SECTION 2. Management in firms and organizations

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ETFs: finding your way around active risk

Abstract

This paper analyzes the influence factors for market imperfections in the ETF market. The specific imperfections studied here are empirical tracking errors and deviations of market prices from net asset values. The data under analysis consists of daily, weekly and monthly prices and values for 122 European ETFs. Using four different regression models, the authors derive the total expense ratio, the benchmark volatility and the replication structure and identify the market imperfections. The results are a clear improvement over prior research, and our estimated models have a higher explanatory power than those produced previously in this field. At the end of the analysis the authors briefly address the possible implications of these results for different market participants.

Keywords: exchange traded funds, tracking error, premium over NAV, price deviations, market imperfections.
JEL Classification: G12, G14.

Introduction

Since their introduction to the market in 1993, Exchange Traded Funds (ETFs) have steadily gained in popularity. The first product family consisted of the Standard & Poor's Depository Receipts (also called Spiders), which tracked the S&P 500 index. As a consequence of the increasing levels of interest in this new product type, the global market volume for ETFs already exceeded USD1 trillion in 2009[1].

The benchmarks covered by ETFs range from broad and liquid equity indices to specialized sector indices, fixed income indices, commodities, and more exotic products such as leveraged and inverse tracking of benchmarks.

Seven years after being introduced to the market in the United States, iShares offered the first ETFs for the European market. Since then, the market has grown at 90% p.a. to more than 900 funds with over USD200 billion assets under management.

The increasing interest of investors has also led to a large diversity of products, making it more difficult for investors to determine the advantages and disadvantages of a single ETF. While only a few years ago investors normally chose between an ETF and several alternative possibilities to track the same benchmark, investors now often choose between several seemingly similar ETFs tracking the same benchmark.

A comparison of the explicit costs of different ETFs is fairly simple, but the implicit costs (in the form of return differences) need to be more carefully considered. For these return differences, two measures dominate the relevant academic literature. The first is the tracking error of the net asset value (NAV) vs. the benchmark, and the second is the deviation of the market price from the NAV.

Previous research has shown that both of these types of market imperfections are statistically significant. Most of this research, however, has concentrated on the occurrence and significance of tracking error and price deviations, while ignoring the reasons they exist.

In this paper we focus on the European market, which has largely been ignored by former research. Specifically, we analyze the relevant factors influencing the development of the mentioned market imperfections. The results will help to explain the price dynamics of ETFs and will also provide the investor with a clearer basis for investment decisions.

We conducted our research with a broad selection of equity, fixed income and exotic ETFs over several years based on daily, weekly and monthly data.

1. Tracking error definitions

The literature focusing on ETFs can be subdivided into three different areas: introductory literature, comparative literature and research on market imperfections. The introductory research provides an overview of the history, market, structure, and advantages of ETFs. Following Jheon (2009), there are three structural generations of ETFs: fully replicating funds, swap-based ETFs with one counterpart, and ETFs with various swap counterparts, which mitigates counterpart risks.

The advantages of ETFs have been extensively discussed in prior research. According to Bennet and Kerins (2009), these advantages include comparably low management fees, a high degree of risk diversification (both advantages of classic open-ended index funds), high liquidity, and exchange trading as such offering the possibility of different order types.

Hill and Mueller (2001) and Holderith (2009) concentrate on the most common applications of ETFs. One use of ETFs is to gain immediate exposure to a certain asset class, sector or other benchmark. ETFs are also widely used for hedging purposes, since they

[1] Blackrock (2010).

enable an investor to counter active investments in the portfolio at relatively low cost. A third application is as a transitional investment: because of low transaction and search costs, ETFs can serve as a temporary source of exposure. For example, when an institutional investor is experiencing a large cash inflow from a new client, the investor can offer the desired broad exposure to a specific sector with ETFs while taking time to digest the new cash in the market and transfer it into more active investments.

There are several different definitions of tracking error in the literature. Some of them have been converted into optimization algorithms in Rudolf, Wolter, and Zimmermann (1999). One cannot determine a dominant measure for tracking error, because the interpretation and usability of a calculated tracking error is highly dependent on the investor's preferences. As the most simple form of the tracking error definition in period t, $TE_{1,t}$ expresses the return difference between the NAV return $TE_{NAV,t}$ and the respective benchmark return $TE_{BM,t}$:

$$TE_{1,t} = R_{NAV,t} - R_{BM,t}. \quad (1)$$

Many researchers such as Frino and Gallagher (2001) and Rompotis (2006) rely on the sum of the mean absolute return difference, when n is the number of observations:

$$TE_2 = \frac{\Sigma_{t=1}^{n} \left| TE_{1,t} \right|}{n}. \quad (2)$$

Rompotis (2008) additionally uses a variance measure, also called tracking error volatility (see also Roll, 1992). This approach is shared by Hill and Mueller (2001). Another frequently used definition of tracking error is the standard error of the regression of the NAV return against the benchmark return[1]:

$$TE_3 = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(TE_{1,t} - \overline{TE_1})^2} = \sigma_{TE_1}. \quad (3)$$

In addition to determining the significance of the tracking error for ETFs, some researchers also addressed the reasons for its existence. Hill and Mueller (2001), for example, mention delayed dividend payments, the total expense ratio (i.e. the management fee) and the replication structure as important factors determining the occurrence and magnitude of tracking error. In addition to the total expense ratio, Rompotis (2008) tests the significance of the ETF volatility and the bid-ask spread in his analysis of several German ETFs.

The second commonly used indicator for market imperfections are deviations (premium or discount) of the market price vs. the NAV of an ETF. Thanks to the creation/redemption in kind mechanism, the size and duration of these price deviations are supposed to be relatively small[2]. However, the phenomenon has received considerable attention in academia. As for the tracking error, the most intuitive measure is simply the actual deviation of the market price from the NAV (e.g. on a daily basis). Whereas Rompotis (2009) calculates the straightforward percentage deviation, most researchers use the logarithmic deviation measure[3] $PD_{1,t}$ for period t ($1 \le t \le n$):

$$PD_{1,t} = \ln\left(\frac{P_t}{NAV_t}\right). \quad (4)$$

According to equation (4), we gain a linear measure for mean absolute price deviation

$$PD_2 = \frac{\sum_{t=1}^{n}\left| PD_{1,t} \right|}{n}, \quad (5)$$

and according to equation (6), we obtain a tracking error volatility measure based on absolute price deviation:

$$PD_3 = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(PD_{1,t} - \overline{PD_1})^2} = \sigma_{TE_1}. \quad (6)$$

2. Methodology

Based on the aforementioned prior research and our own preliminary analysis, we have deduced four regression models: two tracking error models and two price deviation models. These include a cross-sectional model estimated using the mean or variance measures (TE_2 and TE_3, respectively PD_2 and PD_3) and a panel regression model for the time series measures (TE_1 and PD_1).

For the potentially relevant factors affecting the tracking errors described above, we have included the bid-ask spread (S), the benchmark return (R_{BM}) and its volatility (σ_{BM}) and the total expense ratio (Γ). In addition, we used the dividend distribution mode (capitalization vs. distribution) as well as the replication structure (swap based vs. fully replicating) as two binary variables (Θ and Ψ) in order to capture all significant causes for the analyzed market imperfections. For TE_2, the notation is expanded by the subscript i referring to fund i ($1 \le i \le N$):

$$TE_{2,i} = \alpha + \beta_1\overline{S}_i + \beta_2\Theta_i + \beta_3\overline{R_{BM,i}} + \beta_4\Psi_i + \beta_5\Gamma_i + \\ + \beta_6\sigma_{BM,i} + \varepsilon_i. \quad (7)$$

In addition to the cross-sectional variables of model (7), three more regressors are added in the next

[1] Frino and Gallagher (2001).

[2] Guedj and Huang (2009).

[3] Cherry (2004), Engle and Sarkar (2006), as well as Delcoure and Zhong (2007).

model for $TE_{1,i}$ of fund i. These regressors are the first three lags of TE_1 in order to partially capture the influence of autocorrelation. According to Pope and Yadav (1994), autocorrelation must not be neglected when looking at tracking error data, especially data of higher frequencies (e.g. daily data), since this can skew the results. The empirical tracking error in our data set shows negative autocorrelations of between 21% and 42% over the first three lags, which confirms the relevance for our objective.

$$TE_{1,i,t} = \alpha + \beta_1 S_{i,t} + \beta_2 \Theta_i + \beta_3 R_{BM,i,t} + \beta_4 \Psi_i + \beta_5 \Gamma_i + \\ + \beta_6 \sigma_{BM,i} + \beta_7 TE_{1,i,t-1} + \beta_8 TE_{1,i,t-2} + \beta_9 TE_{1,i,t-3} + \varepsilon_{i,t}. \quad (8)$$

In order to have a consistent model of both imperfections, we amended the significant factors of former studies and used similar models for the estimation of price deviations. However, we integrated the tracking error as an additional regressor. Rompotis (2008) used the price deviations as a regressor in his tracking error model, which is the exact opposite of our approach. We base this procedure on the fact that the tracking error simply depends on the benchmark return (e.g. the daily return of the DJ Euro Stoxx 50) and the NAV return of the ETF in question. This should be largely independent of the ETF market price; it should instead be determined by the share prices of the index components. The market price determining the magnitude of the price deviations, however, clearly relates strongly to the underlying NAV. Therefore, we expect the tracking error to be highly relevant for the occurrence of price deviations, but not vice versa:

$$PD_{2,i} = \alpha + \beta_1 \overline{S}_i + \beta_2 \Theta_i + \beta_3 TE_{2,i} + \beta_4 \overline{R_{BM,i}} + \beta_5 \Psi_i + \\ + \beta_6 \Gamma_i + \beta_7 \sigma_{BM,i} + \varepsilon_i. \quad (9)$$

In equation (9) again, we add the subindex i indicating the respective fund. Also here, the first three PD lags are incorporated in order to explain $PD_{1,t}$:

$$PD_{1,i,t} = \alpha + \beta_1 S_{i,t} + \beta_2 \Theta_i + \beta_3 TE_{1,i,t} + \beta_4 TE_{1,i,t-1} + \\ + \beta_5 R_{BM,i,t} + \beta_6 \Psi_i + \beta_7 \Gamma_i + \beta_8 \sigma_{BM,i} + \beta_9 PD_{1,i,t-1} + \\ + \beta_{10} PD_{1,i,t-2} + \beta_{11} PD_{1,i,t-3} + \varepsilon_{i,t}. \quad (10)$$

Following the recent literature, our expectations for the interdependencies allow us to formulate the following 7 hypotheses.

H1: A high bid-ask spread favors high tracking error and price deviations.

H2: The distribution mode for dividends has been excessively mentioned in the literature, but we expect the structuring itself to be of low relevance. We attribute the influence to other dividend-dependent factors.

H3: A high tracking error usually leads to high price deviations.

H4: The magnitude of the benchmark return has no significant effect, since it does not affect the difficulty of replicating the benchmark.

H5: Swap-based ETFs tend to generate lower tracking error and lower price deviations.

H6: A high total expense ratio favors high observed tracking errors.

H7: High benchmark volatility increases the replication difficulty, and therefore is expected to increase tracking error and price deviations.

In the following section we will present the data set our model estimations are based on and describe our results in detail.

3. Data and descriptive statistics

In this study, 122 ETFs, consisting of 56 swap-based and 66 fully replicating ETFs, are analyzed. The descriptions of these ETFs can be found in Table 1. 63 of these 122 funds are capitalizing dividends, and 59 are distributing funds. The total expense ratio ranges from 0 to 70 basis points, covering the largest part of today's ETF universe. We use ETFs that were issued between 2000 and 2009. The data sample consists of ETFs issued by the four biggest ETF issuers. Moreover, the benchmarks and asset classes covered by our study are highly diversified. Hence, the universe of ETFs considered here is broad, and is representative enough to avoid possible biases[1]. Table 2 gives an overview of the benchmark indices tracked by the 122 ETFs that compose our data set.

Table 1. Summary of ETF data set

This table shows all ETFs that are part of our data set. The ETFs are sorted by provider with their Bloomberg identifier, their launch date, replication structure, dividend distribution mode, and total expense ratio.

ETF name[a]	Bloomberg	Launch	ψ_i^b	Θ_i^c	Γ_i^d
iShares					
ATX	ATXEX	22.05.06	Repl.	Distr.	0.32%
DAX	DAXEX	03.01.01	Repl.	Cap.	0.17%
DJ ES 50	SX5EEX	03.01.01	Repl.	Distr.	0.17%
DJ ES Banks	SX7EEX	04.05.01	Repl.	Distr.	0.52%

[1] Delcoure and Zhong (2007), Tse and Martinez (2007), and Rompotis (2009).

Table 1 (cont.). Summary of ETF data set

ETF name[a]	Bloomberg	Launch	ψ_i^b	Θ_i^c	Γ_i^d
DJ ES Health Care	SXDEEX	04.05.01	Repl.	Distr.	0.53%
DJ ES Sustainability 40	SUBEEX	11.04.06	Repl.	Distr.	0.42%
DJ ES Technology	SX8EEX	04.05.01	Repl.	Distr.	0.52%
DJ ES Telecom	SXKEEX	04.05.01	Repl.	Distr.	0.52%
DJ EURO STOXX	SXXEEX	12.05.05	Repl.	Distr.	0.21%
DJ STOXX 50	SX5PEX	03.01.01	Repl.	Distr.	0.52%
DJ STOXX 600	SXXPIEX	11.04.05	Repl.	Distr.	0.21%
DJ S 600 Auto	SXAPEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Auto S	SXAREX	06.03.06	Swap	Cap.	0.33%
DJ S 600 Banks	SX7PEX	04.05.01	Repl.	Distr.	0.52%
DJ S 600 Banks S	SX7REX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Basic Resources	SXPPEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Basic Resources S	SXPREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Chemicals	SX4PEX	22.07.02	Repl.	Distr.	0.52 %
DJ S 600 Chemicals S	SX4REX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Construction	SXOPEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Construction S	SXOREX	06.03.06	Swap	Cap.	0.33 %
DJ S 600 Financial Services	SXFPEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Financial Services S	SXFREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Food & Beverage	SX3PEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Food & Beverage S	SX3REX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Health Care	SXDPEX	04.05.01	Repl.	Distr.	0.52%
DJ S 600 Health Care S	SXDREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Industrial Goods	SXNPEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Industrial Goods S	SXNREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Insurance	SXIPEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Insurance S	SXIREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Media	SXMPEX	22.07.02	Repl.	Distr.	0.53%
DJ S 600 Media S	SXMREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Oil & Gas	SXEPEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Oil & Gas S	SXEREX	06.03.06	Swap	Cap.	0.32 %
DJ S 600 Personal Goods	SXQPEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Personal Goods S	SXQREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Retail	SXRPEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Retail S	SXRREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Technology	SX8PEX	04.05.01	Repl.	Distr.	0.52%
DJ S 600 Technology S	SX8REX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Telecom	SXKPEX	04.05.01	Repl.	Distr.	0.52%
DJ S 600 Telecom S	SXKREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Travel & Leisure	SXTPEX	22.07.02	Repl.	Distr.	0.53%
DJ S 600 Travel & Leisure S	SXTREX	06.03.06	Swap	Cap.	0.32%
DJ S 600 Utilities	SX6PEX	22.07.02	Repl.	Distr.	0.52%
DJ S 600 Utilities S	SX6REX	06.03.06	Swap	Cap.	0.32%
DJ STOXX Small 200	SCXPEX	11.04.05	Repl.	Distr.	0.21%
Eb.rexx Gov. DE	RXRGEX	06.02.03	Repl.	Distr.	0.16%
Eb.rexx Gov. DE 1,5-2,5	RXP1EX	30.06.03	Repl.	Distr.	0.16%
Eb.rexx Gov. DE 10,5+	RXPXEX	28.09.05	Repl.	Distr.	0.16%
Eb.rexx Gov. DE 2,5-5,5	RXP2EX	30.06.03	Repl.	Distr.	0.16%
Eb.rexx Gov. DE 5,5-10,5	RXP5EX	30.06.03	Repl.	Distr.	0.16%
Eb.rexx Jumbo Pfandbriefe	R1JKEX	09.12.04	Repl.	Distr.	0.10%
FTSE 100	UKXEX	25.01.02	Repl.	Distr.	0.52%
iBoxx € Liq. Sov. Cap. 1.5-10.5	IB83EX	18.07.06	Repl.	Distr.	0.16%
iBoxx € Liq. Sov. Cap. 1.5-2.5	IB85EX	18.07.06	Repl.	Distr.	0.16%
iBoxx € Liq. Sov. Cap. 10.5+	IB87EX	18.07.06	Repl.	Distr.	0.16%

Table 1 (cont.). Summary of ETF data set

ETF name[a]	Bloomberg	Launch	ψ_i^b	Θ_i^c	Γ_i^d
iBoxx € Liq. Sov. Cap. 2.5-5.5	IB89EX	18.07.06	Repl.	Distr.	0.16%
iBoxx € Liq. Sov. Cap. 5.5-10.5	IB8ZEX	18.07.06	Repl.	Distr.	0.16%
MDAX	MDAXEX	25.04.01	Repl.	Cap.	0.52%
SMI	SMIEX	04.04.01	Repl.	Distr.	0.52%
TecDAX	TDXPEX	11.04.01	Repl.	Cap.	0.52%
DJ EURO STOXX 50	EUN2	03.04.00	Repl.	Distr.	0.35%
DJ STOXX 50	EUN1	03.04.00	Repl.	Distr.	0.35%
MSCI Europe ex-UK	IQQU	05.06.06	Repl.	Distr.	0.40%
MSCI Europe	IQQY	20.11.07	Repl.	Distr.	0.35%
DJ Euro STOXX MidCap	IQQM	29.10.04	Repl.	Distr.	0.40%
DJ Euro STOXX SmallCap	IQQS	29.10.04	Repl.	Distr.	0.40%
€ Inflation Linked Bond	IBCI	18.11.05	Repl.	Cap.	0.25%
€ Government Bond 1-3	IBCA	05.06.06	Repl.	Distr.	0.20%
€ Government Bond 3-5	IBCN	15.03.07	Repl.	Distr.	0.20%
€ Government Bond 7-10	IBCM	15.03.07	Repl.	Distr.	0.20%
€ Corporate Bond	IBCS	17.03.03	Repl.	Distr.	0.20%
db x-trackers					
CAC 40 Short	XC4S	10.07.08	Swap	Cap.	0.20%
CAC40	XCAC	10.07.08	Swap	Distr.	0.40%
DAX	XDAX	10.01.07	Swap	Cap.	0.15%
DJ Euro Stoxx 50	XESX	04.01.07	Swap	Distr.	0.00%
DJ Euro Stoxx 50 Short	XSSX	05.06.07	Swap	Cap.	0.40%
DJ Euro Stoxx 50	XESC	29.08.08	Swap	Cap.	0.00%
DJ S 600 Banks	XS7R	26.06.07	Swap	Cap.	0.30%
DJ S 600 Banks Short	XS7S	25.01.08	Swap	Cap.	0.50%
DJ S 600 Basic Resources	XSPR	26.06.07	Swap	Cap.	0.30%
DJ S 600 Food & Beverage	XS3R	03.07.07	Swap	Cap.	0.30%
DJ S 600 Health Care	XSDR	26.06.07	Swap	Cap.	0.30%
DJ S 600 Health Care Short	XSDS	04.02.08	Swap	Cap.	0.50%
DJ S 600 Industrial Goods	XSNR	03.07.07	Swap	Cap.	0.30%
DJ S 600 Insurance	XSIR	03.07.07	Swap	Cap.	0.30%
DJ S 600 Oil & Gas	XSER	26.07.07	Swap	Cap.	0.30%
DJ S 600 Oil & Gas Short	XSES	04.02.08	Swap	Cap.	0.50%
DJ S 600 Technology	XS8R	29.06.07	Swap	Cap.	0.30%
DJ S 600 Technology Short	XS8S	04.02.08	Swap	Cap.	0.50%
DJ S 600 Telecom	XSKR	29.06.07	Swap	Cap.	0.30%
DJ S 600 Telecom Short	XS6S	04.02.08	Swap	Cap.	0.50%
DJ S 600 Utilities	XS6R	03.07.07	Swap	Cap.	0.30%
FTSE 100 Short	XUKS	02.06.08	Swap	Cap.	0.50%
FTSE 100	XUKX	05.06.07	Swap	Distr.	0.30%
SMI	XSMI	22.01.07	Swap	Distr.	0.30%
ShortDAX Daily	XSDX	05.06.07	Swap	Cap.	0.40%
LPX MM Private Equity	XLPE	17.01.08	Swap	Cap.	0.70%
iBoxx € Sovereigns	XGLE	29.05.07	Swap	Cap.	0.15%
Short iBoxx € Sovereigns	XSGL	06.05.08	Swap	Cap.	0.15%
iBoxx € Germany Covered	XBCT	10.10.07	Swap	Cap.	0.15%
Easy ETF					
CAC 40 Double Short	EZC	25.02.09	Swap	Cap.	0.50%
CAC40	E40	17.03.05	Repl.	Distr.	0.25%
DJ Stoxx 600	ETZEUR	23.06.08	Swap	Cap.	0.30%
Euro Telecom	SYT	06.03.02	Repl.	Cap.	0.30%
Euro Stoxx 50 Double Short	EZD	25.02.09	Swap	Cap.	0.50%
Euro Technology	SYQ	06.03.02	Repl.	Cap.	0.30%
Euro Utilities	SYU	06.03.02	Repl.	Cap.	0.30%

Table 1 (cont.). Summary of ETF data set

ETF name[a]	Bloomberg	Launch	ψ_i^b	Θ_i^c	Γ_i^d
Euro Insurance	SYI	06.03.02	Repl.	Cap.	0.30%
iBoxx Liquid Sovereigns Long	ISL	24.03.06	Swap	Cap.	0.15%
Euro Bank	SYB	06.03.02	Repl.	Cap.	0.30%
iBoxx Liquid Sov. Extra Short	ISS	24.03.06	Swap	Cap.	0.15%
Euro Media	SYM	06.03.02	Repl.	Cap.	0.30%
Euro Energy	SYE	06.03.02	Repl.	Cap.	0.30%
Euro Automobile	SYA	15.12.03	Repl.	Cap.	0.30%
Euro Health	SYH	06.03.02	Repl.	Cap.	0.30%
Lyxor ETF					
DJ Euro Stoxx 50	LYSX	19.02.01	Swap	Distr.	0.25%
LevDAX	LYXLEDAX	01.06.06	Swap	Cap.	0.40%
DAX	LYXDAX	01.06.06	Swap	Cap.	0.15%
Leveraged DJ Euro Stoxx 50	LYXLVE	05.06.07	Swap	Distr.	0.40%

Notes: [a]ETF names shortened. [b]Swap: Swap based ETF; Repl.: fully replicating ETF. [c]Distr.: dividend distribution; Cap.: dividend capitalization. [d]Total expense ratio according to the provider.

An analysis of the data reveals that for 68% of the ETFs, we can reject the null hypothesis that $TE_1 = 0$ at the 1% significance level. Comparing swap-based and fully replicating ETFs reveals that 46% of the swap-based and 86% of the fully replicating funds show a significant number of TE_1 tracking errors (see Figure 1). Correspondingly, the price deviations show a smaller share of 53% null hypothesis rejections at the 1% level. Moreover, for the price deviations, we do not see a large difference between swap-based and fully replicating ETFs (48% and 56%) (see Figure 2). Nevertheless, we can confirm the significance of the market imperfections for our data set.

Table 2. Tracked benchmarks

This table contains a detailed overview of the benchmark indices covered by our data set. Some of the benchmarks are tracked by more than one ETF. Furthermore, some fixed-income benchmarks are covered for different maturities.

Country indices	ATX
	CAC 40
	DAX
	FTSE 100
	MDAX
	SMI
	TecDAX
Fixed income indices	Barclays € Govt. Bond*
	Barclays € Govt. Inflation Linked
	eb.rexx Government Germany*
	eb.rexx Jumbo Pfandbriefe
	iBoxx € Germany Covered
	iBoxx € Liquid Sovereigns
	iBoxx € Liquid Sovereigns Capped*
	iBoxx € Liquid Corporates
	iBoxx € Sovereigns Eurozone
Regional indices	DJ Euro Stoxx
	DJ Euro Stoxx 50
	DJ Euro Stoxx Mid Index
	DJ Euro Stoxx Small Index
	DJ Stoxx 50
	DJ Stoxx 600
	DJ Stoxx Small 200
	MSCI Europe
	MSCI Europe ex-UK

Table 2 (cont.). Tracked benchmarks

Sector indices	DJ Euro Stoxx Automobile & Parts
	DJ Euro Stoxx Banks
	DJ Euro Stoxx Health Care
	DJ Euro Stoxx Insurance
	DJ Euro Stoxx Media
	DJ Euro Stoxx Oil & Gas
	DJ Euro Stoxx Sustainability 40
	DJ Euro Stoxx Technology
	DJ Euro Stoxx Telecommunications
	DJ Euro Stoxx Utilities
	DJ Stoxx 600 Automobiles & Parts
	DJ Stoxx 600 Banks
	DJ Stoxx 600 Basic Resources
	DJ Stoxx 600 Chemicals
	DJ Stoxx 600 Construction & Materials
	DJ Stoxx 600 Financial Services
	DJ Stoxx 600 Food & Beverage
	DJ Stoxx 600 Health Care
	DJ Stoxx 600 Industrial Goods & Serv.
	DJ Stoxx 600 Insurance
	DJ Stoxx 600 Media
	DJ Stoxx 600 Oil & Gas
	DJ Stoxx 600 Personal & Household
	DJ Stoxx 600 Retail
	DJ Stoxx 600 Technology
	DJ Stoxx 600 Telecommunications
	DJ Stoxx 600 Travel & Leisure
	DJ Stoxx 600 Utilities
Exotic benchmarks	LPX Major Market

Note: *Different maturities.

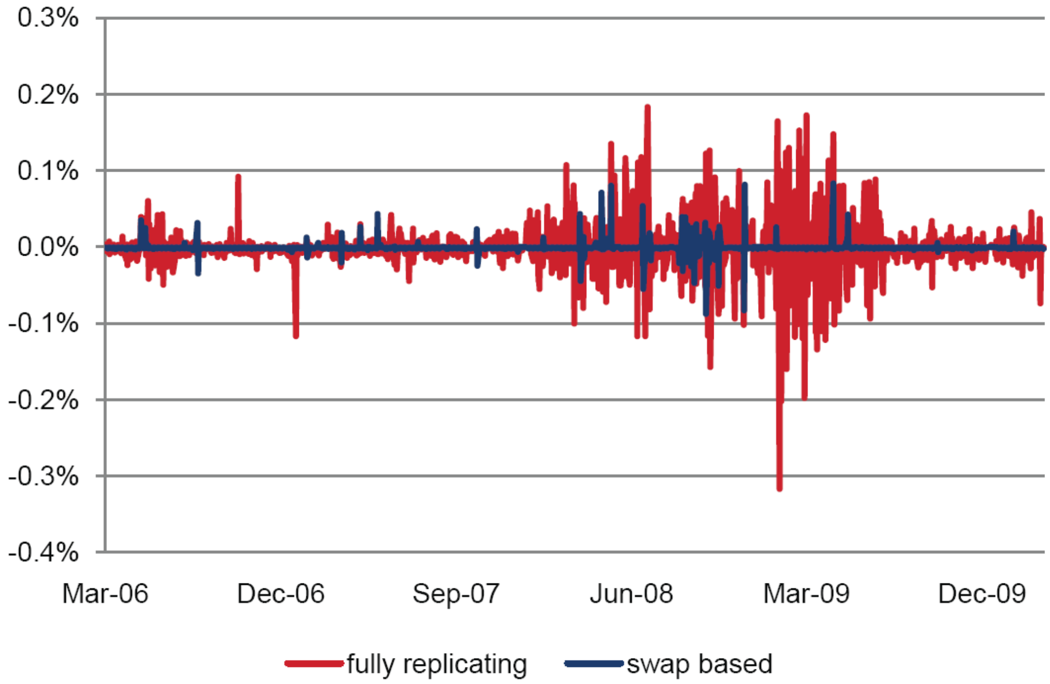

Fig. 1. ***TE*$_1$ for the DJ Stoxx 600 Travel & Leisure as benchmark**

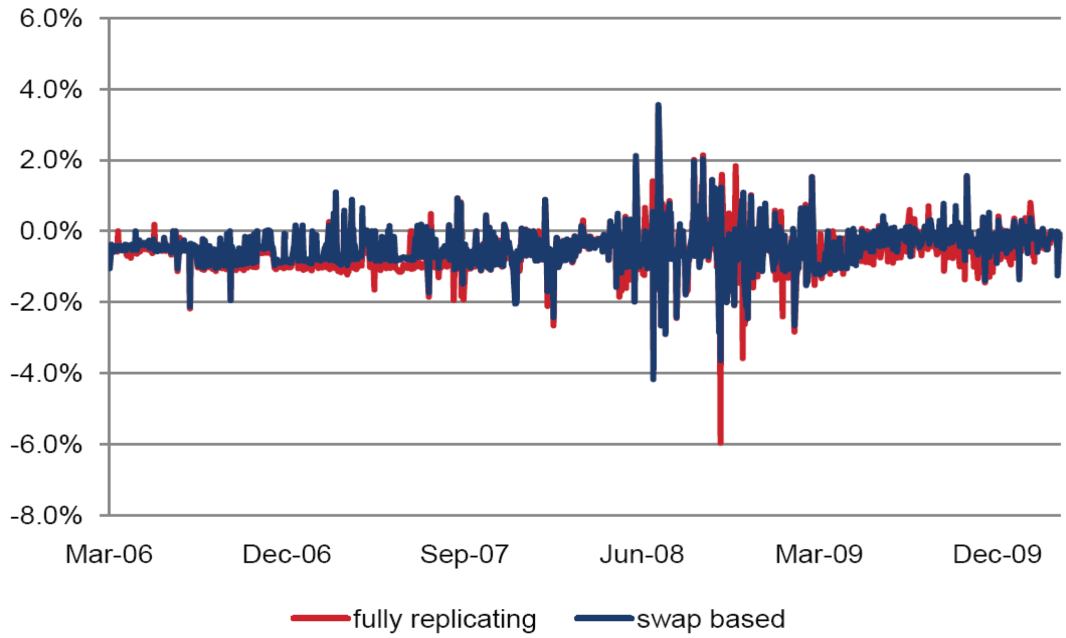

Fig. 2. PD_1 for the DJ Stoxx 600 Travel & Leisure as benchmark

Table 3 contains a breakdown of our data set by benchmark class. We divided the set into regional equity indices (e.g. DJ Euro Stoxx 50), sector oriented equity indices (e.g. DJ Euro Stoxx Banks), fixed income indices (e.g. iBoxx € Liquid Corporates), and exotic indices (e.g. leveraged or inverse indices). The most important results are displayed by class in the table, including an additionally created measure referred to here as the relative tracking error $TE_{rel,t}$ in period t.

$$TE_{rel,t} = \frac{|TE_{1,t}|}{|R_{BM,t}|}. \tag{11}$$

The distribution of the total expense ratios shows that the fixed income ETFs are the cheapest, followed by the plain vanilla regional or sector ETFs, with approximately double the cost (30-32 bps). The most expensive ETFs are those tracking exotic benchmarks. This reflects the higher replication costs faced by the ETF provider.

A look at the indicators Ψ and Θ reveals the prevailing ETF replication structure and dividend payout mode. Fixed income ETFs are mostly fully replicating (Ψ = 0) and dividend distributing (Θ = 0), whereas the analyzed exotic benchmarks are entirely tracked by swap-based and dividend capitalizing funds.

The comparison of market imperfections across categories clearly puts the exotic ETFs in last place regarding linear- and variance-based tracking error. The lowest tracking error measures are found in the sector ETFs, followed by fixed income ETFs and finally the regional funds. Unexpectedly, the introduced relative tracking error shows the lowest (i.e. best) value for exotic ETFs, primarily due to the significantly higher NAV return level. For the price deviation from NAV, no such clear differentiation can be drawn. Only the fixed income ETFs provide a significantly lower level of price deviations.

Table 3. Overview by benchmark category

This table shows the key indicators split by benchmark category. Reported numbers represent the median over the respective ETFs of one category. Exceptions to this are marked with *; in these cases the reported number represents the arithmetic mean.

	All	Regional	Sector	Fixed income	Exotic
Number of ETFs	122	27	60	20	15
Γ (bps.)	32	30	32	16	50
Ψ*	0.459	0.333	0.467	0.200	1.000
Θ*	0.516	0.296	0.617	0.250	1.000
$\lvert R_{NAV}\rvert$ (%)	1.078	1.069	1.122	0.186	1.567
σ_{NAV} (%)	1.568	1.558	1.647	0.254	2.219
σ_{BM} (%)	1.522	1.521	1.637	0.223	1.711
TE_2 (bps.)	1.693	2.427	1.224	1.521	3.905
TE_3 (bps.)	4.644	10.893	2.392	3.751	33.248
TE_{rel} (%)	0.822	1.156	0.543	2.808	0.472
PD_2 (%)	0.538	0.446	0.585	0.096	0.499
PD_3 (%)	0.466	0.476	0.476	0.134	0.770

4. Empirical results

Our models are created primarily with daily data, but we include estimation results for weekly and monthly data, as well, in order to create a broader basis for interpretation. Table 4 summarizes the estimation for the cross-sectional analysis of the tracking error. Together with the results of the panel regression in Table 5, we can draw several conclusions. We observe that the most significant factors are the total expense ratio Γ (negative impact) and the benchmark volatility σ_{BM}. These show statistical significance at the 1% level. The panel regression further shows that the dividend payout mode Θ, the benchmark return $R_{BM,t}$, and the ETF replication structure Ψ are statistically significant factors. However, the estimated coefficients are very low – close to zero – and therefore do not show economic relevance for the influence.

Table 4. Cross-sectional analysis of the tracking error

The values in each upper row show the estimated coefficients from the cross-sectional regression, and the lower row contains the results of the t-tests as an indicators for the statistical significance. The probability of error is indicated by * (10%), ** (5%) and *** (1%).

	α	$\bar{S}$	Θ	R_{BM}	ψ	Γ	σ_{BM}	Adj. R^2	F-statistic
TE_2									
Daily data	0.001 1.453	0.004 0.124	-0.002 -1.250	-2.167 -0.855	0.001 0.852	-0.798 -2.947***	0.201 2.554**	0.161	4.9 0.02%
Weekly data	0.001 0.970	-0.003 -0.059	-0.004 -1.495	-0.502 -0.777	0.003 1.204	-1.027 -2.434**	0.151 2.071**	0.146	4.5 0.04%
Monthly data	0.004 2.158**	-0.062 -1.277	-0.006 -1.880*	-0.131 -0.758	0.003 1.053	-1.532 -2.852***	0.126 2.304**	0.236	7.2 0.00%
TE_3									
Daily data	0.003 2.064**	-0.027 -0.550	-0.003 -0.989	-2.943 -0.697	0.002 0.595	-1.414 -3.193***	0.384 3.038***	0.179	5.4 0.01%
Weekly data	0.004 1.965*	-0.041 -0.576	-0.005 -1.310	-0.657 -0.691	0.003 0.788	-1.774 -2.813***	0.242 2.293**	0.143	4.4 0.05%
Monthly data	0.008 3.308***	-0.100 -1.508	-0.005 -0.973	-4.411 -0.661	-0.001 -0.186	-2.850 -3.644***	0.197 2.683***	0.204	6.2 0.00%
TE_4									
Daily data	0.003 2.302**	-0.030 -0.719	-0.002 -0.824	-2.342 -0.661	0.001 0.404	-1.243 -3.354***	0.338 3.186***	0.181	5.4 0.01%
Weekly data	0.004 2.039**	-0.042 -0.623	-0.005 -1.284	-0.623 -0.689	0.003 0.768	-1.730 -2.864***	0.232 2.301**	0.142	4.3 0.06%
Monthly data	0.007 3.134***	-0.099 -1.506	-0.005 -1.026	-0.167 -0.665	-0.001 -0.141	-2.772 -3.665***	0.191 2.569**	0.215	6.5 0.00%

Table 5. Panel regression of the tracking error

The values in each upper row show the estimated coefficients from the panel regression, and the lower row contains the results of the t-tests as an indicators for the statistical significance. The probability of error is indicated by * (10%), ** (5%) and *** (1%).

	TE_1			$\lvert TE_1 \rvert$		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
α	0.000 -1.686*	0.000 -1.444	0.000 -0.349	0.000 2.268**	0.000 0.769	0.002 2.687***
S_t	0.001 1.441	0.002 0.981	0.000 -0.020	0.001 1.501	0.001 0.476	-0.014 -1.377
Θ	0.000 0.668	0.001 1.721*	0.002 1.586	0.000 -4.405***	0.000 -1.919*	0.000 0.446
R_{BM}	-0.053 -17.389***	-0.020 -6.145***	-0.015 -1.762*	0.005 2.394**	-0.004 -2.188**	-0.012 -1.372
ψ	0.000 -0.168	0.000 -1.310	-0.002 -1.314	0.000 4.602***	0.000 2.305**	-0.001 -0.881
Γ	0.009 0.691	0.016 0.416	0.073 0.643	-0.146 -9.272***	-0.113 -3.588***	-0.388 -5.014***
σ_{BM}	-0.004 -0.669	-0.005 -0.621	-0.008 -0.824	0.041 10.395***	0.017 4.391***	0.021 3.822***
$TE_{1,t-1}$	-0.585 -21.061***	-0.497 -7.305***	-0.152 -1.999**	0.453 14.869***	0.326 5.442***	0.126 1.892*
$TE_{1,t-2}$	-0.381 -11.441***	-0.247 -3.132***	0.266 2.506**	0.089 2.782***	0.239 4.007***	0.453 5.228***
$TE_{1,t-3}$	-0.220 -7.763***	-0.062 -0.947	0.133 2.189**	0.240 8.552***	0.276 5.662***	–
Adj. R^2	0.298	0.216	0.084	0.500	0.596	0.215
F-statistic	6,020.2 0.00%	798.8 0.00%	55.7 0.00%	14,166.4 0.00%	4,277.1 0.00%	192.5 0.00%
DW-statistic	1.959	1.991	1.520	2.096	1.970	1.437

After determining the relevant factors, we review the overall quality of our model estimations. The F-statistics of both analyses indicate high overall statistical significance for the two models. The explanatory power of the models can be assessed with adjusted R^2 values. The adjusted R^2 of the cross-sectional model is, at first sight, fairly limited at 16-18%. The key difference between our model and former estimations (e.g. Rompotis, 2008; with ca. 60%) is the exclusion of the price deviations as regressor. In contrast, we included the tracking error as a regressor in the price deviation models. As a comparative test, we also estimated our tracking error model with an inclusion of the price deviations and achieved adjusted R^2 values of between 61% and 72%. Therefore, the quality of the cross-sectional model can be considered to be at least equal to the quality of previous models. In our view it is more sensible and more realistic to account for the relationship between tracking error and price deviations in the proposed way, leading to significantly smaller R^2 values.

The panel regression delivers an adjusted R^2 of 50%. Since there are no usable, comparable papers, it is difficult to put this value into perspective. In the light of results achieved in cross-sectional analyses, however, as well as on an absolute basis, we believe that 50% is a very good coefficient. Integrating price deviations as an additional regressor only improves the adjusted R^2 to 54%.

In addition to the significant improvement of the model quality, one also has to note that the panel regression is based on much broader and more robust data. While the cross-sectional regression only includes 122 values for each variable (one for each ETF), the panel regression includes development over time, generating a basis of approximately 125,000 data points.

Despite the inclusion of the lagged values in order to capture the autore-gressive components, we still had to rule out autocorrelation in the residuals. For this purpose we looked at the Durbin Watson statistics[1] and can confirm, based on a probability of 95%, that there is no autocorrelation in the residuals. Therefore, the estimation results of our panel regression are not biased due to autocorrelation.

In the second part of our analysis we concentrate on the significant influence factors of price deviations from NAV. For the determination of these factors we used the models as described above (equations (9) and (10)). As for the tracking error, the cross-sectional analysis serves as one basis for the interpretation, complemented with a panel regression analysis for the true and absolute deviations.

As mentioned before, we expect a significant improvement over previous research resulting from the inclusion of the tracking error as a regressor. In accordance with the approach of the tracking error, we also used heteroscedasticity robust standard errors after White[2].

Tables 6 and 7 summarize the coefficients and T-tests of the model estimations. From these we can see that, in line with the tracking error models, the dividend distribution mode has no relevant influence. Although the T-tests in the panel regression show high statistical significance, the coefficients emphasize the results from the cross sectional regression, revealing that the distribution mode is not relevant.

Table 6. Cross-sectional analysis of the price deviations

The values in each upper row show the estimated coefficients from the cross-sectional regression, and the lower row contains the results of the t-tests as an indicators for the statistical significance. The probability of error is indicated by * (10%), ** (5%) and *** (1%).

	α	$\overline{S}$	Θ	TE_2	TE_3	R_{BM}	ψ	Γ	σ_{BM}	Adj. R^2	F-statistic
PD_2											
Daily data	-0.001 -2.829***	0.028 3.727***	0.000 -1.178	0.336 8.725***	–	1.102 3.686***	0.002 5.980***	0.553 4.359***	0.171 7.524***	0.823	81.4 0.00%
Weekly data	-0.001 -2.004**	0.024 2.920***	0.000 -0.926	0.229 12.633***	–	0.242 4.955***	0.002 5.523***	0.487 4.497***	0.078 8.408***	0.826	82.9 0.00%
Monthly data	-0.001 -2.735***	0.032 3.291***	0.000 -1.182	0.217 12.744***	–	0.052 4.830***	0.003 6.671***	0.480 3.096***	0.046 6.531***	0.811	75.2 0.00%
PD_3											
Daily data	0.000 0.445	-0.019 -2.129**	0.000 0.425	–	0.328 15.202***	0.001 2.811***	0.428 1.294	0.416 2.931***	0.174 5.993***	0.834	87.6 0.00%
Weekly data	0.001 1.604	-0.031 -2.549**	0.000 1.100	–	0.236 21.102***	0.001 1.622	0.144 1.932*	0.176 1.401	0.079 5.089***	0.774	60.2 0.00%
Monthly data	0.000 -0.274	-0.022 -1.560	0.000 -0.473	–	0.206 6.063***	0.002 3.156***	0.055 2.438**	0.318 1.669*	0.048 3.850***	0.683	38.2 0.00%

[1] Durbin and Watson (1951).
[2] White (1980).

Table 7. Panel regression of the price deviations

The values in each upper row show the estimated coefficients from the panel regression, and the lower row contains the results of the t-tests as an indicators for the statistical significance. The probability of error is indicated by * (10%), ** (5%) and *** (1%).

	PD_1			$\|PD_1\|$		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
α	0.001 13.231***	0.001 4.635***	0.002 3.527***	0.000 -7.895***	0.000 -1.116	-0.001 -2.455**
S_t	-0.018 -7.517***	-0.015 -4.249***	-0.012 -0.855	0.016 9.821***	0.012 3.947***	0.031 3.445***
Θ	0.001 8.072***	0.001 2.552**	0.002 2.733***	0.000 -4.635***	0.000 -2.125**	-0.001 -2.018**
$TE_{1,t}$	-0.662 -40.755***	-0.374 -11.679***	-0.192 -2.756***	0.280 14.031***	0.161 4.538***	0.096 1.723*
$TE_{1,t-1}$	-0.313 -20.310***	-0.190 -5.470***	-0.028 -0.977	-0.097 -5.822***	-0.021 -0.701	0.031 1.357
$R_{BM,t}$	-0.069 -25.228***	-0.007 -2.305**	-0.013 -4.524***	0.003 1.029	-0.007 -3.198***	-0.012 -5.316***
Ψ	-0.001 -13.384***	-0.001 -4.199***	-0.003 -4.891***	0.001 12.149***	0.001 5.613***	0.003 5.647***
Γ	-0.446 -22.131***	-0.456 -9.936***	-0.689 -6.743***	0.249 15.798***	0.236 6.749***	0.339 4.387***
σ_{BM}	-0.025 -4.991***	-0.008 -1.341	-0.015 -1.932*	0.080 21.045***	0.038 7.788***	0.036 7.111***
$PD_{2,t-1}$	0.224 26.262***	0.181 8.313***	0.062 1.725*	0.114 11.443***	0.177 6.211***	0.246 7.087***
$PD_{2,t-2}$	0.179 21.404***	0.175 8.343***	0.093 2.918***	0.232 22.845***	0.125 5.044***	–
$PD_{2,t-3}$	0.042 5.427***	0.076 3.639***	–	0.176 17.918***	0.164 6.849***	–
Adj. R^2	0.270	0.235	0.130	0.356	0.344	0.263
F-Statistic	3,178.4 0.00%	512.4 0.00%	66.2 0.00%	4,747.7 0.00%	876.8 0.00%	181.1 0.00%
DW-Statistic	1.993	1.981	1.706	2.003	2.037	1.588

The most relevant factors according to our analysis are tracking error, total expense ratio and benchmark volatility. From the panel regression one can see that the autoregressive components (in the form of lagged price deviations) also have a very significant influence.

The bid-ask spread, the benchmark return and the replication structure all show very high statistical significance, with estimated coefficients close to zero. Therefore, these factors need to be taken into account, but are not first priority.

Judging from the F-statistics, the overall significance of the estimated models can be confirmed at the 1% level. The explanatory power is again addressed with the adjusted R^2 values.

The cross-sectional analysis shows comparably high values with adjusted R^2 values above 80%. In the panel regression, on the other hand, we achieve around 30-35%. The closest comparable analysis reached roughly 13%[1]. From that perspective, even the results of the panel regression represent a significant improvement over prior research.

Much of the current literature considers the replication structure to be a highly significant and relevant factor, but this could not be confirmed without limitations in our analysis; thus, we conducted a further analysis. For this we concentrated our database to 17 benchmarks, with 2 ETFs for each benchmark. Of these, one was fully replicating and one was swap based. With this approach we have a direct comparison, filtering out all factors that cannot be allocated to the replication structure.

Table 8 clearly shows that the tracking error of swap-based ETFs is significantly below that of fully replicating funds. The most significant deviation over the reduced sample is to be found for TE_2, with approximately 70% less tracking error. For TE_3 and TE_4 the tendency can be confirmed. However, the difference is much smaller than for TE_2.

Table 8. Direct comparison for a reduced sample of ETFs

This table shows the relative deviation of swap based ETFs versus their fully replicating counterparts in the respective indicators.

ETF benchmark	Γ	σ_{NAV}	TE_2	TE_3	TE_4	PD_2	PD_3
DJ Stoxx 600 Banks	-38.5%	24.8%	-81.3%	-65.3%	-52.8%	8.0%	18.8%

[1] Delcoure and Zhong (2007).

Table 8 (cont.). Direct comparison for a reduced sample of ETFs

ETF benchmark	Γ	σ_{NAV}	TE_2	TE_3	TE_4	PD_2	PD_3
DJ Stoxx 600 Basic Resources	-38.5%	26.3%	-76.9%	-33.6%	5.2%	18.7%	35.2%
DJ Stoxx 600 Chemicals	-38.5%	10.6%	-53.0%	-11.4%	-8.2%	-20.4%	-3.8%
DJ Stoxx 600 Construction	-36.5%	23.1%	-70.4%	-36.3%	-0.7%	4.3%	8.0%
DJ Stoxx 600 Financial Services	-38.5%	20.5%	-79.3%	-75.9%	-70.5%	2.2%	2.1%
DJ Stoxx 600 Food & Beverage	-38.5%	13.5%	-70.7%	-41.6%	-36.5%	1.3%	-3.8%
DJ Stoxx 600 Health Care	-38.5%	1.0%	-60.0%	-14.0%	3.0%	3.5%	2.4%
DJ Stoxx 600 Industrial Goods	-38.5%	19.6%	-72.6%	-54.3%	-39.7%	1.7%	7.2%
DJ Stoxx 600 Insurance	-38.5%	7.0%	-50.4%	31.1%	37.3%	6.3%	11.7%
DJ Stoxx 600 Media	-39.6%	-0.6%	-68.0%	-49.0%	-40.4%	-1.2%	7.1%
DJ Stoxx 600 Oil & Gas	-38.5%	16.1%	-83.1%	-70.4%	-43.4%	3.2%	9.0%
DJ Stoxx 600 Personal Goods	-38.5%	17.0%	-68.6%	-37.9%	-19.7%	-5.0%	5.9%
DJ Stoxx 600 Retail	-38.5%	14.1%	-65.4%	-24.3%	-3.2%	-3.1%	4.8%
DJ Stoxx 600 Technology	-38.5%	-16.3%	-68.4%	-42.3%	-30.0%	3.7%	-2.8%
DJ Stoxx 600 Telecom	-38.5%	-7.0%	-77.9%	-52.9%	-37.9%	13.4%	16.6%
DJ Stoxx 600 Travel & Leisure	-39.6%	10.8%	-79.8%	-69.3%	-62.1%	-7.6%	-2.6%
DJ Stoxx 600 Utilities	-38.5%	20.5%	-71.8%	-27.5%	-6.7%	18.8%	19.6%
Median	-38.5%	14.1%	-70.7%	-41.6%	-30.0%	3.2%	7.1%
Average	-38.5%	11.8%	-70.4%	-39.7%	-23.9%	2.8%	8.0%

If we look at the price deviations over the reduced sample, there is no clear tendency in the differences. The average and median show slightly higher price deviations for swap-based ETFs.

Conclusion

The most important factors influencing ETF tracking errors proved to be the total expense ratio, the benchmark volatility, the replication structure, and the lagged tracking error itself. For deviations of the market price from the NAV, the relevant factors are the tracking error, total expense ratio, and benchmark volatility. Similar to the tracking error, the lagged price deviations also have a highly significant influence.

It is now possible to review the hypotheses presented in section 2 in light of our findings. Hypothesis 1 cannot be verified, since the bid-ask spread does not have any significance for the tracking error. While the T-tests in the models for price deviations demonstrate high statistical significance, the estimated coefficients do not confirm economic relevance.

Hypotheses 2 and 3 have been confirmed, as the dividend distribution mode has not proven significant for tracking error or price deviations, and the tracking error could be determined to be statistically and economically significant for the occurrence of price deviations. Hypothesis 4 can largely be verified. The benchmark return was revealed to have limited significance for price deviations, but no statistical or economical significance was detected for the tracking error. Hypothesis 5 has been partially confirmed. The evaluation of the descriptive statistics clearly shows significantly lower tracking error for swap-based ETFs. On the other hand, we could not detect a large deviation in the occurrence or extent of price deviations from NAV between swap-based and fully replicating ETFs. Hypothesis 6 held the opposite of our findings. The estimated coefficients are all negative, showing high tracking errors for ETFs with low expense ratios. Finally, hypothesis 7 can be confirmed since benchmark volatility was found relevant for both market imperfections.

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