ISCTE Business School
Instituto Universitário de Lisboa

The tracking ability of Oil and Gas Exchanged Traded Funds (ETFs)

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- Spine -

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Resumo

Apesar do vasto reportório de trabalhos existentes sobre *Exchanged Traded Funds* (ETFs), poucos são aqueles que têm analisado *commodities* ETFs e a respetiva adequabilidade como substitutos de investimentos diretos em *commodities*. Para analisar se esta classe específica de ETFs é uma boa alternativa, analisámos uma amostra de 11 ETFs e se seguiam os respetivos *benchmarks*. Para tal procedemos a uma análise de regressão linear, ao cálculo do tracking error, e uma análise de cointegração, sendo esta última focada na relação de longo prazo entre variáveis. As análises de regressões e tracking error evidenciam uma forte ligação com os *benchmarks* na maior parte dos ETFs, mas os testes de cointegração apresentam resultados díspares, sugerindo uma relação mais fraca no longo prazo para a maior parte dos ETFs. Por outro lado os ETFs que têm como *benchmarks* índices de *commodities* apresentam melhores resultados do que aqueles que seguem as *commodities* propriamente ditas. O uso de produtos derivados, nomeadamente futuros nestes ETFs, e o facto de os mesmos terem de ser constantemente renegociados (*Roll Over*) são uma das razões para a diferença de performances entre os ETFs e respetivos *benchmarks*.

Palavras-Chave: Cointegração; *Commodities*; ETFs; Regressões Lineares;

Classificação JEL: G10 - *General* e G11 - *Portfolio Choice; Investment Decisions*

Abstract

Despite the vast literature on Exchanged Traded Funds (ETFs), few are those focused on commodities ETFs and their suitability as a replacement for direct investments in commodities. To examine whether this specific class of ETFs is a good alternative we have analyzed the tracking ability of a sample of 11 ETFs and their respective benchmarks. To this end, we have performed a linear regression analysis, a tracking error analysis, and a cointegration analysis, the latter being focused on the long-term relationship. Regressions analyses and tracking error show a strong relationship in most ETFs, but cointegration tests show uneven results, suggesting a weaker relationship in the long run between ETFs and their benchmark. On the other hand the ETFs that follow benchmarks indexes have better results than those who follow the commodities themselves. The use of derivative products such as futures in these ETFs, and the fact that those must be constantly renegotiated (Roll Over) are one of the reasons for the difference in performance between ETFs and their benchmarks.

Keywords: Cointegration; Commodities; ETFs; Linear Regressions;

JEL classification: G10 - General and G11 - Portfolio Choice; Investment Decisions

Thanks

First and foremost I would like to thank to my supervisor, Professor Sofia Ramos, for all the help, patience and dedication through almost two years of constant and repeated delays from my part to finish this work. I would also like to recognize the constant exchange of ideas with my former masters' colleague, Pedro Rodrigues, whom is also finishing his work in a much related field of expertise.

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Sumário Executivo

No seguimento do desenvolvimento dos mercados financeiros em geral, e dos produtos derivados em particular, o aparecimento dos *Exchanged Traded Funds* (ETFs) no fim dos anos 80 e início dos anos 90 veio disponibilizar aos investidores interessados mais uma opção para diversificar as suas carteiras e investir em certas categorias de investimento que anteriormente, quer pela sua impraticabilidade, quer pelos seus elevados custos, não eram viáveis. As evidentes vantagens do uso de ETFs, principalmente os reduzidos custos associados, fez com que estes produtos financeiros se tornassem rapidamente num sucesso, tendo o seu crescimento sido bastante considerável principalmente a partir do ano 2000, altura que coincide com o aparecimento dos *commodities* ETFs.

Das diferentes classes de ETFs disponíveis, os focados em *Equitys* dominam claramente o mercado quer em ativos sobre gestão quer em número de produtos disponíveis, sendo que nos últimos anos os ETFs de Obrigações têm vindo a ganhar cada vez mais importância e adeptos, sendo o mesmo também verdade para os ETFs de *commodities*, mas numa escala menor. Em Fevereiro de 2012, segundo a BlackRock, uma das maiores empresas gestoras de ativos do mundo, o mercado total de ETFs ascendia a mais de 1.500 mil milhões de Dólares de ativos sobre gestão por parte dos quase 3500 produtos disponíveis, sendo que a quota-parte correspondente aos ETFs de *commodities* era de apenas 35,8 mil milhões de Dólares, uma pequena parte considerando o total, mas em claro crescimento nos últimos anos.

O facto de os *commodities* ETFs serem, no total do mercado de ETFs, relativamente insignificantes, pode ser apontado como uma das razões para a existência de poucos estudos sobre esta classe comparativamente às restantes classes de ETFs, pelo que em nossa opinião será um tema que se justifique explorar e tentar perceber se existe uma relação entre os ETFs de *commodities* estudados e os respetivos *benchmarks* que cada ETF se propõe a replicar.

O resto deste trabalho está organizado da seguinte maneira: a Secção 1 apresenta uma pequena introdução sobre ETFs estando dividida em quatro partes; na primeira apresentamos um pequeno resumo da história e evolução do mercado dos ETFs desde que foram introduzidos em 1989; na segunda damos a conhecer o *"in-kind" Creation/Redemption Process*, umas das características mais importantes que caracterizam os ETFs; na terceira parte listamos os principais riscos associados aos ETFs bem como os principais tipos de ETFs existentes; na quarta parte explicitamos os objetivos a que nos propusemos com este trabalho. Na Secção 2 apresentamos uma revisão de literatura de trabalhos anteriores similares, o seu objectivo é atualizar o leitor com a corrente literatura no assunto a ser discutido. A Secção 3 descreve os dados que vão ver analisados e os critérios que foram utilizados para a seleção dos mesmos. A Secção 4 introduz os métodos usados para analisar os dados recolhidos; os métodos utilizados são regressão linear, análise de *tracking error* e análise de cointegração. A Secção 5 apresenta os resultados obtidos após os métodos selecionados terem sido aplicados. A Secção 6 faz um resumo com uma pequena discussão das mais importantes conclusões a que chegámos. A Secção 7 discrimina a bibliografia consultada na elaboração deste trabalho e por fim a Secção 8 engloba alguns anexos que não sendo significativa a sua inclusão no corpo principal considerámos ser importante incluí-los no trabalho.

1. Introduction

1.1 History and Evolution

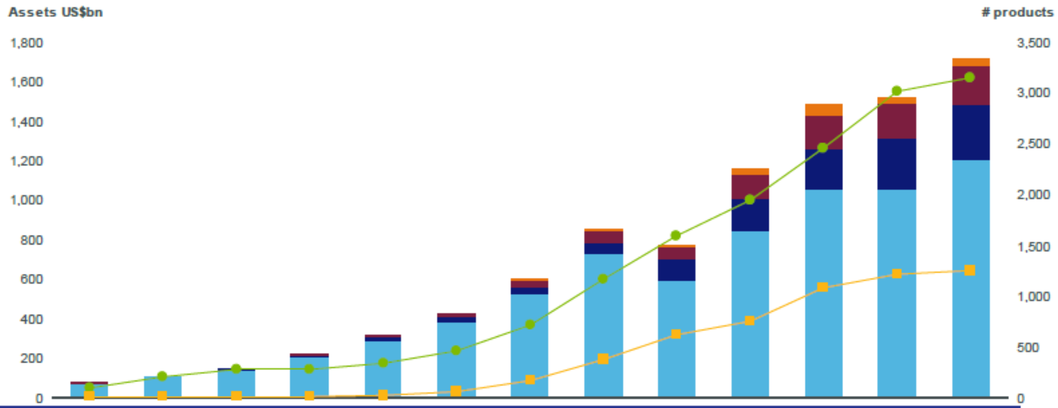
Exchange traded funds (ETFs) are investment products that allow investors to be exposed to a different range of assets such as indexes, bonds and commodities, through a single financial instrument. Like shares of any individual companies, ETFs are funds that trade on a stock market throughout the day. They can be traded at any time during market hours and can be sold short or margined, but in reality they are shares of a portfolio, not of an individual company. Although many investors regard ETFs simply as a form of diversified investment, their novelty and legal specificity lead to an exponential increase since they were first introduced in 1989, their popularity has grown so quickly that they have become one of the most successful financial products of the last two decades.

The first ETF appeared in Canada in 1989 with the TIP 35 (Toronto Index Participation Fund). It aimed to track the exchange's 35 largest and most liquid stocks. In November 2000, the Toronto Stock Exchange announced plans to phase out the popular TIP 35 index participation units, and replace it with its new i60 units, which track the 60 stocks in the new S&P/TSE 60 Index. The first American and nowadays the biggest ETF in the world, was launched in 1993, the Standard & Poor's 500 Depository Receipts, also known as SPDRs or "Spiders", and aimed to track the S&P 500 index. In 1999 the first Asian ETF was created as the Hong Kong Tracker Fund and was not until 2000 that the first European ETF was launched on 11 April, when Merrill Lynch unveiled two ETFs tracking the Eurostoxx 50 and Stoxx 50 indices on the Frankfurt Stock Exchange. Shortly after on 28 April, iShares created and listed the first ETF in the UK, with the launch of its FTSE 100 fund on the London Stock Exchange. Today most national stock exchanges list some sort of ETFs.

Figure 1 shows the Global ETP[1] multi-year asset growth since 2000 to February 2012, either in Assets Under Management (AUM) in the scale to the left, and total number of products in the scale to the right.

[1] The ETP category encompasses any portfolio exposure security that trades intra-day on an exchange, including exchange traded funds (ETFs), exchange traded commodities (ETCs), exchange traded notes (ETNs) and exchange traded instruments (ETIs).

Figure 1 - Global ETP multi-year asset growth



Assets (US$bn)	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Feb-12
ETF total	74.3	104.8	141.6	212.0	309.8	412.1	565.6	796.7	711.1	1,036.0	1,311.3	1,350.9	1,524.5
ETF equity	74.3	104.7	137.5	205.9	286.3	389.6	526.5	729.9	596.4	841.6	1,053.8	1,057.4	1,205.8
ETF fixed income	0.1	0.1	4.0	5.8	23.1	21.3	35.8	59.9	104.0	167.0	207.3	257.7	277.6
ETF commodity	–	0.0	0.1	0.3	0.5	1.2	3.4	6.3	10.0	25.6	45.7	31.1	35.8
Other ETPs total	5.1	3.9	4.1	6.3	9.3	15.9	32.5	54.6	61.2	119.7	171.3	173.5	195.8
# ETFs	92	202	280	282	336	461	713	1,170	1,595	1,944	2,460	3,011	3,145
# Other ETPs	14	17	17	18	21	63	170	371	625	750	1,083	1,210	1,250

Source: BlackRock

From Figure 1 we can clearly see the strong growth since 2000, with only 2008 showing a negative growth in AUM, due to the sub-prime crisis, and even in that year the total number of products increased despite the global crisis. Most of this growth comes from Equity ETFs, by far the most traded and recognized ETP. Another important aspect of this chart is the appearance in 2001 of a new ETF. The commodities ETF, or Exchanged Traded Commodities (ETCs), that are analyzed in this work.

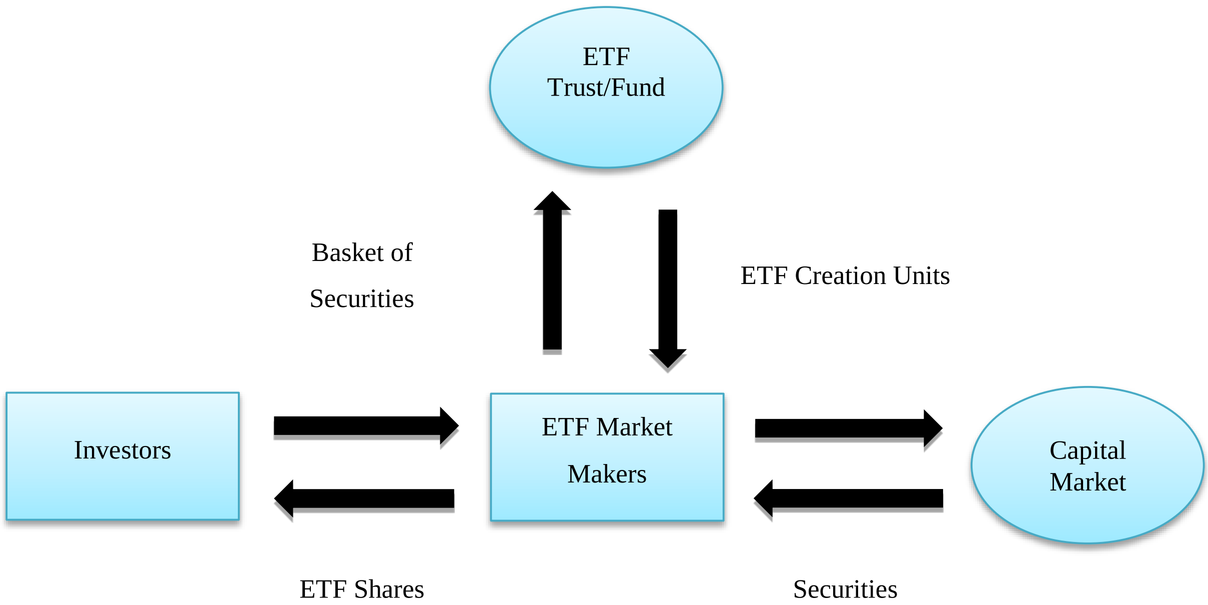
1.2 The "in-kind" Creation/Redemption Process

The usual ETF structure adopted worldwide is that of open-end funds[2] with special characteristics, such as the "in-kind" process for creation and redemption of shares. This "in-kind" process is a major distinguishing feature of ETFs, buyers who buy directly from the fund (Authorized Participants or market makers) pay for their shares with a portfolio of securities rather than with cash. Similarly, sellers (Funds) receive a portfolio of securities. Creation/Redemption units are created in large multiples of individual ETF shares, these units are available to Authorized Participants (AP) that are authorized by the fund and who usually act as market makers on the individual ETF shares. The prices at which ETFs trade rarely differ much from the Net Asset Value (NAV), because APs have the option to trade directly with the

[2] Open-end funds issue new shares and redeem existing shares on demand, usually on a daily basis. In contrast, closed-end funds issue shares in primary market offerings that the fund or its investment bankers arrange. Once issued, investors cannot sell their shares back to the fund by demanding redemption, instead they must sell their shares to other investors in the secondary markets.

ETF, therefore if the ETF shares market price is sufficiently below its NAV, APs will buy shares in the secondary market at market price and redeem those same shares at NAV with the fund. Conversely, if the price of an ETF is sufficiently above its NAV, APs will do the opposite transaction, buy the shares from the fund at NAV and sell them in the secondary market at market price. As a result, the market price and NAV of ETFs tend to converge. This Creation/Redemption process is identical to all type of ETPs. Figure 2 shows this process.

Figure 2 – Creation/Redemption process of ETFs



As opposed to traditional open-end funds, such as Mutual Funds, the "in-kind" redemption means that no capital gain will be realized in the fund's portfolio on redemption. If the redemption were in cash, the fund would have to sell stocks held in the fund's portfolio and possible capital gains would be realized and the tax burden would have to be passed to all existing fund shareholders. That is not the case with ETFs[3]. Other advantage over mutual funds is cost effectiveness; because most ETFs are passively managed[4] the expense ratio can be kept low relative to actively managed funds.

[3] There are situations in which capital gains distributions are generated for the ETF, such as capital gains resulting from selling securities directly to the capital market due to an index reconstitution. Thus, zero capital gains distributions are not guaranteed.

[4] Actively managed ETFs were launched recently in 2007.

1.3 Types and Risks

Before advancing it is important to mention some of the different types of ETFs available and the risks associated with investing in ETFs. According to several authors ETFs can be grouped by investment categories, based on their investment target:

- *Broad domestic market index:* In many countries, the most active ETFs are those launched on the major local stock index;
- *Style:* Some ETFs track a specific investment style, usually value or growth.
- *Sector or industry:* Some ETFs track a sector index or invest in baskets of stocks from specific industry sectors, like Basic Materials and Processing, Consumer Discretionary, Consumer Staples, Energy, Financial Services, Health Care, Industrial/Producer Durables, Technology, Telecommunications, and Utilities;[5]
- *Foreign country or region:* A fast growing segment of the ETF market if funds tracking foreign-country and regional indexes;
- *Fixed income:* This category is a recent addition to the universe of ETFs, so far their success compared to equity ETFs has been low;
- *Commodity:* As with fixed income, commodity ETFs are a recent addition, as mentioned earlier this class of ETFs appeared for the first time in 2003. ETFs have been introduced on commodities such as precious metals and oil, and on some broad-based commodity index such as the GSCI. Oil and Gas ETFs are the subject analyzed in this work;
- *Actively managed funds:* Some providers have introduced "active" ETFs, mostly in Europe;

More recent leveraged ETFs have drawn the attention of investors. These are ETFs that have derivatives or are leveraged to magnify the underlying asset return (or its inverse in case of short ETFs) by two or three times, with the portfolio being rebalanced once a day. Shum (2011) describes leveraged ETFs as funds that aim to track daily returns, instead of the price of an underlying index at a higher frequency. She refers that what attracts investors to these products is the ability to increase their market exposure and to hedge without a margin account. Avellaneda and Zhang (2009 and 2010) also wrote extensively about leveraged ETFs, in their

[5] This list is based on Commercial Industry Classification Systems. Major index providers, including Standard & Poor's, MSCI Barra, Russell Investments, Dow Jones and FTSE, classify companies in their equity indices into industry groupings. Governmental Industry Classification Systems are also available.

2009 paper they refer that investors must be aware of the suitability of leveraged ETFs for long term investments, as evidence shows that in the long run discrepancies between leveraged ETFs and the underlying product start to appear. The authors present two explanations for this effect: the difference between daily compounded and annually compounded interest rates, an effect also referred as convexity and volatility. Regarding the compounding effect, the reason given is that leveraged ETFs have a daily return target, usually a return target different from the underlying product. Cheng and Madhavan (2009) argue that that the gross return of a leveraged or ETF has an embedded path-dependent option that under certain conditions can lead to value destruction for a long term investor and that the unsuitability of these products is reinforced by the drag on returns from high transaction costs and tax inefficiency. Shum (2011) also finds that tracking errors were not caused by the effects of compounding alone and that depending on the fund, the impact of management factors can outweigh the impact of compounding, and substantial premiums/discounts can exacerbate further distorted performance. She shows that short ETFs deviate from their benchmark return faster than their counterparts as the holding period lengthens and that returns to leveraged ETFs can deviate from their benchmark even if investors rebalance on a daily basis, contradicting some established beliefs.

Concerning the major risk faced by ETFs we can divide them in two types of risk, the ones that affect all ETFs, like for example market risk, trading risk and tracking error risk, and those that affect specific ETFs, like sector risk, currency risk, country risk and derivatives risk. We will focus on the risks that are common to all ETFs and later on more attention will be given to tracking error risk, since tracking error is a good measure of the tracking abilities of ETFs.

- *Market risk:* ETF shareholders are subject to risks similar to those of holders of other diversified portfolios;
- *Trading risk:* Although an ETF is designed to make it likely that it will trade close to its NAV, impediments to the securities markets may result in trading prices that differ, sometimes significantly from the NAV. Moreover, there is no assurance that an active trading market will always exist for the ETF on the exchange, so the bid-ask spread can be large for some ETFs. The overall depth and liquidity of the secondary market also may fluctuate;
- *Tracking error risk:* Although ETFs are designed to provide investment results that generally correspond to the price and yield performance of their respective underlying products, the funds may not be able to exactly replicate the performance of the products

because of fund expenses and other factors. Tracking risk comes from trading risk, but also from the fact that the ETF NAV differs from the index value;

1.4 Goals

The investment in commodities has grown exponentially since 2000 and has become an asset class in asset allocation strategies[6]. Commodities ETFs can be a good alternative to invest in commodities, however there are not many studies about commodities ETFs. We proposed ourselves to study these relatively new products and to assess if they could be a viable alternative to the traditional method of investing in commodities. More specifically we will focus in relevant classes of commodities: Oil and Gas ETFs traded on Germany, with the purpose of assessing whether these products are doing what they are supposed to do: track their Benchmarks returns as close as possible. The objects of our analysis are both index tracking ETFs that track indexes like the DJ STOXX 600 Oil and Gas and the S&P GSCI Crude Oil, and ETFs that track the price of oil like the Brent[7] and the WTI[8].

Investing in commodities has gained momentum in the last few decades with the surge in commodity prices, but on the other hand it has been hindered by the physical problem of having to own the goods. One way to avoid this problem was to invest in derivatives, such as future contracts, but future contracts, are in general, better designed for short term trading, not only because of their liquidity but also because of their high leverage and the fact that futures positions needs to be continuously rolled from one contract to the next. Financial innovation lead to the creation of commodities ETFs as a better long term investment compared to future contracts.

We used short term and long term methods to analyze our data and we concluded that commodities ETFs are better suited for short term investments as show by the linear regression results as opposed to the cointegration analysis, which shows a weaker relationship between ETFs and their benchmarks. We also concluded that index tracking ETFs provide better tracking abilities that ETFs tracking the price of oil like the Brent and the WTI.

[6] Asset allocation strategies consist of attempting to balance risk versus returns by adjusting the percentage of each asset in the investor's portfolio. Asset allocation is based on the principle that different assets perform differently in different markets and economic conditions.
[7] Brent is the leading global price benchmark for Atlantic basin crude oils.
[8] West Texas Intermediate (WTI), also known as Texas light sweet, is a grade of crude oil used as a benchmark in oil pricing.

2. Literature Review

Academic studies on ETFs followed the increasing acceptance and popularity of ETFs and started to appear mostly in the end of the ninety's and begin of the twenty first century. Gastineau[9] (2001) was one of the first authors to write on ETFs. *The Exchange-Traded Funds Manual* is the first comprehensive book on ETFs and the author covers diverse themes such as the low expense ratios of ETFs and how ETFs manage to avoid significant capital gains contributions.

The first studies focused on ETFs were mainly aimed to describe the advantages over similar mutual funds. Fuhr (2001) refers that investors looking to increase or reduce their risk exposure to different markets and styles should consider investing in ETFs, as they provide a viable alternative to future contracts due to their specific characteristics. He also points out that ETFs can be a good option to individual and institutional investors as the potential use for them are numerous. Dellva (2001) describe, besides other advantages, that the in-kind creation and redemption processes makes ETFs very tax efficient, with investor no longer paying taxes over capital gains created by trading within the fund. Poterba and Shoven (2002) compare the pretax and after-tax returns on the largest ETF at the time, the SPDR trust, with the returns on the largest equity index fund, the Vanguard Index 500, with both funds tracking the S&P 500. They concluded that both these funds show a very identical performance, with the Vanguard Index 500 showing a slightly higher pretax and after-tax return. Svetina and Wahal (2008) find that almost 83% of all ETFs track indices for which there are no mutual funds equivalents, therefore increasing the number of passive investment opportunities available to investor. They also found that for ETFs with mutual funds equivalents, the ETFs usually present a better performance.

2.1 Tracking Performance

The performance of ETFs and how close they track their benchmark has been an issue of interest among the academic research. Studies seem to conclude that tracking errors are caused by factors such as transaction costs, index-composition changes, corporate activity, fund cash flows, index volatility, the reinvestment of dividends, and index replication strategies (see, e.g. Chiang 1998; Elton, Gruber, Comer, and Li 2002; Frino and Gallagher 2002). The volatility of the asset is a further source of tracking error (Shin and Soydemir 2010).

[9] Gary L. Gastineau is actually the principal of ETF Consultants LLC.

Some authors report that ETFs underperform benchmarks while others find opposite evidence. Frino and Gallagher (2001) show that on average and after expenses, the S&P 500 index funds, delivered better performances than active funds over the sample period. On the other hand, Elton, Gruber, Comer and Li (2002) documented that the Standard & Poor's Depository Receipts (SPDR) underperforms the S&P Index by 28.4 basis points, citing as the cause the management fee and the loss of return from dividend reinvestment. Gallaghar and Segara (2005) find that classical ETFs in Australia reward investors with returns similar with the underlying benchmark before costs and Milonas and Rompotis (2006) study the performance and the trading characteristics of a sample of 36 Swiss ETFs, concluding that Swiss ETFs underperform their benchmark, exposing investors to greater risk than the risk of standard deviation of the indexes.

Tracking error can also be evaluated using market prices instead of the NAV (see, e.g. Harper, Madura, and Schnusenberg 2006). Any market-price deviations from NAVs should disappear quickly because of the in-kind and in-cash creation/redemption processes, but the market price tracking error can substantially deviate from the NAV tracking error. DeFusco, Ivanov and Karels (2011) show that the pricing deviations of Spiders, Diamonds and Cubes[10] are different from zero. The authors claim that the pricing deviation can be considered an additional cost of administering an ETF. Furthermore, seasonal patterns in tracking errors have been detected (see, e.g. Frino and Gallagher 2001 and 2002; Frino, Gallagher, Neubert, and Oetomo 2004; Rompotis 2010). Chu (2011) investigates the tracking errors of ETFs traded in Hong Kong and finds that they are higher compared with those in the US and Australia. He assumes that one possible explanation could be the use of synthetic investment tools instead of holding the underlying stocks. Blitz, Huij and Swinkels (2010) examine the tracking error of European index funds and ETFs as measured by their underperformance against the gross total return indices. They find that European funds underperform their benchmarks and that dividend withholding taxes and fund expenses have similar explanatory power.

Elia (2011) investigates the ability of traditional and synthetic European ETFs to replicate the returns of the target benchmarks. The findings show that both traditional and synthetic ETFs traded in Europe are affected by a significant tracking error. Evidence suggests that the ETFs that follow a synthetic replication strategy instead of holding the benchmark underlying

[10] Spiders, Diamonds and Cubes refer to ETFs that track the S&P Indices, the Dow Jones Industrial and the Nasdaq respectively.

securities enjoy a lower tracking error and higher tax efficiency. However, synthetic ETFs underperform both the benchmarks and the traditional counterparts.

2.2 Arbitrage Mechanism and Mispricing

Mispricing and the efficiency of the arbitrage mechanism has also been the subject of several works and papers. This branch of literature focus on whether ETFs are traded at premium or discount, or in other words, if ETFs trading prices deviate from their Net Asset Value.

Elton, Gruber, Comer and Li (2002), and Ackert and Tian (2000, 2008) report that the mispricing in United States ETFs is small. Ackert and Tian (2008) investigate the pricing of ETFs relative to their benchmarks, and argue that the mispricing of country ETFs is related to momentum, illiquidity, and size effect. Cherry (2004) finds that ETFs consistently trade away from their net asset value. Moreover, ETFs, on average, are found to be about 17% more volatile than their underlying assets; 70% of the excess volatility can be explained by proxies for transaction and holding costs which inhibit successful arbitrage. The findings in this paper are consistent with noise trader models of costly arbitrage and are inconsistent with hypotheses of financial market efficiency. Jares and Lavin (2004) and Engle and Sarkar (2006) find that mispricing is not small in the case for international ETFs. This is probably due to the fact that for international ETFs where there is little or no overlap in trading hours with their underlying markets. Delcoure and Zhong (2007) concluded that iShares ETFs trade at economically significant premiums for 10 to 50% of the time even when taking into account transaction costs and time-zone measurement errors, with iShares price returns showing high volatility relative to their NAV returns. They also showed that the deviations of most iShares' prices from their NAVs are not persistent and converge to zero in the short run. Aber, Li and Can (2009) analyzed the tracking ability of four iShares ETFs using three measures, the premium and discount position, daily return and tracking error, compared with conventional index mutual funds tracking the same index and find that conventional index funds track better than ETFs. Petajisto (2011) also confirm that the prices of exchange-traded funds can deviate significantly from their net asset values, in spite of the arbitrage mechanism that allows authorized participants to create and redeem shares for the underlying portfolios. The deviations are larger in funds holding international or illiquid securities where net asset values are most difficult to determine in real time. Despite these studies, very few analyze commodities ETFs.

3. Data

A sample of eleven Oil and Gas ETFs traded on the Frankfurt Stock Exchange in Germany[11] was selected to be analyzed. Table 1 summarizes the information concerning those eleven ETFs. The decision to go with ETFs from just one exchange is based on the fact that we do not think that the tracking ability of ETFs is better or worse depending on the exchange they trade, in fact some of the companies that provide most ETFs also market those products in other markets, only the distribution channel changes. Of the eleven ETFs, one is a leveraged ETFs. Leveraged ETFs are specialized funds that aim to amplify returns in relation to their benchmark, this products employ financial engineering methods like derivatives to magnify returns, by leveraging returns this ETFs can often produce two or three times[12] the returns (positive or negative) of a non-leveraged ETF that follows the same benchmark. Leveraging is achieved through the issuance of debt (borrowing) or through the use of derivatives by the funds. One ETF in our sample is a short ETF[13]. Short ETFs are designed to perform as the inverse of the benchmark they track, these funds achieve their objective using short selling, derivatives and others financial techniques. Concerning the Benchmarks, four funds track the STOXX 600 Oil and Gas, three funds track the S&P GSCI (Goldman Sachs Commodity Index) Crude Oil Index, three funds track the WTI (Western Texas Intermediate) and one fund tracks the Brent Crude Oil. The data was gathered from DataStream. The observations are weekly and since their inception[14], the number of observations is not equal in all ETFs. Weekly observations were chosen over daily observations because weekly returns appear to show a stronger correlation with the weekly benchmarks returns than daily returns[15].

Table 2 summarizes the most important statistic characteristics of our sample. The standard deviation (%) was calculated based on the returns, notice that the leveraged fund has by far the highest risk measured by the highest standard deviation, as expected.

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[11] The Frankfurt Stock Exchange accounts for over 90 percent of the turnover in the German market and a very large share of the European market.

[12] This ETFs are referred to as 2x and 3x Leveraged ETFs.

[13] Short ETFs are also known as Inverse ETFs or Bear ETFs.

[14] Some observations in some funds were deleted due to missing values in the DataStream, so the observations from those funds are not since inception.

[15] Preliminary results not reported.

***Table 1*. ETFs Description**

This table includes the name, type, number of observations and the respective benchmark for each ETF.

N.º	Name	Type	Obs.	Benchmark
1	iShares DJ STOXX 600 Oil and Gas (de)	Normal	371	STOXX Europe 600 Oil and Gas
2	ETFS Commodity Securities WTI Oil	Normal	196	WTI
3	DB X-Trackers DJ STOXX 600 Oil and Gas ETF	Normal	235	STOXX Europe 600 Oil and Gas
4	DB X-Trackers DJ STOXX 600 Oil and Gas Shutter	Short	184	STOXX Europe 600 Oil and Gas
5	S&P GSCI Crude Oil Total Return T-ETC	Normal	144	S&P GSCI Crude Oil Index
6	ETFS Commodity Securities Leveraged Crude Oil	Leveraged	144	WTI
7	DJ STOXX 600 Optimized Oil and Gas Source ETF	Normal	117	STOXX Europe 600 Oil and Gas
8	S&P GSCI Enhanced Crude Oil Source T-ETC	Normal	116	S&P GSCI Crude Oil Index
9	Rici Enhanced Brent Crude Oil	Normal	72	Brent
10	Rici Enhanced WTI Crude Oil	Normal	72	WTI
11	S&P GSCI Crude Oil Official Close Index ETC	Normal	72	S&P GSCI Crude Oil Index

***Table 2*. Summary Statistics**

Table 2 shows besides the name and type for each ETF, the mean of the returns, the absolute standard deviation, the returns standard deviation, and the minimum and maximum absolute value for all ETFs.

N.º	Name	Type	Mean (%)	St. Dev.	St. Dev. (%)	Minimum	Maximum
1	iShares DJ STOXX 600 Oil and Gas (de)	Normal	0,0863	5,41	3,30	24,57	47,25
2	ETFS Commodity Securities WTI Oil	Normal	-0,1135	13,04	4,80	26,00	83,55
3	DB X-Trackers DJ STOXX 600 Oil and Gas ETF	Normal	0,0334	7,87	3,98	42,64	77,55
4	DB X-Trackers DJ STOXX 600 Oil and Gas Shutter	Short	-0,1459	4,53	3,58	19,84	38,42
5	S&P GSCI Crude Oil Total Return T-ETC	Normal	0,3450	7,97	4,00	77,32	118,84
6	ETFS Commodity Securities Leveraged Crude Oil	Leveraged	0,5681	0,52	8,27	2,21	4,68
7	DJ STOXX 600 Optimised Oil and Gas Source ETF	Normal	0,2090	9,97	3,14	117,25	156,21
8	S&P Gsci Enhanced Crude Oil Source T-ETC	Normal	0,2456	10,39	3,49	110,31	151,16
9	Rici Enhanced Brent Crude Oil	Normal	0,4469	8,41	2,80	74,11	107,58
10	Rici Enhanced WTI Crude Oil	Normal	0,2959	6,27	3,29	72,39	97,38
11	S&P Gsci Crude Oil Official Close Index ETC	Normal	0,2994	8,38	4,02	85,39	117,94

4. Methodology

In this section attention will be given to the methods used in analyzing the tracking ability of our sample ETFs. I will use linear regression analysis, tracking error analysis and co-integration analysis**.**

4.1 Linear Regression Analysis

Linear regression allows us to use one variable to make predictions about another, test hypotheses about the relation between two variables, and quantify the strength of the relationship between the two variables.

4.1.1 Linear Regression with One Independent Variable

Since we are working with returns, prices had to be transformed in returns; we did that using Equation 1:

$$r_t = \frac{Price_t - Price_{t-1}}{Price_{t-1}} = \frac{Price_t}{Price_{t-1}} - 1 \qquad \textbf{(1)}$$

Where r_t is the weekly return that we are looking for, $Price_t$ is the price on week t, and $Price_{t-1}$ is the price on week $t-1$, the week before.

Regression analysis begins with the dependent variable *Y*, the variable that we are seeking to explain, in our case the ETFs returns. The independent variable *X*, the benchmark returns, is the variable we are using to explain the changes in the dependent variable.

After computing the returns we are ready to perform the linear regression analysis, linear regression assumes a linear relationship between the dependent variable and the independent variable, Equation 2 describes that relation:

$$Y_i = b_0 + b_1 X_i + \varepsilon_i \, , i = 1,2,3, \dots, n \qquad \textbf{(2)}$$

Equation 2 states that the dependent variable, Y_i, is equal to the intercept, b_0, plus a slope coefficient, b_1[16], times the independent variable, X_i, plus as error term, ε_i. The error term represents the portion of the dependent variable that cannot be explained by the independent variable.

Linear regression estimates b_0 and b_1 by computing a line that best fits the observations, it chooses values for the intercept and slope that minimizes the sum of the squared vertical distances between the observations and the regression line, by that reason linear regression is also known as linear least squares. If the ETFs do a good job at tracking the benchmarks the intercept should be close to zero and the slope should be close to one, in the case of the leveraged ETFs the slope should be close to two or three depending on the type of leverage used, and in the case of short ETFs the slope should be negative.

Another measure from the linear regression is the Coefficient of Determination (R^2), where we should expect values close to one.[17]

4.1.2 Time Varying Analysis

To complement we will also analyze the evolution of the correlation and the slope coefficients through time using moving windows of forty observations, meaning that at any point in time the computed correlation and slope coefficient refers to the last forty observations.

All the estimations are done using the SPSS and the STATA10 packages for data analysis.

4.2 Tracking Error Analysis

As referred in the introduction Tracking Error (TE) is one of the types of risks – a deviation from benchmark – associated with ETFs, it measures how closely an ETF follows the index or product to which it is benchmarked. We will present three measures of the TE that were used in other studies:

[16] The coefficients b_0 and b_1 are also sometimes referred to as α and β respectively.

[17] In the extreme best case scenario when the dependent variable is perfectly correlated with the independent variable, the error term will be 0 and the coefficient of determination will be 1. The coefficient of determination measures the fraction of the total variation in the dependent variable that is explained by the independent variable. We can compute the coefficient of determination by squaring the correlation coefficient between the dependent and independent variable. In our analysis, expect coefficients of determination of 1 would be unrealistic, but we should definitely see high values.

4.2.1 Standard Error of Regression

This measure is very straightforward, as explained earlier in the linear regression analysis section, when a linear regression is performed there is an error term that represents the portion of the dependent variable that cannot be explained by the independent variable, this values can be used as a proxy to tracking error.

$$SE_x = \frac{s}{\sqrt{n}} \tag{3}$$

Where s is the sample standard deviation and n is the size of the sample.

4.2.2 Average of the Absolute Differences

The second method we will use computes the tracking error by calculating the average of the absolute differences between the returns of ETFs and their benchmarks. We take into account the absolute value of returns' differences because either a positive or a negative difference reflects non-similar performance. Equation 4 shows us how to compute the tracking error using this method:

$$TE = \frac{\sum_{t=1}^{N} |R_d|}{N} \tag{4}$$

Where $|R_d|$ is the absolute return differences and *N* is the number of weeks in our sample.

4.2.3 Standard Deviation of Returns Differences

The third measure that we present defines tracking error as the standard deviation of the difference between the fund and the benchmark returns over time as shown in Equation 5:

$$TE = \sqrt{\frac{\sum_{t=1}^{N} (R_t - B_t)^2}{N-1}} \tag{5}$$

Where R_t is the ETFs weekly return, B_t is the Benchmarks weekly return, and *N* is the number of weeks in our sample. This is the definition generally applied in the academic literature.

For presentation purposes we will annualize all the tracking error measures using Equation 6:[18]

$$TE_{Annual} = TE_{Weekly}\sqrt{52} \qquad \textbf{(6)}$$

4.3 Cointegration Analysis

Although we already used linear regression analysis to analyze the relationship between two time series, in that section we completely ignored unit roots. A time series that contain a unit root is not covariance stationary. If any time series in a linear regression contains a unit root, ordinary least squares estimates of regression test statistics may be invalid.

In cointegration analysis we first use a unit root test, such as the Dickey-Fuller test, based on the work of Dickey and Fuller (1981), for each of the time series, to determine whether any of them has a unit root or are stationary over time. We test for stationary using the following Augmented Dickey-Fuller regression model shown in Equation 7, which is estimated using ordinary least squares:

$$\Delta Y_t = b_0 + b_1 t + \rho Y_{t-1} + \sum_{k=1}^{m} \gamma_k \, \Delta Y_{t-1} + \varepsilon_t \qquad \textbf{(7)}$$

Equation 7 is estimated both for price levels and for first differences of price levels, the following hypotheses are tested:

$$H_0: \rho = 0$$
$$H_a: \rho < 0$$

$$H_0: (c_2; \rho) = (0; 0)$$
$$H_a: (c_{2;}\rho) < (0; 0)$$

If the statistics are insignificant for price levels but are significant for the first differences we conclude that the series is a difference-stationary, or non-stationary series, see Perman (1991).

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[18] Observations are assumed to be independent and identically distributed.

There are several possible scenarios related to the outcome of these tests. One possible scenario is that we find that neither of the time series has a unit root; we can then safely use linear regression to test the relations between the two time series. Otherwise, we might have to use additional tests. A second possible scenario is that we reject the hypothesis of a unit root for the independent variable but fail to reject the hypothesis of a unit root for the dependent variable; in this case, the error term in the regression would not be covariance stationary, therefore, one or more of the linear regression assumptions presented earlier would be violated, namely assumptions two, three and four. Consequently, the estimated regression coefficients and standard errors would be inconsistent. The regression coefficients might appear significant, but those results would be spurious.[19] A third possible scenario is the reverse of the second scenario, we reject the hypothesis of a unit root for the dependent variable but fail to reject the hypothesis of a unit root for the independent variable, the conclusions are the same as in the second scenario.

The next possibility is that both time series have a unit root; in this case, we need to establish whether the two time series are cointegrated before we can rely on regression analysis.[20] Two time series are cointegrated if a long term financial or economic relationship exists between them such that they do not diverge from each other without bound in the long run, that is, if they share a common trend. In the fourth scenario both time series have a unit root but are not cointegrated, in this case, as in the second and third scenarios, the error term in the linear regression will not be covariance stationary and some regression assumptions will be violated, the regression coefficients and standard errors will not be consistent and we cannot use them for hypothesis tests, the linear regression would be meaningless. Finally, the fifth possible scenario is that both time series have a unit root and are cointegrated, in this case the error term in the linear regression will be covariance stationary, accordingly, the regression coefficients and standard errors will be consistent and we can use them for hypothesis tests. Although we should be cautious in interpreting the results of a regression with cointegrated variables, since the cointegrated regression estimates the long term relation between the two series but may not be the best model for the short term relation between the two series. Short term models of cointegrated series are discussed in Engle and Granger (1987) and Hamilton (1994).

In the last two scenarios described above the Engle-Granger two step procedure is used to test for cointegration. First we estimate the regression as we did in the linear regression section.

[19] The problem of spurious regression for nonstationary time series was first discussed by Granger and Newbold (1974).

[20] Engle and Granger first discussed cointegration (1987).

Second the residuals are tested for stationary by running the ADF regression as shown in Equation 8:

$$\Delta\varepsilon_t = -b\varepsilon_{t-1} + \sum_{k=1}^{m} \gamma_k \, \Delta\varepsilon_{t-k} + \theta_t \qquad \textbf{(8)}$$

The null hypothesis is $b = 0$, no cointegration exists. The unit root and cointegration tests were performed using the software program STATA 10.

$$H_0: b = 0$$
$$H_a: b < 0$$

5. Empirical Results

In this section we will show the results from the data analyzed using the methods presented in Section 4.

5.1 Linear Regression Analysis

We start by presenting the Augmented Dickey-Fuller unit root tests results in Table 3, where we can see that all the eleven ETFs and the four Benchmarks are all covariance stationary, therefore immediately validating the linear regression results.

Table 4 presents the results from the several methods applied under the linear regression analysis. We can see that the coefficient of determination (R^2) is, as expected, below one but in some cases it is relatively high, higher than 0.9 in two ETFs, and overall it is higher for ETFs that track indexes relatively to ETFs that track the Brent and the WTI, as a matter of fact the three lowest coefficients of determination are from ETFs that track either the Brent or the WTI, with only one ETF tracking the WTI achieving a coefficient of determination above 0.7. Concerning the intercept coefficient we can see that all the eleven funds are very close to zero like we were expecting, but of those, we reject the null hypotheses that $b_0 = 0$ for two of the funds. Regarding the slope coefficient we have some mixed results, some coefficients are close to the value that we were expecting of one, but some are a little far away, mostly the ETFs that track the Brent and the WTI. Notice that the short ETF in our sample has a negative slope value as we expected, and the leveraged ETF has slope close to two, also as expected, indicating that the strategy followed by that ETF is a 2x Leveraged ETF. In the case of the slope coefficient, we reject the null hypotheses that $b_1 = 0$ for all funds. Relatively to the F-test, we also reject the null hypotheses that $b_1 = 0$ for all funds, not contradicting the results from the t-test, as expected.

From Graph 1 to Graph 11, we present the time varying evolution of the correlation and the slope coefficient for the eleven ETFs.

***Table 3*. Unit Root Tests**

Table 3 presents the Augmented Dickey-Fuller unit root tests results for the eleven ETFs and the four benchmarks, with tests for the levels and for the differences and the respective *p*-value.

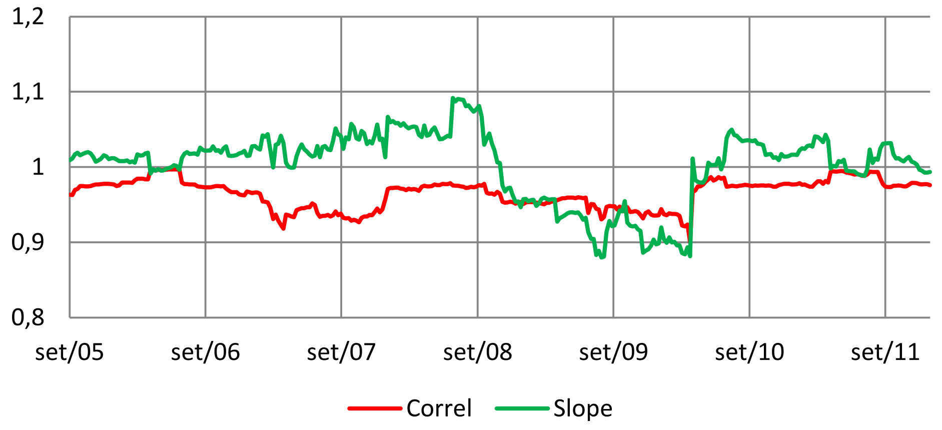
			t-test						
N.º	**Name**	**Obs.**	**Level**	***p*-value**	**Differences**	***p*-value**	**1%**	**5%**	**10%**
1	iShares DJ STOXX 600 Oil and Gas (de)	370	-2,762	0,2113	-8,118	0,000	-3,986	-3,426	-3,130
2	ETFS Commodity Securities WTI Oil	195	-2,717	0,2289	-4,015	0,001	-4,013	-3,439	-3,139
3	DB X-Trackers DJ STOXX 600 Oil and Gas ETF	234	-1,789	0,7100	-6,394	0,000	-4,000	-3,434	-3,134
4	DB X-Trackers DJ STOXX 600 Oil and Gas Shutter	183	-2,929	0,1529	-5,212	0,000	-4,017	-3,441	-3,141
5	S&P Gsci Crude Oil Total Return T-ETC	143	-2,816	0,1913	-6,152	0,000	-4,031	-3,446	-3,146
6	ETFS Commodity Securities Leveraged Crude Oil	143	-2,959	0,1440	-5,875	0,000	-4,031	-3,446	-3,146
7	DJ STOXX 600 Optimised Oil and Gas Source ETF	116	-2,398	0,3806	-4,541	0,000	-4,040	-3,450	-3,150
8	S&P Gsci Enhanced Crude Oil Source T-ETC	115	-2,161	0,5116	-4,737	0,000	-4,040	-3,450	-3,150
9	Rici Enhanced Brent Crude Oil	71	-1,850	0,6803	-4,653	0,000	-4,137	-3,494	-3,176
10	Rici Enhanced WTI Crude Oil	71	-1,514	0,8243	-3,542	0,007	-4,137	-3,494	-3,176
11	S&P Gsci Crude Oil Official Close Index ETC	71	-1,637	0,7774	-3,639	0,005	-4,137	-3,494	-3,176
	Brent	370	-2,001	0,601	-6,555	0,000	-3,986	-3,426	-3,130
	GSCI	370	-2,334	0,4152	-6,793	0,000	-3,986	-3,426	-3,130
	WTI	370	-2,419	0,3696	-7,116	0,000	-3,986	-3,426	-3,130
	STOXX 600	370	-2,749	0,2162	-8,091	0,000	-3,986	-3,426	-3,130

***Table 4*. Linear Regression Results**

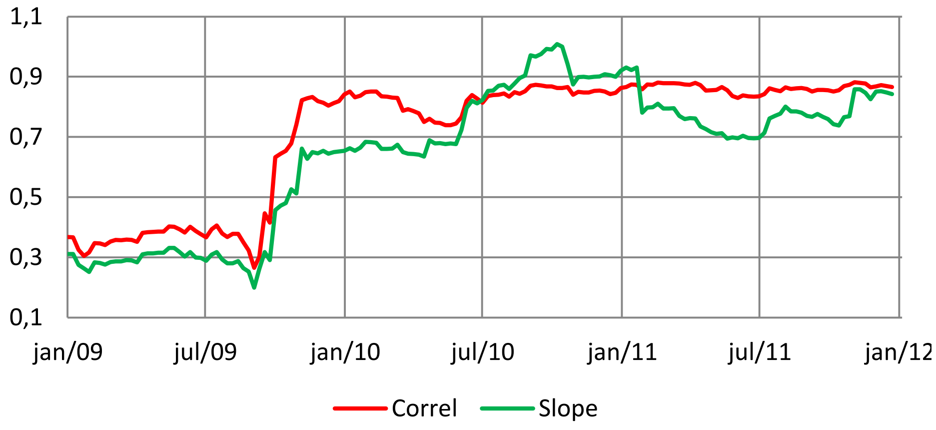
Table 4 includes for all ETFs the coefficient of determination (R^2), the intercept coefficient (b_0), the slope coefficient (b_1) and their respective test value and *p*-values, and finally the *F*-test regarding the analysis of variance (ANOVA) and its *p*-value.

N.º	**Name**	**Type**	**Obs.**	R^2	b_0	***t*-test**	***p*-value**	b_1	***t*-test**	***p*-value**	***F*-test**	***p*-value**
1	iShares DJ STOXX 600 Oil and Gas (de)	Normal	370	0.930	-0,001	-2,300	0.022	0,992	69,703	0,000	4858,439	0,000
2	ETFS Commodity Securities WTI Oil	Normal	195	0.352	-0,004	-1,572	0,118	0,507	10,236	0,000	104,774	0,000
3	DB X-Trackers DJ STOXX 600 Oil and Gas ETF	Normal	234	0.745	-0,001	-0,655	0,513	0,941	26,067	0,000	679,591	0,000
4	DB X-Trackers DJ STOXX 600 Oil and Gas Shutter	Short	183	0.842	-0,002	-2,198	0,029	-0,888	-31,100	0,000	967,211	0,000
5	S&P GSCI Crude Oil Total Return T-ETC	Normal	143	0.729	-0,003	-1,891	0,061	0,875	19,499	0,000	380,229	0,000
6	ETFS Commodity Securities Leveraged Crude Oil	Leveraged	143	0.773	-0,012	-3,490	0,001	1,804	21,923	0,000	480,606	0,000
7	DJ STOXX 600 Optimised Oil and Gas Source ETF	Normal	116	0.943	0,000	-0,174	0,862	0,995	43,590	0,000	1900,072	0,000
8	S&P Gsci Enhanced Crude Oil Source T-ETC	Normal	115	0.758	-0,002	-1,296	0,207	0,857	18,822	0,000	354,270	0,000
9	Rici Enhanced Brent Crude Oil	Normal	71	0.569	0,001	0,399	0,691	0,598	9,545	0,000	91,099	0,000
10	Rici Enhanced WTI Crude Oil	Normal	71	0.648	-0,001	-0,580	0,568	0,664	11,282	0.000	127,292	0,000
11	S&P Gsci Crude Oil Official Close Index ETC	Normal	71	0.786	-0,003	-1,397	0,167	0,945	15,930	0,000	253,751	0,000

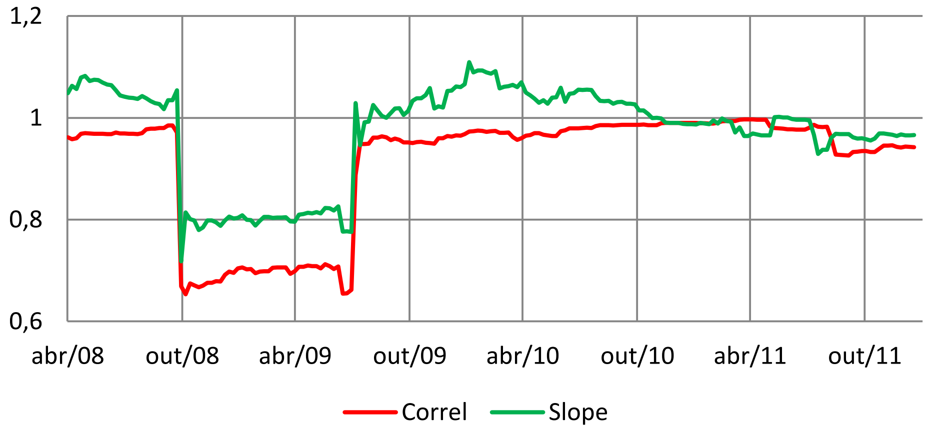
Graph 1 - iShares DJ STOXX 600 Oil and Gas



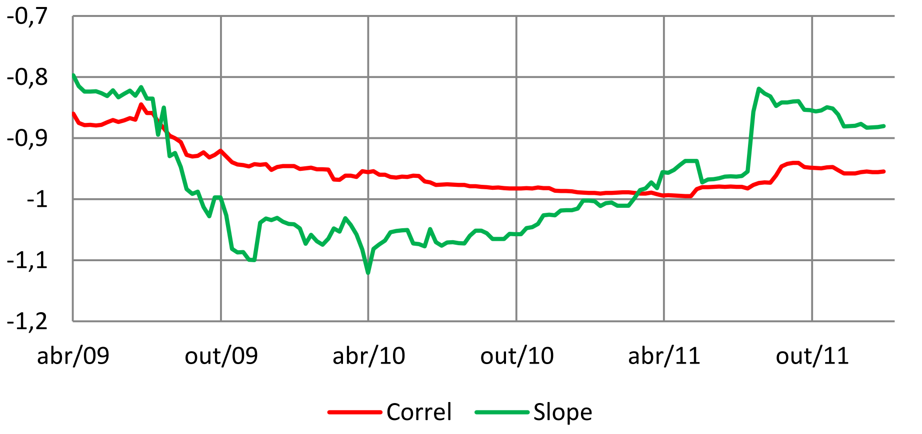
Graph 2 - ETFS Commodity Securities WTI Oil



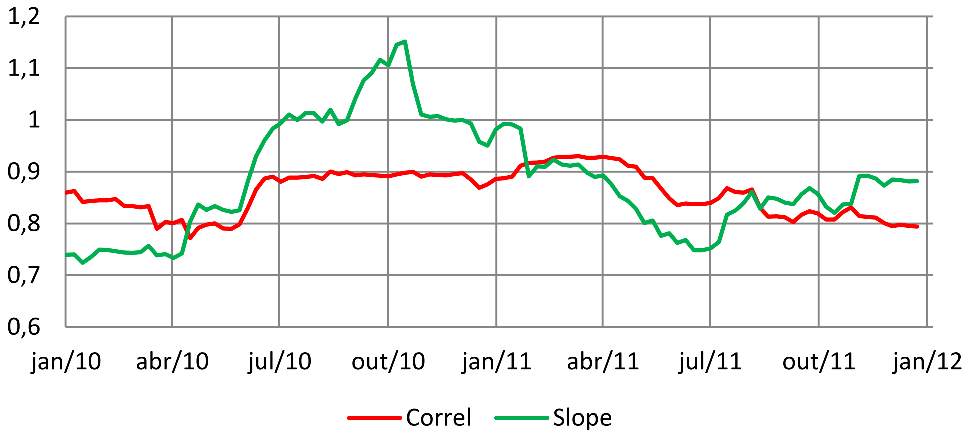
Graph 3 - DB X-Trackers DJ STOXX 600 Oil and Gas ETF



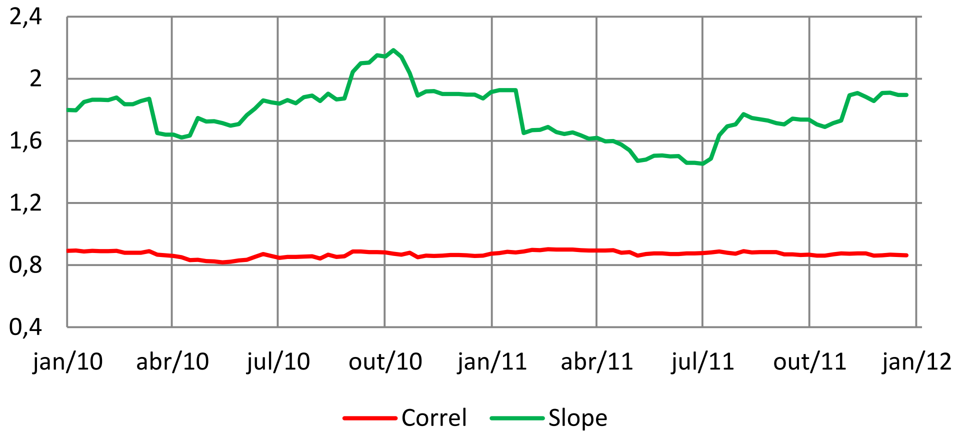
Graph 4 - DB X-Trackers DJ STOXX 600 Oil and Gas Shutter



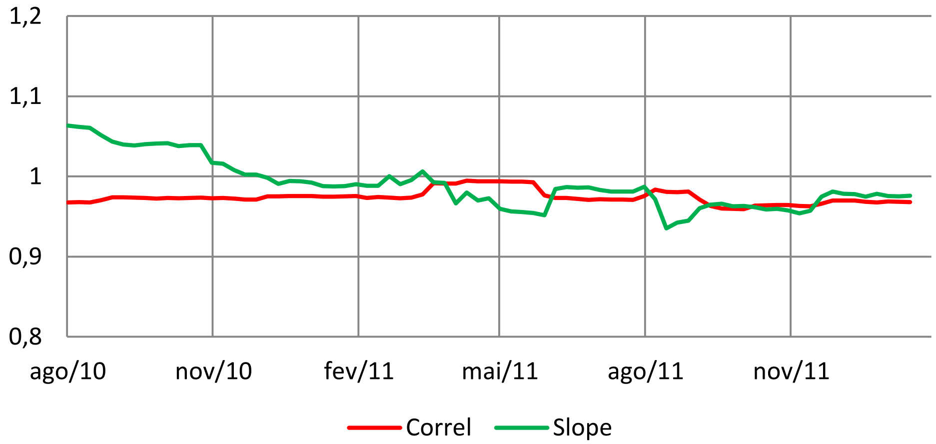
Graph 5- S&P Gsci Crude Oil Total Return T-ETC



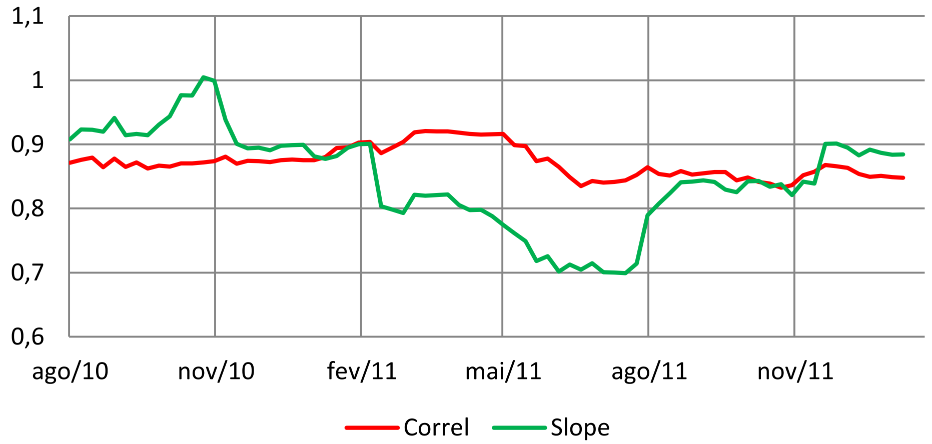
Graph 6 - ETFS Commodity Securities Leveraged Crude Oil



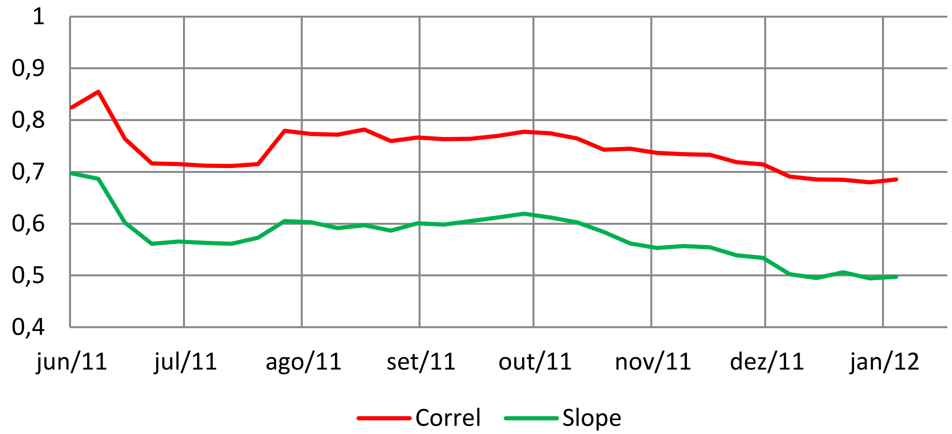
Graph 7 - DJ STOXX 600 Optimized Oil and Gas Source ETF



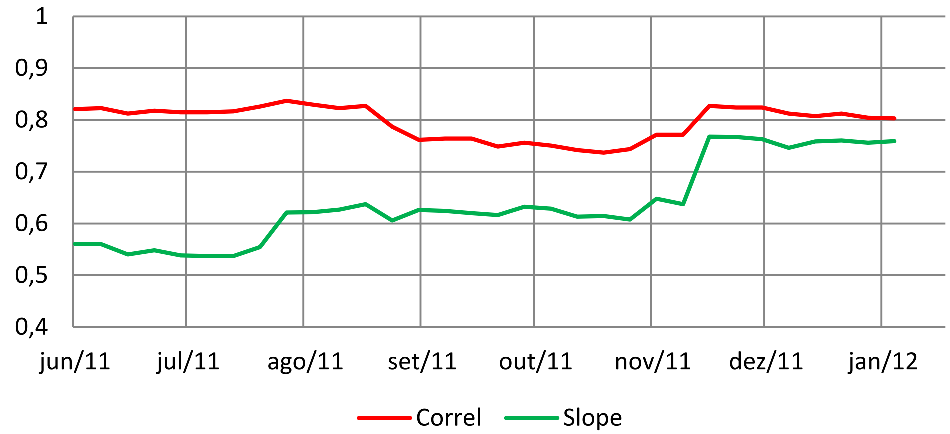
Graph 8 - S&P Gsci Enhanced Crude Oil Source T-ETC



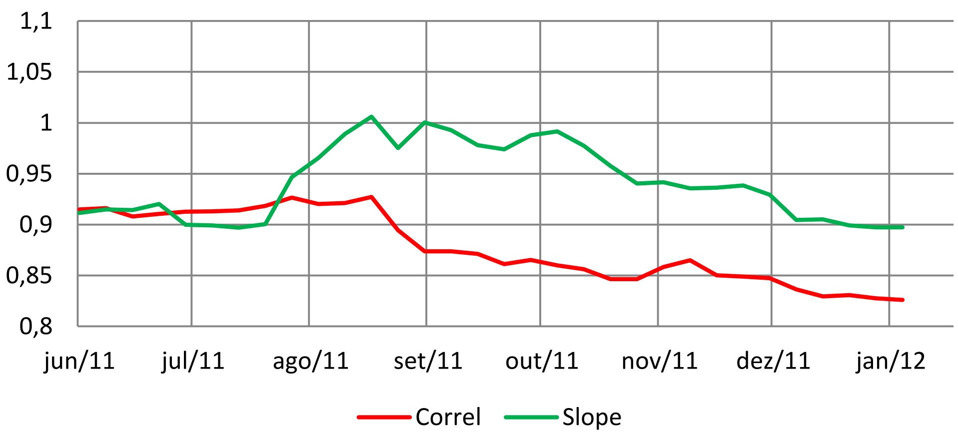
Graph 9 - Rici Enhanced Brent Crude Oil



Graph 10 - Rici Enhanced WTI Crude Oil



Graph 11 - S&P Gsci Crude Oil Official Close Index ETC



5.2 Tracking Error

Table 5 shows us the results from the three tracking error methods used, with T_1 being the standard error of regression, T_2 the average of the absolute differences, and T_3 the standard deviation of returns differences. Overall the funds that track the DJ STOXX 600 Oil and Gas present the lowest tracking error values, followed by the funds that track the S&P GSCI Crude Oil. Once again the funds that track the Brent and the WTI present the worst tracking abilities, with the highest values of tracking error. One exception to this is the short fund, the DB X-Trackers DJ STOXX 600 Oil and Gas Shutter, with this fund showing the highest values of tracking error in two of the three measures presented.

***Table 5*. Tracking Error**

This table presents the results from the three methods used to compute the tracking error: the standard error of regression (T_1), the average of the absolute differences (T_2) and the standard deviation of returns differences (T_3). Also shown are the annualized values.

							Annualized		
N.º	**Name**	**Type**	**Obs.**	T_1	T_2	T_3	T_1	T_2	T_3
1	iShares DJ STOXX 600 Oil and Gas (de)	Normal	370	0,009	0,0053	0,0088	0,0649	0,0384	0,0636
2	ETFS Commodity Securities WTI Oil	Normal	195	0,039	0,0269	0,0479	0,2812	0,1942	0,3455
3	DB X-Trackers DJ STOXX 600 Oil and Gas ETF	Normal	234	0,020	0,0078	0,0202	0,1442	0,0560	0,1458
4	DB X-Trackers DJ STOXX 600 Oil and Gas Shutter	Short	183	0,014	0,0532	0,0714	0,1010	0,3834	0,5146
5	S&P Gsci Crude Oil Total Return T-ETC	Normal	143	0,021	0,0158	0,0218	0,1514	0,1137	0,1570
6	ETFS Commodity Securities Leveraged Crude Oil	Leveraged	143	0,040	0,0382	0,0515	0,2884	0,2757	0,3713
7	DJ STOXX 600 Optimised Oil and Gas Source ETF	Normal	116	0,007	0,0049	0,0075	0,0505	0,0351	0,0538
8	S&P Gsci Enhanced Crude Oil Source T-ETC	Normal	115	0,017	0,0137	0,0181	0,1226	0,0988	0,1303
9	Rici Enhanced Brent Crude Oil	Normal	71	0,019	0,0171	0,0233	0,1370	0,1230	0,1678
10	Rici Enhanced WTI Crude Oil	Normal	71	0,020	0,0160	0,0238	0,1442	0,1153	0,1719
11	S&P Gsci Crude Oil Official Close Index ETC	Normal	71	0,019	0,0137	0,0190	0,1370	0,0988	0,1373

5.3 Cointegration

Table 6 presents the Augmented Dickey-Fuller Cointegration results unit root tests for each ETF relative to its own benchmark. Three of the eleven regressions result in significant Fuller's t-values at the 0.10 level. The other eight funds are not significantly related to their respective benchmarks.

***Table 6*. Cointegration Tests**

Table 6 includes the cointegration test results for all the eleven ETFs, as well as their *p*-value.

			t-test				
N.º	**Name**	**Obs.**	**Level**	***p*-value**	**1%**	**5%**	**10%**
1	iShares DJ STOXX 600 Oil and Gas (de)	370	-1.788	0,3864	-3,452	-2,876	-2,570
2	ETFS Commodity Securities WTI Oil	195	-2,777	0,0616	-3,483	-2,885	-2,575
3	DB X-Trackers DJ STOXX 600 Oil and Gas ETF	234	-2,774	0,0667	-3,470	-2,882	-2,572
4	DB X-Trackers DJ STOXX 600 Oil and Gas Shutter	183	-2,064	0,2593	-3,487	-2,885	-2,575
5	S&P Gsci Crude Oil Total Return T-ETC	143	-1,448	0,5589	-3,500	-2,888	-2,578
6	ETFS Commodity Securities Leveraged Crude Oil	143	-1,365	0,5990	-3,500	-2,888	-2,578
7	DJ STOXX 600 Optimised Oil and Gas Source ETF	116	-2,734	0,0683	-3,509	-2,890	-2,580
8	S&P Gsci Enhanced Crude Oil Source T-ETC	115	-1,649	0,4577	-3,510	-2,890	-2,580
9	Rici Enhanced Brent Crude Oil	71	-1,890	0,3367	-3,570	-2,924	-2,597
10	Rici Enhanced WTI Crude Oil	71	-1,812	0,3743	-3,570	-2,924	-2,597
11	S&P Gsci Crude Oil Official Close Index ETC	71	-1,868	0,3471	-3,570	-2,924	-2,597

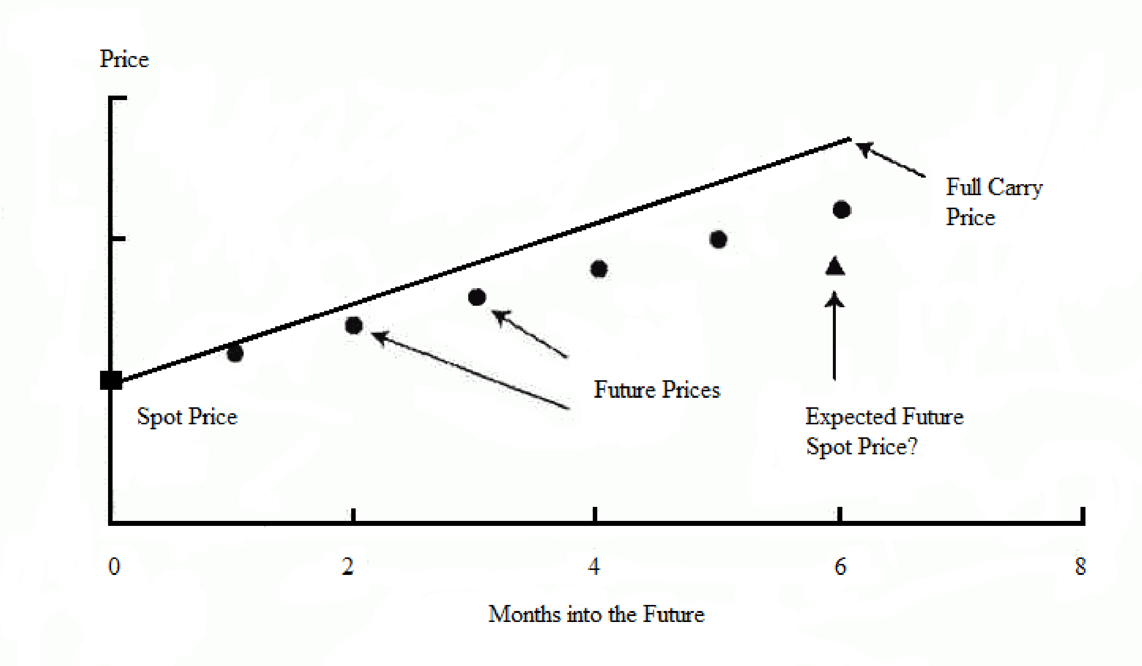
6. Discussion and Conclusions

Overall the ETFs that track the STOXX present the better tracking abilities, this should be of no surprise since the STOXX 600 Oil and Gas is composed of 32 European oil and gas companies and to replicate the performance of the benchmark the fund managers must just invest in those same companies in the same weights that each companies represents in the STOXX 600 Oil and Gas, with fees probably representing the only differences in performance. Concerning the ETFs that track the others benchmarks presented, that's a different history, since those ETFs use future contracts to track their benchmarks a different problem arises, rollover costs. In the futures market there are two types of settlement, delivery and cash settlement. Cash settlement contracts have some advantages over delivery contracts, particularly with respect to significant savings in transactions costs, however, cash settlement has been somewhat controversial, if a contract is designated as cash settlement, it implies that the buyer of the contract never intended to actually take possession of the underlying asset, some people feel that this design is against the spirit of the law, which views a future contract as a commitment to buy the asset at a later date, even though parties often offset futures contracts prior to expiration in delivery settlement contracts, the possibility of actual delivery is still present in those contracts. But anyway, since commodity contract expire, a trader who wants to maintain a position over time must close out the expiring contract and re-establish a new position with a settlement date further into the future. This process is referred to as "Rolling over" the position and leads to gains or losses which are termed the roll yield. The roll yield can be positive or negative depending on whether the commodity market is in contango or backwardation. If the future price is above the spot price, this is referred to as *"contango"*. If the future price is below the spot price it is referred to as *"backwardation"*.

6.1 Contango

When a commodity market is in contango, as shown in Figure 3, futures prices are higher that the spot price because market participants believe the spot prices will be higher in the future.

Figure 3 – Contango



Contango often occurs when a commodity's price is high and volatile, as in the case currently with oil. For example an oil consumer, such as an airline, drives the price of futures higher than the spot price as it attempts to hedge against the risk of higher spot prices, which could ultimately cause it to go out of business. The amount by which the price of the futures can rise is limited, however, by a classic arbitrage trade. If the futures price goes to high, an investor can buy the commodity at the spot price, store it, insure it, and sell it forward. This *"carry trade"* is a pure financing activity and theoretically limits the futures price to a level called *"full carry"*. Different commodities have unique features that affect this relationship. For a future in contango, the roll yield is negative. Since contango means the future price is greater than the spot price, an unchanged spot price over the life of the contract means the future price will have fallen and losses will result when the position is closed out. In current market conditions, futures are typically in contango. Due to the contango market, the ETFs that attempt to track, in this case, the oil price using futures contracts fail to deliver the exact same return as the benchmarks, and our regression analysis showed that.

7. References

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8. Annexes

8.1.1 Assumptions of the Linear Regression Model

To be able to draw valid conclusions from a linear regression model with a single independent variable we need to make six assumptions, known as the classic normal linear regression model assumptions, is it important to be aware of these assumptions since we will go back to them later on. The assumptions are:

1. The relationship between the dependent variable, Y_i, and the independent variable, X_i, is linear in the parameters b_0 and b_1;
2. The independent variable, X_i, is not random;
3. The expected value of the error term is 0: $E(\varepsilon_i) = 0$;
4. The variance of the error term is the same for all observations: $E({\varepsilon_i}^2) = \sigma_\varepsilon^2$;
5. The error term, ε_i, is uncorrelated across observations. Consequently $E(\varepsilon_i, \varepsilon_j) = 0$ for all $i \neq j$;
6. The error term, ε_i, is normally distributed;

8.1.2 Hypothesis Testing

Hypothesis testing is critical in practice, when we do hypothesis testing we start by stating the hypotheses, we always state two hypotheses: the null hypothesis, H_o, and the alternative hypothesis, H_a. The null hypothesis is the hypothesis to be tested, the alternative hypothesis is the hypothesis accepted when the null hypothesis is rejected. The null hypothesis is a preposition that is considered true unless the sample we use to conduct the hypothesis test gives convincing evidence that the null hypothesis is false, when such evidence is present we are led to the alternative hypothesis. Basically the t-tests of the b_0 and b_1 coefficients test the hypothesis that those coefficients are statistically different from zero.

In our case the null hypothesis and the alternative hypothesis are the following:

$$H_0\colon b_0 = 0$$
$$H_a\colon b_0 \neq 0$$

For the hypothesis test concerning the intercept coefficient b_0, and:

$$H_0: b_1 = 0$$
$$H_a: b_1 \neq 0$$

For the hypothesis test concerning the slope coefficient b_1, both these test are two-sided hypothesis tests or two-tailed hypothesis tests.
We can perform a hypothesis test using the confidence interval approach if we know three things:

1. The estimated parameter value: in our cases the computed intercept coefficient, $\dot{b}_0$, and the computed slope coefficient, $\dot{b}_1$;
2. The hypothesized value of the parameters: as stated before we expect the value of the intercept coefficient to be zero and the value of the slope coefficient to be different from zero;
3. A confidence interval around the estimated parameters: to compute a confidence interval we must select the significance level for the test and know the standard error of the estimated coefficient. We will use a 95 percent confidence interval for our tests, we can also say that the test has a significance level of 0.05;

To construct the confidence interval Equation 9 should be used:

$$\dot{b}_i \pm t_c s_{b_1} \qquad \textbf{(9)}$$

Where $\dot{b}_i$ is the estimated parameter value, we have two in our case, the intercept and the slope, t_c is the critical t value, and s_{b_1} is the standard error of the coefficient. The critical value for test depends on the number of degrees of freedom for the t-distribution under the null hypothesis. The number of degrees of freedom equals the number of observations minus the number of coefficients estimated; in our case we estimate two coefficients. If our confidence interval includes the value we are testing, we can be 95 percent confident in not rejecting the null hypothesis.

In practice, the most common way to test a hypothesis using a regression model is with a *t-test* of significance, to test the hypothesis we need Equation 10:

$$t = \frac{\dot{b}_i - b_i}{s_{b_1}} \tag{10}$$

Where $\dot{b}_i$ is the estimated parameter value, b_i is the hypothesized value, and s_{b_1} is the standard error of the coefficient. This test statistic has a *t*-distribution with *n*-2 degrees of freedom, as stated before, because two parameters were estimated in the regression. We then compare the absolute value of the *t*-statistic to t_c, if the absolute value of *t* is greater than t_c we can reject the null hypothesis.

One alternative approach to hypothesis testing is called the *p*-value approach, the *p*-value is the smallest level of significance at which the null hypothesis can be rejected, the smaller the *p*-value, the stronger the evidence against the null hypothesis and in favor of the alternative hypothesis. If the *p*-value is less than our specified level of significance, we reject the null hypothesis; otherwise, we do not reject the null hypothesis. Using the *p*-value approach we reach the same conclusions as we do using the interval approach.

8.1.3 Analysis of Variance (ANOVA)

In regression analysis we use ANOVA to determine the usefulness of the independent variables in explaining variation in the dependent variable. An important statistical test conducted in analysis of variance is the *F*-test. The *F*-statistic tests whether all the slope coefficients in a linear regression are equal to zero. In our case with only one independent variable this is a test of:

$$H_0: b_1 = 0$$
$$H_a: b_1 \neq 0$$

Notice that we already presented one method to test the slope coefficient, so one method should not contradict the other.