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Differences in Performance between Physical and Synthetic Exchange Traded Funds

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ABSTRACT

Title: Differences in Performance between Physical and Synthetic Exchange Trade Funds

This work studies the main differences in performance between traditional and synthetic exchange traded funds, based on a sample of twenty-two ETFs. The tests performed throughout this study demonstrate the higher ability of synthetic replicated funds to track the underlying index. Additionally, despite the effects of COVID-19 pandemic in ETFs performance, funds that follow a synthetic replication strategy keep tracking better than physical funds, and, moreover, present higher return values than their own benchmark.

Keywords: Asset Management; Exchange Traded Fund; Tracking Error; Performance of ETFs; Synthetic; Physical

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1. INTRODUCTION

The first exchange traded fund (ETF) was launched in 1993 when the American Stock Exchange (AMEX) released the Standard & Poor's Depositary Receipts (SPDRs), tracking the S&P 500. In 2000, the first two European ETFs were listed in Germany, with the EURO STOXX 50 and the STOXX Europe 50 as their benchmarks. These where the first steps of an industry that grew substantially and became very popular because of its tax efficiency, liquidity, low fees, and transparency. At the end of 2020 this industry had a total of 7600 ETFs worldwide, representing a total of 7.74 trillion US dollar (Statista). A major part of this industry is represented by Physical ETFs (Vanguard).

In 2001 was introduced the first synthetic ETF, in Europe. This type of fund was created to replicate the return of an underlying index, as any other ETF, but instead of holding the underlying securities, a synthetic ETF use derivatives to reach the pretended results. Rapidly they became immensely popular, but after the Global Financial Crisis there was a great decrease in the use of these funds. However, the interest in synthetic ETFs has been growing again, due to their tax advantages.

During approximately a decade, BlackRock, the world's biggest asset manager, was critical of synthetic ETFs. In 2011, Larry Fink, CEO and chairman of BlackRock, warned that derivatives-based ETFs exposed investors to intolerable levels of counterparty risk and complained about the transparency of some ETFs. After so many years against these products, surprisingly BlackRock launched a synthetic S&P 500 ETF, encouraged by growing demand for synthetic replication with US equities. This rebirth of synthetic ETFs and the change of mind of the world's largest asset manager motivated this research.

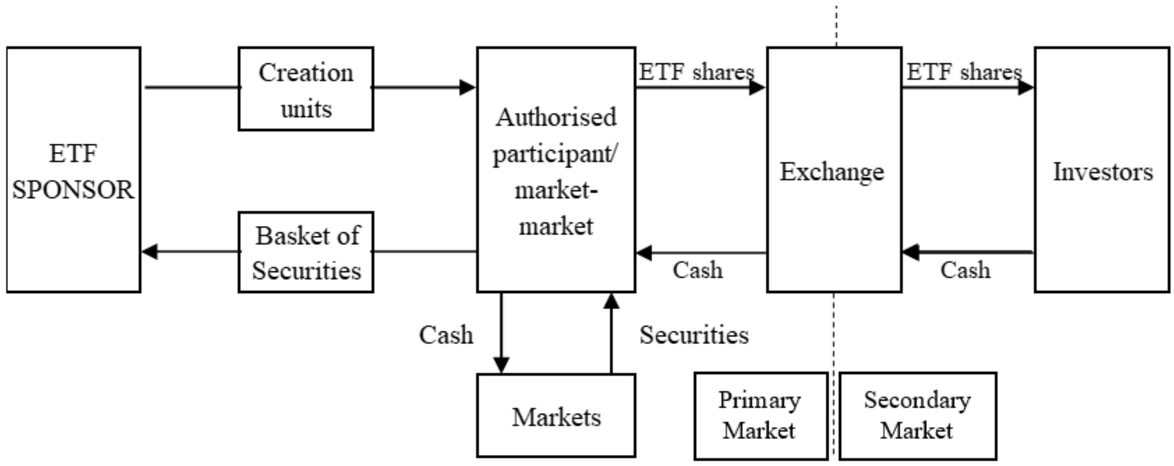
This study investigates and analyses the performance of twenty-two physical and synthetic ETFs and their ability to replicate their underlying indexes, and determines the explanatory variables of returns and tracking error. Furthermore, given the context in which we live, these analyzes are also done with the objective of understand the effect of a stress period – COVID-19 – on ETFs performance.

2. LITERATURE REVIEW

Exchange Traded Funds are created to track the performance of a benchmark index. It could be accomplished through a traditional replication, that is physically, or through a synthetic replication. These different ways are explained below, based on Ramaswamy 2011.

The process starts with an ETF sponsor, which is usually a financial institution, deciding to create an ETF and defining its purpose. Then, the sponsor contacts possible market-makers/authorised-participants (APs), mostly investment banks, and offer them blocks of ETF shares (“creation units”) in exchange for a basket of securities. This transactions between the ETF sponsor and APs happen in the primary market, then APs can hold ETF shares or trade them with investors in secondary market.

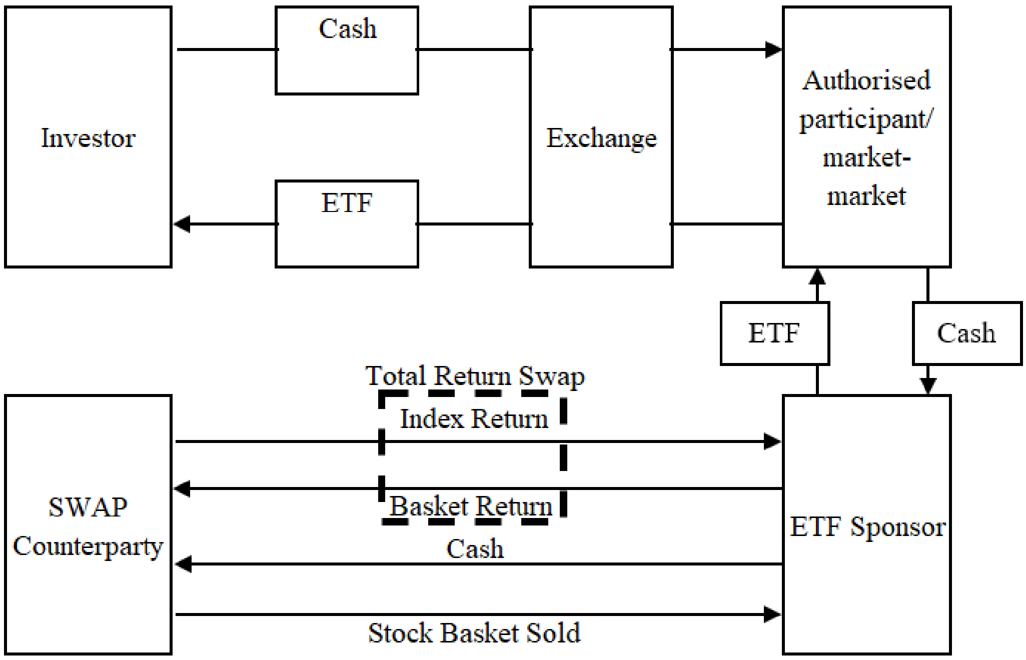
Figure 1- Traditional ETF Structure



In place of owning the physical assets, synthetic ETFs allow the replication of the index through derivatives, being Total Return Swaps the most popular. In this replication method, APs pay cash in exchange of creation units from ETF sponsor, instead of offering a basket of securities.

The ETF sponsor will use the cash to enter total return swap, through a financial intermediary, paying an agreed fee to the counterparty to receive the total return of the targeted index.

Figure 2 - Synthetic ETF Structure



A swap-based ETF does not hold the precise underlying index constitutes, but ensure that the benchmark return is paid, transferring tracking error risk to the swap provider. Therefore, the risk that ETF managers face is that the swap counterparty will not fulfil its contractual obligations. One of the reasons for an ETF investor choose this replication method is reducing costs. If an index is focused in a sector or region and is actively traded, replicating it physically can be more efficient in terms of cost. Nevertheless, when tracking fixed income or emerging market equity indexes, or just illiquid market indexes, owning the underlying securities can be more expansive. In less liquid markets the difference between bid and ask prices, mainly when the fund has a large turnover, multiply replication costs. Also, in volatile market conditions considerable deviations in tracking errors can happen when only a subgroup of benchmark securities is physically replicated. Finally, the last reason proposed by Ramaswamy (2011) is the use of synergies between derivative counterparty bank practices of using collateral and the financing of their warehoused securities.

ETFs attract a huge research interest since their creation. Many studies have been carried out on this type of funds, their performance in terms of returns, and their ability to track the underlying indexes. Roll (1992), Pope and Yadav (1994) and Larsen and Resnick (1998) identify three ways of measure the tracking error, that become popular and are used later in so many other studies.

Frino and Gallagher (2001 and 2002) analyse the performance of S&P 500 and Australian equity index funds. They find out difficulties on indexes replicating the returns of their benchmarks, due to market frictions, and detect seasonality and size as two explaining determinants of tracking error.

Rompotis (2006) investigates the performance and trading characteristics of iShares, where he finds that iShares do not achieve to track index return precisely. He presents a mean last trading price tracking error equal to 97 b.p. for iShares and show, through a regression, that its tracking error is clearly dependent by risk and expense ratio. Additionally in 2006, Rompotis also study the performance, trading characteristics and tracking errors of Swiss exchange traded funds, and it is concluded that ETFs underperform the corresponding benchmarks, while place greater risk on their investors. Furthermore, he determines that Swiss exchange traded funds do not follow full replication scheme, obtains a tracking error close to 1.02%, and conclude that its value is positively associated to the risk and the management fees of ETF.

Elia (2012), based on a sample of 48 exchange traded funds, studies the impact of replication method on tracking error and compares the traditional and the synthetic methods. In this research, despite they underperform the underlying indexes, it is statistically concluded that synthetic ETFs present lower tracking error values, especially when following emerging-market benchmarks. Additionally, after built research regressions to find out factors that influence tracking errors, Elia determines replication method, expense ratio and whether the fund tracks an emerging market benchmark index as some of the main explanatory variables. Meinhardt (2014) explores the believe that a synthetic fund offers investors lower tracking error comparing to physical or traditional exchange traded funds, using a sample of 421 equity and fixed income ETFs, traded at the Frankfurt Stock Exchange. Estimating it with daily closing prices from 2010 until 2011, Meinhardt concludes that the replication method does not have much influence in tracking error when analysing equity ETFs. However, when studying fixed income funds, synthetic ETFs present smaller tracking error values.

Naumenko (2015) empirically studies the differences between physical and synthetic ETFs, based on a sample of 35 ETFs listed on the Swiss Stock Exchange. Contrary to most studies and despite popular opinion, in his research physical ETFs appears to be more effective in replicating the corresponding benchmark returns. Additionally, he investigates tracking error explanatory variables and present expense ratio, number of securities in the benchmark and type of replication as the main ones. On the other hand, it is also concluded that the average daily trading volume does not influence the tracking error.

3. METHODOLOGY

3.1.Data

To carry out this study, twenty-two ETFs were selected, offered by five different providers - Amundi, UBS, Invesco, DWS, and BlackRock - and listed in three of the main European stock exchanges. All funds that make up this sample are equity ETFs, which track some of the main world indexes, such as the S&P 500 Net Total Return and MSCI World Net Total Return, with eighteen of them corresponding to developed markets, and the remaining four to emerging markets.

As the main purpose of this research is to compare Synthetic ETFs and Traditional ETFs, in this twenty-two ETFs, an half is fully replicated, and another half is swap based. For the analysis to be as accurate as possible, the sample is divided into eleven pairs of ETFs, with the only difference in each pair being the replication method of the respective index, which means that they are offered by the same provider, have the same domicile, are denominated in the same currency, are traded in the same stock exchange, and track the same benchmark. With this, possible factors that may influence the analysis results, such as exchange differences or different trading hours, are annulled.

ETFs closing daily prices and other essential information about the funds – assets under management, total expense ratios, number of securities per benchmark, inception dates – necessary for the tests to be carried out, were obtained from the Bloomberg Database and the respective funds fact sheets. The time frame chosen for this study corresponds to three years, starting in November 2018 and ending in October 2021, which ensure a considerable data history. Despite the choice of this interval, the number of observations is not the same for each pair, since several of the synthetic ETFs were created more recently. In each pair, the oldest observation corresponds to the inception date of the most recent ETF.

3.2. Descriptive Statistics

The table below presents the profile of the twenty-two ETFs that will be used in this study.

Table 1 – Sample of ETFs

Ticker	ETF Name	Underlying Asset	Replication Method	Inception Date	Expense Ratio
CW8	AMUNDI MSCI WORLD UCITS ETF - EUR	MSCI WORLD	Synthetic	18/04/2018	0.38%
MWRD	AMUNDI INDEX MSCI WORLD UCITS ETF DR	MSCI WORLD	Physical	11/11/2016	0.18%
CEU	AMUNDI MSCI EUROPE UCITS ETF - EUR	MSCI EUROPE	Synthetic	22/03/2018	0.15%
CEU2	AMUNDI INDEX MSCI EUROPE UCITS ETF DR	MSCI EUROPE	Physical	10/11/2016	0.15%
AEEM	AMUNDI MSCI EMERGING MARKETS UCITS ETF - EUR	MSCI EM	Synthetic	18/04/2018	0.20%
AEME	AMUNDI INDEX MSCI EMERGING MARKETS UCITS ETF DR	MSCI EM	Physical	04/05/2017	0.20%
MUUSAS	UBS ETF (IE) MSCI USA SF UCITS ETF (USD) A-ACC	MSCI USA	Synthetic	03/03/2011	0.15%
USAUSW	UBS ETF (IE) MSCI USA UCITS ETF (USD) A-ACC	MSCI USA	Physical	20/09/2016	0.14%
EQQD	INVESCO NASDAQ-100 SWAP UCITS ETF DIST	NASDAQ-100	Synthetic	23/06/2021	0.20%
EQQQ	INVESCO EQQQ NASDAQ-100 UCITS ETF DIST	NASDAQ-100	Physical	02/08/2005	0.30%
XMEM	XTRACKERS MSCI EMERGING MARKETS SWAP UCITS ETF 1C	MSCI EM	Synthetic	03/09/2007	0.49%
XMMS	XTRACKERS MSCI EMERGING MARKETS UCITS ETF 1C	MSCI EM	Physical	04/05/2018	0.18%
XMWD	XTRACKERS MSCI WORLD SWAP UCITS ETF 1C	MSCI WORLD	Synthetic	03/09/2007	0.45%
XWLD	XTRACKERS MSCI WORLD UCITS ETF 1C	MSCI WORLD	Physical	28/07/2014	0.19%
XMUS	XTRACKERS MSCI USA SWAP UCITS ETF 1C	MSCI USA	Synthetic	03/09/2007	0.15%
XDUS	XTRACKERS MSCI USA UCITS ETF 1C	MSCI USA	Physical	01/07/2014	0.07%
I500	ISHARES S&P 500 SWAP UCITS ETF	S&P 500	Synthetic	06/11/2020	0.07%
CSSPX	ISHARES CORE S&P 500 UCITS ETF USD (ACC)	S&P 500	Physical	19/05/2010	0.07%
S5USAS	UBS ETF (IE) S&P 500 SF UCITS ETF (USD) A-acc	S&P 500	Synthetic	03/03/2011	0.19%
SP5USY	UBS ETF (IE) S&P 500 UCITS ETF (USD) A-dis	S&P 500	Physical	20/07/2012	0.12%
XCHA	XTRACKERS CSI300 SWAP UCITS ETF - 1C	CSI300	Synthetic	13/07/2012	0.50%
ASHR	XTRACKERS HARVEST CSI300 UCITS ETF - 1D	CSI300	Physical	16/01/2014	0.65%

This table describes the name of each exchange traded fund included in the sample, the corresponding ticker, the underlying index, the replication method, the inception date, and the total expense ratio (TER) in percentage.

3.3. Tracking Error Measures

Tracking error is an essential element when analysing the performance of an ETF, since it measures how close the fund follows its underlying index. It is generally reported as the standard deviation of the difference in returns between the ETF and its benchmark or as the divergence between their price behavior. Therefore, a higher tracking error means worse ability to track an index. To evaluate this ability, this study considers three popular methods, identified by Roll (1992), Pope and Yadav (1994) and Larsen and Resnick (1998), and used by other authors, such as Frino and Gallagher (2001 and 2002), Rompotis (2006), Meinhardt et al. (2014), Elia (2012). But initially, for a first analysis, it is calculated the mean of return differences between ETFs and their underlying benchmarks, where the tracking error results can be positive or negative numbers, which allow us to determine if an ETF underperforms or overperforms its benchmark.

In day *t* the tracking error is obtained subtracting the index return from the ETF return ($e_{ft} = R_{ft} - R_{bt}$), being the daily average tracking error ($TE_{0,f}$), of a fund *f*, calculated as follows:

$$TE_{0,f} = \frac{\sum_{t=1}^{n} e_f}{n} \tag{1}$$

Regarding the three popular methods selected for study the tracking ability of ETFs, in the first one the average of the difference in returns between the fund and index is estimated as before. However, in this case the daily average tracking error ($TE_{1,f}$) is obtained through absolute differences:

$$TE_{1,f} = \frac{\sum_{t=1}^{n} |e_f|}{n} \tag{2}$$

Equation (3) describes another method of estimating the tracking error, which is measured as the standard deviation of return differences between the fund and index ($TE_{2,f}$), that is the standard methodology used in industry.

$$TE_{2,f} = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(e_{ft} - \bar{e}_f)^2} \quad (3)$$

The third and last method is to quantify tracking error as the standard error of the residuals of a regression ($TE_{3,f}$), of fund returns ($R_{f,t}$) over benchmark returns ($R_{b,t}$):

$$R_{f,t} = \alpha + \beta R_{b,t} + \varepsilon_{f,t} \quad (4)$$

Although the tracking error estimations through this way should be close to the ones obtained in second method, following Pope and Yadav (1994), if the ETF beta is not equal to one, this approach is imperfect and the regression residuals will differ from the tracking error value given by $TE_{2,f}$.

3.3.1. Determinants of Tracking Error and Returns

The performance of exchange traded funds can be affected by several factors. In this research some possible determinants are checked, including the replication scheme, which is expected to a have a negative coefficient on tracking error, meaning a higher ability to track the correspondent benchmark. To identify possible factors that influence ETFs, the following multivariate regression model is estimated:

$$TE_{f,t} / Return_{f,t} = \alpha + \beta 1\ SYNTH_f + \beta 2\ TER_f + \beta 3\ AUM_f + \beta 4\ EMERG_f + \beta 5\ SYNTH_f \times EMERG_f + \beta 6\ AGE_f + \beta 7\ SEC_f + \varepsilon_f \quad (5)$$

where the dependent variables tracking error, that is the absolute returns difference between an ETF f and its underlying index in period t ($TE_{f,t}$), and return are separately regressed on the dummy variable *SYNTH,* that equals one if the fund replicates synthetically and zero otherwise, the total expense ratio (*TER*), the natural logarithm of the assets under management of the fund (*AUM*), in millions of US dollars, the dummy variable *EMERG*, that equals one if the fund tracks an emerging market benchmark index and zero otherwise, the dummy variable *AGE*, that takes the value of one if the fund has an inception date more recent than the median inception date and zero otherwise, and the number of securities that constitute the underlying index (*SEC*). Additionally, to understand if the economy of a benchmark affects the performance of an ETF, whether synthetic or traditional, the regression also includes an interaction term *SYNTH* x *EMERG*.

As the world has been experiencing a major pandemic for over a year, which has had a great impact on all markets, it is also important to understand the effects of this stress period on the behavior of ETFs, and how these controls are affected. To explore these implications, a similar regression is estimated:

$$TE_{f,t} \,/\, Return_{f,t} = \alpha + \beta 1\ SYNTH_f + \beta 2\ TER_f + \beta 3\ AUM_f + \beta 4\ EMERG_f + \beta 5\ SYNTH_f \times COVID_f + \beta 6\ COVID_f + \beta 7\ SEC_f + \varepsilon_f \tag{6}$$

where the additional dummy variable COVID takes the value of one if the observation date is after 11th of March 2020, the day the World Health Organization declared COVID-19 as a global pandemic. In addition, the model also includes an interaction term *SYNTH* x *COVID* to test whether the effect of this pandemic on ETFs performance depends on the replication method.

Finally, to investigate and understand what could influence the existent returns spread between ETFs of the same pair, the following multivariate regression model is estimated:

$$RS_{p,t} = \alpha + \beta 1\ SEC_p + \beta 2\ COVID_{p,t} + \beta 3\ EMERG_p + \beta 4\ Amundi_p + \beta 5\ UBS_p + \beta 6\ Invesco_p + \beta 7\ DWS_p + \beta 8\ BlackRock_p + \varepsilon_p \tag{7}$$

where $RS_{p,t}$ is the returns spread between ETFs of a pair p, in period t, and were also created five dummy variables for each of the providers that offer the ETFs.

4. RESULTS AND DISCUSSION

In table 2 are presented the results of the average of the differences in returns (TE_0) for each ETF, based on the last three years. This measure of tracking error is a measure of the expected underperformance of the funds relative to the index. Taking all these values, the average of all the sample is close to -0.3021%. But while the physical ETFs underperform their benchmarks by 0.6879%, approximately, the synthetic ETFs of this sample, surprisingly, overperform their benchmark by, in average, 0.083%.

Table 2: Average of the differences in returns

ETF	Average of the differences in returns (TE0)
CW8	-0,00033
MWRD	0,00032
CEU	0,00100
CEU2	0,00100
AEEM	0,00016
AEME	0,00036
MUUSAS	-0,00240
USAUSW	-0,00265
EQQD	-0,00067
EQQQ	-0,05459
XMEM	-0,00099
XMMS	0,00034
XMWD	0,00024
XWLD	-0,00047
XMUS	-0,00184
XDUS	-0,00266
I500	0,00136
CSSPX	0,00058
S5USAS	-0,00188
SP5USY	-0,00736
XCHA	0,01455
ASHR	-0,01056

The table reports the results of the equation (1) for each ETF of the sample.

Table 3 and Table 4 report the results of estimation the tacking error, through the three different methods: average of the absolute difference in returns (TE_1), standard deviation of return differences between the ETF and its underlying index (TE_2), and the standard error of an ETF returns regression on its benchmark returns (TE_3). Table 3 presents all estimations for each ETF, as also the average TE, determined from the three approaches, and the number of observations used for the analysis of each fund. In Table 4 is computed the mean, median, maximum, and minimum of tracking error values for synthetic ETFs, traditional ETFs, and the full sample.

Table 3: Tracking Error

ETF	Average of the absolute differences in returns (TE1)	Standard deviation of return differences (TE2)	Standard error of regression (TE3)	Average TE	#obs
CW8	0.461	0.760	0.710	0.644	766
MWRD	0.472	0.785	0.710	0.656	766
CEU	0.085	0.138	0.137	0.120	766
CEU2	0.082	0.119	0.119	0.107	766
AEEM	0.518	0.732	0.726	0.658	766
AEME	0.513	0.724	0.719	0.652	766
MUUSAS	0.798	1.280	1.006	1.028	768
USAUSW	0.759	1.269	1.027	1.018	768
EQQD	0.033	0.165	0.157	0.118	93
EQQQ	0.092	1.916	1.916	1.308	93
XMEM	0.548	0.891	0.888	0.776	758
XMMS	0.527	0.736	0.735	0.666	758
XMWD	0.474	0.787	0.739	0.667	758
XWLD	0.485	0.798	0.737	0.673	758
XMUS	0.686	1.178	0.955	0.939	758
XDUS	0.686	1.172	0.949	0.936	758
I500	0.574	0.821	0.724	0.706	252
CSSPX	0.511	0.733	0.669	0.638	252
S5USAS	0.851	1.396	1.104	1.117	768
SP5USY	0.819	1.359	1.105	1.094	768
XCHA	0.754	1.110	1.091	0.985	758
ASHR	0.732	1.071	1.049	0.951	758

This table provides the tracking error values of each ETF, calculated by the three different methods (equations (1), (2) and (3)), the average of these methods, and the number of observations used for these calculations.

Table 4: Summary Statistics on Tracking Error

	Average of the absolute difference in returns (TE1)	**Standard deviation of return differences (TE2)**	**Standard error of regression (TE3)**	**Average TE**
Mean				
All	0.521	0.906	0.817	0.753
Synthetic	0.525	0.842	0.749	0.705
Physical	0.516	0.971	0.885	0.791
Median				
All	0.523	0.809	0.738	0.706
Synthetic	0.548	0.821	0.739	0.706
Physical	0.513	0.798	0.737	0.673
Minimum				
Synthetic	0.033	0.138	0.137	0.118
Physical	0.082	0.119	0.119	0.107
Maximum				
Synthetic	0.851	1.396	1.104	1.117
Physical	0.819	1.916	1.916	1.308

The table reports the summary statistics of each tracking error method. It presents the mean, median, minimum and maxium values of synthetic ETFs, physical ETFs, and for all the sample.

Considering all the metrics and the full sample, the average tracking error ranges between 0.107% and 1.308%, and its mean equals 0.753%. The estimation through the average of daily differences (TE_1) presents the lowest value, ranging between 0.033% and 0.851%, with a mean TE of 0.521%. Standard deviation of return differences and standard error of a return's regression estimations (TE_2 and TE_3) are slightly above, with means corresponding to 0.906% and 0.817%, respectively.

Relatively to the first way of estimating tracking error (TE_1), physical ETFs exhibit a lower value of error, 0.516%, but very close to the one estimated for synthetic ETFs, 0.525%. On the other hand, when using the other two metrics (TE_2 and TE_3), synthetic ETFs demonstrate higher capacity of tracking their benchmarks, being that, in average, they present values of 0.842% and 0.749% against 0.971% and 0.855%, respectively. The average TE consolidates this idea reporting an 0.705% value for synthetic fund, in contrast to 0.791% for traditional funds.

Looking at the ETFs individually, the results document that the ETFs with higher tracking error are the ones provided by UBS, with estimated values above 1% when measuring through *TE_2* and *TE_3* metrics. Although their estimated daily average of absolute returns difference (*TE_1*) is not that high, this does not prevent their average TE also exceeding 1%. Although in general the pairs have similar TE values between their ETFs, there is yet another pair that draws attention in this sample, since it is the only one where it does not happen. The two ETFs provided by Invesco (EQQD LN and EQQQ LN) present very different values for tracking error. While the average error of EQQD LN, the swap-based ETF, is 0.118%, EQQQ LN also have an estimated value above 1%, and it is even the highest value of the entire sample, 1.308%. Nonetheless, the number of observations of this pair is only ninety-three days, as the inception date of the newest ETF of this pair was in June of the current year, 2021. Additionally, their average of absolute difference in returns (TE1) is extremely low, below 0.1%.

In Table 5 are presented the results of two regressions that test the determinants of ETFs performance, and their significance, measured by the returns and the absolute returns difference of the overall sample.

Table 5: Determinants of Tracking Error

	Dependent variable	
	TE	Returns
Intercept	0.0135***	0.0006
	(30.802)	(0.451)
SYNTH	-0.0008***	0.0000
	(-5.434)	(0.860)
TER	-0.2333***	-0.0050
	(-5.190)	(-0.947)
AUM	-0.0009***	0.0000
	(-15.096)	(0.646)
EMERG	0.0007**	-0.0002
	(2.887)	(-0.447)
SYNTH x EMERG	-0.0003	-0.0000
	(-0.911)	(-0.184)
AGE	-0.0028***	-0.0001
	(-17.724)	(-0.477)
SEC	0.0000***	-0.0000
	(5.385)	(-0.238)
Adjusted R^2	0.045	0.000
F-Statistic	97.49	0.2384

The table reports the coefficients and t-values (below the coefficients) of each independent variable of a multivariate regression model, where the dependent variables tracking error, that is the absolute returns difference between an ETF f and its underlying index in period t ($TE_{f,t}$), and returns are separately regressed on the dummy variable *SYNTH,* that equals one if the fund replicates synthetically and zero otherwise, the total expense ratio (*TER*), the natural logarithm of the assets under management of the fund (*AUM*), in millions of US dollars, the dummy variable *EMERG*, that equals one if the fund tracks an emerging market benchmark index and zero otherwise, the dummy variable *AGE*, that takes the value of one if the fund has an inception date more recent than the median inception date and zero otherwise, and the number of securities that constitute the underlying index (*SEC*). Additionally, the regression also includes an interaction term *SYNTH* x *EMERG.* *, **, *** suggest statistical significance at the 10%, 5% and 1% level, respectively. Note: number of observations = 14,400

The results obtained in these regressions indicate that the model does not apply to returns and that returns are not significantly affected by none of the coefficients of the independent variables. On the other hand, tracking errors are significantly influenced by the explanatory variables, with different confidence levels.

The coefficient on *SYNTH* is negative and significant, which suggests that a swap-based ETF performs better than a fully replicated ETF, as expected. In this sample of ETFs, the average tracking error for synthetic funds is 0.08% lower than for physical funds. The coefficients on *TER* are both negative and, for tracking error, the coefficient is also significant. Thus, the higher the fund expense ratio, the lower is the ETF return, and the higher is the performance. Relatively to *AUM*, that is the natural logarithm of the assets under management, the coefficient is -0.0009 and significant, which means that a 1% change in *AUM* is associated with a -0.0009% change in tracking error. Another explanatory variable with a negative and significant coefficient is *AGE*, which indicates that recent funds are more efficient than older ones. In contrast, *SEC* and *EMERG* have positive and significant coefficients, suggesting that track emerging markets benchmark indexes or indexes with a higher number of securities will negatively affect the TE. Lastly, the coefficient of the interaction term, as *SYNTH*, *TER*, *AUM* and *AGE*, is also negative and significant. Thus, when tracking emerging markets benchmark indexes, synthetic ETFs also perform better than traditional ETFs.

Table 6 reports the results of a similar test but including an explanatory variable COVID, in order to realize the effects of a stress period on ETFs performance.

Table 6: Determinants of Tracking Error - Effects of the Pandemic (COVID-19)

	Dependent variable	
	TE	Returns
Intercept	0.0128***	0.0005
	(29.419)	(0.620)
SYNTH	-0.0002	0.0000
	(-1.009)	(0.095)
TER	-0.0333	0.0057
	(-0.788)	(0.081)
AUM	-0.0011***	-0.0000
	(-18.983)	(-0.392)
EMERG	0.0004*	-0.0002
	(1.940)	(-0.732)
COVID	0.0018***	0.0010***
	(9.911)	(3.256)
SYNTH x COVID	-0.0004*	-0.0000
	(-1.696)	(-0.094)
SEC	0.0000	-0.0000
	(0.406)	(-0.000)
Adjusted R^2	0.034	0.002
F-Statistic	74.13	3.134

The table reports the coefficients and t-values (below the coefficients) of each independent variable of a multivariate regression model, where the dependent variables tracking error, that is the absolute returns difference between an ETF f and its underlying index in period t ($TE_{f,t}$), and returns are separately regressed on the dummy variable *SYNTH,* that equals one if the fund replicates synthetically and zero otherwise, the total expense ratio (*TER*), the natural logarithm of the assets under management of the fund (*AUM*), in millions of US dollars, the dummy variable *EMERG*, that equals one if the fund tracks an emerging market benchmark index and zero otherwise, the dummy variable *COVID*, that takes the value of one if the observation date is after 11th of March 2020 and zero otherwise, and the number of securities that constitute the underlying index (*SEC*). Additionally, the regression also includes an interaction term *SYNTH* x *COVID.* *, **, *** suggest statistical significance at the 10%, 5% and 1% level, respectively. Note: number of observations = 14,400

As in the previous regression, Equation (5), *SYNTH* and *AUM* have negative and significant coefficients, even during a stress period, which consolidates the idea that synthetic ETFs are more efficient than physical ETFs. During pandemic, the average tracking error is 0.02% lower for synthetic funds. Additionally, now COVID coefficient is also significant, and positive, for both measures of ETFs performance. The coefficient suggests an average tracking error 0.18% higher when the observation day belongs to COVID-19 pandemic. It shows that, during this pandemic, ETFs returns are higher, but ETFs ability to track its underlying index is worse. All the other coefficients are insignificantly different from zero, meaning that they do not impact the performance of an ETF during this stress period.

The results on return spreads regression determine an adjusted R^2 of 0.12. All dependent variables of the model present significant coefficients, at different statistical significance levels, except SEC. The coefficient on COVID suggests a positive impact on return spreads, which means that the difference between synthetic and physical ETFs returns increased slightly after the beginning of the pandemic. On the other hand, the negative coefficient of EMERG means that the difference between returns of ETFs with different replication methods is lower when replicating emerging market indexes. Regarding providers, in this sample of ETFs, while UBS and BlackRock present higher contrast on returns spread, Amundi, Invesco and DWS produce physical and synthetic ETFs with more similar returns.

Table 7: Determinants of Return Spreads

	Dependent variable
	Return Spreads - Synth. vs Phys.
Intercept	0.0014***
	(13.997)
SEC	-0.0000
	(-1.214)
COVID	0.0003***
	(4.211)
EMERG	-0.0002**
	(-2.128)
Amundi	-0.0006***
	(-5.762)
UBS	0.0024***
	(24.246)
Invesco	-0.0005*
	(-1.680)
DWS	-0.0002**
	(-2.478)
BlackRock	0.0003*
	(1.603)
Adjusted R^2	0.12
F-Statistic	139.8

The table reports the coefficients and t-values (below the coefficients) of each independent variable of a multivariate regression model, where the dependent variable Return Spreads, that equals the return spreads between ETFs of the same pair, is regressed on the dummy variable *COVID,* that takes the value of one if the observation date is after 11^{th} of March 2020 and zero otherwise, the number of securities that constitute the underlying index (*SEC*), and the dummy variables *Amundi, UBS, Invesco, DWS* and *BlackRock,* that take the value of one when the observation is from a corresponding ETF. *, **, *** suggest statistical significance at the 10%, 5% and 1% level, respectively. Note: number of observations = 7,200

Tables 8 and 9, in Appendix, report the results of two additional regressions that test the performance of ETFs, as in tables 5 and 6, but testing eight extra dummy variables for each of the indexes that ETFs track. Even including these dummies for each index, the main results do not present a significant change.

5. CONCLUSION

This research is dedicated to the study of whether a synthetic ETF perform compared to a similar but physically replicated ETF. After a brief description of some differences in the structure of each method of replicating and mentioning the context in which we live and that motivates this study, an empirical study is conducted on the performance of a sample of twenty-two ETFs.

As expected, most of the funds underperform their benchmark. However, when observing synthetic ETFs separately, it is concluded that, in average, they overperform their benchmark. Relating to tracking errors, after applying three different methods of estimating it, synthetic ETFs once again perform better than traditional ones.

Empirical statistic tests show that synthetic replication reduces tracking errors, even in periods of COVID-19 pandemic. The tests also prove the negative impact of the pandemic in ETFs performance, which worsened the ability to track underlying indexes. About return spreads in each pair of ETFs, they also increase, meaning that the pandemic reinforces the difference between synthetic and physical ETFs.

Overall, the tests suggest that synthetic ETFs perform better than traditional ones. Synthetic funds can do a better job tracking the performance of an index, especially when the index corresponds to emerging markets, or other less liquid markets, that become more expensive for physical ETFs to operate. But this higher ability to track an index, and even sometimes overperform it, has also a higher risk that many investors do not want to take, and this risk is called counterparty risk. After the global financial crisis and the consequent decline of synthetic ETFs, their reputation has not returned to what it was. The fear that the counterparty (the bank that made the swap agreement) will not comply with its payments is still present in many investors. However, these financial crises are rare and banking regulation has significantly improved. Furthermore, synthetic ETFs have had some tax advantages compared to traditional ETFs, and all this together has led to a new increase in demand for the swap-based funds.

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7. APPENDIX

Table 8: Determinants of Tracking Error including the indexes

	Dependent variable	
	TE	Returns
Intercept	0.0084***	0.0001
	(-17.159)	(0.168)
SYNTH	-0.0002*	0.0001
	(-1.589)	(0.395)
TER	-0.2654**	0.0097
	(-2.510)	(0.053)
AUM	-0.0008***	0.0000
	(-11.196)	(0.791)
EMERG	-0.0002**	-0.0000
	(-2.356)	(-0.506)
SYNTH x EMERG	0.0004	-0.0000
	(1.326)	(-0.141)
AGE	-0.0004*	0.0000
	(-1.569)	(0.141)
SEC	0.0000***	-0.0000
	(11.321)	(-0.449)
MSCI WORLD EUR	-0.0018***	0.0000
	(-10.107)	(0.250)
MSCI EUROPE	-0.0019***	-0.0004
	(-6.920)	(-0.829)
MSCI EM	-0.0002**	-0.0000
	(-2.356)	(-0.506)
MSCI USA	0.0035***	0.0000
	(17.116)	(0.070)
MSCI WORLD USD	-0.0008***	0.0000
	(-5.244)	(0.021)
NASDAQ100	0.0021***	0.0002
	(4.522)	(0.286)
S&P 500	0.0027***	0.0002
	(12.201)	(0.580)
CSI300	0.0049***	0.0000
	(11.191)	(0.093)
Adjusted R^2	0.076	0.001
F-Statistic	100.1	0.2441

The table reports the coefficients and t-values (below the coefficients) of each independent variable of a multivariate regression model, where the dependent variables tracking error, that is the absolute returns difference between an ETF f and its underlying index in period t ($TE_{f,t}$), and returns are separately regressed on the dummy variable *SYNTH,* that equals one if the fund replicates synthetically and zero otherwise, the total expense ratio (*TER*), the natural logarithm of the assets under management of the fund (*AUM*), in millions of US dollars, the dummy variable *EMERG*, that equals one if the fund tracks an emerging market benchmark index and zero otherwise, the dummy variable *AGE*, that takes the value of one if the fund has an inception date more recent than the median inception date and zero otherwise, and the number of securities that constitute the underlying index (*SEC*). Additionally, the regression also includes an interaction term *SYNTH* x *EMERG,* and a dummy variable for each of the indexes that those ETFs track. *, **, *** suggest statistical significance at the 10%, 5% and 1% level, respectively. Note: number of observations = 14,400

Table 9: Determinants of Tracking Error including the indexes – Effects of the Pandemic (COVID-19)

	Dependent variable	
	TE	Returns
Intercept	0.0082***	0.0004
	(19.337)	(0.579)
SYNTH	0.0000	0.0000
	(0.128)	(0.204)
TER	-0.2014**	-0.0437
	(-2.373)	(-0.299)
AUM	-0.0010***	-0.0000
	(-13.945)	(-0.418)
EMERG	-0.0002**	-0.001
	(-2.022)	(-0.839)
COVID	0.0018***	0.0010***
	(9.835)	(3.226)
SYNTH x COVID	-0.0004*	-0.0000
	(-1.644)	(-0.119)
SEC	0.0000***	0.0000
	(14.354)	(0.393)
MSCI WORLD EUR	-0.0021***	-0.0000
	(-12.201)	(-0.212)
MSCI EUROPE	-0.0017***	-0.0000
	(-7.092)	(-0.217)
MSCI EM	-0.0002**	-0.0001
	(-2.022)	(-0.839)
MSCI USA	0.0039***	0.0002
	(20.840)	(0.535)
MSCI WORLD USD	-0.0008***	0.0000
	(-5.080)	(0.109)
NASDAQ100	0.0015***	0.0000
	(3.440)	(0.075)
S&P 500	0.0026***	0.0000
	(13.473)	(0.076)
CSI300	0.0049***	0.0000
	(12.601)	(0.600)
Adjusted R^2	0.086	0.001
F-Statistic	113.5	1.895

The table reports the coefficients and t-values (below the coefficients) of each independent variable of a multivariate regression model, where the dependent variables tracking error, that is the absolute returns difference between an ETF f and its underlying index in period t ($TE_{f,t}$), and returns are separately regressed on the dummy variable *SYNTH,* that equals one if the fund replicates synthetically and zero otherwise, the total expense ratio (*TER*), the natural logarithm of the assets under management of the fund (*AUM*), in millions of US dollars, the dummy variable *EMERG*, that equals one if the fund tracks an emerging market benchmark index and zero otherwise, the dummy variable *COVID*, that takes the value of one if the observation date is after 11th of March 2020 and zero otherwise, and the number of securities that constitute the underlying index (*SEC*). Additionally, the regression also includes an interaction term *SYNTH* x *COVID,* and a dummy variable for each of the indexes that those ETFs track. *, **, *** suggest statistical significance at the 10%, 5% and 1% level, respectively. Note: number of observations = 14,400