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Comparison of the prescribed model on predicted returns by the ESMA to a sophisticated time-series model

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Abstract

This paper investigates and compares the performance of the European Securities and Markets Authority (ESMA) methodology and a sophisticated time-series prediction model (also called: TSP model) in predicting 1-year future returns for European passive ETFs. The ESMA methodology for predicting future returns solely relies on past return data as an explanatory variable for future returns, which contradicts the weak form of the Efficient Market Hypothesis (EMH). The results show that the ESMA methodology is rigid and does not capture the dynamics of market fluctuation, leading to inaccurate and biased predictions for both European passive stock and bond ETFs. On the other hand, the TSP model, which uses important explanatory variables from the existing literature, provides more accurate and unbiased predictions for European passive stock ETFs, but does not provide significant accuracy or unbiasedness for European passive bond ETFs. The paper concludes with a recommendation for the ESMA to consider the TSP model as an alternative model to predict future return, given the importance of accurate performance scenario disclosure in the mandatory Key Information Documents (KIDs) for fund managers.

Key words

ESMA | KID | ECB | Performance scenarios | Forecasting | Time-series | OLS regression | EMH | European passive stock ETFs | European passive bond ETFs

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Chapter 1: Introduction

In the history of financial markets multiple regulations have been introduced in order to create more stable markets and to protect investors. Especially since the Global Financial Crisis in 2008, the number of regulations and required policies and the strictness of these regulations and policies have increased. In Europe the European Central Bank (ECB) and European Securities and Markets Authority (ESMA) are predominantly responsible for the regulations in financial markets. One of the most recent new regulations from the ESMA is the Commission Delegated Regulation (EU) 2017/653. This regulation document is supplemented by Commission Delegated Regulation (EU) 2021/2268. These regulation documents describe what fund managers need to disclose in the Key Information Documents (KIDs) by the first of January 2023. Elements such as risk indicators, performance scenarios and costs are covered in the KID. The KID aims to inform and warn investors before they buy an investment product. These products are also often called Packaged Retail and Insurance-based Investment Products (PRIIPs).

One of the elements in the KID is the Performance Scenario analysis in which a moderate scenario of the fund needs to be disclosed. This is the average return an investor can expect for a particular holding period of the fund. The methodology for calculating the moderate scenario is described in the ESMA guidelines. For this calculation a lookback period of at least 10 years of historical monthly returns needs to be used. Then based on a particular holding period the moderate scenario is calculated by using the median result within the 10-year historical lookback period. This is a very simplistic way of calculating an expected return. However, this way of calculating the expected return is prescribed by the ESMA and all fund managers in Europe are obligated to be compliant with this regulation.

This paper researches the current ESMA methodology for predicting returns with a holding period of 1 year. The 1 year holding period is selected because most funds have a recommended holding period of at least 1 year. The way of calculating an expected return according to the ESMA seems too simplistic. It is merely based on past returns, which contradicts the weak form of efficiency in Fama's (1970) Efficient Market Hypothesis. According to the weak form of efficiency, one should not be able to predict returns by using past return data. This is not in line with the ESMA guidelines for predicting future returns. Moreover, the literature shows that multiple factors can predict returns but no other factors than previous returns are incorporated in the ESMA prediction methodology. For instance, Fama and French (1992) show that factors such as size and book-to-market ratios are significant for predicting returns. Also, macro economic factors, such as yield rates and inflation, seem to have predictive power. The most important predictive factors are described in the literature chapter. These papers that show predictive power of other factors reject the semi-strong form of efficiency in the Efficient Market Hypothesis. According to the semi-strong form of efficiency, one should not be able to predict returns by using all publicly available information. The objective of this paper is to research whether ESMA's assumption about the predictive power of past returns is true and, thus, whether the weak form of efficiency is violated or not. Besides, this research tries to introduce a new methodology for predicting returns whereby the semi-strong form of efficiency is challenged.

Another argument pointing out the importance of this research is that the ESMA has introduced its regulation in order to protect investors. However, if the methodology for the calculations that aims to inform investors lacks in quality, it will not protect investors. Moreover, investors could act upon the expected returns in the KID. If the expected returns are incorrect, it harms the investors' decision-making process.

In this research a more sophisticated time-series model will be built in order to correctly predict 1-year future returns. This new methodology aims to improve the current ESMA methodology and, thus, to inform investors about the characteristics of the investment product in a correct way. Instead of only using past returns according to the ESMA guidelines, the new time-series model incorporates forward looking factors. The forward looking factors are based on existing literature. Thereafter, the LASSO BIC technique (Angrist & Frandsen, 2022) is applied in order to select the most important factors in the prediction model. The LASSO BIC method is a machine-learning technique that is used to select the most important factors by comparing multiple optional models whereby the model with the lowest BIC value is evaluated as the best predictive model. The ESMA forecasts and forecasts from the time-series model are evaluated in the out-of-sample dataset on unbiasedness and accuracy.

The regulation applies to European fund managers since the regulation comes from the ESMA. Hence, only European funds can be used. This also means that the target group of this paper is predominantly European fund managers and investors. The data in this research consists of passive Exchange Traded Funds (ETFs). Only passive ETFs are used because of data availability. European Stock ETFs and European Bond ETFs are separated in the analysis. The research question is as follows:

How does the ESMA methodology on predicting 1-year future returns for European passive ETFs deviate from a more sophisticated time-series prediction model?

1.1 Reading guide

After the introduction, the existing literature about the topic will be discussed in chapter 2. Firstly, the Efficient Market Hypothesis is explained and the relationship between the Efficient Market Hypothesis and this research is stressed. Thereafter, the differences between predictive factors for bonds and stocks are explained. Thirdly, the most important predictive factors from previous studies are elucidated and the link to this study is explained. Lastly, a short explanation is given about which variables are selected. In chapter 3, the methodology of the ESMA forecasts and the sophisticated time-series forecasts are discussed. Chapter 4 presents the results of this research, including a comparison between the forecasts of ESMA and the sophisticated time-series model. In chapter 5, the conclusion, discussion, and limitations of the study are stressed.

Chapter 2: Literature

The literature chapter consists of four parts. The first part focuses on the economic argument of this paper, the Efficient Market Hypothesis. The second part explains the differences between stock return prediction factors and bond return prediction factors. The third part focuses on the predicting factors that were important in previous prediction studies. Lastly, the fourth part explains why some predicting factors from the literature will or will not be incorporated in the sophisticated time-series model as a result of LASSO BIC.

2.1 Efficient Market Hypothesis

Eugene Fama published the Efficient Market Hypothesis (EMH) in the Journal of Finance in 1970 (Fama, 1970). The EMH is a central concept in finance and economics. The EMH theory states that all available and relevant information is immediately incorporated in asset prices. In the paper of Fama (1970) it is described as: "*In general terms, the ideal is a market in which prices provide accurate signals for resource allocation: that is, a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time 'fully reflect' all available information. A market in which prices always 'fully reflect' available information is called efficient*" (p. 383). Fama argues that it is impossible to consistently achieve above-average returns through individual security selection or market timing. According to Getmansky et al. (2004), price changes must be unforecastable in an informationally efficient market. This means that the most efficient market of all is one in which price changes follow a random walk. This idea of efficient markets corresponds to the EMH of Fama (1970). In line with the theory of Fama, Jensen (1978) states: "*The EMH is an extension of the zero profit competitive equilibrium condition from the certainty world of classical price theory to the dynamic behavior of prices in speculative markets under conditions of uncertainty*" (p. 3). In the EMH, Fama categorizes the market efficiency into three forms: the weak form, the semi-strong form, and the strong form (Fama, 1970).

The weak efficiency form states that prices are purely based on past returns (Fama, 1970). This means that past returns and financial data are fully reflected in current asset prices. If markets are efficient in the weak form, one cannot predict future returns with past returns. Technical analysis can thus not be used when markets are efficient in the weak form. The semi-strong efficiency form states that prices are not only reflected in the current asset prices, but also all publicly available information such as financial statements and factors are incorporated in the asset prices (Fama, 1970). This means that future returns cannot be predicted when using past returns and all publicly available information. The strong efficiency form states that all information, including insider information, is incorporated in the asset prices (Fama, 1970).

Since the publication of Fama's (1970) EMH theory, the EMH has been tested extensively using both theoretical and empirical methods. However, even after more than half a century of research, financial literature has not reached a consensus on the presence or absence of the validity of the EMH (Lekovic, 2018). The study of Jensen (1978) argues that there is no theory with more evidence for the validity than the EMH. However, Jensen also acknowledges that there are anomalies and inconsistencies in the EMH when more advanced econometric analyses are executed. Critics of the EMH argue that financial markets are not perfectly efficient, and that there are opportunities for abnormal returns. Grossman and Stiglitz (1980) argue that markets cannot be perfectly efficient, as there would be no incentive for professionals to uncover the information to be reflected in the market prices. Also Malkiel (2003) states that further apparent departures from efficiency will be documented with the increasing sophistication of databases and empirical techniques. Moreover, behavioral finance researchers have argued that psychological biases and market inefficiencies can lead to persistent deviations from the EMH. Researchers, such as De Long et al. (1990), Shleifer and Vishny (1995) and Thaler (1999), exhibit market anomalies which contradict the EMH (Yalcin, 2010).

As already mentioned, there is no consensus about the validity of the EMH. In this paper the weak and semi-strong form of efficiency are tested. The ESMA guidelines state that the expected returns need to be calculated by merely using past return data. This suggests that the ESMA is convinced that past returns can provide a good prediction of future returns. This is in conflict with the weak form of efficiency, as one should not be able to predict future returns by using past returns. This research tries to provide an alternative prediction methodology in which returns can be predicted more accurately. This is done by developing a sophisticated time-series model in which multiple forward looking factors are incorporated in order to make predictions. In this new methodology, the weak and semi-strong form of efficiency are challenged. The weak form is challenged since the autocorrelations and partial autocorrelations for past returns are calculated for multiple lags. This leads to the following hypothesis:

Hypothesis 1: *1-year future returns cannot be predicted by merely using past returns, which is in line with the weak form of efficiency in the EMH.*

The semi-strong form is challenged, because this research tries to make better predictions by using publicly available information such as liquidity measures, yield rates, etc. By using the LASSO BIC method the most explanatory factors are selected for the prediction model. This leads to the following hypothesis:

Hypothesis 2: *1-year future returns can be predicted by using publicly available information, which contradicts the semi-strong form of efficiency in the EMH.*

2.2 Prediction stock ETFs vs bond ETFs

In this paper stock ETFs and bond ETFs are analysed separately, as stock prices and bond prices have different walks and are affected differently by various variables. Hence, there is a high probability that the best fitting model for a specific in-sample estimation period for stock ETFs is different than for bond ETFs. The macro-economic variables such as inflation and the interest rates on the yield curve may be more explanatory for bonds than for stocks (Diebold & Piazzesi, 2005). The liquidity variable may be better explanatory for stock prices (Dong, Feng, & Sadka, 2019), while bond prices are also affected by other factors such as the bond rating (Hull, Predescu & White, 2004) which is not included in this research. This leads to the following hypothesis:

Hypothesis 3: The performance of the *1-year future returns prediction of stock ETFs is equal to the bond ETFs in the sophisticated time-series model.*

Also bond prices are less volatile than stock prices. The ESMA model is a very flat forecast as it takes the median of past returns to predict future returns. As bond prices are more flat in their returns it could be that the less dynamic ESMA model performs better in predicting the future returns, which leads to the fourth and last hypothesis:

Hypothesis 4: *The ESMA prediction model performs better on bond returns than the sophisticated time-series model.*

2.3 Important prediction factors

In this part several prediction factors are discussed that were reported in earlier studies for having explanatory power on future asset returns. These are the market premium and other four factors of Fama and French (2015), a lagged return, the ETF specific factor called liquidity and six macro-economic forward-looking variables. These macro-economic variables are leverage, inflation rate, 1-year to maturity yield spot rate, term spread, Covid-19 crisis dummy and Euro-dollar exchange rate.

2.3.1 The Market Premium

In 1952 Harry Markowitz invented the Portfolio Theory. The Modern Portfolio Theory (MPT) states that investors maximize their expected returns of their asset portfolio for a given level of risk. Their risk preference is determined by basic utility. Based on this theory William Sharpe (1964), Jack Treynor (1962), John Lintner (1965) and Jan Mossin (1966) developed the coherent framework called the CAPM in the early 1960s to explain how the risk of an investment should affect its expected return (Perold, 2004). As the CAPM is still one of the most famous financial models, it also has its implications. The CAPM only consists of the market premium as an explanatory variable of a return. It states that an increase of the return is only caused by an increase in the market premium risk factor. One of the assumptions is that all investors behave according to the portfolio theory and have mean-variance utility. However, many studies found other significant explanatory factors on returns.

2.3.2 The Fama and French five factor model

In 1992 Fama and French found that there are two more factors besides the market risk premium that significantly explain returns. These two factors are: Small Minus Big (SMB) and High Minus Low (HML). They found that on average in a portfolio smaller stocks are associated with higher returns and stocks with a high Book-to-Market (BtM) value also have higher returns (Fama & French, 1992).

The Small Minus Big factor captures the size effect as it goes long in small stocks and short in big stocks. The High minus Low factor goes long in high BtM stocks and short in low BtM stocks and thus captures the BtM effect.

However, in 2015 Fama and French found two additional significant explanatory factors: Conservative Minus Aggressive (CMA) and Robust Minus Weak (RMW). The CMA risk factor measures the investment effect. It goes long in stocks with conservative (low) investments and short in stocks with aggressive (high) investments. It implies that stocks with less investments, that are more conservative, have higher returns on average. The RMW risk factor measures the profitability effect (Fama & French, 2015). This factor goes long in stocks with the highest operating profitability and short in the lowest operating profitability. This implies that stocks with higher profitability have higher returns compared to stocks with lower profitability. Their results show that these additional four factors besides the market risk premium predict returns. Hence, these four additional factors with the market risk premium are included in the selection method of the sophisticated time-series model. This is described in chapter 2.4.

2.3.3 The Lagged Return

Lagged returns are often used in forecast models for asset returns. This is because there could be autocorrelation between return t and return t-1. By extracting the autocorrelations, the lagged return can be used as a predictor in forecast models (Stock & Watson, 2002). However, lagged returns should not be the only factor considered when predicting asset returns. Besides, autocorrelations between return t and return t-1 are often significant for daily data or more high frequency data. For the ETF predictions only monthly data is used, which indicates a lower chance of significant autocorrelations between return t and return t-1. This means that lagged return could have less predictive power in the model of this paper. Hence, it is important to test whether there is autocorrelation or partial autocorrelation in the lagged returns (Maasoumi & Racine, 2002). If there is significant autocorrelation between return t and return t-1, it should be incorporated in the prediction model. If there is no significant autocorrelation, the lagged return data should not be used.

A significant return lag that has predictable power violates the weak form of Fama (1970), in the sense that the expected return for each asset, based on this known previous month's return, is different from the expected return based only upon the current asset price (Rosenberg & Rudd, 1982). If there is autocorrelation in the lagged returns, one could adjust its investing strategy to make use of this inefficiency. For example, if there is positive autocorrelation, an investor could increase its bets when an ETF is performing well, and in months when the returns are poor decrease its positions (Getmansky, Lo & Makerov, 2004).

2.3.4 Liquidity

The relationship between liquidity and security returns has been a topic of interest for financial economists for many decades. Liquidity consists of two forms: market liquidity and funding liquidity. Market liquidity is the ability of the market to buy or sell an asset for a fair price, without reducing the initial price (Baker & Stein, 2004). Funding liquidity is the ability of a firm to meet its obligations as they come due (Apostolik & Donohue, 2015). For return prediction models the market liquidity is used as the liquidity measure.

Some older studies, such as Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Brennan et al. (1998), suggest that liquidity predicts asset returns. They found that measures of increased liquidity are associated with lower future returns (Baker & Stein, 2004). Also in the study of Amihud (2002) and Jones (2002) is shown that market-wide movements in liquidity forecast aggregate returns. According to Datar & Radcliffe (1998), liquidity plays a significant role in explaining the cross-sectional variation in asset returns. They also showed that this effect persists after controlling for determinants like firm-size, book-to-market ratio and the firm beta.

Also the relationship between liquidity risk and future returns has been investigated. Investors tend to invest in liquid assets, bonds and ETFs, since more liquid products are seen as less risky. The higher demand for liquid products leads to higher prices and thus lower expected yields. The study of Dong, X., Feng, S., & Sadka, R. (2019) investigated liquidity risk as a predictor of fund performance. They found that funds with a high liquidity-risk exposure earned significantly high future returns during 1984-2009. This result also suggests that high liquidity leads to lower expected returns. However, the result could also be a consequence of investment skills. Hence, it is important to combine liquidity-risk with other fund characteristics in order to predict fund performance (Dong et al., 2019).

In the paper of Amihud (2002), the relationship between illiquidity and asset returns is investigated. Amihud found a positive relationship between illiquidity and returns. The Amihud ratio has been used as a measure of illiquidity. The formula for the Amihud ratio is: $\frac{|\Delta r_t|}{Vol_t}$. A higher Amihud ratio means that the illiquidity is greater, because the asset is relatively harder to trade quickly due to a low trading volume. As literature shows that liquidity could be an important predictor of asset returns, the liquidity factor is incorporated in the selection method as described in chapter 2.4. In this research the Amihud ratio is also used as a measure of illiquidity. This means that the relationship between illiquidity and returns is inverted compared to the relationship between liquidity and returns.

2.3.5 European leverage

Leverage is the amount of debt in relation to the amount of assets. Companies with high leverage have higher total debt outstanding in relation to their assets. Leverage is a main driver of risk exposure and macro-economic fluctuations (Gomes & Schmid, 2016). Highly leveraged firms also have a higher probability of default. Expectations of those losses affect the pricing of corporate debt (Gomes & Schmid, 2016). If companies have higher leverage this increases their probability of default which increases credit risk by definition. Also, these companies may have more money to cover for expenses or investments. Hence, it accelerates companies to implement more possible expansions.

However, during times of crisis a deterioration of intermediary capital will disrupt lending and borrowing in a way that raises credit costs (Gertler & Karadi, 2010). This relates to the "leverage effect"; negative shocks on returns lead to deterioration of the firm value and increase the debt-to-equity ratio, i.e. financial leverage, making the equity riskier and more volatile (Banid & Renò, 2012). This increases credit risk and leads to a total decrease in leverage. Understanding the link between balance sheet conditions and the real economy has become a key priority and has explanatory power on forecasting equity returns. Leverage could be an indicator of economic activity and may be a good predictor for future returns (Kollmann & Zeugner, 2012). This paper aims to improve its forecasting by adding the European leverage level over time as a predicting variable. Moreover, the studies of Korteweg (2004), Dimitrov and Jain (2005) and Penman (2007) show a negative relationship between leverage and future asset returns (Muradoglu et al., 2008). Hence, the leverage factor needs to be included as a potential return predictor in the selection method of this paper. This is described in chapter 2.4.

2.3.6 European inflation rate

The inflation rate has a major impact on the European economy as it decreases consumers' and companies' purchasing power and leads to a decreasing economic growth. An economy with increasing inflation rates leads to real value decline of money which implies less purchasing power and a reduction in the real returns on investments (Eldomiaty, Saeed & Hammam, 2020). Most studies cite the work of Fama (1981) on the relation between inflation and asset prices. The research concludes that there is a negative relation between inflation and asset prices; an increase in inflation results in a decrease of an asset price connected to this inflation in a specific region.

A tool of the ECB is the adjustment of the interest rate, as this incentivises market participants, which results in higher expenses, less profitability and it also signals to investors that investing in bonds rewards higher return than investing in equities (Eldomiaty, Saeed & Hammam, 2020). Moreover, an increase in the interest rate motivates participants to save more money as it yields more return to save money on a deposit account or invest in bonds, while lower interest rates motivates participants to lend money and spend more, which increases consumption and economic activity. European inflation is a good indicator of the economic status of Europe for different types of assets (Marshall, 1992) and does well in explaining and hence predicting returns (Engsted & Tanggaard, 2002). Many studies have reported the pricing of inflation in asset returns (Nelson, 1976; Reddy, 2012), thus it could possibly be a significant predictor of future returns. Hence, the inflation factor is included in the selection method of this paper as described in chapter 2.4.

2.3.7 European 1-year to maturity yield spot rate

The yield curve has different maturities on the x-axis with different types of marginal investors. Institutional investors such as pension funds focus on long term maturities, thus have higher demand for longer maturity assets, referring to the preferred habitat theory (Greenwood, 2018). This demand effect impacts the yield of these longer maturities and makes it important to take into account the differences in yields of shorter maturity assets and longer term maturities (Greenwood, 2018). This paper focuses on a holding period of one year, as prescribed by the ESMA, which is a short-term period. Hence, the best fitting maturity of the yield curve is the 1-year maturity yield spot rate and it may have explanatory power on the ETF returns, as the yield curve affects asset prices (Altavilla, Brugnolini & Gükaynak, 2019). Therefore, the yield curve factor is incorporated in the selection method as described in chapter 2.4.

2.3.8 European Term Spread

There are many papers that have shown that the yield spread is a very good predictor of future economic activity (Leombroni, Vedolin & Whelan, 2021) and is derived from the yield curve. The curve shows the risk-free interest rates for different maturities. An upward sloping yield curve means that long-term risk-free interest rates are higher than short-term risk-free interest rates, which is considered to be a normal or positive yield curve. It typically indicates that the economy is growing and that interest rates are expected to rise in the future. When the curve is decreasing it can be a sign of a future recession (de Lint & Stolin, 2003). The slope of the curve is measured by the yield spread (Leombroni, Vedolin & Whelan, 2021). The yield curve is affected by interest rates. An increase in short-term interest rates results in a decline in stock prices and in an upward shift in the yield curve that becomes smaller at longer maturities (Rigobon & Sack, 2004). Using the Term Spread as a forecasting variable has proved to be a robust predictor of asset returns in developed markets (Hjalmarsson, 2010). Faria & Verona (2020) state the following: "*We show that the term spread is a good and robust out-of-sample predictor of stock market return.*" (p. 16). Hence, it can be concluded that term spread could be an important future return indicator. Hence, the term spread is included in the selection method of this paper as described in chapter 2.4. In this paper, the Term Spread is computed by subtracting the European 30-year maturity interest rate of the 1-year maturity interest rate.

2.3.9 Covid-19 crisis dummy

The World Health Organisation (WHO) declared the Covid-19 outbreak as a pandemic on the 11th of March 2020 which caused a shock in the global financial market. The returns on varying types of assets drastically decreased as a result of this crisis. The negative spike in returns can be captured by using a Covid-19 dummy. The period that is used as Covid-19 dummy period is 14 days prior to the declared pandemic by the WHO and 30 days after the declared pandemic. This is similar to the methodology of Chowdhury, Khan and Dhar (2022). Hence, as monthly data is analysed, the dummy period is for the months February and March in 2020. The Covid-19 crisis dummy could have explanatory power for predicting returns. Hence, the Covid-19 dummy is incorporated in the selection method as described in chapter 2.4.

2.3.10 Euro-dollar exchange rate

The charge for exchanging currency of one country for another currency is called the exchange rate. Exchange rate movements frequently focus on changes in credit market conditions, reflected by changes in interest rate differentials across countries, and changes in the monetary policies of central banks (Singh, Mehta & Varsha, 2011). Furthermore, it is important to note that this variable may be correlated to the leverage variable or one of the other macroeconomic variables (Gjerde & Saettem, 1999). Studies have shown evidence (Choi, Elyasiani and Kopecky, 1992; Zarei, Ariff & Bhatti, 2019; Wong, 2022) that prices of assets are affected by the exchange rate that reflect not only credit market conditions but also monetary policy changes. Changes in monetary policy have significant impact on the returns of the researched ETFs (Wong, 2022). Adding a variable that does well in explaining these monetary policy changes improves the model, however this is taken into account in this paper's selection method for the best fitting model. This is described in chapter 2.4.

2.4 Selected variables

This research uses the LASSO BIC model selection method to determine whether the forward-looking factor has enough explanatory power for the forecast of the 1-year return. The LASSO BIC method is performed on all described variables in the literature. Nevertheless, there is a high probability that some factors will not be incorporated in the prediction model of a particular year, because the LASSO BIC method prefers a parsimonious model. If a specific variable is not incorporated in the model, it can be concluded that this variable does not have enough explanatory power for that year according to the LASSO BIC method.

Chapter 3: Methodology and data

In this paper two different methodologies of calculating 1-year expected returns are compared. First, the methodology of calculating 1-year expected returns according to the ESMA guidelines is explained. Thereafter, the new methodology of calculating 1-year expected returns is explained. The new self-made methodology is a more sophisticated time-series methodology. It is important to note that the 1-year expected returns are separately calculated for stocks and bonds. The different methodologies for calculating 1-year expected returns will be tested on accuracy and unbiasedness.

3.1 ESMA methodology for calculating 1-year expected returns.

3.1.1 Data

According to the ESMA guidelines, the predicted annual returns merely use past returns as input for the calculations of future returns. This is in conflict with the weak form of the EMH (Fama, 1970). The dataset that is used for the ESMA calculations consists of 25 European stock ETFs and 25 European bond ETFs. Only past monthly returns are incorporated in the dataset for stock ETFs and bond ETFs. The monthly returns are retrieved from Blackrock (2023). The time horizon of monthly returns differs between stock and bond ETFs, because there were less bond ETFs available with a long lookback period. The European stock ETF dataset consists of 25 stock ETFs with for each ETF monthly returns from 31-01-2007 to 30-11-2022. One part of this dataset is used as input for the calculations of the predicted annual returns. The other part is used as out-of-sample data. The composition of incorporated monthly returns deviates for each calculation as the calculations are rolling through time. This will be explained in more detail in the next chapter. The forecasts are made for each stock ETF individually, but for the statistical tests and comparison with the sophisticated time-series model the average values of the 25 ETFs are used. An overview of the 25 European stock ETF data that is used in the ESMA calculations is shown in table 1.

Table 1. *Descriptive statistics European stock ETFs 31-01-2007 to 30-11-2022.*

Variable	Obs	Mean	Std. Dev.	Min	Max
Returns Stock ETFs	155	.007	.043	-.17	.178

The European bond ETF dataset consists of 25 bond ETFs with for each ETF monthly returns from 31-01-2010 to 30-11-2022. Also here one part of the data is used as input for the predicted annual returns and the other part is used as out-of-sample data. The composition of incorporated monthly returns deviates for each calculation as the calculations are rolling through time. This will be explained in more detail in the next chapter. Also for the bond ETFs the forecasts are made individually, but for the statistical tests and comparison with the sophisticated time-series model the average values of the 25 ETFs are used. An overview of the 25 European bond ETF data that is used in the ESMA calculations is shown in table 2.

Table 2. *Descriptive statistics European bond ETFs 31-01-2010 to 30-11-2022.*

Variable	Obs	Mean	Std. Dev.	Min	Max
Returns Bond ETFs	155	.001	.011	-.043	.036

3.1.2 Methodology of forecast

The ESMA model that is used to calculate expected returns is backward looking and, thus, merely focused on past return data. Dependent on the Recommended Holding Period (RHP) of the ETF, it requires a substantial amount of past return data. When the RHP is 5 years or shorter, then the last 10 years of monthly returns are required for the calculations. When the RHP is longer than 5 years, then the required input data is equal to the RHP + 5 years. In this research a historical time period of 10 years is used because of data availability. The dataset of European stock ETFs starts at 31-01-2007. This means that, by using a 10 year lookback period, the 1-year forecasts for 2018, 2019, 2020, 2021 and 2022 can be calculated. The European bond ETF dataset starts at 31-01-2010, which means that only the 1-year returns for 2021 and 2022 can be forecasted.

The ESMA guidelines are introduced in order to set up performance scenarios. Fund managers need to calculate a stress, unfavorable, moderate and favorable scenario. This paper only focuses on the moderate scenarios since this is used as an average return of the ETF performance. The calculation of the expected return is rolling. This means that within the 10 year historical monthly return series a separate series of annual returns is created on a rolling basis. The rolling return series is used to calculate the expected return. Based on the previous rolling annual returns within a time frame of 10 years, the median return is used as expected return in the ESMA guidelines. When a new month starts, the lookback period of 10 years also moves one month further. This implies that the first monthly return needs to be removed and that the most recent monthly return is added to the lookback period. Then the 1-year expected return needs to be forecasted again for the new month. This procedure iterates for each forecasted year. The next paragraph explains the ESMA methodology in more detail.

The out-of-sample period of the European stock ETFs is 31-01-2018 to 30-11-2022. The out-of-sample period of the European bond ETFs is shorter because of data availability. Hence, the out-of-sample period of European bond ETFs is 31-01-2021 to 31-11-2022. For the ESMA calculations of the 1-year expected returns an automated Excel model is built. For European stock ETFs the first input data corresponds to the monthly returns between 31-02-2007 to 31-01-2017. Within this time frame, a series of 1-year returns are calculated on a rolling basis. The median return of the series of 1-year returns in the time frame is the forecast for the annual return of 31-01-2018. Hereafter, a macro is created in Excel to update the calculations for the next month. This means that the first monthly return (31-02-2007) will be deleted and a new monthly return needs to be inserted (31-02-2017). By using the updated dataset, the expected return for 31-02-2018 can be calculated. This methodology has been repeated until 31-11-2022 such that the expected annual returns of between 31-01-2018 to 31-11-2022 can be calculated for each month. The same methodology is used for the bond ETFs.

By using the programmed Excel model the expected returns of the stock and bond ETFs are calculated. The results are expected annual returns. The forecast errors are calculated by subtracting the forecasted annual returns from the actual achieved annual return. This resulted in a series of monthly forecast errors from 31-01-2018 to 31-11-2022 for the stock ETFs and from 31-01-2021 to 31-11-2022 for bond ETFs. The tests for unbiasedness and accuracy are performed on the forecast errors.

3.2 Sophisticated time-series methodology for calculating 1-year expected returns

3.2.1 Data

The sophisticated time-series methodology for calculating 1-year expected returns uses more explanatory variables compared to the ESMA methodology. In this new forecast methodology all variables from the literature chapter are incorporated. For the European inflation rates, European yield rates, European spread rates and euro-dollar exchange rates the deltas are used as input variables because the deltas have more explanatory power in the model. The Amihud ratio has been log-transformed in order to make it less skewed and more interpretable. The data is on a monthly basis and the dataset starts at 31-01-2010 for the stock and bond ETFs. In this way the dataset of stock and bond ETFs is similar. However, the forecasts for the stock ETFs are still made for 2018-2022 and for bond ETFs for 2021-2022 because the goal is to compare the results to the ESMA forecasts. This means, thus, that stock ETFs use less data points for the calculation of 2018, 2019 and 2020. The 5 Fama French factors (market premium, SMB, HML, RMW and CMA) are retrieved from French's Data Library (2023). The returns, lagged returns and Amihud ratios are retrieved from the data in iShares.com documents. The leverage factor is retrieved from morningstar.com. Covid is a self-created dummy, but it is based on the methodology of Chowdhury, Khan and Dhar (2022). The European inflation rates, 1-year to maturity yield spot rates, yield spread rates (30 year yield minus 1 year yield) and euro-dollar exchange rates are retrieved from the Statistical Data Warehouse of the European Central Bank. An overview of the European stock and bond ETF data that is used in the sophisticated time-series methodology is shown in table 3.

Table 3. *Descriptive statistics European stock ETFs and bond ETFs data and factors 31-01-2010 to 30-11-2022.*

Variable	Obs	Mean	Std. Dev.	Min	Max
Returns Stock ETFs	155	.007	.043	-.17	.178
Returns Bond ETFs	155	.001	.011	-.043	.036
LaggedReturn	155	.001	.011	-.043	.036
logAmihud	155	-5.086	.565	-6.443	-3.722
MktRF	155	.525	5.189	-15.44	16.62
SMB	155	.139	1.684	-5.06	4.72
HML	155	-.175	2.912	-11.3	12.09
RMW	155	.367	1.659	-5.4	3.52
CMA	155	-.12	1.484	-4.39	5.22
Leverage	155	.004	.017	-.149	.083
Covid	155	.019	.138	0	1
DeltaEUinflation	153	-.02	.632	-4	2
DeltaEUYieldrates	155	-.062	.957	-5.415	3.22
DeltaEUYieldSpread	155	-.016	.184	-1.58	.368
Deltaeurodollar	155	-.002	.025	-.076	.076

3.2.2 Methodology of forecast

The sophisticated time-series model methodology consists of many factors to predict the European ETF returns. This model is predicted by the ordinary least squared (OLS) linear regression method on past return data, called the estimation period. The holding periods are equal to those used for the prescribed ESMA model. The new methodology of calculating 1-year expected returns consists of a few steps. These steps are explained in the model selection method.

Model selection method

First of all, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are plotted and analysed. These plots show whether there are autocorrelations in lagged returns that could be incorporated in the model to improve the forecast. In this research only monthly data is used. Hence, there is a high probability that there are no autocorrelation patterns between month t and month t-1, t-2, t-3, etc. This has also been explained in the literature chapter (Stock & Watson, 2002). The outcomes of the ACF and PACF plots give a partial answer to hypothesis 1. This will further be discussed in the results chapter. The ACF and PACF of the stock ETFs and bond ETFs are visualized in figure 1 and 2, respectively.

Figure 1. *ACF and PACF of stock ETFs*

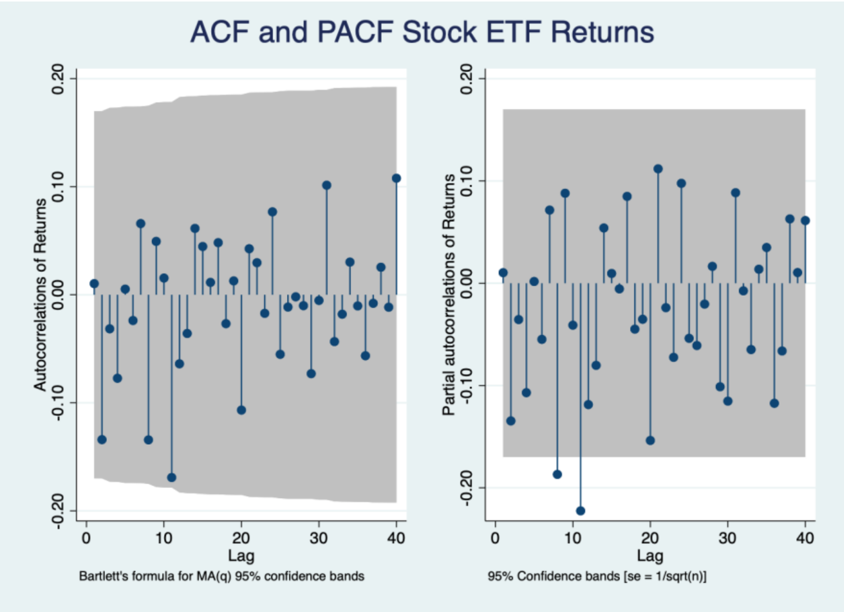


Figure 2. *ACF and PACF of bond ETFs*

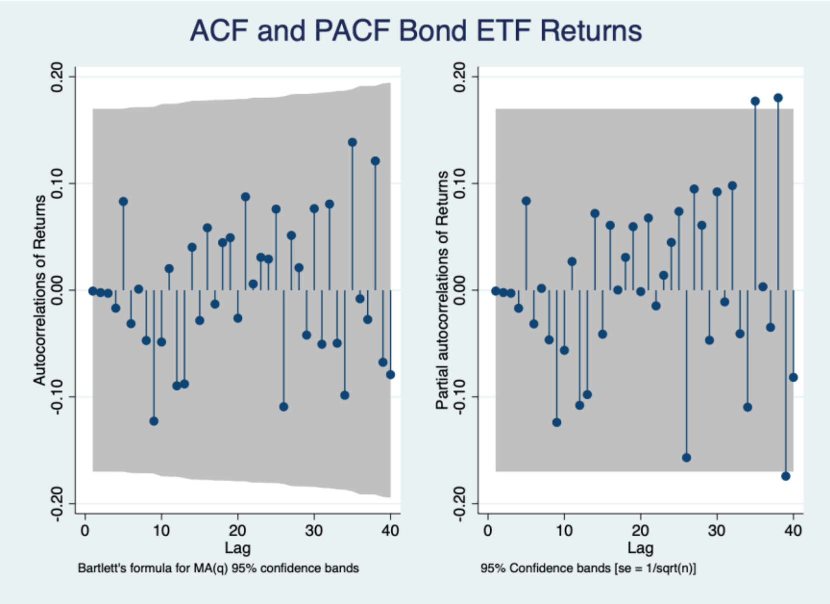


Figure 1 and 2 show that there is no significant (partial) autocorrelation in the lagged returns of the stock and bond ETFs. Hence, the lagged returns will not be incorporated in the sophisticated time-series model.

Now the 1-year forecast model consists of all explanatory variables as described in the literature chapter, except for the lagged returns. However, not all variables can be incorporated in the model since a parsimonious model is preferred. To determine which independent variables are best explanatory and should be added to the model for the stock and bond ETFs, the LASSO technique (Angrist & Frandsen, 2022) is applied. The LASSO technique should be repeated for each year one wants to forecast, because the explanatory variables may change over time. This technique has recently been developed to automatically select OLS control variables. It is a machine learning based selection method that shrinks the size of the coefficients of the independent variables that have less predictive power. The LASSO technique consists of several options to implement, where CV uses a new randomized sample of the data every time it is runned and BIC uses the selected estimation period without randomly choosing samples from it (Angrist & Frandsen, 2022). In this way the LASSO BIC gives the same result when calculating the LASSO BIC with the same data and is easier to implement. Bayesian Information Criteria (BIC) is an important metric used for model evaluation and selection. By comparing the BIC outcomes of the optional models the model with the lowest BIC can be selected as the best fitting model.

The ESMA model uses a holding period of one year, which is also used for this model. Moreover, to predict the stock ETF returns of 31/01/2018, data is used from 31/01/2010 to 31/01/2017 and for

28/02/2018 the same estimation period is used. This means the estimation period is not rolling, which could make the forecast even better but more complicated. For the forecast of the next year (31/01/2019), an estimation period from 31/01/2010 to 31/01/2018 is used, etc. This means that the dataset that is used for the forecast expands over time which should make the forecasts better. Table 4 shows the estimation periods for the stock ETFs. For the bond ETFs hold the same, but then only the estimation period for the forecast of 2021 and 2022 are used.

Table 4. *Estimation periods stock and bond ETFs*

	Forecast 2018	Forecast 2019	Forecast 2020	Forecast 2021	Forecast 2022
From	31/01/2010	31/01/2010	31/01/2010	31/01/2010	31/01/2010
To	31/01/2017	31/01/2018	31/01/2019	31/01/2020	31/01/2021
Selection method	LASSO BIC	LASSO BIC	LASSO BIC	LASSO BIC	LASSO BIC

Every ETF has different returns as well as different characteristics. This holds especially between stock ETFs and bond ETFs in general, but also between stock ETFs themselves and between bond ETFs themselves. Furthermore, for each ETF, as a result of the different estimation period for each year that is forecasted, some variables may become more explanatory or less and hence results in a change in the best fitting model. Thus, the LASSO BIC technique is executed separately for every newly forecasted year.The results of the LASSO BIC technique for the stock and bond ETFs are shown in table 5 and 6, respectively.

Table 5. *LASSO BIC results stock ETFs*

Variables	Forecast 2018	Forecast 2019	Forecast 2020	Forecast 2021	Forecast2022
MktRF	x	x	x	x	x
SMB	x				
HML	x	x	x	x	x
RMW	x	x	x		
CMA	x				x
Leverage	x	x	x	x	x
DeltaEUinflation	x	x	x	x	x
DeltaEUYieldrates	x				x
Deltaeurodollar	x	x	x	x	x
DeltaEUYieldSpread					x
Covid					x
_cons	x	x	x	x	x

Legend:
b - base level
e - empty cell
o - omitted
x - estimated

Table 6. *LASSO BIC results bond ETFs*

Variables	Forecast 2018	Forecast 2019
DeltaEUYieldSpread	x	x
_cons	x	x

Legend:
b - base level
e - empty cell
o - omitted
x - estimated

As is shown in figure 3, the LASSO BIC results change over time for the stock ETFs. This means that the variables incorporated in the OLS regression change over time. The LASSO BIC results of the bond ETFs do not change over time, as is shown in figure 4. This means that the same OLS regression is used. However, the estimation period of the OLS regression is larger for the forecast of 2022 compared to 2021, as is shown in table 5. The OLS regression for the bond and stock ETFs are shown below:

Stock ETFs

Regression I (2018): $R_t = \alpha + \beta_1 MktRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 Lev_t + \beta_7 \Delta Inf_t + \beta_8 \Delta Yield_t + \beta_9 \Delta EURDOL_t + \varepsilon_t$

Regression II (2019): $R_t = \alpha + \beta_1 MktRF_t + \beta_2 HML_t + \beta_3 RMW_t + \beta_4 CMA_t + \beta_5 Lev_t + \beta_6 \Delta Inf_t + \beta_7 \Delta EURDOL_t + \varepsilon_t$

Regression III (2020): $R_t = \alpha + \beta_1 MktRF_t + \beta_2 HML_t + \beta_3 RMW_t + \beta_4 Lev_t + \beta_5 \Delta Inf_t + \varepsilon_t$

Regression IV (2021): $R_t = \alpha + \beta_1 MktRF_t + \beta_2 HML_t + \beta_3 Lev_t + \beta_4 \Delta Inf_t + \beta_5 \Delta EURDOL_t + \beta_6 Covid_t + \varepsilon_t$

Regression V (2022): $R_t = \alpha + \beta_1 MktRF_t + \beta_2 HML_t + \beta_3 Lev_t + \beta_4 \Delta Inf_t + \beta_5 \Delta Yield_t + \beta_6 \Delta EURDOL_t + \beta_7 Covid_t + \varepsilon_t$

Bond ETFs

Regression VI (2021): $R_t = \alpha + \beta_1 \Delta Yieldspread_t + \varepsilon_t$

Regression VII (2022): $R_t = \alpha + \beta_1 \Delta Yieldspread_t + \varepsilon_t$

R_t is the actual return at time *t*

$MktRF_t$ is the market premium at time *t*

SMB_t is the size factor at time *t*

HML_t is the book-to-market factor at time *t*

RMW_t is the profitability factor at time *t*

CMA_t is the investments factor at time *t*

Lev_t is the European Leveraged Loan index at time *t*

ΔInf_t is the delta European inflation at time *t*

$\Delta Yield_t$ is the delta European 1-year to maturity yield spot rate at time *t*

$\Delta EURDOL_t$ is the delta EUR/USD currency rate at time *t*

$\Delta Yieldspread$ is the delta European YieldSpread (30-year maturity – 1-year maturity) at time *t*

$Covid_t$ is the Covid-19 dummy at time *t*

ε_t is the error term

After the model selection procedure, the model is estimated by using the OLS regressions from above. The OLS regression assumes that the residuals of the regression are normally distributed. However, normality can be assumed in the OLS regression of this paper since > 30 observations are used. Normality can be assumed due to the Central Limit Theorem (Cessie et al., 2020). The coefficient of the relevant independent variables are estimated and used for the prediction. For the forecasts of the stock ETF returns from the years 2018 to 2022, five OLS regressions are runned and used for the prediction of the returns. For the forecasts of the bond ETF returns from years 2021 to 2022, two OLS regressions are runned and used for the prediction of the returns. The sophisticated time-series OLS regressions result in a new model. From now on, this model is called the TSP model.

3.3 Comparison of model predictions

The ESMA model and TSP model both generate forecasts of annual returns. By subtracting the forecasts from the actual achieved returns the forecast errors for both models are calculated. The forecasts of both models can be compared to each other in a graph and by using some general statistics. To evaluate the forecasts on significance, the predictions of the ESMA model and the TSP model are tested on unbiasedness and accuracy.

Unbiasedness test

The t-test on the forecast error is used to evaluate the unbiasedness of the prediction. The H0 of this test is that the forecast is unbiased, whereas the alternative hypothesis (H1) states that the forecast is biased. The forecast error is equal to the true value minus the forecasted value. To check for unbiasedness, the t-test evaluates whether the average forecast error differs significantly from zero. A 95% confidence level is used to evaluate whether the forecast error is significantly different from zero or not. The formula that is used for the unbiasedness test is as follows: $\frac{\bar{e}}{\sqrt{\frac{\sigma_e^2}{p}}}$

, where $\bar{e}$ is the average forecast error and σ_e^2 is the variance of the forecast error and p is the number of observations in the out-of-sample.

Accuracy

The Mean Squared Prediction Error (MSPE) and Mean Absolute Prediction Error (MAPE) can be used to evaluate the accuracy of the forecasts. In this paper the MSPE is used because the forecast errors are expressed in percentages and thus small in absolute value. The MSPE is more flexible for small numbers than the MAPE. In the MSPE the prediction errors need to be squared. The squared prediction errors will be accumulated for all out-of-sample results and divided by the amount of observations in the out-of-sample. This leads to the accuracy measure of the forecasts. The closer the MSPE value to zero, the more accurate the forecast. The formula is the following: $MSPE = \frac{1}{p}\sum_{t=T_1}^{T-1}(y_{t+1} - F_{t+1})^2$, where p is the number of observations, T the end of the forecast window, y_{t+1} the actual value and F_{t+1} the forecasted value.

Chapter 4: Results

The results of this research consists of a comparison between the forecasts of the ESMA methodology and the TSP methodology. The differences between the predictions and actual achieved returns can be visualized in a graph. Also, the forecast errors are calculated to test the deviations from the actual achieved returns statistically. In total four predictions are executed: two ESMA model predictions (one for stock ETFs and one for bond ETFs) and two predictions of the TSP model (also one for stock ETFs and one for bond ETFs). This chapter consists of three parts: i) the comparison of the ESMA model to the TSP model for stock ETFs , ii) the comparison of the ESMA model to the TSP model for bond ETFs and iii) the comparison of the predictions between these two categories. These predictions are compared with a test on unbiasedness and accuracy. By using the average returns of both European stock ETFs and European bond ETFs as dependent variables, one can draw overall conclusions.

4.1: Comparison of the stock ETFs predictions

For the stock ETFs predictions are performed for the years 2018, 2019, 2020, 2021 and 2022. Every prediction is based on a different estimation period for both the ESMA model and the TSP model. For the TSP model procedure this results in different (some may be equal) regression models for each prediction. However, all are based on the same procedure and on the same input of optional independent variables and selection based on the LASSO BIC method, as described in the methodology and data chapter. Hence, OLS regressions I, II, III, IV and V from chapter 3.2.2 are performed to respectively forecast the stock ETFs' returns of 2018, 2019, 2020, 2021 and 2022. The ESMA methodology is applied to calculate the forecasted bond returns according to the current EU guidelines. The regression output for the stock ETFs is shown in table 7 below:

Table 7. *OLS regression output stock ETFs 2018, 2019, 2020, 2021 and 2022*

Variables	Forecast 2018	Forecast 2019	Forecast 2020	Forecast 2021	Forecast 2022
MktRF	0.00943***	0.00953***	0.00972***	0.00980***	0.00997***
	(0.00028)	(0.00022)	(0.00020)	(0.00019)	(0.00018)
SMB	-0.00004				
	(0.00052)				
HML	0.00162***	0.00155***	0.00115**	0.00126***	0.00150***
	(0.00061)	(0.00056)	(0.00049)	(0.00028)	(0.00025)
RMW	-0.00029	-0.00018	-0.00016		
	(0.00079)	(0.00070)	(0.00068)		
CMA	-0.00118	-0.00116*			
	(0.00072)	(0.00068)			
Leverage	0.13121	0.11848	0.12298	0.11439	0.01348
	(0.09321)	(0.07997)	(0.07849)	(0.07611)	(0.04423)
DeltaEUinflation	0.00151	0.00153	0.00135	0.00134	0.00125
	(0.00107)	(0.00104)	(0.00104)	(0.00101)	(0.00083)
DeltaEUYieldrates	0.00055				0.00064
	(0.00062)				(0.00063)
Deltaeurodollar	-0.94976***	-0.95962***		-0.97918***	-0.99783***
	(0.04460)	(0.03466)		(0.03241)	(0.03161)
Covid				-0.00892	-0.00350
				(0.00604)	(0.00436)
Constant	0.00001	0.00003	-0.00015	0.00003	0.00050
	(0.00086)	(0.00075)	(0.00070)	(0.00063)	(0.00062)
Observations	83	95	107	119	131
R-squared	0.97678	0.97476	0.97423	0.97426	0.97910

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Statistics	Actual return	TSP predicted return	ESMA predicted return	TSP prediction error	ESMA prediction error
Observations	59	59	59	59	59
Mean	6.40%	6.31%	10.19%	0.37%	-3.82%
Std. Dev.	0.16	0.16	0.01	0.11	0.17
Min	-16.85%	-18.45%	8.10%	-46.64%	-27.66%
Max	48.72%	46.06%	12.34%	34.62%	40.52%

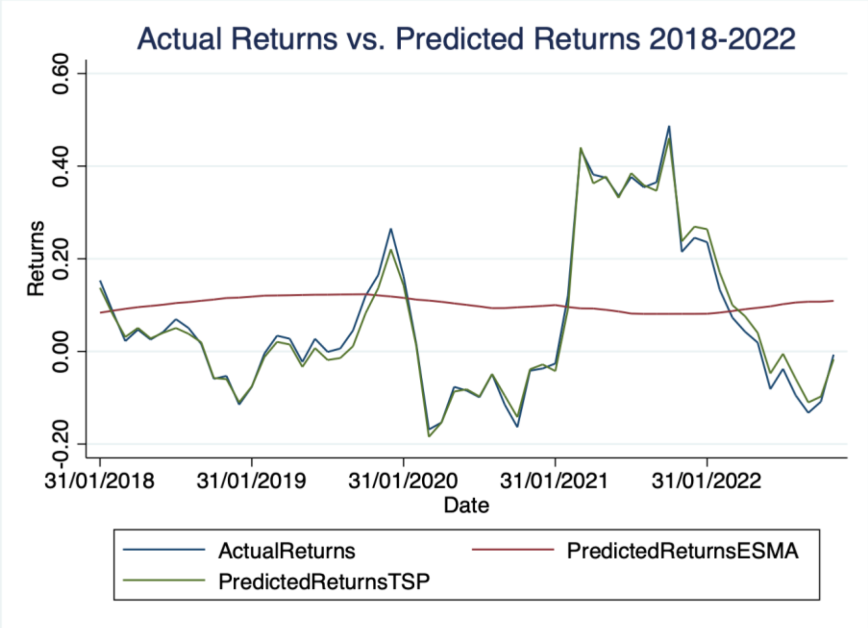
The observations of each regression make a jump of twelve, which is in line with the methodology as for each forecast the estimation window is rolled one year extra. As expected, each forecast has different selected independent variables. Overall, the variables MtRF, HML and Deltaeurodollar show significant results for each forecast; most of them being significant on a 99% confidence level. Furthermore, Leverage and DeltaEUinflation are included in every regression, hence these variables are explanatory enough according to the LASSO BIC method that penalises for the addition of extra variables. For the forecast of the year 2022 the variable Covid is included, meaning that the returns at the beginning of the Covid-19 crisis measured for the months February and March in 2020 make significant jumps and should be included in the regression.

The R-squared of the five regression models are high, meaning that the variation of the dependent variable is well explained by the independent variables. However, as an important note, the regressions perform well in explaining the in-sample variation. The prediction is performed out-of-sample for which the forecast is based on the estimated coefficients from the in-sample period. The descriptive statistics of both the ESMA model and the TSP model are shown below in table 8.

Table 8. *Descriptive statistics of the predictions of both models for stock ETFs*

Overall this table shows that the TSP model performs better than the ESMA model. The TSP model has an average return that is closer, a standard deviation that is equal in two decimals, minimum and maximum value that are closer to the actual values compared to the ESMA model. Furthermore, the TSP model has a relatively small average prediction error compared to the ESMA model. These observations are also supported by figure 3:

Figure 3. *Predictions of stock ETFs of both models for the years 2018-2022*



The methodology of the ESMA uses an estimation period of 10-years and computes the prediction solely based on the median of these past returns. As a result, past returns are made more flat for the predictions, which is also illustrated in the graph. The forecast does not take into account much of the actual values' dynamics. In contrast, the TSP model performs significantly better in predicting the average stock ETFs returns. It walks closely to the actual average returns of the stock ETFs and does catch the dynamics of the actual values. The forecasts are compared based on the accuracy measure and on the unbiasedness test, shown in table 9 below:

Table 9. *Results of stock ETFs forecasts comparison measurements*

Tests	TSP predicted return	ESMA predicted return
Unbiasedness	1.94**	-13.24
Accuracy	0.02	-0.05

*** p<0.01, ** p<0.05, * p<0.1

First of all, the results of the unbiasedness test are extremely different. The TSP model prediction is not significant on a 5% confidence level (<1.96), hence the H0 can be accepted that the forecast is unbiased. For the ESMA model prediction the test-statistic is highly significant (>1.96) H0 is rejected, thus the alternative hypothesis is accepted stating that the forecast is biased. The accuracy measurement also confirms that the TSP model prediction is more accurate, as the result is closer to zero.

4.1.1: Conclusions hypotheses

It is concluded that the average returns of the stock ETFs are not semi-strong efficient as they are well predicted by the selected variables, which is visible in both table 6 and in figure 3 and supported by the results of the unbiasedness test and the accuracy measurement shown in table 7. Hence, this evidence supports hypothesis 2 of this paper that rejects the semi-strong form of efficiency, stated in chapter 2.1. This also proves that the ESMA model is not sufficient as the monthly returns are well predicted by these variables without adding lagged returns, thus hypothesis 1 is accepted. This is also grounded by the ACF and PACF plots in the methodology (figure 1**)** that show no significant autocorrelation in the lagged returns meaning adding lagged returns to the model has no explanatory power over future returns. On top of that, the unbiasedness test and the accuracy measurement results also support this conclusion, showing that the ESMA model is biased and less accurate. Hypotheses 3 and 4 are discussed in *conclusions hypothesis bonds.*

4.2: Comparison of the bond ETFs predictions

The ESMA methodology is applied to calculate the forecasted bond returns according to the current EU guidelines. The TSP model executed the forecasts according to the methodology of chapter 3.2. Hence, OLS regressions IV and VII from chapter 3.2.2 are performed to forecast the bond returns of 2021 and 2022. The regression output for the bond ETFs is shown in table 10:

Table 10. *OLS regression output bond ETFs 2021 & 2022.*

VARIABLES	Forecast 2021	Forecast 2022
DeltaEUYieldSpread	-0.05318***	-0.04919***
	(0.00527)	(0.00479)
Constant	0.00265***	0.00250***
	(0.00058)	(0.00057)
Observations	121	133
R-squared	0.46077	0.44629

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As is shown in table 10, only the delta European Yield Spread is selected by LASSO BIC as explanatory variable of bond ETF returns in the in-sample. This variable is significant at a 99% confidence interval. Because only one variable is evaluated as explanatory for bond ETF returns, the R-squared of this model is much lower than the R-squared of the stock ETF returns. From this, it can be concluded that the in-sample TSP model and methodology performs worse for bond ETFs compared to stock ETFs. The descriptive statistics of both the ESMA model and the TSP model for bond ETFs are shown below in table 11:

Table 11. *Descriptive statistics of the predictions of both models for bond ETFs*

Statistics	**Actual return**	**TSP predicted return**	**ESMA predicted return**	**TSP prediction error**	**ESMA prediction error**
Observations	23	23	23	23	23
Mean	-4.02%	1.65%	2.71%	-4.35%	4.87%
Std. Dev.	0.05	0.03	0.00	0.07	0.21
Min	-13.73%	-1.20%	2.12%	-28.02%	-25.80%
Max	2.45%	14.29%	2.93%	2.53%	40.34%

The descriptive variables show that the average predicted return of the TSP model (1.65%) is a bit closer to the average actual return (-4.02%) than the predicted return of the ESMA model (2.71%). However, it is still not close to the actual return. Moreover, the maximum value of the TSP model is very high (14.29%). This indicates that the TSP model predicts an annual return of 14.29% while the maximum actual return is only 2.45%. This means that the TSP model is not very accurate for bond ETFs. On the other hand, the prediction errors show that the TSP model has a slightly closer value to zero which indicates a better performing forecast. To obtain a better understanding of the development of the actual, TSP predicted and ESMA predicted bond returns, the returns are also shown in figure 4.

Figure 4. *Predictions of bond ETFs of both models for the years 2021-2022*

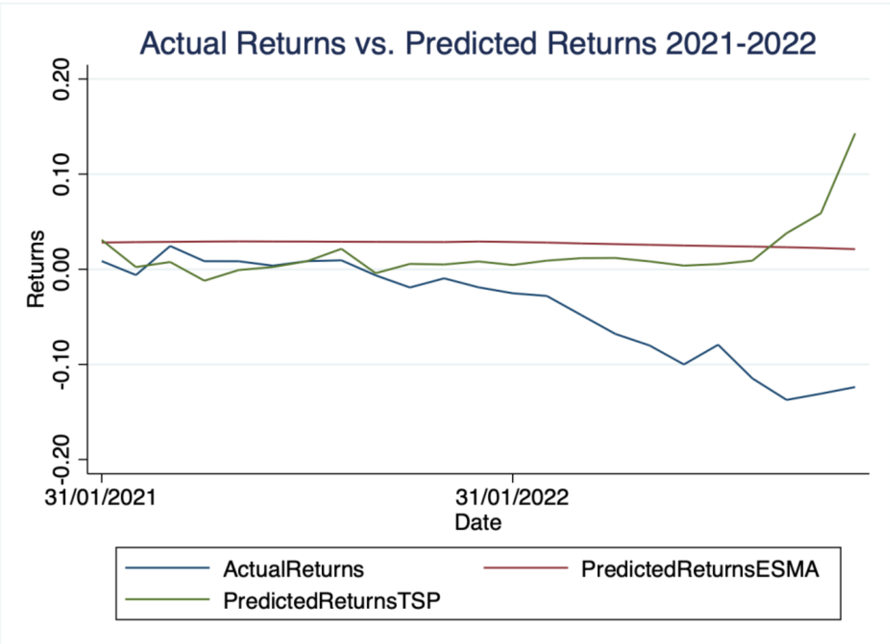


Figure 4 illustrates the development of the bond ETF returns. The ESMA predicted bond ETF return line is flat, indicating not a lot of deviation in the predictions. The TSP predicted bond ETF line shows that the bond ETF returns are well predicted for 2021, but in 2022 the deviation from the actual bond ETF returns becomes very large. This means that the TSP model does not predict the bond ETF returns as good as the stock ETF returns.

The ESMA predicted returns and TSP predicted returns are also tested on significance for unbiasedness and accuracy. As described in the methodology chapter, the forecast errors are used for these tests. The results are shown in table 12.

Table 12. *Unbiasedness and accuracy test bond ETFs*

Tests	TSP predicted return	ESMA predicted return
Unbiasedness	-13.94	13.60
Accuracy	-0.08	0.14

*** p<0.01, ** p<0.05, * p<0.1

The results of the unbiasedness and accuracy test show that both models are biased and not very accurate. For the unbiasedness test, H0 needs to be rejected as the t-statistics are larger than 1.96 or lower than -1.96. The TSP model is a bit more biased than the ESMA model. However, the TSP model is more accurate than the ESMA model. This is presumably since the TSP model predicts the returns quite accurately in 2021 (see figure 4). On the other hand, it is still not very accurate as the MSPE of -0.08 differs quite a lot from zero.

4.2.1: Conclusions hypotheses

The first hypothesis of this paper is accepted for bond ETFs. The ACF and PACF from the methodology chapter (figure 2) already showed that there are no (partial) autocorrelations between the returns t and t-1, t-2, t-3, etc. This indicates that future returns cannot be predicted by merely using past returns. Also, the graph (figure 4) shows that the ESMA predicted bond ETF returns, that merely uses past return data, deviate a lot from the actual bond ETF returns. This indicates that the ESMA prediction model does not perform well. This is also supported by the unbiasedness test and the accuracy measurement, indicating that the ESMA prediction is biased and not accurate. Thus, 1-year future bond ETF returns cannot be predicted by merely using past returns, which is in line with the weak form of efficiency in the EMH.

The second hypothesis is rejected for bond ETFs. The TSP model, including publicly available information as mentioned in the second hypothesis, shows that the expected bond ETF returns are not predicted well. This is visualised in figure 4. Also, the unbiasedness and accuracy test of the TSP model show that the bond ETF returns are biased and not accurate. The t-statistic of unbiased is equal to -13.94, which is far beyond -1.96. The accuracy measure is equal to -0.08, which is quite different from zero as the unit of this measure is in percentages.

The third hypothesis in this paper is rejected. The TSP model performs very well for stock ETFs. This is shown in the graph (figure 3), descriptive statistics (table 8) and in the statistical tests of unbiasedness and accuracy (table 9). These statistics show that the TSP model provides an accurate and unbiased forecast for the stock ETFs. However, the bond TSP model performs worse for the bond ETFs. This is also shown in the graph (figure 4) and the descriptive statistics (table 11). Moreover, from the statistical tests of unbiasedness and accuracy is concluded that the TSP model for bond ETFs is biased and not accurate. Hence, the performance of the TSP model on stock ETFs is not equal to the performance on bond ETFs. As a result, it is concluded that the incorporated factors in the selection method are more explanatory for stock ETFs than for bond ETFs. This was also expected from the different results of the R-squared in the in-sample between stock ETFs and bond ETFs. The TSP model only incorporates the delta term spread as an explanatory variable for the bond ETFs, while more explanatory variables are included in the stock ETF model.

The fourth hypothesis in this paper is rejected. The ESMA model on bonds performs worse for the forecast of the year 2021, however it does better at the end of the year 2022 as the TSP model forecast makes an upward jump while the actual returns during this time decrease. This is shown in figure 4. The results in table 11 show that the average return prediction of both models deviate largely from the actual returns. Both are positive while the average actual returns are negative. However, the average returns of the TSP model prediction are closer to the actual returns compared to the ESMA model. Moreover, the t-statistic of the unbiasedness test for the bond ETFs predictions is more significant for the TSP model, which supports the conclusion that the ESMA model is less biased than the TSP model. However, the accuracy of the TSP model is closer to zero, hence the TSP model is more accurate than the ESMA model. Based on these results, it can be concluded that the ESMA prediction model for bonds is more unbiased but less accurate. This means that the overall performance of the ESMA prediction model on bonds is not necessarily better than the TSP model. Hence, the fourth hypothesis is rejected.

Chapter 5: Conclusion

5.1 Conclusion and relevance discussion

This paper investigated the research question: "*How does the ESMA methodology on predicting 1-year future returns for European passive ETFs deviate from a more sophisticated time-series prediction model?*". The results of the ESMA methodology 1-year return forecasts deviate a lot from the forecasts of the sophisticated time-series model, also called TSP model. The overall conclusion is that the ESMA methodology for forecasting bond and stock ETFs is rigid and it does not incorporate the dynamics of market fluctuation. The TSP model of European passive stock ETFs does capture the dynamics of market fluctuation very well. However, the dynamics of European passive bond ETFs are not captured well in the sophisticated time-series model.

The ESMA methodology merely uses past returns as an explanatory variable for predicting future returns. This contradicts the weak form of Fama's (1970) EMH. This paper concludes in two ways that past returns are not explanatory variables in forecast models. Firstly, the ESMA model does not predict accurate and unbiased returns for stock ETFs nor for bond ETFs. Secondly, the TSP model calculated the (partial) autocorrelations between past returns and concluded that the lags were not significant. This concludes that past returns are not explanatory and that future returns cannot be predicted by using merely past returns.

The TSP model has been introduced as an alternative methodology to the ESMA model for predicting stock and bond ETF returns. The TSP model uses the most important explanatory variables from the existing literature. The LASSO BIC technique determines which variables are incorporated in the model. The results show that the TSP model provides more accurate and unbiased predictions for European passive stock ETFs than the ESMA model. The TSP model is also statistically significantly unbiased and the accuracy test shows good accuracy. This gives statistical evidence of a violation of the semi-strong form of the EMH. However, the TSP model does not provide accurate and unbiased predictions for European passive bond ETFs, as the results are ambiguous. The TSP model still performs better on accuracy for bond ETFs, but the unbiasedness is worse than in the ESMA model. Moreover, the unbiasedness and accuracy of the TSP model are not significant. This leads to the conclusion that the semi-strong form of the EMH is not violated for the TSP prediction on European passive bond ETFs.

This paper studies the new regulations from the ESMA called the Commission Delegated Regulation (EU) 2017/653. This regulation document is supplemented by Commission Delegated Regulation

(EU) 2021/2268. These regulation documents describe what fund managers need to disclose in the Key Information Documents (KIDs) by the first of January 2023. This is also applicable to European passive ETFs. This paper has focused on the mandatory performance scenario disclosure in the KIDs. This performance scenario consists of a prediction of expected returns of a specific fund, which is solely based on past returns of the fund. As it is mandatory for fund managers to upload these documents, it is of significant importance what the results are of these performance scenarios as it affects investors' decision making whether to invest in the fund. An adjustment of the prescribed model on predicting returns is advised, as the ESMA model performs poorly in predicting the returns which most importantly negatively affects investor's returns expectations. The TSP model could be an alternative model to consider by the ESMA, since it predicts European passive stock ETFs very well.

5.2 Limitations

This study also has some limitations. Only European passive stock and bond ETFs are incorporated in the analysis. This means that this study cannot make conclusions for active ETFs or mutual funds, while the ESMA guidelines are also applicable to those funds. Besides, only conclusions about Europe can be made as the guidelines are only applied in Europe. Also, for the European passive bond ETFs only a forecast of 2021 and 2022 has been made because of data availability. This means that the current forecast of the TSP model seems not good, but maybe it performs better for a longer time horizon since the prediction of 2021 is good. The forecasted returns are also on an annually basis, meaning that the holding period of the ETF is 1 year. The conclusions about the forecasts, thus, only apply to performance with respect to a holding period of 1 year. Further studies could investigate the TSP model for holding periods of longer than 1 year. Lastly, the forecasts in the TSP model are based on in-sample coefficients which are used in the out-of-sample. However, the x-values in the OLS regression are the current values. In further studies, these values could also be forecasted.

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