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PREDICTING BEAR TREND IN THE UAE STOCK MARKETS USING MACRO-FINANCIAL VARIABLES

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Declaration of Original Work

I, Hamood Abdulla Ismail Alyasi, the undersigned, a graduate student at the United Arab Emirates University (UAEU), and the author of this dissertation entitled "*Predicting Bear Trend in the UAE Stock Markets Using Macro-Financial Variables*" hereby solemnly declare that this dissertation is the original research work, which has been done and prepared by me under the supervision of Prof. Aktham Al-Maghaireh, in the College of Business and Economics at UAEU. This work has not previously been presented or published or formed the basis for the award of any academic degree, diploma or a similar title at this or any other university. Any materials borrowed from other sources (whether published or unpublished) and relied upon or included in my dissertation have been properly cited and acknowledged in accordance with appropriate academic conventions. I further declare that there is no potential conflict of interest with respect to the research, data collection, authorship, presentation and/or publication of this dissertation.

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Abstract

Understanding the effects of macroeconomic and financial variables on stock market trends, especially bear markets, can help different stakeholders and concerned parties to react according to their goals and tasks. Investors can make better investment decisions and allocate assets in their portfolios based on trend expectations. Regulators and decision-makers can adopt adequate precautious regulations to protect the stock market and economy in general from any negative consequences in the case of a stock market recession.

The purpose of this study is to investigate whether it is possible to predict UAE stock market bear states through the use of macro-financial variables. Monthly data from the Abu Dhabi Securities Exchange (ADX) and the Dubai Financial Market (DFM) were gathered, along with the publicly available Macroeconomic and Financial data. The stock markets indices between January 2004 and August 2022 were utilized to identify the market states or regimes (bear and bull). The Markov-regime switching model (MS), as a parametric measure, was used to identify market states. Three different models (Constant, Trend, Three-regimes) were used to test the prediction ability of each model. The binary logit model using the naïve approach was employed to compute variables prediction ability. Out-of-sample tests were conducted to examine the prediction's robustness.

The first hypothesis (H1) assumes that it is possible to predict the UAE bear stock market by using the macroeconomic and financial variables. The computed results of the three models showed that all of the variables, in at least one model, were statistically significant to predict both ADX and DFM trends. Therefore, H1 was supported.

The practical economic benefits of such a prediction were then assessed, as a study application. The second hypothesis (H2) assumes that the investment return of implementing a switching strategy (buy and sell relying on a prediction model) will significantly outperform a buy-and-hold strategy. The test results confirmed and supported this second hypothesis (H2). Implementing a switching strategy in the DFM index yielded considerable profit due to the stationary feature of the DFM index movements. The significant output indicates that investors will be better off if they adopt the switching strategy (assuming that they can predict the market trends).

During this study, a range of tests were conducted using different techniques and methods to achieve the objectives. First, the graphical trends of all variables were analyzed to check for similar movement patterns. Then fluctuations in the stock market were identified and classified. The cyclical variations (regime classification) in ADX and DFM indices were empirically examined using parametric approaches. After the bull and bear periods were identified and classified, different types of Markov-switching models (Constant, Trend, Three-regimes) were employed to investigate whether the market trends could be predicted by the study variables. The variables considered were: Crude Oil price; Saudi Tadawul (TASI) index; S&P 500 index; Broad Effective Exchange Rate for UAE; Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity (default spread); and 10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity (interest spread).

Both in-sample and out-of-sample tests were conducted. The empirical results from monthly data on ADX and DFM price index suggest that the variables are useful predictors of the market trend in all the three models. Finally, a further out-of-sample test for forecasting measure was conducted. The empirical results are robust for the different types of MS models but suggest that the variable can predict ADX out-of-sample more accurately compared to that of DFM, and this was supported by the calculated MAPE values, which are used to assess a model's forecasting ability. This result may demonstrate the usefulness of forecasting market trends.

The thesis is structured as follows: Chapter 1 presents the introduction; Chapter 2 presents the literature review; Chapter 3 presents the methodological framework and hypotheses building; Chapter 4 describes the research methodology; and Chapter 5 represents the empirical results of the applied models, bull or bear market classification, and model predictability when using the study variables as leading indicators. Robustness tests and the economic value of predicting bear markets are provided in this chapter as well. Finally, the conclusion, limitations, remarks, and recommendations are offered in Chapter 6.

Keywords: UAE stock markets, predicting market trend, DFM, ADX, nonlinear models, Markov-regime switching.

Title and Abstract (in Arabic)

التنبؤ بالاتجاهات الهابطة في أسواق الأسهم الإماراتية باستخدام المتغيرات المالية الكلية

الملخص

يمكن أن يساعد فهم تأثيرات متغيرات وعوامل الاقتصاد الكلي والمتغيرات المالية على اتجاهات أسواق الأوراق المالية (وخاصة اتجاهات الأسواق الهابطة) مختلف الأطراف المعنية على الاستجابة وفقا لأهدافها ومهامها. يمكن للمستثمرين اتخاذ قرارات استثمارية أفضل وتخصيص وتبديل الأصول في محافظهم بناء على توقعات اتجاهات الاسواق سواء في حالة توقعات هبوط او صعود الاسواق. ويمكن ايضا لمنظمي الاسواق المالية وصناع القرار الاستفادة من هذه التنبؤات واعتماد لوائح وقرارات احترازية لحماية سوق الأوراق المالية والاقتصاد بشكل عام من أي عواقب سلبية في حالة ركود هذه الاسواق.

الغرض من هذه الدراسة هو التحقق مما إذا كان من الممكن التنبؤ باتجاهات أسواق الأسهم الإماراتية باستخدام بعض المتغيرات الاقتصادية الكلية والمالية. في هذه الدراسة تم جمع البيانات الشهرية لمؤشرات الاسهم من سوق أبو ظبي للأوراق المالية (ADX) وسوق دبي المالي (DFM) جنبا إلى جنب مع بعض بيانات الاقتصاد الكلي والبيانات المالية المتاحة للجمهور. تم استخدام مؤشرات أسواق الأسهم بين يناير 2004 وأغسطس 2022 لتحديد حالات أو وضع السوق (الدب والثور). ثم تم استخدام نموذج ماركوف لتبادل الانظمة (MS) كمقياس بارومتري، لتحديد حالات واتجاهات الاسواق المالية الاماراتية. وتم ايضا استخدام النماذج اللوجستية الثنائية لقياس القدرة على التنبؤ باستخدام المتغيرات الاقتصادية الكلية والمالية. وللتأكد من فعالية النماذج، تم إجراء اختبارات خارج العينة لفحص متانة التنبؤ واثبتت فعالية بعض النماذج على التنبؤ باتجاهات السوق بشكل جوهري.

تفترض فرضيتنا الأولى (H1) في هذه الدراسة أنه من الممكن التنبؤ باتجاه سوق الأسهم الاماراتية للهبوط باستخدام المتغيرات الاقتصادية الكلية والمالية. تم دعم الفرضية الاولي بناء على نتائج الدراسة و لوجود الادلة الاحصائية والنماذج الدالة على صحة فرضيتنا (H1).

كتطبيق للدراسة على الواقع العملي، قمنا بتقييم الفائدة الاقتصادية والعملية لمثل هذا التنبؤات في الفرضية الثانية (H2) حيث تفترض الفرضية الثانية أن عائد الاستثمار في حالة تطبيق استراتيجية تبديل وتنويع الاستثمارات باستخدام مبدا الشراء والبيع بالاعتماد على الاوقات المناسبة المستخلصة من نموذج التنبؤ سوف يكون اعلى بكثير من عائد الاستثمار في حالة تطبيق استراتيجية الشراء والاحتفاظ للمدى البعيد جدا. أكدت نتائج اختبارات الدراسة ارتفاع عوائد استراتيجية التبديل والتنويع بشكل جوهري مقارنة بالاستراتيجية الاخرى وبالتالي دعم ذلك فرضيتنا الثانية (H2).

أجرينا اختبارات مختلفة في دراستنا باستخدام تقنيات وأساليب مختلفة لتحقيق أهدافنا. قمنا أولا بتحليل الاتجاه الرسومي لجميع متغيرات الدراسة للتحقق من أنماط الحركة المماثلة بين المتغيرات ومؤشرات الاسواق. ثانيا، حددنا وصنفنا اوقات التقلبات الهابطة والصاعدة في سوق الأسهم من عام 2004 لغاية 2022. كما قمنا بتحديد الاختلافات

الدورية وتم تصنيف الدورات في الاسواق (هبوط، صعود) المستقاة من تحركات مؤشرات سوق ابوظبي للأوراق المالية او سوق دبي المالي باستخدام الأساليب البارا مترية. وبعد تحديد فترات الصعود والنزول وتصنيفها، استخدمنا أنواعا مختلفة من نماذج ماركوف لتبديل الانظمة وهم: النموذج المعياري، النموذج الاتجاهي ونموذج ذو الثلاثة انظمة او دورات (Constant, Trend, Three-regimes) للتحقق مما إذا كان يمكن التنبؤ باتجاهات السوق. المتغيرات التي أخذناها في الاعتبار في دراستنا هي: سعر النفط الخام، مؤشر تداول السوق السعودي (TASI)، مؤشر ستاندرد آند بورز 500 الامريكي، سعر الصرف الفعلي الواسع لعملة درهم دولة الإمارات العربية المتحدة، عائد سندات الشركات Baa بالنسبة إلى العائد على الاستحقاق الثابت للخزينة لمدة 10 سنوات (ويسمى ايضا فرق افتراضية عدم السداد)، استحقاق سندات الخزينة الثابت الامريكية لمدة 10 سنوات مطروحا منه استحقاق الخزينة الثابت لمدة 3 أشهر (فرق نطاق الفائدة).

تم إجراء اختبارات فعالية النماذج من داخل العينة ومن خارج العينة. تشير النتائج التجريبية إلى أن نماذجنا ومتغيراتنا لها قدرة جوهرية على إعطاء تنبؤات لاتجاهات الأسواق الاماراتية في جميع النماذج الثلاثة المستخدمة. لكن نتائج معيار دقة التنبؤ (MAPE) لسوق ابوظبي للأوراق المالية من خارج العينة كان أكثر دقة مقارنة بتلك النتائج الخاصة بسوق دبي المالي. توضح هذه النتائج فائدة التنبؤ باتجاهات السوق.

دراستنا البحثية منظمة على النحو التالي. يعرض الفصل الأول المقدمة ويقدم الفصل الثاني مراجعة البحوث السابقة. يعرض الفصل الثالث الإطار المنهجي للبحث وبناء الفرضيات. يصف الفصل الرابع منهجية وأساليب البحث. يعرض الفصل الخامس النتائج التجريبية والاحصائية ويصنف أنظمة ودورات السوق الصاعدة والهابطة، ويقيس إمكانية التنبؤ للنماذج عند استخدام متغيرات الدراسة، كما يتم توفير اختبارات المتانة والقيمة العملية والاقتصادية للتنبؤ بالأسواق الهابطة في هذا الفصل أيضا. أخيرا، وفي الفصل السادس يتم تقديم ملخص للدراسة وتبيان نقاط محدودية النتائج وملاحظات الدراسة مع اعطاء التوصيات للدراسات المستقبلية بهذا الخصوص.

مفاهيم البحث الرئيسية: اسواق الاسهم في دولة الامارات العربية المتحدة، تنبؤ اتجاهات الاسواق المالية، سوق دبي المالي، سوق ابوظبي للأوراق المالية، النماذج غير الخطية، نموذج ماركوف لتبادل الانظمة.

Author's Contribution

The contributions of Hamood Abdulla Alyasi to the dissertation were as follows:

I. Participated in the planning of the research agenda.
II. Held the main responsibility for designing the research structure prior to collecting research data.
III. Held the main responsibility for data collection, analysis, and interpretation of results.

Author Profile

Hamood Abdulla Ismail Alyasi is an experienced Emirati businessman who currently manages a private investment company in the UAE. With his in-depth expertise in asset management, banking, and real estate markets, he manages a sizeable portfolio of privately held assets in the UAE. The competitive business environment in Dubai motivated him to combine his professional experience with extensive academic knowledge through his studies in a DBA program at the United Arab Emirates University. He has developed his finance career by holding senior management positions with various employers. His key positions include:

- General Manager – ENBDS – Subsidiary of Emirates NBD Bank Group, which is one of the top stock brokerage companies, (2000-2010)
- Ex-board member of two different companies.

Hamood lives with his family in Dubai. He earned his Master's degree with honors from the University of Miami in the USA. His contact information is as follows:

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Dedication

To my beloved family

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List of Abbreviations

ADNOC	Abu Dhabi National Oil Company
ADQ	Abu Dhabi Development Holding Company PJSC
ADX	Abu Dhabi Securities Exchange
AIC	Akaike Information Criterion
APT	Arbitrage Pricing Theory
BAA10YM	Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-year Treasury Constant Maturity
DFM	Dubai Financial Market
DFSA	Dubai Financial Services Authority
ESCA	Emirates Securities and Commodities Authority

Chapter 1: Introduction

1.1 Overview

This study seeks to develop models that can predict the direction of movement of the UAE stock market, especially in the case of a bear market. A bear market evolves when investors grow pessimistic about the stock market, and that is usually when share prices fall as supply begins to outpace demand. The causes of a bear market often vary, but in general a weak, slowing, or sluggish economy has the potential to trigger a bear market. This study investigates whether macroeconomic and financial variables can predict a decline in the UAE stock market (also known as bear markets). After using different types of Markov-regime switching models (MS) to identify bull and bear regimes in the stock market, the same models are implemented both in-sample and out-of-sample to assess the variables' predictive ability. The research area falls under the early warning systems (EWS) in forecasting capital market direction. The study relies on two disciplines; the first is Finance with a concentration on Financial Capital Markets, the second is Econometrics, as an econometrics procedure was used to predict market directions.

In the empirical literature, various fundamental macroeconomic factors which presage the economic conditions have been proposed to predict stock fluctuations. They include: interest rate, default spread, term spread, inflation, aggregate output, money stocks, unemployment rate, consumption level, and many other macro variables (Engle, Ghysels, & Sohn, 2013; Fama & French, 1989). Other financial variables such as dividend-price ratio, earning-price ratio, dividend-payout ratio, stock variance, book-market ratio, market aggregate capital and trading value have also been proposed and investigated to examine their effect on stock market returns (Chowdhury, Uddin, & Anderson, 2018; Indrayono, 2019).

Chen (2009) used some macroeconomic variables to predict a bear market state in the US and found most of them to be significant, but term spread and inflation were found to be the most significant predictors. Nyberg (2013) followed that same approach but used dynamic binary time series models and confirmed the predictive ability of some of the macroeconomic variables. This study builds on prior research, especially the work of Chen (2009), with some modifications, omissions, and additional variables that are relevant to the economy, stock market and business cycle in the UAE. The added variables are Oil prices, US S&P500, KSA Tadawul indices (TASI), and Broad Effective Exchange Rate for the UAE. All these variables are theoretically supported by existing literature.

Theoretically, finance literature offers various theories that explain the relationship between the stock market and macroeconomic and financial variables. For example, the first hypothesis (H1) is underpinned by the Rational Expectation Theory (Muth, 1961), as the predictive ability can be explained by the theory which states that people base their decisions on human rationality, the available information, and their past experiences. Meanwhile, the Arbitrage Pricing Theory (APT) developed primarily by Ross (1976) assumes that the expected return of financial assets is a linear function of its expected returns, alongside other macroeconomic factors that do not have firm control. Therefore, the second hypothesis (H2) relies upon this theory. The second hypothesis will assess the practical application of the prediction model by determining if there is significant return difference between two investment strategies (switching strategy vs buy-and-hold strategy). More elaboration on both hypotheses will be discussed in the next section.

Investors, regulators, policy makers and other parties can benefit from such an ability to predict movements. The UAE stock market attracts many investors, including international and institutional investors. It has witnessed many substantial drops in stock prices that affected the market liquidity and transactions. The drops affected the country's economy and business sectors as investment and wealth got blocked in negative (loss) investment positions (Mnif & Kammoun, 2015).

Financial and Macroeconomic data from January 2004 to August 2022 were collected, and the Markov-regime switching models were used to identify the bull and bear markets (Maheu & McCurdy, 2000). Once the filtered probabilities identified the bull and bear markets, the proposed predictive statistical tool was used to assess whether the study variables can predict the ADX and DFM market indices movement during the bull and bear markets. In-sample and out-of-sample tests of predictability were then employed to evaluate the findings and the robustness of the results.

This study is highly significant because if the empirical results support the hypotheses and suggest that it is possible to predict a bear stock market state in the UAE using macroeconomic and financial variables, such a predictive ability will help different investors to form market-timing strategies. The second hypothesis (H2) was tested to see if the "in-and-out" or switching strategy generates significantly higher returns compared to the "buy-and-hold" strategy. If H2 is supported, then an investment organization could incorporate this strategy into their investment model, enabling them to be selective and dynamic when timing their investments in the UAE stock markets. Policy makers and regulators could also benefit from such predictions by implementing proper policies and precautious procedures to protect investors, the stock markets, and any related parties from anticipated negative consequences.

1.2 Research Motivation

The motivation of this study is to investigate the trends in the UAE stock markets and examine if the trends, especially bearish trends, are predictable using the Markov-regime switching models as the predictive models. The application is very helpful for any practical work, especially in asset management. The strategic objectives of most institutional investors are to invest and profit from capital appreciation and dividend income. They avoid daily speculation or unclear market direction transactions. They prefer to enter and exit the market at the right time. As a professional investor, I also would like to explore and benefit from the early warning system studies.

1.3 Research Aims

This study seeks to determine if macroeconomic and financial variables can predict bull and bear trends in the UAE stock markets. The focus is on the bear market due to its significant impact on investors and financial institutions that are involved in equities investment in the UAE stock market. The study incorporates many variables that, according to an extensive literature review, have not been used together in one study to investigate the market trend in the UAE stock market. The purpose of this study is to test whether these predictions can enable investors to apply a switching investment strategy to earn better investment returns over the long run.

1.4 Research Objectives

The objective of the study is to use Chen (2009) as a foundation for this research idea and modify it to fit the UAE market. The modification includes adding new variables and approaches. The economic value of such predictions will be tested to establish the advantage of using a switching investment to benefit from market fluctuations. The results might help investors and policy makers to understand the effect of the selected variables on the UAE stock market.

1.5 Research Questions

The main aims of this study can be summarized with the following three questions:

1. To what extent can investors use the publicly available macroeconomic and financial data to predict the market trend in the UAE stock market?
2. To what extent is the UAE stock market linked with major international stock markets such as the USA stock market (S&P 500) and regional markets such as KSA TASI?
3. Can investors benefit from such a prediction if they adopt a switching investment strategy compared to a buy-and-hold strategy?

Based on the extensive and thorough review of existing literature, this is the first attempt to study this issue in the context of the UAE stock markets, and the results will hopefully provide useful insights for investors, the UAE Security and Exchange Commission (ESCA), regulators, academics, and business researchers.

1.6 Why is the Researcher Interested in Bear Market?

A bear market might mean losses to investors who are investing in long positions. It will be more difficult for investors to recoup their original portfolio value in cases of significant losses. For example, if a portfolio loses 50% of its investment during market drop, the portfolio value has to gain 100% in order to go back to its original value. Warren Buffett's first rule is "Never lose money". His second rule is "Never forget rule number one".

1.7 Research Methodology

The research methodology is based on the positivism paradigm using a quantitative approach. Secondary data was collected and analyzed using econometric models to arrive at findings. The literature review led to building a theoretical framework and deductive justification for the study hypotheses and findings. Two theories are used to underpin the study hypotheses, assumption, and findings: the first one is the Rational Expectation Theory (RET) (Muth, 1961), and the second one is the Arbitrage Pricing Theory (APT) (Ross, 1976). The secondary data for each variable is collected from public sources. Each variable is plotted in a graph for analysis and comparison. The dependent variables are the market price index (in points) for Abu Dhabi Securities (ADX), the Dubai Financial Market (DFM), and the independent variables are the macroeconomic and financial data for each variable. Nonlinear time series choice is selected in the OxMetrics program and used. The choice is based on the data nonlinearity issue. Markov regime-switching models are used to identify the regime classification (number of regimes and the duration of each regime). Each model involves multiple structures (equations) that can characterize the time series behaviors in different regimes by permitting switching between these structures. Therefore, these models can capture more complex dynamic patterns.

Binary logit model using the naïve trend classification approach is used to predict the stock market trend. Out-of-sample tests are used to evaluate the robustness of the three parametric prediction models. Based on the regime classification, a hypothetical test (H2) is conducted to test whether a switching investment strategy will yield higher returns than the classical "buy-and-hold" investment strategy.

1.8 Research Applicability

If the prediction model using the selected variables can predict the market trend, then investors can obtain higher returns by following a timing switching strategy rather than a "buy-and-hold" strategy. In addition, policy makers can use the study results to help predict the fluctuations in the UAE stock market and their connection to business cycles. Policy makers can adopt policies to prevent or mitigate the problems caused by liquidity issues during bearish market states, since illiquidity in a market can cause credit crunches.

Market trend prediction can help to improve portfolio management performance. Investors can manage assets and avoid losses especially during market recession cycles. Investors might prefer to use prediction models to assess the investment risk, if applicable.

In summary, the study results are important to the following different potential users:

1.8.1 Investors

Investors who trade in the UAE stock market can benefit from knowing some of the variables that can affect the stock market direction, so that they may be able to recognize and mitigate their investment risks and be aware of them.

1.8.2 Regulators

The market trend prediction can help the financial market regulators such as ESCA, ADX, and DFM to implement policies and strategies to ease the effect of the stock market recession. Severe bear markets can cause significant stress on investors and financial institutions. Margin trading payment defaults can create adverse effects on investors and financial institutions. The regulators can plan to reduce this risk by implementing restrictions on excess lending exposures or lowering the leverage ratios. Also, they can classify the quality of loan collaterals to avoid pressure on shares that have low turnover ratios. Regulators can also adjust the leverage/ margin trading policies by implementing preventive measurement such as restricting short selling facilities in order to reduce market panic and avoid adding pressure on bear market transactions.

1.8.3 Stock Brokerage Firms and Financial Institutions

Stock brokerage firms tend to provide facilities such as margin trading or short selling to their clients. Appropriate market trend predictions can help to reduce the risk of the client's credit default.

1.8.4 Future Research

The study makes a valuable contribution to the UAE financial markets literature. Future similar studies can help to improve the predictive ability or the prediction models. For example, new studies could include different significant/potential variables. If we look at the price index movement, we can see a sharp rise or drop in certain regimes. Therefore, it might be advantageous to test for the hot-money effect or use money supply as a potential variable that might explain such stock rises and drops. Also, it might be interesting to investigate the effect of both retail and institutional market share trading. The stock market provides daily statistics of the trading shares of different segments of investors. It would be interesting to investigate the institutional investor's role and the effect on the market trend. There are many "heavy" investors or market players that can affect the market direction and trading volume/value.

1.9 Research Significance

This study offers a unique contribution to this field as, based on a thorough investigation of the existing literature, no similar study has been done in the UAE stock market. Moreover, although using the research methodology outlined by Chen (2009) as a baseline, this study selectively chose a few variables before incorporating some additional variables related to the UAE stock market.

This study used the ADX and DFM market price indices as dependent variables instead of the market return, and aimed to predict the market trend, especially the bear market.

1.10 Structure of the Dissertation

The dissertation is organized as follows: Chapter 2 reviews the literature and provides an overview of the UAE economy and stock markets (ADX and DFM) development, performance, and characteristics. Market trend prediction studies were reviewed to develop the prediction model structure, such as how to identify the bull and bear markets using the parametric or nonparametric approaches by implementing different econometric approaches. The emphasis on parametric approach using nonlinear Markov-regime switching models was discussed and the relevant studies from the literature were presented.

Chapter 3 presents the theoretical and conceptual framework including the two theories that underpin our two hypotheses. The study variables were discussed with the proper literature supporting the variable selection.

Chapter 4 explains the research paradigm, research methods, and research design. This chapter includes the methodology, secondary data collection sources, data analysis processes including the software used (OxMetrics program), and the Markov-regime switching model structure. The data analysis process starts with the descriptive statistics and regime classification identification, the three prediction models development, logit model, out-of-sample robustness test, and the second hypothesis (H2) testing with a detailed explanation on how to calculate the performance of the two investment strategies chosen to evaluate the applicability of our study.

Chapter 5 presents the results of the descriptive statistics, unit root tests, graph analyses for each variable to explore its movement over the study period, empirical analysis of the effect of implementing the three models on ADX and DFM separately. The results of the logit model using the naïve approach were also summarized and discussed. The out-of-sample forecasting, including the trajectory line and the MAPE results, are presented. Finally, the second hypothesis (H2) was evaluated based on the final value of the hypothetical investment performance.

Chapter 6 provides the conclusion to the dissertation and discusses the findings, application, and limitations as well as recommendations for any future research.

Chapter 2: Literature Review

2.1 Introduction

This chapter explores the literature and reviews the studies related to our research objectives. It also outlines the UAE economy's development and discusses the key factors which have contributed to the substantial growth over the previous years, helping the UAE to become one of the most attractive business hubs in the region.

The UAE stock market is one of the investment channels that local and multinational investors use to invest in the capital market. This chapter offers a summary of the background of the stock markets in the UAE and discusses various articles that have investigated the different aspect and characteristics of the country's stock market – including market efficiency, literacy, investors' segments, and correlation with the international and regional markets. Understanding the characteristics of the UAE market was necessary to formulate the basic assumption for this study's argument regarding the predictive ability of a model using the aforementioned study variables. There are various studies about different international market trend predictions that explore different variables using different econometrics and statistical techniques which support the proposition of this thesis, the selection of the study variables, and the selected technique and research methodology.

The UAE stock market consists mainly of Abu Dhabi Securities Exchange (ADX) and Dubai Financial Market (DFM), and both ADX price index and DFM price index are used as dependent variables in this study. We presented and explored different studies that used the market index as the dependent variable instead of the market return and provided proper justification for the selection based on previous studies.

To build the appropriate model in different market trends/cycles/regimes (bull or bear markets), the focus was on studies that can help to identify and classify such regimes and the parametric approach using Markov-regime switching (MS) was chosen. One of the advantages of this tool is its ability to identify the regimes automatically using the appropriate econometrics model. Once the regimes have been classified using MS models, the variables are tested for their predictive ability. The advantage of using Markov-regime switching is that the variables are allowed to affect the stock market differently in bear and bull regimes. The variables were examined for normality and found to be nonlinear. Different Markov-regime switching models were used since the variables sampled were nonlinear time series variables. The literature was explored to identify similar studies that used similar techniques. There were many studies done in different international markets that found and significantly supported the assumption that the selected variables can affect the stock market return/prices. Such findings supported the selection of the study variables. Therefore, the study hypotheses were based on the assumption that these variables can be considered as good market direction predictors.

2.2 UAE Economy

The UAE economy has witnessed substantial growth since the discovery of oil in the 1950s. Oil revenue has played a significant role in the development of the UAE's economy. The Gross Domestic Product (GDP) in the UAE is expected to be approximately USD 519 billion in 2023 (FRED, 2023). GDP in the UAE averaged USD 137.54 billion from 1973 until 2018, reaching an all-time high of USD 504 billion in 2022 and a record low of USD 2.85 billion in 1973 (World Bank).

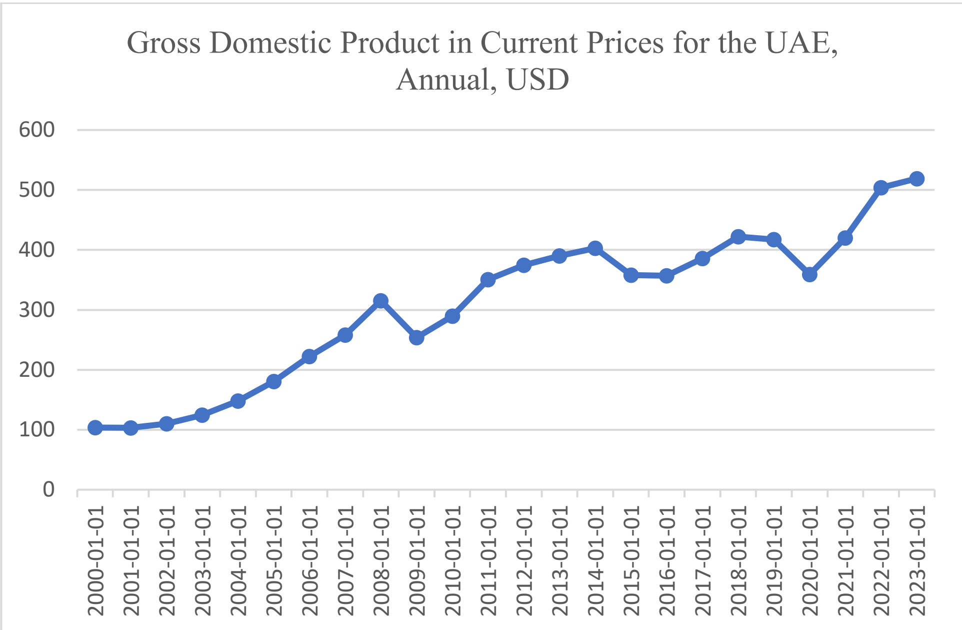

Figure 2.1: UAE GDP (2000–2023)

The country enjoys a strategic location between Asia, Europe, and Africa. Many international companies and investors use it as a hub for conducting business. The Abu Dhabi Investment Authority is one of the largest sovereign wealth funds in the world (ranked 5th) with a total asset value of USD 792 billion (Sovereign Wealth Fund Institute, 2016). The UAE has adopted economic diversification plans that have helped the country to reduce its dependence on hydrocarbon-based income. Currently, oil industries contribute less than 30% of GDP in the UAE economy. According to the economic report by the UAE Ministry of Economy (2018), the UAE attracted almost USD 10.4 billion in foreign direct investment (FDI) during 2017. The UAE ranked 1st as the most attractive country in the MENA and African region in terms of investment attractiveness of foreign direct investment. Banjeree and Majumdar (2021) studied the effect of the FDI on the UAE stock markets. The study highlighted that the FDI inflows play as a key driver of stock market performance during the last decade and emphasizes the success of the intense reforms in the UAE initiated for the diversification of its economy. Conducting business in the UAE is relatively easy and the country ranked 1st in the Arab world and 11th globally in terms of "ease of doing business" (World Bank, 2019). The rapid growth in the economy during the last few decades has attracted international investors and encouraged many of the UAE's residents to invest in various sectors, including the UAE stock markets.

The UAE has put plans in place to attract FDI and encourage capital flow. The stability of the financial system, free income taxes, many free zones, open market policy, labor availability, and many other incentives all contribute to foreign investor confidence and a desire to invest in a strong economy with remarkable growth. Foreign investment opportunities exist in different sectors including tourism, construction, manufacturing, financial services, logistics, and health services.

The UAE has become a leader in FDI and attracted international investors. According to Alshamlan et al. (2021), the inflow of foreign direct investment into the UAE has gradually increased year-on-years. The relevant factors that make the country an attractive destination for investors include the political stability, geocentric location, and the well-developed infrastructure all of which provide opportunities for multinational organizations to expand geographically and diversify their operations.

The UAE is one of the least restrictive countries in terms of non-tariff barriers. The multinational mix of investors, culture, strong purchasing power, and low energy prices are just some of UAE's competitive advantages, along with an open trade regime with low tariffs and a few non-tariff barriers (International Trade Administration, 2022). Trade barriers include tariffs and non-tariff barriers.

In 2020, ratings agency Moody's issued the credit profile of the UAE. The UAE government received an Aa2 rating in creditworthiness – which is the highest sovereign rating in the region – denoting Moody's projections for a stable outlook for the UAE economy. This rating reflects the success story of the country's financial and economic vision and policies (Zawya, 2020). The rating is supported by the assumed full backing of the government of Abu Dhabi and its strong balance sheet. The economic strength score of "aa3" considers the country's remarkably high GDP per capita, a large hydrocarbon endowment, and superior infrastructure; the institutions and governance strength score of "a2" is based on a strong institutional framework and effectiveness.

2.2.1 The UAE Stock Markets

The UAE stock market, which opened in 2000, is considered a young market when compared to other markets in the MENA region. Nonetheless, it is now considered the second biggest market in MENA region after the Saudi Stock Exchange in terms of market capitalization. Prior to year 2000, UAE shares were traded in an over the counter (OTC) market which lacked proper organization and regulations (Khedhiri & Muhammad, 2008). OTC market transactions were not properly monitored since prices could be easily speculated. In 1998, The OTC market experienced a significant crash that affected the UAE economy. Many investors lost substantial wealth due to that market crash.

The UAE official stock market was established in 2000 to regulate public companies, monitor the capital market transactions, help improve market inefficiency, and solve issues created by the unregulated OTC market. The UAE stock market experienced rapid market development as well as significant regulatory and economic changes. Like any other stock market, the UAE stock market witnessed substantial volatilities between 2000-2022. Some of these periods can be classified as boom and recession (bull and bear) periods. The objective of this study is to examine the prediction, if any, of bull or bear markets using macroeconomic and financial variables. The focus will predominantly be on the bear market, and explore the variables that affect its direction. The variables that affect the bull market might overlap with the variables that affect the bear market to a great extent. However, there may be other variables that affect the bull market (statistically significant) and not affect the bear market (statistically insignificant).

The idea that public information can be used to predict a bear market state is a violation of the market efficiency hypotheses. Since the UAE market is considered a relatively new market compared to other developed and broadly regulated markets such as the USA and other Western markets, one should expect some market inefficiency. The 2019 study by Al-Shboul and Alsharari offered found evidence that DFM and ADX exhibit signs of evolving efficiency (Al-Shboul & Alsharari, 2019). Both markets were found to be mostly inefficient with a trend of improvement towards the weak form of efficiency. In an earlier study, Awan and Subayyal investigated GCC stock markets and tested their weak form of market efficiency (Awan & Subayyal, 2016). The results showed that the GCC markets are inefficient in the weak form. Liquidity issues, lack of information, insider trading, and speculation after getting some significant information are some of the reasons that led to this market inefficiency. Nonetheless, investment decisions based on technical analysis of the stock market can produce extraordinary returns for investors. Using past prices and other variables to predict the future trend is possible in the GCC market.

Such findings suggest that market trends might be predictable because the effect of the variables chosen might not be impounded or reflected in the market prices, and consequently, the market index. An investigation of the financial literacy and portfolio diversification in the Tunisian market found that the investor's experience, financial literacy level, use of the availability heuristic, age, familiarity bias and portfolio size all have a significant effect on the investor's portfolio diversity (Mouna & Jarboui, 2015). Meanwhile, a 2009 study suggests that the financial literacy of investors in the UAE is below the optimal level (Hassan Al-Tamimi & Anood Bin Kalli, 2009). Given the low level of market efficiency and literacy, it is likely that some of the variables will have the capability of predicting bear market movements. Karlsson and Nordén investigated differences in home investment bias, as opposed to well-known benefits from international diversification, on an individual level by studying portfolios built as a part of the new defined contribution pension plan in Sweden (Karlsson & Nordén, 2007). Their research revealed that the likelihood of home bias is caused by both rational and irrational variables. The study identified the type of individual with the highest likelihood of home bias as an older, low educated person, with no or very low experience with risky investments outside the pension plan, and who invests only a small percentage of their income. An investors' perception to information might differ across various regions. For example, one 1999 research publication suggested that the Korean stock market reflects macroeconomic variables on stock prices indices and that the indices are cointegrated with some of the macroeconomic variables, such as the exchange rate, trade balance, money supply and production index (Kwon & Shin, 1999). However, the study also found that the Korean investor's perceptions of stock price movements are different from those of US and Japanese investors. The market perception affects the way investors react to macroeconomic and financial information. A significant portion of the transactions in the UAE stock markets are conducted by normal (individual) investors as opposed to mutual funds and institutional investors (Khan, 2011), as is the case in developed markets. Therefore, the perception and late response to macroeconomic and financial information are liable to create an index lag that can support the assumption of the market trend prediction possibility.

2.2.2 Abu Dhabi Securities Exchange (ADX)

Abu Dhabi Securities Exchange (ADX) was established on 15/11/2000 by Local Law No. (3) Of 2000, the provisions of which vest the market with a legal entity of independent status, finance, and management. The law also provides ADX with the necessary supervisory and executive powers to exercise its functions. In 2020, ADX was converted from a "Public Entity" to a "Public Joint Stock Company PJSC". ADX is part of ADQ, one of the region's largest holding companies with a broad portfolio of major enterprises covering key sectors of Abu Dhabi's diversified economy. ADX is a market for trading securities; including shares issued by public joint stock companies, debt instruments issued by governments or corporations, exchange traded funds, and any other financial instruments approved by the UAE Securities and Commodities Authority (ESCA). One of the ADX strategies is to provide stable financial performance with diversified sources of incomes which is aligned with the guiding principles of the UAE "Towards the next 50" agenda.

ADX is the 2nd largest market in the Arab region (ADX official site) after KSA's market. The market capitalization as of 7 November 2022 is approximately 2.5 trillion AED (approx. USD 680 billion). Abu Dhabi Securities Exchange (ADX) contains different markets: The first one is the main market where investors buy and sell securities they already own after the company has sold its offering on the primary market. The second market is part of the existing infrastructure of ADX to list private companies. Investors can buy and sell securities of private companies depending on fundamentals like supply, demand, financial statements, and other disclosures. The third market, newly launched, is the ADX growth market which is a specialized equity market for private companies looking to accelerate the growth of their business by tapping into new pools of capital. Companies can directly list shares on the exchange, without the need for an initial public offering (IPO). It helps companies to attract capital, enhance their brand equity and corporate governance, extend their investor base, optimize cost of capital, and expand business networks. Companies listing on the growth market benefit from access to post-listing assistance, access to AGM management, dividend distribution, corporate communication support and the option of a subsequent IPO on ADX main market.

2.2.3 Dubai Financial Market (DFM)

Established as a public institution with an independent legal entity by virtue of Decree 14/2000 issued by the Government of Dubai, the Dubai Financial market (DFM) launched its activities on 26/3/2000. On 27/12/2005, the Executive Council of Dubai decided to transform the DFM into a public shareholding company with a capital of AED 8 billion divided into 8 billion shares, and 20% of the capital, equal to 1.6 billion shares, was offered through an IPO (DFM official site). On 7/3/2007, the Dubai Financial Market Company was listed on the market with the trading symbol DFM. The DFM is the first financial market to have offered its shares through an IPO in the MENA region, and this reflects the leading role played by the Emirate of Dubai in selling shares of governmental institutions in the region.

The DFM operates according to Shari'a principles. The DFM is regulated and governed by the UAE Securities and Commodities Authority (ESCA), which has the authority to enact laws and policies which the DFM must comply with. The DFM functions as a secondary market for the trading of securities issued by public shareholding companies, bonds issued by federal or local governments, local public institutions, and mutual funds as well as other local, regional, or foreign DFM approved financial instruments.

In 2010, the DFM consolidated its operations with Nasdaq Dubai. The consolidation provides investors with a larger choice of asset classes and easier access to DFM and Nasdaq Dubai via a single investor number (NIN), which means investors can trade easily across the two exchanges. Both exchanges continue to be regulated separately, with DFM regulated by ESCA and Nasdaq Dubai by the Dubai Financial Services Authority (DFSA).

The DFM ensures that members go through a rigorous application process to become accredited brokers and custodians and to protect investors and their rights. Market participants include investors, brokers, listed companies (issuers), and custodians, all of whom play a key role within the financial market dynamics. The DFM was the first regional market to adopt the highly sophisticated trading system ''X Stream" in 2009, known to be one of the best trading systems amongst the world's financial markets.

A study by el Alaoui *et al.* (2015) investigated the co-movement dynamics at different time scales or horizons of Islamic Dubai Financial Market (DFM) index returns with their counterpart regional Islamic indices returns, such as the GCC index (Alaoui, Dewandaru, Rosly, & Masih, 2015). They found that the DFM and the GCC index (with higher emphasis from the Saudi stock market) are converging, in the long run, to the same level of risk and volatility with the Global Sukuk index. The analysis indicates a strong non-homogeneous correlation across scales and for different periods of time. Closer markets tend to suggest a contagion effect showing higher correlation and higher interdependence with a certain time delay. Salameh and Alzubi (2018) found that the volatility of DFM Index is largely dependent on its own shocks and part of the external shock; in particular, S&P500. However, other external volatility (FSTE) cannot contribute to this volatility. Mohite and Bhandari (2022) investigated the integration hypothesis in both short term and long-term causal relationships in the GCC stock markets: namely TASI (KSA); the DFM (UAE); the Kuwait stock Exchange (Kuwait); the Bahrain Stock Exchange (Bahrain); and the Muscat Stock Exchange (Oman). The results obtained establish long run linkages among all the stock markets of GCC and asymmetric short run causality among the six markets. Abdennadher and Helara (2021) investigated the possible factors controlling fundamental and pure contagion and volatility, especially during the periods of global financial crises, for MENA and US stock markets. The investigated markets are the USA market (Dow Jones Index, DJI) and seven from Middle East and African region: Bahrain; Dubai (DFM); Jordan; Morocco; the Kingdom of Saudi Arabia; Turkey; and Tunisia. The results presented evidence about the coexistence of “pure” and “fundamental-based contagion” during the global financial crises and its effect on the stock market volatility spillovers.

2.3 Market Trend Prediction

Market trend prediction is an important topic in the academic and professional domain. Professional programs are developed to predict different segments of the financial markets and businesses. Some of the techniques are publicly available. However, some of the prediction programs that are developed by private companies are kept for their own use. Developing sophisticated market prediction programs might have excessive costs, but if the programs have robust and accurate predictions, then this could lead to higher returns which will have greater benefits and rewards for such developers. Prediction or forecasting strategies are considered as part of the early warning systems.

2.3.1 Early Warning System

Financial crises such as Black Monday (1987), the Gulf War aftermath (1990), the Asian financial crisis (1997), the Russian financial crisis (1998), the dotcom bubble (2000), the subprime mortgage crisis that led to global financial crisis (2007-2008), the European debt crisis (since 2010), and many other financial crises have often produced overwhelming economic, social, and political consequences. These financial crises were, in many cases, not limited to individual economies but also spread to other markets. As a result, early warning system (EWS) models have been developed, with the aim of identifying economic weaknesses and vulnerabilities in developed and emerging markets and ultimately anticipating such events. The International Monetary Fund (IMF) has taken a lead in putting significant effort into developing EWS models. However, many central banks, academics, and various private sector institutions have also developed models in recent years.

For this reason, there exists plentiful literature regarding the prediction of crises. Many approaches are used, including signal extraction, binary classification tree models, logit models, logit and signal extraction, logit and binomial trees, probit models, and Markov-regime switching models.

Early warning system models can offer substantial value to policymakers, allowing them to detect and predict underlying economic weaknesses, and possibly take proactive steps to reduce the risks of undergoing a crisis. By anticipating such risk, policy makers can change or modify policies and regulations. Also, investors can avoid substantial losses to their capital by avoiding risky markets if they feel the market has become overvalued compared to certain factors and indicators. In addition, investors can also benefit from undervalued markets if they anticipate a market boom is expected within a reasonable period.

2.3.2 Market Prediction Studies

The average person's interest in the financial markets has experienced significant growth over the last few decades. Securities worth billions of dollars are traded on stock exchanges every day, with investors acting on the market with the objective of making a profit in their investment portfolio. If a market participant such as individual, private, or institutional investor could forecast the behavior of the market accurately, this would enable them to consistently earn higher risk-adjusted returns (versus the average market return).

There are many studies that attempt to evaluate the effect of different macroeconomic, financial, and other variables on market trend or direction prediction. This section will discuss some studies that used the market index as the dependent variable to support our assumption that the market index can be used as a proxy for market prices.

This discussion will be followed by analysis of how some of the studies identified the bull and bear markets. In particular, this literature review will focus on studies that used parametric and nonparametric approaches to identify the bull and bear markets. Thirdly, since this thesis focuses on the parametric approach, different studies that used Markov regime-switching models and the advantages of using such models will also be evaluated. Finally, a selection of studies that focused on investigating the bear market trend will be examined, especially those that used macroeconomic and financial variables relevant to this study.

2.3.3 Relationship Between Stock Market Index/Returns and Macroeconomic and Financial Variables

Many studies focused on the effects of macroeconomic variables on a stock market index as well as stock market returns. Fama (1981) investigated the linkages between stock market returns, real activity, and inflation, and found a significant relationship between these variables. Mukherjee and Naka (1995) found that the Japanese stock market is cointegrated with six variables indicating a long-run equilibrium relationship between the stock market return and the study's macroeconomic variables (industrial production index, inflation, exchange rate, money supply, the long-term government bond rate and call money rate). Vani and Ray (2003) studied the relationship between macroeconomic variables and the Indian stock market. The study found that: interest rates, industrial production, money supply, inflation rate and the exchange rate have significant effects on stock prices. Gopinathan and Durai identified strong evidence of cointegration which indicates nonlinearity in the long-run relationship between macroeconomic variables and the stock market in India (Gopinathan & Durai, 2019). An earlier study explored studied the relationship between the New Zealand market and a group of macroeconomic variables (namely inflation rate, long term interest rate, short term interest rate, the real trade weighted exchange rate index, GDP, M1, and domestic retail oil prices) (Gan, Lee, Yong, & Zhang, 2006). This study found that NZSE40 is consistently determined by the interest rate, money supply, and real GDP. In their 2007 study, Brahmasrene and Jiranyakul examined the relationship between a stock market index and selected macroeconomic variables between pre and post financial crisis in Thailand (Brahmasrene & Jiranyakul, 2007). They found that money supply has a positive impact on the Thailand stock market index, while the industrial production index, the exchange rate and oil prices have a negative impact during the pre-financial crisis. Another study examined the relationship between the Karachi stock exchange index and macroeconomic variables and the results indicated that stock prices were positively related with money supply and short-term interest rates and negatively related with inflation and foreign exchange reserves (Akbar, Khan, & Khan, 2012). Meanwhile Naik and Padhi investigated the relationships between the Indian stock market index (BSE Sensex) and five macroeconomic variables (industrial production index, wholesale price index, money supply, treasury bills rates and exchange rates) (Naik & Padhi, 2012). Their research suggests that a long-run equilibrium relationship exists between the macroeconomic variables and the stock market index. The stock prices are positively related to the money supply and industrial production but negatively related to inflation. The short-term interest rate exchange and exchange rate are found to be insignificant in determining stock prices. In an investigation of the relationship between macroeconomic variables and abnormal returns in the Amman stock exchange, Al-Shubiri found the consumer price index, gross fixed capital formation and money supply to be statistically significant (AL-Shubiri, 2013). Alam investigated the relationship amongst the chosen variables: inflation, short term interest rate, money supply, crude oil price and oil price shocks on the capital market of KSA represented by Tadawul stock index (TASI) (Alam, 2020). The results suggest that a long-run equilibrium relationship exists between the KSA stock market and the selected macroeconomic variables.

The study also showed that there is a positive relationship between the money supply and the stock market. However, inflation, short-term interest rate, and crude oil prices showed a negative relationship. The findings implied the presence of both long-run and short-run unidirectional causality running from inflation, money supply, short-term interest rates, and the oil price shocks. In an exploration of the volatility transmission effect and conditional correlations among crude oil, stock market and sector stock indexes in Saudi Arabia, Almohaimeed and Harrathi found significant volatility transmission between oil prices and the Saudi stock market (Almohaimeed & Harrathi, 2013). In addition, sector stock return significantly reacts to oil prices changes. The results showed the presence of volatility transmission between the stock market and sector stock market returns, except for the telecom sector. Such results offer insights for Saudi stock market investors seeking information on how the value of their portfolios may be affected by large variations observed in oil prices.

Fama and French (1989) argue that dividend yield, default spread, and term spread are related to business conditions, and these variables are reliable predictors of future stock returns as these variables are high in strong economic conditions and low in weak economic conditions. Meanwhile, Bahrami *et al.* (2019) found financial variables such as book-to-market ratio and dividend yield to be important predictors of stock returns in both the low and high volatility regimes (Bahrami, Shamsuddin, & Uylangco, 2019).

Many of the previous studies have used time series analysis to evaluate the relationship between macroeconomic variables and stock market directions or trends. Most of them found that macroeconomics variables can affect the market direction in different ways. Some of the variables can affect the market within a short period of time and some might take longer to see their effect on the market direction (lag effect). Moreover, the magnitude of this effect may vary among the variables as some of the variables can have a significant effect and some could have a more moderate effect.

2.3.4 Identifying the Bull and Bear Markets Periods

Measuring stock market cycles and their cross-border synchronization is very important for regulators and investors. Investors will try to rebalance their positions depending on the expected market cycle by purchasing undervalued stock during or at the anticipated end of bearish periods and selling overvalued stocks during highly overpriced bullish markets that is expected to experience a downturn at any time. This suggests there are two key questions to ask. First, how can we predict the duration of such a cycle/regime? And second, how can we classify such a cycle?

There are many approaches to identify the bull and bear market periods. However, there is no consensus among the researchers on the exact states of bear and bull market (Candelon, Piplack, & Straetmans, 2008). Emerging markets are more obvious candidates for identifying changes in cyclical stock market synchronization due to the quick transformation of their financial systems and the periodic financial crises (Bekaert &

Harvey, 2000). The financial media usually focuses on the increase or decline of the market being greater or less than 20%-25% (Pagan & Sossounov, 2003). One approach is to classify a bullish stock market as having turned bearish if prices have declined for a significant period since their previous peak. For example, if the prices have declined for the last six months from the previous peak, then that period or window can be classified as a bearish stage. Such a definition does not exclude cycles of price drops/rises during a bull/bear period, but there are restrictions on the extent to which these sequences of price reverses can occur and yet still be considered part of any given bull or bear periods.

Let pt denote the log stock price i at time t (i = 1 ,,…, n; t = 1,….,T). Bull and bear periods are identified using the marginal transform ω (•). Such that $\omega(p_{it}) = S_{it\ (\forall i)}$ where S_{it} is 0 or 1 in case of bear/bear period, respectively. The main methodological approaches in the literature to determine ω (•) are the parametric and non-parametric approaches. Hamilton (1989) used a parametric two regime Markov-switching model on ω(•) that allows for bear and bull periods. The nonparametric dating algorithms locates the turning points (peaks and troughs) that resemble the local maxima and minima of the series. More complicated methods are also proposed to determine the stock market's cycles. Bry and Boschan offer one such approach, focusing on determining the stock market's turning points and, once the turning points are known, the bull (bear) periods can be identified as periods between troughs (peaks) and peaks (troughs), respectively (Bry & Boschan, 1971).

2.3.5 Identifying Market Trend Using Markov-Switching Model

Markov-regime switching models can be used to analyze the behavior of a time series disturbance by shocks that produce different dynamics, regimes, or states (Hamilton, 1989). The models are popular in stock market return analysis and can be used to identify recessionary or expansionary market states (bear or bull). Markov switching models have become increasingly popular in economic studies of industrial production, stock prices, interest rates, unemployment rates, etc. Markov-regime switching models are often used by researchers wishing to account for specific features of economic time series such as the asymmetry of economic activity over the business cycle (Hamilton, 1989). MS models belong to a general class of mixture distributions. Econometricians' initial interest in this class of distributions was based on their ability to flexibly estimate general classes of density functions and generate a broader range of values for the skewness and kurtosis than is available through use of a single distribution. Along these lines, Granger and Orr (1972) and Clark (1973) considered time-independent mixtures of normal distributions as a means of modeling non-normally distributed data. These early models, however, did not capture the time-dependence in the conditional variance found in many economic time series using ARCH models. By allowing the mixing probabilities to display time-dependence, Markov-regime switching models can be seen as a natural generalization of the original time-independent mixture of normal this feature enables them to generate a wide range of coefficient of skewness, kurtosis, and serial correlation even when based on a small number of underlying states. Regime switches in economic time series can be represented by Markov regime-switching models by allowing the mean, variance and possibly the dynamics of the series depend on the recognition of a limited number of distinct states. Timmermann (2000) has shown that Markov-switching models are highly appropriate for applications to economic time series, as they are able to comprise typical characteristics such as asymmetries, fat tails, autocorrelation, and volatility clustering.

The advantage of MS is that the causality linkages are not constrained to be constant across phases of the economic states, which means that the variables are allowed to affect the stock market differently in bear and bull periods. The mean of a regression model can be allowed to differ between recession and expansions. Therefore, by allowing the mean growth rate in a recession to be different from that in the expansion, we may be able to classify the market states as being in recession or expansion (bear or bull). The model can easily draw a probabilistic inference, given the data of time series. The inference used to distinguish the unobserved regimes is observed through the filtered state probabilities and the smoothing (using full sample) probabilities.

In their study, Bahrami *et al.* (2019) found that Markov-regime switching captures the effects of predictors on stock return more accurately when compared to models with time-invariant parameters, and the results show a significant forecasting ability. Also, they found that combining return forecast results from different Markov-regime switching models helps to improve predictability in advanced emerging markets.

Meanwhile, Just and Echaust used a two-regime Markov switching model to investigate the relationship between US stock market returns (S&P 500) and three indicators of the market, which includes implied volatility, implied correlation, and liquidity indices during the Covid-19 crisis (Just & Echaust, 2020). Short range dependence between both total Covid-19 cases and deaths in twelve countries and market movements were also considered. The MS model was used to find the structural break between stock market returns and the study indicators. The findings show close dependence between returns and both implied volatility and implied correlation, but not with liquidity.

In their study, Duprey and Klaus (2017) explored the prediction of phases of the financial cycle by combining a continuous financial stress measure in an MS framework. The results revealed that the debt service ratio and property market variables signal a switch to a high financial stress regime, while economic sentiment indicators and credit-to-GDP provide signals for a switch to a calm state. The in-sample analysis suggests that these indicators can provide an early warning signal up to several quarters prior to the respective regime change. The study concluded that by comparing the prediction results with a standard binary early warning model, the Markov-regime switching model is outperforming in most model specifications for a horizon of up to three quarters prior to the beginning of financial stress.

Using Markov-regime switching models, Bahloul *et al.* (2017) investigated the impact of conventional stock market returns, volatility, and some macroeconomic variables (including short-term interest rate, the slope of the yield curve, money supply and inflation rate) on Islamic stock markets returns for twenty developed and emerging markets (Bahloul, Mroua, & Naifar, 2017). The study covered the period from June 2002 to June 2014 for ten developed markets (USA, UK, Australia, Canada, Germany, France, Japan, Netherlands, Spain, Switzerland) and ten emerging markets (India, Chile, China, Korea, Czech Republic, Russia, Malaysia, Mexico, South Africa, and Thailand). The results show that both developed and emerging Islamic stock indices are influenced by conventional stock indices returns and money supply for both the low and high volatility regimes. The study used Markov-regime switching vector autoregressive model (MS-

VAR) to study the causation effects from these variables to stock market Islamic indices returns.

Comparing semi-parametric, rule-based ones, and parametric regime switching models, van Dijk and Kole sought to date past bull and bear market trends and to forecast the future state/trend of the stock market (van Dijk & Kole, 2013). Their study revealed that Markov-regime switching models are more appropriate than semi-parametric methods for forecasting. The study argued that the forecasts differ from those generated by semi-parametric because Markov-regime switching models focus on means and volatilities or fluctuations in market states or cycles. Markov-regime-switching models are also faster to select a switch between states. Rule-based methods need a longer time before they can signal a trend or cycle switch. In an investigation of the difference between rule-based and model-based methods for dating business cycles/trends, Harding and Pagan's research indicates that the main differences are the larger transparency for the rule-based approaches versus the deeper insight into the data generating process for the regime-switching models (Harding & Pagan, 2003). For a financial time series model, volatility is important and useful for forecasting.

The predictive ability of Markov-regime switching models as discussed in the previous studies supports our selection of these nonlinear parametric models to be used in our study to predict trends in the UAE stock market. The high fluctuation and volatility in ADX and DFM price indices are the main reason that led us to select Markov-regime switching models.

2.3.6 Bear Market Prediction Studies

The study of Chen (2009) used both parametric and nonparametric methods to identify bull and bear stock markets. The data was collected from US monthly returns of the S&P 500 price index from the year 1957-2007. Macroeconomic variables data were collected, and Markov-regime switching was used to get the filtered probability of market states (bear or bull). The macro variables included: Interest rate spreads, inflation rates, aggregate output, money stocks, unemployment rates, federal government debt, federal funds rates, and nominal exchange rates. All the macro variables were evaluated individually and the results showed that most of them were significant and useful to predict recession in US stock markets.

Nyberg (2013) used monthly US stock market data and similar macroeconomic variables that were used by Chen (2009), but added some financial data to predict US stock market direction (bull or bear). A nonparametric approach was used to identify the curve and turning points for bull or bear markets (peak and troughs). The study used both static and dynamic Probit models to check for prediction accuracy. The study concluded that market recessions and booms are predictable in both in-sample and out-of-sample tests. It also found that the Dynamic Probit model is a more accurate measurement of the market state when compared to the static model. Two significant variables were found to be good predictors of market state: Spread of long and short-term interest rates, and the dividend-price ratio.

Wu and Lee (2015) investigated the predictability of several simultaneous bear stock markets. Simultaneous bear stock market means, conceptually, that several different markets are in bear market simultaneously. The study covered ten developed markets: Belgium, France, Canada, Germany, Japan, Norway, Sweden, the UK, the Netherlands, and the US. The study examined a set of 11 US macroeconomic variables: relative 3-month treasury bill rate; relative money market rate; inflation rate; term spread; industrial production growth; narrow money growth; broad money growth; stock return; change in the unemployment rate; and the credit spread. The study concluded that the future severe simultaneous bear stock markets are predictable in all the in-sample and out-of-sample results from Probit models with one macroeconomic variable and with many macroeconomic variables. The inflation rate was the strongest predictor given a longer forecast horizon. Stock return and long-term government bond yields perform best given shorter forecast horizons.

Chen *et al.* (2017) examined the imperfect credit market as variables to check its ability to predict the bear market (Chen, Chen, & Chou, 2017). In addition to that, the study employed several macroeconomic and financial variables: earning-price ratio; dividend-payout ratio; stock variance; net equity expansion; book-to-market ratio; inflation; long-term yield; long-term return; term spread; default yield spread; and default return spread. The study used the Markov-regime switching model to identify bull and bear markets (two states). Filtered probabilities of the estimate of the probability of a bear market at time (t) was calculated. Also, the smoothing probabilities, which use all the information in the sample, were also computed for each state. The results showed that default yield spread provides superior out-of-sample predictability for bear markets one to three (1-3) months ahead. The external finance premium was found to be a significant indicator for predicting bear markets. Overall, the sample results show that most of the variables, including long-term government bond returns, stock variance, default yield spread and information, have a significant predictive power for bear markets. The study also tested the economic value of a regime switching trading strategy based on the prediction of bear markets out-of-sample performance and found that the switching strategy produced higher compounded (terminal value) return compared to buy-and-hold strategy based on a time-varying threshold (30%). The results demonstrate the usefulness and economic significance of predicting bear markets.

This study will build on Chen (2009) but modify it by adding more macroeconomic and financial variables found in the literature. Çakmaklı and van Dijk (2016) argued that using a limited number of individual macroeconomic variables over a long period is unlikely to predict return. Therefore, they used a wide range of macroeconomic variables and found a positive predictive ability for the monthly US excess stock return. Also, Paye (2012) considered many macro variables predictors in his study, whereby he argues that discarding this aspect can affect out-of-sample results. Therefore, this thesis will incorporate additional variables, supported by literature, that are assumed to be relevant to this study on UAE stock market trend prediction.

Chapter 3: Theoretical Framework and Hypotheses Building

3.1 Introduction

The previous chapter reviewed the literature related to this study's research idea, aim, and objective. This chapter uses well known theories to develop the central hypotheses based on the theoretical framework, namely the rational expectation theory (Muth, 1961) to develop the first hypothesis and the Arbitrage Pricing Theory (APT) to develop the second hypothesis. The rational expectation theory argues that the price of a stock depends on the individual evaluations of buyers and sellers trading in the financial market who base their decision on their human rationality. Human rationality is affected by the information available to them, and their experience. Therefore, the first hypothesis is that changes in the significant macroeconomic and financial variables are expected to affect the stock prices, and consequently, market indices.

To test the practicality of this proposition that the study variables can help to predict the market trend, we propose that investors who follow the predicted market trend and swing their portfolio following the model prediction will earn greater returns compared to investors adopting a "buy-and-hold" strategy. The study variables are discussed and explained briefly. To support the logic in selecting the variables, the relevant literature is presented. The study selected variables are Oil prices, Interest rate spreads (3M Treasury bills vs. 10Years Treasury bonds), Broad effective exchange rates of the UAE, Default rate spread (Baa bonds vs. 10-year Treasury bonds), KSA stock market index (TASI), and S&P 500 price index.

3.2 Predictive Ability

Investors are keen to predict market direction using the available information. The rational investor will search for relevant information to benefit from such predictions. In reality, not all investors who trade in the UAE stock markets possess the same level of marketplace literacy or financial expertise. Indeed, marketplace literacy is below the optimal level (Hassan Al-Tamimi & Anood Bin Kalli, 2009). Therefore, a reaction gap among investors who trade in the UAE stock markets is anticipated. This assumption is based on The Rational Expectation Theory (RET) that was first proposed by Muth (1961), which posits that investors analyze past events to predict future conditions. Investors monitor numerous factors that might affect stock markets directly or indirectly. If there are any sudden negative or positive events, the stock prices will move up or down depending on the effect on the future earnings of the companies, overall cash flows and discount rate. RET theory can support our proposition for the prediction ability in the UAE stock market. From the literature, there are many macroeconomic and financial variables that affect the market direction, but the market might not be in equilibrium due to the investor's rationality differences.

3.2.1 Rational Expectation Theory

The theory of rational expectations (Muth, 1961) describe the various economic situations when the outcome depends partly on market sentiment. For example, the price of a stock depends partly on what prospective sellers and buyers believe it will be in the future. The theory suggests that people base their decisions on three main factors: human rationality, the information available to them, and their past experiences.

The theory suggests that an individual's current expectations of the economy can influence what the future state of the economy will become. The main assumptions of the theory are:

1. People use their rationalization ability when making a decision.
2. On average, peoples' expectations will be fulfilled.
3. Rational expectations are the best prediction for the future outcome.
4. On average, people are right in their prediction and learn from past experiences and mistakes.
5. People behave in ways that help them to maximize their life satisfaction and their profits or return on investment.
6. People build expectations based on all available information.
7. People's predictions are close to market equilibrium.

If the predictive ability of the model outperforms market sentiment indicators, then there would be benefits to using the knowledge to profit from its predictive ability. Profit opportunities would not exist if the aggregate expectation of the people is the same as the prediction of the theory.

Investors try to predict what will occur because they have to make a better decision to make profits. The more accurate the prediction, the higher the profit. In a case when people have to predict a price over and over again, they adjust their prediction rules to reduce prediction error. They rely on their experience to form their current prediction.

Rabin (1998) argues that traditional finance theory assumes that investors will take rational decision when investing, but behavioral finance argues that investors will not be fully rational, and their decisions are influenced by several biases. There are biases in the judgment under uncertainty. For example, under-use base rates, inferring too much from too little evidence, and misreading evidence as confirming previously held hypotheses are example of such decision biases. There are psychological shreds of evidence confirming that people make systematic errors in their investment decisions. Investors might chase past trends to gain an abnormal return or behave irrationally by taking more risk.

Based on the Rational Expectation Theory and the literature findings discussed earlier, we would expect that a number of investors in the UAE stock market will exhibit suboptimal decision-making abilities that are not fully rational, which will, in turn, create opportunities to make profits in the stock market trading because the investors rationality might have systemic biases, incomplete or incorrect information, poor memory, etc. Based on all the above argument the following hypothesis is drawn:

H1: Macroeconomic and Financial variables have a significant ability to predict the bear market direction in the UAE stock market.

3.2.2 Practical Value of Predicting Bear Stock Markets

Predicting the market direction in this study, if applicable, can have a practical implication for investors. Investors can time their buying and selling positions. Long-term investors usually prefer not to get involved in daily or short-term trading. Instead, they prefer to adopt the strategy of “buy-and-hold” for a prolonged period and might not ever sell. Investors adopting the switching or swinging strategy change positions when anticipating that the market is entering a different cycle. One of the objectives of the study is to build a practical model that can guide investors to decisions that will lead to a gain from such knowledge and improve investment return when predicting the bear and bull market regimes probabilities.

Over time, there have been an increasing number of questions of the efficient market hypothesis and the fact that securities are priced rationally (Borovkova & Tsiamas, 2019). There have been several market irregularities such as the overreaction of financial markets and their underreaction (De Bondt & Thaler, 1990), the existence of long-term reversal, short-term momentum, and the high volatility of securities' prices (Daniel, Hirshleifer, Subrahmanyam, 1998) which represent support against the efficient market hypothesis (particularly in its weak-form).

This study assumes that it is possible to make a profit from the UAE stock market if one can predict the bear and bull markets ahead of time. This assumption is based on the Arbitrage Pricing Theory (APT) which was originally proposed by (Ross, 1976).

3.2.2.1 Arbitrage Pricing Theory (APT)

This theory is a multi-factor asset pricing model based on the idea that an asset's return can be predicted using the linear relationship between the asset's expected return and several macroeconomic variables that capture the systematic risk. The asset price today should equal the sum of all future cash flows discounted at the APT rate. The expected return of the asset is a linear function of several factors, and sensitivity to changes in each factor is represented by a factor-specific beta coefficient. Unlike CAPM, which assumes markets are perfectly efficient, APT assumes markets sometimes misprice securities, before the market eventually corrects itself and securities correct themselves to fair value. An asset is mispriced when its current price diverges from the price predicted by the APT model. Arbitragers can make positive return from overvalued or undervalued securities in an inefficient market without any incremental risk and zero additional investment. The arbitrager can sell the assets which are relatively overvalued and uses the proceeds to buy undervalued assets. APT factors represent the systematic risk that cannot be reduced by the diversification of an investment portfolio.

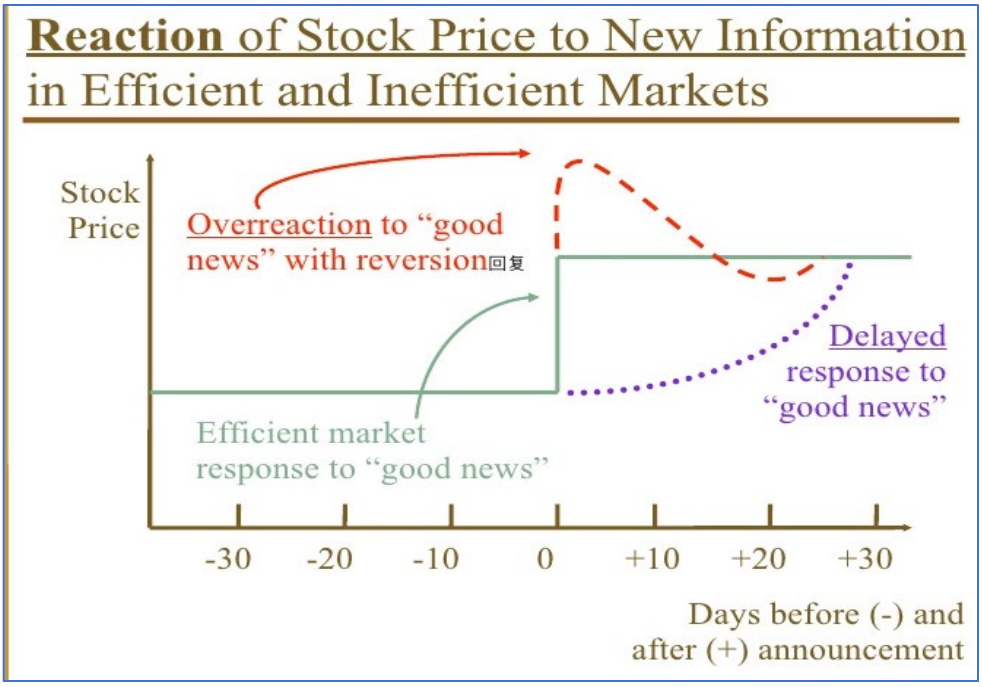

Figure 3.1: Reaction of Stock Price to New Information in Efficient and Inefficient Markets

From Figure 3.1, we can see the reaction differences to news and information. In a less efficient market where retail investors make up a significant portion of the investor pool, the reaction to information differs among investors based on education and interpretation. The market might overreact or underreact to information. However, eventually, the prices correct themselves to their fair prices. The assumption is that there are opportunities in the UAE market due to these over/underpriced conditions. Therefore, the hypothesis is constructed on the grounds that if the market direction can be anticipated ahead of time using the study variables, then investors will benefit from such predictions.

If H1 is supported, the usefulness of the UAE market prediction models will be evaluated by conducting a simple test to compare the expected profit of a switching strategy versus a benchmark buy-and-hold strategy, assuming no transaction costs. The switching strategy is adopted by selling the holding position (i.e., market index fund) at the beginning of the bear market regime. The selling proceeds will be re-invested in a short position. Short selling involves borrowing a security whose price is expected to fall and selling it on the open market. Expecting to buy it back at a lower price and take the difference after repaying the initial loan. Once the bear market probability ends, the short position will be closed and the proceeds will be invested again in a new position in the market (market index fund) by buying at the beginning of the bull market as so on. If the macroeconomic and financial variables are reliable predictors of a market regime, and the regime classification can reasonably identify and classify the bull and bear regimes start and end date, then we can draw the following hypothesis:

H2: The terminal value of a USD 1 million investment in a portfolio would hypotheticall yield a higher end value with a switching strategy as opposed to a traditional buy-and-hold strategy.

3.3 The Study Variables

3.3.1 Macroeconomic Variables

Changes in macro variables levels can have significant consequences on the general level of economic activity and on the aggregate stock market volatility. Theoretically, the value of a firm's stock should equal the expected present value of the firm's future cash flow, and the future cash flow is dependent on the performance of the firm. Additionally, the performance of the firm is dependent on the changes in different variables including the macroeconomic variables of a country or the global market. Therefore, a change in any macroeconomic variable could potentially affect stock prices.

The objective of this study is to understand if the market reaction to macroeconomic conditions and financial variables can be predicted. We used some of the macroeconomic variables used by Chen (2009), but added additional variables that we assume to be significant factors in the UAE stock market trend. Hadhri and Ftiti (2017) examined the return predictability in twenty-four emerging markets, including the UAE stock market. The study defeated the notion that considered a standard model of asset return predictability for all countries. Each country has specific domestic macroeconomic and financial variables that are useful to predict future stock market returns. Using macroeconomic variables, especially from the US economy, is widely known and referenced in the literature. The US interest yield offers an example of this; in their 2013 study, Rapach *et al.* examined the lead-lag relationships among monthly country stock returns and found that lagged US returns significantly predict returns in different non-US industrialized countries even better than the countries' economic variables, including lagged nominal interest rates and dividend yields (Rapach, Strauss, & Zhou, 2013). On the contrary, lagged non-US return has limited predictive ability with respect to US returns. Maghyereh (2022) examined the spillover effects of the USA economic policy uncertainty (EPU) on the UAE stock market volatility. The results indicate that the effect of EPU on the volatility of UAE stock markets is time-varying and that impact is stronger and synchronous with the financial crisis and geopolitical turbulence periods.

The study variables:

1. Interest rate spreads (10-year Treasury bonds minus 3-month Treasury bills).
2. Broad effective exchange rate for the UAE currency.
3. Default rate spread (Baa bonds vs. 10-year Treasury bonds).
4. Crude Oil price (Oil).
5. KSA stock market index (TASI).
6. S&P 500 price index.

1. Interest rate spread (10-year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity)

The interest rate spread is an indicator of economic growth that has been extensively researched in the literature. Much research has been done using long-term (10-year) Treasury Bonds and short-term (3-month) Treasury Bills (T-Bills). The spread in the yield curve is the difference between the yield of a 10-year bond and a 3-month bill. The spread has been found to contain information that is helpful to predict macro-economic factors such as inflation, industrial production, consumption, and recessions. Several different researchers have tried to establish a horizon for the forecasting ability of the yield spread. Estrella and Mishkin (1998) found that the yield spread outperforms other predictive variables in a one-on-one comparison for horizons beyond one quarter. Bernard and Gerlach (1998) studied the ability of the term structure to predict recessions in eight European and North American countries. The results suggested that the yield curve predicts future recessions in all countries. Second, term spreads forecast recessions as much as two years ahead. Third, US and German spreads are frequently significant in the regressions for some countries. Fourth, while leading indicators contain information beyond that in term spreads, this information is only useful for forecasting recessions in the immediate future.

The yield curve is a tool used in explaining the term structure of interest rates. Wheelock and Wohar (2009) argue that the yield curve's ability to predict the state of the economy depends on the Federal Reserve's monetary policy regime. As per the segmented market theory, the inverted yield curve occurs due to contractionary monetary policy, but the expectation hypothesis hypothesizes that higher short-term interest rates cause an economic slowdown by reducing aggregate investment (Brandl, 2020). Historically, the spread has shown a great ability in predicting future macroeconomic direction and could be beneficial as an economic predictor for investors and regulators. The term structure of interest rates is the relationship between the yield to maturity for bonds with different times to maturity. The normal term structure of interest rates is an upward-sloping yield curve indicating that long-term bonds yield higher interest rates than shorter-term bonds. The contrary is an inverted yield curve with a downward-sloping trend. This occurs when the short-term interest rate is higher than the long-term interest rate and is usually interpreted as a sign of a looming recession. In our study we will use the Long-Term spread (10 years-3Months) = The difference between the 10-year treasury constant maturity rate and the 3-month Treasury bill rate.

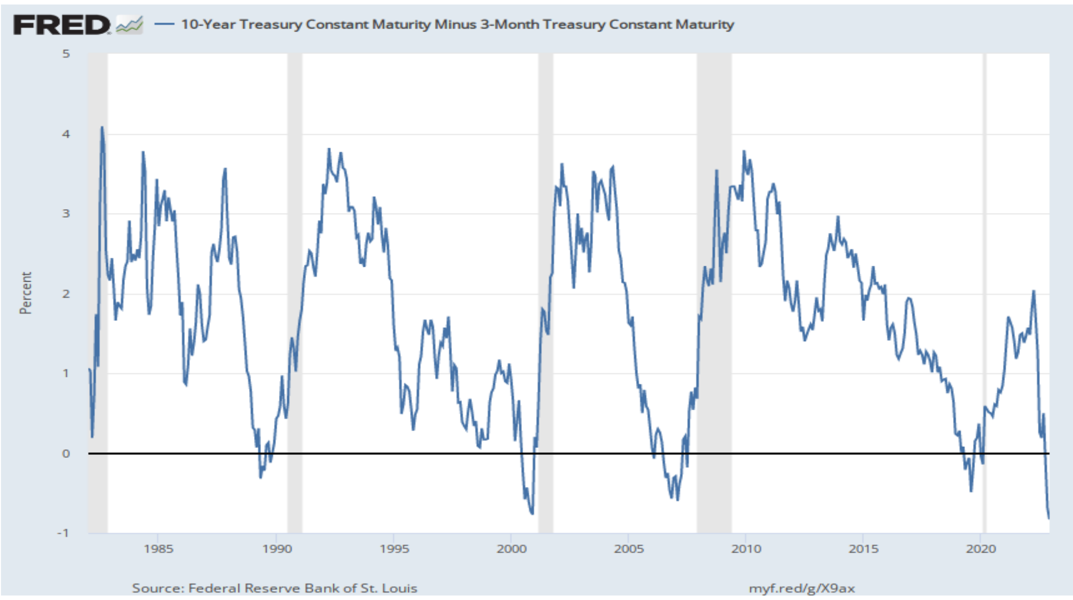

Figure 3.2: United States 10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity

2. Broad Effective Exchange Rates for the UAE Currency

The rapid expansion in international trade since the 1970s, and the adoption of freely floating exchange rate regimes by many industrialized countries signaled a new era of increased exchange rate risk and volatility as the economic exposure of firms to exchange rate risks has increased. Exchange rates are also more sensitive to global portfolio investments because the rapid integration and deregulation of global financial markets has made the capital flows across borders easier and faster than ever before. The link between exchange rate fluctuations and stock markets has captured the interest of both regulators and investors as it plays a significant role in the development of an economy through investment decisions and market attractiveness. The relationship between exchange rates and stock prices is bidirectional. There are two approaches to explain the relationship between exchange rates and stock market prices. According to the goods market approach (traditional approach/flow-orientated approach), changes in exchange rates affect stock prices. A depreciation of the home currency makes exports cheaper, leading to an increase in both price competitiveness and the earnings of the export-oriented firm, hence the firm benefits from a depreciation of the home currency. In this case, the exchange rates affect stock prices positively. The second approach is the portfolio, or the stock-orientated approach. In this case, the stock prices affect exchange rates via portfolio adjustments. A decline in stock prices will lead to a reduction of the wealth of the domestic investors and thus, demand for money will fall and interest rates will decline, causing capital outflows and leading to depreciation of the home currency. In this case, the stock prices affect exchange rates negatively.

Wong (2017) examined the relationships between real exchange rate returns and real stock price returns in Malaysia, the Philippines, Singapore, Korea, Japan, the United Kingdom (UK) and Germany. The study showed that real exchange rate return and real stock price return are found to be negative and significant for Malaysia, Singapore, Korea, and the UK whereas to be insignificant relationships for the Philippines, Japan, and Germany. Overall, the exchange rate markets are important in affecting the stock markets.

The UAE currency (Dirham) is pegged against the USA currency (Dollar) which makes it very attractive for international investors who prefer to avoid currency fluctuation associated with unknown or unpredicted factors. Figure 3.3 shows the Dirham broad effective exchange rate from 1994 to 2022.

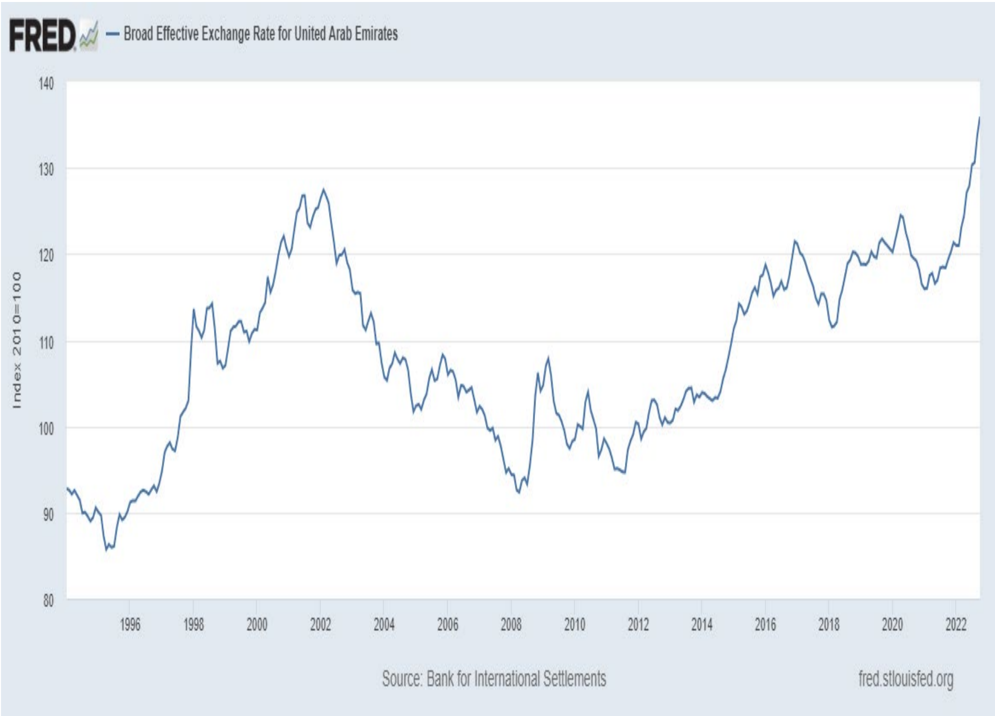

Figure 3.3: Broad Effective Exchange Rate for the United Arab Emirates

3. Default Yield Spread (Baa Bonds vs. 10-Year Treasury Bonds)

The Moody's Seasoned Baa Corporate Bond Yield is a good indicator of general business conditions that can capture the effect of business cycle variation on stock market return (Welch & Goyal, 2008). The indicator assesses the yield on corporate bonds that are rated Baa and measured by Baa-rated US corporate bond yields minus US 10 years treasury bond yields. Corporate bonds are rated based on their default probability, strength of the corporation's debt structure, as well as the overall health of the economy. An AAA bond is the top of the pile; the AAA bond rate is also known as the prime rate. This bond comes with high confidence of repayment including interest rate, and the risk of default is low. The Baa rating is considered investment grade; however, it is only one grade above a junk bond rating. A bond rated Baa may be at the bottom of this category, meaning it offers a higher return for higher risk, but both bonds fall into the investment-grade classification, meaning the likelihood of bonds paying out true as expected is high enough to achieve this rating.

Within Moody's ratings, Aaa bonds and Baa bonds represent opposite ends of the spectrum of bonds included within the investment-grade category; they are both bonds that are recommended based on security and risk. The difference in yield between an Aaa bond (the top of the investment grade) and a Baa bond (at the bottom) represents a yield spread or yield grade. A higher yield spread implies a recession, as investors switch to the more guaranteed returns on Aaa bonds. According to Kwark (2002) the interest rate spread between risky loan rates and risk-free rates has indicated high predictive power for subsequent fluctuations in real output. During the financial crisis in 2008-2009 (sub-prime), the spread between Aaa and Baa bonds widened because of the unpredictability of bonds and increased default rates.

4. Oil Prices

Oil production revenue plays a significant role in the UAE economy that witnessed substantial growth since the discovery of oil. It is generally believed that economic and financial performance in oil-rich countries is interlinked to oil price movements.

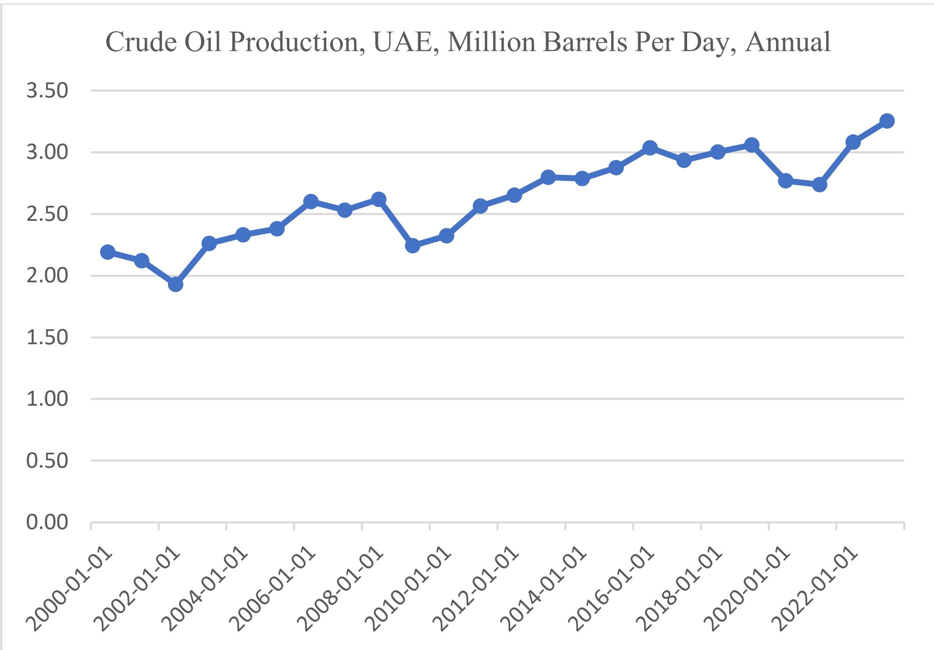

Figure 3.4: Crude Oil Production, UAE, Million Barrels per Day, Annual

The fluctuation in oil market prices affects the country's revenue and expected future growth (Figure 3.4). The collapse of oil prices could have a significant effect on the economy. Evidence suggests that oil prices can affect the stock market movement. Arouri and Rault (2012) found evidence for cointegration between oil prices and stock markets in GCC countries. Maghyereh and Al-Kandari (2007) found that oil price levels influence stock markets in GCC countries in a nonlinear fashion. Balcılar et al. (2017) examined the time-variation in the level of herding in the GCC stock markets by using a Markov switching time-varying parameter herding model and found that investors in GCC markets take the speculative signals from the oil markets as a sign of positive expectation in oil prices and try to use these signals by investing into the stock market hoping to make higher profits (Balcılar, Demirer, & Ulussever, 2017). The findings suggest that speculative signals from the oil market can have predictive ability over the investors' trading behavior in energy sensitive GCC stock markets.

Wang (2021) investigated the effects of oil price shocks on the local banking businesses in all counties in the United States. Exposed banks with significant business in oil-concentrated counties witnessed a decline in demand deposit, a rise in distressed loans, and a rush in credit line reduction. Al-Khazali and Mirzaei (2017) investigated the impact of oil prices shocks on bank non-performing loans (NPLs), and whether the effect is homogenous across banks. They used data from 2310 commercial banks in 30 oil-exporting countries over the period 2000–2014. The study revealed changes in oil prices do have a significant impact on bank NPLs as a rise (fall) in oil prices is correlated with a decrease (increase) in NPLs. Second, oil prices shocks have asymmetric effects on bank trouble loans, with negative oil price changes mostly have a greater impact than positive oil price changes. Third, the negative impact of adverse oil prices shocks on the quality of bank loans tends to be more evident in large banks.

Banks are major lenders to commercial and retail customers who invest in different sectors including the stock market in the UAE. When oil price shocks affect bank liquidity and appetite for lending, the bank pressure causes investors to liquidate investment to avoid bank pinches.

The relationship between oil prices and stock market movements indicates that oil prices can be used as predictor of market trends.

3.3.2 Other Stock Market Indices and Financial Variables

The access to the UAE stock market is quite easy and the market is open for all types of investors. The transaction in the stock markets is relatively thin compared to the UAE GDP. The fluctuation in the important regional and international stock markets might affect the UAE stock markets as well. We choose the KSA (TASI) market index and the USA S&P500 market index as important predictors of the UAE stock market trend.

5 & 6. USA S&P 500 and Saudi Tadawul Indices

The fluctuation in the neighboring KSA stock market (TASI) as well as international markets affects the UAE stock market, and it can be reflected in its stock market indices. There are many studies regarding the spillover effect. Nguyen and Ngo (2014) found that Asian emerging markets, compared to Asian developed markets, respond stronger to the USA macroeconomic news in terms of extent of the reaction and number of responses. Such findings suggest that emerging stock markets are affected by the US stock markets. Istiak and Alam (2020) found that unexpected increases in the US economic policy uncertainty significantly decreases the stock market indices of the GCC countries. The GCC indices increase and decrease by the same amount when the US economic policy uncertainty decrease and increase, respectively. Information movements and macroeconomic linkage across the GCC are important factors of cross patterns among those markets. Factors such as trade and customs relationship, direct investment, tariff, taxation, interrelated portfolios, monetary and fiscal policy arrangement, and exchange rate play significant role in that pattern. Oil price volatility can have a significant impact on the market spillover across the GCC stock markets. Therefore, GCC markets as a group often behave similarly but to varying degrees during normal and crisis periods. Khalifa *et al.* (2012) examined the volatility transmission across the GCC stock markets and the linkage between them and US stock and oil prices using the Markov-regime switching model (Khalifa, Hammoudeh, & Otranto, 2012). The findings revealed strong interdependence between the oil price, US Standard and Poor's 500 index, KSA and ADX, and interdependence with DFM.

Ziadat *et al.* (2020) found significant return and volatility spillovers from the European Union and the US to the GCC markets, with greater spillovers from the European Union (Ziadat, Herbst, & McMillan, 2020). Intra-regionally, the UAE is the main transmitter and receiver of spillovers between the GCC and globe markets. Benlagha and El Omari (2022) identified several economic and financial variables that significantly contribute to explaining the dynamic patterns of dependence among Qatar stock market index and some selected stock markets. These variables consist of: the returns of the Qatar stock market, gold prices, crude oil prices, the movement volatility of the USA S&P500 index, and the world economic policy uncertainty index. The results obtained show that the fluctuations in these variables significantly affect the structure of dependence between the study stock markets.

Chowdhury (2020) found that the KSA stock market and UAE stock market are well integrated and any shift in sentiment in one of them will affect the other market. Alfreedi (2019) found a positive correlation between GCC markets indicating the presence of a common factor driving the markets in the same direction. He found that UAE stock market is significantly affected by spillovers (shocks, return, and volatility) from developed markets. Hatemi-J (2012) assessed the degree of integration or segmentation of the UAE stock market with the USA stock market by conducting new causality tests developed by Hatemi-J that separate the effect of positive shocks from the negative ones. The results based on standard symmetric causality tests showed that the UAE market is segmented from the USA stock markets. However, when the asymmetric causality tests are applied, the results revealed clearly that the UAE market is integrated with the USA market. These results show, in addition, that the degree of integration is stronger when the markets are falling than when they are rising. Based on the earlier findings we assume that this variable (external factor) to be a good predictor in this study which will also use the KSA stock market index and S&P 500 price index to assess if they influence the UAE market direction and prediction. Based on the literature review the expected signs of the chosen variables are:

- Negatively correlated with: Interest rate spreads (10-year Treasury bonds minus 3-month Treasury bills), Default rate spread (Baa bonds vs. 10-year Treasury bonds).

- Positively correlated with: Broad effective exchange rate for the UAE currency. Crude Oil price (Oil), KSA stock market index (TASI), S&P 500 price index.

Discrepancies might occur between the expected sign and the actual sign produced by the models. The discrepancies are expected because the lead or lag effects are not accounted for. Change in one variable might not necessarily cause immediate change in the dependent variable. The study did not investigate the lead and lag effect. Also, this study did not investigate any asymmetric effect of the variables in both market states, as the same variable might have light or moderate effect in the bull market but can have a severe effect in the bear market or vice versa.

3.4 The Study Hypotheses

The study hypotheses were discussed earlier and built on an underlined theoretical framework. In summary, these are the study hypotheses:

H1: Macroeconomic and financial variables are significant predictors of bear market directions in the UAE stock market.

H2: The terminal value of a USD 1 million investment in a portfolio would hypothetically yield a higher end value with a switching strategy as opposed to a traditional buy-and-hold strategy.

Chapter 4: Research Methodology

4.1 Research Paradigm and Theoretical Framework

The research is following the positivism paradigm using quantitative approach. Secondary data was collected and analyzed using econometric models to arrive at findings. Literature review led to building theoretical framework and deductive justification for the study hypotheses and findings.

Two theories are used to underpin the study hypotheses, assumption, and findings:

1. Rational Expectation Theory (RET) (Muth, 1961).
2. Arbitrage Pricing Theory (APT) (Ross, 1976).

Particularly, the research started with the development of research hypotheses based on theoretical background and literature review. Later, the appropriate data sample was collected and econometric analysis used to compute the results. The results were interpreted and assessed, and conclusions produced regarding the overall findings, implications, and recommendation.

4.2 Research Method

4.2.1 Study Data

The study uses a sample of time series data obtained from various sources. The price index movement in Abu Dhabi Securities Exchange (ADX) and Dubai Financial Market (DFM) were collected from the Bloomberg data stream. The stock market price index is used as the dependent variable (y) for each market separately. The stock market price index is used as a substitute for all stock prices, as the assumption is that the prices of all or most stocks listed in the market are represented in the stock market price index proportionally. Therefore, the price index was selected to present the stock prices that interact with the chosen study variables. The justification for using the market price index was based on similar studies that used the market price index in their studies. These studies were presented and discussed earlier in the literature review section. This study covers the period from January 2004 till August 2022. The selection sample is from January 2004 to August 2022. Both ADX and DFM started trading in 2000. However, due to the low transaction value and the unavailability of some of the study variables prior to 2004, the beginning of 2004 is denoted as the start of the study sample. All variables were collected on a monthly basis. The total number of sample observations is 224.

The study variables are:

The dependent variables (y):

- ADX = Abu Dhabi Securities Price Index
- DFM = Dubai Financial Market Price Index

The independent variables (x):

- Oil price = Global Price of Brent Crude, USD per Barrel
- Baa_10YT = Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-year Treasury Constant Maturity
- B_Exch rate = Broad Effective Exchange Rate for United Arab Emirates currency.
- T10_3M = 10-year Treasury Constant Maturity Minus 3-month Treasury Constant Maturity
- S&P500 = USA S&P500 Index
- TASI = Saudi TADAWUL All Share Index

4.2.2 Data Collection Sources

This study used monthly data from January 2004 to August 2022 on the DFM and ADX price indices. The time span is selected based on the availability of the data. The study uses secondary data collected from public sources. The data type is numerical. The macroeconomic and financial variables were collected from Bloomberg, and Federal Reserve Economic Data (FRED). The researcher visited the ADX and DFM head offices to collect price index and transaction data and any related information regarding the current and historical events. financial information was extracted from the financial reports published by ADX, DFM, and ESCA.

4.2.3 Market Experts and Analysts' Opinion

Markey expert and analyst opinion was obtained regarding the historical events witnessed during the 18-year study period. Their opinion and explanation helped to find answers for this investigation regarding the major events that affected the market index movement.

4.3 The Data Analysis Method and Processes

Since the UAE has two different stock markets, separate analyses for ADX and DFM will be run. The analysis will be done following these main steps.

1. Conduct the descriptive statistics analysis, and Unit root test.
2. Compare and contrast each variable graph with the independent variables (ADX, DFM) to identify movement resemblances.
3. Identify bull and bear regimes and duration.
4. Apply different prediction models and analyze the data accordingly.
5. Conduct out-of-sample tests to check for the robustness of our results.
6. Calculate the investment gain (losses), if any, by comparing the end portfolio profit (losses) generated using the two investment strategies, namely the "switching" strategy and "buy-and-hold" strategy. If the value of the "switching" strategy is significantly greater than the value of "buy-and-hold" strategy, then the second hypothesis (H2) is supported.

4.3.1 OxMetrics Program and Data Input

The OxMetrics program (version 9.05) was used as the econometric analysis program. A separate file was created that includes all the study variables. In the file dataset, separate columns were created for each variable and given a short name. There are a total number of eight variables, which include two dependent variables (ADX, DFM) and six independent variables, mentioned earlier.

4.3.2 Markov-Regime Switching Models

Parametric dating method is based on Markov-regime switching model, introduced in economics by Hamilton (1989). This methodology has been used in various to identify bulls and bear regimes in order to study the volatility dynamics and make portfolio investment decisions studies (Chen, 2009; Hamilton & Lin, 1996; Maheu & McCurdy, 2000).

This study relies on the Markov-regime switching to identify the two (or more) market states (regime classification) and compute the filtered probability and smoothing probability as well. The Markov-regime switching approach is preferred due to its specialized ability and software program availability.

The advantages of such an approach were discussed in the literature review section.

To build the basic Markov switching model, the same approach used as that employed by (Candelon, Ahmed, & Straetmans, 2014),with a minor modification to represent the use of the ADX or DFM price index instead of the return of price index:

Let t represent the stock market index, calculated as the change of the price index, Y_t, i.e., t = 100 × (Y_t/Y_{t-1}). Let st = i denote one of the two states of the variable, i.e., bear (st = 1) or bull (st = 0) market. Then a two-state Markov-regime switching model, where both mean µst and variance-covariance **Ω**st vary with state st, is given by, t = $\mu s_t + \varepsilon_t$, $\varepsilon_t \sim$ i.i.d. N (0, Ωst). The state variable st is assumed to be controlled by first order Markov chain process whose fixed transition probabilities, pij , are given by: $P\{s_t = j|s_{t-1} = i\}$ = pij ∀i, j = 0, 1. specifically, p11 = $P\{s_t = 1|s_{t-1} = 1\}$ denotes the probability of starting in a bear state and ending up in the same state and p00 = $P\{s_t = 0|s_{t-1} = 0\}$ likewise is the probability of bull state given that prior state was also a bull. The persistence of a regime can be thus computed as $1/(1 - p_{11})$ for bear market and $1/(1 - p_{00})$ in case of bull state. The probabilities and the parameters are estimated via maximum likelihood. We consider filtered probabilities, which represents the inference about the state variable, st, given information up to time t, i.e., P r(st = i|t).

And the models will be:

Model 1: Constant

Y = Constant (0,1) + β Oil + β S&P 500 + β TASI + β Baa10YM + β B. Exchange Rate + β T10Y3MM + ϵ

Model 2: Trend model

Y = Constant (0,1) + β Trend + β Oil + β S&P 500 + β TASI + β Baa10YM + β B. Exchange Rate + β T10Y3MM + ϵ

Model 3: Three-regime

Y = Constant (0,1,2) + β Oil + β S&P 500 + β TASI + β Baa10YM + β B. Exchange Rate + β T10Y3MM + ϵ

4.3.3 Descriptive Statistics Analysis

From the OxMetrics program, the descriptive statistics option was selected to evaluate the variable's means, standard deviations, and correlations. Also, we opted to evaluate the unit root to check if the data is stationary or nonstationary. The Augmented Dickey-Fuller (ADF) test was used to check and evaluate whether the data is stationary or nonstationary.

4.3.4 Regime Classification – Identifying Bull and Bear Markets

Once the market indices were selected (DFM and ADX, as well as the other variables entered in the OxMetrics file), we selected "Models for time-series data" ➔ "regime-switching models" ➔ select the variables ➔ enter the variables and select the options, based on the analysis/model required. The results are presented in the "Results," "Models" or "Data plot" outputs.

The model, based on the selected criteria, identifies the bull and bear market periods (y = (bull = 0, bear = 1)) using the parametric approach in Markov-regime switching model.

In this study, the parametric approach is used because of its ability to quickly generate results given the appropriate parameters. The use of a parametric approach has been supported in the literature to provide reliable results.

4.3.5 Prediction Models/Analyses

Once the regime classification (bull and bear) and duration are identified, we will venture to explain:

1. The regime classification is based on the smoothed probabilities table generated using Markov regime-switching models.
2. The predictive power of each variable, which will be measured by the t-statistic corresponding to the variable.

Other models' parameters will be looked at and evaluated, such as sigma and the transition probabilities.

4.3.6 Logit Model

Binary logit regression is used when the response variable (bull, bear) is categorical with two categories (bull = 0, bear = 1). This logit model allows the calculation of the probability of the dependent variable given the set of our study (explanatory) variables.

The naïve approach of calculating the market trend (bull = 0, bear = 1) based on the index movement for each month was assessed. This is a simple nonparametric approach. If the index in month t > month t+1, then the value of month t+1 will be (1 = bear). If the index in month t < month t+1, then the value of month t+1will be (0 = bull).

To build the model, the dependent variable in the logit model is considered to be the odds ratio, which is another way of expressing probability.

Odds ratio (y) = probability of event / (1- probability of event) and the model will be:

$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \beta_k x_k + \epsilon.$

We will calculate all the values of our index movement direction (bull = 0, bear = 1) and run the binary data in logit model available in the OxMetrics program to test the model predictive ability. Our approach is explanatory. We tried to resemble the naïve investor perception of the market given the monthly movement of the index.

4.4 Robustness (Out-of-Sample Test)

It is well known that a model with a good in-sample prediction does not necessarily perform well when using out-of-sample observations. Also, there might be a look-ahead bias in the in-sample estimation using the full sample. Therefore, both in-sample and out-of-sample tests will be conducted to assess the predictive power of the study variables.

This test will be conducted by setting the in-sample period from January 2004 till August 2017. The out-of-sample period will be from September 2017 to August 2022. The results of the in-sample model(s) will be compared and the predictive abilities of the study variables will be assessed by comparing the t-statistic. Model (A) is the model which covers the period from 1/2004 – 8/2017 and model (B) is the one which covers the period from 9/2017 – 8/2022. It is assumed that both models will have many similar results regarding the predictive ability.

The out-of-sample results and the forecasting graph will be assessed to evaluate the projected forecast and the actual index value. To test the forecasting accuracy, the Mean Absolute Percentage Error (MAPE) test will be used.

The mean absolute percentage error (MAPE) is the most common measure used to forecast error, and that is most likely because the variable's units are scaled to percentage units, which makes it easier to understand. It works best if there are no extremes to the data (and no zeros). MAPE returns error is used as a percentage, which makes it possible to compare values across different datasets and models. No adjustments are required to compare these values making it easy to understand the "goodness" of the error value. The goodness of MAPE score depends on the used case and dataset but, in general, the following values can be considered:

MAPE (%)	**Interpretation**
<10	Very Good
10–20	Good
20–50	Ok
>50	Not Good

The formula to calculate MAPE is as follow:

Step 1: Calculate the forecast error: positive or negative

Forecast error = | actual – forecast |

The bars represent using the absolute value, meaning the outcome of the equation will always be positive as the forecast error focuses on the magnitude of the error only.

Step 2: Forecast error percent

= [(| actual – forecast |) / | actual |] × 100

The forecast error % represents the accuracy of the forecast. If the forecast error percentage is close to 100%, this indicates the forecast is totally or very inaccurate. On the contrary, if the forecast error % is closer to 0%, this implies the forecast is accurate.

Step 3: Calculate MAPE

MAPE = (1/ sample size) × Σ [(│actual – forecast│) / │actual │] × 100

4.5 Applicability (Hypothesis 2) Test

To investigate the economic value of predicting stock market trends, a simple calculation is needed to compare the market value of the investment using the two investment strategies:

4.5.1 Buy-and-Hold Strategy

The first investment strategy is the typical benchmark "buy-and-hold" strategy where the investor buys the stock at the beginning of the study period (1/2004) at the index value and holds the investment position perpetually (theoretically). In this study, it is assumed that the stock price is the index value. It is further assumed that the investor bought certain units of the index on 1/1/2004 at a cost of USD 1 million (p_1). The index on 1/1/2004 was around 1757 for ADX and 1000 for DFM. These starting points are used as the base index (i_0). If the index was on any given time 'x,' then the index value will be (i_x). The percentage (%) growth in the original investment (positive or negative) would be:

Growth (g) = $((i_x – i_0) / i_0) * 100$

The profit (losses) from the investment will be.

Investment profit = Value at the end of the investment $_{\text{(index value 8-2022)}}$ - value at i_0 $_{\text{(index value 1-2004)}}$

4.5.2 Switching Strategy

This strategy assumes that the investor buys and sells depending on their future expectations regarding market trends. The future expectation in this study is based on regime classification of the best fitted forecasting model. It is assumed that the investor will buy on 1/2004 and maintain the "long" position until the end of the bull regime and liquidate the position at that time. After that, the investor will take a “short” position at the beginning of the bear regime and hold the short position till the end of the bear regime and liquidate the position again. Once the investor believes that the bearish market state is ending based on the regime classification indications, s(he) will liquidate the “short” position and use the sell proceeds to enter (buy) a “long” position again in the next bull period, and so on until the last regime. The value of the portfolio is calculated at the end of this switching or swinging strategy to arrive at the value and profit (losses) of adopting such a strategy.

In H2, it is assumed that the beginning portfolio value to be USD 1 million. Therefore, the terminal value of a USD 1-million fund invested at the beginning of the study (January 2004) that is kept as a long-term investment (buy-and-hold strategy) over the study period (around 18 years) will be compared with the accumulated fund value generated using the switching strategy. If the results show that the return on investment using the switching strategy is significantly higher than benchmark buy-and-hold strategy, then H2 will be supported.

Chapter 5: Empirical Results and Analyses

5.1 Introduction and Chapter Objective

This chapter presents the results of all the tests conducted to evaluate whether the results are significant and consistent with our theoretical assumption and hypotheses. In the testing process the following actions were performed:

1. Plotted and analyzed ADX and DFM price index movement over the study period and identified the major events that affected the stock market and consequently the stock market price index movement. There were several major events that can be classified as "bubble burst" effect in 2005-2006 and the subsequent crash in 2008 due to the US sub-prime crisis which affected most of the international markets. Also, there was a market boom in 2013-2014 and a sharp drop in March 2020 due to covid-19 pandemic negative market sentiment.
2. Plotted both markets (DFM and ADX) index movement and compared their trend and movement relative to each other.
3. Plotted and analyzed each market index movement with each variable to examine and compare both variables' movement, resemblance, direction, and correlation relative to each other.
4. Assessed the descriptive analysis and unit root test for all variables.
5. Conducted parametric tests to find the regime classification to identify the bull and bear markets.
6. Ran the appropriate models (Constant, Trend, Three-regime) to check if the selected variables are statistically significant predictors of the market direction and check the relevant parameters of the results generated.
7. Compared the results of all tested models.
8. Checked the model robustness by testing the out-of-sample results.
9. Tested the binary logit model using the naïve approach and assessed the results.
10. Tested the second hypothesis (H2) by comparing the accumulated investment value at the end of the investment period for "buy-and-hold" vs "switching" strategies.

5.2 Descriptive Statistics

All variables are analyzed to evaluate the descriptive statistics such as means, standard deviations, correlations, normality, and other tests as shown in Table 5.1. The data distribution is nonlinear for all the variables, and this is the main reason that this study uses the nonlinear Markov-regime switching models. The correlation matrix shows a noticeable correlation between the dependent variable and some of the independent variables.

Table 5.1: Descriptive Statistics

Means, standard deviations and correlations

The sample is: 2004(1) - 2022(8) (224 observations and 8 variables)

Means

	DFM	ADX	Oil	S&P500	TASI	BAA10YM	B Exch Rate	T10Y3MM
	3134.2	4192.1	73.606	1992.2	8323.6	2.5278	108.58	1.6385

Standard deviations (using T-1)

	DFM	ADX	Oil	S&P500	TASI	BAA10YM	B Exch Rate	T10Y3MM
	1467.8	1590.3	25.820	965.22	2543.0	0.77299	9.1224	1.0701

Correlation matrix

	DFM	ADX	Oil	S&P500	TASI	BAA10YM	B Exch Rate	T10Y3MM
DFM	1.0000	0.42613	–0.0046649	–0.013271	0.75930	–0.34608	–0.029103	–0.41507
ADX	0.42613	1.0000	0.066081	0.80340	0.63033	–0.34200	0.64239	–0.35088
Oil	–0.0046649	0.066081	1.0000	–0.068879	0.11988	0.058885	–0.46817	0.24966
S&P500	–0.013271	0.80340	–0.068879	1.0000	0.27129	–0.34844	0.80565	–0.38062
TASI	0.75930	0.63033	0.11988	0.27129	1.0000	–0.47754	0.15245	–0.43430
BAA10YM	–0.34608	–0.34200	0.058885	–0.34844	–0.47754	1.0000	–0.20668	0.46429
B Exch Rate	–0.029103	0.64239	–0.46817	0.80565	0.15245	–0.20668	1.0000	–0.40809
T10Y3MM	–0.41507	–0.35088	0.24966	–0.38062	–0.43430	0.46429	–0.40809	1.0000

Table 5.1: Descriptive Statistics (Continued)

Normality tests and descriptive statistics

The sample is: 2004(1) – 2022(8) (224 observations and 8 variables)

Normality test for DFM			**Normality test for TASI**		
Observations	224		Observations	224	
Mean	3134.2		Mean	8323.6	
Std. Devn.	1464.5		Std. Devn.	2537.4	
Skewness	1.0362		Skewness	1.6119	
Excess Kurtosis	1.0337		Excess Kurtosis	3.2897	
Minimum	1006.0		Minimum	4348.3	
Maximum	8439.3		Maximum	19385.0	
Median	2876.4		Median	7665.8	
Madn	1462.1		Madn	1739.6	
Asymptotic test: Chi^2(2)		50.056 [0.0000]**	Asymptotic test: Chi^2(2)		198.00 [0.0000]**
Normality test: Chi^2(2)		56.486 [0.0000]**	Normality test: Chi^2(2)		129.30 [0.0000]**
Normality test for ADX			**Normality test for BAA10YM**		
Observations	224		Observations	224	
Mean	4192.1		Mean	2.5278	
Std. Devn.	1586.8		Std. Devn.	0.77126	
Skewness	1.3536		Skewness	1.8922	
Excess Kurtosis	2.8129		Excess Kurtosis	5.2764	
Minimum	1756.9		Minimum	1.5600	
Maximum	10081.0		Maximum	6.0100	
Median	4336.7		Median	2.3400	
Madn	1181.4		Madn	0.682000	
Asymptotic test: Chi^2(2)		142.26 [0.0000]**	Asymptotic test: Chi^2(2)		393.51 [0.0000]**
Normality test: Chi^2(2)		68.349 [0.0000]**	Normality test: Chi^2(2)		145.51 [0.0000]**
Normality test for Oil			**Normality test for B Exch Rate**		
Observations	224		Observations	224	
Mean	73.606		Mean	108.58	
Std. Devn.	25.762		Std. Devn.	9.1020	
Skewness	0.40017		Skewness	0.23832	
Excess Kurtosis	–0.94121		Excess Kurtosis	–1.1199	
Minimum	26.850		Minimum	92.350	
Maximum	133.59		Maximum	130.60	

Table 5.1: Descriptive Statistics (Continued)

Median	68.050		Median	106.10	
Madn	26.257		Madn	11.409	
Asymptotic test: Chi^2(2)		14.247 [0.0008]**	Asymptotic test: Chi^2(2)		13.825 [0.0010]**
Normality test: Chi^2(2)		32.977 [0.0000]**	Normality test: Chi^2(2)		27.251 [0.0000]**
Normality test for S&P500			**Normality test for T10Y3MM**		
Observations	224		Observations	224	
Mean	1992.2		Mean	1.6385	
Std. Devn.	963.06		Std. Devn.	1.0677	
Skewness	1.1227		Skewness	–0.061514	
Excess Kurtosis	0.43005		Excess Kurtosis	–0.81981	
Minimum	735.09		Minimum	–0.52000	
Maximum	4796.6		Maximum	3.6900	
Median	1601.9		Median	1.6350	
Madn	694.21		Madn	1.1861	
Asymptotic test: Chi^2(2)		48.780 [0.0000]**	Asymptotic test: Chi^2(2)		6.4140 [0.0405]*
Normality test: Chi^2(2)		122.80 [0.0000]**	Normality test: Chi^2(2)		8.1487 [0.0170]*

5.3 Unit-Root Test Results

The Unit-root tests were conducted for all the study variables to investigate if these time series data are stationary or nonstationary (Table 5.2). Stationary data is a time series variable exhibiting no significant upward or downward trend over time. Nonstationary data is a time series variable exhibiting a significant upward or downward trend over time. The cyclical variation is an upturn or downturn not tied to seasonal variation and usually results from changes in economic conditions. The main test used for Unit-root is the Augmented Dickey-Fuller test (ADF). In each test, the null hypothesis is that the series has a unit root. Test critical values for ADF are -3.46 (1%), -2.87 (5%) and -2.57 (10%).

Table 5.2: Unit-Root Tests (Constant)

Unit-Root tests							
DFM: ADF tests (T = 220, Constant; 5% = –2.87 1% = –3.46)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.999*	0.95271	331.4	0.06887	0.9452	11.63	
2	–3.043*	0.95291	330.6	6.032	0.0000	11.62	0.9452
1	–2.200	0.96352	356.6	1.046	0.2966	11.77	0.0000
0	–2.102	0.96534	356.6	11.76	0.0000		
ADX: ADF tests (T = 220, Constant; 5% = –2.87 1% = –3.46)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–0.5554	0.99244	283.0	0.2127	0.8318	11.31	
2	–0.5189	0.99320	282.3	2.044	0.0422	11.30	0.8318
1	–0.002630	0.99997	284.4	2.311	0.0218	11.31	0.1247
0	0.4784	1.0060	287.2	11.33	0.0243		
Oil: ADF tests (T = 220, Constant; 5% = –2.87 1% = –3.46)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.789	0.95558	5.777	–0.5907	0.5554	3.530	
2	–2.945*	0.95391	5.769	–0.008724	0.9930	3.523	0.5554
1	–3.008*	0.95389	5.755	6.541	0.0000	3.514	0.8400
0	–2.084	0.96534	6.283	3.685	0.0000		
S&P500: ADF tests (T = 220, Constant; 5% = –2.87 1% = –3.46)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	0.6661	1.0048	98.99	–0.8037	0.4225	9.213	
2	0.5475	1.0039	98.91	0.6739	0.5011	9.206	0.4225
1	0.6545	1.0046	98.79	–0.8888	0.3751	9.199	0.5779
0	0.5560	1.0039	98.74	9.194	0.5972		
TASI: ADF tests (T = 220, Constant; 5% = –2.87 1% = –3.46)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.745	0.94777	678.4	1.123	0.2627	13.06	
2	–2.572	0.95199	678.8	2.196	0.0292	13.06	0.2627
1	–2.218	0.95882	684.8	1.983	0.0486	13.07	0.0497
0	–1.955	0.96379	689.4	13.08	0.0195		
BAA10YM: ADF tests (T = 220, Constant; 5% = –2.87 1% = –3.46)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.891*	0.94822	0.1962	0.01082	0.9914	–3.235	
2	–2.953*	0.94826	0.1957	–0.6024	0.5475	–3.244	0.9914

Table 5.2: Unit-Root Tests (Constant)(continued)

1	–3.152*	0.94606	0.1954	6.556	0.0000	–3.251	0.8348
0	–2.078	0.96154	0.2134	–3.080	0.0000		
B Exch Rate: ADF tests (T = 220, Constant; 5% = –2.87 1% = –3.46)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–0.4406	0.99617	1.128	0.9692	0.3335	0.2625	
2	–0.3002	0.99742	1.127	–1.545	0.1238	0.2578	0.3335
1	–0.5292	0.99548	1.131	6.270	0.0000	0.2597	0.1920
0	0.4724	1.0043	1.226	0.4171	0.0000		
T10Y3MM: ADF tests (T = 220, Constant; 5% = –2.87 1% = –3.46)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.245	0.96938	0.2109	1.104	0.271	–3.09	
2	–2.146	0.97086	0.2110	–0.5945	0.5528	–3.094	0.2710
1	–2.226	0.96999	0.2107	4.575	0.0000	–3.101	0.4570
0	–1.703	0.97614	0.2201	–3.018	0.0001		

From Table 5.2 above we notice that the ADF test (Constant; 10% = –2.57, 5% = –2.87, 1% = –3.46) rejected for some of the variables. This suggests that some of the variables are stationary, and some are not stationary. Also, some of the variables are within the borderline limits. Therefore, both the standard (constant) and the trend models were tested, and another ADF test run assuming the trend in the variables to check for any result differences, if any. The results of ADF are presented in Table 5.3. The results show that most of the variables are nonstationary (ADF (Constant + Trend); 5% = –3.43 1% = –4.00).

Table 5.3: Unit-Root Tests (Constant + Trend)

Unit-root tests

The sample is: 2004(5) – 2022(8) (224 observations and 8 variables)

DFM: ADF tests (T = 220, Constant + Trend; 5% = –3.43 1% = –4.00)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–3.173	0.94870	331.2	0.09387	0.9253	11.63	
2	–3.216	0.94897	330.5	6.020	0.0000	11.62	0.9253
1	–2.393	0.95928	356.4	1.025	0.3067	11.77	0.0000
0	–2.304	0.96098	356.4			11.77	0.0000

ADX: ADF tests (T = 220, Constant + Trend; 5% = –3.43 1% = –4.00)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–1.410	0.97597	282.0	0.3781	0.7058	11.31	
2	–1.361	0.97772	281.4	2.175	0.0308	11.30	0.7058
1	–0.8340	0.98666	283.8	2.391	0.0177	11.31	0.0908
0	–0.3633	0.99425	286.9			11.33	0.0154

Oil: ADF tests (T = 220, Constant + Trend; 5% = –3.43 1% = –4.00)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.795	0.95538	5.789	–0.5894	0.5562	3.539	
2	–2.950	0.95371	5.780	–0.00389	0.9969	3.531	0.5562
1	–3.012	0.95370	5.767	6.525	0.0000	3.522	0.8407
0	–2.092	0.96513	6.295			3.693	0.0000

S&P500: ADF tests (T = 220, Constant + Trend; 5% = –3.43 1% = –4.00)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–1.454	0.97799	98.30	–0.698	0.4859	9.203	
2	–1.552	0.97670	98.18	0.7689	0.4428	9.196	0.4859
1	–1.479	0.97795	98.09	–0.7959	0.4270	9.190	0.5844
0	–1.565	0.97680	98.01			9.184	0.6358

TASI: ADF tests (T = 220, Constant + Trend; 5% = –3.43 1% = –4.00)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.737	0.94775	680.0	1.120	0.2638	13.07	
2	–2.564	0.95200	680.4	2.190	0.0296	13.07	0.2638
1	–2.210	0.95885	686.4	1.979	0.0491	13.08	0.0505
0	–1.947	0.96383	691.0			13.09	0.0200

BAA10YM: ADF tests (T = 220, Constant + Trend; 5% = –3.43 1% = –4.00)

D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.922	0.94742	0.1965	0.01308	0.9896	–3.227	
2	–2.984	0.94746	0.1960	–0.6047	0.5460	–3.237	0.9896
1	–3.183	0.94526	0.1957	6.542	0.0000	–3.244	0.8337

Table 5.3: Unit-Root Tests (Constant + Trend) (continued)

0	–2.114	0.96067	0.2138			–3.072	0.0000
B Exch Rate: ADF tests (T = 220, Constant + Trend; 5% = –3.43 1% = –4.00)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.503	0.96533	1.110	1.147	0.2526	0.2349	
2	–2.366	0.96751	1.110	–1.321	0.1878	0.2319	0.2526
1	–2.604	0.96464	1.112	6.378	0.0000	0.2309	0.2184
0	–1.801	0.97353	1.210		0.3944	0.0000	
T10Y3MM: ADF tests (T = 220, Constant+Trend; 5% = –3.43 1% = –4.00)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	–2.266	0.96824	0.2113	1.128	0.2607	–3.082	
2	–2.150	0.97004	0.2115	–0.5700	0.5693	–3.085	0.2607
1	–2.239	0.96907	0.2111	4.572	0.0000	–3.092	0.4514
0	–1.699	0.97562	0.2206			–3.009	0.0001

Both unit root tests (constant and trend) hold almost the same results. The data is nonstationary for most of the variables, some are borderline such as DFM and BAA10YM and Oil.

Based on that, the decision was made to run the Standard (Constant) and Trend Markov-regime switching models and examine the trend coefficient to check if it is statistically significant or not. If the trend coefficient is significant, then the trend exists, otherwise there is no significant trend pattern.

5.4 Graph Analyses

The graphs of all the variables were evaluated to assess:

- Market price index movement over the study period for both markets (ADX, DFM) from 4/2004 to 8/2022 to identify and discuss the major events witnessed, especially the bull and bear market events.
- Comparison of both markets index movement.

How each independent variable is related and correlated with the dependent variables (ADX, DFM) and how the dependent and independent variables move during the market cycles and economic conditions.

5.5 Section 1 - ADX Empirical Results and Analyses

ADX has witnessed significant fluctuations in the last 18 years (2004-2022). It is noticeably apparent from Figure 5.1 that there are periods of bull and bear market trends where the market index has swung dramatically.

Figure 5.1: ADX Index (2004–2022)

ADX index moved significantly upward and reversed the movement in 2004-2005, 2007-2008, 2013-2014 periods. The market boomed in 2004-2005 as the market index moved from 1700 to +6000 points. Later, the market index dropped significantly similar to the "bubble burst" scenario in 2005 when the market index dropped sharply to 3000 points. In 2007-2008 the market boomed again but dropped sharply in 2008 in line with the US subprime mortgage crisis (a multinational financial crisis that contributed to the 2008 global financial crisis). The global financial crisis affected many international financial markets.

If we look further at the index movement in Figure 5.1, we can notice that in 2013 the market moved significantly upward and stayed stable for a relatively longer period at high levels. It seems that the market boomed in 2013 and stayed at a level where the upwards and downwards fluctuations are relatively less severe compared to the earlier witnessed fluctuation in 2005 and 2008. In 2020, there was a sudden sharp drop in the market index due to covid-19 pandemic effect which also affected the global markets, but the market recovered within a short period and continued growing remarkably and reached a record high during 2022. Moreover, the market jumped to a record high in the 2021-2022 cycle, with a high level of transaction volume and value. The number of IPO listings was also relatively high during this period (The National News, November 2022). The new listings increased the market capitalization and attracted new and regular investors to participate in the market. The increased activities added depth to the market.

5.5.1 ADX and Oil

Oil is a major element in the UAE economy structure; therefore, ADX price index movements and Oil price movements were plotted over the study period to compare their movement and seasonal differences.

Figure 5.2: ADX Index vs. Oil Price Graph

When the ADX index is contrasted with Oil price movement (Figure 5.2), there are clear movement resemblances. Such resemblances will be statistically assessed later. Oil prices moved in the same direction alongside the ADX index from 2004 till 2008, the movement was in the same direction for most of the time but deviated in some periods.

Since oil prices are determined based on the global supply and demand, oil price is independent from ADX market index movement. ADX index was relatively stable from 2009 to 2013 while the Oil price exhibited high volatility as it moved upward to above $100 and dropped to below $40 and recovered later. Both variables dropped in early 2020 due to the Covid-19 pandemic but recovered significantly at almost the same time and reached their high level in 2022.

The seasonal differences graph in Figure 5.3 shows the differences in ADX and Oil price movements. Both movements are in the same direction all the time, which shows a positive correlation.

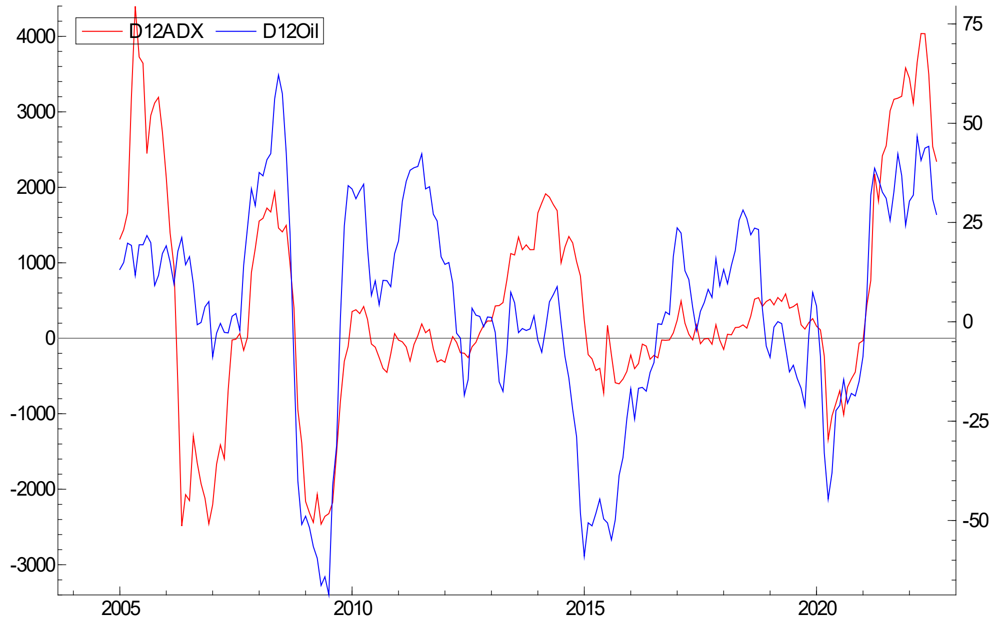

Figure 5.3: Seasonal Differences (ADX vs. Oil)

5.5.2 ADX and S&P 500

Both ADX and the S&P 500 indices move in the same direction most of the time over the study period (Figure 5.4). The exception is the early years of the study (2004-2007) when ADX fluctuations were high due to the 2005 and 2008 index jumps. The movement after the sub-prime crisis in 2008 is noticeable as both indices move in the same direction most of the time and the growth rate is close to each other.

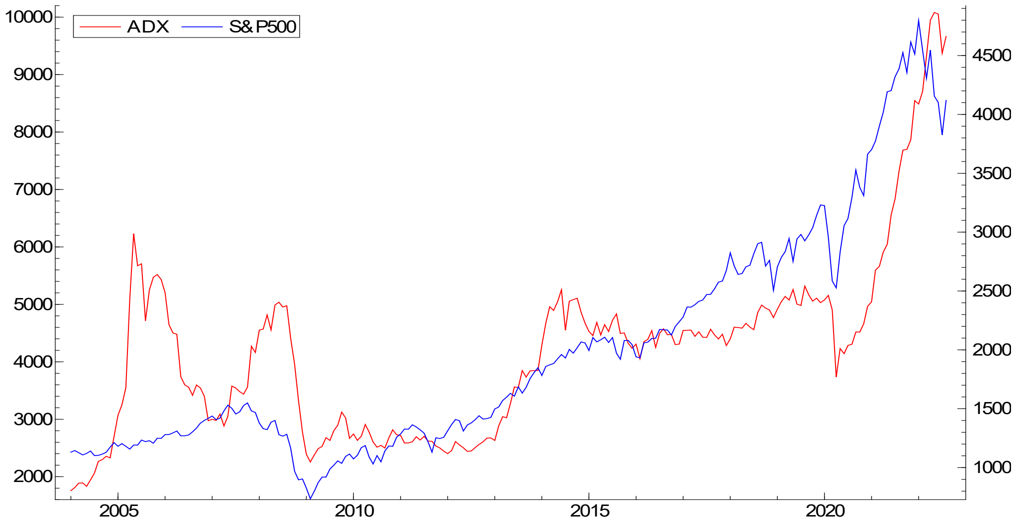

Figure 5.4: ADX vs. S&P500 Graph

When looking at the seasonal difference in Figure 5.5, it is evident that the differences are close to each other. Therefore, we expect to find S&P500 to be positively correlated with ADX index and a good predictor of the ADX market index movement during the study period.

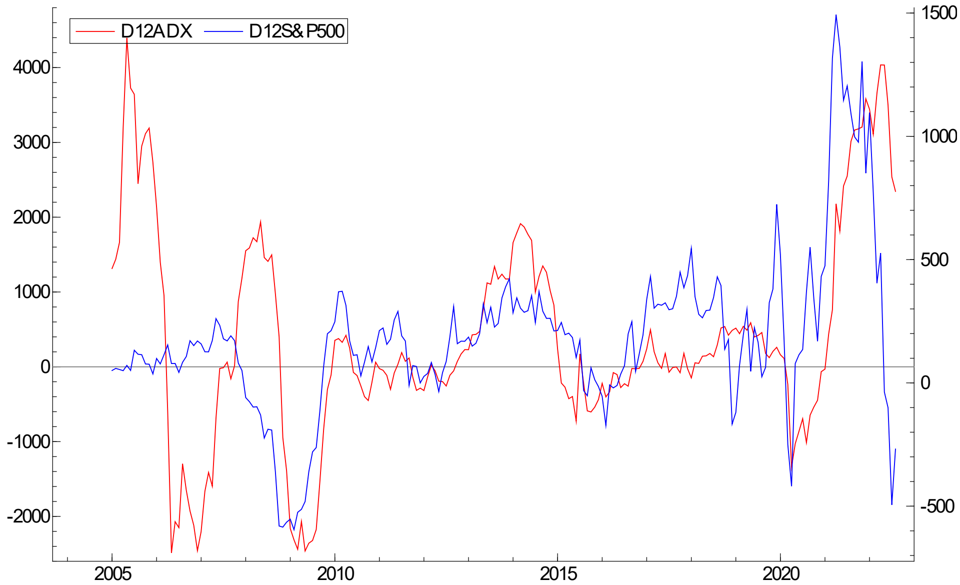

Figure 5.5: Seasonal Differences (ADX vs. S&P500)

5.5.3 ADX and TASI

If the ADX index is compared with the TASI index (Figure 5.6), it is evident that they often move in the same direction and have almost the same growth during the study period. They even share the same extreme upward trends in 2005 and 2008 and post-covid 19 period. There are many studies, mentioned in the literature review section, which support the assumption that both markets share similar factors which affect their movement. There are several economic, geographical, political, factors which contribute to the similarities in both markets alongside other factors, as witnessed in the graph. Therefore, we expect to find TASI to be a significant predictor of the ADX price index direction and both are positively correlated with each other in our statistical results using Markov-regime switching models.

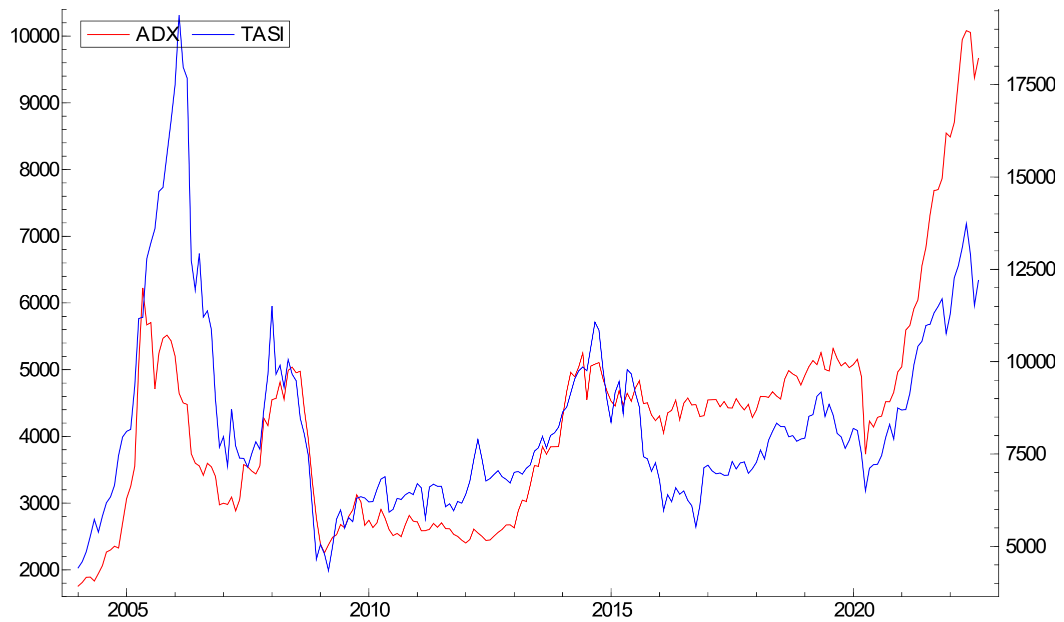

Figure 5.6: ADX Index vs. TASI Graph

The seasonal differences (Figure 5.7) show that the differences from 2005 to 2022 are moving in the same direction at almost the same rate. KSA stock market (TASI) witnessed a severe downturn (bubble burst effect) as the index reached the highest point in 2005-2006 cycle, and since then, the market has not reached that point, while ADX reached a high point during that time but dropped significantly. Later, ADX reached that point again in 2021, which is approximately after almost 15 years.

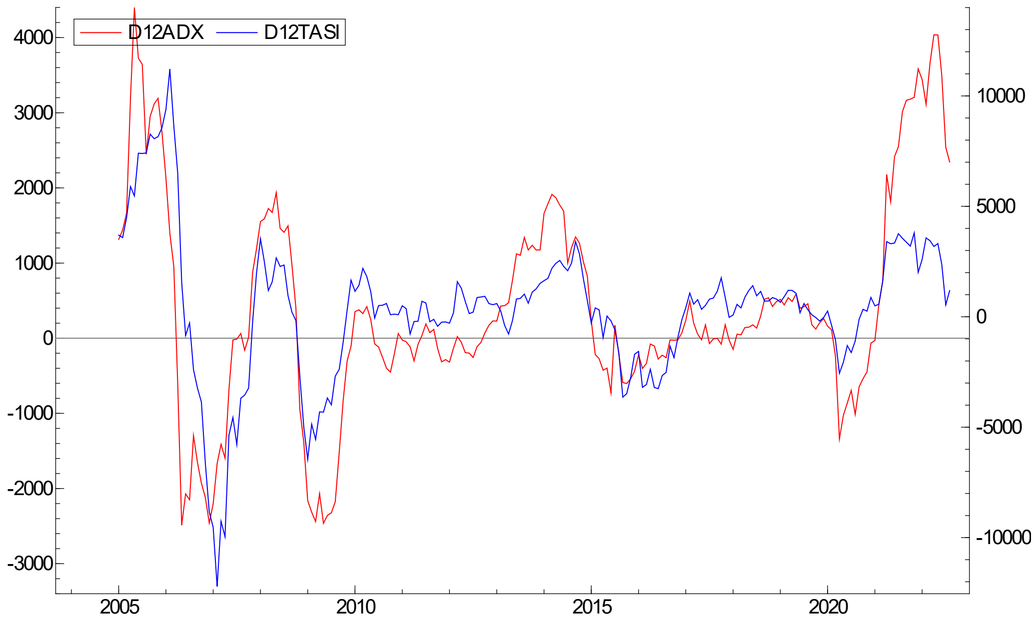

Figure 5.7: Seasonal Differences (ADX vs. TASI)

5.5.4 ADX and Baa10YM

Moody's seasoned Baa corporate bond yield relative to yield on 10-year treasury constant maturity (BAA10YM) is one of the significant economic indicators that reflects the future forecast of the economy direction in general. From Figure 5.8, one can see the opposite direction of the two variables. When Baa10YM increases, ADX goes down relatively.

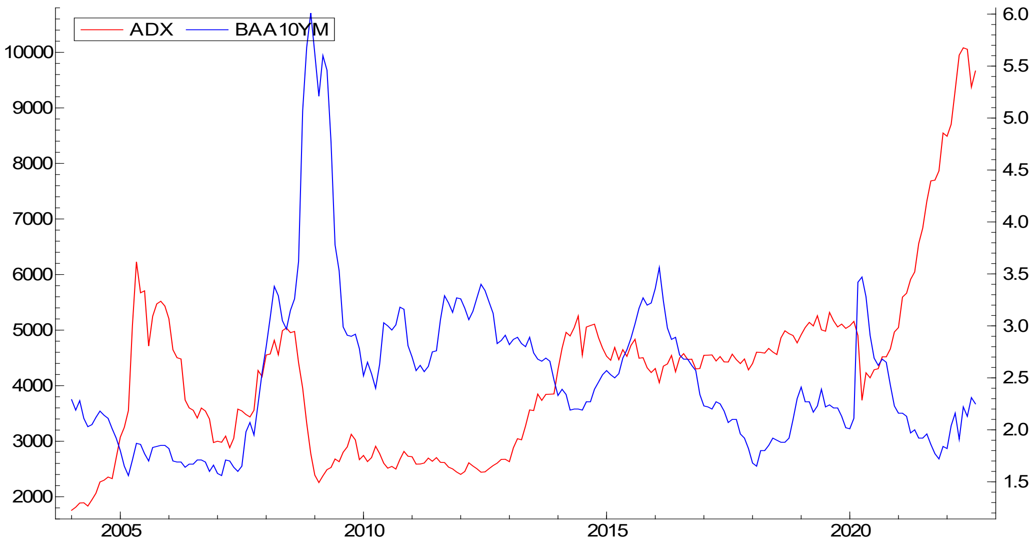

Figure 5.8: ADX Index vs. BAA10YM Graph

The seasonal differences reflect this inverse relationship as seen in Figure 5.9. The relationship is not apparent in the period from 2005 to 2007, but it can be seen in the period from 2008 to 2022 as an inverse relationship. Therefore, we expect the find a negative relationship between Baa10YM and ADX.

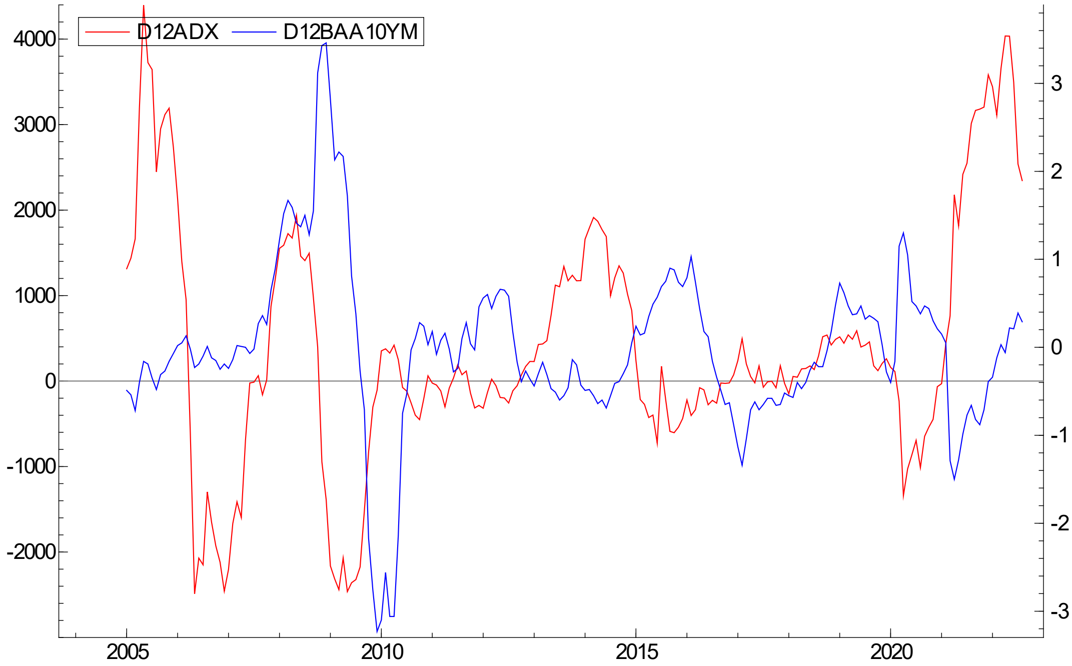

Figure 5.9: Seasonal Differences (ADX vs. BAA10YM)

5.5.5 ADX and Broad Effective Exchange Rate

When the two graphs in Figure 5.10 are compared, relationships appear between the two variables, but sometimes they move in the opposite direction and sometimes they move in the same direction, but overall they move in the same direction and trajectory.

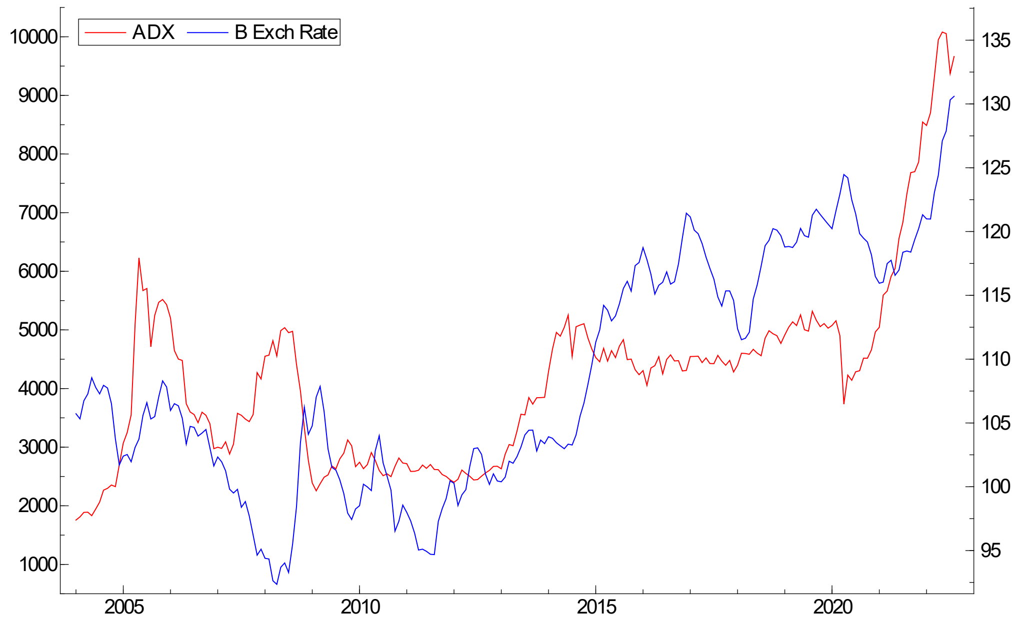

Figure 5.10: ADX Index vs Broad Effective Exchange Rate

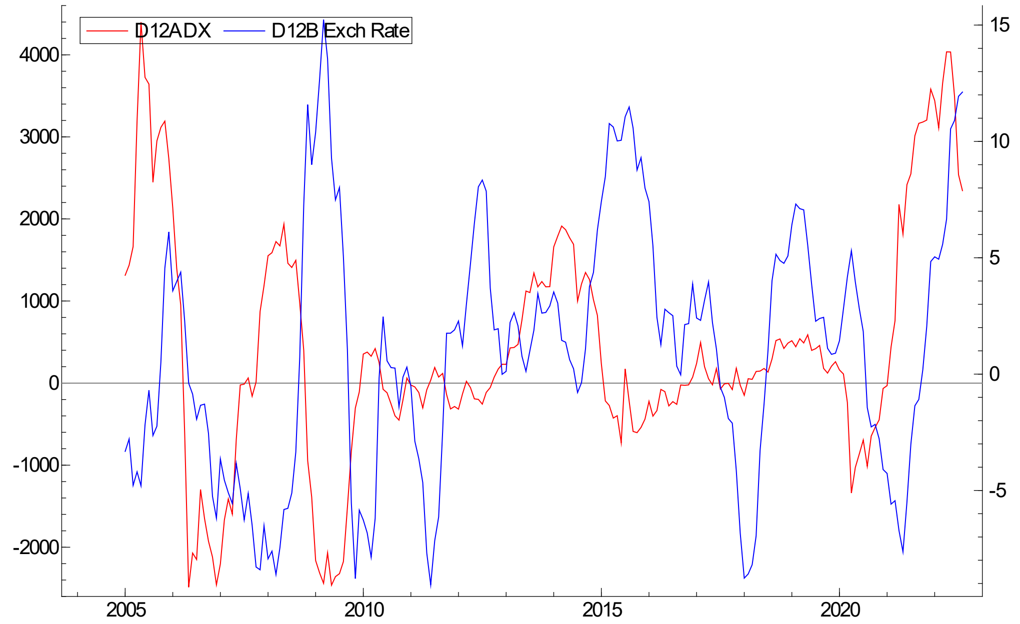

Figure 5.11: Seasonal Differences (ADX vs. B. E. Exchange Rate)

Also, the seasonal differences shown in Figure 5.11 suggest that the exchange rate trajectory is in line with the ADX index movement, especially after the year 2010. The direction gets disturbed during the severe upward or downward cycles as the volatility in broad exchange rate is higher than that of the ADX index. We expected to find a positive relationship between both variables (B Exchange rate and ADX) in our results unless the lag effect hinders the results as we are not investigating the lag effect in our models.

5.5.6 ADX and T10Y3MM (Interest Spread)

Figure 5.12 presents the graph of the two variables (ADX, T10Y3MM). Both of them have moved in the same direction for considerable period, but the upward and downward movement magnitude differs sometimes, as they do not move in the same speed in some periods. These observation could be explained by the lag reaction assumption, if applicable.

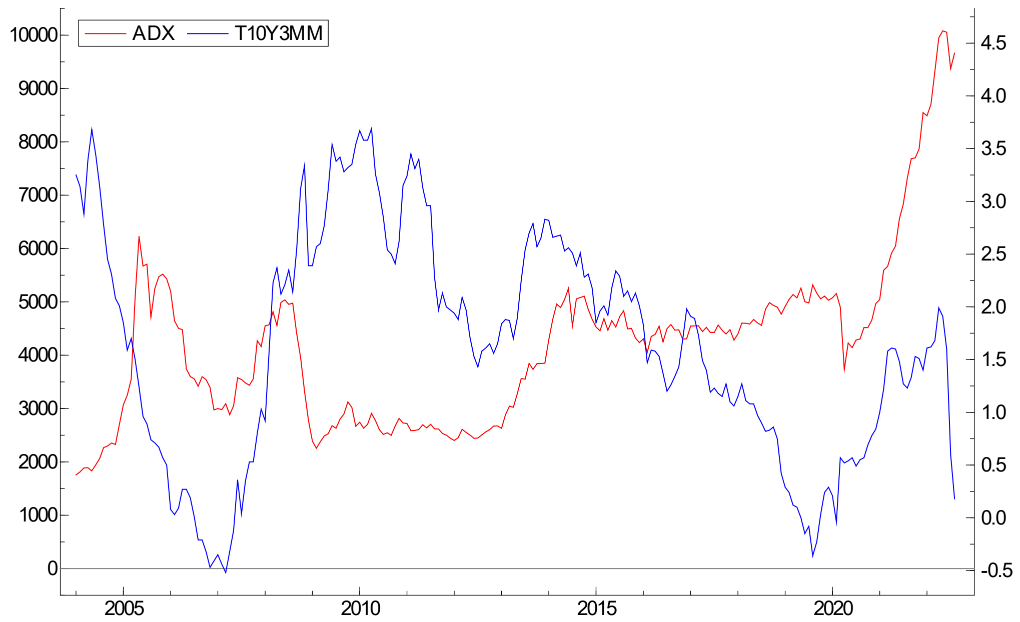

Figure 5.12: ADX Index vs. T10Y3MM Graph

Figure 5.13 shows the seasonal differences of both variables move in mixed direction. The changes in the interest rate spread are in line with the direction of the economy in the US and it's a good stimulation tool used by US government to rectify unfavorable issues. Such changes are found in different studies to affect and predict the stock market index or return direction. From the resemblance between the seasonal differences between ADX and the interest rate spread, we anticipate finding good predictive ability of our independent variable to predict the movement of the dependent variable (ADX).

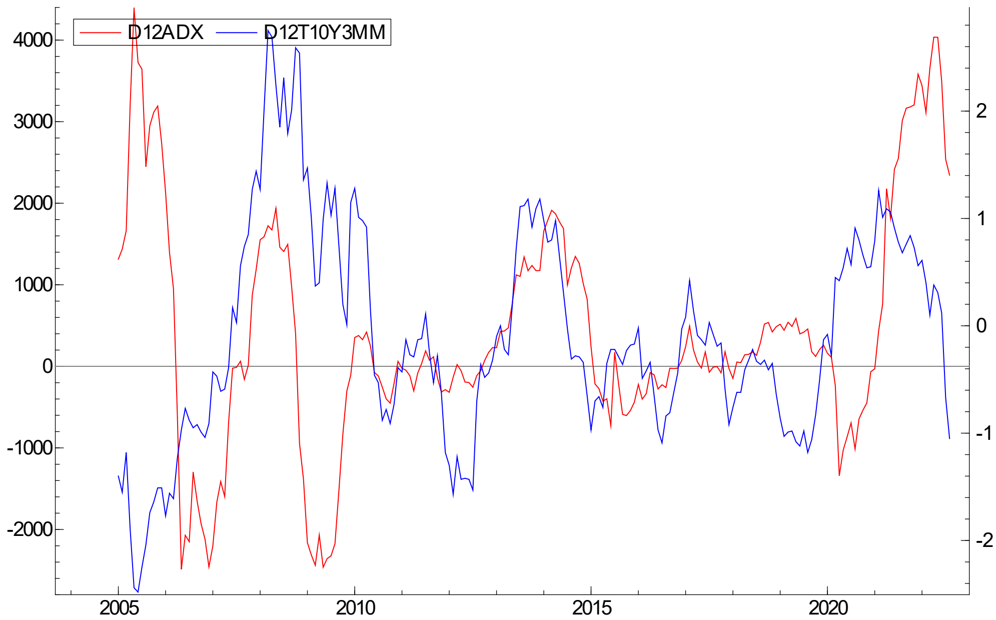

Figure 5.13: Seasonal Differences (ADX vs. T10Y3MM)

5.6 Statistical Results

In this section, the statistical analyses of the models will be presented. The index movement data was tested using the OxMetrics program to investigate regime classification based on smoothed probabilities. The results indicated that there are distinguished bear and bull regimes. The process in the Markov-regime switching model is allowed to switch between regimes. Each regime has a different mean and variance. There are many different techniques in the program that can be used to arrive at robust predictive models. Different models were tested and evaluated separately.

The first step in the analysis is to identify the regime classification (0,1). By comparing the index movement and trend with the regime classification, the bull and bear cycles/regimes can be identified and classified. The second step is to try to build our models using our variables. The third step is to evaluate the model's parameters.

5.6.1 Market Classification and Cycles

The Markov-Switching models are used in the OxMetrics program to identify the bear and bull regimes/trend/cycle. The predicted classification can be compared with the actual index movement to check the result resemblance between the regime classification and the actual price index movement.

5.6.2 Models

To check the robustness of the empirical results, we considered constructing and testing different models to evaluate the forecasting power of our variables. Three different models will be built and tested using the chosen variables and data, and the differences among the three models will be compared. The first model is the standard (constant) model. This is the default model in the program. It automatically checks for a constant trend. The second model is the trend model. The objective is to test if the trend pattern exists in the data, and consequently, the prediction model. The third model is the three-regime. The three-regime fits the data which exhibits both high and moderate volatility in its fluctuation. Both ADX and DFM have high and medium levels of volatilities. Lastly, we will consider a binary model using naïve method calculation to identify the bull and bear markets.

5.6.3 ADX Regime Classification

5.6.3.1 Model 1 – Standard (Constant) model

The two-regime classification was tested to evaluate how the models will fit. From Table 5.4, a clear distinction of such periods can be seen. Regime (0) represents the bull market trend and regime (1) represents the bear market.

Table 5.4: Model 1 – ADX Regime Classification

ADX		
Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(1) – 2005(11)	11	0.951
2006(11) – 2009(11)	37	0.993
2015(8) – 2016(10)	15	0.968
2021(12) – 2022(8)	9	0.994
Total: 72 months (32.14%) with average duration of 18.00 months.		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2004(12)	12	0.988
2005(12) – 2006(10)	11	0.955
2009(12) – 2015(7)	68	0.995
2016(11) – 2021(11)	61	0.991
Total: 152 months (67.86%) with average duration of 38.00 months.		

a. Regime (0) – Bull market

There are four bull (0) regimes/periods:

1. January 2005 to November 2005 which lasted almost eleven months. This was the first bull period in our data sample. This period can be seen in Figure 5.14 in the blue (turquoise) color and the prediction's dotted line is almost in line with the actual ADX index line, which indicates at a glance that we have a good prediction model and significant variables. During this first bull regime, the index moved steeply upwards from mid-2004 to its peak in 2005 as the index jumped from 2000 points to above 6000 points. The prediction line captures this trend at a high level of precision.
2. November 2006 to November 2009 – a period of 37 months. Compared to the first bull market in the study, this bull market took a longer time to achieve its peak

index value for that period. However, it dropped sharply in mid-2008. The parametric prediction captured most of the trend from inception but missed part of the significant drop in 2008. Nonetheless, the regime start point and end point can be considered as a bull market, if the two points (the inception point is less than the end point) are contrasted and compared.

3. August 2015 to October 2016. This short trend lasted almost 15 months. The cycle curve moved upward slowly and dropped less sharply compared to the other previous regimes/cycles.
4. Feb 2021 to August 2022. This regime is the most recent one in this study period. The MS regime classification did not capture the regime from the beginning. The trend was stable starting from late-2016 but dropped sharply at the beginning of the COVID-19 pandemic crisis when the market dropped sharply in early 2020 but recovered and somewhat maintained the uptrend until the end of the study period (August 2022).

The total duration of the bull market based on smoothed probabilities is 72 months which represents (32.14%) of the total study period and the average duration of 18 months. Overall, the regime classification generated by the standard (constant) model resembles the index movement to a high degree.

b. Regime (1) – Bear market

The other type of regime classification is regime (1), which is considered as the bear market. The output generated by the OxMetrics program shows that regime (1) has four classifications based on its smoothed probabilities:

1. January 2004 to December 2004 – a 12-month period. When comparing the actual movement of the ADX index with the predicted bear market cycle, it is clear that there is some discrepancy between the prediction and the actual cycle. That might be caused by the mixed movement (ups and downs) in that period. Also, that might be related to the study sample data (2004 is the start year and there was no prior data that can be used to accurately calculate the full trend).
2. December 2005 to October 2006 – an 11-month period. This is the shortest bear cycle among the four bear cycles. The market dropped significantly in this period (the

bubble burst scenario). The index dropped from the highest point that the ADX index had reached. This high-level price index record remained for 15 years until it got "broken" in 2021.

3. December 2009 to July 2015 – a 68-month period. Compared to previous bear market cycles, this is a very long bear market cycle. The sub-prime crisis in 2008 led to a global stock market crash. It took the market a long time to recover. Despite that, the market eventually stood at a stable level for a considerable time. The prediction results seem reasonable when compared to the actual index movement, except for the period when the market turned upward from early 2013 until mid-2014.
4. November 2016 to November 2021 – a 61-month period. The market turned bearish in 2016 and continued that trend until November 2021. The market recovered from the Covid-19 effect and the new IPOs introduced to ADX increased the number of the listed companies which added depth to transaction volume and value as well as the total market capitalization which helped ADX to introduce different products and initiatives to stimulate market activities.

The bear regime totaled 152 months which represents 67.86% of the study period with average duration of 38 months.

5.6.3.2 Market trend prediction model

All of the study variables were tested. Table 5.5 shows that all the variables are good predictors of the market trend. The variable BAA10YM was significant at (<0.10) as the t-prob was (0.061). The other variables were significant(<0.05):

Oil price (0.000), S&P500 (0.000), TASI (0.000), Broad Exchange rate (0.000), T10Y3MM (0.000).

Table 5.5: Model 1 – ADX - Standard (Constant)

ADX				
The estimation sample is: 2004(1) – 2022(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	13.7530	1.234	11.1	0.000
S&P500	0.798245	0.04580	17.4	0.000
TASI	0.274424	0.01425	19.3	0.000
BAA10YM	–87.8852	46.62	–1.88	0.061
B Exch Rate	66.7366	4.663	14.3	0.000
T10Y3MM	240.911	34.11	7.06	0.000
Constant(0)	–7389.99	507.4	–14.6	0.000
Constant(1)	–8457.45	523.2	–16.2	0.000
	Coefficient	**Std. Error**		
sigma	374.895	19.98		
p_(0|0)	0.956114	0.02479		
p_(1|1)	0.973271	0.01320		
log-likelihood –1670.75465				
No. of observations	224	No. of parameters	11	
AIC	15.0156665	SC	15.1832027	
mean(ADX)	4192.06	se(ADX)	1590.33	
Linearity LR–test Chi^2(3) = 150.16 [0.0000]** approximate upperbound: [0.0000]**				
Transition probabilities p_(i|j) = P(Regime i at t+1 | Regime j at t)				
	Regime 0,t	**Regime 1,t**		
Regime 0,t+1	0.95611	0.026729		
Regime 1,t+1	0.043886	0.97327		

As discussed and outlined in the literature review, oil prices affect the stock market direction in the GCC countries as it generates appropriate income that impacts the economy's growth. Since the UAE is one of the major oil producers in the world, oil revenue has a significant effect on its economy and can be used as a good predictor of market movement. The Emirate of Abu Dhabi produces most of the UAE's Oil. Some of the companies in ADX work directly or indirectly in the oil production industry. ADNOC and its subsidiaries work in this industry and some of the subsidiaries are listed in the ADX. Therefore, the amount of Oil revenue will affect these companies' operation and income.

S&P500 index movement is also a significant predictor of ADX index movement. The USA stock market movement affects many international markets, and such effect is supported in the literature, as discussed earlier. Accordingly, such an effect on the ADX market is also expected. The time gap between the opening and closing of both markets creates opportunities for some investors. Many investors examine the market direction in the USA and anticipate the same direction to lead the UAE market in the next trading session. Given the fact that there are many foreign institutional investors who invest in the ADX market, the spillover effect between the two markets is expected to be present in the ADX market. Many investors anticipate the effect of the US stock market to control emerging market direction since the US market is the market for the world largest economy.

KSA TASI is also a significant variable. The KSA stock market has the largest market capitalization, volume, turnover, and liquidity (in terms of transaction value) in the GCC and the MENA region. The UAE and KSA share a lot of economic factors which affect the market movement and sentiment. There might be also many active Saudi investors who invest in ADX, and their executed transactions (trade value and volume) may affect market sentiment.

According to the discussed rational expectation theory, we expect the investors to make their decision based on previous experience. Therefore, some investors will assume that ADX movement will be in parallel (same direction) with the KSA and S&P 500 movements and will base their decisions in line with the anticipated direction.

The broad exchange rate is also an important predictor. ADX is open to all types of international investors that can benefit from currency fluctuations to exchange or transfer their investment back and forth to their home if there is a positive premium in such a transfer. The exchange rate is also an important predictor of market direction. It affects the index movement in the UAE stock markets due to the pegging strategy with the USD.

T10Y3MM is also a significant predictor. This variable reflects the investors' expectations of the future economic situation in the USA's economy.

Evaluation of the 1-step prediction

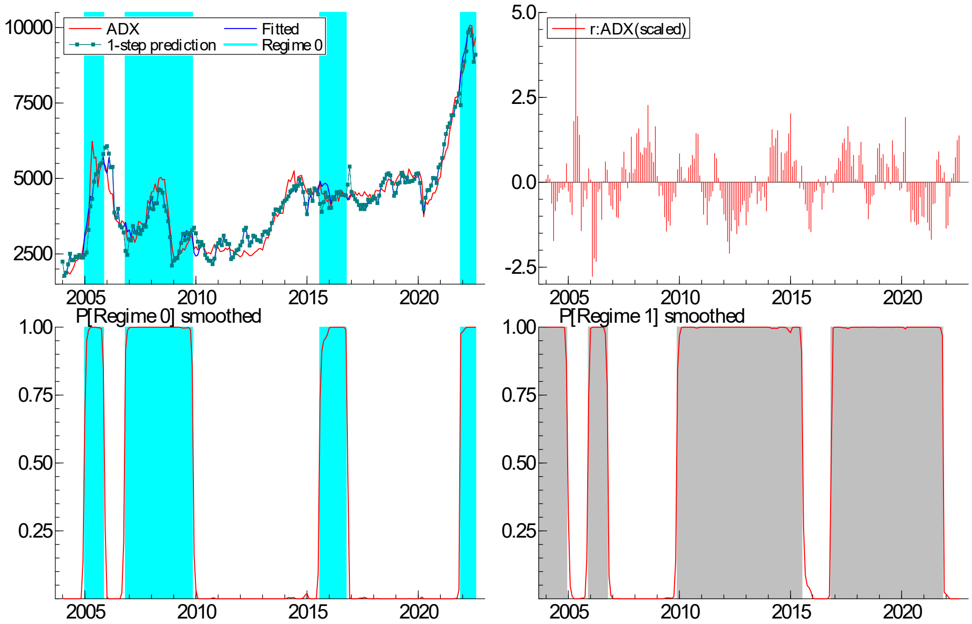

Figure 5.14: Model 1 – ADX - Prediction Line, Regimes (0,1), Scaled Residual

If we look at the predicted line in Figure 5.14, the results indicate that the chosen variables are good predictors of the bear market trend as the predicted index movement line (green) is very close to the actual index movement line (red). The smoothed probability signals the likelihood that the market is bull (0) or bear (1). In the first period where the color is gray, the predicted line is in the bear market (regime 1), but in 2005, the market has shifted to a bull market which reached its peak and has hence dropped in 2006. In the actual index, the bear market started in almost mid-2005. The prediction misses the exact index drop by few months. Nonetheless, the prediction line has captured the actual bear market starting curve in 2008 and this is an important prediction because the ADX market has grown over time in terms of the number of investors and number of listed companies. Also, the average investors have gained more trading experience over the previous years. ADX is considered a young market (started in 2000). We assume that investors did not have enough experience in estimating the effect of macroeconomic factors on market trends. Markov-regime switching program has not classified the period as bear from the beginning of the downward line because the crash in 2008 was related to the global financial crisis, which happened too fast and caused a sharp drop in stock prices, and consequently, the market indices. Such sudden and large drops in a short time span might not be associated with the study variables due to the magnitude and pace of the sudden index drop. In other words, the momentum in the index drop in 2008 was faster than the changes in the macroeconomic factors, which can explain the lag in the prediction line. The prediction line is almost consistent with the actual line from the end of 2008 to mid-2013. The market was bearish in that period and remained that way for a relatively long period.

5.6.3.3 Model 2 – Trend model

Since there were some nonstationary variables when the variables were tested for Unit-root, the test was repeated using the trend analysis (Table 5.6) with two regimes to compare the results for discrepancies.

The results were almost the same as the pervious Constant model. The default spread (BAA10YM) became a significant predictor (t-prop = 0.0000). The Trend coefficient was also significant (0.000), and that supports the existence of trend pattern in ADX price index movement.

Table 5.6: Model 2 – ADX - Trend Pattern

ADX				
The estimation sample is: 2004(1) – 2022(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	18.4283	1.160	15.9	0.000
S&P500	1.45569	0.08702	16.7	0.000
TASI	0.248344	0.01542	16.1	0.000
BAA10YM	242.727	48.60	4.99	0.000
B Exch Rate	68.4310	2.278	30.0	0.000
T10Y3MM	149.030	33.32	4.47	0.000
Trend	–11.1791	1.192	–9.38	0.000
Constant(0)	–8808.87	95.10	–92.6	0.000
Constant(1)	–9777.33	92.12	–106.0	0.000
	Coefficient	**Std. Error**		
sigma	361.833	18.57		
p_{0|0}	0.971741	0.01501		
p_{1|1}	0.939843	0.02694		
log-likelihood –1665.14925				
No. of observations	224	No. of parameters	12	
AIC	14.9745469	SC	15.1573137	
mean(ADX)	4192.06	se(ADX)	1590.33	
Linearity LR-test Chi^2(3) = 149.90 [0.0000]** approximate upperbound: [0.0000]**				
Transition probabilities p_{i|j} = P(Regime i at t+1 | Regime j at t)				
	Regime 0,t	**Regime 1,t**		
Regime 0,t+1	0.97174	0.060157		
Regime 1,t+1	0.028259	0.93984		

The prediction dotted line as shown in Figure 5.15 has improved slightly, and the regime classification (Table 5.7) has changed from four cycles to five cycles for each bull or bear market. The selection of the regime was more sensitive, which identified five bull markets and five bear markets. The results differ slightly from the Constant model (model

1). In an overall evaluation, there is a noticeable improvement in model 2 when compared to model 1.

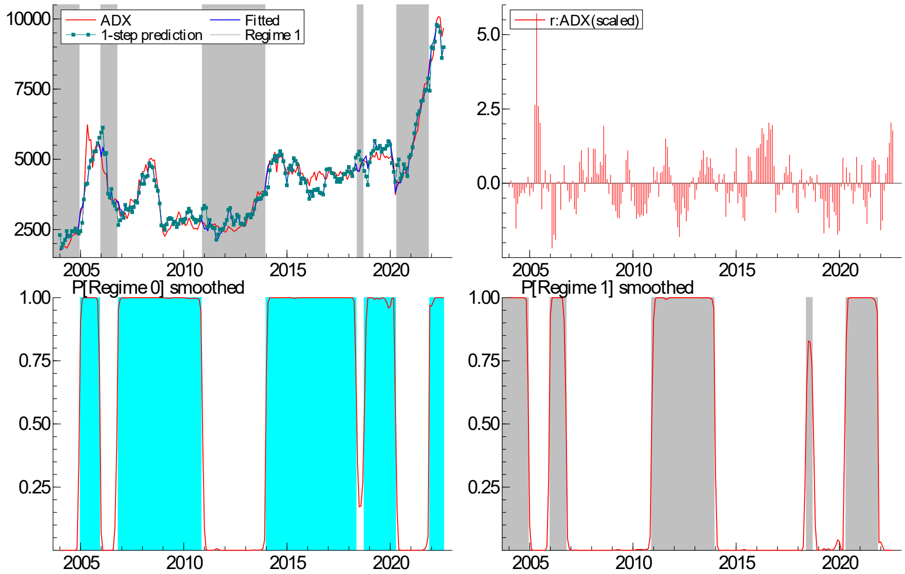

Figure 5.15: Model 2 – ADX - Prediction Line, Regimes (0,1), Scaled Residual

Table 5.7: Model 2 – ADX Regime Classification

Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(1) – 2005(12)	12	0.967
2006(11) – 2010(11)	49	0.997
2014(1) – 2018(5)	53	0.989
2018(10) – 2020(4)	19	0.942
2021(12) – 2022(8)	9	0.991
Total: 142 months (63.39%) with an average duration of 28.40 months		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2004(12)	12	0.971
2006(1) – 2006(10)	10	0.944
2010(12) – 2013(12)	37	0.984
2018(6) – 2018(9)	4	0.761
2020(5) – 2021(11)	19	0.987
Total: 82 months (36.61%) with average duration of 16.40 months		

5.6.3.4 Model 3 – Three-regime

One of the advantages of Markov-regime switching application is the option to select more than two regimes. The selection should be based on the theoretical background or the analysis of data behavior. From index movement analysis, there were noticeable extreme volatilities in the ADX and DFM price indices during 2005 and 2008. In addition, ADX index has moved upward since 2021 and recorded the highest level ever accompanied with high market value and volume. Therefore, we chose to investigate the three-regime option in Markov-regime switching application using the OxMetrics program because the periods in 2005 and 2008 are considered as extreme regimes/cycles in the UAE stock market history and should therefore not be skipped over or deleted from the study sample. However, one might still argue that keeping them might disturb the statistical findings due to the high fluctuation which might create study or sample "outliers".

From Table 5.8, it is evident that the statistical results from our three-regime model are encouraging and significant. All variables are significant at the (0.05) level.

Table 5.8: Model 3 – ADX - Three-Regime

Switching(1) Modelling ADX by MS(3) The estimation sample is: 2004(1) – 2022(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	11.3503	1.061	10.7	0.000
S&P500	0.431614	0.05682	7.60	0.000
TASI	0.233258	0.01396	16.7	0.000
BAA10YM	189.172	60.19	3.14	0.002
B Exch Rate	44.7734	2.533	17.7	0.000
T10Y3MM	201.489	30.35	6.64	0.000
Constant(0)	–4827.20	134.4	–35.9	0.000
Constant(1)	–5954.76	179.3	–33.2	0.000
Constant(2)	–3191.66	141.7	–22.5	0.000
	Coefficient	**Std. Error**		
sigma	319.461	15.53		
p_{0|0}	0.967711	0.01589		
p_{1|0}	0.0164021	0.01151		
p_{0|1}	0.0370189	0.02102		
p_{2|2}	0.936481	0.06151		
log-likelihood –1642.96755				
No. of observations	224	No. of parameters	14	
AIC	14.7943531	SC	15.007581	
mean(ADX)	4192.06	se(ADX)	1590.33	

The prediction model (Figure 5.16) revealed three distinguished regimes (0,1,2,). The prediction dotted line moves closely with the actual ADX index movement as seen in Figure 5.16. Also, the regimes are highlighted in:

- Green (regime 0) which represents the bull market.
- Gray (regime 1) which represents the bear market.
- Yellow (regime 2) which represents the extreme bull market.

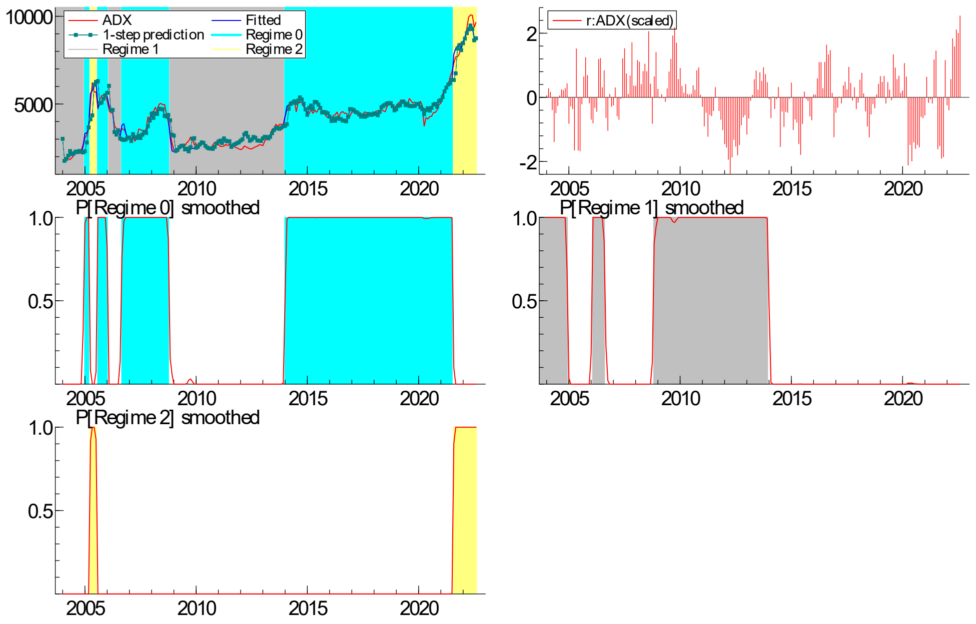

Figure 5.16: Model 3 – ADX - Prediction Line, Regimes (0,1,2), Scaled Residual

Table 5.9: Model 3 – ADX Regime Classification

Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(1) – 2005(3)	3	0.988
2005(8) – 2006(1)	6	0.969
2006(9) – 2008(10)	26	0.985
2014(1) – 2021(7)	91	0.994
Total: 126 months (56.25%) with an average duration of 31.50 months		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2004(12)	12.00	0.973
2006(2) – 2006(8)	7	0.980
2008(11) – 2013(12)	62	0.995
Total: 81 months (36.16%) with an average duration of 27.00 months		
Regime 2	**Months**	**Avg. prob.**
2005(4) – 2005(7)	4	0.960
2021(8) – 2022(8)	13	0.992
Total: 17 months (7.59%) with average duration of 8.50 months		

The regime classification in Table 5.9 represents the predicted cycles based on our study variables. If the actual index movement is compared with this mentioned classification, improved resemblances should be displayed in comparison with the results generated from the first and second models discussed earlier. The bull market (0) lasted for 56.25% of the study period and the bear market (1) lasted for 36.16% and the extreme bull market lasted for 7.59%.

We conclude that the three-regime Markov-regime switching model provides the best prediction results for the ADX price index. The extreme fluctuation presented challenges to the two-regime models. Such challenges were handled effectively by the three-regime model. The findings support the selection of the nonlinear Markov-regime switching models to predict the UAE stock market trends.

5.6.3.5 Summary of the three MS models and diagnostic rests

The three models were tested in order to investigate if there is a trend pattern existence and whether there are more than two regimes. Also, since the study variables have a mix of stationary and nonstationary dataset, we opted to test for constant and trend pattern. The results show that ADX has a significant trend coefficient. The finding is very important for investors wishing to trade or invest in upward market.

The diagnostic test results of the three models are summarized in the following table:

Table 5.10: Log-likelihood and AIC Diagnostic Tests (ADX)

Test	Constant	Trend	Three-regime
Log-likelihood	–1670.75	–1665.14	–1642.96
AIC	15.01	14.974	14.794

A log-likelihood test is a measure of how well a particular model fits the data (goodness of fit). The log-Likelihood of the three-regime model is the highest. it fits our dataset better. On the other hand, AIC (Akaike Information Criterion) is an estimator of prediction error and estimates the quality of each model, relative to each of the other models. The lower the AIC score the better. Again, the three-regime model has the lowest AIC score. In conclusion the three-regime has the best fits compared to the constant and trend models.

5.6.4 Model 4 – Binary Logit Model

A simple binary model is used to investigate if can predict the market states (0 = bull, 1 = bear) based on the study variables. The index movement is calculated. If the index level in points increases (decreases) compared to the previous or last month level, the current month is considered as bear (bull) and takes the binary value of 0 (1). This is a naïve way of guessing the market trend. The assumption is that the average individual perceives the market news and economic information in a basic level. Most of the individual investors rely on public information from different sources. If a naive investor links or associates the movement in this study variables with the market trend without running and utilizing prediction programs, then the results would be interesting.

Table 5.11: Model 4 – ADX - Binary Logit

CS(1) Modelling ADX Nv by LOGIT				
The estimation sample is 2004(1) – 2022(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Constant	–8.85305	4.049	–2.19	0.030
Oil	0.0150287	0.008225	1.83	0.069
S&P500	–0.00106019	0.0003762	–2.82	0.005
TASI	9.44318e-05	7.168e-05	1.32	0.189
BAA10YM	0.192983	0.2265	0.852	0.395
B Exch Rate	0.0813259	0.03962	2.05	0.041
T10Y3MM	–0.329581	0.1678	–1.96	0.051

The naïve logit model (Table 5.11) presents some interesting findings as some of the variables are significant. Oil is significant at 10% level (0.069), S&P500 (0.005), B Exch Rate (0.041), T10Y3MM (0.051).

The results of the prediction accuracy were evaluated by comparing the actual and predicted states. Table 5.12 below presents the comparison. The model predicted 102 out of 127 cases correctly when the market was in bull state (0). The model also predicted 38 cases of 97 cases correctly when the market was in the bear state (1). The overall results show that the prediction gets more accurate 80% (102/127) in the state (0) compared with 40% (38/97) when it is in the state (1). There are ways to improve the naïve prediction by using other calculation methods (such as extending the calculation period to more than one month or taking the average movement etc.). Such improvements, if applicable, are left for future investigations. Since ADX has a significant trend coefficient and the binary naïve model shows reasonable predication, it will be a good idea to investigate the assumption that when the market trend is significant, the prediction of bull market, based on the naïve approach, will be reasonably accurate.

Table 5.12: Binary Logit Model – Prediction Accuracy

Table of actual and predicted			
	State 0	**State 1**	**Sum actual**
State 0	102	25	127
State 1	59	38	97
Sum pred	161	63	224

5.7 Out-of-Sample Tests

The out-of-sample results are obtained by setting the out-of-sample period to be for five years starting from August 2017 to August 2022 so that the ratio is more than 25% of the total sample. To examine the out-of-sample forecasting, the mean absolute percentage error (MAPE) was used, also called the mean absolute percentage deviation (MAPD), which can be used to measure the accuracy of a forecasting model. It measures this accuracy as a percentage, and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values. The MAPE was discussed earlier in the methodology chapter.

To conduct the out-of-sample evaluation process, the following steps were performed:

- Select the in-sample-period.
- Select the out-of-sample period.
- Test the model and variables.
- Check the output graph and MAPE.

For all models tested, the in-sample period from April 2004-August 2017 was selected and for all out of sample period, the period from September 2017 – August 2022 was chosen. Model 1, 2, 3 (Constant, Trend, and Three-regime) were tested. The results are presented below.

5.7.1 Model 1 – Standard (Constant) MS Model

The in-sample model test (Table 5.13) shows that all the variables are significant, except T10Y3MM (0.069) which is still significant at the 10% level. The results presented in Table 5.13 suggest that the study variables have good predictive power, as documented in the t-statistic.

Table 5.13: Model 1 – ADX - In-sample Results

Modelling ADX by MS(2)				
The estimation sample is: 2004(1) – 2017(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	–9.20772	1.195	–7.70	0.000
S&P500	0.944829	0.1220	7.75	0.000
TASI	0.190342	0.01487	12.8	0.000
BAA10YM	145.166	44.90	3.23	0.002
B Exch Rate	–59.1615	4.228	–14.0	0.000
T10Y3MM	–58.0989	31.75	–1.83	0.069
Constant(0)	8057.97	343.6	23.5	0.000
Constant(1)	6710.91	321.7	20.9	0.000
	Coefficient	**Std. Error**		
sigma	296.446	16.76		
p_{0|0}	0.970066	0.02084		
p_{1|1}	0.968764	0.01775		

Also, the in-sample model shows a good prediction dotted line and a good resemblance with the actual ADX index movement line, as demonstrated in Figure 5.17. The blue (0) and grey (1) regimes represent each regime classification, and the prediction line moves along the index line.

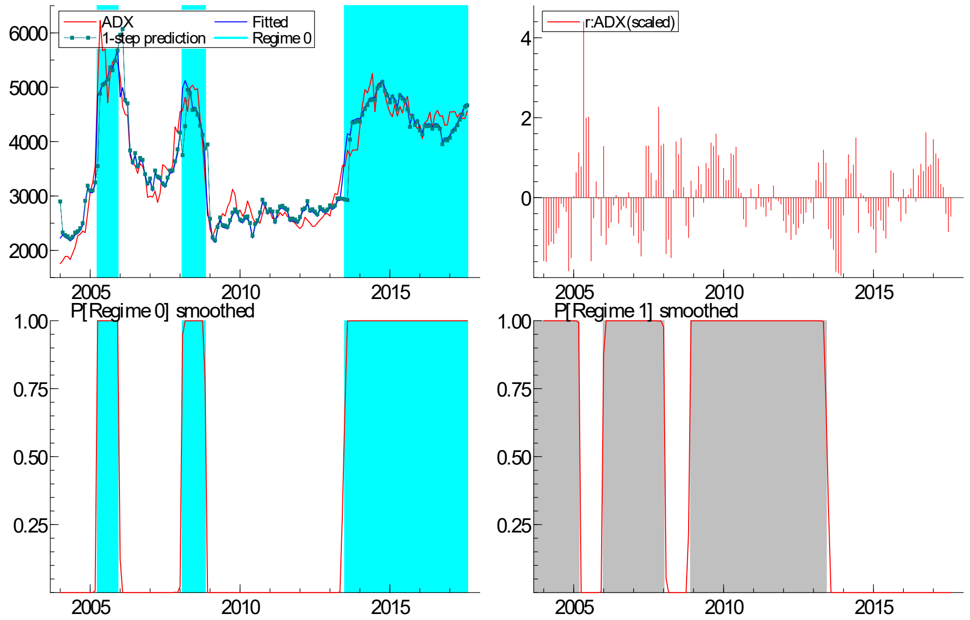

Figure 5.17: Model 1 – ADX - In-sample Prediction Line, Regime Classification, Scaled Residuals

5.7.1.1 Forecasting graph

The graph in Figure 5.18 shows that the prediction line moves closely with the actual index line. The prediction was very good from August 2017–June 2018, but the prediction accuracy fell slightly after that date. However, both lines (actual vs forecasting) are moving in parallel as the trajectory is very good until April 2021. The forecasting misses after that date as the ADX market moved rapidly upward due to the high value and volume of transactions. It is assumed that the chosen variable could not explain this projection error in mid-2021 due to many other factors. It is also assumed that money supply, new IPOs, foreign and institutional investors demand/transactions and many other variables can be incorporated in future studies to test if the forecasting can be enhanced, especially the period after mid-2021.

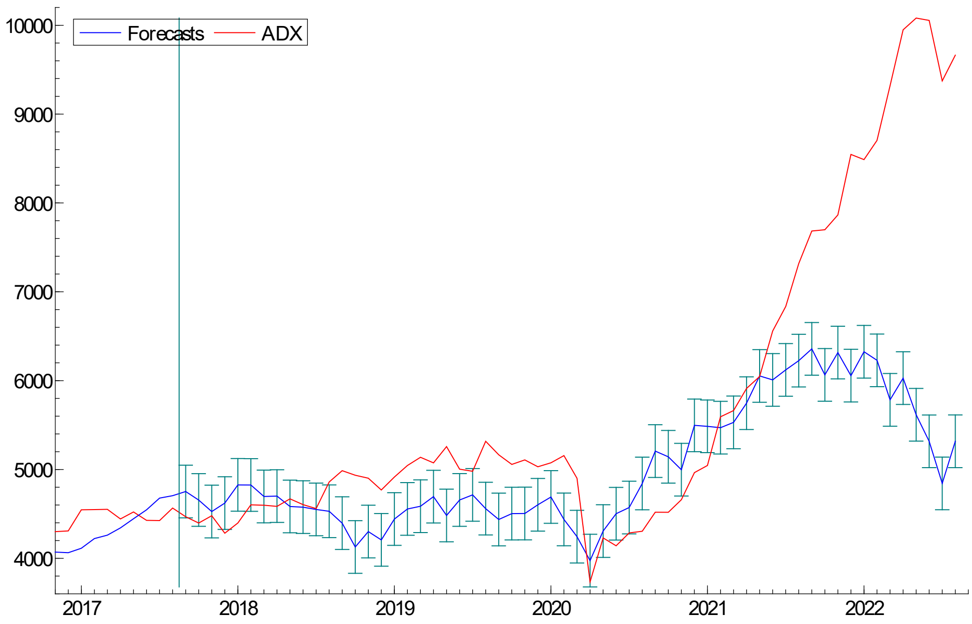

Figure 5.18: Model 1 – ADX - Out-of-Sample Forecasting

Table 5.14: Model 1 – ADX Forecasting – MAPE Value

Forecasting ADX from 2017(9) to 2022(9)							
Horizon	**Forecast**	**(SE)**	**Actual**	**Horizon**	**Forecast**	**(SE)**	**Actual**
1	4752.2	296.45	4468.4	31	4244.2	296.45	4901.4
2	4656.4	296.45	4397.4	32	3974.4	296.45	3734.7
3	4526.7	296.45	4479.6	33	4307.1	296.45	4230.4
4	4621.9	296.45	4283.1	34	4502.3	296.45	4141.6
5	4826.9	296.45	4398.4	35	4571.9	296.45	4285.8
6	4825.5	296.45	4602.2	36	4842.7	296.45	4304.7
7	4696.4	296.45	4597.7	37	5207.3	296.45	4519.3
8	4700.5	296.45	4585.4	38	5143.2	296.45	4518.1
9	4583.7	296.45	4669.5	39	4997.9	296.45	4660.0
10	4576.1	296.45	4605.0	40	5496.8	296.45	4964.9
11	4550.5	296.45	4560.0	41	5486.0	296.45	5045.3
12	4529.8	296.45	4859.5	42	5470.8	296.45	5593.5
13	4396.1	296.45	4986.9	43	5530.3	296.45	5663.6
14	4127.6	296.45	4935.4	44	5746.5	296.45	5912.6
15	4301.6	296.45	4901.9	45	6053.1	296.45	6046.8
16	4207.5	296.45	4770.1	46	6008.6	296.45	6558.7
17	4442.2	296.45	4915.1	47	6121.4	296.45	6835.4

Table 5.14: Model 1 – ADX Forecasting – MAPE Value (continued).

18	4555.7	296.45	5044.9	48	6225.6	296.45	7318.2
19	4586.6	296.45	5137.8	49	6358.0	296.45	7684.6
20	4694.6	296.45	5074.6	50	6065.3	296.45	7698.8
21	4482.7	296.45	5258.0	51	6316.2	296.45	7865.1
22	4656.9	296.45	5003.6	52	6056.7	296.45	8546.5
23	4714.3	296.45	4980.0	53	6325.7	296.45	8488.4
24	4559.5	296.45	5317.9	54	6228.8	296.45	8704.3
25	4437.6	296.45	5165.6	55	5784.0	296.45	9319.4
26	4503.5	296.45	5057.3	56	6028.6	296.45	9948.8
27	4505.0	296.45	5107.8	57	5616.1	296.45	10081.0
28	4603.1	296.45	5030.8	58	5317.2	296.45	10055.0
29	4690.4	296.45	5075.8	59	4843.8	296.45	9374.7
30	4438.3	296.45	5156.2	60	5317.7	296.45	9663.5
mean(Error) = 752.55 RMSE = 1552.7 SD(Error) =1358.2				**MAPE = 13.294**			

From Table 5.14 above, the mean absolute percentage error (MAPE) = 13.294 which is considered as a good forecasting percentage. The error in forecasting the period from May 2021 might have raised the MAPE, otherwise it could have been lower and in the very good category.

5.7.2 Trend Model

The in-sample results (Table 5.15) show that all variables, except for S&P500 and BAA10YM, are significant. It is assumed that the main reason for that is found in the extreme fluctuations in 2005 and 2008 which affected the data's distribution. The prediction dotted line as per Figure 5.19 identified the bull and bear market and resembles the actual line. Nonetheless, there are some anomalies, especially in 2005, 2008, and mid-2013.

Table 5.15: Model 2 – ADX - In-sample Results

Modelling ADX by MS(2)				
The estimation sample is: 2004(1) – 2017(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	–10.6209	1.174	–9.05	0.000
S&P500	0.0670129	0.2391	0.280	0.780
TASI	0.185693	0.01584	11.7	0.000
BAA10YM	–40.4583	53.45	–0.757	0.450
B Exch Rate	–50.5706	4.928	–10.3	0.000
T10Y3MM	–79.2175	31.97	–2.48	0.014
Trend	6.71196	1.487	4.51	0.000
Constant(0)	8619.98	273.5	31.5	0.000
Constant(1)	7182.59	270.1	26.6	0.000
	Coefficient	**Std. Error**		
sigma	289.514	16.13		
p_{0|0}	0.971554	0.01982		
p_{1|1}	0.967586	0.01841		
Constant(0)	8619.98	273.5	31.5	0.000
Constant(1)	7182.59	270.1	26.6	0.000
	Coefficient	**Std. Error**		
sigma	289.514	16.13		
p_{0|0}	0.971554	0.01982		
p_{1|1}	0.967586	0.01841		

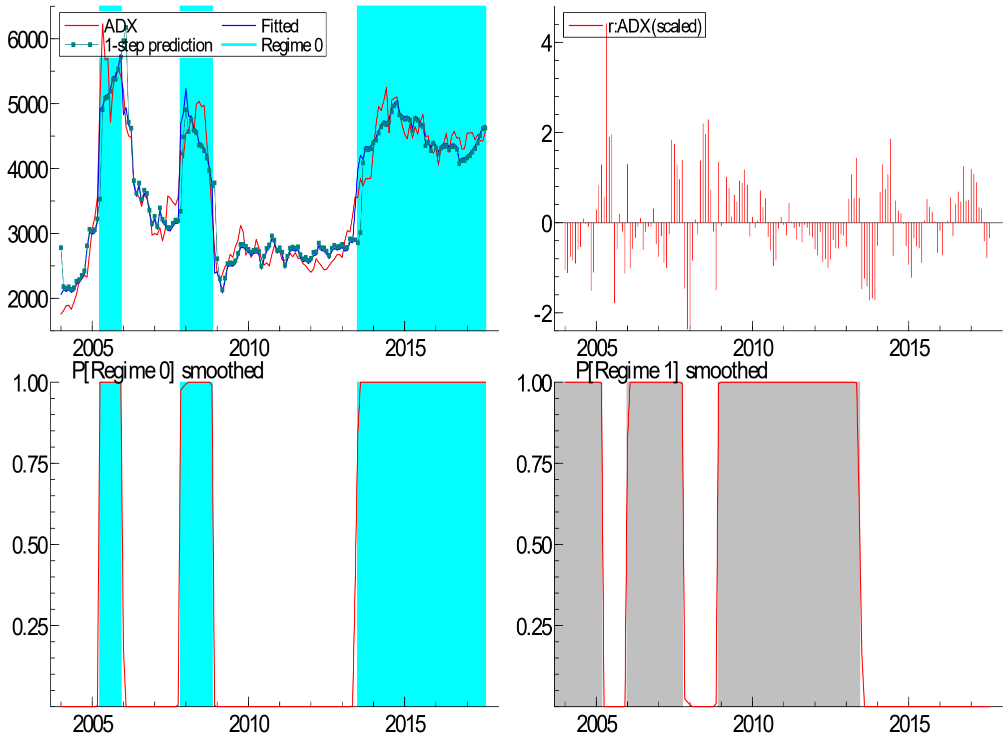

Figure 5.19: Model 2 – ADX - In-sample Prediction Line, Regime Classification, Scaled Residuals

5.7.2.1 Forecasting graph

The graph in Figure 5.20 indicates that the forecasting line misses the actual index line especially from early 2021 and onwards. The forecasting was normal prior to that period. It was very close to the actual line but did not forecast the significant drop at the beginning of the Covid-19 pandemic drop after March 2020. The trajectory after 2021 stayed stable even though the index moved significantly upward due to the high value and volume of transactions. The study variables could not explain this forecasting error due to many other factors. It is assumed that money supply, new IPO, foreign and institutional investors demand and many other variables that are not included in our study and can be tested in the future to test if such variables can improve the forecasting ability.

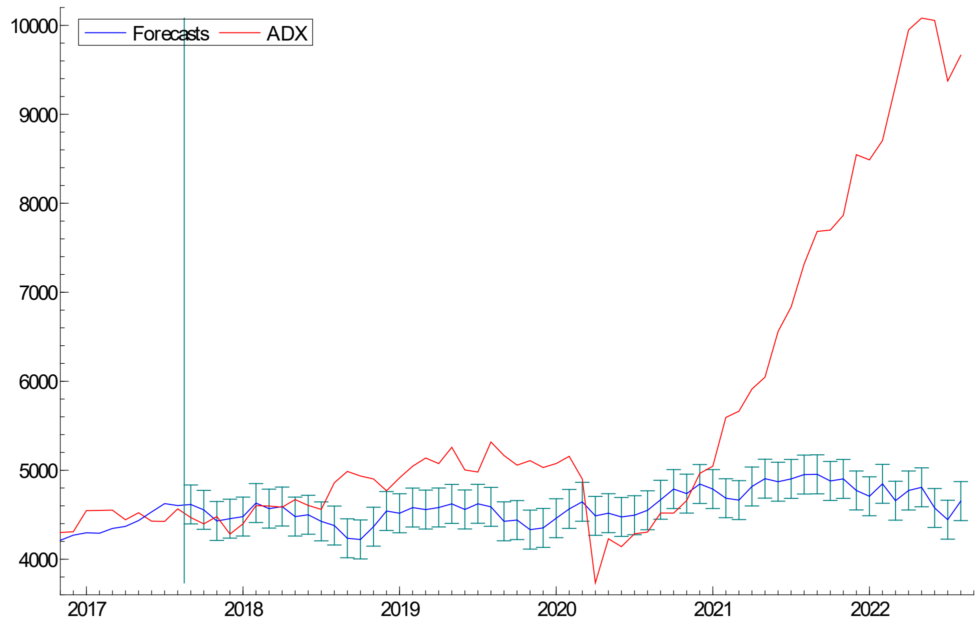

Figure 5.20: Model 2 – ADX - Out-of-Sample Forecasting

Table 5.16: Model 2 – ADX Forecasting - MAPE Value

Forecasting ADX from 2017(9) to 2022(9)							
Horizon	**Forecast**	**(SE)**	**Actual**	**Horizon**	**Forecast**	**(SE)**	**Actual**
1	4664.0	289.51	4468.4	31	4162.6	289.51	4901.4
2	4556.0	289.51	4397.4	32	3969.8	289.51	3734.7
3	4429.1	289.51	4479.6	33	4064.3	289.51	4230.4
4	4463.2	289.51	4283.1	34	4109.5	289.51	4141.6
5	4540.0	289.51	4398.4	35	4162.4	289.51	4285.8
6	4640.0	289.51	4602.2	36	4277.8	289.51	4304.7
7	4557.2	289.51	4597.7	37	4432.8	289.51	4519.3
8	4556.5	289.51	4585.4	38	4502.6	289.51	4518.1
9	4400.7	289.51	4669.5	39	4454.6	289.51	4660.0
10	4387.4	289.51	4605.0	40	4659.3	289.51	4964.9
11	4301.1	289.51	4560.0	41	4620.1	289.51	5045.3
12	4233.1	289.51	4859.5	42	4533.2	289.51	5593.5
13	4092.0	289.51	4986.9	43	4490.6	289.51	5663.6
14	4004.8	289.51	4935.4	44	4637.9	289.51	5912.6
15	4131.8	289.51	4901.9	45	4777.5	289.51	6046.8
16	4244.1	289.51	4770.1	46	4744.5	289.51	6558.7
17	4283.9	289.51	4915.1	47	4773.6	289.51	6835.4

Table 5.17: Model 2 – ADX Forecasting - MAPE Value

18	4351.6	289.51	5044.9	48	4825.0	289.51	7318.2
19	4343.1	289.51	5137.8	49	4852.3	289.51	7684.6
20	4373.6	289.51	5074.6	50	4720.1	289.51	7698.8
21	4339.5	289.51	5258.0	51	4772.7	289.51	7865.1
22	4335.5	289.51	5003.6	52	4610.7	289.51	8546.5
23	4391.4	289.51	4980.0	53	4616.0	289.51	8488.4
24	4315.4	289.51	5317.9	54	4687.3	289.51	8704.3
25	4161.2	289.51	5165.6	55	4427.4	289.51	9319.4
26	4175.6	289.51	5057.3	56	4526.3	289.51	9948.8
27	4097.0	289.51	5107.8	57	4419.1	289.51	10081.0
28	4134.2	289.51	5030.8	58	4200.3	289.51	10055.0
29	4233.8	289.51	5075.8	59	4008.4	289.51	9374.7
30	4237.0	289.51	5156.2	60	4261.6	289.51	9663.5
mean(Error) = 1363.6 RMSE = 2176.5 SD(Error) = 1696.4				**MAPE = 19.164**			

From Table 5.16 above, the mean absolute percentage error (MAPE) = 19.164 which is considered as a good forecasting percentage in that category (10-20%). The period from May 2021 onwards might have raised the MAPE. Despite being classified as a good forecaster, the Constant model outperforms the trend model in terms of forecasting accuracy.

5.7.3 Three-Regime Model

The in-sample regime classification based on smoothed probabilities (Table 5.17) shows that there are three regimes (0,1,2) for bull, bear, extreme bull markets, respectively. The dotted prediction line in Figure 5.21 shows more resemblance to the actual index movement line. The regime classification (Table 5.17) presents better results which are very close to the actual index fluctuation. Overall, the three-regime MS model provides better results compared with the other two models (Constant, Trend).

Table 5.18: Model 3 – ADX - In-sample Regime Classification

Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(8) – 2006(1)	6	0.962
2007(11) – 2008(5)	7	0.925
2008(9) – 2008(11)	3	0.836
2013(7) – 2017(8)	50	0.994
Total: 66 months (40.24%) with an average duration of 16.50 months		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2005(3)	15	0.999
2006(2) – 2007(10)	21	0.999
2008(12) – 2013(6)	55	0.991
Total: 91 months (55.49%) with an average duration of 30.33 months		
Regime 2	**Months**	**Avg. prob.**
2005(4) – 2005(7)	4	0.998
2008(6) – 2008(8)	3	0.997
Total: 7 months (4.27%) with average duration of 3.50 months		

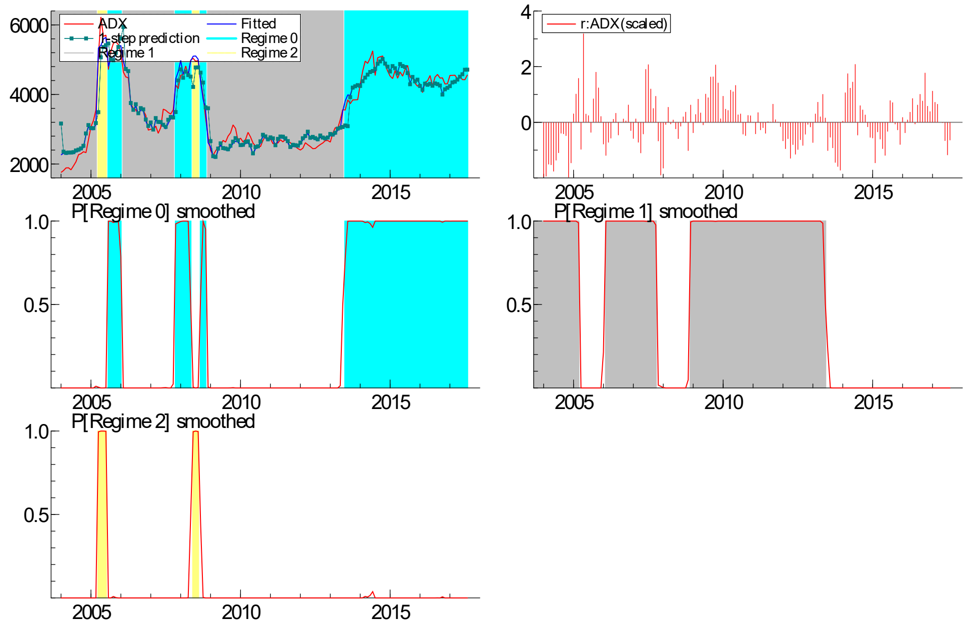

Figure 5.21: Model 3 – ADX - In-sample Prediction, Regimes, Scaled Residuals

The results of the in-sample three-regime MS model (Table 5.18) show that all the variables are significant at (0.05) level, except the interest spread (T10Y3MM) which is not significant.

Table 5.19: Model 3 – ADX - In-sample Results

Modelling ADX by MS(3)				
The estimation sample is: 2004(1) – 2017(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	–8.14224	1.082	–7.53	0.000
S&P500	1.13164	0.1345	8.42	0.000
TASI	0.192044	0.01541	12.5	0.000
BAA10YM	152.547	38.08	4.01	0.000
B Exch Rate	–41.8559	3.519	–11.9	0.000
T10Y3MM	–5.25947	29.15	–0.180	0.857
Constant(0)	5489.11	233.5	23.5	0.000
Constant(1)	4476.52	203.2	22.0	0.000
Constant(2)	6375.47	249.5	25.6	0.000
	Coefficient	**Std. Error**		
sigma	256.726	14.39		
p_{0|0}	0.951252	0.02757		
p_{1|0}	0.0318450	0.02216		
p_{0|1}	0.0219883	0.01538		
p_{1|1}	0.967285	0.01858		
p_{2|2}	0.741873	0.1589		
log-likelihood –1173.65536				
No. of observations	164	No. of parameters	15	
AIC	14.4957971	SC	14.7793215	
mean(ADX)	3615.42	se(ADX)	1044.24	
Linearity LR-test Chi^2(7) = 145.78 [0.0000]** approximate upperbound: [0.0000]**				
Transition probabilities p_{i|j} = P(Regime I at t+1 | Regime j at t)				
	Regime 0,t	**Regime 1,t**	**Regime 2,t**	
Regime 0,t+1	0.95125	0.021988	0.25813	
Regime 1,t+1	0.031845	0.96728	0.00000	
Regime 2,t+1	0.016903	0.010727	0.74187	

5.7.3.1 Forecasting graph

The out-of-sample forecast (Figure 5.22) is in line especially at the beginning of the forecasting period (Sep. 2017) till March 2020 (Q1-2020). ADX was affected due to the Covid-19 pandemic starting from the 2nd quarter-2020. The forecasting was also affected starting from that period. Nonetheless, the trajectory until May 2021 was in line, but the forecasting line dropped after that. Overall, the trajectory and forecasting show good results which reflect the robustness of the chosen study variables as predictors of the ADX price index movement.

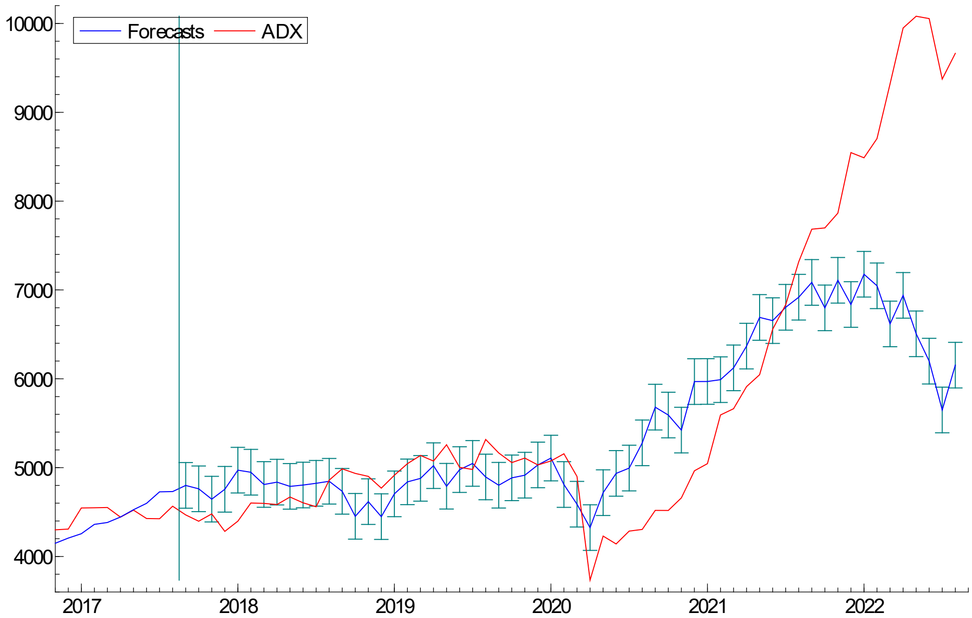

Figure 5.22: Model 3 – ADX - Out-of-Sample Forecasting

Table 5.20: Model 3 – ADX Forecasting - MAPE Value

Forecasting ADX from 2017(9) to 2022(9)							
Horizon	**Forecast**	**(SE)**	**Actual**	**Horizon**	**Forecast**	**(SE)**	**Actual**
1	4800.3	256.73	4468.4	31	4589.0	256.73	4901.4
2	4761.9	256.73	4397.4	32	4325.3	256.73	3734.7
3	4645.7	256.73	4479.6	33	4718.6	256.73	4230.4
4	4756.6	256.73	4283.1	34	4935.7	256.73	4141.6
5	4972.0	256.73	4398.4	35	4995.6	256.73	4285.8
6	4948.7	256.73	4602.2	36	5279.4	256.73	4304.7
7	4810.7	256.73	4597.7	37	5681.4	256.73	4519.3
8	4837.0	256.73	4585.4	38	5592.5	256.73	4518.1
9	4789.5	256.73	4669.5	39	5422.9	256.73	4660.0
10	4804.4	256.73	4605.0	40	5969.1	256.73	4964.9
11	4824.0	256.73	4560.0	41	5970.4	256.73	5045.3
12	4846.8	256.73	4859.5	42	5990.6	256.73	5593.5
13	4733.9	256.73	4986.9	43	6123.3	256.73	5663.6
14	4452.2	256.73	4935.4	44	6368.4	256.73	5912.6
15	4617.7	256.73	4901.9	45	6691.2	256.73	6046.8
16	4448.7	256.73	4770.1	46	6655.1	256.73	6558.7
17	4705.1	256.73	4915.1	47	6805.5	256.73	6835.4
18	4840.3	256.73	5044.9	48	6918.8	256.73	7318.2
19	4879.3	256.73	5137.8	49	7085.5	256.73	7684.6
20	5022.8	256.73	5074.6	50	6799.1	256.73	7698.8
21	4790.8	256.73	5258.0	51	7109.1	256.73	7865.1
22	4978.2	256.73	5003.6	52	6837.0	256.73	8546.5
23	5047.8	256.73	4980.0	53	7177.3	256.73	8488.4
24	4895.4	256.73	5317.9	54	7047.1	256.73	8704.3
25	4802.4	256.73	5165.6	55	6618.0	256.73	9319.4
26	4885.7	256.73	5057.3	56	6939.7	256.73	9948.8
27	4915.4	256.73	5107.8	57	6506.9	256.73	10081.0
28	5031.0	256.73	5030.8	58	6199.1	256.73	10055.0
29	5108.0	256.73	5075.8	59	5649.6	256.73	9374.7
30	4810.2	256.73	5156.2	60	6153.9	256.73	9663.5
mean(Error) = 302.89 RMSE = 1229.7 SD(Error) = 1191.8				**MAPE = 11.438**			

The MAPE (11.438) as shown in Table 5.19 is considered a good forecast and the results are better than the results of the Constant (model 1) and the trend (model 2) MS models.

Table 5.21: MAPE Summary

Constant model	MAPE = 13.294
Trend model	MAPE = 19.164
Three-regime model	MAPE = 11.438

The results presented in Table 5.20 suggest that applying the three- regime model to the study variables resulted in a model that has good forecasting power (MAPE = 11.438). The variables considered in this thesis are useful for predicting bear markets. It is worth noting that the capacity of these study variables to predict market index direction has already been investigated in this study and our test methods using the same data, sample periods, and investigation methods makes the models more informative.

5.8 Economic Values of Predicting Stock Market Regimes

Finally, the question of whether predicting the stock market direction is useful for investors looking to time their investment choices to market booms and recessions was investigated. To test the second hypothesis (H2), a very simple test was conducted based on the regime classification generated by the three-regime MS model to compare the profitability of a switching strategy versus a benchmark buy-and-hold strategy, assuming no transaction costs. The three-regime classification output was chosen because the MAPE was the lowest in the out-of-sample robustness test. The switching strategy is employed as follows - the market index is treated as a portfolio of USD 1 million at the beginning of the study period and then the following investment strategy is applied:

Buying and holding the index (long position) when the regime is in a bull market state (0). Investors should continue to hold if the following regime is an extreme bull market (2) and sell the position at the end of that regime if the following regime is a bear market (1).

Taking a short-position equivalent to the accumulated portfolio value at the beginning of bear market regime and holding the short-position till the end of that specific bear market as stated in the classification regime output.

Buy and hold strategy: start the portfolio of One million and link the portfolio profit (losses) to the value of the portfolio at the end of the study period or to the end of the last bear market.

Calculate and compare the portfolio value between the two investment strategies to compare the differences.

Table 5.22: Comparison Between Switching and Buy and Hold Strategies (2004–2022) using MS 3-regime Classification (ADX)

		Index					
#	**Switching Strategy**	**From**	**To**	**Regime**	**Diff.**	**% Gain (Loss)**	**Investment value**
1	2004(1) – 2004(12)	1757	2700	1			1,000,000
2	2005(1) – 2005(3)	3071	3551	0		0	1,000,000
3	2005(4) – 2005(7)	5085	5707	2	3,950	225	3,248,082
4	2005(8) – 2006(1)	4715	5203	0	488	10	3,584,367
5	2006(2) – 2006(8)	4646	3418	1	(1228)	–26	4,532,056
6	2006(9) – 2008(10)	3596	3957	0	361	10	4,986,673
7	2008(11) – 2013(12)	3326	3850	1	524	16	4,201,279
8	2014(1) – 2021(7)	4290	6835	0	2,545	59	6,693,647
9	2021(8) – 2022(8)	7318	9663	2	2,345	32	8,839,007
	Buy and Hold Strategy						
1	2004(1) – 2022(8)	1757	9663		7907	450	4,500,233
	Conclusion: Switching strategy end value > Buy and Hold strategy end value → (8,839,007 > 4,500,223)						

Table 5.21 shows the terminal values of a $1,000,000 investment over the study period. Investing USD 1 million in a buy-and-hold strategy would yield $4,500,233 at August 2022 and yearly rate of return is 20% per annum. On the other hand, a switching strategy based on different bull and bear market regime classification would yield $8,839,007 at August 2022 and yearly rate of return of 42%. Therefore, a switching strategy produces a higher terminal wealth and compounded returns. This simple exercise demonstrates the usefulness of predicting a market trend. Switching strategies, with forecasted information about the bear market probability, outperforms buy-and-hold strategies. This means that hypothesis H2 is supported.

5.9 Section 2 - DFM Results

To analyze the DFM market, the same tests and analyses were conducted that were used for the ADX market. The graph analysis of each variable's relationship with the DFM price index movement was examined to evaluate the movement over the 18 years of the study period (2004-2022). In addition, the three types of Markov-regime switching models (Constant, Trend, 3-regime) were also tested to evaluate the results, binary logit model, out-of-sample robustness for each model. Finally, the second hypothesis was tested.

5.9.1 DFM Price Index Graph Analyses

From Figure 5.23, the price index fluctuations between 2004-2022 are clear. The market has witnessed different bear and bull periods. The index jumped almost 800% from 2004 until mid-2005. That was one of the highest stock market growth rates in the world at that time. The market boom was associated with the new IPOs introduced into the market and the new policies permitting foreign ownership. The UAE stock markets (ADX and DFM) eased the foreign ownership regulations by allowing the international investors to gradually buy and own most of the UAE stocks. Such changes attracted and increased the demand from foreign investors, institutional and hedge funds.

Figure 5.23: DFM Price Index Movement (2004–2022)

The UAE economy witnessed significant growth in general. By mid-2005, the DFM suffered the effect of the "bubble burst" scenario as the index dropped from +8000 points to less than 4000 points. The market stayed at a stable level in 2006 but gained momentum again in mid-2007 and suffered an extreme drop in mid-2008 due to the global sub-prime financial crisis. DFM stabilized close to 2000 points from 2009 to early 2013. During 2013, the market started to rally again, and the market price index reached above 5000 points for some time and dropped later to 3000 points and stabilized in that range until early 2020. The graph shows many fluctuations in the DFM index. Large fluctuations can lead to significant changes in the investor's wealth (positively or negatively). Such fluctuations attracted retail investors and institutional investors who prefer to invest in or speculate in such markets. If this study variables can predict the market trend, then such predictions can be considered as a comparative advantage for regular and potential investors.

5.9.2 Comparison Between ADX and DFM Index Movement

From Figure 5.24, it is clear that ADX and DFM markets exhibit almost the same movement. During earlier years, the DFM price index's growth exceeded that of ADX. In 2005, the growth momentum in DFM took the index from the 1000-point level to 8400 points which is approximately a 740% gain, compared to 250% growth rate in the ADX as the index jumped from the 1770-point level to 6250 points. On the other hand, starting from 2020, ADX showed a remarkable recovery after the covid-19 pandemic and the ADX index rose from 3700 points in April 2020 to the 10,000-point level which is equal to a 170% growth rate. DFM index jumped from 1770 to 3700 during the 2020-2022 cycle, which represents a growth of 110%.

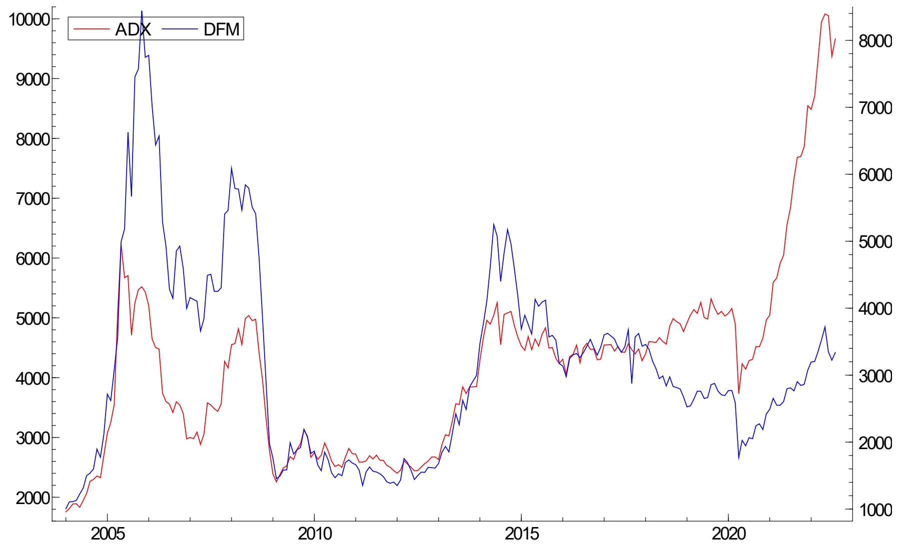

Figure 5.24: DFM vs. ADX Graph

If we compare the seasonal differences, we can notice that both markets move in the same direction except for a few periods.

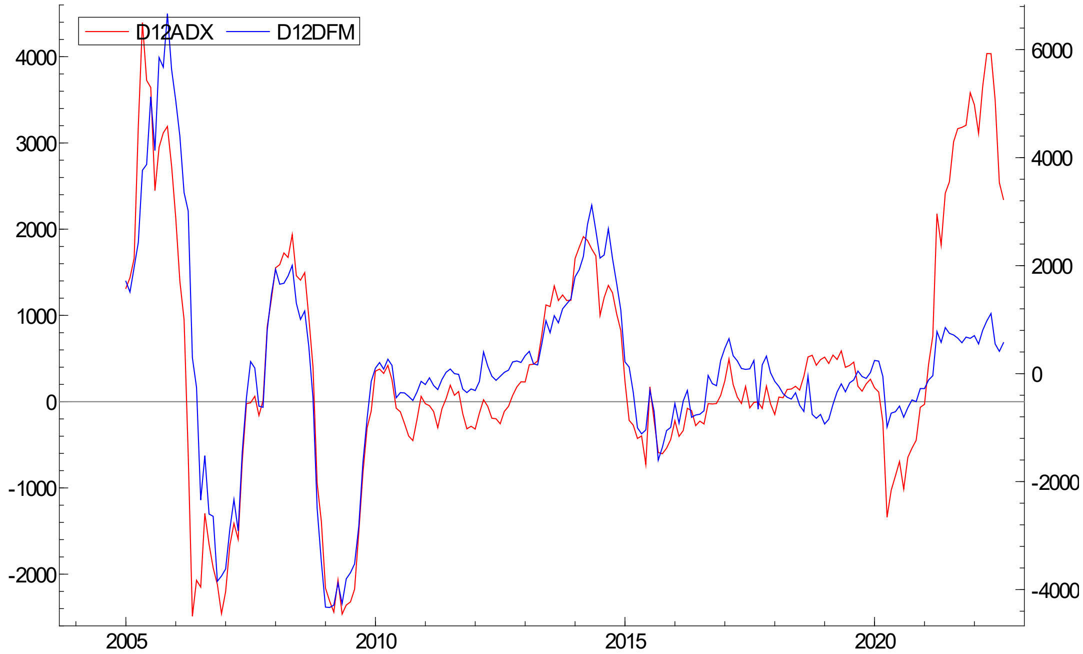

Figure 5.25: Seasonal Differences (ADX vs. DFM)

5.9.3 DFM and OIL

In most cases, both variables move in line with each other (Figure 5.26), but there are periods of discrepancies (2012-2014) as DFM is moving upwards but oil fluctuates at the same level. Also, there are some movement lags in some cases. Between 2009-2013, oil prices increased but the market index was slowly recovering. Also, when oil prices dropped in 2015, the market index dropped slowly.

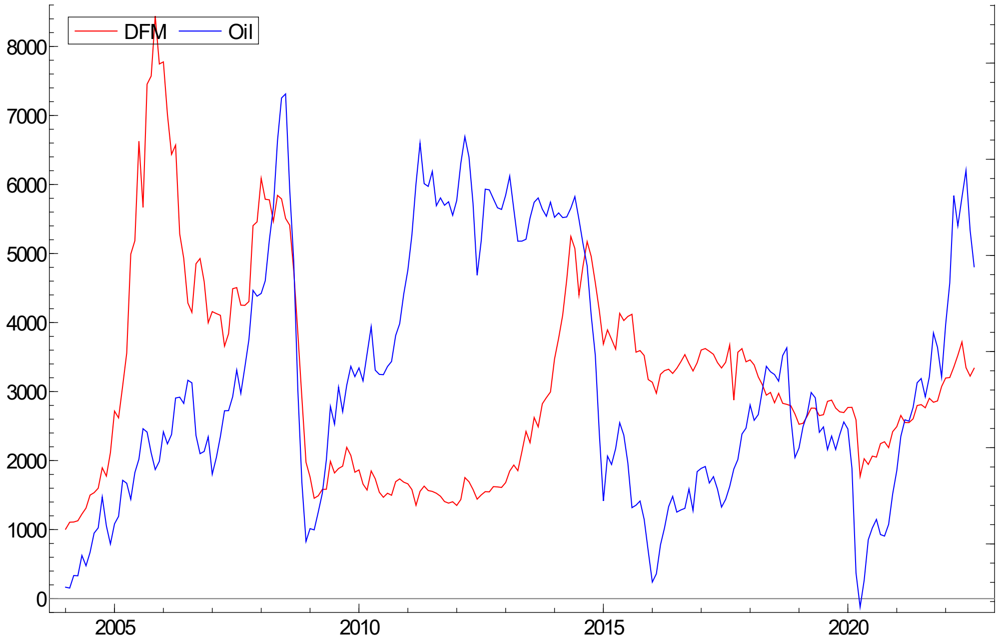

Figure 5.26: DFM vs. OIL Graph

From the seasonal differences (Figure 5.27), similar movement patterns are visible most of the time. The magnitude of change differs sometimes.

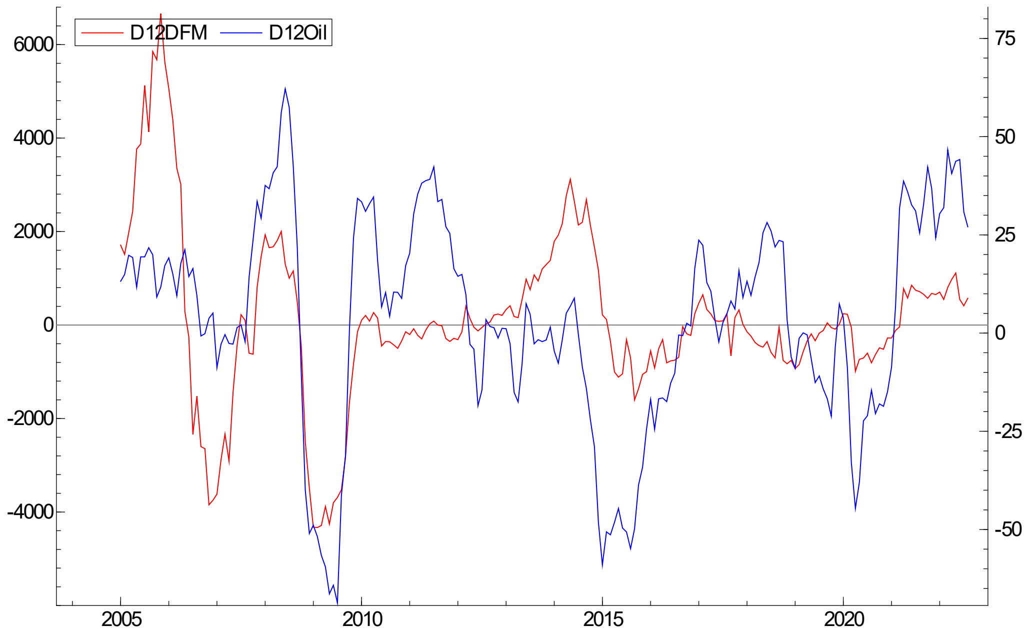

Figure 5.27: Seasonal Differences (DFM vs. OIL)

5.9.4 DFM vs. S&P 500

The movement graph (Figure 5.28) displays movement differences between DFM and S&P 500. The 2005 peak in DFM was unique to the UAE market. S&P 500 movement in that period was less volatile compared to the DFM. However, there is a noticeable drop in both indexes in 2008 due to the sub-prime financial crisis effect. Both markets indices moved upward and crossed during mid-2016. Also, both market indices recovered after the covid 19 pandemic effect in April 2020 and continued the upward trend during the remaining of 2020, 2021, and part of 2022.

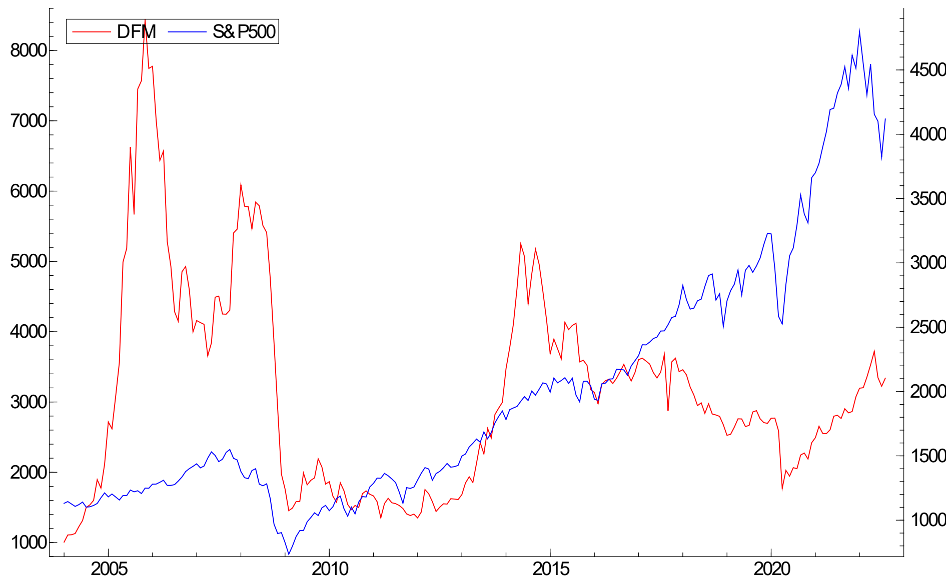

Figure 5.28: DFM vs. S&P500 Graph

The seasonal differences (Figure 5.29) show a reasonable resemblance. DFM fluctuations were rapid in 2005-2008 period but S&P500 fluctuations became more volatile after 2018.

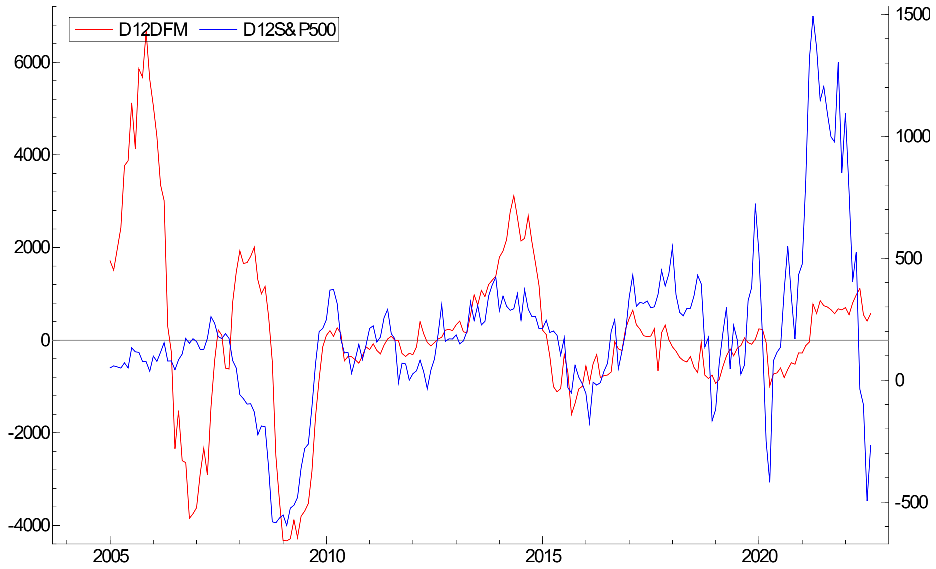

Figure 5.29: Seasonal Differences (DFM vs. S&P500)

5.9.5 DFM vs TASI

Both markets move in line most of the time (Figure 5.30). This is a noticeable resemblance. Even the 2005 (bubble burst effect) is present in both markets at almost the same time. The seasonal differences (Figure 5.31) are also in line to a great extent. Since KSA is the leading market in the GCC and the trading volume and value of TASI is much higher than that of DFM, we believe that the TASI index movements are a good predictor of the DFM market trend.

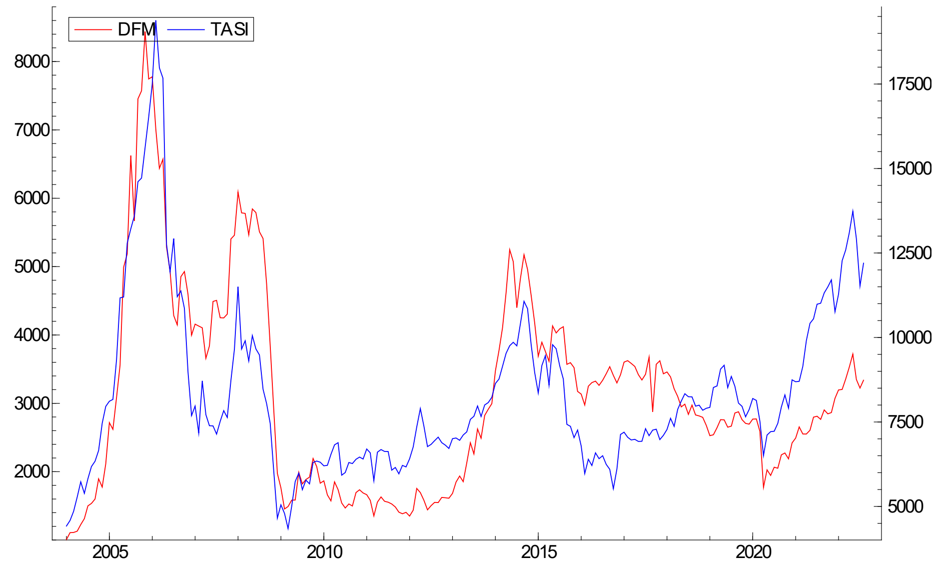

Figure 5.30: DFM vs. TASI Graph

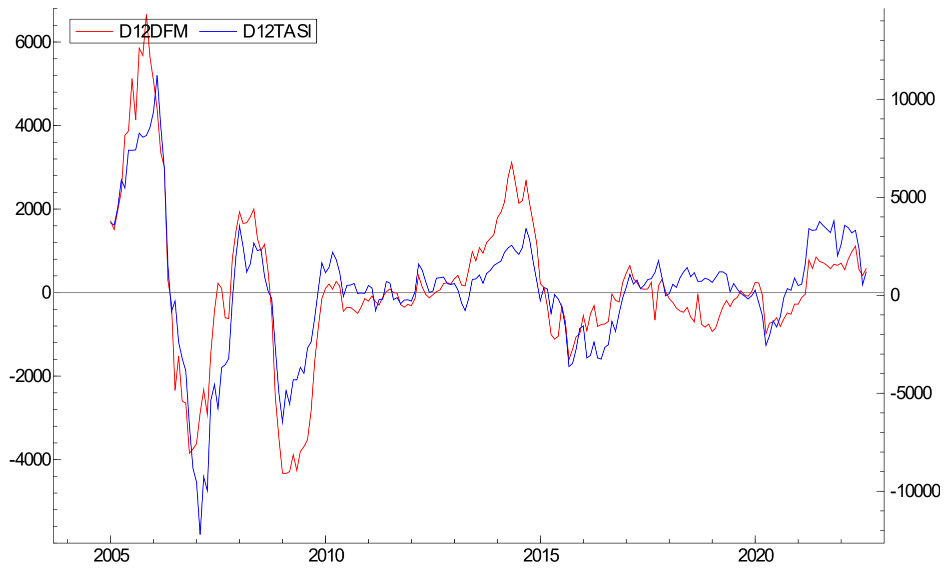

Figure 5.31: Seasonal Differences (DFM vs. TASI)

5.9.6 DFM vs Default Spread (BAA10YM)

The default spread was at low in 2005 (Figure 5.32) and started to raise starting from mid-2007 when the world started to anticipate the financial crisis and reached at the highest level of 6% in 2009 and started to reduce till it reached at 2.5% in 2010 and continued within that range with an average fluctuation of 2% range until 2022 with a noticeable rise in 2016 and 2020 (Covid-19 effect). Based on Figure 5.32, it seems that there is an inverse relationship between default spreads and the DFM price index, especially from 2007 onwards. Such direction implies the possibility of getting significant prediction correlation between the two variables.

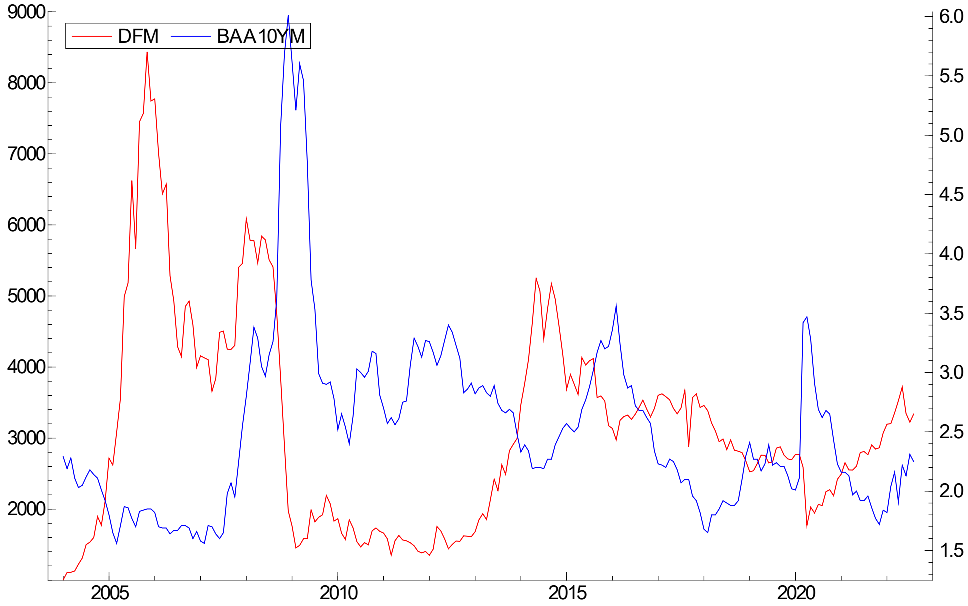

Figure 5.32: DFM vs. BAA10YM Graph

The seasonal differences (Figure 5.33) move inversely to each other as when the default rate (BAA10YM) takes a downwards trend, the DFM index takes an upwards trend and vice versa. In 2004-2006 period when DFM reached high levels and drop subsequently, the default rate was almost stable. But after the 2008 crisis, the seasonal differences are moving in the opposite direction with some reaction lag in some periods.

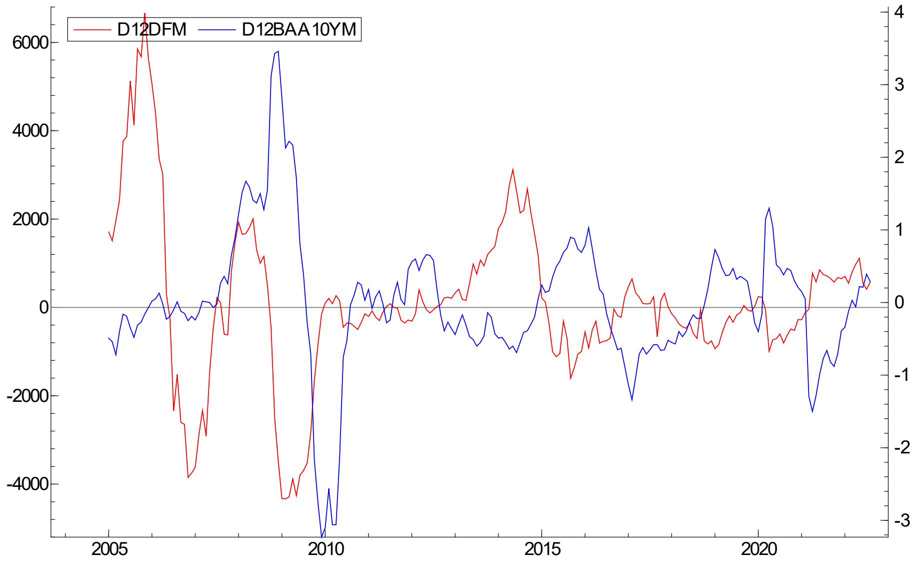

Figure 5.33: Seasonal Differences (DFM vs. BAA10YM)

5.9.7 DFM vs B. Exchange Rate

The movement of both variables as seen in Figure 5.34 indicates a good correlation between them. During the period from 2004-2006, DFM index has risen due to internal domestic factors related to the UAE demand. Since the UAE currency is pegged with USD, the change in movement of both variables is not correlated during that period due to the isolation of the domestic boom in DFM index from the global effect. After that date, movement resemblances appear over the long run after 2011. Both variables exhibit almost the same upward long-term trend/direction.

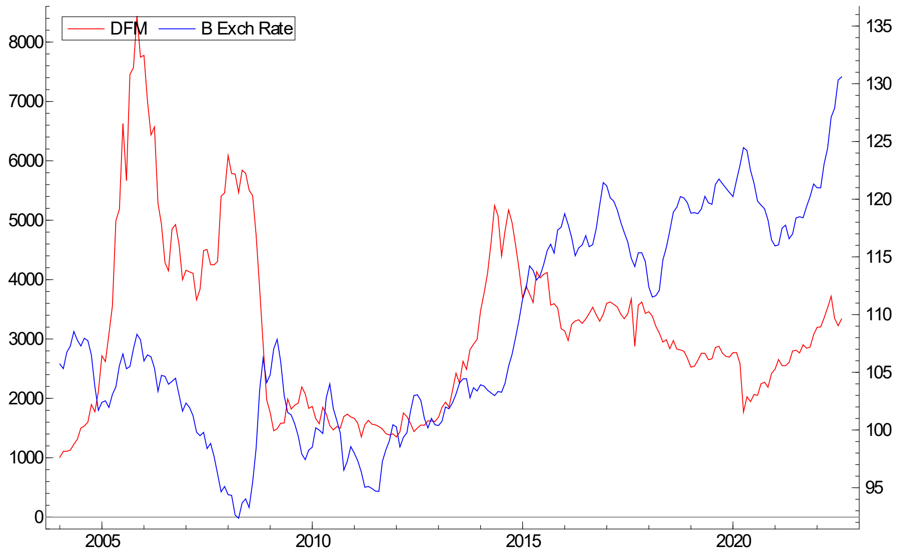

Figure 5.34: DFM vs. B. E. Exchange Rate Graph

The seasonal differences in Figures 5.35 show that the volatility movements in the seasonal differences of the exchange rate is much higher than the volatility movement in DFM index seasonal differences. Such fluctuations might be perceived by hedge funds and professional investors as opportunities to enter and exit the market with the intention of making capital gains on stock prices or currency exchange gain, assuming they can anticipate or project the movement at an acceptable rate to make positive investment profit/gain.

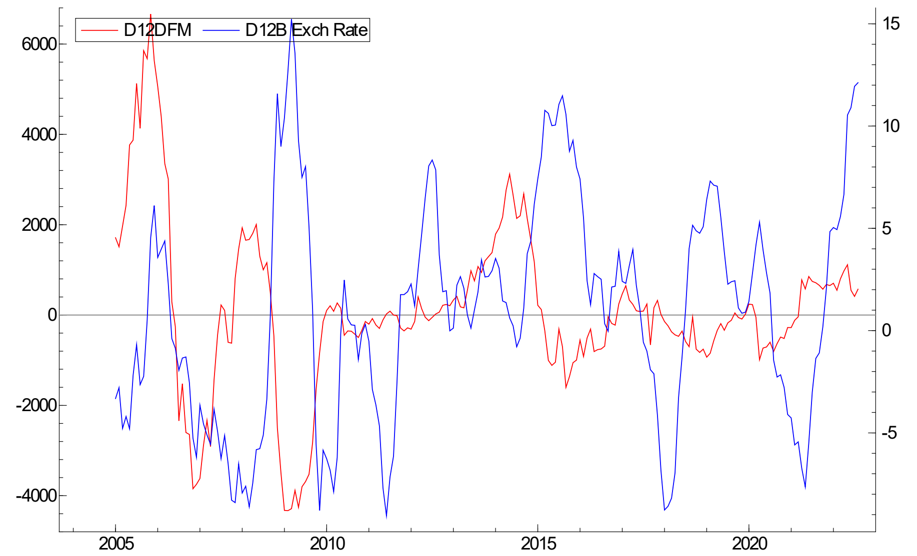

Figure 5.35: Seasonal Differences (DFM vs. Broad Exchange Rate)

5.9.8 DFM vs T10Y3MM

From Figure 5.36, good movement resemblances are visible between the two variables in the graph, especially after 2013. The DFM index and the interest rate spread move almost in the same direction. The seasonal differences (Figure 5.37) also reflect this observation from 2008 onwards.

Figure 5.36: DFM vs. T10Y3MM Graph

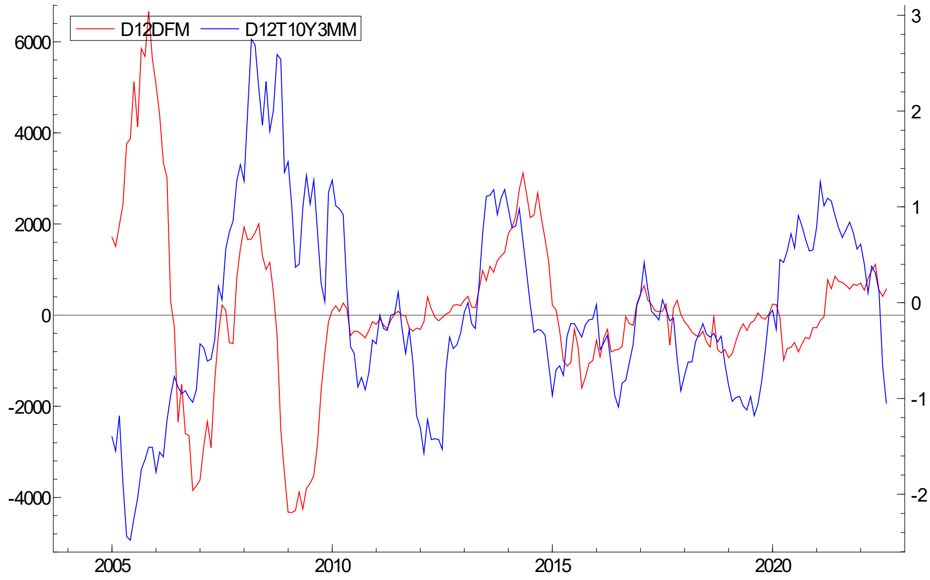

Figure 5.37: Seasonal Differences (DFM vs. T10Y3MM)

5.10 Statistical Results

A separate analysis was run for the DFM which includes the results for the three MS models predictive ability, out-of-sample robustness, and the assessment of the second hypothesis (H2).

5.10.1 Models

Four different models will be used: Constant (Model 1), Trend (Model 2), Three-regime (Model 3) and the Binary logit (Model 4).

5.10.2 Model 1 – Constant Model

The results (Table 5.22) show that regime classification based on smoothed probabilities is possible and that clear distinctions of regimes are identified. The results show that there are four bull markets (0) and four bear markets (1). The bull market totaled 85 months (38%) with average duration of 28.33 months. The bear market totaled 139 months (62%) with average duration of 34.75 months.

Table 5.23: Model 1 – DFM - Regime Classification

Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(7) – 2006(1)	7	0.992
2006(10) – 2008(11)	26	0.988
2014(1) – 2018(4)	52	0.994
Total: 85 months (37.95%) with average duration of 28.33 months		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2005(6)	18	0.959
2006(2) – 2006(9)	8	0.987
2008(12) – 2013(12)	61	0.993
2018(5) – 2022(8)	52	0.995
Total: 139 months (62.05%) with average duration of 34.75 months		

The dotted prediction line shown in Figure 5.38 suggests that the prediction is in line with the actual index movement most of the time except for some periods where we see deviation. For example, the prediction turned downward earlier than what actually happened and did not capture the upward trend movement fully in 2008. The same can be said for the period between 2012-2014. But overall, the prediction is reasonable.

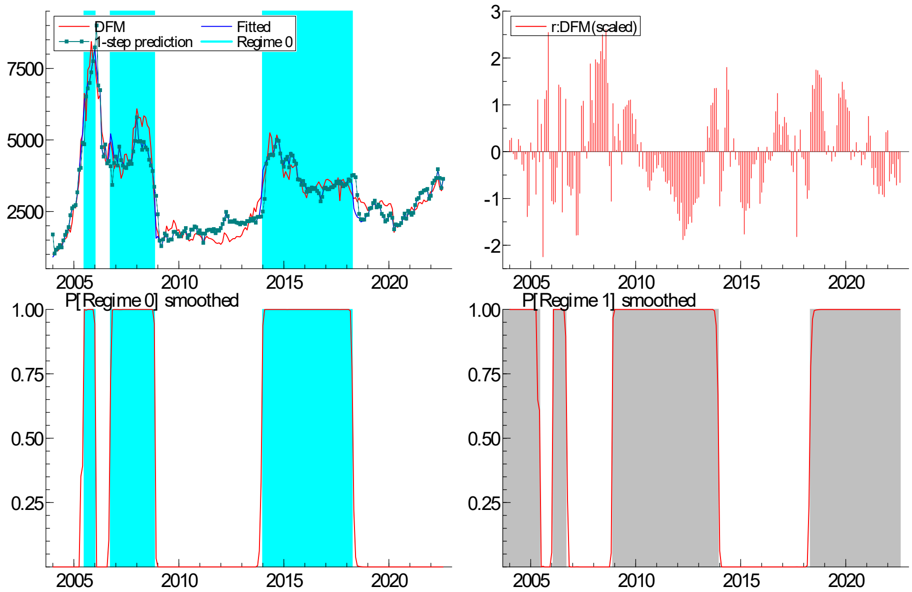

Figure 5.38: Model 1 – DFM - Prediction Line, Regimes, Scaled Residuals

The regime classification as in Figure 5.38 captured most of the drop and movement acceleration but sometimes misses the correct movement. Such misses might be related to limiting the regimes switching option to two regimes. Nonetheless, the regime classification, as highlighted in different colors in Figure 5.38, is reasonable.

The Constant model prediction results as outlined in Table 5.23 reveal that the predictive ability of the variables is promising as all the variables are significant at the 0.05 level, except Oil (0.06) and BAA10YM (0.096), but both of them are significant at the (0.10) level.

From the graph analysis that was discussed earlier, in the early period in the DFM index movement, there were extreme volatilities in 2005. These extreme volatilities created challenges for the predictive ability of our models as the volatilities can be considered as outliers. But, as mentioned earlier, this era/period was retained in the sample as it represents a historical part of the UAE stock market trend that needs to be studied and understood to underpin the reasons that caused such volatilities.

Table 5.24: Model 1 Results – DFM

Modelling DFM by MS(2) The estimation sample is: 2004(1) – 2022(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	–2.66782	1.413	–1.89	0.060
S&P500	–0.157970	0.06210	–2.54	0.012
TASI	0.411609	0.01597	25.8	0.000
BAA10YM	85.4323	51.06	1.67	0.096
B Exch Rate	–15.6925	5.364	–2.93	0.004
T10Y3MM	–174.553	32.45	–5.38	0.000
Constant(0)	2976.85	501.6	5.94	0.000
Constant(1)	1381.68	461.6	2.99	0.003
	Coefficient	**Std. Error**		
sigma	400.926	20.68		
p_{0|0}	0.964543	0.02012		
p_{1|1}	0.978200	0.01245		
log-likelihood –1684.11423				
No. of observations	224	No. of parameters	11	
AIC	15.1349485	SC	15.3024847	
mean(DFM)	3134.24	se(DFM)	1467.83	
Linearity LR-test Chi^2(3) = 288.49 [0.0000]** approximate upperbound: [0.0000]**				
Transition probabilities p_{i|j} = P(Regime i at t+1 | Regime j at t)				
	Regime 0,t	**Regime 1,t**		
Regime 0,t+1	0.96454	0.021800		
Regime 1,t+1	0.035457	0.97820		

5.10.3 Model 2 – Trend Model

The trend coefficient in Table 5.24 is not significant (0.289) which means that DFM data is stationary and there is no trend in the data. This information might be considered as explanation of why some of the variables are not significant in this model. For example, Oil (0.179), S&P500 (0.255) are not significant. Therefore, the trend prediction model results are not as good as the Constant model results. The dotted prediction line as in Figure 5.39 has a good prediction line overall and moves smoothly along the actual index movement.

Table 5.25: Model 2 Results – DFM

Modelling DFM by MS(2)				
The estimation sample is: 2004(1) – 2022(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	–1.71063	1.267	–1.35	0.179
S&P500	–0.104225	0.09134	–1.14	0.255
TASI	0.404945	0.01702	23.8	0.000
BAA10YM	103.582	52.26	1.98	0.049
B Exch Rate	–11.3468	2.398	–4.73	0.000
T10Y3MM	–178.380	33.77	–5.28	0.000
Trend	–1.31530	1.237	–1.06	0.289
Constant(0)	2498.49	109.8	22.8	0.000
Constant(1)	891.634	105.2	8.47	0.000
	Coefficient	**Std. Error**		
sigma	400.228	19.28		
p_{0|0}	0.964543	0.02012		
p_{1|1}	0.978198	0.01245		
log-likelihood –1683.75831				
No. of observations	224	No. of parameters	12	
AIC	15.1406992	SC	15.323466	
mean(DFM)	3134.24	se(DFM)	1467.83	
Linearity LR-test Chi^2(3) = 280.40 [0.0000]** approximate upperbound: [0.0000]**				
Transition probabilities p_{i|j} = P(Regime i at t+1 | Regime j at t)				
	Regime 0,t	**Regime 1,t**		
Regime 0,t+1	0.96454	0.021802		
Regime 1,t+1	0.035457	0.97820		

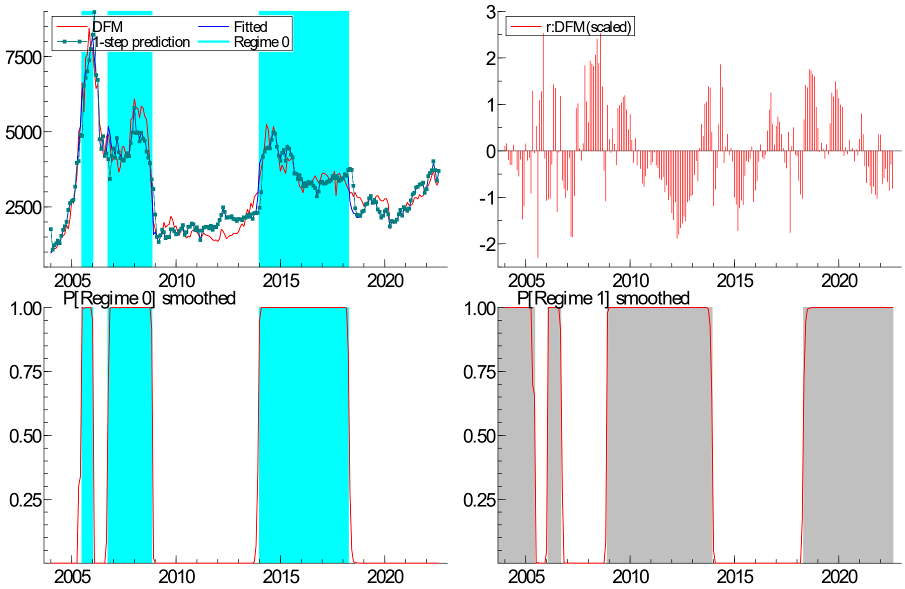

Figure 5.39: Model 2 – DFM - Prediction Line, Regimes, Scaled Residuals

The regime classification based on smoothed probabilities (Table 5.25) identified three bull market regimes (0) with total duration of 85 months (38%) and identified four regimes with a duration for 34.75 months (62%).

Table 5.26: Model 2 – DFM - Regime Classification

DFM – Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(7) – 2006(1)	7	0.993
2006(10) – 2008(11)	26	0.985
2014(1) – 2018(4)	52	0.996
Total: 85 months (37.95%) with average duration of 28.33 months		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2005(6)	18	0.964
2006(2) – 2006(9)	8	0.989
2008(12) – 2013(12)	61	0.993
2018(5) – 2022(8)	52	0.993
Total: 139 months (62.05%) with average duration of 34.75 months		

Overall, the model provided good prediction results as seen in the prediction line movement. Also, the model has significant coefficients and parameters. The trend coefficient is not significant, which shows that the fluctuation in the market takes place but over the long run, the market index corrects itself to the reasonable basis.

5.10.4 Three-Regime

The three-regime classification (Table 5.26) is more precise and has identified different bear and bull markets that are not identified in the previous models. If we compare the dotted prediction line with the actual line movement, we can see a good resemblance. The regime classification identifies regime (2) which is the third regime that represents the extreme period where the index undertook a steep or sharp direction.

Table 5.27: Model 3 – DFM - Regime Classification

Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(5) – 2005(6)	2	1.000
2005(8) – 2005(8)	1	0.998
2006(2) – 2006(6)	5	1.000
2006(9) – 2007(10)	14	0.995
2008(10) – 2008(11)	2	0.991
2013(11) – 2014(4)	6	0.931
2014(7) – 2018(4)	46	0.994
Total: 76 months (33.93%) with average duration of 10.86 months		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2005(4)	16	1.000
2006(7) – 2006(8)	2	0.917
2008(12) – 2013(10)	59	0.986
2018(5) – 2022(8)	52	0.998
Total: 129 months (57.59%) with average duration of 32.25 months		
Regime 2	**Months**	**Avg. prob.**
2005(7) – 2005(7)	1	0.935
2005(9) – 2006(1)	5	0.997
2007(11) – 2008(9)	11	1.000
2014(5) – 2014(6)	2	0.995
Total: 19 months (8.48%) with average duration of 4.75 months		

From Figure 5.40, it is evident that the shaded classification area almost captures, in most cases, the actual index movement. The index movement is clearly better represented and predicted in this model.

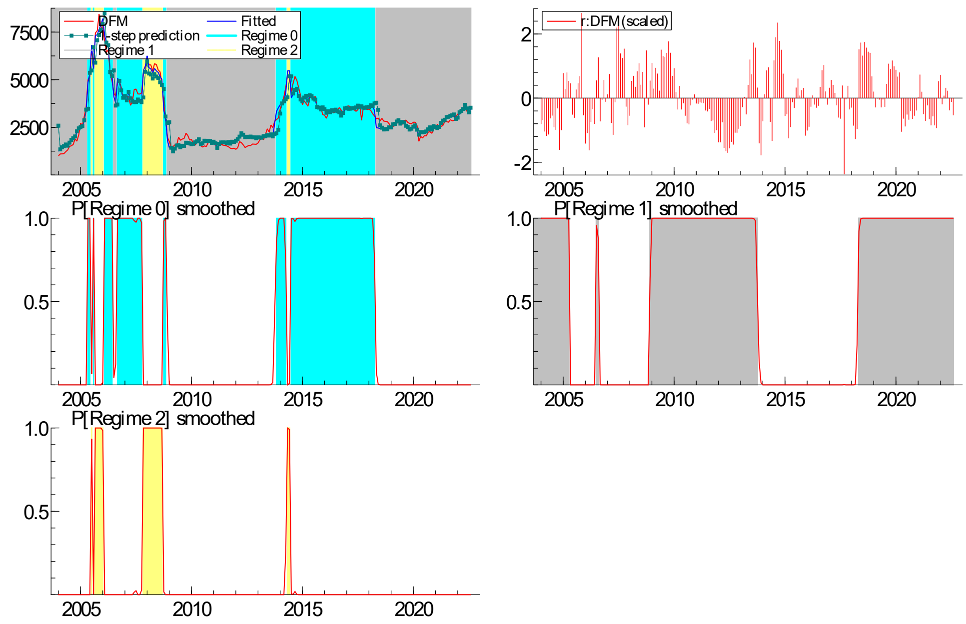

Figure 5.40: Model 3 – DFM - Prediction Line, Regimes, Scaled Residuals

From the prediction model parameters (Table 5.27) we can see that most of the variables are significant at (0.05) level; oil (0.042), S&P500 (0.002), TASI (0.000), T10Y3MM (0.000). However, the other variables BAA10YM and B. Exchange rate are not significant in this model.

Table 5.28: Model 3 Results – DFM

Modelling DFM by MS(3)				
The estimation sample is: 2004(1) – 2022(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	–2.11960	1.037	–2.04	0.042
S&P500	–0.110417	0.03476	–3.18	0.002
TASI	0.286066	0.01160	24.7	0.000
BAA10YM	–37.4770	53.30	–0.703	0.483
B Exch Rate	2.30296	2.120	1.09	0.278
T10Y3MM	–141.709	25.93	–5.46	0.000
Constant(0)	1891.17	109.8	17.2	0.000
Constant(1)	479.149	105.3	4.55	0.000
Constant(2)	3330.06	135.6	24.6	0.000
	Coefficient	**Std. Error**		
sigma	300.984	14.85		
p_{0|0}	0.908608	0.03368		
p_{1|0}	0.0392336	0.02260		
p_{0|1}	0.0230646	0.01337		
p_{2|2}	0.793303	0.09356		
log-likelihood –1644.58931				
No. of observations	224	No. of parameters	14	
AIC	14.8088332	SC	15.022061	
mean(DFM)	3134.24	se(DFM)	1467.83	
Linearity LR-test Chi^2(6) = 367.54 [0.0000]** approximate upperbound: [0.0000]**				
Transition probabilities p_{i|j} = P(Regime i at t+1 | Regime j at t)				
	Regime 0,t	**Regime 1,t**	**Regime 2,t**	
Regime 0,t+1	0.90861	0.023065	0.20670	
Regime 1,t+1	0.039234	0.97694	0.00000	
Regime 2,t+1	0.052159	0.00000	0.79330	

The overall results of the prediction models show that the third model (3-regimes) has better prediction accuracy as the AIC (Akaike information criterion) is 14.8088332 which is lower than that of model 1 (15.1349485) and model 2 (15.1406992).

5.10.5 Summary of the Three MS Models and Diagnostic Tests

The three models were tested for trend pattern existence and checked if there are more than two regimes. The results show that DFM does not have significant trend coefficient. The findings are very important for investors. The constant market presents opportunities for professional investors who prefer the switching strategy. They can sell at peak and buy at trough in a stationary market.

The diagnostic test results of the three models are summarized in the following table:

Table 5.29: Log-likelihood and AIC Diagnostic Tests (DFM)

Test	**Constant**	**Trend**	**Three-regime**
Log-likelihood	–1684.11	–1683.75	–1644.599
AIC	15.13	15.14	14.80

The log-Likelihood of the three-regime model is the highest. It fits DFM dataset better. AIC (Akaike Information Criterion) is an estimator of prediction error and estimates the quality of each model. The three-regime model has the lowest AIC score. In conclusion the DFM three-regime has the best fits compared to the constant and trend models. The extreme fluctuation in DFM index can be better explained by the three-regime model based on "in-sample" dataset.

5.10.6 Model 4 – Binary Logit Model

The naïve prediction test was conducted using the binary logit model. The results in Table 5.29 show that some of our variables are not significant except for T10Y3MM and border line for BAA10YM and S&P 500. The model results are not as robust as the Markov-regime switching models. One of the explanations might be that the naïve method of calculating the bull and bear market is based on the monthly index movement trend, and any tiny movement can affect the binary independent variable (0,1) since the DFM has no significant trend over the study period, as most of the movement is stationary around the mean. Therefore, tiny movement in the same level can disturb the identification of bull and bear market (0,1). Although the model results are not strong enough to build market trend expectations on it to make investment decisions with great confidence, the conclusion and the findings are important to simplify different arguments. Most unsophisticated investors rely on the available macroeconomic, financial, political, and different types of information to build market trend expectations based on past experience. The naïve method of calculating the market states or regimes can be misleading. Therefore, investors need more sophisticated and robust methods to anticipate the market direction.

Table 5.30: Model 4 – DFM - Binary Logit Model

Modelling DFM Nv by Logit				
The estimation sample is 2004(1) – 2022(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Constant	–4.63080	3.871	–1.20	0.233
Oil	0.0112390	0.007987	1.41	0.161
S&P500	–0.000545410	0.0003349	–1.63	0.105
TASI	–2.76514e-05	6.601e-05	–0.419	0.676
BAA10YM	0.417053	0.2358	1.77	0.078
B Exch Rate	0.0444100	0.03744	1.19	0.237
T10Y3MM	–0.497943	0.1678	–2.97	0.003
log-likelihood	–147.95128	No. of states	2	
No. of observations	224	No. of parameters	7	
Baseline log-lik	–155.1846	Test: Chi^2(6)	14.467 [0.0248]*	
AIC	309.902561	AIC/n	1.38349358	
mean(DFM Nv)	0.486607	var(DFM Nv)	0.249821	
BFGS estimation (eps1 = 0.0001; eps2 = 0.005): Strong convergence				
Table of actual and predicted				
	State 0	**State 1**	**Sum actual**	
State 0	70	45	115	
State 1	43	66	109	
Sum pred	113	111	224	

5.11 DFM – Out-of-Sample Tests

In this robustness check, the in-sample data set for the DFM index was selected as 1/2004 to 8/2017 and the out-of-sample was 9/2017 – 8/2022. The regime classification was evaluated, along with the prediction dotted line, and the three different prediction models (Constant, Trend, Three-regime) to see if the variables are significant factors in prediction. Lastly, the out-of-sample forecasting graphs will be discussed and the MAPE metric of the forecasting will be evaluated.

5.11.1 The Constant Two-Regime MS Model

The regime classification results are presented in Table 5.30. The regime prediction partially presents the actual movements in the index, but still represents reasonable resemblances. The model calculated two bull and two bear markets.

Table 5.31: Model 1 – DFM - In-Sample Regime Classification

Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(5) – 2008(10)	42	0.999
2014(1) – 2017(8)	44	0.998
Total: 86 months (52.44%) with average duration of 43.00 months		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2005(4)	16	1.000
2008(11) – 2013(12)	62	0.993
Total: 78 months (47.56%) with average duration of 39.00 months		

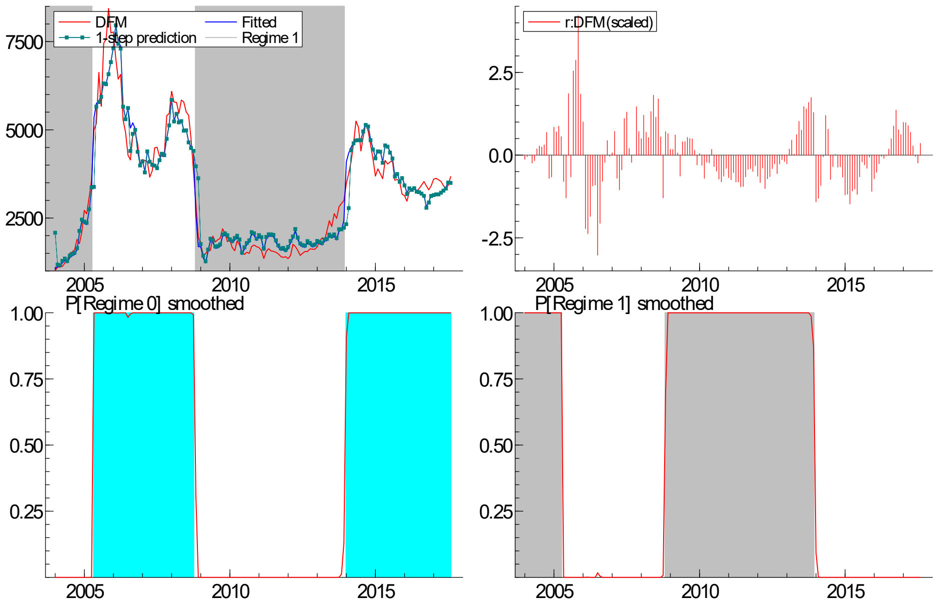

Figure 5.41: Model 1 DFM – In-sample Prediction Line, Regimes, Scaled Residuals

The prediction line has a good prediction movement as seen in Figure 5.41. Also, the two regimes are identified broadly due to the shorter in-sample data.

Table 5.32: Model 1 – DFM - In-sample Prediction Results

Modelling DFM by MS(2)				
The estimation sample is: 2004(1) – 2017(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	–7.60206	1.706	–4.46	0.000
S&P500	0.253315	0.1929	1.31	0.191
TASI	0.364049	0.02152	16.9	0.000
BAA10YM	169.215	68.64	2.47	0.015
B Exch Rate	–59.9680	5.333	–11.2	0.000
T10Y3MM	61.9358	47.65	1.30	0.196
Constant(0)	7165.76	230.5	31.1	0.000
Constant(1)	5151.92	318.8	16.2	0.000
	Coefficient	**Std. Error**		
sigma	437.041	24.55		
p_{0|0}	0.987926	0.01201		
p_{1|1}	0.974344	0.01791		
log-likelihood –1243.90595				
No. of observations	164	No. of parameters	11	
AIC	15.3037311	SC	15.5116489	
mean(DFM)	3251.04	se(DFM)	1682.25	
Linearity LR-test Chi^2(3) = 111.47 [0.0000]** approximate upperbound: [0.0000]**				
Transition probabilities p_{i|j} = P(Regime i at t+1 | Regime j at t)				
	Regime 0,t	**Regime 1,t**		
Regime 0,t+1	0.98793	0.025656		
Regime 1,t+1	0.012074	0.97434		

The prediction model (Table 5.31) shows that some of the study variables are significant predictors of the market trend. Although, the results have some variation when compared with the earlier findings using the full sample. The shorter period sample (2004-2017) is one reason for such results. Also, the data includes the 2005 and 2008 extreme volatilities which might have disrupted the model prediction accuracy and parameters.

The out-of-sample forecasting (Figure 5.42) shows a good resemblance with the actual DFM index. The forecasted line started to deviate from the 3rd quarter 2018 till 2nd quarter 2019. Nonetheless, both lines (the actual and the forecasted) move in parallel most of the time in the same direction but in different magnitudes in some cases. The Covid-19 effect led to a significant drop in the first half of 2020. The drop pulled the DFM index downward to a degree compared with that of the forecasted. Therefore, both lines deviated from each other, but the important observation is that the trajectory of the forecasted line is moving in parallel with the actual index movement line. This trajectory can be considered as very good forecasting results even if there is a gap between the actual line and the forecasted line. It is assumed that the gap was caused by the systematic calculation method of the DFM price index. Companies listed in the DFM have different weighted effects on the market price index. Large companies such as ENBD bank, Emaar Properties company, Dubai Islamic Bank have a larger effect/weight on the index calculation compared to smaller companies' price movement. The price fluctuation of all listed companies does not have the same effect across the board when taken in the index calculation.

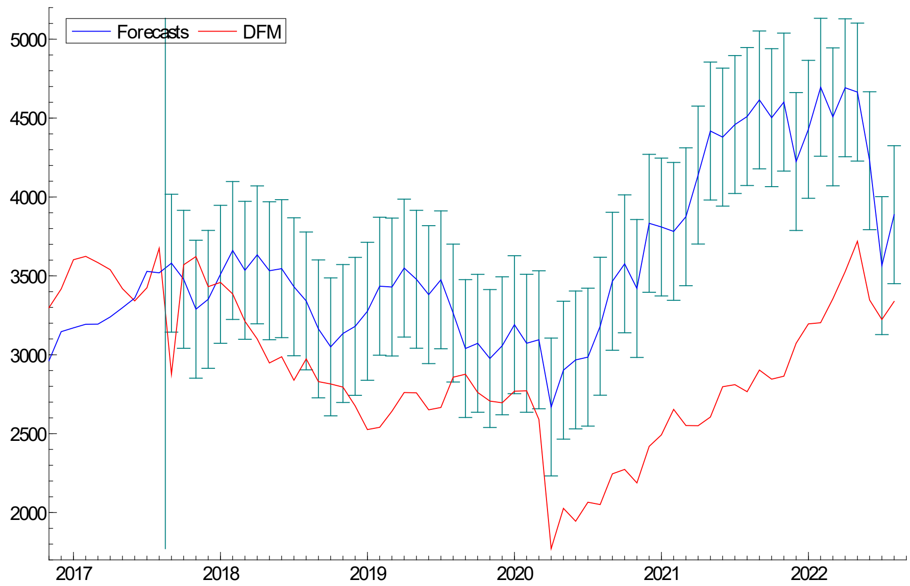

Figure 5.42: Model 1 – DFM - Out-of-Sample Forecasting

As shown in Table 5.32, the forecasting MAPE = 31.37 is considered "ok." The results show that the model can forecast the market direction for five years ahead with reasonable accuracy.

Table 5.33: Model 1 – DFM Forecasting - MAPE Value

Forecasting DFM from 2017(9) to 2022(9)							
Horizon	**Forecast**	**(SE)**	**Actual**	**Horizon**	**Forecast**	**(SE)**	**Actual**
1	3580.4	437.04	2876.4	31	3095.0	437.04	2590.0
2	3478.4	437.04	3570.2	32	2669.0	437.04	1771.3
3	3288.9	437.04	3622.2	33	2902.3	437.04	2026.6
4	3351.3	437.04	3431.8	34	2967.2	437.04	1945.1
5	3510.1	437.04	3458.8	35	2985.1	437.04	2065.3
6	3661.0	437.04	3385.8	36	3180.9	437.04	2050.8
7	3535.3	437.04	3212.0	37	3465.8	437.04	2245.3
8	3633.2	437.04	3100.4	38	3576.3	437.04	2273.5
9	3532.5	437.04	2948.0	39	3420.1	437.04	2187.9
10	3545.7	437.04	2987.3	40	3833.1	437.04	2419.6
11	3431.0	437.04	2838.5	41	3809.7	437.04	2492.0
12	3341.2	437.04	2973.9	42	3781.9	437.04	2654.1
13	3164.2	437.04	2829.6	43	3874.7	437.04	2551.5
14	3050.0	437.04	2815.0	44	4138.9	437.04	2550.2
15	3134.7	437.04	2795.0	45	4417.8	437.04	2605.4
16	3180.2	437.04	2675.9	46	4379.5	437.04	2797.5
17	3275.7	437.04	2526.0	47	4459.1	437.04	2810.6
18	3434.7	437.04	2540.3	48	4509.8	437.04	2765.7
19	3429.4	437.04	2642.3	49	4615.2	437.04	2903.0
20	3549.5	437.04	2760.5	50	4502.5	437.04	2845.5
21	3478.5	437.04	2758.5	51	4601.2	437.04	2864.2
22	3381.1	437.04	2651.0	52	4224.6	437.04	3072.9
23	3474.9	437.04	2666.0	53	4428.7	437.04	3195.9
24	3264.5	437.04	2857.9	54	4695.3	437.04	3203.1
25	3039.4	437.04	2876.4	55	4507.9	437.04	3354.6
26	3072.7	437.04	2761.0	56	4692.0	437.04	3526.6
27	2976.3	437.04	2706.6	57	4664.9	437.04	3719.6
28	3056.8	437.04	2695.6	58	4229.7	437.04	3347.2
29	3190.6	437.04	2769.1	59	3564.9	437.04	3223.3
30	3073.0	437.04	2771.3	60	3887.6	437.04	3338.0
mean(Error) = –821.60 RMSE = 973.92 SD(Error) = 522.96				**MAPE = 31.373**			

5.11.2 Trend Model

The regime classification as seen in Table 5.33 represented overall broad regime classification. Two bull markets and two bear markets for each regime. The in-sample results show a good prediction dotted line compared with the actual line as seen in Figure 5.43. The regime classification identified two bull periods and two bear periods. The classification is very broad and missed some of the regimes. Overall, the classification covered the broader picture of the trend.

Table 5.34: Model 2 – DFM - In-sample Regime Classification

DFM – Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(5) – 2008(10)	42	0.996
2014(1) – 2017(8)	44	0.997
Total: 86 months (52.44%) with average duration of 43.00 months		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2005(4)	16	1.000
2008(11) – 2013(12)	62	0.999
Total: 78 months (47.56%) with average duration of 39.00 months		

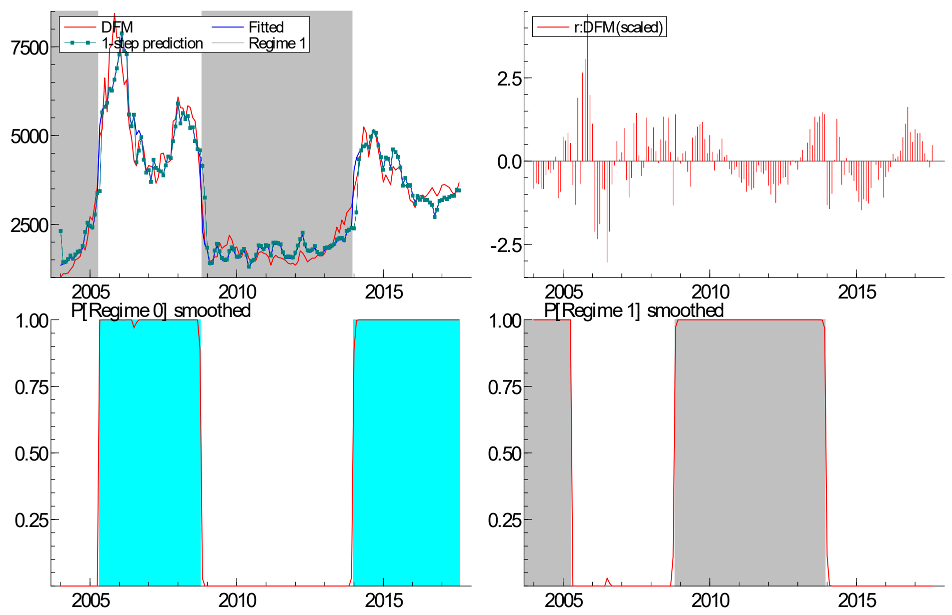

Figure 5.43: Model 2 – DFM - In-sample Prediction line, Regimes, Scaled Residual

The out-of-sample forecasting graph (Figure 5.44) shows a reasonable forecasting line. It has a good trajectory line moving along with the actual index. However, there is still a gap between the forecasted line and the actual index line. Previously, some of the possible explanations for this gap were discussed. The MAPE value is 53 as seen in Table 5.34, which shows unsatisfactory forecasting results, but overall the trajectory line is moving in an acceptable line direction with the actual movement.

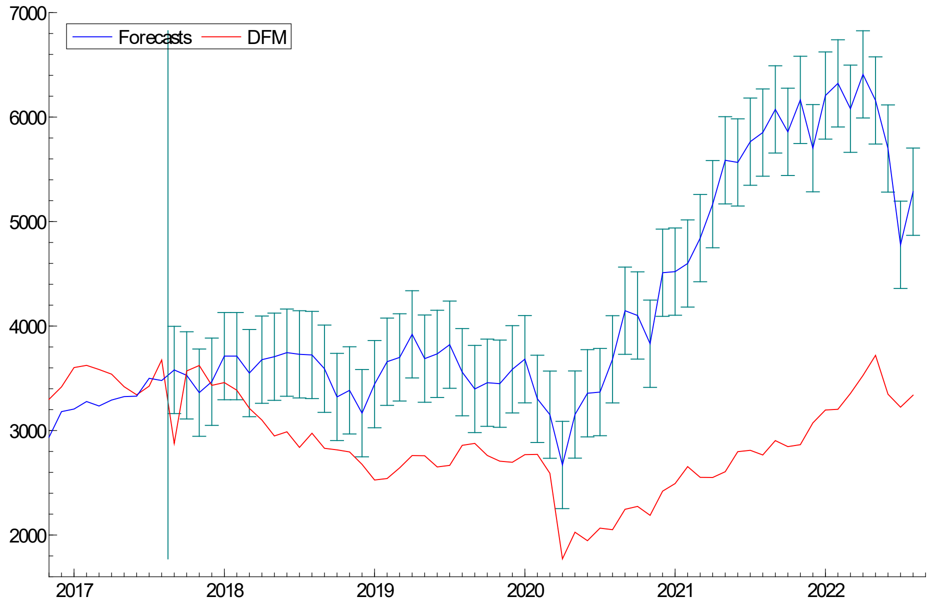

Figure 5.44: Model 2 – DFM - Out-of-Sample Forecasting

Table 5.35: Model 2 – DFM Forecasting - MAPE Value

Forecasting DFM from 2017(9) to 2022(9)							
Horizon	**Forecast**	**(SE)**	**Actual**	**Horizon**	**Forecast**	**(SE)**	**Actual**
1	3579.7	417.52	2876.4	31	3151.7	417.52	2590.0
2	3528.1	417.52	3570.2	32	2670.2	417.52	1771.3
3	3362.5	417.52	3622.2	33	3152.9	417.52	2026.6
4	3467.2	417.52	3431.8	34	3356.4	417.52	1945.1
5	3712.0	417.52	3458.8	35	3367.9	417.52	2065.3
6	3711.9	417.52	3385.8	36	3681.6	417.52	2050.8
7	3549.7	417.52	3212.0	37	4146.8	417.52	2245.3
8	3678.2	417.52	3100.4	38	4101.2	417.52	2273.5
9	3706.3	417.52	2948.0	39	3830.6	417.52	2187.9
10	3745.4	417.52	2987.3	40	4510.2	417.52	2419.6
11	3729.3	417.52	2838.5	41	4521.0	417.52	2492.0
12	3723.3	417.52	2973.9	42	4598.8	417.52	2654.1
13	3591.6	417.52	2829.6	43	4841.7	417.52	2551.5
14	3321.2	417.52	2815.0	44	5166.5	417.52	2550.2
15	3384.5	417.52	2795.0	45	5586.5	417.52	2605.4
16	3166.1	417.52	2675.9	46	5566.1	417.52	2797.5
17	3443.9	417.52	2526.0	47	5764.9	417.52	2810.6
18	3658.5	417.52	2540.3	48	5851.9	417.52	2765.7
19	3699.9	417.52	2642.3	49	6073.5	417.52	2903.0
20	3920.8	417.52	2760.5	50	5858.8	417.52	2845.5
21	3688.0	417.52	2758.5	51	6164.5	417.52	2864.2
22	3733.6	417.52	2651.0	52	5702.2	417.52	3072.9
23	3821.5	417.52	2666.0	53	6206.6	417.52	3195.9
24	3558.4	417.52	2857.9	54	6322.9	417.52	3203.1
25	3397.4	417.52	2876.4	55	6080.1	417.52	3354.6
26	3457.5	417.52	2761.0	56	6409.0	417.52	3526.6
27	3448.0	417.52	2706.6	57	6159.4	417.52	3719.6
28	3585.9	417.52	2695.6	58	5699.2	417.52	3347.2
29	3682.6	417.52	2769.1	59	4777.4	417.52	3223.3
30	3303.1	417.52	2771.3	60	5285.9	417.52	3338.0
mean(Error) = –1451.0 RMSE = 1748.7 SD(Error) = 975.88				**MAPE = 53.208**			

5.11.3 Three-Regime Model

The results of the three-regime MS model show a good prediction result for the in-sample data (Table 5.35). However, the out-of-sample forecasting accuracy (Figure 5.45) is not as good as the in-sample prediction results. The in-sample prediction shows that most of the variables are significant, and the dotted line (Figure 5.46) is aligned with the actual index movement. The regime classification (Table 5.36) shows a good classification which is almost in consistent with the actual bull or bear market trends during the in-sample period. The MAPE value is 52.87 (Table 5.37). Despite the high MAPE value, we believe the forecasting is reasonable as the trajectory movement is consistent with the actual line most of the time. However, there is a gap between the forecasted line and the actual line. This gap reduced the MAPE value significantly. According to Tayman and Swanson (1999), MAPE overstates the error found in a population forecast which creates a test validity issue. As discussed earlier, the index calculation method might have caused this gap, according to the DFM market expert opinion.

Table 5.36: Model 3 – DFM - In-sample Prediction

Switching(1) Modelling DFM by MS(3)				
The estimation sample is: 2004(1) – 2017(8)				
	Coefficient	**Std. Error**	**t-value**	**t-prob**
Oil	–9.59265	1.249	–7.68	0.000
S&P500	0.396652	0.1284	3.09	0.002
TASI	0.308941	0.01774	17.4	0.000
BAA10YM	76.7593	44.60	1.72	0.087
B Exch Rate	–40.7935	3.667	–11.1	0.000
T10Y3MM	–54.8850	36.49	–1.50	0.135
Constant(0)	5574.38	183.9	30.3	0.000
Constant(1)	4090.19	170.3	24.0	0.000
Constant(2)	6918.09	206.0	33.6	0.000

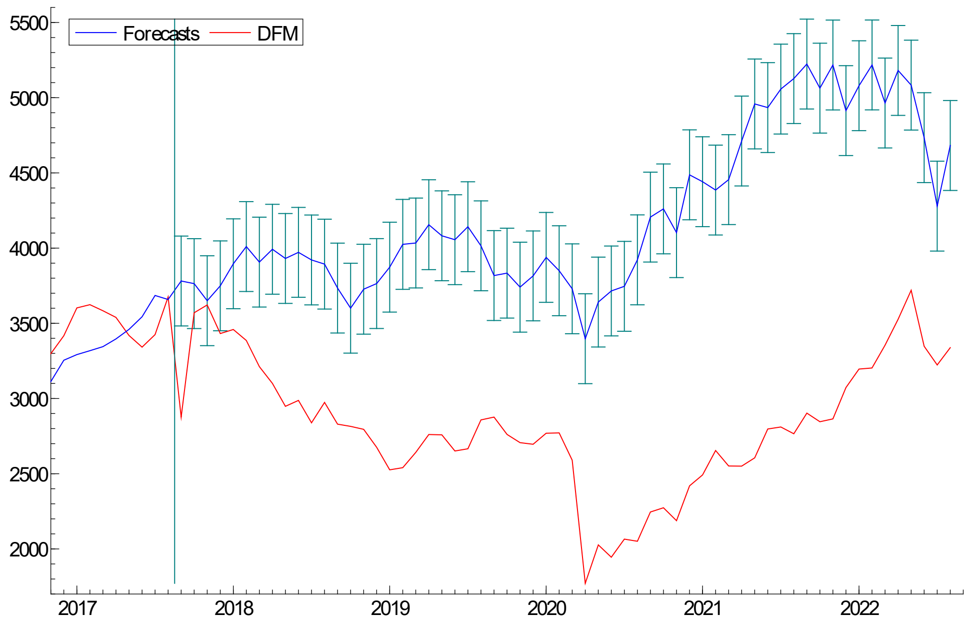

Figure 5.45: Model 3 – DFM - Out-of-Sample Forecasting

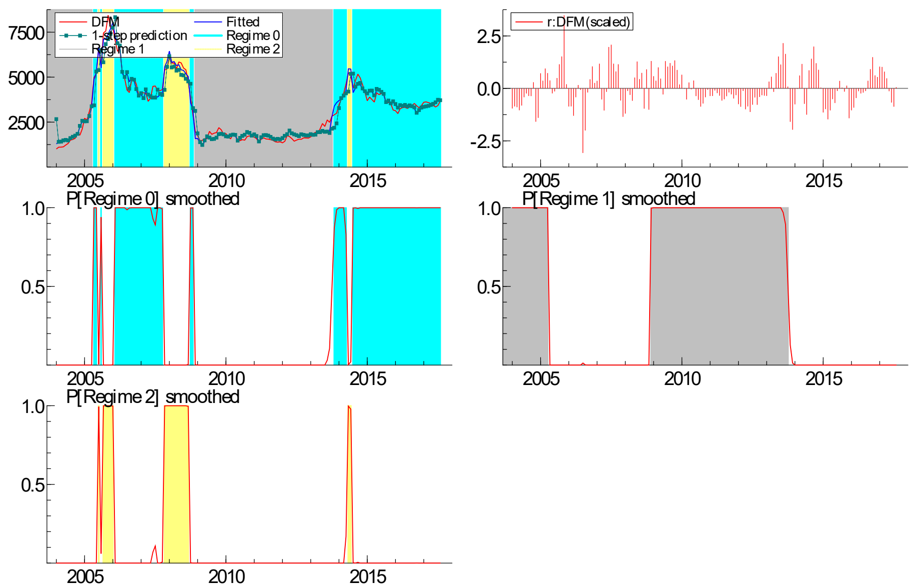

Figure 5.46: Model 3 – DFM - Prediction Line, Regimes, Scaled Residuals

Table 5.37: Model 3 – DFM - In-sample Regime Classification

DFM – Regime classification based on smoothed probabilities		
Regime 0	**Months**	**Avg. prob.**
2005(5) – 2005(6)	2	1.000
2005(8) – 2005(8)	1	0.940
2006(2) – 2007(10)	21	0.990
2008(10) – 2008(11)	2	0.999
2013(11) – 2014(4)	6	0.948
2014(7) – 2017(8)	38	1.000
Total: 70 months (42.68%) with average duration of 11.67 months		
Regime 1	**Months**	**Avg. prob.**
2004(1) – 2005(4)	16	1.000
2008(12) – 2013(10)	59	0.989
Total: 75 months (45.73%) with average duration of 37.50 months		
Regime 2	**Months**	**Avg. prob.**
2005(7) – 2005(7)	1	0.994
2005(9) – 2006(1)	5	1.000
2007(11) – 2008(9)	11	1.000
2014(5) – 2014(6)	2	0.988
Total: 19 months (11.59%) with average duration of 4.75 months		

Table 5.38: Model 3 – DFM Forecasting - MAPE Value

Forecasting DFM from 2017(9) to 2022(9)							
Horizon	**Forecast**	**(SE)**	**Actual**	**Horizon**	**Forecast**	**(SE)**	**Actual**
1	3781.2	298.78	2876.4	31	3729.5	298.78	2590.0
2	3763.7	298.78	3570.2	32	3397.6	298.78	1771.3
3	3650.3	298.78	3622.2	33	3641.5	298.78	2026.6
4	3749.2	298.78	3431.8	34	3715.2	298.78	1945.1
5	3895.6	298.78	3458.8	35	3746.1	298.78	2065.3
6	4010.3	298.78	3385.8	36	3921.9	298.78	2050.8
7	3907.0	298.78	3212.0	37	4206.1	298.78	2245.3
8	3992.4	298.78	3100.4	38	4260.6	298.78	2273.5
9	3931.1	298.78	2948.0	39	4102.7	298.78	2187.9
10	3971.6	298.78	2987.3	40	4487.2	298.78	2419.6
11	3921.1	298.78	2838.5	41	4441.4	298.78	2492.0
12	3893.6	298.78	2973.9	42	4386.1	298.78	2654.1
13	3734.3	298.78	2829.6	43	4455.4	298.78	2551.5
14	3600.6	298.78	2815.0	44	4712.1	298.78	2550.2
15	3726.9	298.78	2795.0	45	4958.5	298.78	2605.4
16	3764.3	298.78	2675.9	46	4934.1	298.78	2797.5
17	3873.4	298.78	2526.0	47	5057.1	298.78	2810.6
18	4024.8	298.78	2540.3	48	5127.0	298.78	2765.7
19	4034.0	298.78	2642.3	49	5223.5	298.78	2903.0
20	4155.5	298.78	2760.5	50	5063.4	298.78	2845.5
21	4081.6	298.78	2758.5	51	5217.4	298.78	2864.2
22	4056.0	298.78	2651.0	52	4914.0	298.78	3072.9
23	4142.2	298.78	2666.0	53	5079.8	298.78	3195.9
24	4015.0	298.78	2857.9	54	5217.7	298.78	3203.1
25	3817.5	298.78	2876.4	55	4964.6	298.78	3354.6
26	3833.8	298.78	2761.0	56	5181.2	298.78	3526.6
27	3740.3	298.78	2706.6	57	5083.7	298.78	3719.6
28	3815.1	298.78	2695.6	58	4734.3	298.78	3347.2
29	3938.1	298.78	2769.1	59	4279.2	298.78	3223.3
30	3849.5	298.78	2771.3	60	4682.3	298.78	3338.0
mean(Error) = –1411.5 RMSE = 1520.6 SD(Error) = 565.56				**MAPE = 52.857**			

The three regime-switching models MAPE results (Table 5.38) show that the standard (constant) model has the best MAPE value. The scores of the other two models are high, and the reasons that could have led to these high MAPE values have already been suggested. Overall, the trajectory is reasonably good and consistent with the predictive ability of our significant variables.

Table 5.39: Three MS Types Out-of-Sample MAPE Values

Constant model	**MAPE = 31.373**
Trend model	**MAPE = 53.208**
Three-regime model	**MAPE = 52.857**

5.12 Economic Values of Predicting Stock Market Regimes

The question of whether predicting the market is useful for investors looking to time market rises and drops has been investigated. To test the second hypothesis (H2) a very simple test was conducted based on the regime classification generated by the study model to compare the profitability of a switching strategy versus a benchmark buy-and-hold strategy, assuming no transaction costs. The switching strategy calculation was discussed earlier in the methodology section and in the ADX section. In the DFM calculation for H2, the standard (constant) two-regime (model 1) was selected as it held the best forecasting MAPE results. The regime classification of model 1 was used to calculate and assess the hypothesis. The market index was treated as a portfolio of USD 1 million at the beginning of the study period and then the following investment strategy was applied:

Buying and holding the index (long position) when the regime is bull market and sell it at the end of that regime.

- Take a short-position equivalent to the accumulated portfolio value at the beginning of bear market cycle and hold the short-position till the end of the that specific bear market as stated in the classification regime output.

- For the buy and hold strategy: start the portfolio of One million and link the portfolio profit (losses) to the value of the portfolio at the end of the study period or to the end of the last bear market.
- Calculate and compare the portfolio value between the two investment strategies to compare the differences.

Table 5.39 shows the terminal value of a $1,000,000 investment over the study period. Investing USD 1 million in a buy-and-hold strategy would yield $3,337,960 in August 2022 and the total investment profit of $2,337,960 will total yield of 234% and yearly rate of return is 13% per annum (234/18year). On the other hand, a switching strategy based on different bull and bear market regime classification from model 1 would yield $10,188,781 at August 2022 and the total investment profit of $9,188,781 with total yield of 919% and yearly rate of return of 51% per annum (919% / 18 years).

Table 5.40: Assessment of Investment Strategies – DFM

Switching Strategy								
Regime	**From**	**Index**	**To**	**Index**	**Position**	**Diff.**	**% Gain (Loss)**	**Investment value**
Sell	Jan-04	1000	Apr-05	3491.06				1,000,000
Buy (Bull)	May-05	4942.65	Jan-06	7426.37	Long	6426.37	643	6,426,370
Sell (Bear)	Feb-06	7309.60	Aug-06	4175.49	Short	3250.88	44	9,239,502
Buy (Bull)	Sep-06	4791.85	Nov-08	2942.03	Long	–1233.46	–30	6,510,108
Sell (Bear)	Dec-08	1964.66	Jul-13	2222.57	Short	719.46	24	8,102,125
Buy (Bull)	Aug-13	2623.87	Nov-18	2794.98	Long	572.41	26	10,188,781
Sell (Bear)	Dec-18	2668.66	Aug-22	3337.96				
								10,188,781
Buy and Hold Strategy								
2004 (1) – 2022 (8)	1000	3337.96				2337.96	234%	**3,337,960**
Conclusion: Switching strategy end value > Buy and Hold strategy end value → (10,188,781 > 3,337,960)								

Therefore, switching strategy produces higher terminal wealth and returns. This simple exercise demonstrates the usefulness of predicting a market trend. Switching strategies, with forecasting information about the bear market probability, outperforms buy-and-hold strategies and we can support our second hypothesis (H2).

Chapter 6: Discussion and Conclusion

This chapter first presents a summary of the main findings and elaborates on the contributions to current literature as well as the limitation of the dissertation and suggests areas of future research. This dissertation research contributes to the UAE stock market (ADX, DFM) trend prediction and to the early warning system (EWS) research. Different variables and techniques are used in this research that, to the researcher's knowledge, were not used together in one study to investigate the market trend of the UAE stock market.

6.1 Summary of Main Findings

This dissertation study attempted to predict the market trend in the UAE stock market for both Abu Dhabi securities Exchange (ADX) and Dubai Financial market (DFM) via Markov-regime switching models as nonlinear techniques using macro-financial variables. An investigation was conducted into whether the chosen variables are useful in predicting the UAE stock market trend, especially the bear markets, i.e., recessions in the stock market. Time series variables such as interest rate spreads, default rate spread, oil prices, broad effective exchange rate for the UAE currency, Kingdom of Saudi Arabia stock market index (TASI), Standard and Poor's 500 (S&P500) were selected as the independent variables and evaluated using the different prediction models. Different predicting techniques that include different Markov-regime switching models were considered, namely constant, trend, and three-regime models. We also used different measures of predicting the index movement applying the Binary Logit model using the naïve approach. We extracted and analyzed the regime classification, using the parametric approach impeded in the Markov-regime switching techniques, to identify the bulls and bears market trends and then explained these with aforementioned models. All the models presented good predictive ability and all of the study variables were significant in predicting the market direction, therefore the first hypothesis (H1) was supported. The three-regime model for both markets enhanced the predictive ability due to the fact that the third regime contained the extreme market price index volatilities in 2005 and 2008. The in-sample and out-of-sample forecasting ability was evaluated to test the three models' robustness by comparing the forecasted results using the mean absolute prediction error (MAPE) metrics. The forecasted results of ADX market were better than that of

DFM. Nonetheless, the trajectory lines in both market were reasonably well performing. The MAPE was at best for the ADX three-regime model and the standard (constant) model for DFM.

The results show that the different models presented useful value in predicting the market trend in terms of both in- and out-of-sample fit. Using the nonlinear Markov-regime switching models shows that all the study macro-financial variables reveal predictive ability including the bear market trend. Finally, the results show that Markov-regime switching models can be a useful tool for forecasting the ADX and DFM index movement and hence can be utilized by policy makers as well as investors. It can be used by the regulators as an early warning tool. Monetary authorities would also benefit from such forecasts when deciding monetary policy. For the investors, the economic significance and utility has been demonstrated via the switching strategy which held significant better investment profit or gain compared with the classical buy-and-hold strategy, relying on the regime classification predictive ability. A confidence measure for the probabilities could be useful for various applications, such as portfolio optimization or asset pricing. The results also have implications for risk management and hedging.

The first hypothesis was underlined based on the rational expectation theory. Investors make rational decisions based on different informational sources, past experience, and intuition. The hypothesis is that the chosen study variables are important predictors of the market's direction, and the investors will make decisions by taking into consideration the macroeconomic and financial variables articulated in this study. The results showed that the variables are significant predictors of the market trends. Therefore, the first hypothesis is supported by the statistical findings and in line with the theory background and literature discussed earlier.

The second hypothesis proposes that arbitrage opportunities exist in the markets, especially if the stock prices are undervalued or overvalued or the future direction is anticipated. The models identified different bull and bear regimes in ADX and DFM. The models were used that have the best MAPE score for each market to test H2. We used the regime classification generated using an ADX three-regime model to calculate the hypothesized portfolio value by comparing the "switching" strategy and the "buy-and-hold" strategy outcomes. The results supported H2 as the portfolio value of the switching strategy significantly outperformed the portfolio value of the "buy-and-hold" strategy.

Meanwhile, we used the regime classifications results generated from DFM constant model to calculate the portfolio value. The results showed that the "switching" strategy significantly outperformed the "buy and hold strategy". The application of such findings is very important. It implies that when the market is found to be constant over a long period, the investors will be better off switching or swinging investment positions and the switching will lead to a better investment performance and higher yields and returns.

6.2 Limitations

Six variables were used in this study as an effort to predict UAE market index movement. There are many other variables that could have been included in our study to improve the prediction accuracy, however they were not included for reasons such as nonavailability and interval contradiction (monthly vs yearly interval). The market price index calculation method also presented a challenge to the study. But overall, the forecast was reasonably accurate.

6.3 Recommendations for Future Research

Future research can assess the prediction ability using different variables or adding more variables, especially variables related to the UAE economy such as inflation rate, GDP, money supply and financial variables such as market capitalization, normal investors vs institutional investor trading (buy and sell percentages), political risk etc.

The ADX and DFM general price index were used. Future studies can use sub-indices as dependent variables. Sub-indices might include the indices of the banking sector, real estate sector, telecommunication industry, transportation industry, energy industry. The objective is to differentiate the stock market's different segment reaction to the macro-financial variable's changes.

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The purpose of this study is to investigate whether it is possible to predict UAE stock market bear states through the use of macro-financial variables. Monthly data from the Abu Dhabi Securities Exchange (ADX) and the Dubai Financial Market (DFM) were gathered, along with the publicly available Macroeconomic and Financial data. The variables considered were: Crude Oil price; Saudi Tadawul (TASI) index; S&P 500 index; Broad Effective Exchange Rate for UAE; Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity (default spread); and 10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity (interest spread). After the bull and bear periods were identified and classified, different types of Markov-switching models (Constant, Trend, Three-regimes) were employed. The empirical results suggest that the variables are useful predictors of the market trend in all the three models.

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