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MASTER THESIS

Technical Analysis in Exchange Traded Funds

Author:
George Drosos

Supervisor:
Professor Stephanos Papadamou

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Abstract

The scope of this Thesis is to examine the effectiveness of using technical indicators for trading decisions. With the implementation of the technical analysis indicators, and based on their position signals given, we created an indicator for the relevant positions. In the first part of our research, we created a trading signal based on technical indicators in the 3-factor Fama-French model. In the second part, we used a back-testing approach and extracted trade statistics in order to further support that technical indicator signals can lead to profitable results.

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Περίληψη

Ο σκοπός της εκπόνησης της συγκεκριμένης Διπλωματικής Εργασίας είναι η μελέτη για την αποτελεσματικότητα των δεικτών Τεχνικής Ανάλυσης στην λήψη επενδυτικών αποφάσεων. Εξάγοντας τους τεχνικούς δείκτες από το σύνολο ιστορικών δεδομένων των ETF που είναι το καθεαυτό αντικείμενο μελέτης, και βασιζόμενοι στα σήματα που μας δίνονται, δημιουργήσαμε μια μεταβλητή απόφασης. Στο πρώτο μέρος της μελέτης αυτής, η μεταβλητή αυτή συμπεριλήφθηκε σαν επιπλέον ερμηνευτική μεταβλητή στο μοντέλο τριών παραγόντων Fama-French. Στο δεύτερο μέρος της μελέτης, ακολουθόντας μια λογική προσομίωσης εκτέλεσης εντολών αγοράς και πώλησης τίτλων στα ιστορικά μας δεδομένα, εξάγοντας περιγραφικά στατιστικά, ενισχύσαμε ακόμη περισσότερο την θέση μας για την αποτελεσματικότητα της Τεχνικής Ανάλυσης, όπου μπορεί να μας δώσει αξιόπιστα σήματα για μια επικερδή επενδυτική δραστηριότητα.

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Contents

1. Introduction

In this thesis we are setting our focus on a specific asset category, Exchange Traded Funds (ETFs), which is a pooled investment type of asset, having many similarities with mutual funds. ETFs have the characteristic of common stocks, traded regularly in a stock exchange market. ETFs are the kind of investment we are going to analyze in this Thesis, because we are interested in facilitating a trading strategy where frequent long and short positions take place, using technical analysis indicators. This kind of analysis, using statistics (and repeated graph patterns, but we are not focusing on that) to predict future prices, although it is not yet fully supported by the academic society, has gained massive popularity through the years and many professionals, as well as academics have applied technical rules and found that positive returns can be gained, when implementing those rules in the investment decisions they make. Technical Analysis relies on the weak market efficiency, where the market price of a security at any given point does not accurately reflect all available information. The scope of this Thesis is to develop an investment decision model on the ETF market relying on the already known Fama-French model, using technical analysis indicator signals as inputs in its first part, and in the second part we approach those frequent trades with a back-testing strategy. We considered ETFs as a targeted asset investment under the scope of an individual trader, who has direct access to various brokers available with limited country or currency restrictions.

2. Facts

2.1 Exchanged Traded Funds Origins

Pooled investments are defined as the vehicles that pool money from many investors for investment in a portfolio of securities. Pooled investment vehicles that are active until today are mutual funds, investment trusts, depositories and hedge funds, which they issue securities, which represent a shared ownership in the assets included in the specific vehicles. The main benefit of pooled investments is that individual investors can benefit from the diversification opportunities created from the investment management firms who issue these securities, an aspect that is not readily available to them on an individual basis.

The origins of the first pooled investment vehicle (a mutual fund of this age) were established in the Dutch Republic (Netherlands) in 1774, more specifically in Amsterdam. A Dutch businessman, named Adrian van Ketwich formed the first mutual fund, named ‘’Eendragt Maakt Magt’’ which means ‘’Unity Creates Strength’’, which was a great innovation mainly for small investors with limited means. This fund was composed of company securities from Austria, Denmark, Germany, Spain, Sweden, Russia, and various securities from companies located in colonial plantations in Central and South America, accumulating a considerable amount of securities, offering the investors a chance for exposure and diversification through various markets. The fund, which still holds the record of the longest pooled investment vehicle, existed for about 120 years, sustaining several socio-political and economic crises.

U.S. investment firms drew the concept of pooled investments, in the form of investment trusts in 1893, 28 years after the ending of the American Civil War. The issuer, Boston Personal Property Trust, offered its shares to the public for a limited time. The issuing company, made clear from the beginning the objectives and policies of the fund, defined in the investment policy statement, where the fund manager was responsible for the appliance of these statements, rules that apply up to today's pooled investments. This investment vehicle is known as a closed-end investment fund. The investors could not sell back the security to the issuing company, in order to liquidate their position, nor could buy new securities, because the offering was for a limited amount of time. The prospective buyers could buy the security, and then sell it to the stock exchange market, or in private transactions, in order to profit from the whole process, thus, like other securities, its price was defined by demand and supply for the fund shares. That, although it goes hand in hand with economic structural definitions, was the main drawback of the fund: the market price of the fund's share would not always be the same as it's per share net asset value, because demand or supply for the fund's share may wasn't the same with the demand or supply for the underlying securities included in the fund.

This effect created discrepancies, and the exaggerated premiums and discounts on the fund's shares held the investors back from this security. This led to another major innovation, meaning the creation of open-ended funds. In 1907, at Philadelphia, Pennsylvania, the Alexander Fund introduced the homonymous fund, where new shares were issued semiannually, and the investors could directly liquidate their shares at net asset value prices. Alexander Fund was then succeeded from the Massachusetts Investor Trust in 1924, furtherly improving the liquidity and trade ability of pooled investments, where the security issuing and the right for share redemption was on a daily basis.

Multiple changes were made over time, giving more options to the investors, and of course the necessary regulations to minimize conflicts of interest and protect investors from frauds (Securities Exchange Act of 1934 and the Securities Exchange Commission foundation). From that time to the present, the main idea of the pooled investment vehicles remained the same, sustaining rough global turmoil over the years. Further development in pooled investments, led to a new open-ended mutual investment, the exchange traded fund, with the first one ever to be released in 22nd January, 1993, by State Street Corporation in Boston. This ETF (SPY) is active until today, and led the way into the inception of other ETFs.

2.2 Exchange Traded Funds Nowadays

The Exchange Traded Fund (ETF) is defined as a pooled investment vehicle with shares that investors can buy and sell throughout the day on a stock exchange market, at a market-determined price. ETFs offer the investors the viability to be traded through a professional broker or a personal brokerage account, in the same way that they could trade any publicly traded company. ETFs introduced in the United States are structured as open-ended funds, like mutual funds, and the same regulations and transparency applies to all ETFs. Exemptions are the ETFs which are not investing in stocks and indices: ETFs comprised of commodities, futures and currencies may have different structures and be subject to different regulatory requirements. ETFs have similarities with mutual funds, because both vehicles are in essence pooled investments. There are two major differences though: Firstly, ETFs can be traded on the stock exchange (secondary market) regularly, unlike mutual funds, which can be bought or sold through specific channels, like investment professionals, brokers, insurance companies, or directly from a fund company. Secondly, ETFs price is continuously determined based on the market's demand and supply, through the trading period, while the mutual funds price is determined once per trading day (most commonly at 16:00, Eastern Time, when the stock exchanges close).

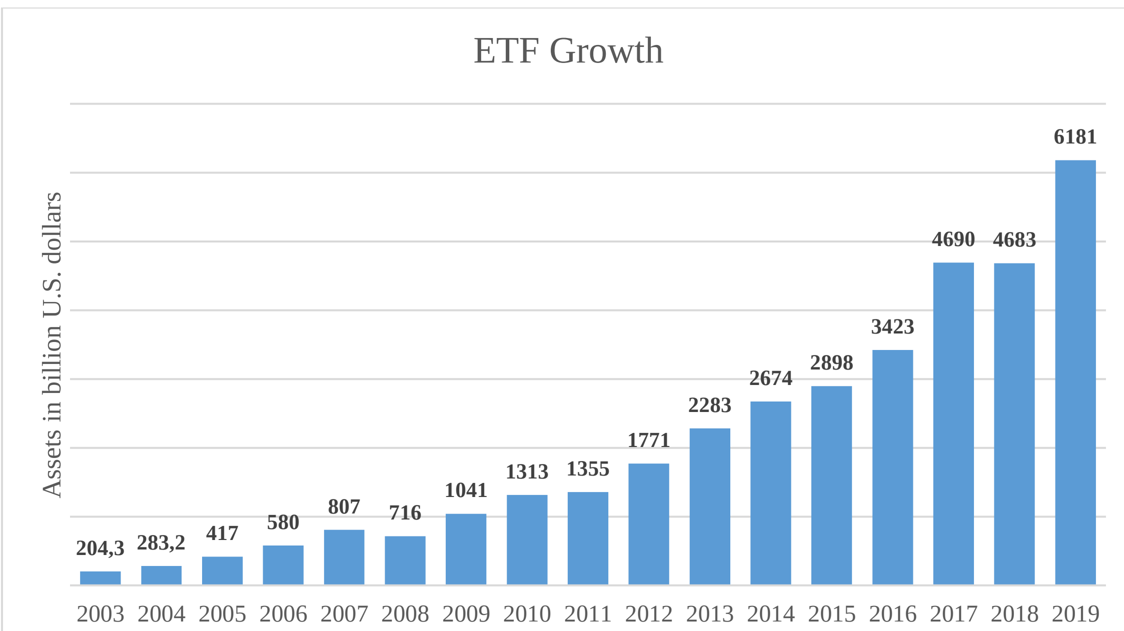

Figure 1: Development of total assets invested in Exchange Traded Funds, from 2003 to 2019. Source: statista.com

As of April 2019, the value of the assets managed by ETFs globally is approximately 6.18 trillion dollars, with 6970 ETFs in total being available for trade on a worldwide basis. The world leading ETF provider is the global investment management and technology provider firm, BlackRock. More specifically, in the United States the total net assets channeled in ETFs are 3.4 trillion dollars, with the staggering 88% of financial advisors to recommend the inclusion of ETFs to their client's portfolios. The ease of exposure to the various markets, combined with the indigenous diversification the ETFs provide and the strong support of regulating authorities made this investment vehicle extremely popular through the years.

The ETFs we chose to include in this thesis are classified as common equity ETFs, issued in U.S., as we are going to use the Fama-French model for the first part of our research, which includes company fundamentals. The ETFs are of micro, small, mid, and large capitalization, but we also included a total market ETF, and an international grade ETF. Based on this criterion, the chosen ETFs have the highest number of assets under management (AUM), and they are considered popular and of a high liquidity. ETF figures and data provided are based on the relevant fact sheets released on a regular basis by the issuing companies, and this means that the presented facts are subject to change.

2.2.1 iShares Micro-Capitalization ETF (IWC)

IWC is included in the iShares ETF universe issued by BlackRock. The scope of this ETF is to track the investment results of a portfolio composed of micro-cap U.S. equities. An investor would prefer IWC to gain the exposure on the market segment comprised of very small companies, and as an asset to diversify the stock allocated part of a portfolio.

Key Facts		**Fund Characteristics**	
Fund Launch Date	08/12/2005	Beta vs. S&P 500	1.32
Expense Ratio	0.60%	Std. Deviation (3yrs)	22.23%
Benchmark	Russel Micro	Price to Earnings	9.87
30 Day SEC Yield	1.63%	Price to Book Ratio	1.18
Number of Holdings	1,392		
Net Assets	$562,085,384	**Fees & Expenses Breakdown (%)**	
Ticker	IWC	Management Fee	0.60%
Exchange	NYSE Arca	Acquired Fund Fees & Expenses	0.00%
		Foreign Taxes & Other Expenses	0.00%

Top Sectors (%)		**Top Holdings (%)**	
Health Care	31.92	FORTY SEVEN INC	0.96
Financials	21.66	RA PHARMACEUTICALS INC	0.66
Information Technology	11.42	CHEMOCENTRYX INC	0.65
Industrials	10.39	AXSOME THERAPEUTICS INC	0.63
Consumer Discretionary	6.50	ONTO INNOVATION INC	0.62
Real Estate	4.55	KODIAC SCIENCES INC	0.53
Energy	3.73	INNOVATIVE INDUSTRIAL	
Communication	3.08	PROPERTIES INC	0.49
Materials	2.49	KARYOPHARM	
Consumer Staples	2.32	THERAPEUTICS INC	0.46
Utilities	1.73	PRINCIPIA BIOPHARMA INC	0.43

Cash and/or Derivatives	0.23	PALOMAR HOLDINGS INC	0.43
			5.86

IWC is outperforming the Russel micro-cap index which uses as benchmark by 3.60% since its inception. It is showing great liquidity and a high trading volume which is a great aspect for individual traders, and has a relatively high but still competitive expense ratio compared to other peer ETFs. IWC is rated with BB by MSCI, with a score of 3.04 out of 10, and the most recent Morningstar rating is of 3 stars.

2.2.2 iShares Core S&P Small-Capitalization ETF (IJR)

IJR, another iShare ETF issued by Blackrock, offers exposure to small-cap equities as its name suggests. It is suggested by BlackRock to be included for a long-term growth and is offered a considerably low cost.

Key Facts		**Fund Characteristics**	
Fund Launch Date	22/05/2000	Beta vs. S&P 500	1.37
Expense Ratio	0.07%	Std. Deviation (3yrs)	22.04%
Benchmark	SML	Price to Earnings	12.77
30 Day SEC Yield	2.35%	Price to Book Ratio	1.31
Number of Holdings	603		
Net Assets	$31,821,094,673	**Fees & Expenses Breakdown (%)**	
Ticker	IJR	Management Fee	0.07%
Exchange	NYSE Arca	Acquired Fund Fees & Expenses	0.00%
		Foreign Taxes & Other Expenses	0.00%

Top Sectors (%)		**Top Holdings (%)**	
Industrials	17.96	LHC GROUP INC	0.79
Financials	17.17	EXPONENT INC	0.71
Information Technology	15.25	NEOGEN CORP	0.67
Health Care	13.85	EHEALTH INC	0.67
Consumer Discretionary	11.37	COGENT COMMUNICATIONS HOLDINGS INC	0.65
Real Estate	7.92	BALCHEM CORP	0.61
Materials	4.65	MOMENTA PHARMACEUTICALS INC	0.59
Consumer Staples	3.90	STRATEGIC EDUCATION INC	0.59
Utilities	2.89	AEROJET ROCKETDYNE HOLDINGS INC	0.58
Communication	2.74	COMMUNITY BANKING SYSTEM INC	0.58
Energy	1.85		6.44
Cash and/or Derivatives	0.46		

IJR tracks the S&P 600, representing approximately 3% of the total publicly available traded stocks. IJR shows the largest trading volume among its peer ETFs, and shows great liquidity, as it can be easily converted into cash. IJR holds a score of 3.58 out of 10 (BB) from MSCI ratings, and a 4-star Morningstar rating. It overperforms its benchmark index by 7.74% since its inception, and offers a great exposure and market coverage based on its small-cap orientation principals.

2.2.3 iShares Core S&P Mid-Capitalization ETF (IJH)

Key Facts		Fund Characteristics	
Fund Launch Date	05/22/2000	Beta vs. S&P 500	1.28
Expense Ratio	0.06%	Std. Deviation (3yrs)	19.83%
Benchmark	MID	Price to Earnings	14.41
30 Day SEC Yield	2.32%	Price to Book Ratio	1.58
Number of Holdings	400		
Net Assets	$35,722,277,942	**Fees & Expenses Breakdown (%)**	
Ticker	IJH	Management Fee	0.06%
Exchange	NYSE Arca	Acquired Fund Fees & Expenses	0.00%
		Foreign Taxes & Other Expenses	0.00%

Top Sectors (%)		Top Holdings (%)	
Information Technology	16.33	DOMINOS PIZZA INC	0.98
Industrials	16.14	TYLER TECHNOLOGIES INC	0.90
Financials	15.71	WEST PHARMACEUTICAL SERVICES INC	0.88
Consumer Discretionary	12.03	TELEDYNE TECHNOLOGIES INC	0.85
Health Care	11.84	FACTSET RESEARCH SYSTEMS INC	0.77
Real Estate	9.88	TERADYNE INC	0.71
Materials	5.88	MEDICAL PROPERTIES TRUST REIT INC	0.70
Utilities	5.09	FAIR ISAAC CORP	0.70
Consumer Staples	3.66	ESSENTIAL UTILITIES INC	0.69
Communication	1.98	MOLINA HEALTHCARE INC	0.68
Energy	1.01		7.86
Cash and/or Derivatives	0.46		

IJH holds a MSCI score of BB, or 4.15 out of 10 and a 4-star Morningstar rating. It is tracking the S&P 400 mid-cap index, which also uses as its benchmark. IJH is another great choice for individual investors, having great liquidity, a large trading volume, and relatively tight (bid-ask) spreads, and it belongs to the iShare ETF universe from BlackRock.

2.2.4 SPDR® S&P 500 ETF Trust (SPY)

SPY, as its full name suggests, is comprised with the 500 largest companies listed on stock exchanges in United States, in alignment with the S&P 500 Index. It is currently the most traded ETF, with a volume of ≈224 million (as of March 28th) and can offer exposure to large and well-known companies included in the index. SPY is appealing to both long-term investors, because of the large cap growth companies that are included, as well as short-term investors, because of the quite narrow spreads offered, and the liquidity of the asset. SPY has a 5-star Morningstar analyst rating, and an A (or 5.89 out of 10) MSCI rating.

Key Facts		**Fund Characteristics**	
Fund Launch Date	01/22/1993	Est. 3-5 Year EPS Growth	10.76%
Expense Ratio	0.00945%	Index Dividend Yield	1.85%
Benchmark	GSPC	Price to Earnings	19.99
30 Day SEC Yield	1.71%	Price to Book Ratio	3.39
Number of Holdings	500		
Net Assets	$255,110,322,72	**Fees & Expenses Breakdown (%)**	
Ticker	SPY	Management Fee	0.06%
Exchange	NYSE Arca	Acquired Fund Fees & Expenses	0.00%
		Foreign Taxes & Other Expenses	0.00%
Top Sectors (%)		**Top Holdings (%)**	
Information Technology	23.20	APPLE INC	4.58
Health Care	14.20	MICROSOFT CORP	4.50
Financials	12.96	AMAZON.COM INC	2.88
Communication Services	10.39	FACEBOOK INC CLASS A	1.85
Consumer Discretionary	9.77	BERKSHIRE HATHAWAY INC CLASS B	1.66
Industrials	9.05	JP MORGAN CHASE & CO	1.63
Consumer Staples	7.20	ALPHABET INC CLASS A	1.50
Energy	4.35	ALPHABET INC CLASS C	1.49
Utilities	3.31	JOHNSON & JOHNSON	1.43
Real Estate	2.92	VISA INC CLASS A	1.20
			22.72

2.2.5 Vanguard Total Stock Market ETF (VTI)

Key Facts		Fund Characteristics	
Fund Launch Date	05/24/2001	Return on Equity	15.7%
Expense Ratio	0.03%	Median Market Cap	$83.0B
Benchmark	CRSP	Price to Earnings	22.6
30 Day SEC Yield	2.32%	Price to Book Ratio	3.2
Number of Holdings	3,579	Earnings Growth Rate	10.8%
Net Assets	$35,722,277,942	Foreign Holdings	0.4%
Ticker	VTI	Turnover Rate (most recent year)	3.5%
Exchange	NYSE Arca	Std. Deviation (3yrs)	12.37%

Top Sectors (%)		Top Holdings (%)	
Information Technology	21.80	MICROSOFT CORP	3.80
Financials	19.40	APPLE INC	3.70
Consumer Services	13.30	ALPHABET INC	2.50
Industrials	13.20	AMAZON.COM INC	2.40
Health Care	13.00	FACEBOOK INC	1.60
Consumer Goods	7.90	BERKSHIRE HATHAWAY INC	1.40
Oil & Gas	4.10	JP MORGAN CHASE & CO	1.30
Utilities	3.20	JOHNSON & JOHNSON	1.20
Basic Materials	2.20	VISA INC	1.00
Telecommunications	1.90	PROCTER & GAMBLE CO	1.00
			19.9

VTI tracks the CRSP U.S. total market index, which also uses as its benchmark, constituting of nearly 95% of the total publicly available traded stocks. It is inclined towards IT companies, usually has tight (bid-ask) spreads, has a huge trading volume and is of great liquidity. VTI holds a BBB rating from MSCI, or 5.51 out of 10, and a 4-star Morningstar analyst rating.

2.2.6 iShares MSCI Emerging Markets ETF (EEM)

EEM, issued by iShares, Blackrock is tracking the MSCI Emerging Markets Index. It is offering exposure to large cap and mid cap companies in emerging markets (Americas, EMEA, APAC) orientated mainly in China (40% of fund), Taiwan (12.11% of total assets included) and South Korea (11.66% of total assets included). This ETF is also heavily traded, with high liquidity and small spreads, and it is offering an internationally – wide diversification for both short-term and long-term investors. EEM has a 3-star Morningstar analyst rating and a BBB rating (4.29 out of 10) from MSCI.

Key Facts	
Fund Launch Date	04/07/2003
Expense Ratio	0.68%
Benchmark	MSCIEF
30 Day SEC Yield	2.18%
Number of Holdings	1.225
Net Assets	$19,334,637,859
Ticker	EEM
Exchange	NYSE Arca

Fund Characteristics	
Beta vs. S&P 500	0.93
Std. Deviation (3yrs)	17.35%
Price to Earnings	12.16
Price to Book Ratio	1.32

Fees & Expenses Breakdown (%)	
Management Fee	0.68%
Acquired Fund Fees & Expenses	0.00%
Foreign Taxes & Other Expenses	0.00%

Top Sectors (%)	
Financials	21.27
Information Technology	16.61
Consumer Discretionary	15.12
Communication	12.84
Materials	6.55
Consumer Staples	6.54
Energy	5.80
Industrials	4.90
Health Care	3.49
Real Estate	2.86
Utilities	2.44
Cash and/or Derivatives	1.57

Top Holdings (%)	
ALIBABA GROUP HOLDING ADR PETERSEN	6.96
TENCENT HOLDINGS LTD	5.80
TAIWAN SEMICONDUCTOR MANUFACTURING	4.60
SAMSUNG ELECTRONICS LTD	3.86
CHINA CONSTRUCTION BANK CORP H	1.62
NASPERS LIMITED N LTD	1.31
PING AN INSURANCE (GROUP) CO OF CH	1.14
BLK CSH FND TREASURY SL AGENCY	0.95
CHINA MOBILE LTD	0.94
INDUSTRIAL AND COMMERCIAL BANK OF CHINA	0.92
	28.10

2.3 Technical Analysis Indicators

Technical Analysis originated from the Dow Theory, developed in the late 1800s by Charles Dow. Dow's approach to the market is based on 6 principals, which are the very foundations of the technical analysis as we know it today. Briefly, these principals are as follows: 1) asset prices discount everything except the investor's sentiment, 2) market movements can be confirmed by the use of primary, secondary, and minor trendlines, 3) market tends to move in recurring motion, or cycles (accumulation, public participation and distribution phases), 4) confirmation between indices (transportation and industrial averages, designed by Dow, predecessors of the Dow Jones Industrial Average), is mandatory, 5) volume should confirm the trend, meaning that a strong volume reflects the direction of the masses in contradiction with a weak volume could indicate a possible weak trend, and finally 6) the current trend remains dominant until there is evidence to suggest otherwise. The 6th principal is quite similar with Newton's first law of motion, a classical mechanic fundamental, which states that a body will keep moving until and unless an outer force is applied to it.

Moving forward, we can confirm that technical analysis involves using past prices and other past data to make investment decisions. Technical analysts generally believe these fundamental values are already represented in the prices of the fund's stocks. For technical analysts, the most important aspect of an asset's price history is its trend - the fund's price history, which records investor behavior and indicates investor sentiment. Price charts may be posted for a single day or may extend over periods of up to 10 years. For technical analysts, the most useful charts are the short-term charts, which represents the asset price for multiple time intervals, usually spanning from minutes to days.

Technical analysis only works if markets are weakly efficient. That means that the market price of a security at any given point does not accurately reflect all available information, and therefore does not represent the fair value of a security (contradiction with the Efficient Market Hypothesis, EMH). While EMH as an assumption is believed to be true, it can be minorly or majorly affected by a series of events, such as news and company announcements (most likely applying to a short-period horizon). These events, along with investor's sentiment, can lead to volatile prices which frequently change the bid and ask levels, giving the investors the opportunity to speculate, therefore profit from these changes.

As far as the academic society is concerned, Technical Analysis seems to be a subject for debate. Popular academics believe that implementing Technical Analysis in the investment decision making will not be profitable at all (Fama, 1965), newer researchers support that Technical Analysis, sometimes under specific circumstances, can lead to profitable results.

Technical studies are massively designed, implemented and used during the current and the past century by academics and analysts worldwide, and some variations and new findings may be presenting simultaneously with the writing of this Thesis. Although, there is no use of analyzing a chart with way too many studies and indicators, because a cluttered workspace is most likely going to confuse the trader, rather than lead to a good decision. There are mainly four indicator groups that we are going to set our focus on, and then choose one indicator of each group:

Trend-following indicators which as the name suggest indicate the trend that the specific asset is following. They are a lagging type of indicator, because they are based on past price data, therefore the give a trading signal after the trend has already been established, and, by definition, they indicate a general direction that the asset's price could be extended. Some of the most known and heavily used trend indicators are the moving averages and the moving average convergence-divergence (MACD).

Momentum indicators (often called oscillators, because they obviously oscillate above or below a pre-defined level, such as relative strength index (RSI), stochastic, and momentum indicators. This kind is used to measure the relative strength of the recent price moves, to indicate oversold (long signal) or overbought (short signal) price levels, or to depict the ‘’cycles’’ that the asset we examine is following, giving us a possible timing signal.

Volume indicators, such as the on-balance volume (OBV) indicator, which measure the strength of the asset's price moves by using the trading volume as an ‘’explanatory variable’’. Volume indicators incorporate the asset's traded volume, and in that way taking advantage of the large or small trading volume for a quite insightful indication of how strong or weak the next price moves are going to be.

Volatility indicators, which measure the rate of price changes, regardless of the price direction. These indicators, such as Bollinger bands and average true range (ATR) are graphically shown ‘’inflated’’ or abruptly increased when a series of volatile price changes occur, and the opposite when the market is being kept on low trading volumes, or when the bid and ask prices are tending to a temporary balance.

It is often suggested by professionals that an investor should not trade based only on a sole indicator, meaning that a combination of signals could lead to a more probable successful outcome (profit). However, this is not going to be exercised in this Thesis, as our scope is quite ‘’primitive’’: we want to find out if a sole technical indicator could lead to a profitable, or at least not capital-diminishing outcome. Moreover, we are going to apply a partially technical analysis research, meaning that we are not going to use drawings and patterns (such as pivot points, Fibonacci retracements, pitchforks, etc.), because they are mostly considered quite subjective and could lead to biased results.

In the next sub-chapters, the technical studies we chose to facilitate are going to be briefly described. We chose to pick 1 indicator from each aforementioned category. The specific indicators are the most common and widely used, on a worldwide basis. This is an aspect that it maybe appear useful to retail investors, in a way that if multiple investors receive the same bullish (or bearish) signals from the indicators used, the market is eventually going to be bullish (or bearish), but still, this is an assumption made, under specific circumstances.

2.3.1 Moving Average Convergence – Divergence (MACD)

The Moving Average Convergence – Divergence indicator, or simply MACD, was invented in the 1970's, by Gerald Appel, and is a trend-following indicator. MACD, being one of the most popular tools, utilizes the exponential moving average (EMA) technique, which is calculated as follows:

$$EMA_{today} = Closing\ Price_{today} * \frac{2}{Days+1} + EMA_{yesterday} * \left(1 - \frac{2}{Days+1}\right) \rightarrow$$

$$\boldsymbol{EMA_{today} = \left(Closing\ Price_{today} - \ EMA_{yesterday}\right) * multiplier + \ EMA_{yesterday}} \text{ ,}$$

$$where\ multiplier = \frac{2}{Days+1}$$

Comparing to the simple moving average, EMA is more sensitive to the most recent price changes, and a shorter-term EMA will be more sensitive to a longer-term EMA, while the shorter incorporates and reflects with a greater weight the most recent prices, so it will more precisely ''follow'' changes in the underlying asset's price changes.

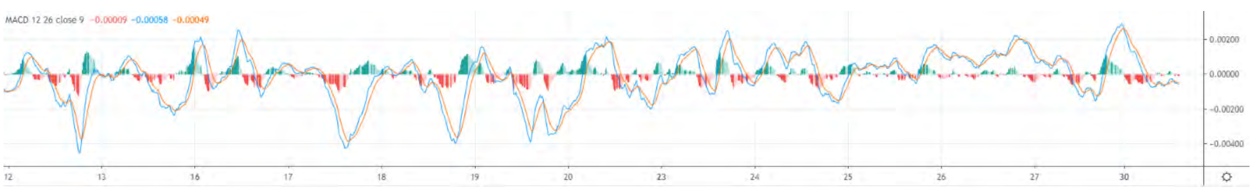

Figure 2: MACD scheme representation, random asset. Blue line is the MACD, orange line is the Signal Line, and the histogram represents the difference between the short and long exponential moving averages, oscillating around the base lane (0 level). Source: tradingview.com

In order to construct the MACD line, we subtract a long-term EMA (usually 26 periods used), from a short-term EMA (usually 12 periods used), of the underlying asset's price. The MACD line is then compared with the ''signal line'' which is the EMA of MACD (usually 9 periods used). Oscillating around 0, this pair of lines triggers buy or sell signals on the crossovers: $MACD_{t-1} < Signal_{t-1}\ and\ MACD_t > Signal_t$ triggers a buy signal. $MACD_{t-1} > Signal_{t-1}\ and\ MACD_t < Signal_t$ triggers a sell signal. Appel suggests that these signals are much more robust when the bullish (long) crossover takes place below level 0, and the bearish (short) crossover takes place above 0 accordingly. MACD scheme also contains a histogram, which depicts the divergence between the short and long EMAs: the bar size shows how big is the difference between them, green color means that the short is above the long, red color means that the long is above the short respectively. MACD has several other uses, such as divergences between the price trend and the MACD trend, which is considered a trading signal for investors: when there is a upward trend in the price and a downward MACD trend, in the same time interval, the interpretation is that a bearish price move is going to be facilitated in the near future, while a bullish price move may take place with a downward price trend and an upward MACD trend. In that way MACD may be considered as a leading indicator, and this type of divergence has been consistently performed well, but it is based solely on the trader's judgement whether is going to be used or not. In this Thesis, we are going to use the MACD crossovers for our MACD-based strategy. The trading rule proposed is then as follows:

- Long position at period t: $MACD_{t-1} < Signal_{t-1}$ and $MACD_t > Signal_t$
- Short position at period t: $MACD_{t-1} > Signal_{t-1}$ and $MACD_t < Signal_t$

2.3.2 Relative Strength Index (RSI)

Relative strength index, or simply RSI, is a momentum indicator. Developed by J. Welles Wilder Jr. in 1978, simply measures the impact of price changes to determine if the asset is overbought or oversold. The RSI calculation formula is defined as follows:

- Calculate the price change: $Change = Price_t - Price_{t-1}$
- Create two variables for each period, one for the up moves and one for the down moves:
  $If\ Change > 0, then\ Up_{move} = Change, else\ Up_{move} = 0$
  $If\ Change < 0, then\ Down_{move} = Change, else\ Down_{move} = 0$
- Calculate the simple moving average of up move and down moves (usually 14 periods used)
- $RSI = 100 - \frac{100}{\frac{Up\ move\ average}{Down\ move\ average} + 1}$

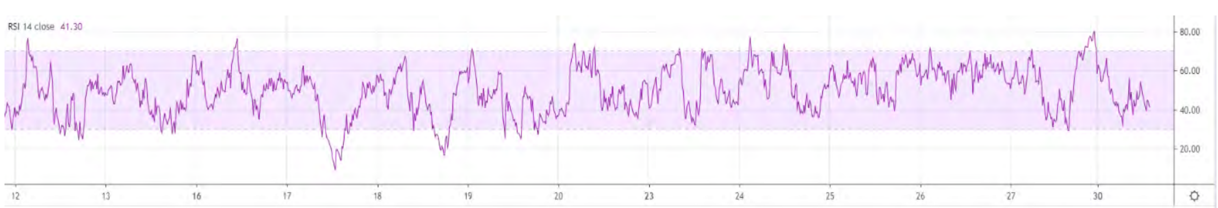

Figure 3: RSI scheme representation, random asset used for the indicator extraction. The RSI line, represented with purple color, oscillates around critical levels of 30 (lower limit) and 70 (upper limit). The highlighted area can make it easier for the analyst to distinguish when the price has move beyond oversold or overbought levels. Source: tradingview.com

RSI, calculated as shown above, oscillates around 0 and its price range is [0,100]. As a momentum indicator, it is considered a leading indicator, while RSI values below (usually) 30 indicate that the asset is oversold (or undervalued), and a trend reversal may take place, because price reached a (local) minimum and may rise in the next periods. RSI values above (usually) 70 indicate that the asset is overbought (or overvalued), and in the same way a reversal may happen – but in the different direction. RSI, has other can of course be calculated with a varied moving average (and not a 14-period moving average), and compared with other critical levels (other than 30-70), in the trader's discretion. RSI has a few other interpretations as well, and an example is a price-indicator trend divergence, like the one mentioned in MACD. For our research we chose to use the RSI-critical levels crossovers as our RSI-trading strategy. The trading rule is as follows:

- Long position at period t: $RSI_{t-1} < 30\ and\ RSI_t > 30$
- Short position at period t: $RSI_{t-1} > 70\ and\ RSI_t < 70$

2.3.3 On Balance Volume (OBV)

OBV, as the name suggests is an indicator that takes into consideration the asset's trading volume, and it was developed by Granville in 1963. Volume reflects critical information about price movements, and shows us how strong is the market sentiment on a given time, so it was considered important to examine a volume-based indicator. OBV indicator is calculated using the asset's closing price and trading volume. Mathematically, the formula is as follows:

$$OBV_t = \begin{cases} OBV_{t-1} + Volume_t, if\ Closing\ Price_t > Closing\ Price_{t-1} \\ OBV_{t-1} - Volume_t, if\ Closing\ Price_t < Closing\ Price_{t-1} \end{cases}$$

It is useful to point out that OBV increases when asset's price increase, and OBV decreases when asset's price decrease. OBV is considered a leading indicator, under the (most often accurate) hypothesis that increases in traded volume may eventually drive the asset's price upwards (downwards). In the same way we chose to develop a trading strategy with the already mentioned indicators, and in order to receive a clarified trading signal from OBV, in this research we will extract the 100-period EMA and look for crossovers between OBV and its EMA. The trading rule is going to be as follows:

- Long position at period t: $OBV_{t-1} < EMA_{t-1}\ and\ OBV_t > EMA_t$
- Short position at period t: $OBV_{t-1} > EMA_{t-1}\ and\ OBV_t < EMA_t$

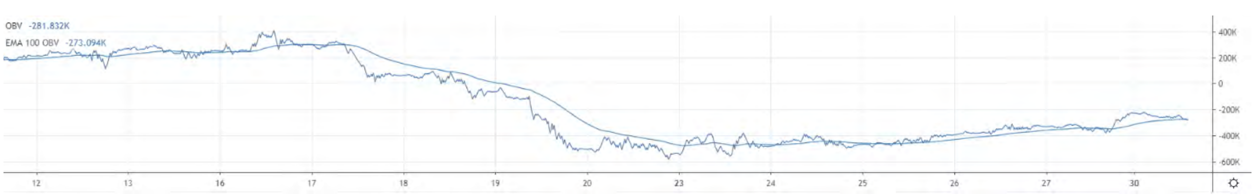

Figure 4: On balance volume indicator is represented with the steep line, while its 100-period exponential moving average with the smoother line. Crossovers between the lines will lead us to trading indications. OBV is extracted from a random asset, just for the graphical representation of OBV. Source: tradingview.com

2.3.4 Bollinger Bands (BB)

Invented by J. Bollinger in the early 1980's, Bollinger bands is a volatility indicator. Its major characteristic is that the price changes over time are within two bands, one upper and one lower (often called envelope). These bands are extracted as follows:

- Calculate the 20-period (usually) simple moving average (SMA)
- Calculate the standard deviation, based on the 20-period SMA
- Upper Band = $\bar{X} + 2\sigma$
- Lower Band = $\bar{X} - 2\sigma$

Standard deviation is used, because it expresses how much the price differs from its mean value, and the prices are meant to stay within the bands most of the time. When a breakout occurs, a continuation of the trend is most likely to take place, meaning that, if price breakouts above the upper trend, we get a long signal, and vice versa for a short signal.

Figure 5: Price of a random asset, with Bollinger Bands applied. Upper and lower bands are depicted with a green color, defining the "channel" that the asset price moves. Moving average is depicted with a red line. Source: tradingview.com

Although this is one interpretation of the indicator, there are several others: one of them is that the prices ''bounce'' between lower and upper band (the bands are potentially dynamic support and resistance levels), triggering signals when price tags the band: long signal when price tags lower band, and vice versa. Combined with price patterns, a ''W'' formation tagging the lower band triggers a long signal, while a ''M'' formation triggers a short signal. Another major aspect of the indicator, is that there are band expansion and contraction periods (large or small price changes with wide or narrow bands), succeeding one another. Breakouts is going to be our Bollinger bands-based trading strategy, with the trading decision rule:

- Long position at period t: $Price_{t-1} < Upper\ Band_{t-1}\ and\ Price_t > Upper\ Band_t$
- Short position at period t: $Price_{t-1} > Lower\ Band_{t-1}\ and\ Price_t < Lower\ Band_t$

3. Literature Review

Technical Analysis gained massive popularity through the years, something that led many academics to considerations whether it can be effectively used or not. J. Nithya and G. Thamizhchelvan (2001) conducted a research based on the equity market, more specifically focused on banking sector stocks. Using MACD and RSI crossovers, similarly with this research, tried to approach the best timing for market entry or exit. They came into three investment recommendations (categorization was made based on the different investor willingness to take low, medium or high risk), using the crossovers discussed, as well as the frequency and the severances of the indicator reversals.

M. Raj and D. Thurston (1996) implemented technical analysis rules in the Hong Kong futures market: the research included two technical analysis rules, based again on crossovers. The first one used a set of two moving averages, one defined as a short-term and the other one as long-term moving average. A trading signal is generated when a crossover occurs: long signal when previously the short-term was lower than the long-term and eventually became higher (this shows an upward price trend; thus, we buy) and vice versa for the short signal. The second trading rule is famously known as the trading range break-out: one of the most common charting techniques in technical analysis, using support and resistance price levels (support level is the price level which the analyst defines, believing that the prices will not go lower, thus we commonly say the price movement finds support, and vice versa for resistance level), with trading range break-outs being much alike crossovers. Results for the moving averages technique provides excess returns, but not significant ones, in alignment with the efficient market theory, which states that excess returns cannot be consistently generated, because moving averages is a lagging indicator: for its extraction past information is used, which is may already incorporated in the asset's price.

D. M. Smith, N. Wang, Y. Wang and E.J. Zychowicz (2016), provide us with insights from the appliance of technical analysis in the hedge fund industry. Based on a previous research from Hong and Stein (1999) which they observed that the fact that multiple changes in an asset's overall trend genuinely create trending patterns: these patterns are created due to the fact that investors underreact and overreact on their investing choices because of the incomplete information they have available. Based also on the information diffusion phenomenon: all people (investors) do not receive the same information simultaneously, they proved that technical analysis users tend to outperform on average the non-users, but only in high sentiment periods.

Evidence from the Greek mutual fund industry, from S. Zontos, C. Skiadas and Y. Valvis (1998) using similarly a moving averages crossover technique. The implementation of technical analysis at this case proved to be profitable, while extra support on this argument was provided comparing the profits generated from multiple trades and the profits from a buy and hold approach. Although that the authors proved the profitable moving averages crossover strategy, this hold only under the limitation that no trading costs were taken into consideration.

L. Menkhoff (2010), after conducting a study based on five popular financial markets (U.S., Germany, Switzerland, Italy and Thailand) approached a total of 692 fund managers to examine if, and into what extent they use technical analysis for their investment decisions. The survey-based research showed some interesting findings: firstly, under the examination of the relation of technical analysis usage with experience, degree, education, and indicators of overconfidence, no evidence shows that technical analysis is preferred by less rational/inferior fund managers. Secondly, research showed that the use of technical analysis may be a rational response to high information costs, especially for smaller management firms who have less capacity to conduct or buy data for investing decisions based on company fundamentals.

W.W.H. Tsang and T.T.L. Chong (2009) examined the profitability of the on-balance volume indicator, applied in stocks included in large stock markets (U.S. Europe and China). The authors created the trading decision rule, using the OBV indicator and its moving average, which similarly to other research is based on crossovers: long signal is generated when OBV was lower from its moving average on the previous period and became higher on the current period, and vice versa for a short signal. This simple, yet efficient technique provided the authors with profitable results. This research's limitation is the transaction costs, which, if taken into consideration lead to unprofitable results for Europe and U.S. markets, leaving the profits from trading (Greater) China stocks unaffected.

C. J. Neely, P. Weller and R. Dittmar (1997), used a different kind of approach to prove if technical analysis can prove to be profitable, implementing their model in the foreign exchange market. A genetic programming approach is used: simply put, they generated a set of 500 hundred random technical rules, from which the ones that had the best goodness of fit combined together to produce a set of "descendants" which were better, and repeating this sequence till the desired number of rules was generated. These rules were then included to the initial equation of returns as pseudo-variables. The implementation of technical analysis turned out to be profitable, with the model designed providing economically significant excess returns.

M.H. Kuo and C.L. Chen (2006) integrated neural networks techniques in combination with technical indicator signals, in their way to prove whether using technical analysis is profitable or not, using indices-comprised ETFs from the Taiwanese market. Using a relatively small data set and by building a neural network decision model, they found that it could be profitable. In fact, if the investors approached investment decisions using the proposed model, they can benefit from it without having much knowledge about technical indicators, as the indicator rules are included in the hidden layer of the neural network.

W. Brock, J. Lakonishok and B. LeBaron (1992), used moving averages and trading-range breaks (support and resistance price levels) in the closing prices of the Dow Jones industrial average index (time series of data). By applying a bootstrapping methodology (model built to complete transactions based on technical indications) and comparing it to null models: random walk, and autoregressive models based in the time series discussed, they found that the returns generated from the technical indicators-based model are significantly higher than the null models, proving that way the benefits of technical analysis indicators.

C. J. Neely, D. E. Rapach, J. Tu, G. Zhou (2012), were the first to use technical indicators to forecast the equity risk premium, by generating regressions, in which the equity risk premiums are regressed on a technical indicator-based variable. Moreover, to fill the gap between fundamental economics-based models and technical analysis indications, they employed fundamentals-based regressions as well, and did the comparison between models. The insights they provide us is that technical variables can have forecasting power on the equity risk premiums, matching or even outperforming the one from fundamentals.

G. Zwart, T. Markwat, L. Swinkels, D. van Dijk (2009) implemented a combination of fundamental and technical rules to test whether they provide profitable results, in the foreign exchange market, including currencies from emerging countries. Using the difference of the emerging country (real) interest rate and the relevant U.S. rate (real interest differential), and the gross domestic product growth for the fundamentally-based signals, support and resistance levels and (slow-fast) moving averages crossovers for the technically-based signals, they found that the combination of those two can provide significant positive risk adjusted returns.

Y. Zhu and G. Zhou (2009), approached the (standard) asset allocation problem investors face. Using technical analysis, more specifically the moving average rule, in combination with the fixed allocation rule (introduced earlier by Markowitz and Tobin), found that it is possible to reliably estimate the investment portion that should be allocated in a specific asset. They also proved that, technical analysis, particularly the moving average rule used, could possibly add value to the initial investment, if the investor follows a fixed allocation rule.

S. R. Trivedi (2018) is providing us with further proof that technical analysis can prove to be justifiably profitable. Trivedi uses a variation of the standard technical analysis candlesticks, the Heikin-Ashi candlesticks, and develops an investing rule (the Heikin-Ashi stochastic) based on the candlestick's formations. The rule implemented, oscillating between 0% and 100%, is initially indicating a trend momentum on levels of 70% and above, and a trend reversal on levels of 30% and below. A set of sub-rules were created, under the consideration for entry and exit points, leading to a considerable amount of profits generated, following this strategy.

T. Oberlechner (2001) conducted a survey about the usage of technical and fundamental analysis, as to find out which one is more important. The survey was conducted in four major European cities: Frnakfurt, London, Vienna and Zurich, which was referring to foreign exchange traders and financial journalists. The vast majority of traders is implementing both analyses for forecasting future prices, while journalists slightly tend to use more fundamentals in their articles, rather than chart analysis. Therefore, this research proved based on the sample used, that technical analysis cannot be considered as a less-reliable predicting tool.

S. Papadamou and S. Tsopoglou (2001) implemented a set of technical rules (moving average crossovers, momentum indicator, MACD), and their variants, to the foreign exchange market. Allthough technical analysis did not provide with better results than a buy and hold strategy, technical analysis trading systems still proved to be profitable. Based on their findings, technical analysis- based investment decisions are of much greater use in periods with a clear trend established, rather than an unclear trend period (much more trades are involved in an unclear trend period, resulting in a higher transaction cost).

Y. H. Lui, and D. Mole (1998) conducted a questionnaire-based survey, to provide us with results of the usage of technical and fundamental analyses of foreign exchange dealers in Hong Kong. While technical analysis tends to be more important for short-term investment decisions, both fundamental and technical analyses are implemented by dealers (approximately 85% of the survey respondents use both analyses). This paper provides further evidence that technical analyses should not be considered as an inferior predicting tool.

H.Y. Chen, C. F. Lee and W. K. Shih (2016) provides us with more evidence from a combined approach to an investment decision model. Technical analysis-wise, they used an enhanced model of the momentum returns approach, which is based in past price data (the covariance of prior returns and the current trading volume). Fundamentally wise, the authors constructed two variables based on company fundamentals, such as ROA, cash flows, liquidity, etc. Combining those two methods, the research showed that higher returns can be generated, by helping investors choose more reliably the stocks that they would include into their portfolios, taking into account both approaches.

4. Data

Back-testing means that we need to search for past data and apply our methodology in order to produce results. In that way, we simulate the trading strategy we intend to use, in historical data, because it is an excellent way to assess the viability of the strategy implied.

For the Fama-French model being used the relative data are taken from the respective database available in the professor’s website. Fama-French data are date on daily intervals, risk free rate (Rf), the market risk premium which is the subtraction of the risk-free rate from the expected market rate (Rm-Rf), SMB and HML factors. Data uploaded in the database is expressed in percentage, so we divided with 100 for our modelling purposes.

ETF data were extracted from Yahoo Finance database. The original dataset extracted from a quick query to the database contains date on daily intervals, open, high, low, close and adjusted close prices. For our research we used the daily closing prices.

Data are on a daily time interval spanning from January 27th, 2010, to November 29th, 2019 (at the time of the research, Fama French Data were up to that date, on daily intervals, and that was our selection criterion). The initial time series created have 2478 observations (2478 days or 9.83 years). Technical indicators started showing signals after a few days, based on the mathematical type of the indicator (e.g. MACD starts showing signals after 34 days, based on the 12-26-9 scheme -these numbers obviously will not and should not sum up to 34). Variables were created that way, and transferred to a new sheet, with the corresponding data we also use for further analysis, starting from the day the indicator produced its first long signal (e.g. MACD for SPY took 34 days to produce its first signal, and 18 days to produce its first long signal, therefore there's a total of 52 days: the MACD-based time series starts from 14th April, 2010). The time series length varies through different combinations of ETFs and technical indicators. Microsoft Excel is used for the data processing.

5. Methodology

As mentioned before, we chose this short-term approach under the consideration that trading and investing has become increasingly popular and widely accessible to retail investors, who have multiple choices of online platforms and brokers. Transactions are completed much quicker than ever before, with spreads being kept at a minimal level, and commission costs being low or even zero in a few brokers for an array of products, including ETFs, and that's why a retail investor could easily include them in a short-term investing portfolio. The trading decisions which will be taken are matching with the swing-trader profile, meaning that the technical indicator signals we are going to create will lead us to a long position, and in the next available period the ETF will be liquidated, and in that way we will have a substantial short-term profit. ETFs were selected mainly based on their classification, their high number of assets under management (AUM), and their high liquidity (high amount of volume traded), so they can be part of a short-term portfolio which we intend to replicate.

5.1 Trading rules

As already mentioned, all technical indicators under consideration are going to produce us signals using crossovers, and are being used as inputs for the following model. Except long and short positions, we added hold position, an auxiliary variable (long cumulative), and finally the signal generated. The generic scheme under each signal is produced is explained in this chapter.

Long	Long signal produced based on the indicator
Long Cumulative	The cumulative sum of the long signal
Short	Short signal produced based on the indicator
Hold	Hold position maintained, based on the formula created
Indicator	Indicator final signal, combining long, hold, and short positions

There are 2 numerical outputs for variables Long and Short, 1 and 0. Analytically, 1 confirms the signal given (e.g. if variable Long becomes 1, that means we indeed have a long signal, if it becomes 0, then no long signal is given). The Indicator variable takes also 2 numerical outputs, 1 and 0: 1 stands for long or hold, and 0 stands for short. Conditions step by step are as follows. The variables explained in Microsoft Excel represent each column of the subset, and each row represents a unique day.

Long:

If $Indicator_{t-1} < Comparable\ Variable\ or\ Constant_{t-1}$
And $Indicator_{t-1} < Comparable\ Variable\ or\ Constant_{t-1}$
Then *→ Put 1*
Else *→ Put 0*

Long Cumulative:

$Cumulative\ Sum\ Formula\ for\ n\ observations: a, a+b, a+b+c, \dots, a+b+c+..+n$

Short:

If $Indicator_{t-1} > Comparable\ Variable\ or\ Constant_{t-1}$
And $Indicator_{t-1} < Comparable\ Variable\ or\ Constant_{t-1}$
Then *→ Put 1*
Else *→ Put 0*

Hold:

If $Long_{t-1} = 1$ ***And*** $Short_t = 0$
Or If $Hold_{t-1} = 1$ ***And*** $Short_t = 0$
Then *→ Put 1*
Else If $Long_{t-1} = 0$ ***And*** $Short_t = 1$
Then *→ Put blank*
Else *→ Put blank*

Indicator:

If $Long_t = 1$

Then → *Put 1*

Else If $Short_t = 1$ ***And*** $Long\ Cumulative_t \geq\ Long\ Cumulative_{t-1}$

Then → *Put 0*

Else if $Indicator_{t-1} = 0$

Then → *Put 0*

Else → *Put* $Hold_t$

Variables Long and Short are fairly straightforward about the way they've been calculated. Hold variable, is calculated in a way that it takes into consideration that firstly we already have an open (long) position, and secondly there cannot be a hold position when a short position is preceded. Long Cumulative indicator is because we only want to take short positions when the cumulative number of long positions at period t is higher or at least equal with long positions at t-1. This simple mathematical structure was created efficiently using 0 and 1 as our function outputs for Long Indicator. Finally, Indicator variable is being calculated in a way that we take a long position when we have an indication, hold when a long (or a previous hold) position is preceded, and a short position when a long -or a hold- position is preceded. Indicator is in statistical terms the pseudo-variable we are going to use for our model, based on the 3-factor Fama-French model.

5.2 Fama-French model

The Fama-French model is an extended version of the capital asset pricing model (CAPM). By definition, CAPM is capturing the relationship between the expected returns of an asset with the systematic risk. In statistical terms, CAPM is a multivariate regression, with the expected asset's return (r_a) as the dependent variable, and the expected market return (r_m), risk free rate (r_f)as the explanatory variables.

$CAPM: r_a =\ r_f + \beta_a * (r_m - r_f)$

The $(r_m - r_f)$ factor is the market risk premium, which is explained as the estimated compensation the investor is about to receive, if he chooses to take the risk to invest, while β_a coefficient is defined as the sensitivity of the expected asset's return in relation with the market. Eugene Fama and Kenneth French, when they initially introduced their model, they took into consideration the fact that there are variables, namely company characteristics, that, based on past data were able to predict pretty accurately the expected asset returns, and therefore being able to capture in more detail risk premiums that could potentially compensate the investor. Therefore, based on CAPM, they introduced their CAPM-enhanced model, known as the 3-factor Fama-French model, by adding two more explanatory variables. The first one, SMB, which means small-minus-big, refers to the small and big capitalization stocks. The second one is HML, which means high-minus-low, and refers to companies that have high and low book-to-market values. Based on empirical results and examining past data, SMB is added to capture the sensitivity to company size, because small capitalization stocks tend to outperform big capitalization stocks. SMB is also known as the ''size effect'', and it is the return of a diversified portfolio of small-cap stocks minus the return of a diversified portfolio of big-cap stocks. Additionally, HML, also mentioned as ‘’value effect’’, captures the sensitivity of a portfolio to value stocks (value stocks tend to outperform the performance of growth stocks), and is the returns of a diversified portfolio of high book-to-market stocks, minus the returns of a diversified portfolio of low book-to-market stocks. Therefore, the model is defined as:

$$r_{it} - r_{ft} = a_i + b_i * (r_{Mt} - r_{ft}) + s_i * SMB_t + h_i * HML_t + e_{it}$$

Where a_i is the intercept value, s_i, h_i the sensitivity factors of the added explanatory variables and e_{it} a zero-mean residual term. In the case that the current model structure can explain completely the asset's performance, the a_i (mentioned also as the abnormal rate of return, or excess return) is going to be zero, meaning that the asset's performance cannot be attributed to the manager's ability to generate profits.

Many researchers over the years, since the first release of the Fama-French model in 1992, and the inventors themselves, have in many cases added more explanatory variables to the original model, such as a momentum, volatility, quality, profitability (RMW factor: robust minus weak, included in 5-factor Fama-French model) and risk profile (CMA factor: conservative minus aggressive, also included in the 5-factor Fama-French model). In this paper, we will add the pseudo-variable we created as explained to the previous chapter, to the initial 3-factor model.

For the purpose of implementing this model, we extracted the logarithmic asset returns: $\ln(Closing\ Price_t - Closing\ Price_{t-1})$. This procedure normalized our returns, and is essentially the continuously compounded rate of return, that will grow (diminish) the closing price of the ETF in consequent periods. Our model is therefore presented as:

$$r_{it} - r_{ft} = a_i + b_i * (r_{Mt} - r_{ft}) + s_i * SMB_t + h_i * HML_t + g_i * Indicator_t + e_{it} \quad (1)$$

In that way, we incorporated the technical analysis aspect to a fundamental-based model, to examine if technical analysis indications can add a risk premium to our expected asset returns, which is our main objective. We then proceeded applying equation (1) for all ETFs under consideration and for each of the technical indicators, giving us a total of 12 regression models.

At this point of our research, we used EViews statistical package for econometric analysis. Since our data has been processed and structured and the model has been established, which in statistical terms is a multivariate regression, we ran the necessary regression diagnostics. Goodness of fit has been checked with R^2, residual analysis and hypothesis testing. Statistical significance has been checked with the F-statistic for the overall regression fit, and with the t-statistics and p-values for the explanatory variables. Results are thoroughly presented in the next chapter. Running equation (1), in all cases under consideration, we found a very high goodness of fit with $R^2 \approx 99\%$, and a very high F-statistic (p-value ≈ 0 for all cases: rejecting the null hypothesis H0 that the regressions do not have predicting ability, for all levels of importance 90%, 95% and 99%), but low t-statistics for explanatory variables ($|t - value| < 2$) indicate that we have multicollinearity between our explanatory variables. This is solved by regressing all the explanatory variables onto the market risk premium $(r_{Mt} - r_{ft})$, and then using the residuals extracted from this process as a new, adjusted market risk premium for all other explanatory variables to our original regression model. This process is mentioned as orthogonalization, or the Gram-Scmidt process. In more detail:

$$\left(r_{Mt} - r_{ft}\right) = c + f_i * SMB_t + l_i * HML_t + q_i * Indicator_t + e_{it} \qquad (2)$$

$$Set \rightarrow \; e_{it} = (r_{Mt} - r_{ft})_{orthogonalized}$$

$$r_{it} - r_{ft} = a_i + b_i * (r_{Mt} - r_{ft})_{orthogonalized} + s_i * SMB_t + h_i * HML_t + g_i * Indicator_t + e_{it} \qquad (3)$$

Equation (3) is the one we used for the final estimation of the (expected) excess return $r_{it} - r_{ft}$, using the technical analysis pseudo-variable among the other explanatory variables. The purpose of using a bivariate (zero and one) pseudo-variable is straightforward: If the investor takes a long position or is in a hold state, positive (logarithmic) excess return is going to be added (remember pseudo-variable=1 means long or hold), while negative excess return is going to be avoided accordingly (when pseudo-variable=0, in a short position that we decided to liquefy our position).

Equation (3) is the one that estimates the outputs presented in the next chapter. Using EViews for the regression estimations, the method of the computation of covariance used is the HAC (heteroskedasticity and autocorrelation) Newey-West estimator, which is used to deal with problems in the error terms in the models (as the name suggests, the problems of heteroskedasticity and autocorrelation in error terms). Covariance is used in the regressions estimation and it is a measure of association (relation) between the dependent and the independent variables.

5.3 Trade Statistics

Trade Statistics are using a subset from the data we already used, plus some variables created for the sake of the statistics extraction. This chapter is supportive to the previous one, with a more practical approach, but is also a part of our general back-testing strategy. In the relevant literature, this technique may be referred as bootstrapping: in an investment environment, bootstrapping is a process from which we intend to generate profits, that starts running without external factors (user inputs), such as more capital available to invest.

Date	The brief date (daily intervals) of long and short positions
Close	The closing ETF price
Signal	Long or short signal, produced from the technical indicators
Available	Available capital at each period
Total Allocated	Allocated Capital on the specific ETF
Units	Units of ETF purchased
Profit / Loss	The potential profit / or loss, after liquidating (short position taken)
Equity	Available equity after completing a transaction

Again, the variables explained in Microsoft Excel represent each column of the subset, and each row represents a unique day. The new variables added are constructed using excel functions and are as follows:

Available:

$$Available = Equity_{t-1} - Total\ Allocated_t$$

Total Allocated:

If $Signal = Long$
Then → Put $Equity_{t-1} * 5\%$
Else → Put 0

Units:

If $Signal = Long$
Then → Put $\frac{Total\ Allocated_t}{Close_t}$
Else → Put blank

Profit / Loss:

If $Signal = Short$
Then → Put $(Close_t * Units_{t-1}) - (Close_{t-1} * Units_{t-1})$
Else → Put 0

Equity:

$$Available + Total\ Allocated + Profit(Loss)$$

For the shake of constructing the trading statistics, presented in the results chapter, we took under the consideration that a retail investor is located in the United States and he/she should oblige to the PDT (pattern day trader) Rule, designed and implemented by FINRA (Financial Industry Regulatory Authority, US), which states a specific trading frequency and a minimum of $25,000 in their brokerage accounts. The initial amount available for investing is then $25,000 which seems to be a reasonable amount for investing for a retail trader, either the trader is located in the U.S. or not. We are taking also into consideration that the hypothesized investing account will remain unaffected of currency conversion commissions, as there are a few secure and reliable digital money transfer services that will not charge any extra fees. Subsequently, to be more realistic, assuming that the investor will not build his portfolio based on one asset class, and he may chooses to keep a percentage of his total equity in the most liquid position (cash) we decided to build up the consequent trades investing a 5% of his total equity at all times, meaning the first long position taken (for 1 ETF using 1 indicator) will be $1,250. Processing accordingly the variables explained, the trading statistics output is as follows:

Output	Interpretation
Summary	
Total net profit/loss	The total net profit or loss accumulated over the period examined
Profit/Loss on initial amount (%)	The profit or loss as a percentage of the initial amount invested ($1,250)
Profit/Loss Ratio	$= \frac{\text{Total Gains}}{\text{Number of winning trades}} \div \frac{\text{Total Losses}}{\text{Number of losing trades}}$
Average Profitability per Trade (APPT)	$= \left(\frac{\text{Winning short trades}}{\text{Total short trades}} * \text{Avg. winning trade}\right) - \left(\frac{\text{Losing short trades}}{\text{Total short trades}} * \text{Avg. losing trade}\right)$

Trade Statistics	
Total no. of trades	The overall number of trades (both long and short trades)
No. of profitable trades	referring to short trades only
Amount of profitable trades	
Largest profitable trade	
Average profitable trade	
Percentage of profitable trades	
No. of losing trades	
Amount of losing trades	
Largest loosing trade	
Average loosing trade	

Trade Durations	
Most consecutive wins	referring to short trades only
Amt. of consecutive wins	
Most consecutive losses	
Amt. of consecutive losses	

6. Results

7.1 IWC Results

IWC Results	MACD	OBV	BB	RSI
Constant	-0.0005***	-0.0002***	0.00003	0.0002***
	(0.00006)	(0.00006)	(0.00006)	(0.00006)
r_m-r_f	0.943***	0.94***	0.945***	0.939***
	(0.008)	(0.008)	(0.008)	(0.008)
HML	0.362***	0.254***	0.372***	0.204***
	(0.014)	(0.015)	(0.014)	(0.014)
SMB	1.639***	1.6***	1.654***	1.552***
	(0.013)	(0.014)	(0.012)	(0.014)
Indicator	0.002***	0.001***	0.0007***	0.0004
	(0.00009)	(0.00009)	(0.00008)	(0.00009)
R-Squared	0.96	0.96	0.96	0.96
Adj. R-Squared	0.96	0.96	0.96	0.96
F-Statistic	15074***	13011***	15036***	11180***
No. Observations	2428	2300	2432	2091

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

The explanatory variables in all regressions ran are statistically significant, with |t-statistic| > 2 and p-values < 0.01, meaning they are statistically significant for all levels of significance. The exception is in the Bollinger Bands based model: the constant (intercept term) is not significant for any level of significance, but due to the fact that it affects our model with a very low value, that would not appear to be a problem to consider. Explanatory variables have positive sign, except the constants for MACD and OBV. This means that if all other variables are zero, IWC returns will be negative at this point of time (it seems though, model-wise that this is not the case), but on the other hand, the fact that the intercept is very close to zero shows that the other explanatory variables capture the most of the variation in expected returns. Adjusted R-squared is at a very high level, meaning that the models ran has a high goodness of fit, and a high and significant F-statistic, indicating that our models overall have a good predicting ability. It seems that the size effect (SMB) is highly attributable for the technical-indicators based models constructed for IWC, with the market factor and the value effect following. The technical indicator added, which in fact is a constructed pseudo-variable, as already mentioned will take the price of 1, for a long or hold signal, and the price of 0, for a short, or a no-entry signal. Therefore, if the pseudo-variable takes the price of 1, and we know that it is statistically significant, it will add up a small amount to the total ETF return.

IWC Results	MACD	OBV	BB	RSI
Summary				
Total net profit/loss	$1,091.34	$766.28	$11.84	$1,041.64
Profit/Loss on initial amount (%)	87%	61.3%	0.9%	83.3%
Profit/Loss Ratio	1.92	3.73	1.66	3.58
APPT	$11.99	$13.44	$0.41	$115.74
Trade Statistics				
Total no. of trades	183	115	59	19
No. of profitable trades	45	23	11	7
Amount of profitable trades	$2,339.97	$1,268.58	$723.56	$1,131.91
Largest profitable trade	$186.19	$232.49	$224.10	$242.62
Average profitable trade	$52.00	$55.16	$65.78	$161.70
Percentage of profitable trades	25%	20%	19%	37%
No. of losing trades	138	92	48	12
Amount of losing trades	$1,248.63	$502.30	$711.73	$90.26
Largest loosing trade	$74.86	$43.62	$139.80	$45.97
Average loosing trade	$27.14	$14.77	$39.54	$45.13
Trade Durations				
Most consecutive wins	5	3	5	4
Amt. of consecutive wins	$253.56	$296.59	$265.84	$691.04
Most consecutive losses	4	7	5	1
Amt. of consecutive losses	$93.59	$121.07	$126.86	$45.97

Metrics show that all trades taken, based on the technical indicators discussed were profitable, with MACD and RSI being the most profitable, and Bollinger Bands based trades giving the weakest results. Profit/loss ratio shows that our trading strategies are performing well, while, in a probability-based approach, APPT shows that we can expect to win approximately 115 dollars per trade following RSI indications. Trading under MACD is generating much more trades, followed by OBV, as we have multiple indicator crossovers (MACD-Signal line crossover, OBV-OBV EMA crossover). Also, it seems that the amount of losing trades is approximately half of the winning ones for MACD and OBV, while Bollinger Bands based trades seem to offset wins and losses. RSI is more robust, with the number of wins being much higher from the amount of losses. The biggest loss from trading IWC was in 2011, generated from MACD indications, and the biggest win was in 2012 (were all indicators generated profits) from RSI.

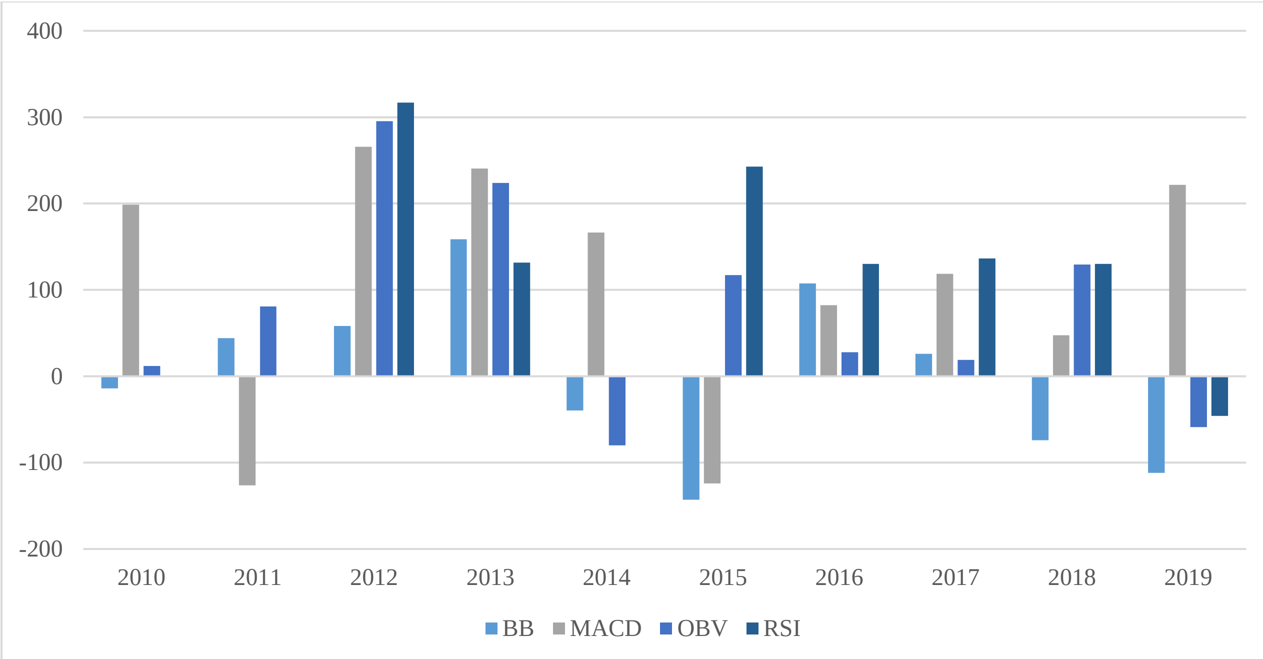

Figure 6:Yearly profits (losses) generated, trading IWC using the 4 technical indicators discussed. RSI based trades did not generate any profit (loss) in years 2010, 2011 and 2014, because no transactions were made. Source: own processing.

6.2 IJR Results

IJR demonstrates the same regressions output characteristics as IWC. High goodness of fit is implied by the price of the adjusted R-squared, as well as a good overall model predicting ability from the (statistically significant in all levels of significance) F-statistic. Explanatory variables in all 4 regressions ran are statistically significant, and the exposures to the market risk premium, the value effect, the size effect and the indicator-based pseudo-variable, capture almost all of the variation of the expected ETF returns (due to the very low value of the constant term). The number of observations varies (this happens to the 4 previous regressions ran on the IWC returns) because some indicators, based on their signal producing ability discussed on previous chapters give signals earlier than others. Most notably, RSI is producing its first long signal later than the other 3 indicators (the difference approximately 1 year later). The exposure of the ETF returns to the pseudo-variables discussed is of a low value, but still, they can be reliably used, based on regression outputs, for the ETF returns variation explanation.

IJR Results	MACD	OBV	BB	RSI
Constant	-0.0002***	-0.0007***	0.0002***	0.0004***
	(0.00005)	(0.00006)	(0.00005)	(0.00004)
r_m-r_f	0.976***	0.98***	0.976***	0.981***
	(0.004)	(0.005)	(0.004)	(0.005)
HML	0.418***	0.32***	0.425***	0.287***
	(0.009)	(0.01)	(0.009)	(0.01)
SMB	1.427***	1.384***	1.439***	1.34***
	(0.009)	(0.01)	(0.009)	(0.01)
Indicator	0.001***	0.002***	0.0004***	0.0004***
	(0.00006)	(0.0001)	(0.00006)	(0.00008)
R-Squared	0.98	0.95	0.98	0.98
Adj. R-Squared	0.98	0.95	0.98	0.98
F-Statistic	26400***	11030***	26446***	21418***
No. Observations	2425	2321	2432	2091

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

The biggest win is attributed to RSI, in 2012, while the biggest loss to Bollinger Bands, in 2019 (trades resulted in a loss of $192 this year). Total net profit/loss show that all trades conducted based on indicator signals were profitable, except Bollinger Bands based trades. The loss was relatively small, about 1% of the initial amount of $,1250 invested, while we can observe that the other indicators produced quite good results, with the most profitable accumulating a profit of 72.7% on the initial amount (MACD). Average profitability per trade (APPT) shows that the expected profit (or loss per trade) generated from RSI massively outperforms the other indicator-based trades, because during back-testing, we found that RSI is producing much more profitable (short) trades than loosing trades: there is a 75% of total short trades that turned out to be profitable.

IJR Results	**MACD**	**OBV**	**BB**	**RSI**
Summary				
Total net profit/loss	$909.35	$583.59	$(13.24)	$854.02
Profit/Loss on initial amount (%)	72.7%	46.7%	(1%)	68.3%
Profit/Loss Ratio	1.92	4.52	1.47	3.53
APPT	$9.67	$6.02	$(0.44)	$106.75
Trade Statistics				
Total no. of trades	189	195	61	16
No. of profitable trades	44	26	12	6
Amount of profitable trades	$2,223.17	$1,413.47	$743.68	$943.06
Largest profitable trade	$191.19	$278.87	$185.41	$243.48
Average profitable trade	$50.53	$54.36	$61.97	$157.18
Percentage of profitable trades	47%	13%	20%	75%
No. of losing trades	50	169	49	2
Amount of losing trades	$1,313.82	$829.87	$756.93	$89.04
Largest loosing trade	$80.34	$55.56	$133.13	$84.07
Average loosing trade	$26.28	$11.69	$42.05	$44.52
Trade Durations				
Most consecutive wins	5	2	3	4
Amt. of consecutive wins	$205.80	$198.64	$128.85	$633.15
Most consecutive losses	5	7	4	1
Amt. of consecutive losses	$119.49	$95.37	$192.39	$84.07

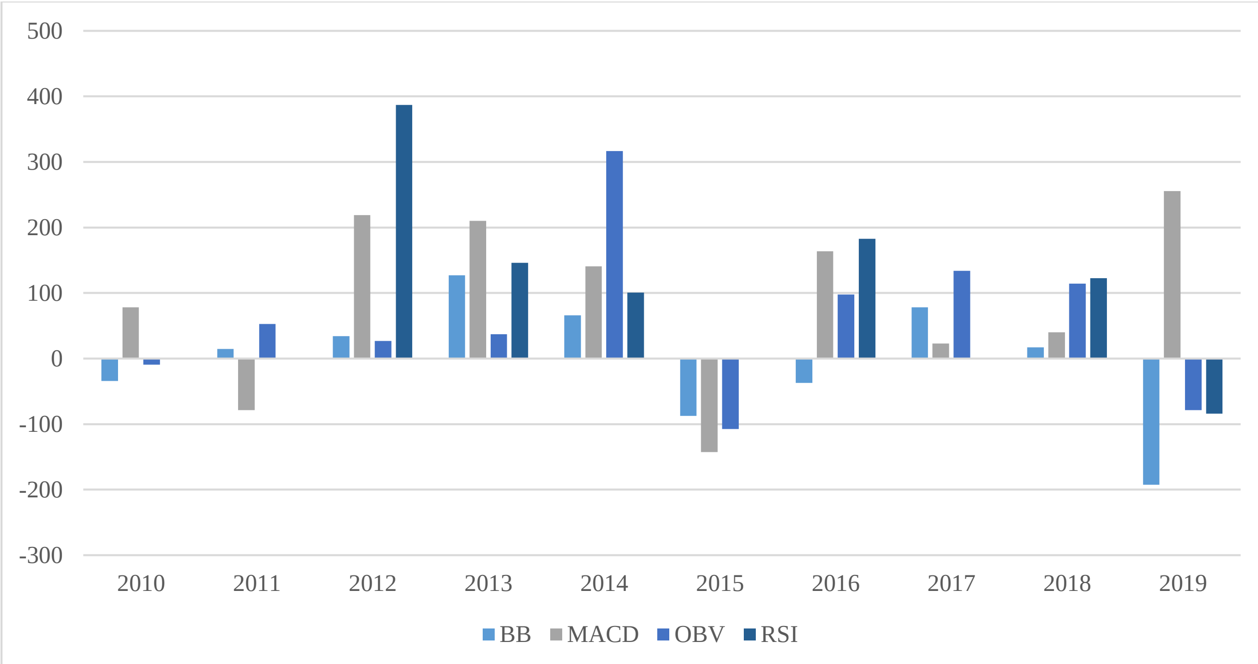

Figure 7: Yearly profits (losses) generated making indicator-based trades of the IJR ETF. Source: own processing.

6.3 IJH Results

IJH Results	MACD	OBV	BB	RSI
Constant	-0.0004***	-0.0006***	0.0002***	0.0004***
	(0.00005)	(0.0001)	(0.00006)	(0.00004)
r_m-r_f	0.983***	0.985***	0.983***	0.99***
	(0.007)	(0.008)	(0.007)	(0.008)
HML	0.35***	0.256***	0.353***	0.24***
	(0.012)	(0.012)	(0.011)	(0.012)
SMB	1.001***	0.965***	1.012***	0.935***
	(0.011)	(0.012)	(0.011)	(0.012)
Indicator	0.002***	0.001***	0.0004***	0.0001
	(0.00008)	(0.0001)	(0.00008)	(0.0001)
R-Squared	0.95	0.95	0.95	0.95
Adj. R-Squared	0.95	0.95	0.95	0.95
F-Statistic	12695***	11030***	12704***	10362***
No. Observations	2425	2321	2432	2095

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

The RSI trading decision rule which fed the pseudo-variable we included in our enhanced type of the Fama-French model is not statistically significant in any level of statistical significance. On a value perspective basis, we can see that in this specific regression the constant (intercept term) is bigger than the exposure of the ETF returns to the pseudo-variable. This combination of facts may suggest that the pseudo-variable is unable to explain some of the return's variation, and that it could be omitted from the regression. Still, the RSI based model, as well as the other regressions shows a high goodness of fit from the value of adjusted R-squared, and a good overall predicting ability, from the (statistically significant in all levels) value of F-statistic. Overall, the explanatory variables are statistically significant to all levels of significance in the regressions ran (except the one we mentioned). We can also notice, that the exposure to the size effect (SMB) is not equally big as it was on the previous examined ETFs.

IJH Results	**MACD**	**OBV**	**BB**	**RSI**
Summary				
Total net profit/loss	$839.80	$497.25	$27.68	$234.85
Profit/Loss on initial amount (%)	67.18%	39.8%	2.2%	18.8%
Profit/Loss Ratio	2.25	2.92	2.17	3.08
APPT	$8.75	$8.43	$0.89	$39.14
Trade Statistics				
Total no. of trades	193	119	63	12
No. of profitable trades	42	21	10	4
Amount of profitable trades	$1,962.57	$1,307.90	$806.70	$280.30
Largest profitable trade	$228.16	$232.15	$314.27	$103.60
Average profitable trade	$46.73	$62.28	$80.67	$70.07
Percentage of profitable trades	44%	36%	32%	67%
No. of losing trades	54	38	21	2
Amount of losing trades	$1,122.77	$810.65	$779.02	$45.45
Largest loosing trade	$70.89	$87.18	$95.40	$39.18
Average loosing trade	$20.79	$21.33	$37.10	$22.72
Trade Durations				
Most consecutive wins	5	3	2	3
Amt. of consecutive wins	$129.96	$218.78	$121.24	$190.39
Most consecutive losses	9	10	5	1
Amt. of consecutive losses	$123.43	$200.75	$133.25	$39.18

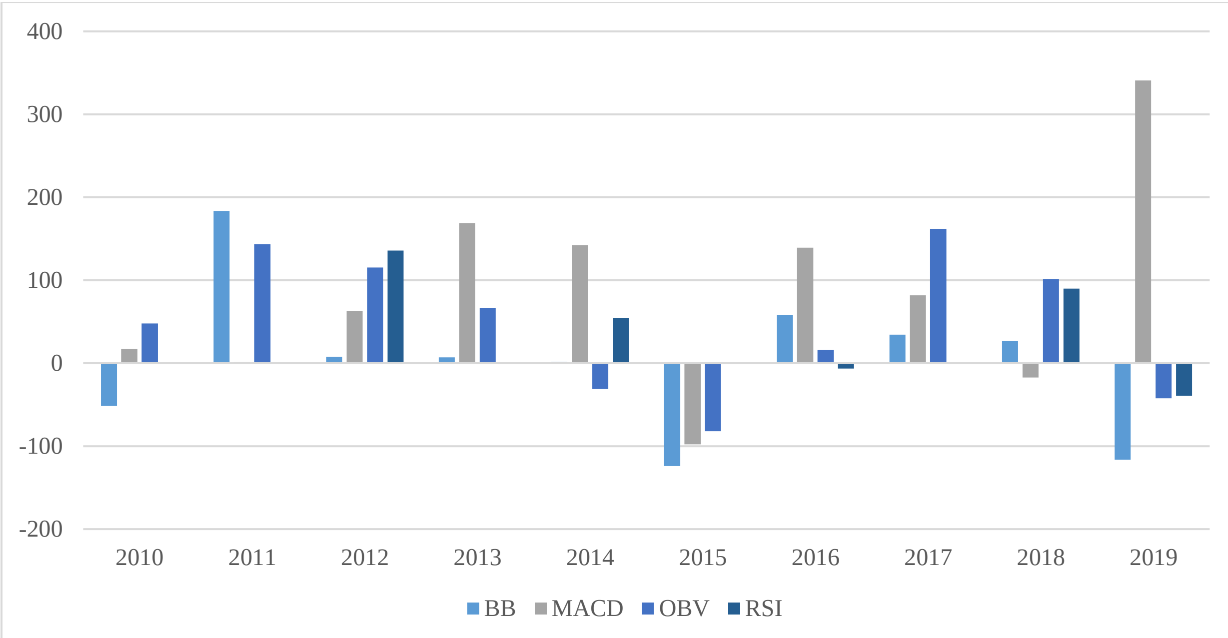

Figure 8: Yearly profits (losses) generated implementing the back-test strategy based on technical indications, trading the IJH mid-cap ETF. Source: own processing.

Overall, based on trade statistic, trading based on the indicators lead to profitable results. The largest win move was noted in 2019, by MACD based trades, while Bollinger Bands trades noted the largest loss in 2015. This does not mean by any means that Bollinger Bands are not a good indicator, since we are partially using the indicator's signals in this research, and moreover, the Bollinger Bands trades at least led to a capital retention state at the end of the period. Moreover, in contradiction with the regression analysis, RSI led to profitable results, noting the best profit/loss ratio and APPT among indicators.

6.4 SPY Results

SPY Results	MACD	OBV	BB	RSI
Constant	-0.0006***	-0.0005***	0.0002***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
r_m-r_f	0.989***	0.988***	0.989***	0.988***
	(0.002)	(0.002)	(0.002)	(0.002)
HML	0.194***	0.088***	0.202***	0.115***
	(0.004)	(0.004)	(0.003)	(0.003)
SMB	0.459***	0.404***	0.465***	0.434***
	(0.003)	(0.003)	(0.003)	(0.003)
Indicator	0.002***	0.002***	0.0005***	0.0007***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
R-Squared	0.99	0.99	0.99	0.99
Adj. R-Squared	0.99	0.99	0.99	0.99
F-Statistic	67159***	59868***	67339***	62473***
No. Observations	2425	2289	2432	2368

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

Regressions ran based on the SPY ETF gave solid results. Every explanatory variable across all regressions is statistically significant on all significance levels. The adjusted R-squares of 99% proves that the explanatory variables can actually explain the dependent variable's behavior with a 99% of accuracy. The F-statistics show that the models developed have strong predicting ability. It is also notable that the RSI-based model is including a larger number of observations (comparing to the previous ETFs discussed), because a long signal based on SPY's data was created much more sooner.

RSI outperformed all the other indicator-based trades on this ETF, with the profit generated as a percentage of the initial amount invested is 85%.

SPY Results	MACD	OBV	BB	RSI
Summary				
Total net profit/loss	$590.25	$547.28	$122.96	$1,063.44
Profit/Loss on initial amount (%)	47.2%	43.8%	9.8%	85%
Profit/Loss Ratio	1.94	4.41	1.89	9.75
APPT	$5.68	$6.59	$5.12	$118.16
Trade Statistics				
Total no. of trades	203	167	49	18
No. of profitable trades	46	27	10	8
Amount of profitable trades	$1,499.60	$1,034.22	$471.18	$1,077.25
Largest profitable trade	$132.16	$182.39	$127.35	$180.88
Average profitable trade	$32.60	$38.30	$47.12	$134.66
Percentage of profitable trades	46%	33%	42%	89%
No. of losing trades	54	56	14	1
Amount of losing trades	$909.35	$486.94	$348.22	$13.81
Largest loosing trade	$55.30	$45.53	$61.60	$13.81
Average loosing trade	$16.84	$8.70	$24.87	$13.81
Trade Durations				
Most consecutive wins	4	3	4	7
Amt. of consecutive wins	$52.39	$289.47	$137.29	$984.53
Most consecutive losses	9	8	8	1
Amt. of consecutive losses	$159.48	$45.10	$45.1	$13.81

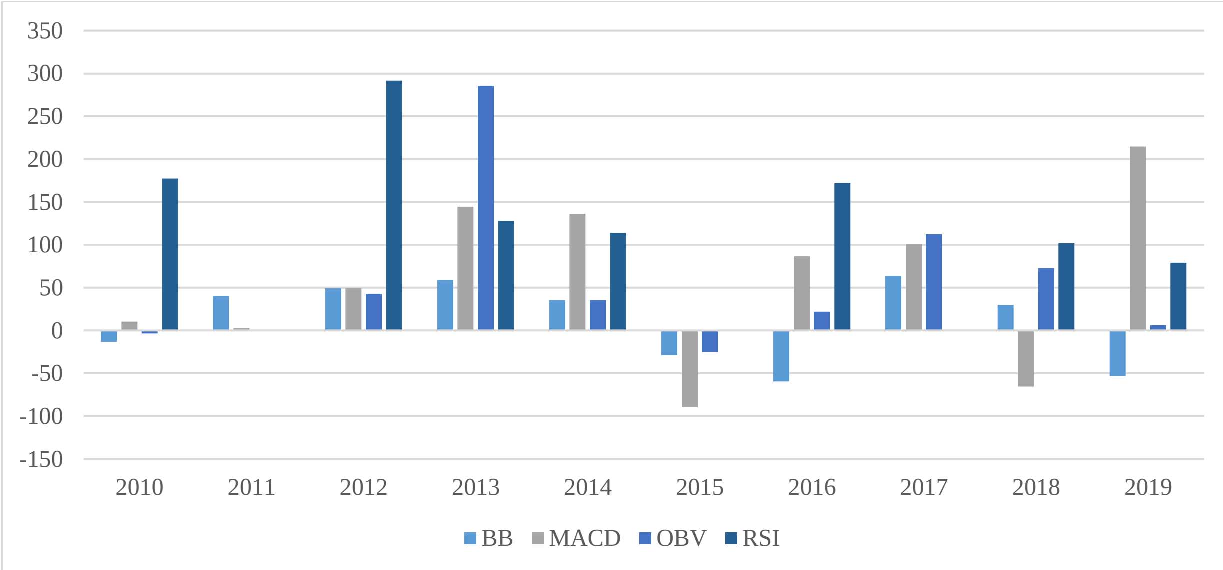

Figure 9: Profits (losses) generated on a per year basis, trading SPY large-cap ETF based on technical indicators. Source: own collaboration.

All indicator-based trades performed well using the backtest approach. RSI gave the biggest amount of profit, having only 1 loosing trade for the time period under consideration. MACD and OBV based trades facilitate much more transactions than Bollinger Bands and RSI ones, while RSI maintains the lowest amount of trades overall. Consecutive wins and losses are going to be examined in an overall point of view later on this research. It is also worth noticing that trading SPY with technical indicators was profitable for 3 consecutive years (2012-2014), while the highest amount of profits generated from RSI in 2012, closely followed by OBV in 2013. The biggest drawdown is due to the MACD based trades, on 2015.

6.5 VTI Results

VTI Results	MACD	OBV	BB	RSI
Constant	-0.0005***	-0.0001***	0.00002	0.0002***
	(0.00002)	(0.00003)	(0.00002)	(0.00006)
r_m-r_f	0.991***	0.99***	0.991***	0.991***
	(0.002)	(0.003)	(0.002)	(0.002)
HML	0.2***	-0.0006	0.205***	0.18***
	(0.002)	(0.004)	(0.005)	(0.004)
SMB	0.575***	-0.026***	0.585***	0.579***
	(0.004)	(0.003)	(0.004)	(0.003)
Indicator	0.002***	0.00005	0.0004***	0.0005***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
R-Squared	0.99	0.99	0.99	0.99
Adj. R-Squared	0.99	0.99	0.99	0.99
F-Statistic	76527***	71566***	76682***	75135***
No. Observations	2425	2379	2432	2407

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

Regressions ran using VTI data have a very high goodness of fit, with R-squared being 99% and a high overall predicting ability, based on the F-statistic. Explanatory variables are statistically significant, in all levels of statistical significance. The one that stands out is the model based on On-balance volume indications, in which HML factor and Indicator (pseudo-variable) are not statistically significant in any level of statistical significance. Furthermore, in this regression HML and SMB seems to have a negative factor sign, something that it is not noticed so far in other ETFs we examined, and also the impact of the indicator is very low, compared to the other regressions run. This may mean that we should omit our constructed variable from this regression.

VTI Results	MACD	OBV	BB	RSI
Summary				
Total net profit/loss	\$629.26	\$491.55	\$241.26	\$903.51
Profit/Loss on initial amount (%)	50.3%	39.3%	19.3%	72.3%
Profit/Loss Ratio	1.86	3.84	2.90	125.81

APPT	$6.29	$5.78	$10.05	$100.39
Trade Statistics				
Total no. of trades	201	171	49	18
No. of profitable trades	47	27	9	8
Amount of profitable trades	$1,597.12	$1,116.52	$566.70	$912.58
Largest profitable trade	$143.51	$180.67	$140.44	$170.59
Average profitable trade	$33.98	$41.35	$62.97	$114.07
Percentage of profitable trades	49%	32%	38%	89%
No. of losing trades	52	58	15	1
Amount of losing trades	$967.86	$624.97	$325.43	$9.07
Largest loosing trade	$52.11	$36.13	$66.16	$9.07
Average loosing trade	$18.26	$10.78	$21.70	$9.07
Trade Durations				
Most consecutive wins	3	2	3	7
Amt. of consecutive wins	$87.76	$111.27	$251.61	$826.36
Most consecutive losses	9	7	3	1
Amt. of consecutive losses	$202.22	$40.97	$61.39	$9.07

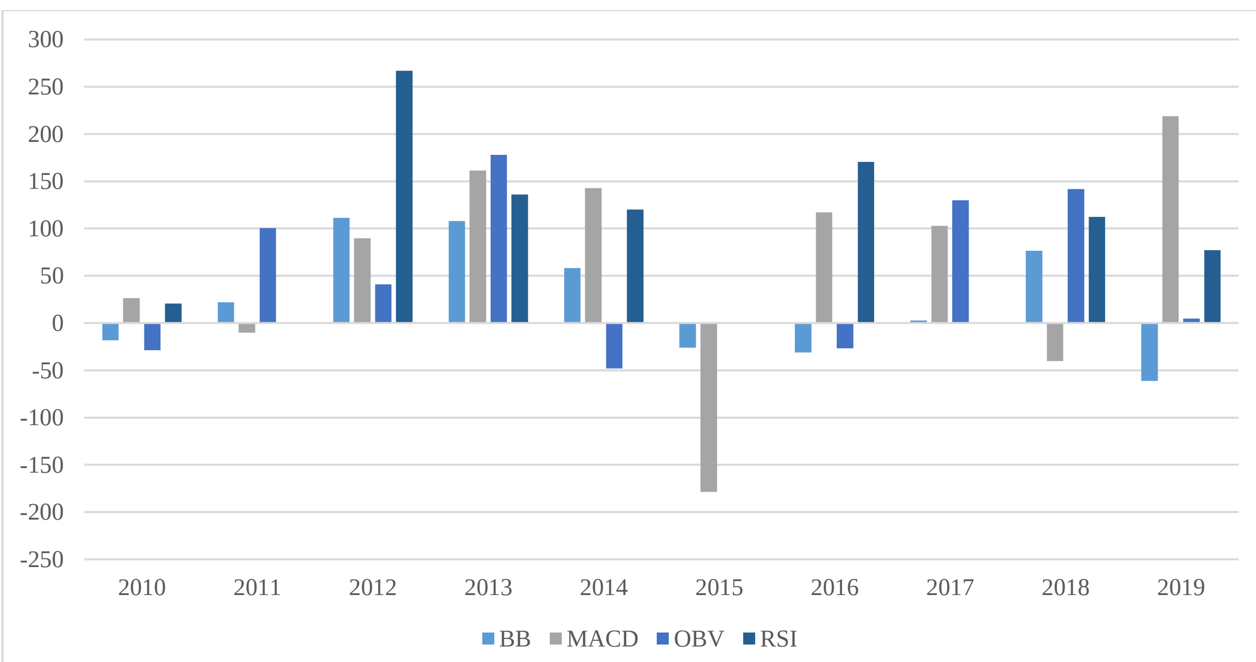

Figure 10: Profits (losses) generated over the total period under consideration, trading VTI ETF using signals based on technical indicators.

In contradiction with the econometric approach, backtesting using VTI data, and trading using On-balance volume indications proved profitable. Also, trading this ETF using Bollinger Bands indication generated the most profitable results, in comparison with the other similar trades conducted (19.3% of the initial amount invested). The profit loss ratio is exceptionally high from RSI trades, due to the fact that we only have one loosing trade using RSI indications.

6.6 EEM Results

EEM Results	MACD	OBV	BB	RSI
Constant	-0.001***	-0.0001***	-0.0006***	-0.0004***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
r_m-r_f	1.117***	1.121***	1.131***	1.13***
	(0.031)	(0.031)	(0.03)	(0.03)
HML	0.297***	0.245***	0.383***	0.354***
	(0.042)	(0.045)	(0.042)	(0.043)
SMB	0.608***	0.587***	0.624***	0.627***
	(0.045)	(0.049)	(0.045)	(0.045)
Indicator	0.003***	0.003***	0.001***	0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
R-Squared	0.66	0.65	0.67	0.67
Adj. R-Squared	0.66	0.65	0.67	0.67
F-Statistic	1167***	1088***	1232***	1208***
No. Observations	2392	2307	2433	2407

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

EEM exchange traded fund was taken under consideration to examine if the Fama-French factors (and our pseudo-variable created) have the same effect in ETFs that are not including U.S. stocks only. As it seems, comparing to the other ETFs, we have a lower goodness of fit, with R-squared spanning from 65% to 67% for the regressions ran on EEM data. Predicting ability from the models is remaining robust, but we can notice that in absolute numbers F-statistic is much lower. All 4 models used the most of the observations, as signals were produced relatively early. Explanatory variables are all significant, in all levels of statistical significance, while the market factor seems to have the greatest effect.

Trade statistics from the simulated trades based on EEM data were the most discouraging in this research. It was the only ETF examined that had losses on MACD, OBV, and Bollinger bands-based trades, while RSI based trades were the only ones that remained profitable. The major drawback was created from on-balance volume trades in 2011, while it was the same ones that created the biggest win in 2017, almost offsetting the losses from 2011. Bollinger bands trades remained so far, the ones that have the lowest amount results comparing to all other trades conducted.

EEM Results	**MACD**	**OBV**	**BB**	**RSI**
Summary				
Total net profit/loss	$(164.05)	$(320.98)	$(32.83)	$418.46
Profit/Loss on initial amount (%)	(13.1%)	(25.67%)	(2.6%)	33.5%
Profit/Loss Ratio	1.71	2.45	1.03	1.68
APPT	$(1.55)	$(3.78)	$(1.17)	$52.31
Trade Statistics				
Total no. of trades	212	171	56	17
No. of profitable trades	37	20	13	6
Amount of profitable trades	$1,826.46	$990.25	$712.60	$522.01
Largest profitable trade	$178.25	$310.53	$168.36	$132.90
Average profitable trade	$49.36	$49.51	$54.82	$87.00
Percentage of profitable trades	35%	24%	46%	75%
No. of losing trades	69	65	14	2
Amount of losing trades	$1,990.51	$1,311.23	$745.43	$103.55
Largest loosing trade	$78.03	$85.33	$159.78	$94.04
Average loosing trade	$28.85	$20.17	$49.70	$51.78
Trade Durations				
Most consecutive wins	4	3	3	6
Amt. of consecutive wins	$163.25	$101.33	$95.02	$522.01
Most consecutive losses	10	11	3	2
Amt. of consecutive losses	$348.98	$150.28	$252.79	$103.55

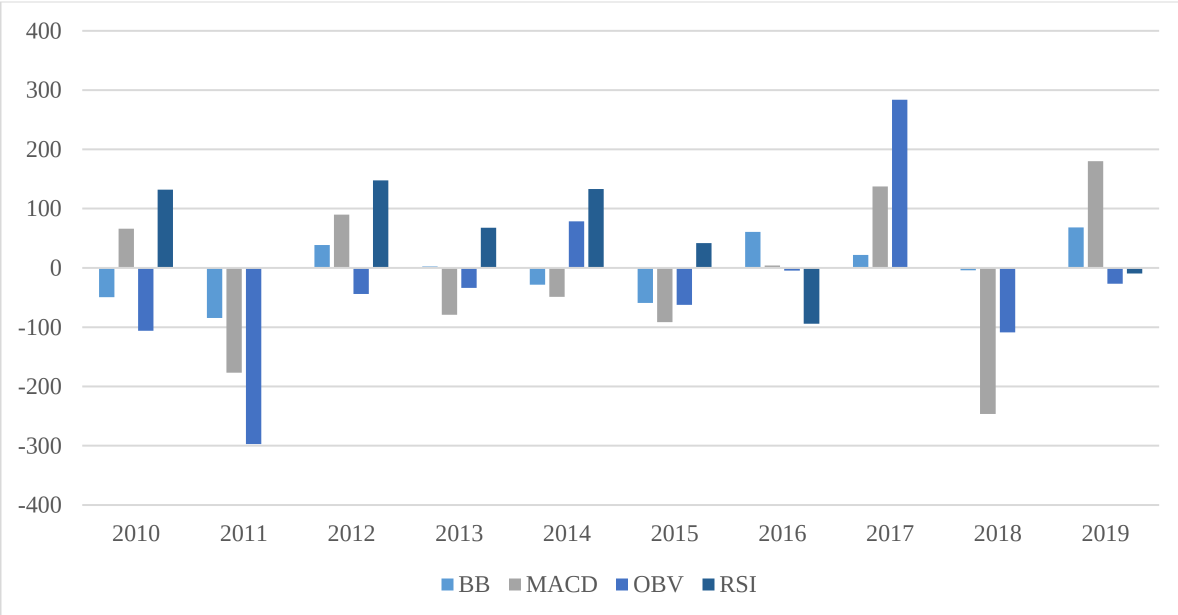

Figure 11: Yearly profits (losses) generated, trading the EEM emerging markets ETF. Source: own processing.

6.7 Overall Trading Results

The graph (number) represents each one of the technical indicator's performance, for all ETFs profit (or loss) accumulated over the years. This implies that we only used one indicator, in order to trade all 6 ETFs: our center of attention is completely on the indicator results. From the ending balance columns, we can confirm that, they all turned out to provide profitable results, regardless the size of the ending balance accumulated. Bollinger Bands indication led to the lowest amount of profit, while RSI proved to be the most profitable overall, recording only one (and small) drawback over the period examined. The profitable years, as well as the magnitude of the profits, for all indicators, is proving that our crossover technique implied that produced our trading signals is well-performing.

The most common drawback, for all indicators except RSI, happened in 2015. During that year, prices of the ETFs under consideration were merely fluctuating for the first eight months (there was no large trading volume: bid-ask spread was very small, meaning that the market price was balanced), leading to two steep downtrends. The first occurred at late August, 2015, and that was followed by a price correction (the buying pressure led the prices to rise) creating a small-lived upward trend, which led to another steep downtrend, at late September, 2015. Technically speaking, the fact that the upward trend did not establish and led to another downtrend had the most negative results for MACD and Bollinger Bands based trades, negatively impacting OBV trades as well. Even though ETF prices were reaching local minimums – leading to a long signal, and local maximums afterwards, leading to a short signal, the (bigger) downtrend led to even smaller prices, so we eventually were buying at higher prices and selling at lower ones.

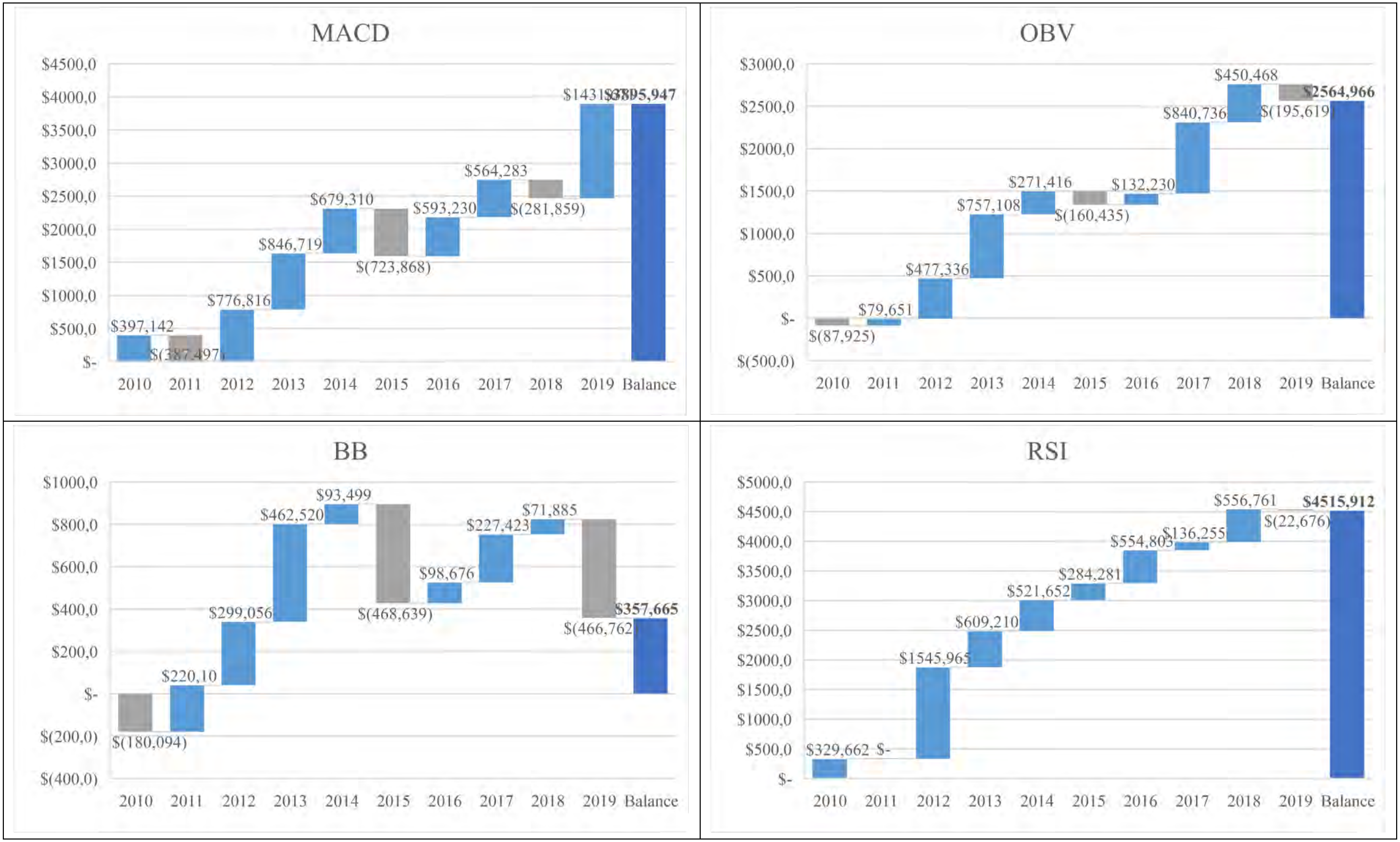

Figure 12: Yearly profits (losses) accumulated from trading all ETFs with one technical indicator at a time. The ending column: "Balance" is the total profit (loss) occurred at the end of the period under consideration. The coloring waterfall-type of chart is: grey for losses, light blue for gains and dark blue for the ending balance. Source: own processing.

The downward trends noticed in August and September are definitely linked with major economic events happened during that time. The contraction in Chinese financial market, which was triggered by the manufacturing sector slowdown and the yuen devaluation (and various other factors) led to a down move on the Shanghai Composite Index by 8.5 percent (the biggest loss occurred since 2007). These events eventually led companies on a worldwide basis to reduce their activity: China at that time was the world's second largest economy, and provoked negative sentiments to the investors on a worldwide basis, resulting to a downward move on major U.S. indices (e.g. Nasdaq, Dow Jones). Long story short, stock markets worldwide were in a downward move at that time, and that can explain the fact that the ETFs included on this research had also a decline in their prices, eventually leading into losses from the trades taken, based on the three out of four technical indicator we used.

7. Conclusions

Our research methodology is a blend of the various techniques discussed in the literature review section: the crossover techniques in technical indicators, the use of a binomial variable, based on a decision we are willing to take (pseudo-variable), the decision-making process based on an algorithm, the merge of fundamentals and technical analysis in the same research. We approached, investment wise, the ETFs using technical analysis indicators to decide when to enter, hold, exit a position or do not take any action. We afterwards used the Fama-French model, which in its initial 3-factor form uses purely fundamental (explanatory) variables, and added our constructed pseudo-variable, based on technical analysis indicators. In that way, we included the characterized as empirical (or subjective sometimes) technical indications into a financial model, able to be statistically analyzed as a multiple linear regression, supported by the academic society. Furthermore, in a more practical approach and to further support our enhanced Fama-French model, we continued our research with a new set of variables and rules, which led us to the trading statistics part. In that way, after we have proven, for the most combinations of ETFs-technical indicators that, firstly the pseudo-variables constructed can be included as explanatory variables in the Fama-French model because they can explain a part of the variation of the ETF's return, and secondly with the back-testing approach we observed that the use of technical indicators for timing and what kind of decision to take (long, short) led us to profitable results, for all indicators under consideration.

Our research results are in alignment with the relevant literature we examined. Profitable results can be achieved when using technical analysis indications. We did not take into consideration trading costs, because nowadays there are more brokers who offer very low, or zero transaction costs. The cost of trading, is implemented already in the price, and the individual trader actually pays the (bid-ask) spread to the broker who's executing trades with. There are several platforms that include an inactivity fee, meaning that the trader is obliged to pay a specified amount if his account remains inactive for a specific period of time, but we did not consider this kind of cost, as our transactions are continuously executed through the period we examined. This research provides with no new findings, rather supporting the previous research including technical analysis-based trades and investment.

We chose ETFs as our asset to conduct our research, for the reason that this kind of product is well balanced, and it offers the diversification an individual trader might not have the skills or capital to achieve. ETFs we included are also very transparent, and largely traded, with big trading volumes, offering the price fluctuation we need in order to speculate, and achieve profits. Trading only one ETF, or even building a portfolio trying to achieve (excess) returns based in one asset class is not something that this research suggests. The main focus was to prove, even in a naive form of technical analysis implementation on trading ETFs, can be profitable or not.

As far as the technical analysis indicators used, one cannot and should not trade basing solely on one indicator. The technical indicators provide better results when combined, and this is not something new, as the very inventors of the indicators suggest the users to combine them with other technical analysis tools. In fact, a well-educated and conscious trader should also include fundamental analysis on his trading-decision scheme, and sources of information he can reach and is comfortable to use beneficially.

Further analysis could include a combined signal produced from all four technical indicators, or even with the use of more indicators. We decided to not designed a model which will signal for a position based in at least one signal from one out of four indicators, because we believe that there should be constructed a rule about how important the indicator signal received is, in any time given during a period examined. According to the findings of our research, a buy and hold strategy for every ETF analyzed, would prove more profitable than the accumulated amount of profits generated from trades taken based on the four technical indicators discussed, with the buy and hold strategy outperforming the constant technical-based transactions significantly. Nevertheless, technical analysis as we already mentioned is not performed in its most beneficial way, meaning that more profitable results could be achieved with a combined trading signal from technical indicators, (with an enriched signal from each technical indicator: e.g. include slope divergences between ETF's price slope – indicator's value slope) or even with the use of chart analysis, and other charting tools that are not included in this research. We did not also take into consideration the leverage effects on any scenario built in this thesis, which, under the scope of day trading, can provide an excess amount of returns to individual traders.

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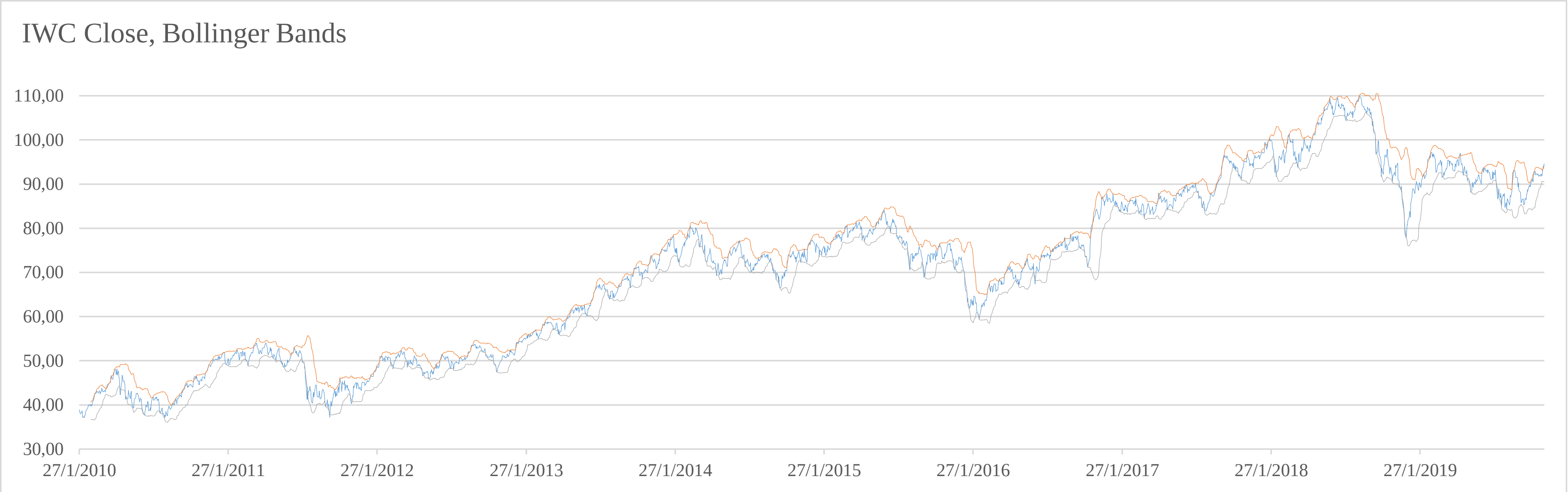
10. Appendix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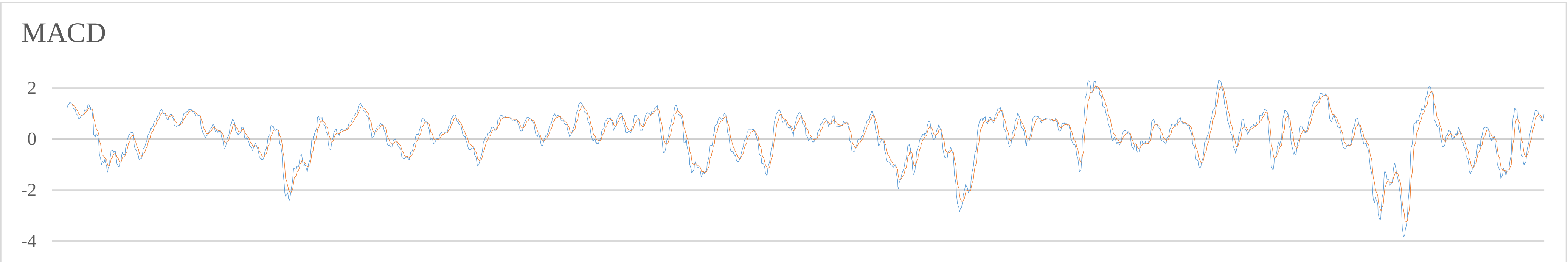
27/1/2019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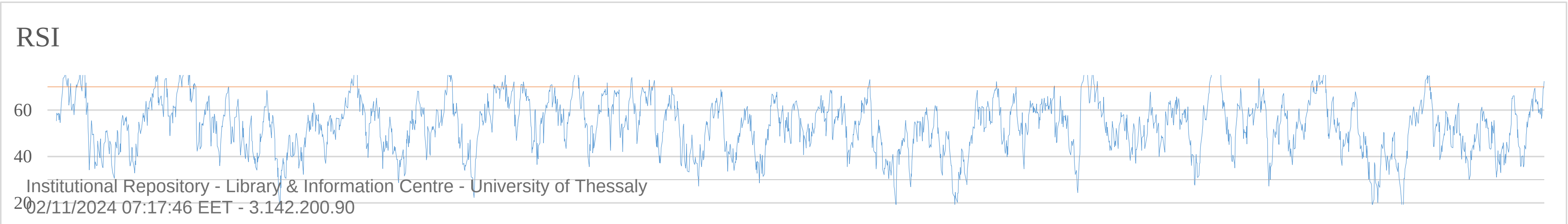
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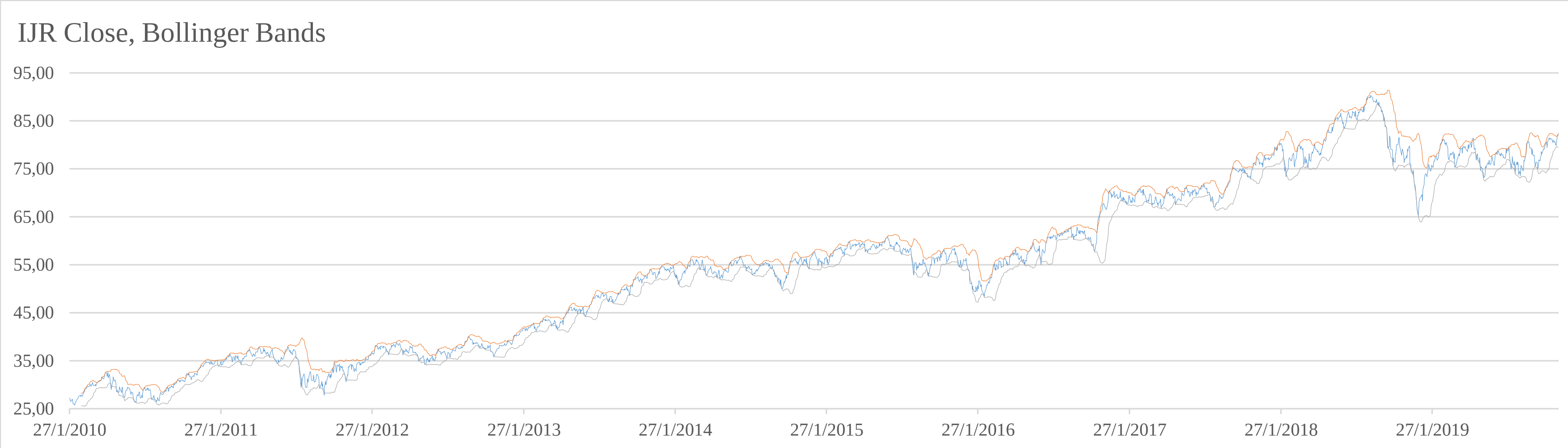
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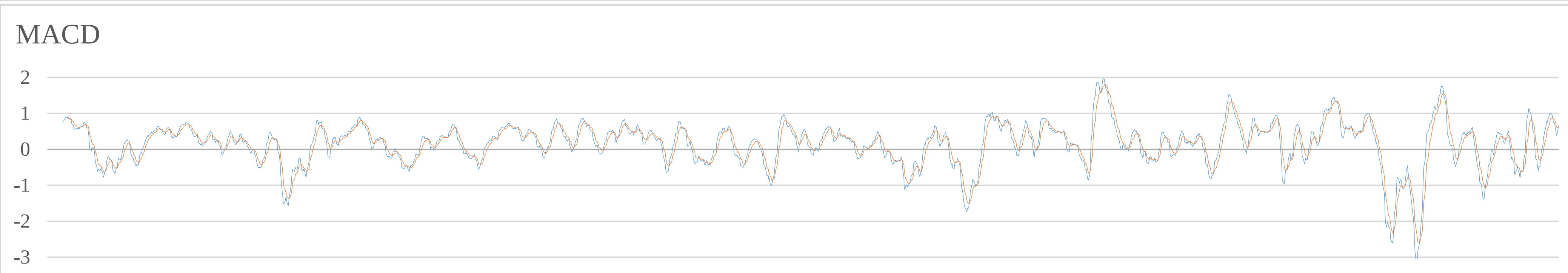
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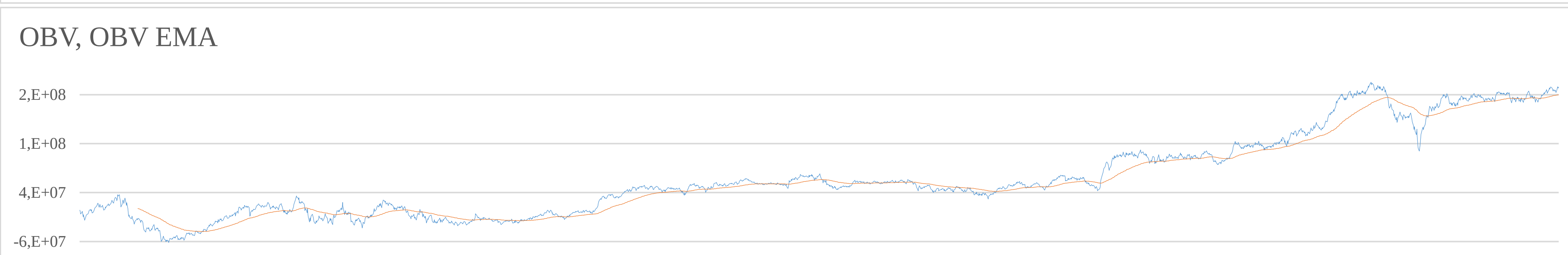
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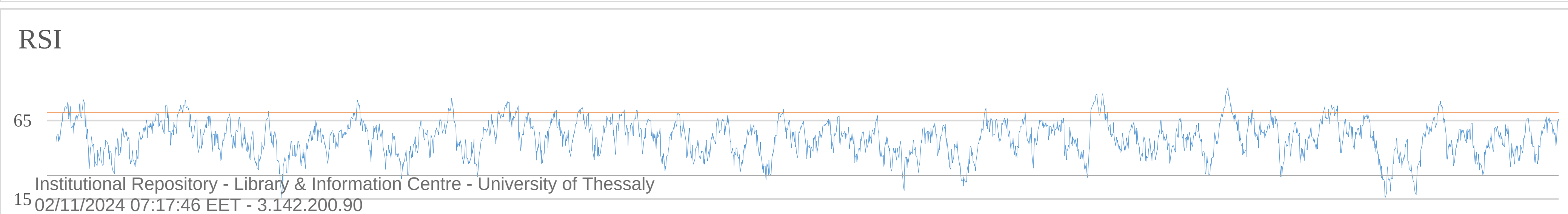
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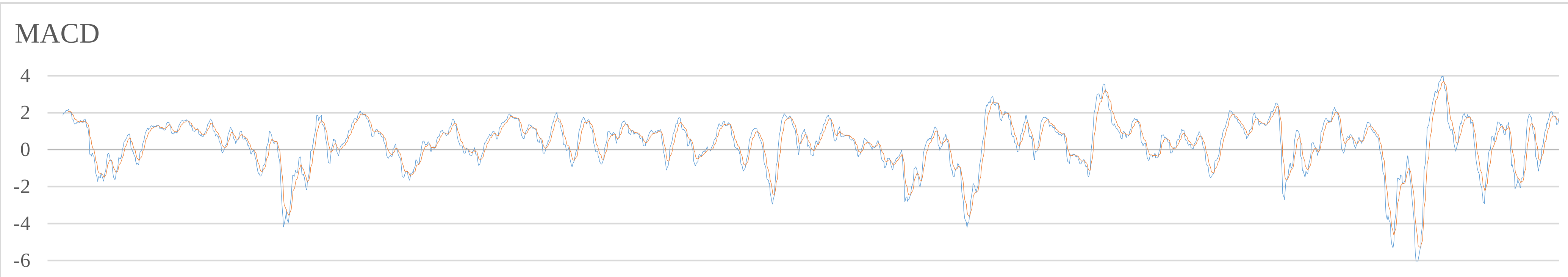
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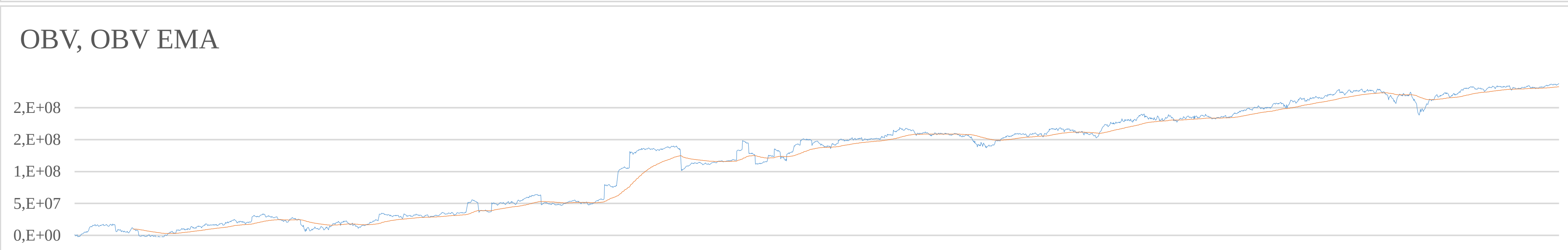
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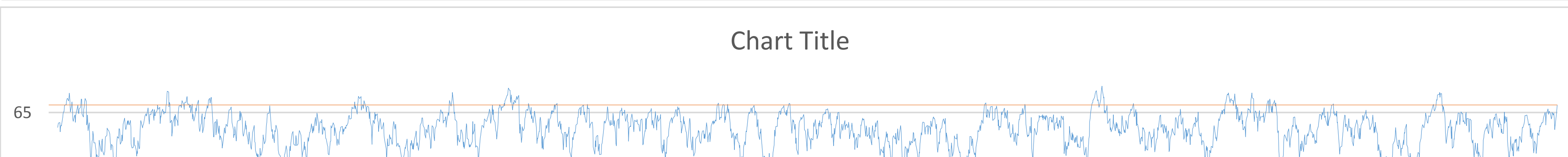
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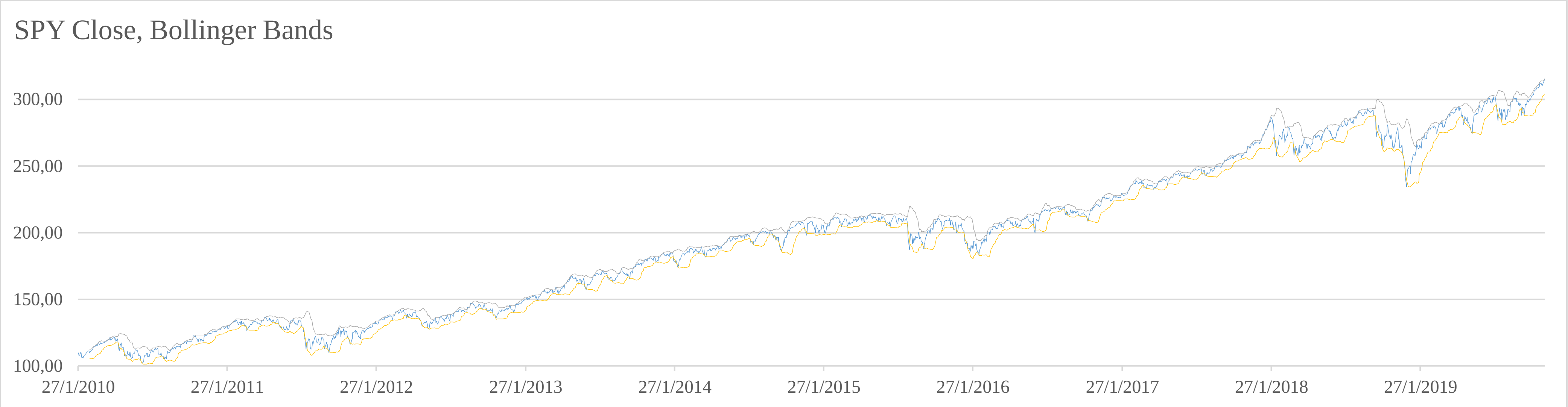
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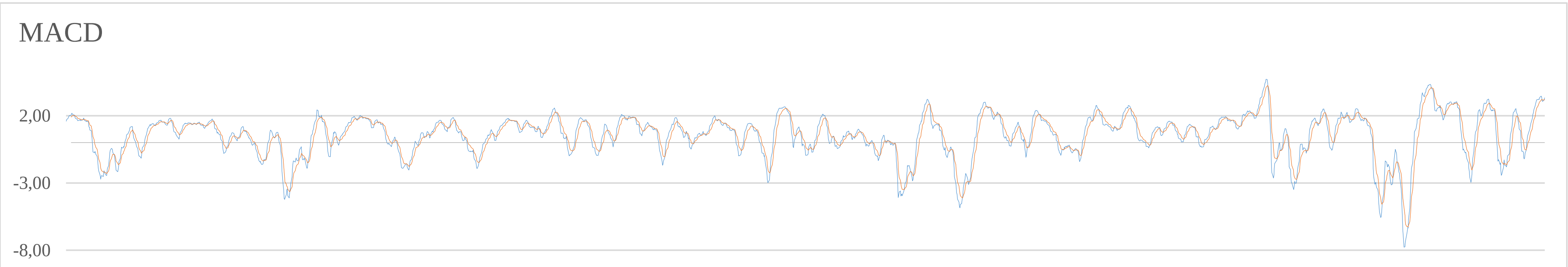
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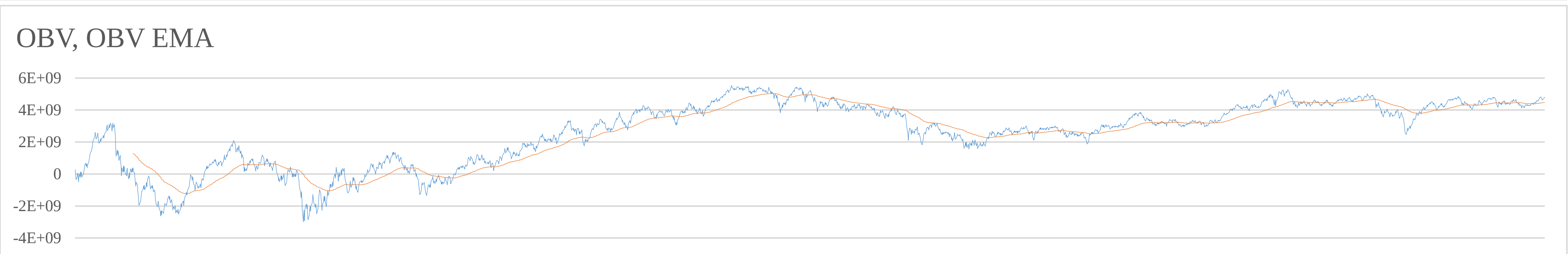
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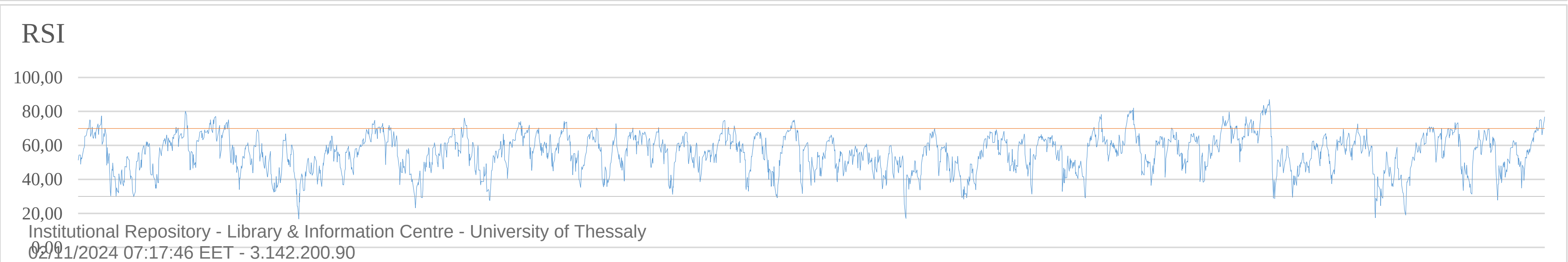
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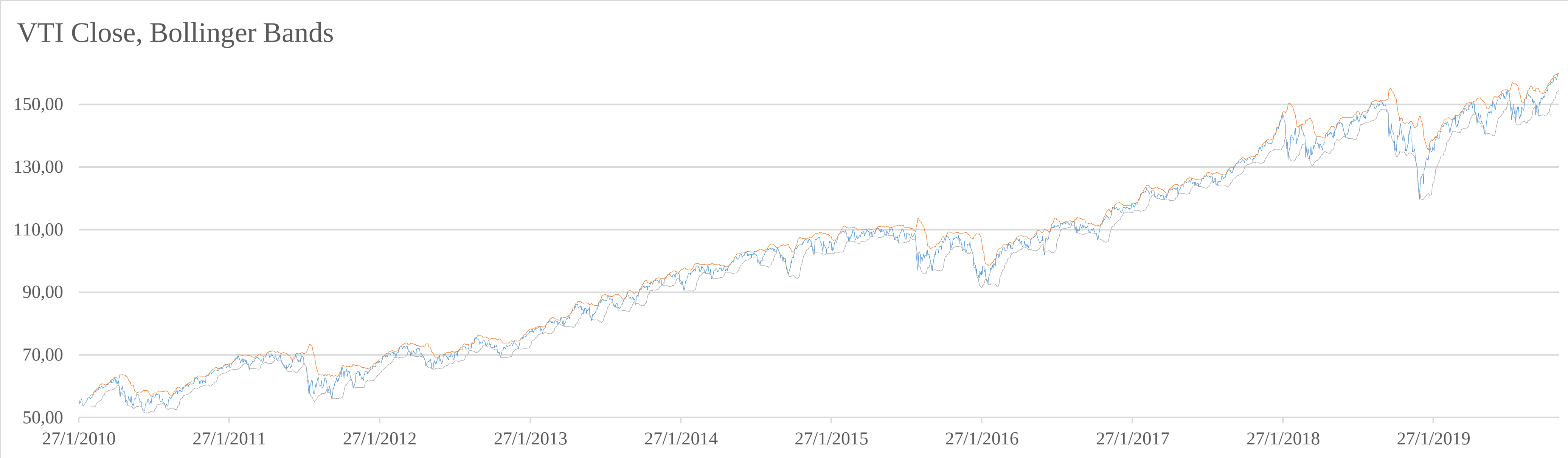
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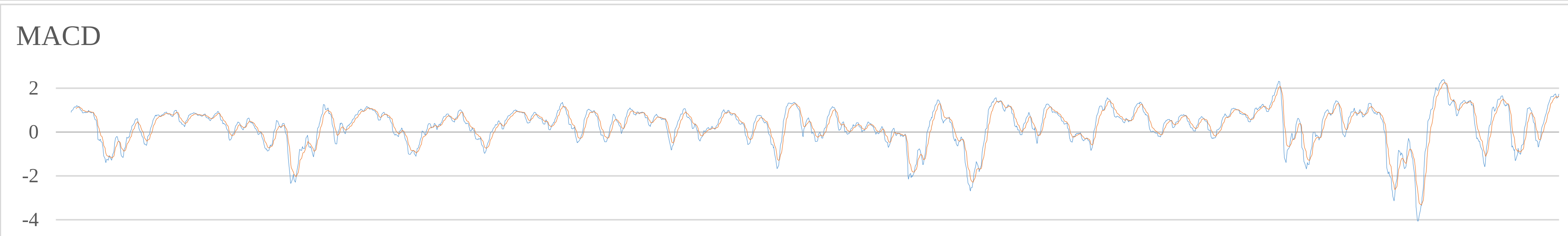
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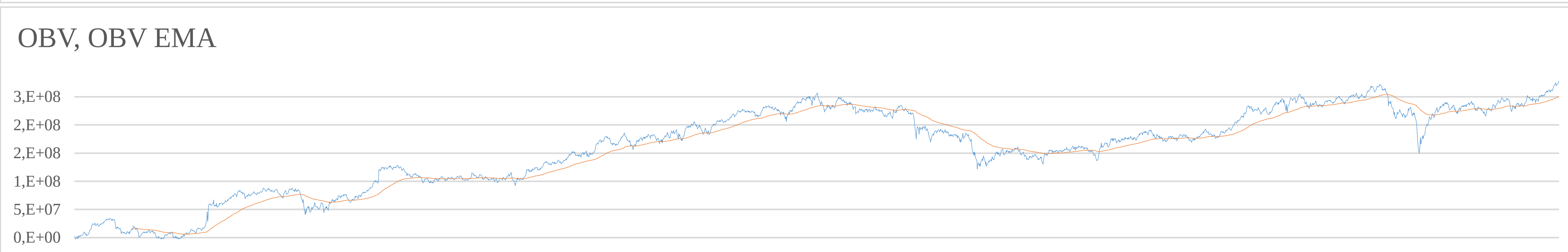
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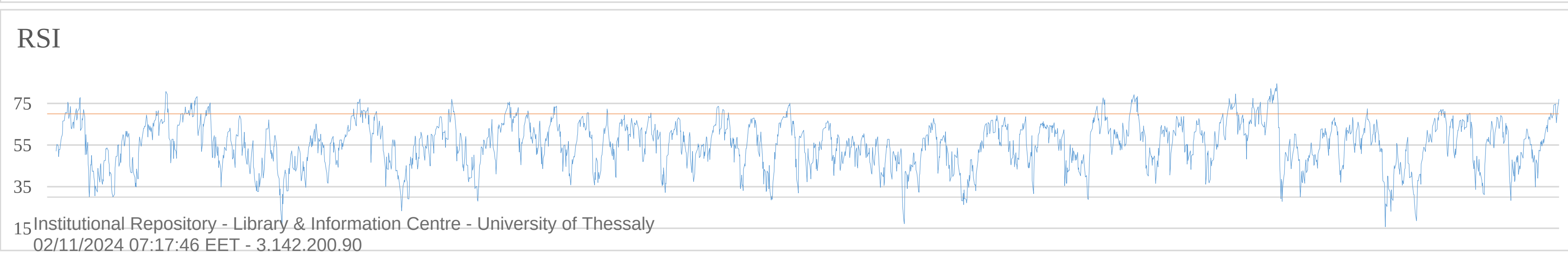
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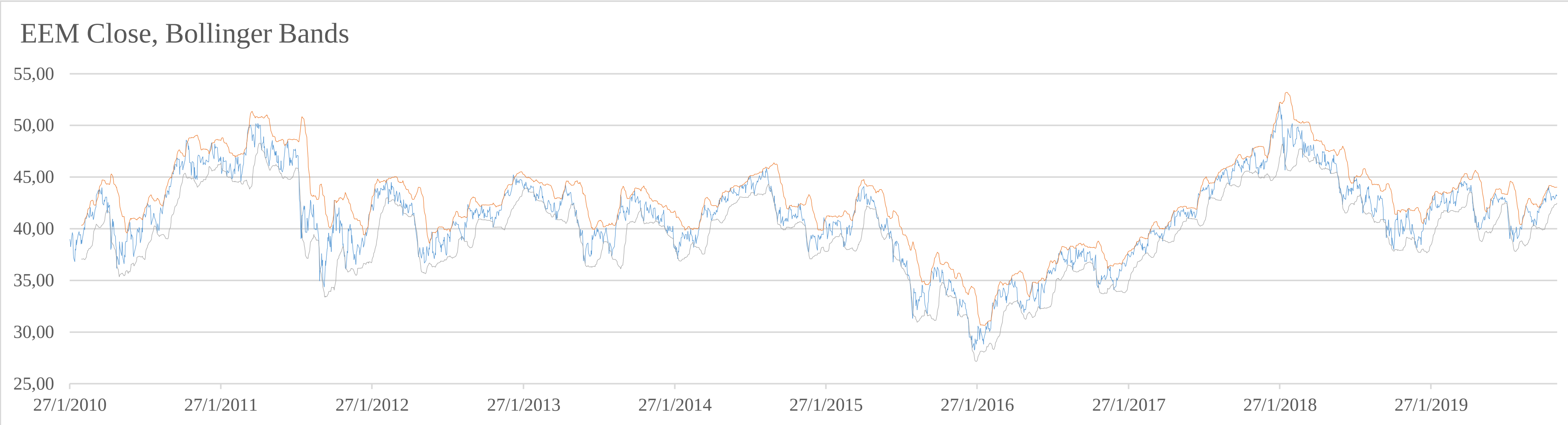
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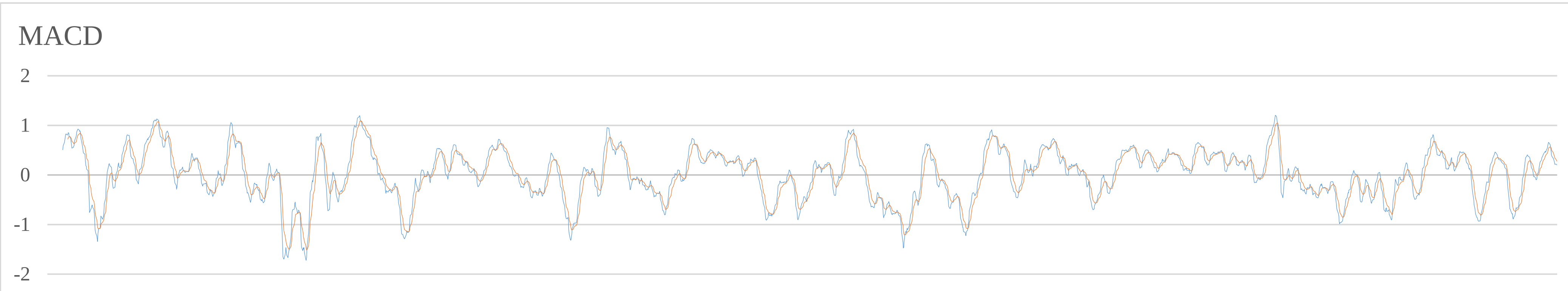
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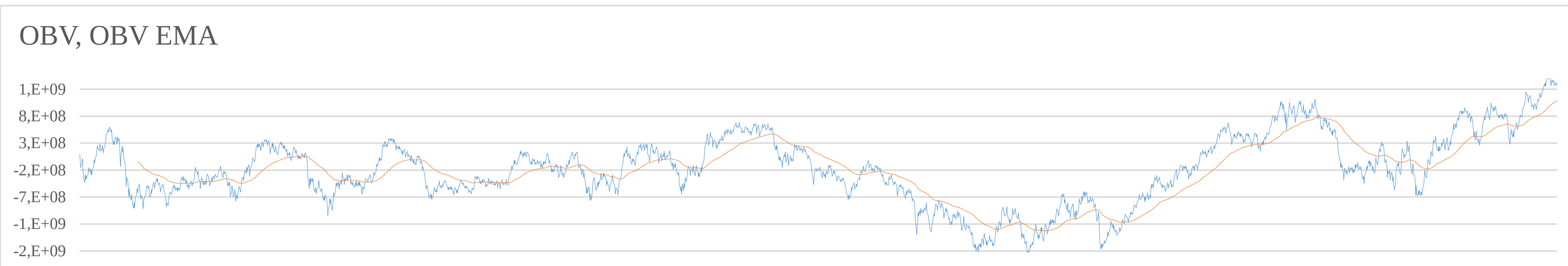
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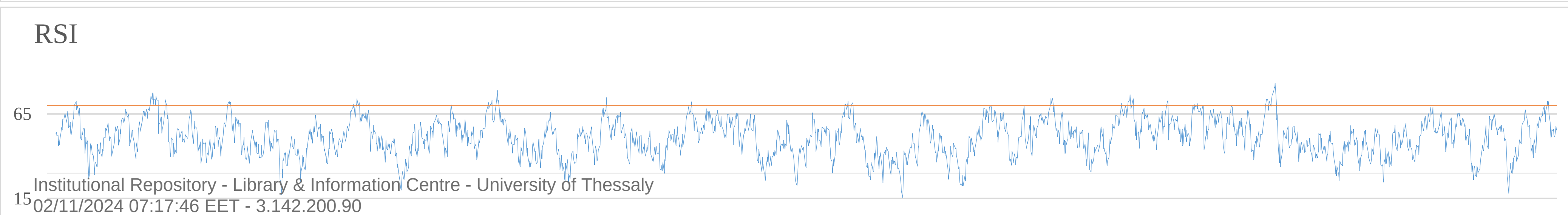
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