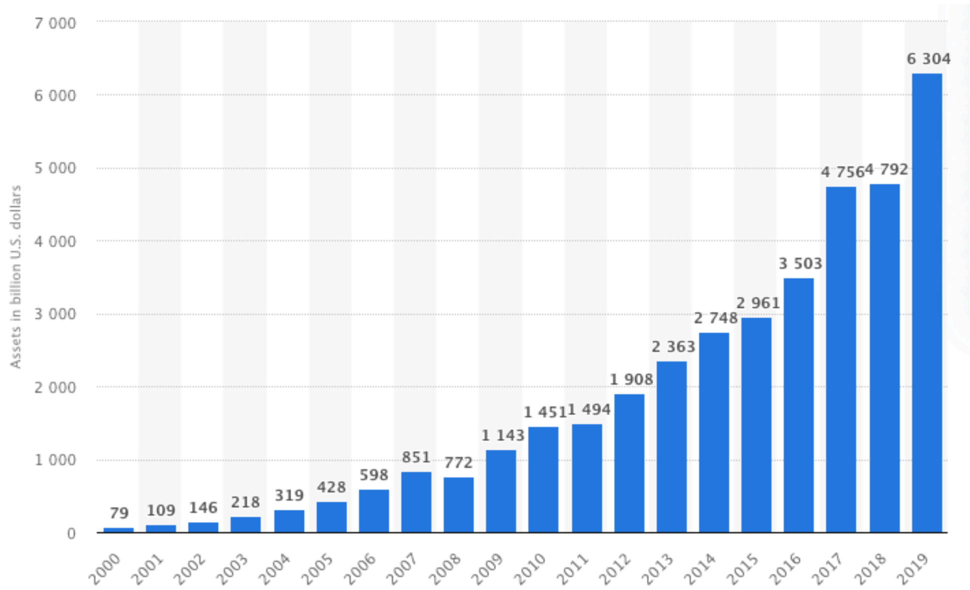
[2] Conversationally, ETF investors usually use tickers and not full fund names. Tickers (symbols) listed as examples of such ETFs can be found on NASDAQ or on the New York Stock Exchange.

(Bajpai, 2020). Since this thesis focuses primarily on ETFs as a part of ETPs, only the broadest descriptions of other ETPs have been provided above.

While most ETFs are not considered as derivatives, most of the products listed above – namely, ETNs, ETCs, and exchange-traded derivative contracts are considered as derivatives. Additionally, the market also supplies *leveraged* and *inverse* “ETFs” which utilize derivatives in order to provide additional (leveraged) exposure to the underlying (tracked) security (Chen, 2020a).

Figure 1 shows the size of the world ETP market. From the year 2000, and with the exception of the 2008 slump, the ETP market has been constantly growing. The geographical and product composition of this rise is mostly focused on ETFs that are traded in developed markets, as evident from Figure 4 in section 1.2.1.

Figure 1: Assets of exchange-traded products (ETPs) - worldwide, billion U.S. dollars



Source: Statista (2020).

1.1.2 Costs and benefits of ETFs

ETFs supposedly come with many benefits that translate well on the cost side – meaning that the argued benefits outweigh many costs. Arguments from both sides of the story are presented in this section.

First, the often-listed broadly defined benefits include:

- Cost benefits – the average costs related to investing through the use of ETFs has been a major factor that evolved in the recent times. Not only have brokerage firms and investment services providers been providing their services for zero transaction costs on their platforms, but there has even been an extension to the so-called *zero-fee war*. With major ETF providers already offering zero-commission trading (e.g. Charles Schwab and Fidelity) the other major cost source an ETF investor bears is the management fee which has been falling in the past couple of years, and has recently even moved to zero in the case of some providers – however, this is not indicative that all management fees will go to zero (Rosenbaum, 2019).

- Availability – compared to rivaling mutual funds, in order to enter an investment position using ETFs, one does not have to come in contact with an investment services provider – historical *modus operandi* for mutual funds. Already, there are additional incurred costs to the investor in the case of mutual funds only because of sales commissions. Additionally, the ETF landscape is more diverse in a limited geographical area as there is a limited number of possible mutual funds providers in a given geographical area. Geographic reach is often a limiting factor for mutual funds providers as their investment options may not always provide desired market exposures. Turning to the ETF side of this comparison, when one is granted market access through a broker, one can invest into practically any instrument that is traded on the market and the investor has more options to pick and choose from (given that the investor is informed about the ETF structure). There are even free online providers and databases on the availability of ETFs and their main components. One can even browse for ETFs by category, geography, issuer, type etc. (ETF Flows LLC, 2020).

- Transparency – historically, high quality market data has been quite far from available to common retail investors. With the advent of the internet, the common retail investor was closer to real-time data that was actually useful for decision making, but the information was still not available – or was available through different market data information providers such as Bloomberg or Reuters. On the contrary, ETFs are required to disclose their full portfolio position to the public. For example, BlackRock Inc. offers a complete listing of holdings for each iShares ETF right on their website in real time. Active ETFs are required by law to report on and fully disclose their portfolio positions on a daily basis. If we compare this to the case of mutual funds from before, the evidence of greater transparency is even bigger given that mutual funds publicly disclose their positions on a quarterly basis (ETF.com, 2018).

- Liquidity – the price of an ETF share that is traded on an exchange is determined based on the value of the underlying portfolio – also called the net asset value of the fund or NAV. The supply of ETF shares is open-ended, and the primary source of liquidity is the trading activity of securities in the underlying portfolio. Vanguard Group Inc. point towards market activity that is not visible to the common retail investor (e.g. over-the-counter trading and trading of ETF shares on other markets) as the main source of ETF liquidity. This is the origin of ETF liquidity that is based on a specialized mechanism only present in ETFs (Vanguard Group Inc., 2015).

- Tax efficiency – it is often suggested that ETFs are more tax efficient in comparison to mutual funds. However, it has to be noted that the instrument itself as a holding (as an asset) is not taxed differently, but enjoys some tax efficiencies due to the structure of the instrument and the legal framework it operates in. The most important part the tax efficiency actually happens within the ETF itself due to its internal pricing mechanisms, but this efficiency is prone to differences with respect to different fund compositions – i.e. the held assets in a fund. In essence, in comparison to a mutual fund, a sale of an ETF share does not impose tax obligations to other ETF shareholders as the ownership is simply internally transferred – no changes in portfolio structure. In contrast, a mutual fund would have to liquidate a part of a portfolio and all the incurred taxes from this operation are transferred to investors (Maverick, 2019). One interesting artefact of this creation units transfer mechanism is a so-called *ETF heartbeat.* A heartbeat is an abnormally highly valued single trade that is performed when an ETF manager reallocates the fund assets and effectively avoids a large tax bill (Mider, Evans, Wilson, & Cannon, 2019).

Secondly, the main drawbacks of ETFs:

- Market risk and concentration risk – as the main risks with liquidity risk in the third place. This is mostly based on the reliance on adequate functioning of both the primary and the secondary ETF market (Goodacre UK Ltd., 2018).

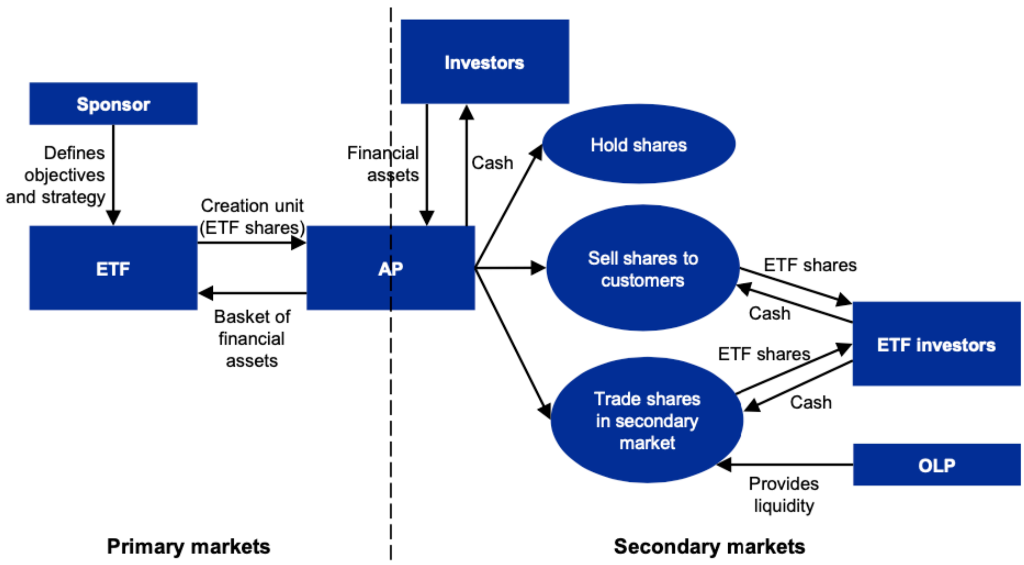
- Systemic risk contribution – a recent report from the European Systemic Risk Board points towards major systemic risk characteristics such as ETF-induced changes in securities risk – increased co-movement of security prices and indices, increased volatility, decoupling from constituent security prices, ETF-induced contagion, and other counterparty and operational risks of ETFs. (Pagano, Sánchez Serrano, & Zechner, 2019).

- Confusion and tax risk – Confusion arises from different definitions of what ETFs are and what they are not. One good example is how retail investors who do not fully research the ETF landscape actually and end up buying leveraged products which have in some cases (e.g. two VIX-linked ETPs) even collapsed (Wigglesworth, 2018). Additionally, leveraged and inverse ETFs that were described above as a different form of an ETF (therefore even more confusing) seem to be relatively tax inefficient. Due to their utilization of financial derivatives for position construction purposes, a major tax inefficiency occurs with buying and selling of financial derivatives as they cannot be delivered in kind (Wiley Global Finance, 2011).

1.1.3 How ETFs function

As it has already been pointed out, exchange-traded funds are traded as equities. The secondary market includes what we called *buyers and sellers* or *ETF investors* of the securities that are traded on a regulated exchange. But in the background, there is a huge framework set-up that supports this financial product. Here, we will only take a look at a *plain vanilla ETF* – the most basic form of an ETF – as ETFs can feature different attachments and/or other augmentations to this common framework that would prove difficult to fully capture in a general description.

Figure 2: Functioning of an ETF



Source: Pagano, M., Sánchez Serrano, A., & Zechner, J. (2019).[3]

Referring to figure 2, an ETF is created by a sponsor who defines the *objective* which includes the investment strategy and the *method* – the replication method and the management structure with fees. Sponsors are usually financial institutions. With the objective, the method and the vehicle defined, the ETF is said to be *originated.* The next step is to exchange *creation units* of the ETF for a *basket of financial assets* or a same amount of cash which is used to acquire the basket. On the other side of this deal is an *authorized participant (AP).* APs are in the ETF scheme as an entity which upon the creation of an ETF provide the ETF with liquidity and/or assets in exchange for creation units. APs are contacted by the ETF sponsor and currently there is no regulatory restriction on the minimum

[3] Note from the original article: AP refers to Aurhorised Participants and OLP to Official Liquidity Providers. Creation units can also be delivered to the AP in exchange for cash.

number of APs an ETF should have; it has been found that ETFs typically have around 30 AP agreements. The AP is not paid in any predefined fees as they are meant to collect profit from arbitrage. The arbitrage mechanism is based on the difference between the net asset value (NAV) and the price at which ETF shares are traded at on the secondary market. The AP has the advantage of knowing the full portfolio composition in order to swiftly execute the arbitrage trades. If ETF shares trade at a premium, the AP will sell ETF shares on the secondary market in order to bring the price down to the actual net asset value of the underlying securities. If ETF shares trade at a discount, the AP will buy ETF shares on the secondary market in order to bring the price back up to the actual net asset value of the underlying securities (Pagano, Sánchez Serrano, & Zechner, 2019).

Figure 2 shows the framework of a plain vanilla ETF. Note that this framework can be altered by including different innovations or attachments - like in the case of synthetic ETFs in Figure 10. If we start from the top left of the figure and go towards the right, the creation process outlined in the previous paragraph can be given a visual. We can clearly see how in the first step, on the primary markets, the sponsor defines the objective and strategy in order to later exchange creation units for the basket of financial assets with the AP.

This new footprint and all the associated footwork results in an efficient instrument which the market accepted, as it will be evident in the section 1.2.1, with welcoming open arms and wallets.

1.1.4 ETF liquidation

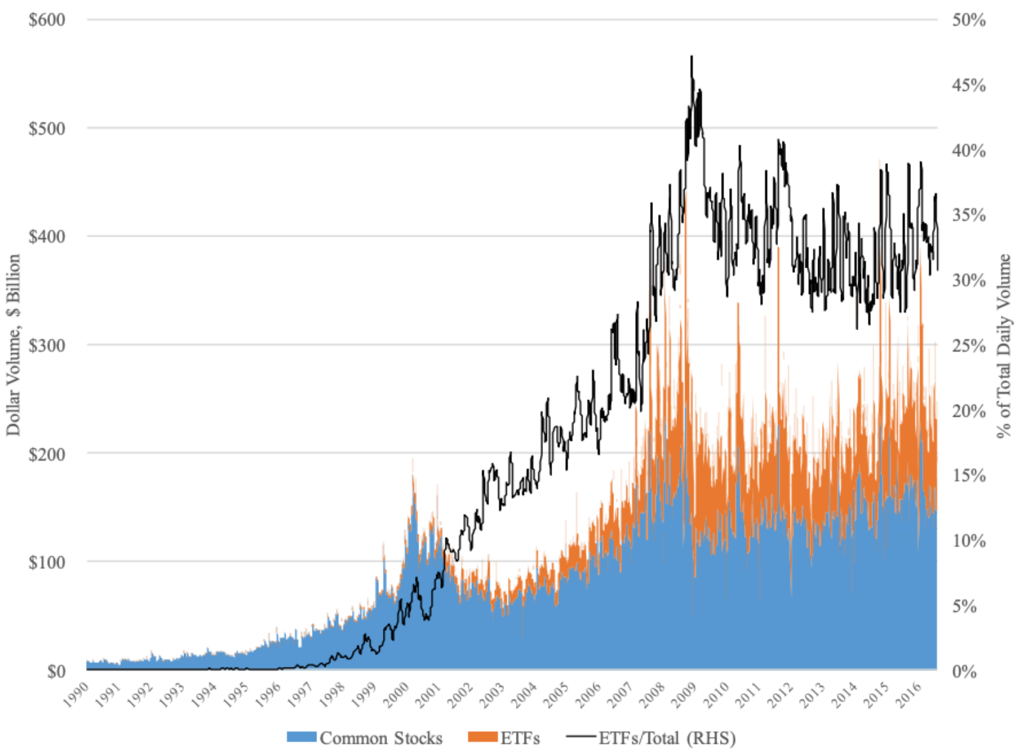
In some rare cases, ETFs may be liquidated. This usually occurs due to low interest in the ETF from the investors or due to limited amount of assets and relatively high fees that are a consequence of it. This may deem an ETF unprofitable and such ETFs can be liquidated by the sponsor.

The liquidation process itself follows a strict liquidation procedure. The basic outline of this process starts when the ETF (the sponsor) notifies the exchanges it trades on that the fund will close down in order for shareholders to be notified about the liquidation process. There are several time constraints or rather time requirements on how soon the investors need to know that the ETF will ultimately be liquidated. During this time, shareholders will be able to redeem shares and acquire creation units, but investors may still opt for selling the shares to the market maker before that occurs in exchange for cash. Remaining holders of creation units will be compensated by receiving a share of cash obtained from the liquidation procedure that is based on the net asset value (Yuille, 2020).

1.2 History

The ETF market has become increasingly more important and present in the financial system as a whole. Figure 3 present day trading volume on the U.S. market for common stocks (blue) and ETFs (orange). From its inceptions in the early nineties, the market has grown to a multitrillion industry with developed providers and new market strategies. The ETF share of daily volume in relation to the common stock volume is plotted in black (RHS scale). As evident, the share of daily trading volume of ETFs has become more pronounced, but it has leveled-off in the 30-40% region in recent years (Ben-David, Franzoni, & Moussawi, 2017). It should be noted that there are underlying structural differences between ETFs, markets, and market participants. This topic is further expanded in section 1.2.1.

Figure 3: Day trading volume - worldwide, billion U.S. dollars



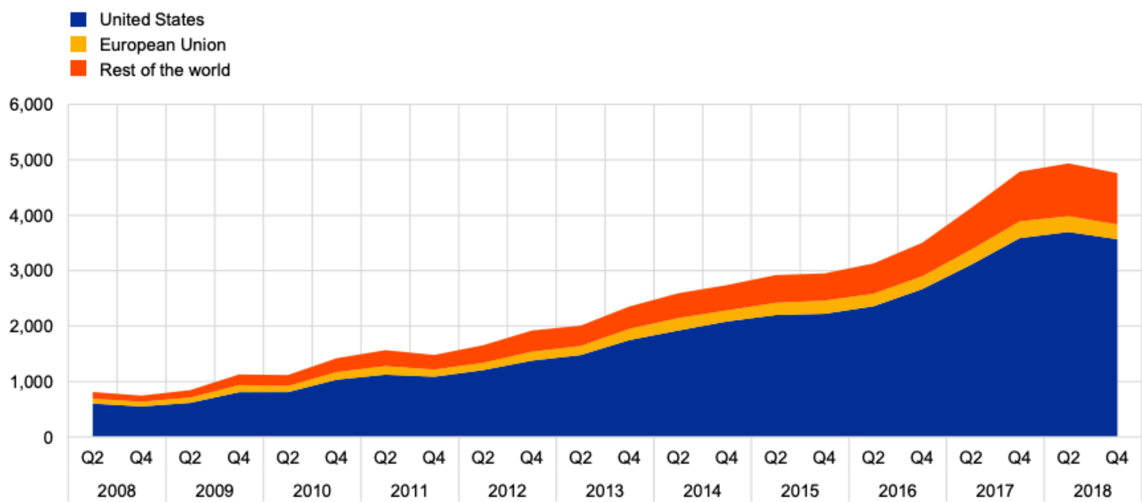
Source: Ben-David, I., Franzoni, F. A., & Moussawi, R. (2017).

The structure of an ETF and the market it is placed on shows significant differences with respect to existing instruments and their respective markets. Knowing the basics of ETFs, their popularity, and the related costs and benefits of these instruments, in this section we will take a look at the market size, the mechanisms behind different alterations and focus points of these instruments, and the legal framework ETFs operate in. This section is meant to expand on the topics that are important for this thesis – as the ETF market grows and evolves, more financial innovations are present in the market and in the instrument's framework. Therefore, the provided explanations in the following sections are meant to serve as a general guide rather than a specific one. Described characteristics would still mostly hold for trackers as trackers are the most basic version an ETF.

1.2.1 Market size

According to Bank of America, the current ETF market size is close to 5 trillion USD (as of 2020). Different point-in-time statistics will provide different estimates. For example, Figure 4 estimates the total 2018 market size at just under 5 trillion USD, but even with different estimates, the upwards sloping trend is undeniable. Bank of America estimates the average ETF assets annual growth rate at 25%. Over the coming years, the ETF market is expected to grow at more than 1 trillion USD per year, rounding up to the total global market size of about 50 trillion USD in 2030 (Reinicke, 2019). Figure 5 shows the count of available ETFs on the market. It is clearly evident that the ETF market does not grow only in value, but also in the count.

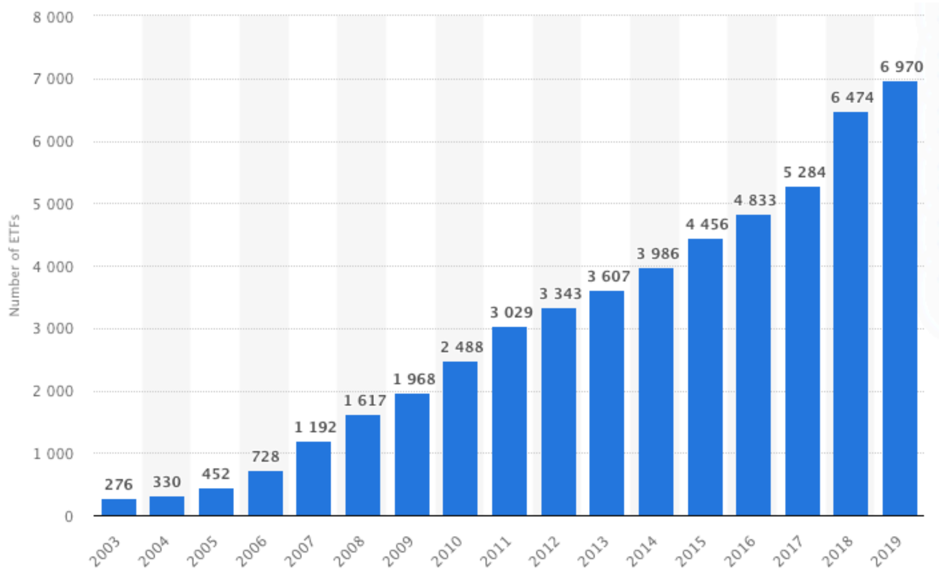
Figure 4: Aggregate total net assets of ETFs - worldwide, billion U.S. dollars



Source: Pagano, M., Sánchez Serrano, A., & Zechner, J. (2019).

On one hand, these instruments are becoming more popular as the ETF market matures and also due to expansion from the institutional and the international side. Another important factor is the digitalization of consumer investor markets which enable retail investors easier and more transparent participation in global financial markets. These instruments come with many benefits, as it has already been pointed out in section 1.1.2. These benefits ultimately provide an easy entrance to investing and financial markets without complex contracts and complex fee structures. It is therefore expected of this market to continue its expansion, as evident from projections mentioned above.

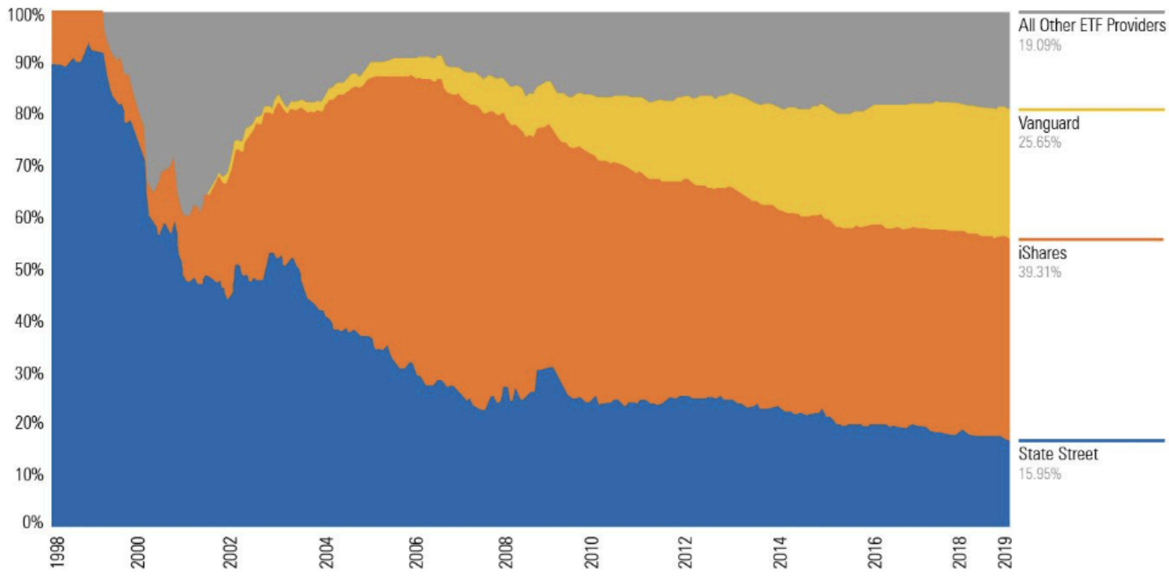
Figure 5: Number of exchange-traded funds (ETFs) – worldwide



Source: Statista (2020).

On the other hand, BlackRock points towards new coming investing trends that enable ETFs to rise above other instruments such as mutual funds. BlackRock points towards investment choices made by individual active investors who are now able to essentially *pick* the market slices they want to be exposed to. The fact remains – ETFs enable different strategies while retaining proximity to liquidity and have a generally low-cost nature. Therefore, BlackRock concludes that ETFs will be more popular among active investors (BlackRock, Inc., 2018).

Figure 6: U.S. Market shares of major ETF providers 1998-2019



Source: DiBenedetto, G., & Lauricella, T. (2019).

As of 2020, the international ETF market is still dominated by providers from the United States of America. As evident in Figure 6, the U.S. ETF market is distributed mostly between Vanguard, BlackRock (iShares) and State Street (SPRD) with BlackRock representing the majority of the market at almost 40% (DiBenedetto & Lauricella, 2019). The European ETF market is smaller and U.S. providers are still notably present. As of 2019, the largest provider (ranked by assets under management – AUM) was BlackRock (iShares) at roughly 400 billion EUR under management with DWS Group (Deutsche Bank and Xtrackers ETFs) coming in second at roughly 100 billion EUR (Eckett, 2020). The gap between EU-based domestic providers and US-based providers on the European market shows how US-based providers continue their expansion internationally.

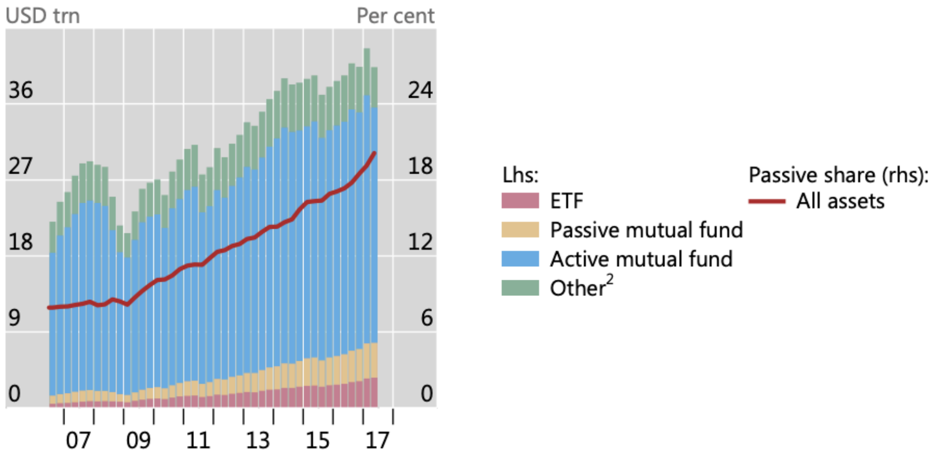
1.2.2 Evolution from mutual funds

Early mutual funds were formed in Europe, in the Dutch Republic in the late 18th century, with the aim of providing an opportunity for investors to diversify their investments. These early financial innovations were later introduced to the US market in the late 19th century (Rouwnhorst, 2004). Later, in the roaring twenties, the age of increasing asset prices was interrupted with the Great Crash of 1929 that also signaled the start of the Great Depression. In the aftermath, the United States government passed a number of new regulations with the aim of stabilizing markets. Proposed and later incorporated regulations included topics and frameworks which included mutual funds. With the Securities Act of 1933, all publicly traded instruments (which included mutual funds) had to be filed with the U.S. Securities and Exchange Commission (the SEC), and in addition to that, the traded securities had to provide adequate transparency about investment opportunities. The SEC itself was incorporated with the Securities and Exchange Act of 1934 as a regulatory body overseeing the securities markets in the United States. Shortly after establishing this regulatory framework which included the overseeing of mutual funds, several additional acts were passed in order to better regulate securities markets of the United States. In addition to that, this period saw the introduction of regulation that introduced flow-through entities, but more on regulation regarding mutual funds and ETFs in section 1.2.3 (McWhinney, 2018).

The 1960s saw the great introduction of mutual funds to retail investors in the form we know today. This was accompanied with great fund inflows and more financial innovation. In 1971, Wells Fargo establishes the first index fund – a type of a mutual fund that invests into stocks that comprise a given index (McWhinney, 2018). This marks the introduction of passive investment as we know them today. Index funds provide exposure – much like modern ETF index trackers – to a selected index. However, it should be noted that active investments remained the dominant investment type. In Europe, these financial innovations were recognized by legal authorities, and in 1985 they introduced a new framework under the name Undertakings for Collective Investment in Transferable Securities (UCITS) with the goal of harmonizing fund structures in the EU. The aim of this legal framework was for all member states to recognize funds that may be authorized in one EU member state. This sparked a new world-renowned marketing label that is associated with quality and approval from European authorities which may, in some respects, be more prudent than their US counterparts (Johnson, 2006).

Passive investment funds are known for their lower fees and no active management. The objective is therefore simple and expected, giving the investor the possibility to not only passively invest, but to also passively oversee the investment. A good example is Vanguard's first index product, the *Vanguard 500 Index Fund*. This fund replicated the S&P 500 index and received inflows due to lower fees originating from the fund's passive nature that required no compensation for active management. Later introduction of the so-called *spiders* (from the pronunciation of the name *SPDR S&P 500 ETF Trust*) was the initial step that realized the potential of a new instrument – the exchange traded fund.

Figure 7: Global assets under management by fund type



Source: Sushko & Turner (2018).[4]

Figure 7 shows global assets under management by fund type in recent years. Note how the ETF market compares to the market of passive mutual funds – event though the ETF market started with a lag of approximately 20 years. What came in the following years was a battle for market shares and fund flows between active and passive investments. The fee war brought the era of passive investments to retail investors and made it possible to partake in the market even with low initial investments. These topics are further discussed in section Active and passive ETFs.

[4] Note: *other* includes investment fund assets of closed-end funds, hedge funds, insurance funds, investment trusts and pension funds.

1.2.3 Legal framework

The historical perspective of the legal framework in which ETFs operate in has already been briefly outlined in section 1.2.2. However, since that section was primarily focused on the legal framework for mutual funds, a more insightful take on the history will also be presented in this section with focus on ETFs. The modern era of financial innovations was mostly institutionalized and defined in the times following the Great Crash of 1929 and the Great Depression. Biggest shifts in regulation were made in the years following the crash; those regulative changes ultimately apply even to the newer financial market innovations – such as exchange-traded funds. Major regulatory acts and events that regulate the ETF market in a chronological order:

- Securities Act of 1933 – under this act, regulation applied to securities traded on exchanges. As it has already been stated above, it mainly requires issuers to provide adequate transparency on investments opportunities. The information provided must also be filed with the Securities and Exchange Commission (SEC), but this institution came with the Securities Exchange act in the following year. ETFs or better – ETPs, which are not filed under the Investment Company Act of 1940 are still regulated by the Securities Act of 1933 (Financial Industry Regulatory Authority, Inc., n.d.).

- Securities Exchange Act of 1934 – this act put forward the establishment of a regulatory institution – the SEC. The act itself regulates the transfer mechanism of the markets.

- Investment Company Act of 1940 – also known shorthand as the *"40 Act"*, the act itself directly regulates responsibilities, structural, and operational requirements for investment companies. Later, financial innovations – such a ETFs – have emerged, but have also fallen under the umbrella of the 40 Act. As an interesting note, this act is said to be restrictive and akin to the legal system of the continental Europe (Gastineau G. L., 2002). Under this act, ETFs cannot exist. Therefore, an exemption is necessary. This exemption was ultimately possible with the introduction of the 1990 release.

- Investment Company Act Release No. 17809 (1990) – the release that enabled exemptions to certain sections of the 40 Act and therefore enabled the creation of ETFs via an exemption in relation to the 40 Act. This opportunity was taken by the American Stock Exchange (AMEX) who petitioned the SEC to allow the creation of the first Standard & Poor's Depositary Receipts (SPDRs) trust. This trust became known as the *SPDR S&P 500 Trust, Series 1* – or as we have already called it, the *spider* – the first ETF (Ferri, 2009).

- Rule 6c-11 (2019) – under this recent rule, the SEC put forward a mechanism that regulates the exemption under the 40 Act process that is required in initiating an ETF. The rule defines a form that speeds-up the exemption approval process and therefore the process of initiating an ETF (U.S. Securities and Exchange Commission, 2019).

Most ETFs are registered with the SEC as investment companies under the Investment Company Act of 1940, and the shares they offer to the public are registered under the Securities Act of 1933. This does not include all other ETPs as they are not registered as investment companies and can even be considered as derivatives (Financial Industry Regulatory Authority, Inc., n.d.).

In Europe, the legal landscape took the following deviations and specifics:

- Undertakings for collective investment in transferable secutities (UCITS) (1985) – this is the key regulatory framework from the EU perspective on the ETF market. The directive regulates cross-border offerings of investment funds. Following updates to the directive have brought grater transparency, the introduction of the key investor information document (known as *KIID*) and higher risk standards – to name a few. Because of these high standards, risk disclosures and other regulative requirements, UCITS as a label in the instruments name has become a mark of high quality instruments (Chen, 2020b).

- UCITS V or Directive 2014/91/EU (2016) – as of 2020, this is currently the latest update in the series of UCITS regulation. This regulation governs all UCITS ETFs, and implements a system of safety standards that include but are not limited to diversification standards (concentration risk), segregation of UCITS vs. non-UCITS ETFs (ring-fencing), liquidity requirements (counterparty risk), and transparency requirements (Riedl, 2017).

1.3 Instrument types

This section presents common divisions and differences between ETFs, or what is known as the ETF market typology. In addition to herein presented different segmentations an ETF market can be divided into, the more general division of active and passive ETFs is also presented in detail and compared to mutual funds for reference. The section also touches on the idea of smart beta ETFs (section 1.3.3).

1.3.1 Market typology

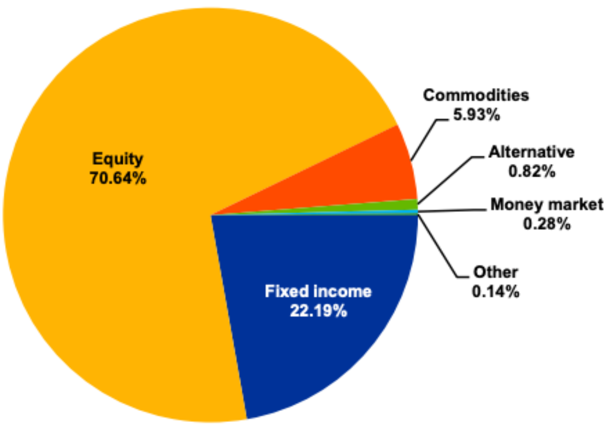
As is tradition in the financial industry, financial instruments can be segmented in several different ways. In relation to the ETF market, there are several types of viewpoints which propose different segmentations:

1. Sectoral segmentation – a common type of segmentation for retail investors. This type of segmentation provides an insight into *how* different ETFs are exposed to different market sectors and market dynamics. As an example, there are agricultural ETFs, biotech ETFs, ETFs that are composed of financial companies, etc. This type of segmentation is often used for industry or sector tracking purposes.

2. Geographical segmentation – provides a more geographically-oriented viewpoint. This segmentation usually divides ETFs into ETFs that are based in the United States, Europe, Asia, etc. One important caveat is that this type of segmentation is more prone to errors in interpretation due to the fact that, for example, an ETF can *track* or provide exposure to a geographical area (e.g. *iShares MSCI Emerging Markets Asia ETF*), but that same ETF can be traded on a local exchange – as is the case for the example ETF which trades on NASDAQ in New York City, USA, but tracks emerging markets in Asia (BlackRock Inc., 2020g). A different viewpoint is focused also on the actual trading location. In the example above, the ETF would fall into the United States geographical locale. For example, the *TraHK* – Tracker Fund of Hong Kong is both based in Hong Kong and tracks the Hang Seng index (State Street Corp., 2020a).

3. Asset-type segmentation – this segmentation is popular due to a very simple division into stock ETFs (also called equity ETFs) and bond ETFs (also called fixed-income ETFs). This segmentation is usually accompanied by segments which may or may not actually be ETFs but rather synthetic (derivative-based) ETFs or even other ETPs. These segments would include *commodity* "ETFs", *currency* "ETFs", and *specialty* "ETFs" – essentially leveraged and inverse "ETFs" (Ashworth, 2019). Figure 8 is an example of an asset-type segmentation of ETFs in the EU (June 2018).

Figure 8: Distribution of ETFs in the EU according to tracked financial assets



Source: Pagano, M., Sánchez Serrano, A., & Zechner, J. (2019).

4. Management type segmentation – this type of segmentation usually boils down to the classic *active vs. passive* debate. On one side, we have ETFs that track indices and/or are invested into pre-defined market segments (using any segmentation methods outlined above) in a passive way – meaning that the portfolio structure does not change in time for *alpha-seeking* purposes. On the other side, we have the actively managed ETFs that actively try to outperform the market. More on these two kinds of ETFs in next section (1.3.2).

5. Replication method segmentation – this segmentation is not common, but it is still very useful for research purposes. However, be advised that this segmentation is often prone to jargon terminology – i.e. ETNs, ETCs and synthetic ETFs are often all labelled simply as "ETFs" even if this may not be the case at hand. Replication methods are described in detail in section 1.4.1.

1.3.2 Active and passive ETFs

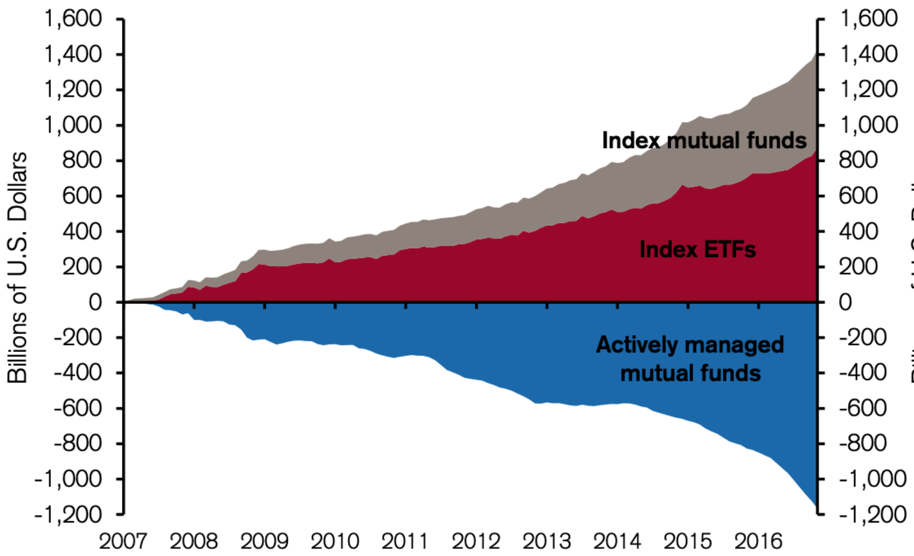
Through innovations in the financial sector, the want to *beat the market* has created instruments which when invested in come with a promise of market research, market analysis and efficient portfolio management. *Active* instruments promise exceptional returns by internally investing into market intelligence activities in return for the increase in total costs. Throughout history, most of the mutual funds market has been flooded with actively managed funds – as evident in Figure 7.

The second type of management is *passive* management. This form of fund management represents a more "hands-off" approach to the market and portfolio allocation. In essence, passive instruments don't promise exceptional returns that are in the case of active instruments based on alpha-seeking activities, but they rather promise *market returns* given selected part of the market an investor is interested in. This is essentially an offer of not having to beat the market since your investment – in a way at least, *is* the market. Therefore, since there is no market intelligence to splurge on, passive funds tend to be a much cheaper option for participating in the market.

Passive management has been gaining traction in recent times. On average, the difference between actively managed funds and passively managed funds (counting index funds and ETFs) is about 400%. This trend has been accelerating in recent years due to investors shifting from actively to passively managed products in what is known as the "cost migration" (Balchunas, 2016). Figure 9 shows flows from actively managed mutual funds to index mutual funds or index ETFs (passive products) between 2007 and 2016. Credit Suisse reports that investors who make the switch from active to passive are akin to weak poker players leaving the table. They conclude that this can make the market even more efficient as those players are less informed than the ones who stay in the active part of the market. Additionally, they identify four key drivers behind the rise of passive instruments.

These include regulation, market environment, technology, and balance between informed and uninformed investors. They especially point towards technology which made market participation simpler than ever before (Mauvoussin, Callahan, & Majd, 2017).

Figure 9: Flows from active to passive funds in U.S. equities – as of 30/11/2016



Source: Mauvoussin, M. J., Callahan, D., & Majd, D. (2017).

1.3.3 Smart beta

Also known as *factor investing*, smart beta is an investment strategy an ETF can specify when defining the objective and strategy for the fund. Smart beta employs a factor analysis toolkit in order to provide a *quantitative approach.* This has been dubbed as "smart" investing. Employing a smart beta strategy results in a different portfolio allocation that is not static, but changes in time with respect to a quantitative function – factors. These factors include but are not limited to classic factors such as value, size, volatility, momentum, quality and dividend yield to name a few. Building on the grounds of Markowitz's mean variance analysis (1952), the CAPM model by Linter (1965) and Treynor (1961), and other academics provided an empirical framework for analysis of different portfolios. In the 1970s, multi-factor models modelled various factors for beta. Most of the today well-known factors such as size, value, volatility, and momentum emerged from those academic works. Fama & French (1992) provided a more developed toolset and approach, one that was soon employed by asset management companies for portfolio selection and allocation. Moreover, additional and alternative investment factors have since then been researched and employed in many smart beta ETFs (Invesco Distributors, Inc., 2018).

The approach to index weighting is based on a rule – a function that returns a portfolio composition. Composition can be re-run on a time basis in order to acquire new portfolio weights on a selected frequency. This is also known as *rebalancing*. Note that frequent portfolio rebalancing translates to higher fund management costs and/or other expenses. It is also debatable if these funds should be called active or passive. Smart beta ETFs may employ the following common strategies when constructing a portfolio (Chen, 2019):

- Equally weighted – strategy will assign equal weights to factors and each holding.
- Fundamentally weighted – strategy assigns weights based on financial fundamentals (profits, revenue and/or other fundamental financials).
- Factor-based – weights are assigned based on factors such as size, underpriced valuations, momentum etc.
- Low volatility – based on mean-variance-like analysis, this strategy will assign higher weights to assets with lower price fluctuations.

1.4 Theoretical aspects of the instrument

An investor should be aware of different types of the instruments that were explored in section 1.3 in order to fully understand the often not so subtle differences between products that may be presented one next to another, say, on an exchange. These differences do not only include the already mentioned segmentations based on geography or market typology (section 1.3.1), but also structural differences that can result in major differences in risk profiles and operational specifics of the instrument.

Main reasons for the occurrence of such differences are presented in this subsection. It includes an overview of different replication methods that is followed by a definition and description of two indicators that are important in that respect – the tracking error and the (total) expense ratio. Understanding subtle differences in instrument structures as a result of different replication methods enables the investor to understand the underlying cost-benefit nature of an instrument he or she may be investing into.

1.4.1 Replication methods

Because active and smart beta ETFs do not truly follow a market index or a selected market segment, only passive ETFs are relevant in this regard. In the context of passive ETFs, several different replication methods exist. Moreover, these differences in replication methods can also serve as a segmentation identifier that groups similar ETFs in the same segment, as stated in section 1.3.1. In general, the following replication methods are available (SAMT AG Swiss Asset Management, n.d.):

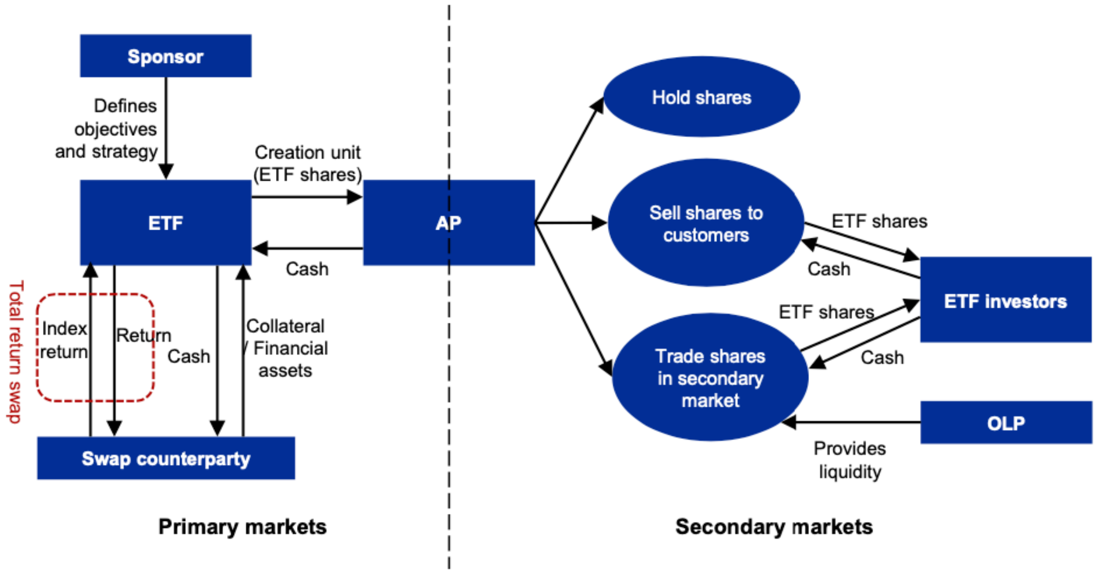
1. Full physical replication – the tracked index is replicated in full physical composition. The underlying index is fully replicated using stocks and/or bonds

scaled to total ETF's asset value. Internal composition or asset weights only change if any changes actually occur in the index composition it is replicating.

2. Sampling physical replication – the composition of the tracked index is sampled using stocks and bonds. This replication method is usually employed in order to bring down the costs as the replicated index may prove to be too expensive for full replication. Usually, this is the case when the underlying index it tries to replicate includes many different assets or illiquid assets that may come with higher acquisition costs for full replication.

3. Synthetic replication – this replication method does not use stocks and/or bonds as it is based on derivatives. These ETFs mostly include swaps. Namely, total return swaps. This method is known for greater exposure to counterparty risk since some typical ETF building blocks are significantly altered in order to include a swap counterparty that engages with the ETF through financial assets and/or collateral on the primary market. Figure 10 includes such a change – marked in red. Figure 2 can be used as reference.

Figure 10: Functioning of a synthetic ETF

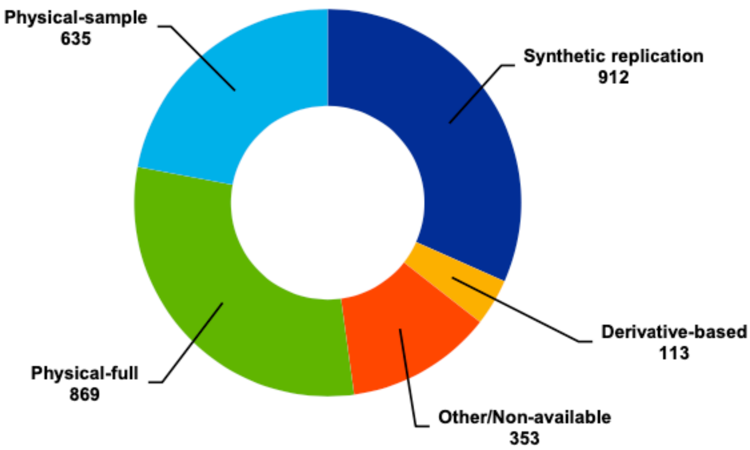


Source: Pagano, M., Sánchez Serrano, A., & Zechner, J. (2019).

4. Derivative-based replication – an umbrella term for leveraged, inverse and other structured ETFs. These instruments have already been explored in section 1.1.1 under the labels of ETNs and ETCs. These instruments employ the use of financial derivatives to either provide an inverse or amplified (leveraged) exposure to a certain market segment.

Figure 11 presents different replication methods' market shares as of June 2018 on the European market. Most popular replication method is the synthetic replication method which leads slightly ahead of the full physical replication method. Active ETFs are also included but are counted as other/non-available. Pagano et al. note that the number of ETFs on the market may not be the most effective way of analyzing replication methods since physical replication (both full and sampling) dominate over other replication methods if we apply a value-based view. The authors also note that synthetic replication methods are more popular in Europe when compared to United States (Pagano, Sánchez Serrano, & Zechner, 2019).

Figure 11: Number of ETFs in the EU by replication method as of June 2018



Source: Pagano, M., Sánchez Serrano, A., & Zechner, J. (2019).

1.4.2 Tracking error

When it comes to the question of ETF's performance, an investor investigating ETF's tracking error is a common approach. There are several types of statistics that could be seen as a tool that explores the performance of an ETF (Qadan & Yagil, 2012). The ETF providers (investment managers) are required to report on performance statistics in the key investor information document. For example, State Street Global Advisors report on cumulative and global performance based on tracking differences in terms of realized returns for their SPDR S&P 500 UCITS ETF in relation to the underlying index. In essence, an ETF with good performance will show low deviations in returns when compared to the underlying index (State Street Corp., 2020b).

There are different measures of tracking errors as different tracking error definitions are useful for different purposes. Some are more comparative while other are useful for quantitative applications (Pope & Yadav, 1994):

$$\mathrm{TE} = \frac{\sum_{t=1}^{T} |e_t|}{T} \tag{1}$$

Where e_t is the difference between the return of the ETF and the underlying index. This statistic measures tracking differences in a given time frame and is the measure most often reported in official ETF regulatory documentation (KIID).

$$\mathrm{TE} = \left(\frac{\sum_{t=1}^{T} (e_t - \overline{e_t})^2}{T - 1} \right)^{0.5} \tag{2}$$

Where $\overline{e_t}$ is the average value of the difference between the return of the ETF and the underlying index over sample period.

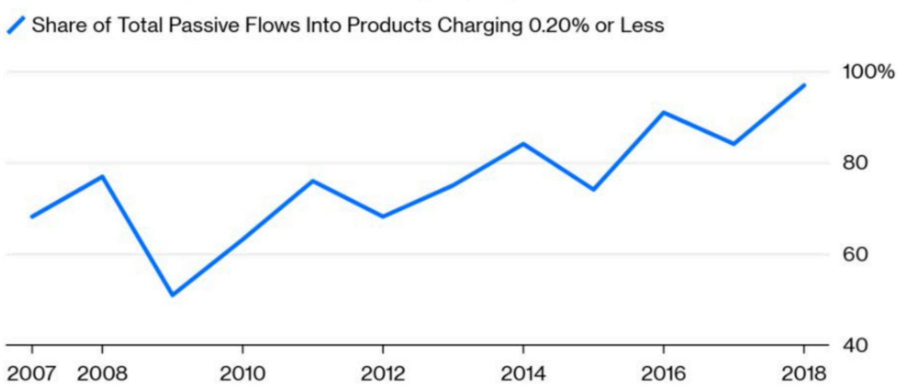
$$\mathrm{TE} = e_t = R_{i,t} - (\alpha + \beta R_{b,t}) \tag{3}$$

Where $R_{i,t}$ is the return of the ETF and $R_{b,t}$ is the return of the underlying index.

1.4.3 Expense ratio

Tracking differences (tracking errors) and fees may add up and significantly contribute to the (total) expense ratio – or what is known as TER of a given ETF. Because TER only excludes transaction costs an investor may bear due to different brokerage terms, the ratio is the most insightful ratio an investor could take a look at. TER should cover all internal expenses of the investment. Overall, the expense ratio can be looked at as a management fee that is deducted from the fund's assets and includes management fees, distribution and/or service fees and other internal expenses. The fact that most ETFs are passive ETFs and since most passive investment vehicles do not perform any additional analytical or quantitative work that could be additionally charged for, most ETFs have expense ratios lower than those of mutual funds due to low management fees. In addition to that, due to many efficiencies ETF present when compared to index mutual funds, the lowest cost ETFs are less expensive than lowest cost index mutual funds. A good example is a comparison between the most popular ETF – the SPDR S&P 500 ETF and an index mutual fund equivalent – the Vanguard 500 Index. The ETF has an expense ratio of 0.09% while the index mutual fund has an expense ratio of 0.14%. In a world of compound interest, these small differences eventually do add-up (Thune, 2019).

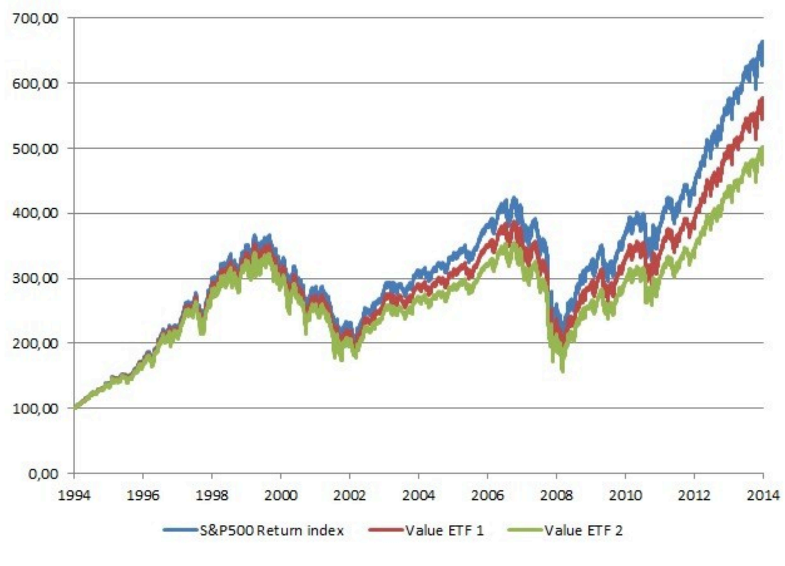
Figure 12: Share of total passive flows into products charging 0.20% or less



Source: Balchunas, E. (2019).

In general, the ETF market has seen a drop in fees, and as reported by Bloomberg, in 2019, the market has seen a significant increase in flows into passive instruments that charge 0.20% or less (Figure 12). A consequence of the *fee war* was not only the introduction of zero-fee ETFs, but even an introduction of negative-fee ETFs although these ETFs are very specific and there's usually a marketing component to the fact of negative fees (Balchunas, 2019).

Figure 13: S&P 500 Index and simulated ETFs with different TER (0.5% and 1%)



Source: Breaking Down Finance (2020).

There exists a slight difference between stated expense ratios and actual expense ratios which also include tracking errors. Some authors mark the distinction between the two by labelling the former as *expense ratio* and the latter as *total expense ratio.* Figure 13 shows the S&P 500 index in blue and two simulated ETFs that efficiently track the S&P 500 index in red and green. The red line is a simulated ETF that has the TER of 0.5%, and the green line is a simulated ETF that has the TER of 1%. Obviously, lower TER means that the actual returns will be closer to the index the ETF replicates. Therefore, an investor should closely examine all incurred costs within an ETF – that includes management fees, other possible hidden fees and/or reward structures, and the tracking performance as all of these elements are included in the TER because small differences in TER will show on a longer time horizon. This is also evident in figure 13 towards the end of simulated time series where these differences become more notable.

2 EMPIRICAL PART

The primary objective of this chapter is to present the methodology and definition of the analytical process. The actual results of the analysis are presented in the final chapter of this thesis (chapter 3). This chapter is organized in the following manner.

First, the topic of research and the scope of the analysis is presented in order to provide background for defined hypotheses. The section presents four key areas of interest – for each of which a hypothesis is constructed. Second, from defined topics, a research objective is defined. This includes a full definition of all 4 hypotheses – a subsection is devoted to each hypothesis and it includes the motivation, description, and a final full formulation for each hypothesis. Third, the methodology section provides an insight into selected methodology by presenting both the method and the data. Full model formulations can be found in chapter 2.3.2. Data sources are also listed for transparency in section 2.3.1. Section Selected ETF and index pairs presents a list of selected ETF and underlying index pairs with their respective geographical locations. An extended world index presentation can be found in section 0. Section 2.6 includes a full presentation of descriptive statistics for all relevant data that is input into the empirical part to produce the final results. This includes individual descriptive statistics and paired plots of returns. Plots of returns and their distributions can be found in the appendix. Selected estimator and all relevant econometric tests are presented in section 2.7. This includes the definition of cointegration methodology.

2.1 Topic of research

The selected topic of research focuses on a part of the ETF market. More specifically, the focus is primarily on tracking ETFs and their tracking errors. Trackers try to replicate the movement (returns) of a given index. They offer the investor exposure to a certain index which cannot actually be invested in on its own. The biggest and oldest example of a tracker is *SPDR S&P 500 ETF* (ticker symbol: *SPY*) which in the year 2015 represented roughly a third of total ETF market flows on the American market (Balchunas, 2015).

As evident from this short summary of the theoretical section above, the ETF market is a significant element of modern financial markets. This conclusion should foster additional research questions on the topic of performance of these instruments. In this light, this master's thesis is focused on a narrow part of the mentioned performance analysis. The hypotheses are constructed in a manner that will provide insight into following parts of market and instrument performance analysis:

1. A general analysis of *tracking errors.* Tracking errors represent a certain market phenomenon that can be observed in the tracker ETF market. Primary focus is on the tracking performance of ETFs relative to their respective index they try to replicate the movement of in terms of returns on a global scale.

2. *Cointegration* analysis. Given that ETFs as instruments are often assigned a *representation objective* (e.g. replication of an index, replication of a certain market), an instrument should demonstrate a level of cointegration in the price movement process.

3. Tracking error *factor analysis*. Subject to theory, a model that explains the variation in the tracking error process can be assumed and econometrically tested. In this part of the analysis, a model that is based on common theory conclusions such as volume and volatility impact is tested using regression analysis.

4. *Diversification benefit* analysis. As it has already been pointed out in the 2nd point of this section, ETFs are commonly assigned an objective to represent a part of the market. This implies a diversification benefit within and across the available instrument space. This is better defined and explored in the forthcoming section (hypotheses). The main goal of this point is to explore whether tracking errors are correlated with world market movements.

2.2 Research objective

The objective of the empirical part of the thesis is to analyze factors behind tracking errors and to provide an insight into market assumptions that are usually found in the ETFs performance analysis area. This section is divided into four parts; each part explores one hypothesis.

The first hypothesis corresponds to the analysis of the long run equilibrium by means of cointegration analysis and a proposed error correction model. Second and third hypotheses explore factors behind the observed tracking errors by employing a theoretical model. Both models expand into fourth hypothesis which gives the proposed tracking error model an interpretation on a global scale. The final hypothesis is less empirical in the sense of utilizing an individual model or test, but it reflects on the previous three hypotheses and tries to conclude whether western markets are more efficient in comparison to eastern markets through the scope of this analysis. Hypotheses are then tested, and results are presented in chapter 3. Conclusions are proposed to each individual hypothesis based on the analysis and the analytical framework from the following sections in this chapter.

2.2.1 Hypothesis 1: Long-run equilibrium

ETFs describe and define their individual objectives in the key investor information document (also abbreviated as *KIID*). As it has already been explored in the theoretical part of the thesis, the managers of a given ETF will try to deliver the objective (the exposure to the defined part of the market) to investors who invest into an ETF on the market by acquiring shares of that ETF. Investors are informed about the specifics of the instrument by consulting the KIID and therefore expect the ETF to perform in a pre-defined manner. In the case of tracking ETFs, the investor therefore expects the instrument to follow a pre-defined underlying instrument's returns minus the fees. To summarize the theoretical part, a tracker can track almost anything the managing institution is willing to provide and define exposure to. In return, ETF providers are required to publish relevant tracking information and information on performance in their respective ETF KIID (Johnson, Bioy, Kellett, & Davidson, 2013). Furthermore, since these institutions take pride in the issuance of ETFs they offer, they try to secure and stimulate their managing performance within reasonable ranges of the underlying's movement through various management reward systems that are structured such that good performance is rewarded (BlackRock, Inc., 2020j).

One of the main questions that arises from such an arrangement must therefore lean on the long-run performance of trackers. Because the distributions of pairs' returns are not identical, in order to explore whether trackers truly perform and capture the underlying instrument's dynamics within reasonable ranges, a cointegration analysis can be considered. As it will be explained further in section 2.7, glancing at correlation between individual ETF-underlying pairs will not prove insightful enough since correlation can only imply short-run relationship, but it is not inferring a long-run one.

To explore the statistically significant existence of a long-run relationship, an Engle-Granger cointegration test is performed (Engle & Granger, 1987) on a pair's returns, and an econometric error correction model is applied in order to provide insight into the significance of different error correction terms as proposed in a paper by Qadan & Yagil (2012). Their approach is constructed after Engle & Granger. As mentioned, the following equation models the pair's returns (ΔETF and ΔUI_t) and previous day's difference in prices between the two $(UI_{t-1} - ETF_{t-1})$. The full explanation of model 1 is available in section 2.3.2.

$$\Delta \mathrm{ETF_t} = \beta_0 + \beta_1 \Delta \mathrm{UI_t} + \beta_2(\mathrm{UI_{t-1}} - \mathrm{ETF_{t-1}}) + \varepsilon_t \tag{4}$$

Final full formulation of the hypothesis:

H1: A long-run relationship within an ETF-index pair exists and can be explained using the proposed error correction model.

The Engle-Granger procedure will be used as a filter to determine which ETF-index pairs will be analyzed by the proposed model 1. The python script performs the analysis on all pairs – therefore, even though the analysis results are reported for all pairs, only the pairs that pass the Engle-Granger test will have their results interpreted.

2.2.2 Hypothesis 2: Tracking error factors

While different tracking error definitions may produce different tracking error series, the dynamics of acquired series should exhibit movement around the underlying instrument's dynamics if we can assume that hypothesis 1 holds and that a long-run equilibrium exists. The next logical step is to try to explain variation in the movement of cointegrated variables. An approach to such an analysis is called *factor analysis*.

The aim of this hypothesis is to explore common factors that are often attributed to price dynamics (e.g. volume and volatility). Different factors can differently affect observed tracking errors, and therefore different authors explore different factors. Research on this topic can be divided into two main camps. While some researchers explore the inclusion of classic technical factors such as volume and volatility (Qadan & Yagil, 2012) other researchers explore more instrument- and market-specific factors such as transaction and rebalancing costs, cash drag, dividend taxation, dividend reinvestment assumptions, etc. (Johnson, Bioy, Kellett, & Davidson, 2013).

The work that proposes the framework for this analysis (Qadan & Yagil, 2012) defines model (that analyzes factors behind tracking errors. More precisely, the equation models absolute gap between daily returns of the underlying index and the ETF on a daily basis. The model factor specification includes volume and variance of the ETF. Additionally, a world dynamics factor is also included in order to capture diversification effects, however, that factor is connected with hypothesis 3 and is therefore not examined in this section.

$$|\mathrm{GAP}_t| = \phi_0 + \phi_1\, \Delta \mathrm{WI}_t + \phi_2 \Delta \mathrm{V}_t + \phi_3 \sigma_t + \mathrm{u}_t, \tag{5}$$

A full explanation of model (is available in section 2.3.2. The expected coefficient signs returned by the analysis positively link faster and more intense changes in prices (increased volatility) to absolute tracking errors (absolute amplification of tracking errors), and negatively link market activity (volume) to absolute tracking errors. The volatility link is expected to be positive due to a less predictable price discovery mechanism in times of higher uncertainty while the volume link is expected to be negative due to information availability (Blume, Easley, & O'hara, 1994).

Final full formulation of the hypothesis:

H2: Tracking errors are positively correlated with index volatility and negatively correlated with changes in market activity (volume).

2.2.3 Hypothesis 3: Diversification benefits

An exchange-traded funds is an instrument broadly related to a mutual fund in terms of certain characteristics. One of the claims that ETF issuers often put forward is a diversification benefit of the instrument because an investor can be exposed to a broader set of assets within an ETF. The ETF therefore disperses investment risk into several moving parts within the instrument. However, a certain kind of an ETF is also present on the market – the so-called *international ETFs* are ETFs which trade on a domestic market but track foreign indices (or rather foreign performance). Research regarding international ETFs has shown that international ETFs may trade with a significant premium and may therefore not prove as an effective instrument in term of offered diversification benefits to a domestic investor who is in search of foreign exposure and foreign dynamics (Delcoure & Zhong, 2007). In this thesis, only domestic ETFs are analyzed.

This hypothesis is focused on the diversification benefit captured by the world dynamics component in model 2:

$$|\mathrm{GAP_t}| = \phi_0 + \phi_1\,\Delta\mathrm{WI_t} + \phi_2\Delta\mathrm{V_t} + \phi_3\sigma_\mathrm{t} + \mathrm{u_t}, \tag{6}$$

The model specifies the movement of the MSCI World index as an explanatory variable (ΔWI) in the regression analysis of the absolute gap between the return of the ETF and the return of the underlying index. The rationale for the inclusion of this variable lies in the proposition by the Qadan & Yagil (2012) article which connects diversification benefits to a master index. In the case of Qadan & Yagil, this task was achieved by including the S&P 500 index since the original analysis was performed on a sub-index basis (industry sub-indices within the S&P 500 index). A juxtaposition of the taken approach and the approach by Qadan & Yagil would therefore imply that the *master* market index in the case of a global analysis (in contrast to a local analysis) requires an inclusion of a world index. The research question that arises from this change is therefore of an empirical and theoretical nature.

This thesis is only focused on the empirical part – the main goal of the inclusion of this variable is to identify diversification benefits of ETFs on a global scale. Similar to the analysis performed by Qadan & Yagil, a statistically significant coefficient would imply limited diversification benefits. This is due to the fact that such a coefficient implies the ability of the world index to affect the ETF price. Due to the fact that western markets are larger and historically more pronounced in terms of financial instruments and the overall level of development, it would be sensible to expect a higher degree of integration and therefore a lower diversification benefit.

Final full formulation of the hypothesis:

H3: ETFs based in the western markets exhibit less diversification benefits.

2.2.4 Hypothesis 4: Market efficiency

The final hypothesis is less empirical as it summarizes hypotheses 1-3 into a coherent summarization in order to draw conclusions about individual global market characteristics. Such a generalized conclusion can be made since selected ETF pairs reflect different indices and therefore different parts of the world. Any observed differences could be attributed to a number of factors – e.g. different regulatory framework, consumer behavior, tax regulation etc. Efficient market in this sense is applied as an identifier for expected market behavior. The main approach is to identify positive and negative characteristics of individual hypotheses:

1. Regarding hypothesis 1, an "efficient market" would be identified by a cointegrated process of returns and low differences between model 1 results.
2. Regarding hypothesis 2, an "efficient market" would be interpreted as consistency of factors with the theory (expected coefficient signs).
3. Regarding hypothesis 3, an "inefficient market" would be characterized by the presence of investor sentiments (insignificant world market effect and significant intercept coefficient) (Qadan & Yagil, 2012).

Final full formulation of the hypothesis:

H4: ETFs based in western markets are more efficient.

2.3 Methodology

The topics above are further explored end evaluated by an empirical approach. I employ an econometric method developed by Qadan & Yagil (2012) that differs in the dataset and in the environment. While the original article focuses on a domestic market – namely, the S&P 500 market, my approach takes the developed technique to a global setting where I employ it to better understand and model differences between multiple world markets. This section discloses data sources and the modelling procedure in full detail. The estimator and the required econometric testing are further disclosed in section 2.7.

2.3.1 Data sources

The preliminary dataset was constructed using data downloaded from Yahoo Finance. Due to low data quality and data inconsistencies, the original dataset was later upgraded to one constructed using data acquired from a Bloomberg terminal. The data used in the analysis is of the standard OHLCV (day's open, high, low and close price, and volume) form that includes price information on the daily open, high, low, close, and volume. Data is adjusted for any stock splits and dividends. Official ETF regulatory information (KIID – key investor information documents) regarding each individual instrument was obtained from the official ETF webpages that are listed in the sources.

In total, the empirical part encompasses 10 ETF-index pairs. These 10 pairs consist of 10 ETFs which provide exposure – or tracking – relative to 10 indices they try to replicate the movement of. In addition to that, as it has already been mentioned, the analysis employs the MSCI World index which is used in model 2 as an explanatory variable for world market dynamics, and steps-in for the diversification benefit analysis.

The MSCI World index is presented in-depth in section 0. Individual pairs are listed and presented in section 2.4. Relevant pair/individual plots and statistics are presented in section 2.6.

2.3.2 Econometric models

This section is intended to expand on the models briefly presented in the research objective sections of the thesis (presentation of hypotheses). Both selected models are fully explained, and all included variables are fully defined in order to provide a complete and transparent description of the employed methodology regarding econometric modelling with respect to selected topic of research and defined research objectives that can be found in sections 2.1 and 2.2.

The thesis approaches the topic of research with two proposed models. The first model (1) is an error correction model; its form is as proposed by Engle & Granger (1987) and stands as employed by Qadan & Yagil in their 2012 article. The model expands on the co-integration analysis and proposes a model that explains the error-correction mechanism present in a cointegrated process of two variables. Qadan & Yagil therefore conclude that such a model is suitable for a long-run relationship (equilibrium) estimation and analysis as the two input variables should not drift apart given that they are cointegrated. Additionally, the authors list a number of economic areas (ranging from finance to macroeconomic variables) in which such an approach was deemed appropriate. Furthermore, Qadan & Yagil find such a model to be an appropriate tool to explore Fama's efficient market hypothesis (Fama, Efficient capital markets: II, 1991) as the proposed model form implies absence of profitable arbitrage opportunities in the long-run.

Model 1 is therefore a model that combines two variables that are not stationary into a combination of the following variables for each ETF-index pair:

$$\Delta \mathrm{ETF_t} = \beta_0 + \beta_1 \Delta \mathrm{UI_t} + \beta_2(\mathrm{UI_{t-1}} - \mathrm{ETF_{t-1}}) + \varepsilon_t \tag{7}$$

ΔETF and ΔUI are nature logs of returns of a selected ETF and its underlying index time series. Both variables need to be stationary – integrated of order I(0). The third variable is a lagged (1-day lag) difference in prices between the underlying index and the ETF. Model 1 includes 3 coefficients; β_0 is the intercept, β_1 is the tracking coefficient between the underlying and the ETF, and β_2 is the error correction coefficient. ε_t is the error term and is also assumed to be I(0). Again, both variables employed in this model are in natural logs. This difference between observed prices is also labeled as:

$$\mathrm{DIFF_{t-1}} = \mathrm{UI_{t-1}} - \mathrm{ETF_{t-1}} \tag{8}$$

The second model employed in the analysis is model 2 as defined by Qadan & Yagil (2012). This model is a factor model that connects the absolute gap between the ETF and the underlying index's returns (in natural logarithms) with the world index returns (in natural logarithm), volume of the ETF (natural log), and daily volatility (σ).

$$|\mathrm{GAP_t}| = \phi_0 + \phi_1 \Delta \mathrm{WI_t} + \phi_2 \mathrm{V_t} + \phi_3 \sigma_t + \mathrm{u_t}, \tag{9}$$

where

$$|\mathrm{GAP_t}| = |\, \Delta \mathrm{ETF_t} - \Delta \mathrm{UI_t}| \tag{10}$$

The model specifies 4 coefficients. ϕ_0 is the intercept, ϕ_1 is the impact of the world market on the absolute gap (a proxy measure of ETF performance), ϕ_2 measures the impact of volume (information flows – pricing mechanism), and ϕ_3 is the volatility impact coefficient.

For this model, Qadan & Yagil use de-trended volume which is implemented in this thesis using a locally weighted scatterplot smoothing moving regression (LOWESS). The estimated trend that is returned from the LOWESS algorithm function is subtracted from the original ETF volume time series. The LOWESS algorithm is further explained in chapter 2.7.2. Daily volatility is defined as:

$$\sigma_t = \ln \frac{\mathrm{HighP_t}}{\mathrm{LowP_t}} \tag{11}$$

Where *high* and *low* are the OHLCV equivalents of the daily highest prices and the daily lowest price of the ETF on the market.

2.4 Selected ETF and index pairs

Table 1 presents the selected ETF and index pairs and lists their respective geographical location denoted in ISO2 country codes. All sources for KIIDs regarding the ETFs listed below are available in the sources list.

Most of the globally recognized major indices have been selected for the analysis. However, due to poor data quality and data availability, no indices from Latin America and Africa were selected for the analysis. Additionally, Australian indices have also been dropped from the analysis. Although the data for those indices was imported and initial analysis steps were taken, I decided not to report on the taken steps and figures because the analysis could not continue due to major data inconsistencies that would only result in dropped series. In order to provide a more consistent approach, the tracking ETFs that were selected for this analysis are, if possible, from a single provider (iShares).

Table 1: Selected ETF and index pairs

Index	ETF	Location
S&P 500	iShares Core S&P 500 ETF	US
Dow 30	iShares Dow Jones U.S. ETF	US
Russell 2000	iShares Russell 2000 ETF	US
FTSE 100	iShares Core FTSE 100 UCITS ETF	EU
DAX Performance-Index	iShares Core DAX UCITS ETF	EU
STOXX 50	iShares Core EURO STOXX 50 UCITS ETF EUR	EU
Nikkei 225	iShares Core Nikkei 225 ETF	JP
Hang Seng Index	Tracker Fund of Hong Kong	HK
SSE Composite Index	Fullgoal SSE Composite Index ETF	CN
FTSE Straits Times Index	SPDR Straits Times Index ETF	SG

Source: Bloomberg L.P. (2020).

Selected pairs represent a mix between western markets (US, EU) and eastern markets (JP, HK, CN, SG). The reason for this selection is to try and potentially capture western versus eastern market differences. Any differences that may arise in the results will be explored by hypothesis 4.

As it has already been mentioned, the selection differs from the original article by Qadan & Yagil by switching from a sub-index basis to the global index view. The original article explores the performance of different industrial sectors relative to their respective iShares

ETFs within the S&P 500 index while the analysis performed in this thesis is done, as evident above, on a global scale – from the global perspective.

Tables 2 and 3 list the tickers and the corresponding indices or ETFs. Listed tickers are also used in the following sections as shorthand labels when referring to a security or a pair in order to conserve space. Because Bloomberg (the data provider for this dataset) is based in New York City (NYC), their internal ticker assignment convention additionally appends two-letter geographical codes to foreign equity tickers.

Table 2: Index tickers

Ticker	Full index name
SPX	S&P 500
DJUST	Dow 30
RU20INTR	Russell 2000
UKX	FTSE 100
DAX	DAX Performance-Index
SX5E	STOXX 50
NKY	Nikkei 225
HSI	Hang Seng Index
SHCOMP	SSE Composite Index
STI	FTSE Straits Times Index

Source: Bloomberg L.P. (2020).

Table 3: ETF tickers

Ticker	Full ETF name	Location	Currency
IVV	iShares Core S&P 500 ETF	NYC	USD
IYY	iShares Dow Jones U.S. ETF	NYC	USD
IWM	iShares Russell 2000 ETF	NYC	USD
ISF LN	iShares Core FTSE 100 UCITS ETF	London	GBP
DAXEX GY	iShares Core DAX UCITS ETF	Frankfurt	EUR
EUN2 GY	iShares Core EURO STOXX 50 UCITS ETF EUR	Frankfurt	EUR
1329 JT	iShares Core Nikkei 225 ETF	Tokyo	JPY
2800 HK	Tracker Fund of Hong Kong	Hong Kong	HKD
510210 CH	Fullgoal SSE Composite Index ETF	Shanghai	CNY
STFF SP	SPDR Straits Times Index ETF	Singapore	SGD

Source: Bloomberg L.P. (2020).

2.5 Inclusion of the world index

In order to apply the proposed methodology, a global index had to be included in the analysis to capture the *master* dynamic. As the mentioned article employs the actual S&P 500 index and performs the analysis on a sub-index level, this thesis requires – by that definition in order to analyze world indices - a global index in order to capture *master* dynamics. The validity of this proposition is tested by hypothesis 3 which compares the results acquired by the original authors to the results produced by this analysis, but this is only performed on an analytical level, and not on a theoretical level. The actual discussion whether this is an appropriate choice remains open to interpretation.

Figure 14 plots the movement of the MSCI World index from the year 2000 up until March 2020. The appropriate timeframe window was cut from the available MSCI World index time series for each individual pair in regression model 2.

Figure 14: MSCI World Index 2000-2020

Source: Bloomberg L.P. (2020).

2.6 Descriptive statistics

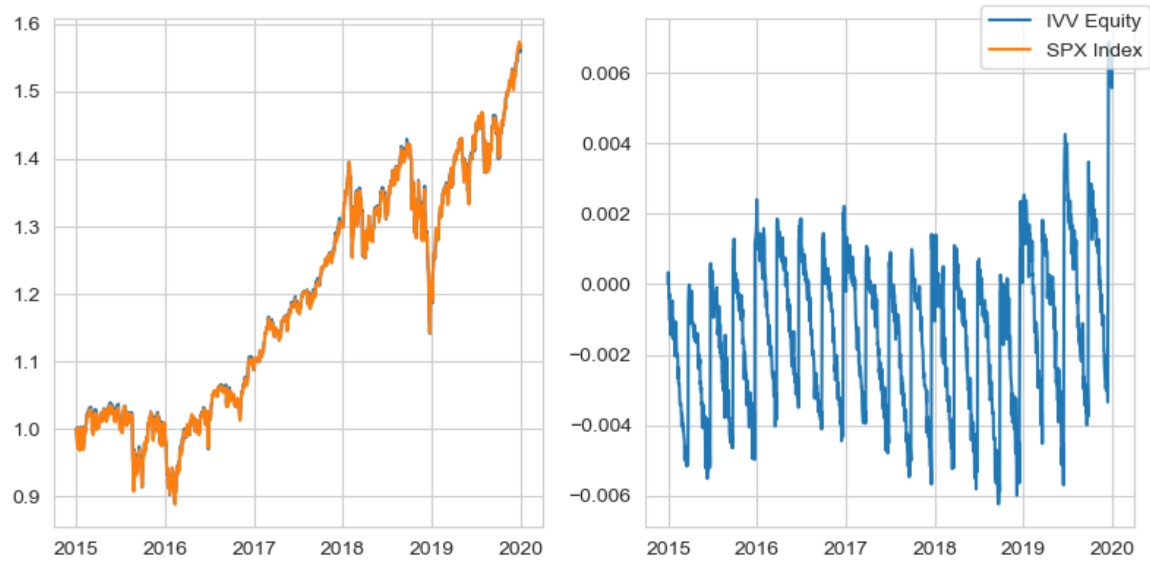
The selected time frame starts on 1/1/2015 and ends on 1/1/2020 making the dataset essentially 5 years long. The frequency of the data is daily, and calculations are performed on natural logs of prices or returns (natural log differences).

Figures 15-24 present price dynamics for the observed ETF-index pairs (as listed in section 2.4) for the observed time period of 5 years (2015-2020). Additional plots of individual log returns and returns distributions (kernel density plots) can be found in the appendix. In this section, one can also find individual security's and index descriptive statistics for the observed period.

2.6.1 ETF-index pairs

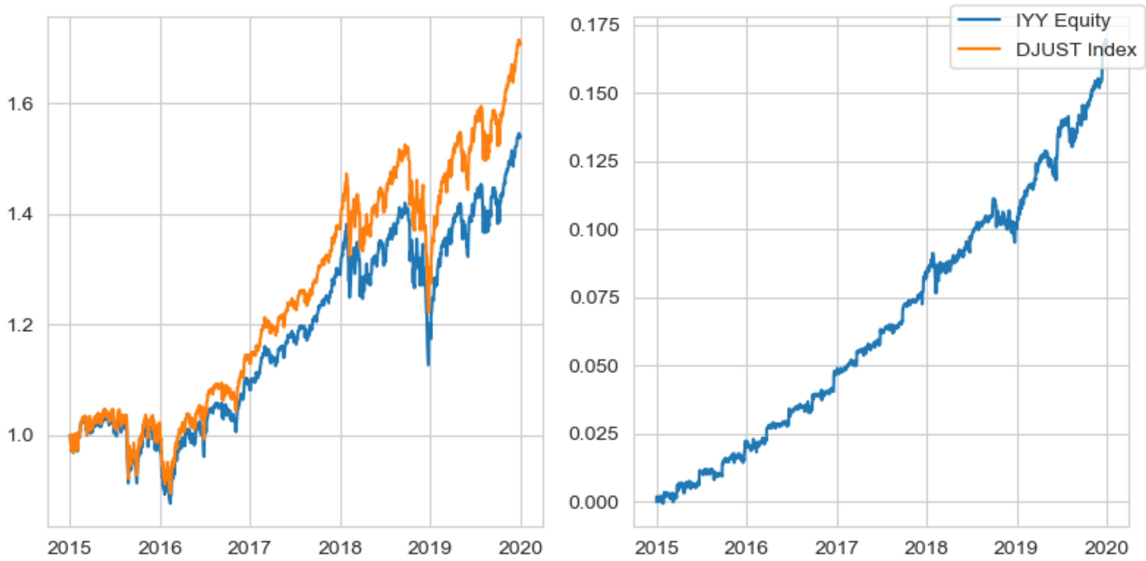
The following plots present a comparison between the ETF and the underlying index (index transformation, 2015=1). For each comparison, the right plot shows the difference between the two series.

Figure 15: Price comparison between IVV and S&P 500 (2015-2020)



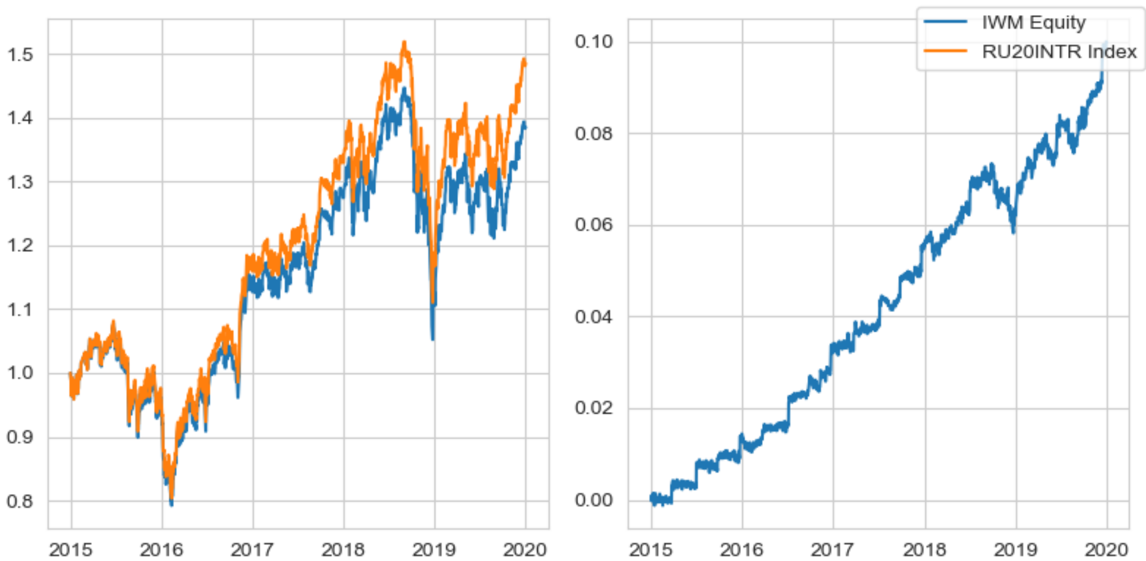
Source: Bloomberg L.P. (2020).

Figure 16: Price comparison between IYY and Dow Jones (2015-2020)



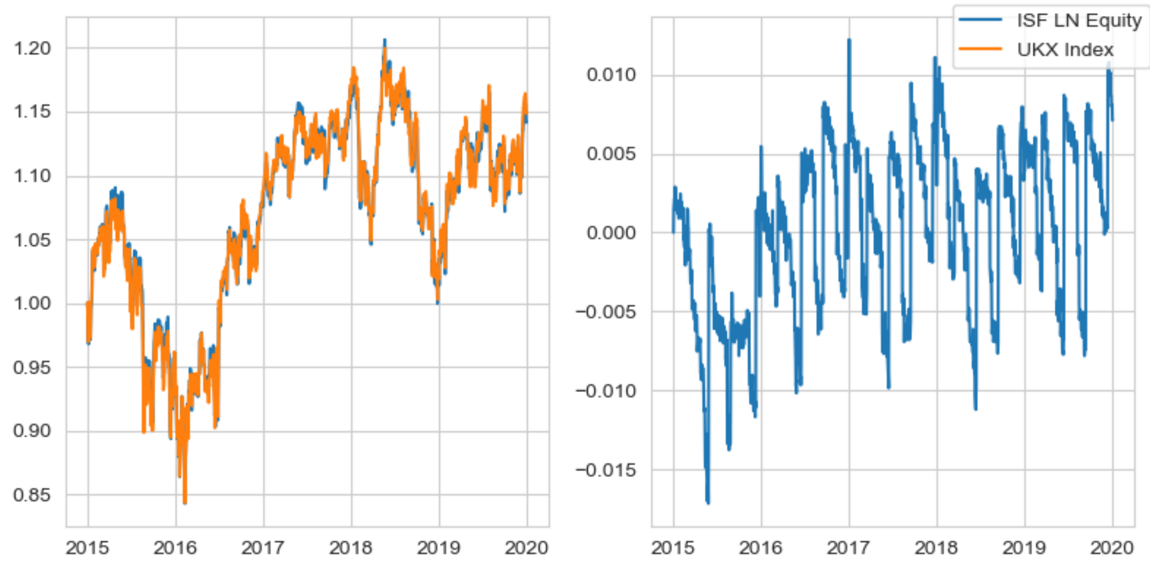
Source: Bloomberg L.P. (2020).

Figure 17: Price comparison between IWM and Russell 2000 (2015-2020)



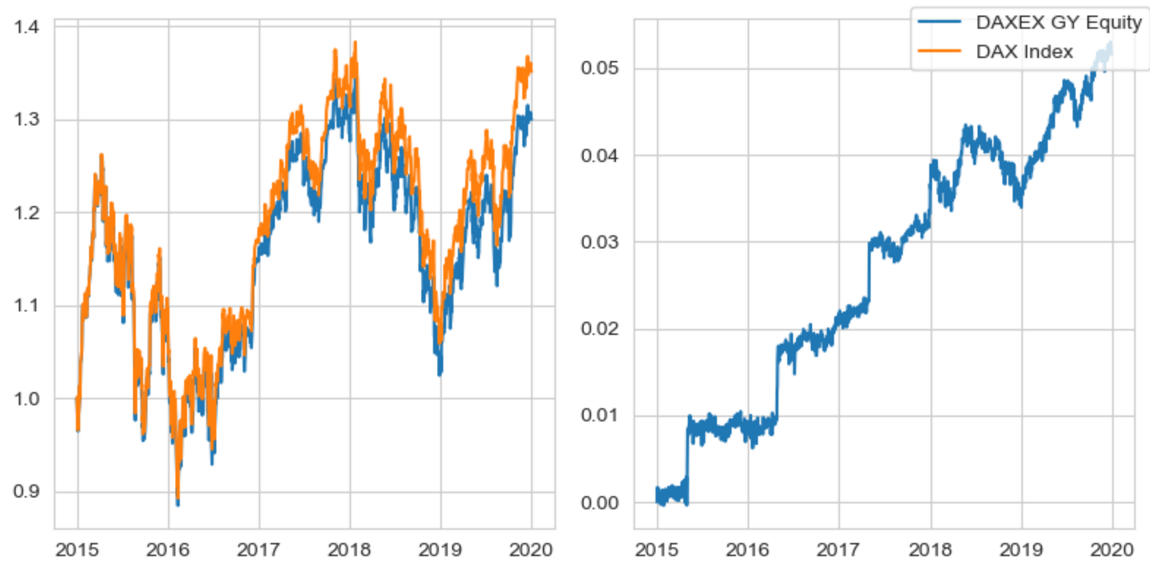
Source: Bloomberg L.P. (2020).

Figure 18: Price comparison between ISF (London) and FTSE 100 (2015-2020)



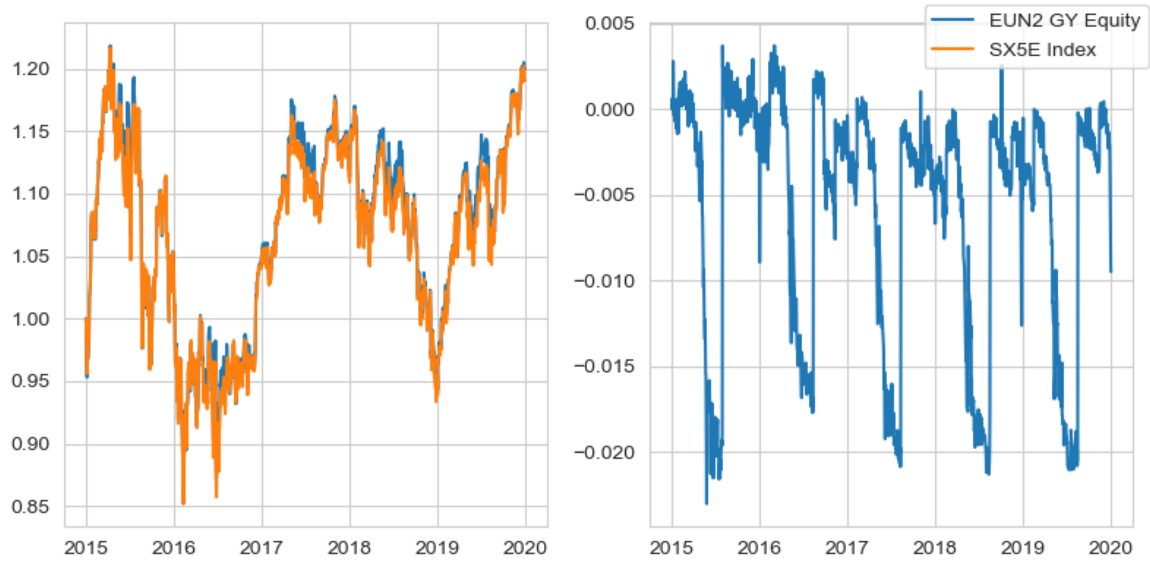
Source: Bloomberg L.P. (2020).

Figure 19: Price comparison between DAXEX (Frankfurt) and DAX (2015-2020)



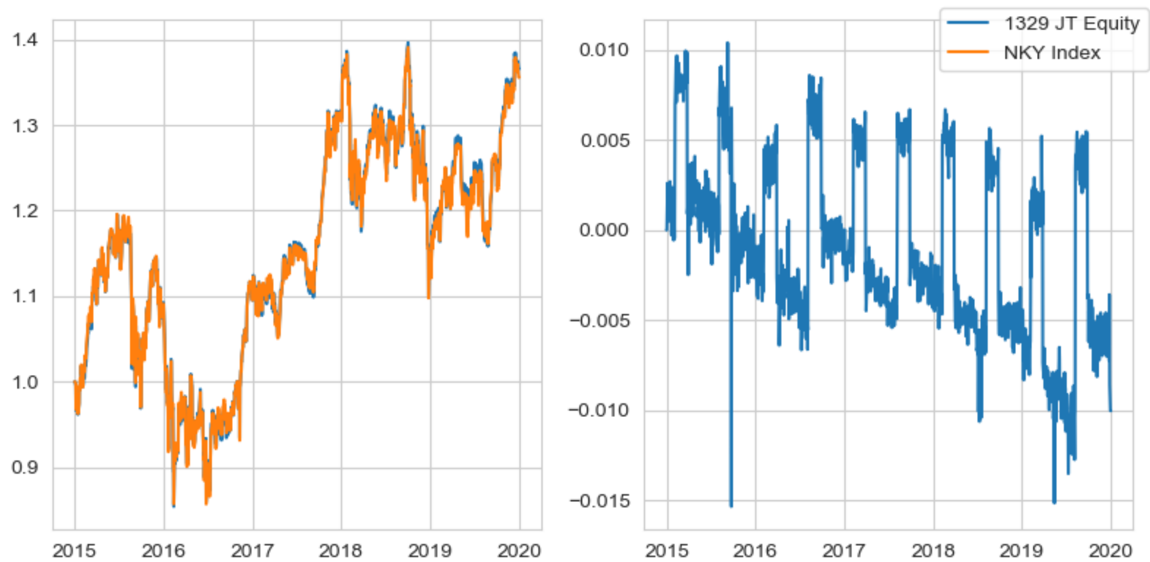
Source: Bloomberg L.P. (2020).

Figure 20: Price comparison between EUN2 (Frankfurt) and Euro Stoxx 500 (2015-2020)



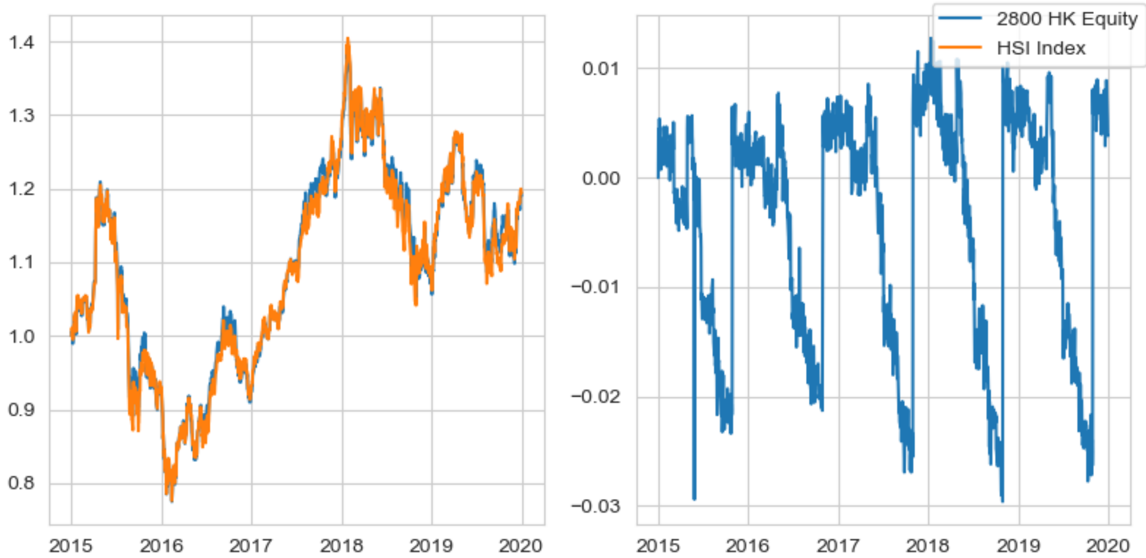
Source: Bloomberg L.P. (2020).

Figure 21: Price comparison between 1329 (Tokyo) and Nikkei (2015-2020)



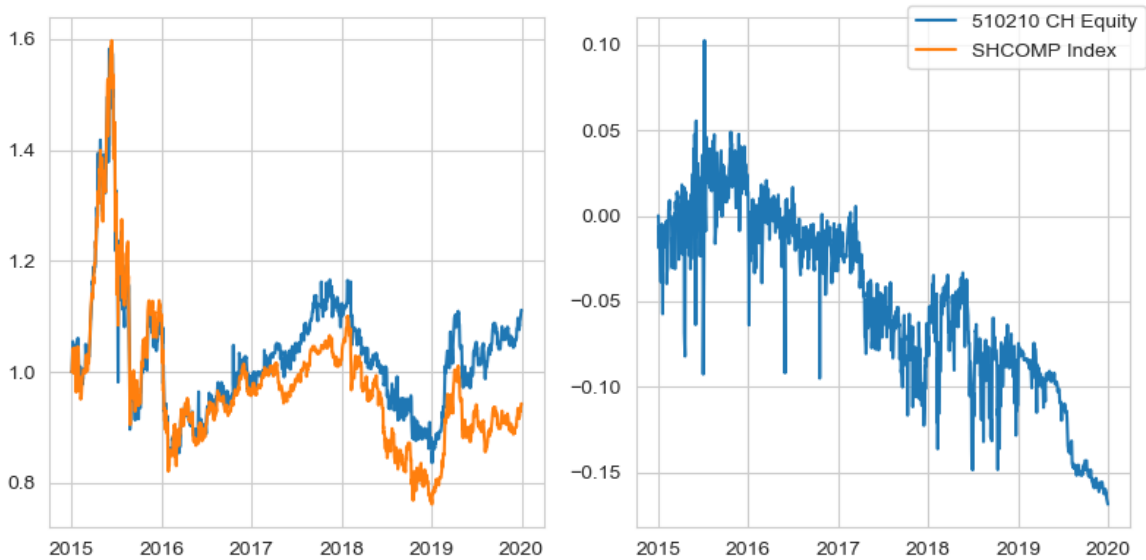
Source: Bloomberg L.P. (2020).

Figure 22: Price comparison between 2800 (Hong Kong) and Hang Seng (2015-2020)



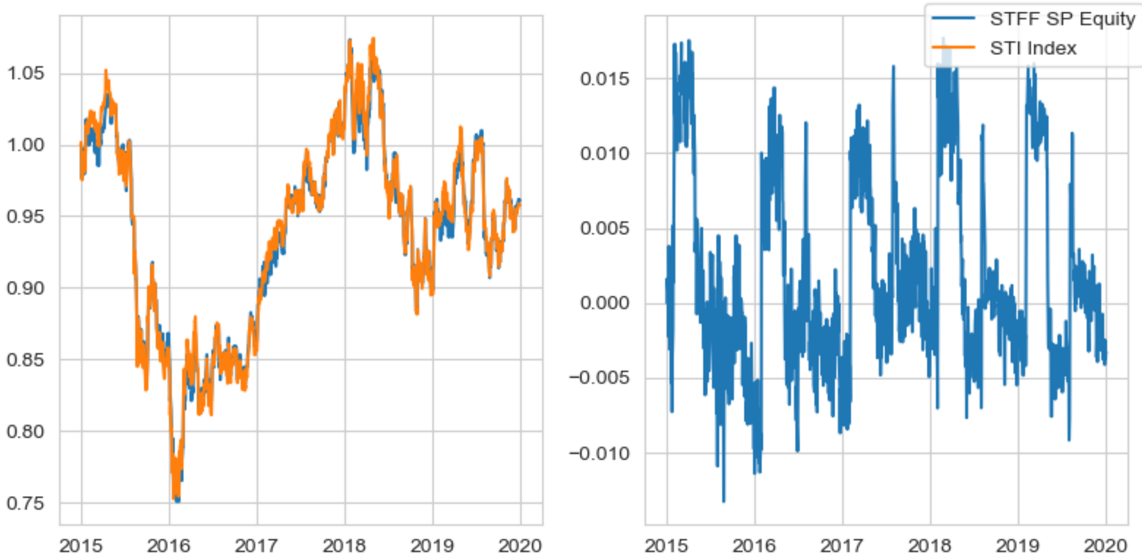
Source: Bloomberg L.P. (2020).

Figure 23: Price comparison between 510210 (Shanghai) and Shanghai Composite (2015-2020)



Source: Bloomberg L.P. (2020).

Figure 24: Price comparison between STFF (Singapore) and Straits Times (2015-2020)



Source: Bloomberg L.P. (2020).

2.6.2 Index descriptive statistics

The sample consists of 10 index returns with 1305 observations each. The time frame and frequency correspond to days between 1/1/2015 and 1/1/2020. Tables 4 and 5 present the number of observations, mean, standard deviation, skewness, and kurtosis. While skewness simply measures the symmetry of the returns, kurtosis can give the investor an insight into the possibility of sudden significant price changes.

Table 4: Index returns descriptive statistics

Ticker	N	Mean	Std. dev	Skewness	Kurtosis
SPX	1305	0.000345	0.000069	-0.529884	4.093000
DJUST	1305	0.000411	0.000070	-0.538835	3.926975
RU20INTR	1305	0.000303	0.000103	-0.377716	1.764950
UKX	1305	0.000106	0.000073	-0.217698	2.676234
DAX	1305	0.000231	0.000119	-0.404569	2.824854
SX5E	1305	0.000134	0.000114	-0.645676	5.812893
NKY	1305	0.000233	0.000141	-0.348406	6.770958
HSI	1305	0.000136	0.000117	-0.348377	2.567635
SHCOMP	1305	-0.000045	0.000213	-1.231446	7.618733
STI	1305	-0.000033	0.000054	-0.242221	2.183636

Source: Own work.

2.6.3 ETF descriptive statistics

Table 5: ETF returns descriptive statistics

Ticker	N	Mean	Std. dev	Skewness	Kurtosis
IVV	1305	0.000342	0.000071	-0.541948	4.038181
IYY	1305	0.000332	0.000069	-0.514380	3.807027
IWM	1305	0.000250	0.000102	-0.387522	1.744184
ISF LN	1305	0.000101	0.000075	-0.261741	2.623962
DAXEX GY	1305	0.000201	0.000119	-0.396486	2.711549
EUN2 GY	1305	0.000140	0.000115	-0.696990	6.067937
1329 JT	1305	0.000239	0.000137	-0.415693	6.602356
2800 HK	1305	0.000134	0.000120	-0.345269	2.386626
510210 CH	1305	0.000081	0.000310	-0.399487	8.449132
STFF SP	1305	-0.000031	0.000055	-0.421505	2.232660

Source: Own work.

Again, the sample consists of 10 ETF returns with 1305 observations. Table 5 presents descriptive statistics for the observed ETFs. Given the nature of instruments' replicational function, the reported statistics should be in the vicinity of the figures presented in table 4. In general, observed ETFs show statistics that are relatively close to their respective index they track. This is especially true for western ETFs (IVV, IYY, IWM, ISF LN, DAXEX GY, EUN2 GY) as their standard deviation is closer to the standard deviation of the index they track. Notice how the Chinese pair (Shanghai Composite, 510210 CH) shows major deviations in the process (highlighted). Backtracking to table 4, the Shanghai Composite index itself also shows the highest values of skewness and kurtosis in the selected sample. Its respective price plot can be found in figure 23.

2.7 Estimator and econometric tests

Because this thesis employs a methodology that is based on regression analysis, this chapter briefly outlines the most important parts of the approach. The first subsection briefly touches on the estimators while the second subsection is about the approach taken with respect to the determination of cointegration. The OLS subsection explains the underlying approach but does not dive into full derivation. This also applies for the LOWESS algorithm and the cointegration parts of the chapters.

2.7.1 Estimators

This analysis employs the ordinary least squares (OLS) estimator. Standard OLS assumptions must hold (Greene, 2000). The statistical package employed in this analysis minimizes the log-likelihood (Seabold & Perktold, 2010). Reported coefficients are tested for significance by applying the Student's *t*-test for statistical significance in comparison to 0. Since the procedure operates with a relatively large dataset due to daily frequency of data, and because heteroskedasticity can be expected in large time series data spanning multiple years, MacKinnon and White's (1985) HC3 heteroskedasticity robust standard errors are calculated as

$$\mathrm{HC3} = (\mathrm{X'X})^{-1}\mathrm{X'}\mathrm{diag}\left[\frac{\mathrm{e}_\mathrm{i}^2}{(1-\mathrm{h}_\mathrm{it}^2)}\right]\mathrm{X}(\mathrm{X'X})^{-1} \tag{12}$$

where

$$\mathrm{h}_\mathrm{it} = \mathrm{x}_\mathrm{i}(\mathrm{X'X})^{-1}\mathrm{x}_\mathrm{i}' \tag{13}$$

2.7.2 De-trending using LOWESS

(Robust) locally weighted regression and smoothing scatterplots (known as LOWESS) is a smoothing algorithm which estimates a smooth trend around data points. Localized subsets of data are determined by the algorithm in order to fit nonlinear data trends. The method is classified as a non-parametric regression method and is also often known as *moving regression*.

De-trending of ETF volume data is performed using the LOWESS function in order to determine the trend of the data series. The resulting locally estimated trend is then subtracted from the original volume time series. The final time series is therefore de-trended and represents deviations from estimated local trend points. This method is preferred to simple moving averages since no data is lost in the head of the time series, and no alignment discrepancies form as the moving average method trails and smooths over large changes over a linear time scale. The moving regression algorithm avoids such discrepancies by implementing a tricube criteria function which, if not satisfied, will split the time series into more local subsets until the criteria is satisfied. The resulting estimated trend runs across the whole time series and is able to address large swings (Cleveland, 1979).

2.7.3 Cointegration tests

Cointegration is a required element of the pair's price movements to assure that the underlying index and the ETF prices exhibit a long-run equilibrium. In general, integrated variables are said to be cointegrated when the resulting regression of the two variables return stationary residuals. This can be expressed in the following manner in a basic scope of two variables given a regression:

$$y_t = \beta x_t + u_t \tag{14}$$

Inclusion of a constant and a trend term can also be assumed and implemented into modelling. The process is cointegrated if the error term of the regression above is stationary:

$$u_t = \beta x_t - y_t \tag{15}$$

Stationarity of the error term can be tested using the (augmented) Dickey-Fuller test (ADF). Under the null hypothesis, the ADF will test for the presence of a unit root. Rejecting the null hypothesis can imply stationarity of the process (Byrne & Perman, 2006):

$$\Delta y_t = \rho y_{t-1} + \sum_{j=1}^{p-1} \gamma y_{t-j} + \mu_t + u_t \tag{16}$$

Therefore, cointegration can be assumed if one can assert stationarity of the residuals. The two-step approach outlined above is based on the original cointegration paper (Engle & Granger, 1987) and is the procedure employed in the first step of the analysis. For the purposes of this analysis, the optimal lag length was determined using BIC (*Bayesian information criterion*; also known as the *Schwarz information criterion*). Additionally, the first step of the process includes a constant and a trend term. The lag order is selected by (Lütkepohl, 2007):

$$SC(m) = \ln\left|\tilde{\Sigma}(m)\right| + \frac{\ln(T)}{T} mK^2 \tag{17}$$

where the selected model minimizes:

$$m_{selected} = \arg\min_{m}\ SC(m) \tag{18}$$

3 RESULTS

This thesis explores the landscape of exchange-traded funds on a global level by comparing tracking errors through the view of the analytical framework that was described in the previous chapter. The final part of this analysis is the interpretation of the results of econometric tests and both models.

Following the outline set out above, the analysis begins by performing econometric tests on the data that serve as inputs. Before testing for the presence of cointegration using the Engle-Granger test, the data is tested whether it is properly specified using the augmented Dickey-Fuller test. Next, both models are estimated. The results are presented and interpreted for each model separately with provided additional commentary regarding the connection between model results and hypotheses. A direct interpretation from the standpoint of hypotheses validity follows, and finally, a short discussion on the selection of world indices, sample bias and alternative interpretations of the results concludes this chapter and the analysis.

3.1 Econometric tests

Econometric tests are required in order to determine whether time series exhibit expected forms that are required by the methodology described in section 2.3. One of the requirements is that time series that enter the modelling phase must be stationary. Stationarity is required for all variables in equations 1 & 2:

$$\Delta \mathrm{ETF_t} = \beta_0 + \beta_1 \Delta \mathrm{UI_t} + \beta_2 \mathrm{DIFF_{t-1}} + \varepsilon_t \tag{19}$$

$$|\mathrm{GAP_t}| = \phi_0 + \phi_1 \Delta \mathrm{WI_t} + \phi_2 \Delta \mathrm{V_t} + \phi_3 \sigma_t + u_t \tag{20}$$

Table 6 presents the results of the augmented Dickey-Fuller test (ADF) for all included variables for each pair. Pairs are denoted by the Bloomberg ticker symbol of the ETF. Tables 1 and 3 can also be used for reference. The following variables are tested for stationarity by the ADF test for each pair: returns of the ETF and the underlying index, the difference between log prices, the absolute gap in returns, volatility, and de-trended volume of the ETF. The included variables correspond to calculations from log prices as described in section 2.3. Under the null hypothesis, the ADF procedure tests for non-stationarity. Reported statistics are p-values where a p-value of ≤ 0.05 implies a rejection of the null hypothesis of non-stationarity; meaning, the time series is likely stationary.

Table 6: Augmented Dickey-Fuller test (p-values)

P-value	ETF	UI	ΔETF	ΔUI	DIFF	|GAP|	σ	ΔV
IVV	0.112	0.126	0.000	0.000	0.000	0.000	0.000	0.000
IYY	0.127	0.16	0.000	0.000	0.000	0.000	0.000	0.000
IWM	0.309	0.296	0.000	0.000	0.000	0.000	0.000	0.000
ISF LN	0.278	0.294	0.000	0.000	0.000	0.000	0.000	0.000
DAXEX GY	0.308	0.31	0.000	0.000	0.042	0.000	0.000	0.000
EUN2 GY	0.289	0.28	0.000	0.000	0.006	0.000	0.000	0.000
1329 JT	0.301	0.349	0.000	0.000	0.000	0.000	0.000	0.000
2800 HK	0.617	0.635	0.000	0.000	0.024	0.000	0.000	0.000
510210 CH	0.107	0.076	0.000	0.000	0.000	0.000	0.000	0.080
STFF SP	0.502	0.558	0.000	0.000	0.002	0.000	0.000	0.000
MSCI World	n.a.	0.208	n.a.	0.000	n.a.	n.a.	n.a.	n.a.

Source: Own work.

ADF test results can be found in Table 6. We can see that almost all included time series do not reject the null reject the null hypothesis of non-stationarity in level form but do reject the null when levels are transformed to log returns. Transformed variables are thus acceptable for modelling purposes. The only time series that does not reject the null is the detrended volume of the Chinese tracker ETF in Shanghai at p-value of 0.08 (510210 CH). This ETF has already been put under the spotlight in the descriptive analysis part (section 2.6) for highest standard deviation and kurtosis. Even though these results may shine a light on certain aspects of the Chinese vs. western markets, these implications will not be explored further since they are not a part of this thesis' research topic. Non-stationarity is not rejected probably due to an unusual spike in the trading activity of the ETF that appears on 22/7/2019 and the LOESSS de-trending algorithm that tries to deal with the anomaly. Additional transformations for the series at hand that would impact the stationarity test results are not pursued, and any results arising from the use of the problematic de-trended volume will be reported as such and used with caution.

Table 7 presents the results for Engle-Granger co-integration tests in terms of the test's p-values for the time series of ETF-index pairs. To conclude that cointegration between the two series may be present, our objective is to reject the null hypothesis of no cointegration. Most pairs successfully reject the null hypothesis of no cointegration with two exceptions. The German pair (DAXEX GY) has the highest p-value of 0.0917 which implies that we cannot reject the null hypothesis of no co-integration. The only other pair that does not pass this part of the econometric procedure is the Hong Kongese pair (2800 HK) as the p-value is above 0.05.

Table 7: Engle-Granger co-integration test (p-values)

ETF	Index	P-value
IVV	SPX	0.0000
IYY	DJUST	0.0000
IWM	RU20INTR	0.0000
ISF LN	UKX	0.0000
DAXEX GY	DAX	0.0917
EUN2 GY	SX5E	0.0180
1329 JT	NKY	0.0000
2800 HK	HSI	0.0663
510210 CH	SHCOMP	0.0000
STFF SP	STI	0.0001

Source: Own work.

The following conclusions and decisions can be made from the econometric step of the thesis:

1. Regarding the appropriateness of the inclusion of variables and variable specification tested by the ADF test, the Chinese ETF de-trended trading activity poses a minor specification problem that is noted. Further interpretation of results that stem from the use of this series will be approached with caution.

2. Regarding the basic test for presence of cointegration tested by the Engle-Granger procedure, the German and the Hong Kongese ETF-index pairs will be excluded from the interpretation of modelling results.

3.2 Model 1 results

In order to explore the long-run relationship between a pair's ETF returns with respect to the returns of the underlying index, a cointegrating error correction model is estimated (Qadan & Yagil, 2012).

Again, model 1 is defined as:

$$\Delta \mathrm{ETF_t} = \beta_0 + \beta_1 \Delta \mathrm{UI_t} + \beta_2 \mathrm{DIFF_{t-1}} + \varepsilon_t \tag{21}$$

Where the ΔETF_t and ΔUI_t are log returns of the ETF and the underlying index in a pair, and $DIFF_{t-1}$ is the difference in the log prices between the ETF and UI from the previous trading day. Model 1 is formulated after the work of Engle & Granger (1987) and corresponds only to the error correction model (also sometimes referred to as the error correction mechanism) – the first step of the two-step procedure. The second step is not performed here, as the whole procedure has already been applied in the previous section in determination of possible exclusion of pairs' model 1 and 2 results from the interpretation. The reason for such a method is in that the *statsmodels* library's (the main statistical modelling library for Python) *statsmodels.tsa.stattools.coint* function does not report error correction model coefficients nor does it report any results on the regression model that is running in the background, but rather only the final results (p-values) of the cointegration test. Therefore, model 1 is manually constructed and estimated for each pair while accepting the actual cointegration test results from the Engle-Granger test itself. This enables us to better understand the relationship, and not only test it for the existence of a long-run relationship. The two-step procedure could be continued manually by performing the ADF test on the residual of the regression.

Table 8 reports estimated model coefficients and their significance as measured by a t-test using HC3 robust standard errors. The level of significance is denoted using asterisks. The table reports estimated parameters for model 1 – each pair (denoted by the Bloomberg ETF ticker; refer to table 3) in each column. Additionally, as it has already been pointed out, the German and the Hong Kongese ETF-index pairs are excluded from the interpretation due to poor Engle-Granger cointegration test performance. Regarding the Chinese pair in this section, the pair is fully interpreted as all the variables that enter model 1 are stationary. Again, the dataset runs from 1/1/2015 to 1/1/2020 which translates to 1304 total observations.

Table 8: Model 1 regression results

	Dependent variable:									
	IVV	IYY	IWM	ISF LN	DAXEX GY	EUN2 GY	1329 JT	2800 HK	510210 CH	STFF SP
β_0 Const.	-0.19***	-0.001	-0.002	-0.124***	-0.012	-0.145***	0.002***	-0.288***	-0.219***	-0.671***
	(0.037)	(0.002)	(0.004)	(0.027)	(0.009)	(0.047)	(0.0)	(0.085)	(0.049)	(0.089)
β_1 Return UI	1.004***	0.989***	0.995***	0.994***	0.999***	0.989***	0.977***	0.978***	0.764***	0.927***
	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)	(0.005)	(0.005)	(0.008)	(0.047)	(0.015)
β_2 DIFF (t-1)	0.083***	0.0	0.001	0.054***	0.003	0.032***	0.08***	0.042***	0.032***	0.097***
	(0.016)	(0.001)	(0.001)	(0.012)	(0.002)	(0.01)	(0.018)	(0.012)	(0.007)	(0.013)
Observations	1304.0	1304.0	1304.0	1304.0	1304.0	1304.0	1304.0	1304.0	1304.0	1304.0
R^2	0.992	0.987	0.994	0.965	0.996	0.977	0.981	0.935	0.41	0.852
Adjusted R^2	0.992	0.987	0.994	0.965	0.996	0.977	0.981	0.935	0.409	0.851
Resid. Std. Err.	0.001	0.001	0.001	0.002	0.001	0.002	0.002	0.003	0.014	0.003
F Statistic	67622.5***	30811.7***	84293.7***	18032.3***	93184.1***	23976.9***	24154.5***	9248.7***	149.0***	1895.6***

Notes: *p<0.1; **p<0.05; ***p<0.01
HC3 robust standard errors.

Source: Own work.

In general, the regression results show quite similar results for ETFs based in western markets with high R^2 (around 0.99) and low residual standard errors (around 0.001 - 0.002). The results for eastern markets show relatively poorer performance with lower R^2. This still holds even if we were to exclude the Chinese market with its highest residual standard error (0.014) and the lowest R^2 from the sample (0.41). The performance of eastern markets is lower *across the board* with the only exception being the Japanese market (1329 JT). Reading the results from table 8 horizontally, β_1 coefficient corresponds to the impact of the underlying index's return on ETF returns. The coefficient is positive and significant for all pairs. This implies that the tracker ETF returns are positively related to the dynamics (returns) of the underlying index the ETF tries to replicate.

Furthermore, these coefficients are very close to value of 1 – if the coefficient is equal to 1, it practically means that the ETF on average perfectly tracks the underlying index. Again, the Chinese pair seems to show the biggest divergence from the result pool with lowest β_1 coefficient indicating that the pricing mechanism is not as efficient. In addition, the Chinese pair's coefficient would be the farthest from 1 in the sample. β_2 coefficient corresponds to the error correction mechanism that arises from *mispricing* of previous day's error in the replication activity of the underlying index's returns and corresponds to investors undertaking corrective arbitrage steps (Qadan & Yagil, 2012). The coefficient is like in the case of Qadan & Yagil – positive for all pairs although not significant for IYY and IWM.

To answer the questions that correspond to hypotheses 1 and 4, the cointegration test excludes 1 western (DAXEX GY) and 1 eastern market (2800 HK). Additionally, inspecting the actual error correction mechanism modelled after Engle & Granger, the regression results and the regression coefficients of the first step in the cointegration analysis show that western markets do seem to perform better in this very limited framework judging by lower errors and higher R^2.

3.3 Model 2 results

Model 2 turns the focus on factors that are expected by Qadan & Yagil (2012) to have a significant impact on the absolute tracking error:

$$|\mathrm{GAP_t}| = \phi_0 + \phi_1\, \Delta \mathrm{WI_t} + \phi_2 \Delta \mathrm{V_t} + \phi_3 \sigma_t + u_t \tag{22}$$

Summarizing the modelling section (2.3.2), the tracking error is in this case defined as the absolute gap between the return series of the ETF and the underlying index. This tracking error is explored using a proposed tracking model (model 2) in order to explore the significance of individual factor impacts on the tracking error. The factor model at hand provides a structure for estimation of regression coefficients for world dynamics, sudden changes in the ETF trading activity and the ETF price volatility. The aim of this method is to simply provide a limited framework in which price and volume data can be analyzed. Therefore, all this analysis pursues with model 2 is not to directly use the factor model in estimation of the tracking error *per se,* but rather to see whether the proposed inclusion of listed factors is justified, significant, and if the factors behave as expected. Furthermore, the coefficients in table 9 have been multiplied by 100 because of the just explained task specifics in order to provide a more readable format that functions better for the needs of this comparison.

Before we take a closer look at model 2 results, I'd like to point out that results provided by Qadan & Yagil for their application of model 2 on a sub-index level show very low R^2 – ranging from 0.06 to 0.66 with most results between 0.10 and 0.20 which is quite low to begin with. I expect my results to be in the same vicinity regarding R^2. Also, it should be noted that the article shows that model 2 performance is not really on par with respect to consistency within industries that are included in their original analysis. In addition to that, results regarding volatility and volume factors show differences between sub-index industry groups. Although, to be fair, the authors did (in addition to a direct comparison of the performance between ETFs) extend the analysis by including a dummy variable for high volatility periods (crisis periods) and conducted a second comparison in that manner. Some divergences from reported results by Qadan & Yagil's article are therefore expected.

Table 9 shows the estimated regression model coefficients and their significance levels as measured by the t-test using HC3 robust standard errors. Again, the columns represent observed ETF-index pairs labelled by the Bloomberg ETF ticker. Due to poor performance in the previous step of the analysis, both the German and the Hong Kongese ETF-index pairs are again excluded from the result interpretation. Additionally, the Chinese pair is also excluded from this part of the analysis due to a probability that de-trended volume series of the 510210 CH ETF is not properly specified since non-stationary has not been rejected. Because this thesis' methodology does not prescribe any possible data remediation steps, the Chinese pair is excluded.

The regression results are – as expected, poor and similar in terms of the performance in comparison to the original article. Reported R^2 for ETF-index pairs range between 0.007 – 0.042 which is *very* low, but to a degree expected if we factor in that on top of the poor results in the original article the approach taken here repositions the whole modelling process from a local sub-index level to a global level with the inclusion of the MSCI World index as a world benchmark for returns in place of the S&P 500 index as was the case in the original work. The mentioned global returns series dynamics (ϕ_1) are shown as significant for 3 out of 7 observed pairs. 2 of these are on the western markets (IVV, IYY) and the remaining 1 is on the Japanese market. The significance of ϕ_1 implies that there exists a limitation to diversification benefits of these ETFs when factoring-in global dynamics as global market shifts still affects their prices. Additionally, the insignificance of this coefficient for the

Table 9: Model 2 regression results

	Dependent variable:									
	IVV	IYY	IWM	ISF LN	DAXEX GY	EUN2 GY	1329 JT	2800 HK	510210 CH	STFF SP
ϕ_0 Const.	0.033***	0.059***	0.051***	0.07***	0.035***	0.062***	0.079***	0.129***	0.224***	0.141***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
ϕ_1 ReturnWrld	-0.561**	-0.898**	-0.229	0.575	-0.209	0.023	0.974*	0.154	1.011	1.562
	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)	(0.007)	(0.005)	(0.009)	(0.043)	(0.011)
ϕ_2 Volume	5.787	9.402	15.786**	11.647*	3.087	1.427	12.383***	10.621	-49.061***	15.752**
	(0.042)	(0.065)	(0.065)	(0.062)	(0.022)	(0.047)	(0.04)	(0.08)	(0.127)	(0.07)
ϕ_3 Volatility	0.612***	-0.01	0.242	1.462*	1.4***	1.843***	1.693**	2.22*	27.74***	8.31***
	(0.001)	(0.015)	(0.004)	(0.009)	(0.002)	(0.005)	(0.007)	(0.012)	(0.022)	(0.027)
Observations	1305.0	1305.0	1305.0	1305.0	1305.0	1305.0	1305.0	1305.0	1305.0	1305.0
R^2	0.021	0.016	0.018	0.007	0.051	0.009	0.028	0.006	0.236	0.042
Adjusted R^2	0.019	0.014	0.016	0.005	0.049	0.007	0.026	0.004	0.235	0.04
Resid. Std. Err.	0.001	0.001	0.001	0.001	0.0	0.001	0.001	0.002	0.01	0.002
F Statistic	14.995***	6.24***	6.24***	3.32**	15.011***	7.304***	5.424***	1.819	52.173***	6.614***

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

Reported coefficients are multiplied by 100.

HC3 robust standard errors.

Source: Own work.

remaining observed pairs would imply that there is a possibility of the existence of noise traders operating under the noise trader hypothesis. This is because for these markets, world dynamics do not explain tracking errors well enough (Qadan & Yagil, 2012). Volatility effects (ϕ_3) show up as significant for 5 out of 7 observed pairs; the two insignificant are in the cases of IVV and IYY. Otherwise, the signs for this factor are positive, as expected. Turning to the results of the effect of changes in volume (ϕ_2), results are inconsistent with expectations. Due to the fact that this proposed factor model didn't work particularly well with the time series at hand, I will comment only the unexpected sign that shows a positive relationship between the defined absolute tracking error and the de-trended volume rather than comment on individual results. Qadan & Yagil base their expectation for negative relationship in terms of model 2 framework on several publications. The authors tried to provide an empirical support to their hypothesis by accepting that trading volume may contribute to a reduction in the tracking error through an information mechanism that is based on the interaction between trading volume, absolute price changes, and the quality of trader's information signal. While most of the ETFs they analyzed failed to support this hypothesis as only 8 out of 42 produced significant negative coefficients, the authors did note that most of the estimated coefficients were still negative. In my case, this does not hold for any observed ETF-index pair. However, it should be noted that while the mechanism the authors suggested is based on empirical work, they do list a number of works which provide empirical evidence that this may not be the case. For example, the work by Wang (1994) provides a case in which the author finds that volume is positively correlated with absolute changes in price and dividends. This result is in line with results from this analysis, but the hypothesis that is connected with this factor will not be adjusted at this point.

Regarding the connection between model 2 and hypotheses 2 and 3, the estimated model provides insight into the connection between volatility and the tracking error, and the volume and the tracking error. This is explored in the following chapter.

3.4 Validity of hypotheses

The results of this analysis suggest that structural differences between ETF landscapes of western versus eastern markets may exist when compared on a global level. Working within the scope of the defined methodology that was employed for the purposes of this analysis, I can support this claim based on the following results in connection to each hypothesis.

3.4.1 Hypothesis 1: Long run equilibrium

H1: A long-run relationship within an ETF-index pair exists and can be explained using the proposed error correction model.

- Transforming OHLCV time series into log returns yields stationary time series suitable for further analysis.
  - The exception being the de-trended volume series for the Chinese ETF (510210 CH). A probable cause for this is an anomaly in the trading activity series (volume) on 22/7/2019.
  - The Chinese ETF market data additionally stands out in the descriptive analysis. It is signified by highest standard deviation and kurtosis.
- Based on the Engle-Granger cointegration test, 8 out of 10 ETF-index pairs show signs of cointegration. Cointegration implies that there exists a long-run relationship.
  - The 2 ETF-index pairs that did not pass the Engle-Granger test were ETFs that track the German and the Hong Kongese markets (DAXEX GY and 2800 HK).
- The error correction model performs well and produces results similar to the results reported by Qadan & Yagil (2012).
  - There is a notable difference in performance between western and eastern markets with western markets showing better performance within the defined framework.
  - One exception in the eastern market group is the Japanese market (1329 JT). This pair shows results that fall within the range variability that is observed in the western markets.

Hypothesis 1 is therefore accepted.

3.4.2 Hypothesis 2: Tracking error factors

H2: Tracking errors are positively correlated with index volatility and negatively correlated with changes in market activity (volume).

- Model 2 performs poorly and produces results that are of lower quality than results reported by Qadan & Yagil (2012).
  - This may be due to the shift from sub-index level to global level and/or due to the longer timeframe. Qadan & Yagil use a 1-year timeframe whereas this thesis performs the analysis on a 5-year one.
  - The German and the Hong Kongese pairs were excluded due insignificant results from the Engle-Granger test as explained for hypothesis 1.

    - The Chinese pair was excluded due to stationarity issues with de-trended volume data.

- Out of 7 remaining pairs, 5 show that tracking errors, defined as the absolute gap between returns, are positively correlated with volatility based on the sign and statistical significance of the factor's coefficients.

    - IWW and IWM from the western market group show statistically insignificant effects of volatility.

- Out of 7 remaining pairs, none show statistically significant negative effects of volume on the tracking error. In contrast, 4 out of 7 pairs actually show a statistically significant positive effect of volume on the tracking error.

    - Positive effect of volume on the tracking error was not expected. Qadan & Yagil base this hypothesis on a mechanism that translates new incoming information to a more efficient price discovery mechanism which would imply lower end-of-the-day tracking errors.

    - There is ample literature on the sign and significance of the effects volume might have on prices (e.g. Wang, 1994) that support the results from this analysis.

Hypothesis 2 is rejected due to unexpected results from the market activity part of the hypothesis.

3.4.3 Hypothesis 3: Diversification benefits

H3: ETFs based in the western markets exhibit less diversification benefits.

- The analysis explores this connection in model 2 that includes the MSCI World index as the world market dynamics factor. The significance of this factor implies that there exists a limitation to diversification benefits of an ETF since the global market has a significant effect on the tracking error.

- The factor is significant for 3 out of 7 observed pairs. 2 cases with significant coefficients are on the western markets (IVV and IYY). The remaining one is on the Japanese market (1329 JT).

    - Out of 6 western pairs, one was excluded in previous steps (DAXEX GY). For the remaining 5 western pairs, only 2 showed significant effects of world market dynamics on their respective absolute tracking errors.

    - Out of 4 eastern pairs, 2 were excluded in previous steps (2800 HK and 510210 CH). Between the remaining 2 pairs, only 1 showed significant effects of world market dynamics on their respective absolute tracking errors.

Because both markets failed to show clear effects of world market returns, there is no clear indication of differences between the two markets regarding diversification benefits that should have been observed in the selected sample. Current stance with respect to the hypothesis remains inconclusive and the hypothesis is neither accepted nor rejected.

3.4.4 Hypothesis 4: Market efficiency

H4: ETFs based in western markets are more efficient.

Taking a step back, the final hypothesis aggregates conclusions regarding hypotheses 1, 2 and 3 by defining *efficient market* based on the results stemming from listed hypotheses. The final synthesis of implications between hypotheses may show differences between the two markets.

- For hypothesis 1, an efficient market would be defined as a market that is signified by a cointegrated process of ETF-index returns and low differences between model 1 results.
    - There is no clear indication that major differences exist between the markets for the selected sample as all non-excluded pairs are consistent with model 1.
- For hypothesis 2, an efficient market would be signified by consistency of factors with the theory (expected coefficient signs).
    - Given that hypothesis 2 was rejected due to a major inconsistency of the volume factor, a decision regarding interpretation for hypothesis 4 is necessary.
    - Even in the case when this major inconsistency is flipped (expecting positive relationship), there are no notable differences between the two markets given exclusions.
- For hypothesis 3, an efficient market would be signified by insignificant world market effects and significant intercept coefficient.
    - There is no clear indication that major differences exist between the markets for the selected sample.

- All pairs included in the sample show significant intercept coefficients, but there are no clear major differences regarding the world market dynamics coefficient that explores diversification benefits as reported for hypothesis 3.

I therefore conclude that there is not enough data that would either support or reject the hypothesis stating that major differences between western and eastern markets exist. Given the selected sample and the observed time period there is not enough data points to support a decision.

3.5 Discussion

Looking at the analysis from a less systematic perspective, one could argue that there are clear differences in the performance between western and eastern security pairs. However, this conclusion would be made solely on the basis of a descriptive analysis which is not systemic in the sense that it institutes a well-defined methodological framework which can account for any irregularities a security pair might show or have embedded. A systemic approach corrects for any such irregularities by either excluding certain cases from the sample and the subsequent interpretation, or by accounting for them. As it turned out during the course of this analysis, some irregularities such as non-stationarity and other data quality anomalies (e.g. the Chinese pair) proved to be too significant to continue with the analysis and therefore had to be either excluded or remedied. The approach taken in this analysis excluded cases which showed inconsistencies, but that in turn translated into dropped security pairs and therefore less data points (observations) that would serve as a basis for decisions. In fact, this is why I neither reject nor accept any conclusions in connection with hypotheses 3 and 4 – at least based on the sample at hand.

Though the Chinese pair was excluded from the second part of the analysis, expanding on the first part of the analysis in relation to the pair at hand is possible. The first part focused on the cointegration analysis which concluded that the Chinese pair does not show the expected cointegration behavior. Therefore, it could be argued that the pair does not cointegrate due to a systemic tracking error present on the Chinese market – a possible indication that Chinese markets are inefficient.

The main critical takeaway of the analysis is that it would be best to expand it to include more ETF-index pairs for better and more general conclusions. In addition to that, a better definition of *eastern* and *western* markets would be welcome as one of the conclusions that may also be pointed out from this analysis is the consistency of the Japanese pair's (1329 JT) dynamics with those observed in the western part of the sample. This may be due to shared history with the West after the Second World War, but it may also be that Japan is simply the *odd one out* – this view can be supported by ratings agencies' geographical segmentations which often exclude Japan from Asia (or Far East).

Coupled with the previous paragraph, this is a good time to touch on the subject of biases. What this section points towards is the probable existence of representativeness issues related to this sample. As I have already pointed out, there are a few open issues connected with this analysis – i.e. inconclusive results for hypotheses 3 and 4, and the issue of a small sample. In defense of this work, I point towards the primary research objective which focuses on the analysis of possible differences between major world indices – of which, there aren't many without entering the sub-index level or including multiple ETF providers for a single index.

CONCLUSION

The ETF market is growing and becoming more popular by the day. Retail investors invest into these products because they are easy to acquire and are less expensive when compared to other options a retail investor may be presented with. Through the purchase of these products, a retail investor can participate in the market at significantly lower entry costs, management costs, and lower minimum initial investments – all while remaining the sole owner of a stock-like asset. In addition to that, retail investors recognize utility in these rather standardized products because they enable a wide palette of exposures to pick from. Modern-day ETFs may have different structures and different objectives, but the asset itself remains standardized as it is actively traded on an exchange. At this point I will also point out that most retail investors don't invest into exotic ETFs, but rather into index trackers as they offer lowest fees and general market exposure with a hands-off approach.

Due to other benefits such as for example tax efficiency, ETFs as instruments have also been a major topic from the regulative side of the market. While the regulation that enables ETFs to exist is old and historically speaking important, ETFs have had a history of legal issues such as the requirement of an exemption that was resolved only recently. More specifically, the Investment Company Act of 1940 that serves as the basis that enables the existence of ETFs still required a rather long process of acquiring an exemption on the basis of ETF initialization. This has been recently resolved by the Rule 6c-11 established in 2019. The new regulative framework therefore envisions a faster process of ETF initialization which will translate into lower costs for issuers and lower costs for investors. This may also translate into even more options for end investors.

While ETFs are becoming bigger, better and more regulated, others point towards the issue of rising systemic importance and risks. For example, market risk and concentration risk together with liquidity risk pose the biggest threats to the ETF market. While risks can be managed through risk mitigation measures, retail investors are starting to show that there may exist a level of confusion with respect to product definition and the marketing sphere around it. Namely, with quite recent collapses of several leveraged exchange-traded products, investors may seek a resolution on the grounds of market and instrument knowledge. Leveraged products can push risk-return profiles beyond what an ill-informed investor may be comfortable with, but this is only connected to ETPs, and not ETFs in general. Therefore, better clarity on what ETFs are and what ETFs are not should be sought in that respect.

The empirical part of this thesis is focused on ETFs that try to replicate the returns of underlying indices market indices. These so-called *trackers* enable investors to invest into market indices. In comparison to older tracking funds, ETFs differ in the sense that the actual security is tradeable on an exchange and the price of it is therefore additionally influenced by supply and demand on the stock exchange. The main empirical question, however, must therefore be connected with the ETF's ability to track the underlying index. For example, when looking at the S&P 500 index, the empirical question focuses on the tracking performance of the iShares Core S&P 500 ETF with respect to the returns the index exhibits.

The tracking performance analysis was performed on 10 ETF-index pairs from different parts of the world. This set was then divided into eastern and western markets to find possible differences between the two. The dataset contained data on each index and security for 5 years. The analysis was based on an approach that first made sure that variables are properly specified for modelling purposes using the augmented Dickey-Fuller test. The second part of the analysis included 2 models. Model 1 tested for the presence of a long-run equilibrium that is based on the presence cointegrated price time series in log returns for each pair. Beforehand, the pairs were tested using a more standardized Engle-Granger cointegration test. Model 2 explored factors behind absolute tracking errors. The approach is based on a paper by Qadan & Yagil (2012) but expanded to a global level instead of the sub-index level. This deviation materializes itself in the need of inclusion of a world index – the analysis employs MSCI World index for this purpose. The empirical task was carried out using OLS with robust HC3 standard errors. This is a common approach when analyzing time series.

Final results are interesting in the sense that there may be some differences present between the two market although out of 4 hypotheses, only 2 showed conclusive results. This is probably due to a smaller sample and a faster approach that excluded ill-defined variables rather than correcting for these specifics. Hypothesis 1 essentially tests for the presence of a long-run equilibrium and is accepted. Hypothesis 2 tests the factors as specified by Qadan & Yagil (2012) and is rejected based on unexpected signs for the volume factor. Results regarding hypotheses 3 and 4 are inconclusive as there is not enough data points to base a decision on. Hypothesis 3 explored diversification benefits based on the significance of the world market dynamics factor in model 2. Looking at hypothesis 4 that explores market differences between the east and west, one has a hard time concluding that any differences exist based on the results for hypotheses 1, 2, and 3.

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APPENDICES

Appendix 1: Povzetek v slovenskem jeziku

Svetoven trg investicijskih skladov, ki kotirajo na borzi (*exhange-traded funds – ETF)* dosega nove rekorde v smislu trgovalne aktivnosti ter dnevno nadaljuje z vzponom v popularnosti. Opažen trend pomeni, da so ti instrumenti vedno bolj prisotni v rokah investitorjev, zato se ta magistrska naloga osredotoči na analizo uspešnosti sledenja investicijskih skladov ETF, ki sledijo lokalnim borznim indeksom. Ti ETF skladi so znani tudi kot angl. *trackers*.

ETF je del širše skupine investicijskih produktov, ki kotirajo na borzi (*exchange-traded products – ETP)*. Instrumenti v ti skupini se lahko klasificirajo kot finančni derivativi – odvisno od strukture in definicije samega instrumenta znotraj skupine. Ti instrumenti in instrumenti v neposredni bližini so raziskani v teoretičnem delu naloge. V direktni povezavi z ETF-ji naloga razišče različne segmentacije skladov, razlike med ETF skladi, regulacijo ter razvoj regulativnega okvirja in kako se ETF-ji razlikujejo od drugih finančnih instrumentov, ki so jim v določeni meri podobni.

Empirični del naloge raziskuje učinkovitos ETF skladov pri replikaciji indeksov, ki jim sledijo. Raziskovalna naloga je opravljena znotraj okvirja, ki je definiran na podlagi obstoječih metod, ki raziskujejo temo učinkovitosti sledenja ETF skladov. Okvir se od obstoječih del razlikuje v tem, da analizo prestavi na svetoven nivo; podrobneje, možne razlike so raziskane v okvirju primerjave med zahodnimi in vzhodnimi trgi. Analiza razišče predlagan *error-correction* model, ki poda vpogled v uspešnost replikacije ter v obstoj dolgoročnega ravnotežja med ETF-ji in indeksi, ki jih poskušajo replicirati. Poleg tega empirični del izvede faktorsko analizo z namenom raziskovanja skladnosti faktorjev, ki prispevajo k napaki sledenja. V tem postopku se obravnava tudi vprašanje pristonosti diverzifikacijiskih prednosti ETF skladov. Empirični del se konča s pogledom na svetovni ravni, ki primerja rezultate na svetovni ravni. Rezultati kažejo, da se faktorji ne obnašajo s pričakovanji, čeprav je dolgoročno ravnotežje prisotno in sprejeto. Poleg tega analiza ostaja nedorečljiva na temi koristi ETF skladov v smislu diverzifikacijskih učinkov in razlik med zahodnimi in vzhodnimi trgi.

Appendix 2: Abstract in English

With the global exchange-traded funds (ETF) market reaching for new records in terms of volume and popularity, and with no changes to that trend in sight, this thesis performs an analysis into the tracking performance of index tracking ETFs (also known as *trackers*).

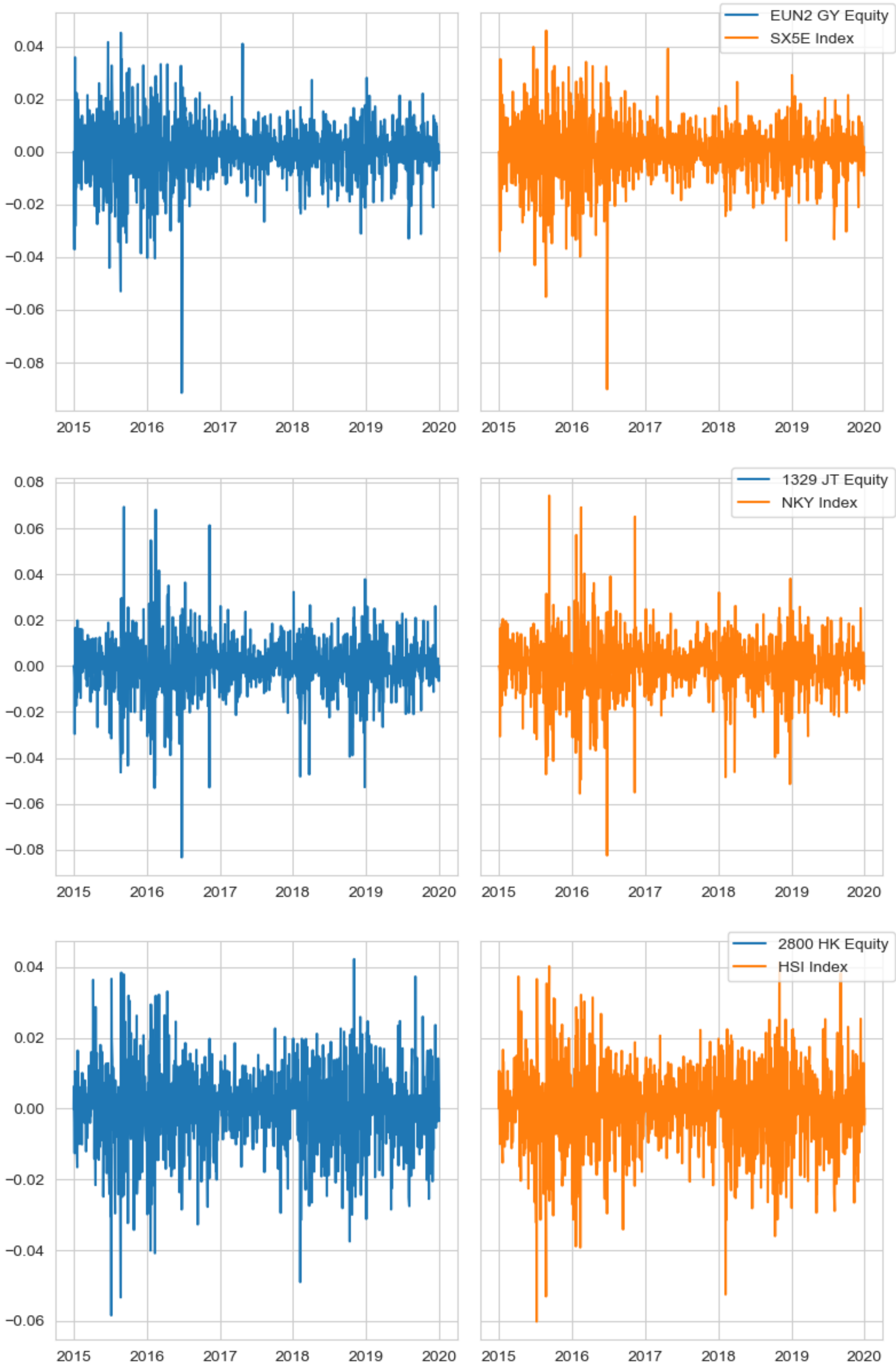
An ETF is a part of a wider group of exchange-traded products (ETP) which may or may not be classified as derivatives – depending on how the product is defined and structured. These instruments and instruments in the close proximity to them are explored in the theoretical part of the thesis. In direct relation to the topic of ETFs, this thesis presents how one can segment different kinds of ETF in multiple ways, how ETFs differ, how they are regulated and how they compare to other financial instruments that may resemble them to a degree.

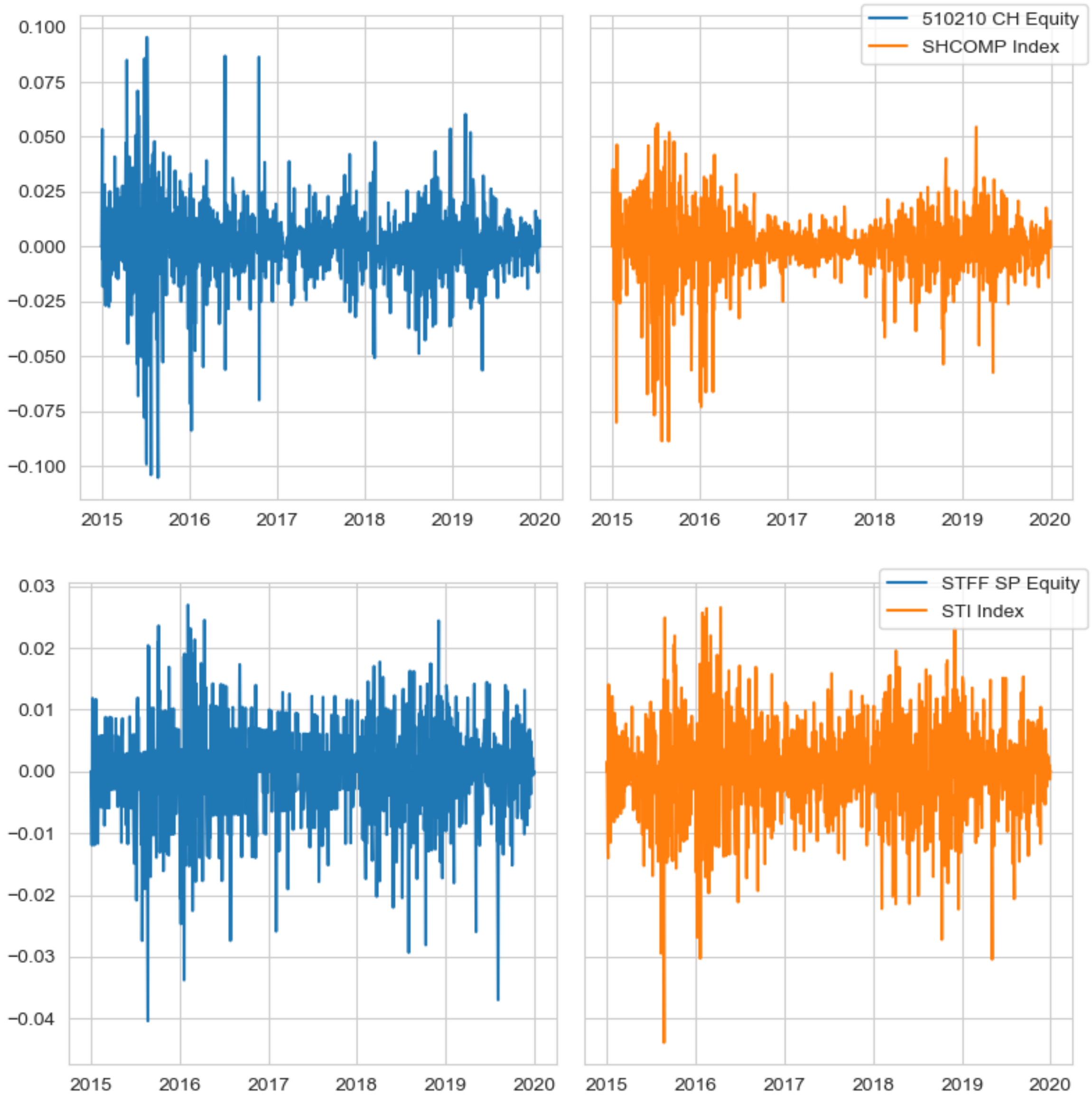
The empirical part of the thesis provides an insight into how effective the replication mechanism of major trackers is in an empirical framework that is based on augmented existing methods focused on the tracking performance analysis on a global scale where major world indices are divided into western and eastern markets. The analysis investigates a proposed error correction model in order to provide an insight into how effective the tracking mechanism is and if a long run equilibrium between the underlying index and the tracker ETF exists. In addition to that, the empirical part performs a factor analysis with the aim of exploring the consistency of factors that contribute to the tracking error. In this process, a diversification benefit question is also tackled. An overview on a global scale concludes the empirical part. The results show that while long-run equilibrium is accepted, factors do not behave in accordance with expectations. In addition to that, the analysis remains inconclusive on the topics of diversification benefits and differences between western and eastern markets.

Appendix 3: Plots of log returns for pairs

Refer to chapter 2.6.1. Source: Own work.

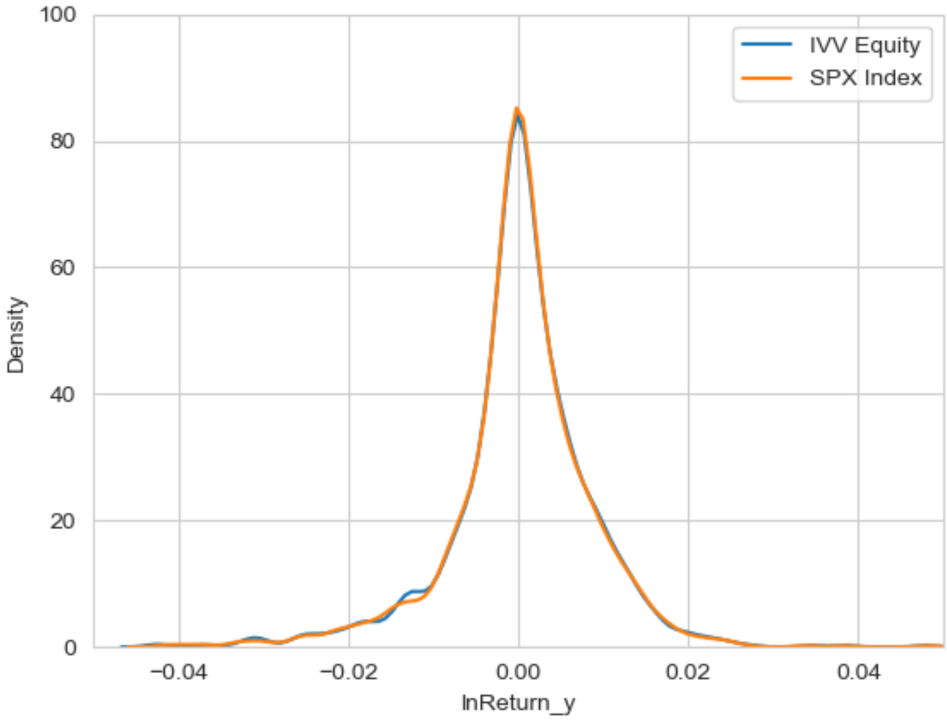

IWM Equity
RU20INTR Index
ISF LN Equity
UKX Index
DAXEX GY Equity
DAX Index
0.04
0.02
0.00
−0.02
−0.04
−0.06
2015
2016
2017
2018
2019
2020

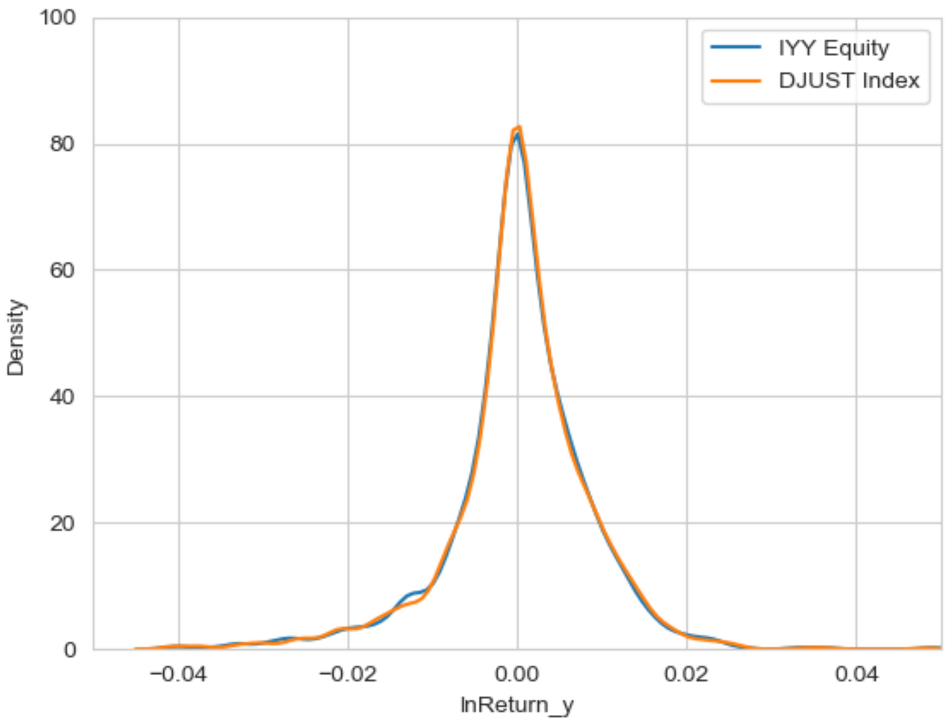

EUN2 GY Equity
SX5E Index
1329 JT Equity
NKY Index
2800 HK Equity
HSI Index
0.08
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
2015
2016
2017
2018
2019
2020

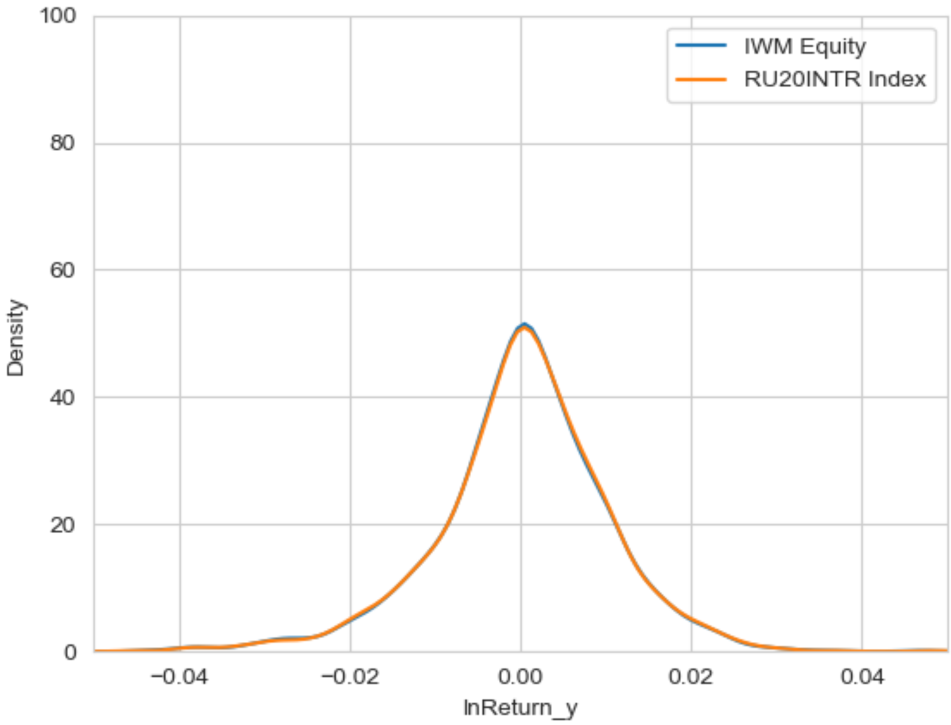

510210 CH Equity
SHCOMP Index
STFF SP Equity
STI Index
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
0.03
0.02
0.01
0.00
−0.01
−0.02
−0.03
−0.04
2015
2016
2017
2018
2019
2020

Appendix 4: Plots of log returns kernel density (KDE plots) for pairs

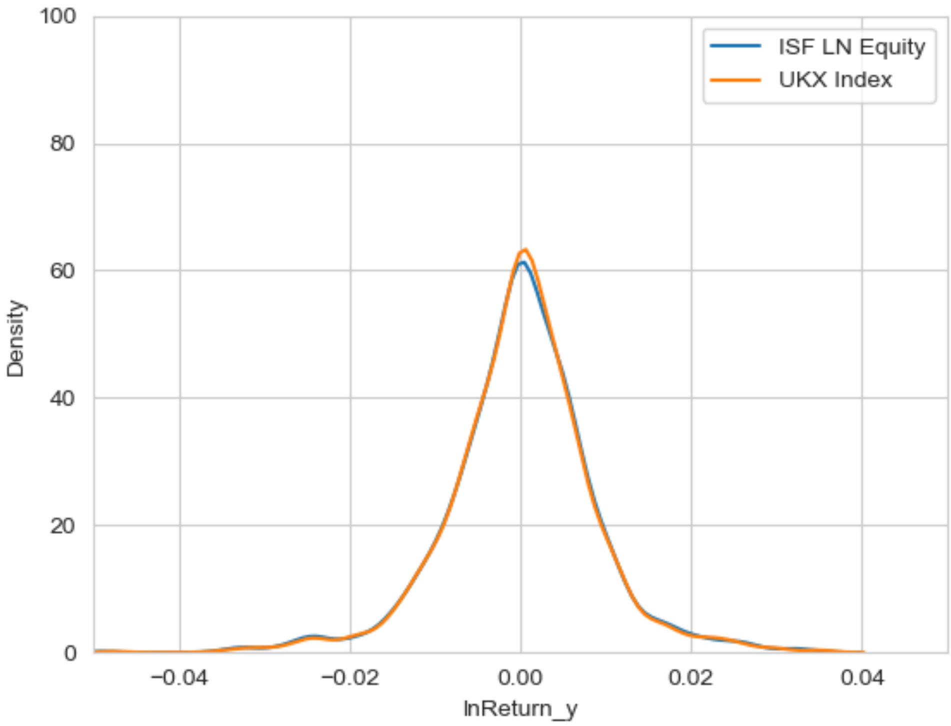
Refer to chapter 2.6.1. Source: Own work.



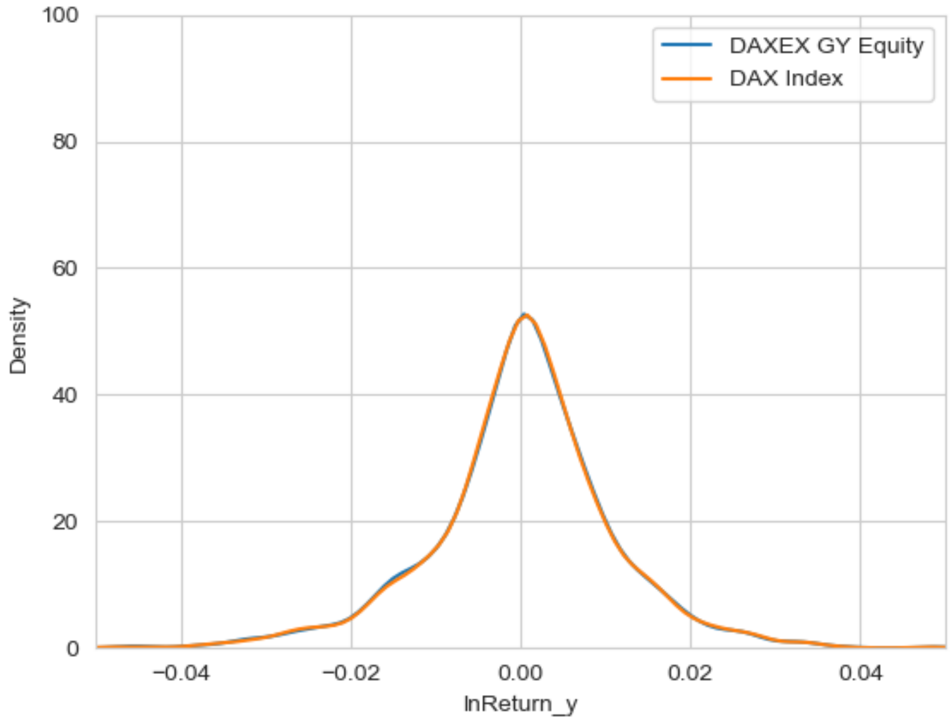




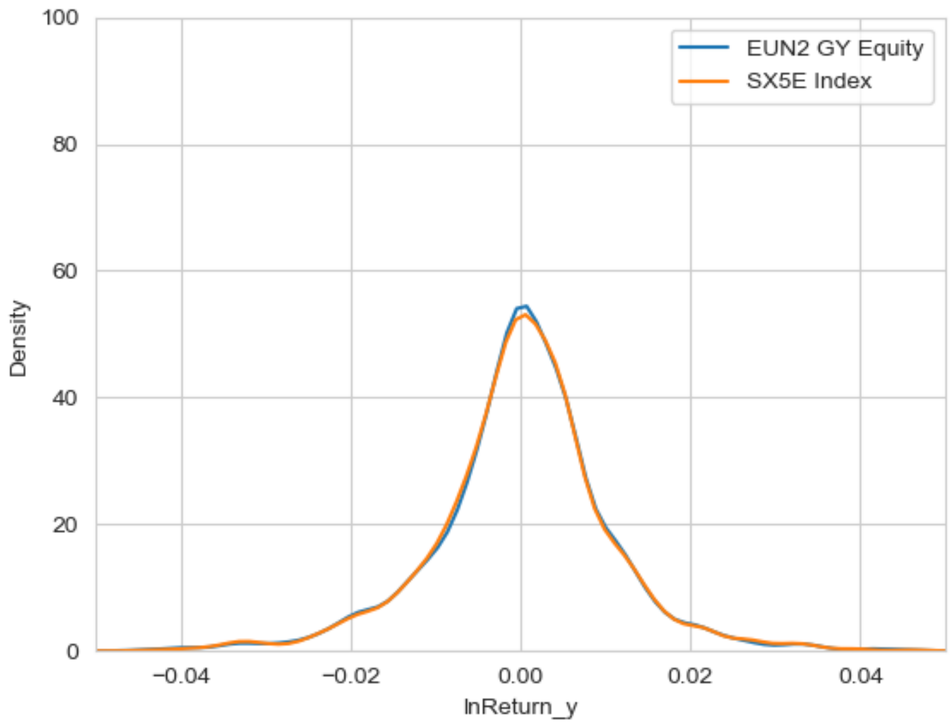
IWM Equity
RU20INTR Index
Density
lnReturn_y
100
80
60
40
20
0
−0.04
−0.02
0.00
0.02
0.04



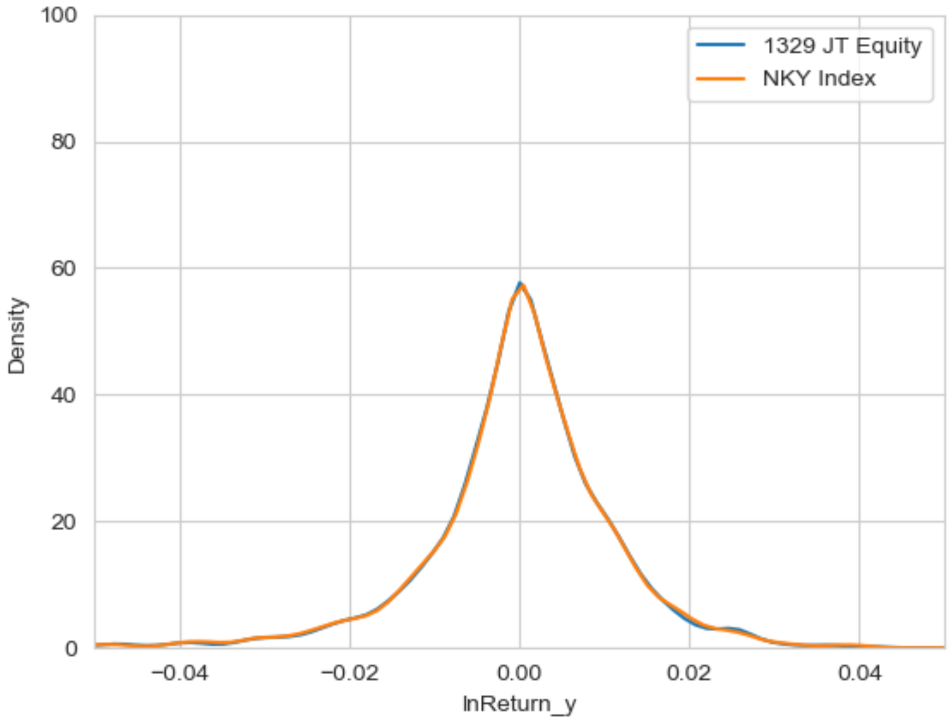
ISF LN Equity
UKX Index
Density
lnReturn_y
100
80
60
40
20
0
−0.04
−0.02
0.00
0.02
0.04

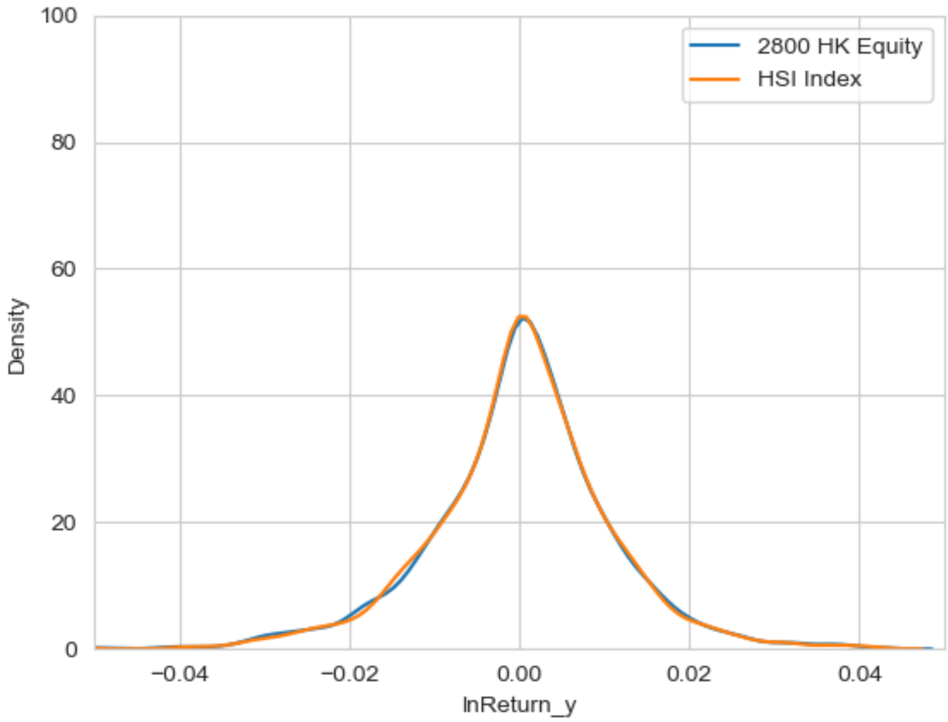


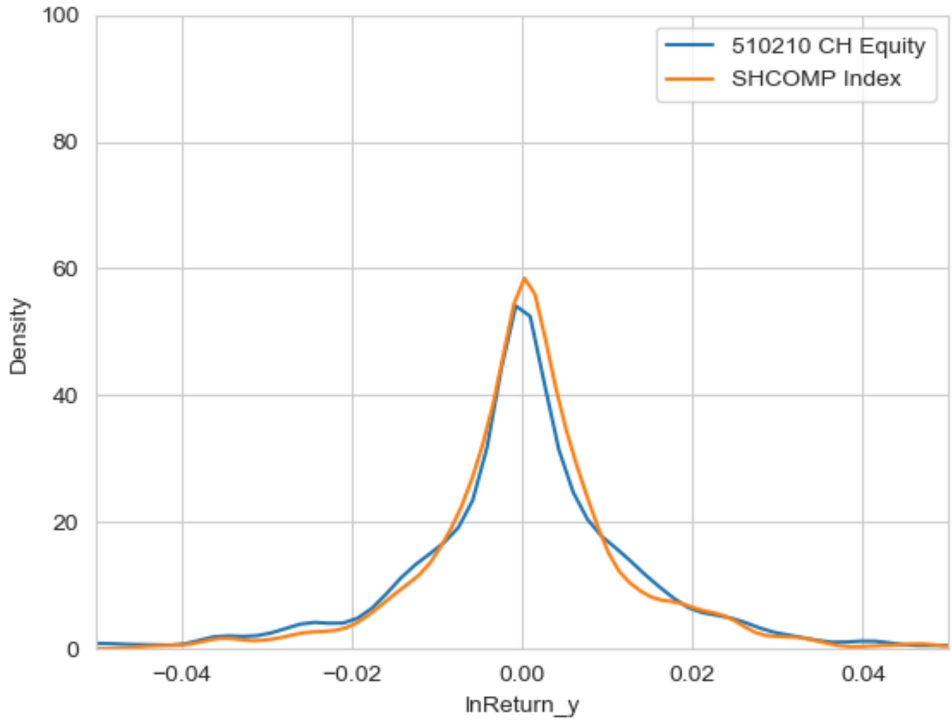
DAXEX GY Equity
DAX Index
Density
lnReturn_y
100
80
60
40
20
0
−0.04
−0.02
0.00
0.02
0.04



EUN2 GY Equity
SX5E Index
Density
lnReturn_y
100
80
60
40
20
0
−0.04
−0.02
0.00
0.02
0.04


1329 JT Equity
NKY Index
Density
lnReturn_y
100
80
60
40
20
0
−0.04
−0.02
0.00
0.02
0.04


2800 HK Equity
HSI Index
Density
lnReturn_y
100
80
60
40
20
0
−0.04
−0.02
0.00
0.02
0.04


510210 CH Equity
SHCOMP Index
Density
lnReturn_y
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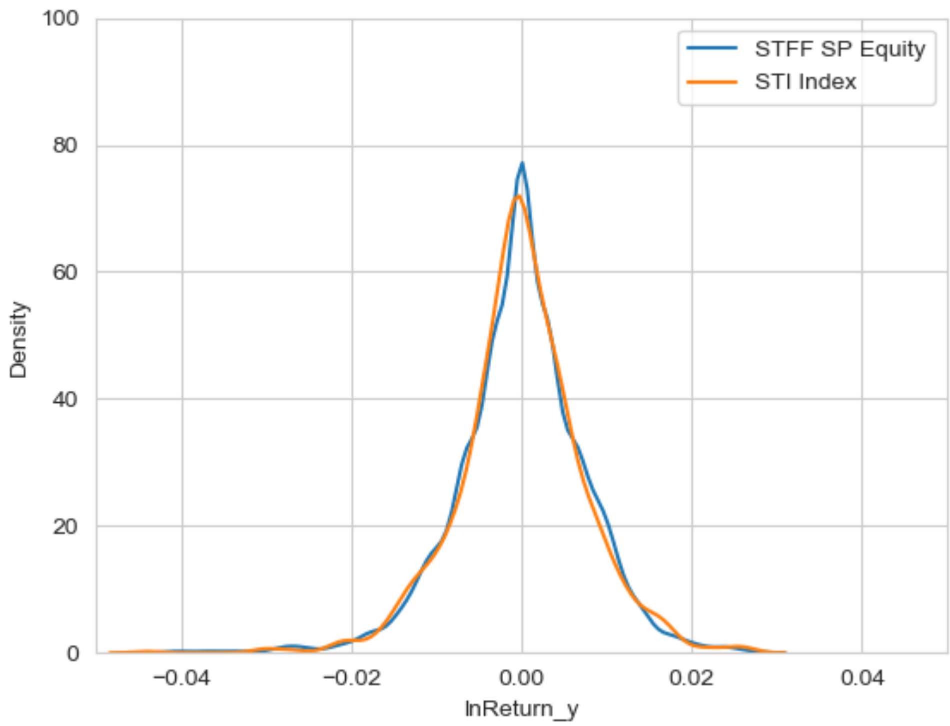
80
60
40
20
0
−0.04
−0.02
0.00
0.02
0.04


STFF SP Equity
STI Index
Density
lnReturn_y
100
80
60
40
20
0
−0.04
−0.02
0.00
0.02
0.04