A Work Project, presented as part of the requirements for the Award of a Master's degree in Finance from the Nova School of Business and Economics.

ECONOMIC EVOLUTION OF TURKISH STOCK MARKET: A REGIME SWITCHING APOPROACH

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Abstract

This work project compares simple linear predictive regressions and regime switching predictive regression, to analyse time varying predictability of the stock returns in XU100 index. The approach is to compare regression statistics in-sample and to compare error statistics and predictive graphs out-of-sample. Findings reveal that employing predictive regime switching models reflect arbitrage opportunities better than predictive linear models in-sample. Out-of-sample analysis, however, provide no evidence for high predictive power for either predictive linear models or regime switching models.

Keywords: Stock Returns, Predictability, Regime Switching Models, Time Varying Predictability

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1 Introduction

One of the main domains of empirical research has long been the search for the predictability of stock returns. The possible set of predictive variables is typically composed of financial and macroeconomic variables. These include valuation ratios such as dividend price ratio, dividend yield, earning price ratio or book to market ratio, as well as macroeconomic variables such as inflation and industrial production.

Hence, predicting stock returns has long been under the scope of financial research. This is not surprising as systematizing the prediction of stock returns is vital for optimising portfolio allocation decisions as well as understanding the trade-off between risk and return. The common approach is to employ linear time series models, such as autoregressive, moving average, or mixed models, and one can argue that these models are successful in numerous applications (Kuan,2002).

In fact, empirical research documenting in-sample predictability of U.S. stock index returns over relatively long horizons have created an enormous literature, including Fama (1981), Campbell and Shiller (1988), and Fama and French (1988,1989). It has since been led to controversies on the predictability of stock indices due to concerns regarding these findings being spurious (Zhu and Zhu, 2013).

Critiques argued differently. Some, such as Stambaugh (1999), argue that strongly persistent predictors lead to biased coefficients in predictive regressions if the information driving the regressor is correlated with returns, e.g., the stock price is a component of both dividend yield and the return. In addition, Goyal and Welch (2003) showed that the increasing persistence of dividend price ratio weakens the stock return predictability, while also showing that this persistence develops over time, eventually leading to the performance out of sample predictions of regressions using similar valuation ratios as predictive variables converge to the performance of no-change strategies.

The same research conducted by Goyal and Welch (2003), also concludes scepticism towards the existence of any variable that can successfully predict annual equity premia. This is also supported by many others such as Ang and Bekaert (2007), Welch and Goyal (2008) and Demetrescu and Rodrigues (2020), stating that the statistical evidence of predictability is considerably weaker and often disappears completely when robust techniques are used.

In fact, within established literature regarding stock return predictability, many are based on the assumptions that the log returns follow a linear stationary process (Hamilton, 1987) and that the coefficients of the predictive regression model are constant over time. However, financial markets present dynamic patterns such as volatility clustering or asymmetries which tend to change their behaviour abruptly. Additionally, the business cycle, time-varying risk aversion, rare disasters, structural breaks, speculative bubbles, investor's market sentiment, and regime changes in monetary policy have all been cited as possible reasons that changes the coefficients of the predictive regression model; see, e.g., Pesaran and Timmermann (2002).

For example, significant changes in monetary policy and financial regulations could lead to shifts in the relationship between macroeconomic variables and the fundamental value of stocks, via the impact of these changes on economic growth and the growth rates of earnings and dividends.

Results of Harvey (1995) revealed that the predictability of emerging market returns is more likely than developed countries to be influenced by local information. One can, therefore, say that, since monetary and financial policy are still in development and more dependent on dynamic governing decisions in emerging markets, predictive models diverge further from these assumptions.

Coupled with the previous findings by Ang and Bekaert (2011) on how stock return predictability is predominantly a short-term phenomenon, and Timmermann's (2008) findings that for most time periods returns are not predictable but that there are `pockets in time' where evidence of local predictability is seen, employing models predicting returns in short spans of time is reasonable.

Moreover, if we consider predictability a result of market inefficiency rather than of time varying risk premia, then we must expect that rational investors will attempt to exploit this inefficiency to earn abnormal profits. Given that a large portion of investors act rationally, the market will eventually correct itself and the predictive power of the deterministic variable will disappear. Therefore, one can say that, if a variable begins to have predictive power, this power will only last until investors learn about the relation between the said variable and the returns, but the relationship will eventually disappear (Paye and Timmermann, 2006; Timmermann, 2008).

It therefore seems reasonable to consider the possibility that the predictive relationship might change over time, so that over a long span of data one may observe some windows of time during which predictability occurs.

In this work project I will use a regime switching model to possibly capture this feature of time varying predictability. The regime switching model involves multiple equations that can govern some time series behaviours under different regimes. The original application by Hamilton (1989) was to explain the relation between business cycle and the shift in positive and negative growth in the US, and found results evidencing validity of using the regime switching model. Additionally, Zhu and Zhu (2013) found out that the regime switching forecast outperforms the historical average by statistical and economic means.

In this paper I analyse different frameworks to predict stock market returns in the Turkish stock market. In an attempt to capture whether or not a regime switching approach outperforms or performs closely to linear regressions, this research employs regime switching models to predict stock returns in the Turkish Stock Market (BIST).

The remainder of the paper proceeds as follows. Section 2 is dedicated to the methods employed and the description of the data used, out of sample forecasting results are presented in Section 3 and Section 4 concludes the research.

2 Data and Methodology

2.1 Dataset

The empirical analysis studies monthly data between 1986M04 – 2020M10. The sample covers the period between when the index price data is available and when the last monthly inflation data is available. Aggregate stock returns are the continuously compounded returns on the XU100 index. The predictive variables used are respectively:

Inflation (infl): Computed from the consumer price index (CPI) provided by the Turkish Statistical Agency (TURKSTAT). In this research we have used two datasets. One is the CPI based on 1978-1979 (1978-1979 = 100) and the other is the CPI based on 2003 (2003 = 100) due to the unavailability of a complete dataset.

Stock Variance (svar): Stock variance is computed as sum of squared daily returns on XU100 index.

Exchange Rate (usdtry): The exchange rate is the exchange rate between the US Dollar and the Turkish Lira presented by the Central Bank of Turkey.

Despite previous research including that of Welch and Goyal (2008) and Zhu and Zhu (2013) have included valuation ratios as potential predictive regressors in their tests alongside macroeconomic variables, I opted for macroeconomic variables. This was because as results of Harvey (1995) documented, the predictability of emerging market returns is more local information driven than the developed economies studied in previous literature. Coupled with the dynamic political conjecture in Turkey between 1986 and 2020, the setup of this work project is built under the assumption that, the states of the economy dominantly change with macroeconomic factors rather than valuation ratios.

2.2 Method

The methodology followed in this research is as follows. First, we employ a simple linear predictive regression for each of the variables; so that the research allows for a clear analysis for performance comparison. Then we apply a regime switching approach for each of these variables with 2 and 3 regimes. Last, we use out-of-sample forecasts to compare the performance of regime switching predictive regressions with that of linear predictive regressions to conclude the research

2.2.1 Linear Regression

A typical specification is to regress stock returns on lagged predictive variables as follows,

$$r_t = \alpha + \beta x_{t-1} + \varepsilon_t \tag{1}$$

where r_t, is the stock return, x_t is the predictor, and ε_t is an error term following a normal distribution, i.e. $\varepsilon_t \sim N(0,\sigma^2_\varepsilon)$. To set a benchmark model for the performance analysis of the regime switching predictive regression, we regress the returns on each of the predictive variables.

2.2.2 Regime Switching Regression

A simple two regime switching predictive regression model can be represented as follows,

$$r_t = \begin{cases} \alpha_0 + \beta_0 x_{t-1} + \varepsilon_t, & s_t = 0 \\ \alpha_1 + \beta_1 x_{t-1} + \varepsilon_t, & s_t = 1 \end{cases} \tag{2}$$

where r_t , is the stock return, $x_{t,}$ is the independent variable, and ε_t is the error term following a normal distribution, i.e. $\varepsilon_t \sim N(0,\sigma^2_\varepsilon)$. This is a stationary AR(1) process with mean $\alpha_0/(1-\beta)$ when the economy is in state 0, that is $s_t=0$, and with mean $\alpha_1/(1-\beta)$ when the economy is in state 1, that is $s_t=1$. Hence, given $a_0 \neq a_1$, one can state that the model is composed of two dynamic models placed at different levels, depending on the state variable s_t. The regime switching predictive regression model also allows for mean, $\mu_{t,st,}$, slope parameter, β_{st} , and the variance σ^2, to be state dependent. In this study, we employed 7 regime switching models for each of the predictive variable where we allowed the intercept, slope, and variance to be regime dependent both individually and in combination with each other.

2.2.3 Out of Sample Forecasting

After estimating the regime switching predictive regressions, we have employed forecasting models for both the linear and the regime switching models. I have computed static forecasts to ensure that the forecast is strictly limited to one month ahead. We have used the period between 1986M04 2018M12 as the training set and forecasted for the time period between 2019M01 and 2020M10.

2.2.4 Performance Evaluation

To evaluate the efficacy of the regime switching specification, results are analysed in two different considerations. One is by evaluating the regression statistics. We looked at the significance of the predictive variables, as well as the constant and volatility per switching regression, looking for estimations where a specific element of the regression is significant in one state while not being significant in some other state. This is done to be able to check for the validity of using a regime switching regression, rather than a simple linear predictive regression. Other is by evaluating the one step ahead out-of-sample forecasts which we conducted for one month ahead forecasting. First, we have compared the forecast evaluation error statistics, in order to understand if regime switching models perform better than linear models. Secondly, we graphed the forecast models and the actual data together to analyse both if regime switching models differ significantly than the linear models, and if there is any predictive power of the regime switching in the actual data.

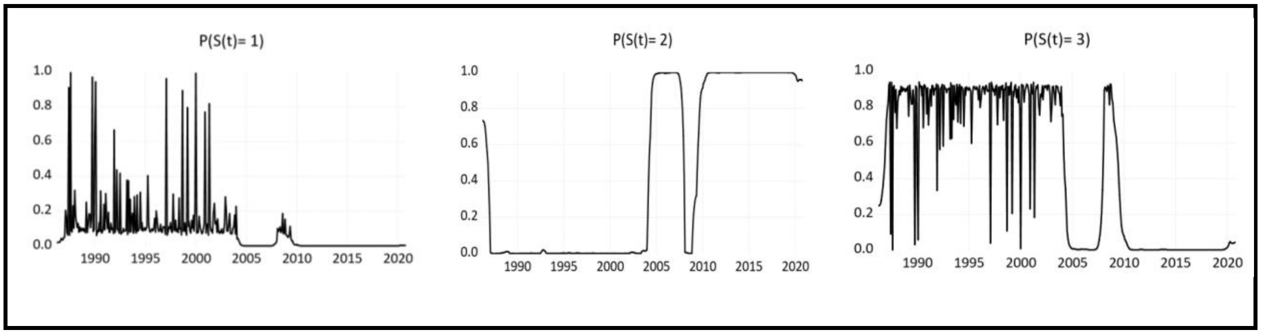
3 Results

3.1 Regression Analysis

3.1.1 General Remarks on Three Regime Models

When I tested for 3 state models, the common result was that the transition probability from some regime to some other was very close to 1, which means that the transition between regimes was too frequent to establish a stable regime where one can determine a regime specific regression. Hence, the 3-state regression is found to be an ineffective application with the current dataset. An example to regime probabilities in a three-regime regression is presented below in Graph 1, which shows the simple switching regime probabilities where the predictive variable is **infl** and β, α and σ^2 are the switching components. Here, one can see that regime 2 is continuous for pockets of periods, regime 1 and regime 3 change tend to change between each other in a very high frequency which may suggest a two regime model of which, the 2nd regime in the three regime model establishes the first and a combination of regimes 1 and 3 establishes the second regime. regime which shows the simple switching regime probabilities where the predictive variable is **infl** and β, α and σ^2 are the switching components.

Graph 1: Markov Switching Smoothed Regime Probabilities



3.1.2 2 Regime Models with ***infl*** *Predictive Variable*

Table 1: Statistical Significance Results Table of Markov Switching Regressions for infl Variable

Switching Components	Regime 1			Regime 2		
	α_0	β_0	σ^2_0	α_1	β_1	σ^2_1
α	0.0000	-	-	0.1161	-	-
α and β	0.1485	0.6085	-	0.0000	0.0011	-
α, β and σ^2	0.4366	0.0103	0.0000	0.7755	0.0961	0.0000
σ^2 and α	0.0116	-	0.0000	0.0157	-	0.0000
β	-	0.0022	-	-	0.7306	-
β and σ^2	-	0.1445	0.0000	-	0.3481	0.0000
σ^2	-	-	0.0000	-	-	0.0000

The table shows p-values of all the switching regressors, for each of regime switching regressions employed for **infl** predictive variable. I have not included any statistics for the non-switching components since I am strictly looking if estimation models for predictability across different regimes. The statistical results for the regime switching regressors are presented in the table above. We can say that the statistical significance of variables differs across states except for three models which are when σ^2 and α, σ^2 and β, and only σ^2 are the switching components. This means that over long periods of time, regressions to predict stock returns tend to change, and hence, simple linear predictive regressions may fall short in explaining the behaviour. Therefore, we can say that for **infl** as the predictive variable, employing regime switching models have more meaning over linear regressions.

*3.1.3 2 Regime Models with **usdtry** Predictive Variable*

Table 2: Statistical Significance Results Table of Markov Switching Regressions for usdtry Variable

Switching Components	Regime 1			Regime 2		
	α_0	β_0	σ^2_0	α_1	β_1	σ^2_1
α	0.0076	-	-	0.0000	-	-
α and β	0.0000	0.0062	-	0.0189	0.3371	-
α, β and σ^2	0.0002	0.0949	0.0000	0.0147	0.2642	0.0000
σ^2 and α	0.0006	-	0.0000	0.0091	-	0.0000
β	NA	NA	NA	NA	NA	NA
β and σ^2	-	0.0319	0.0000	-	0.3628	0.0000
σ^2	-	-	0.0000	-	-	0.0000

The table shows p-values of all the switching regressors, for each of regime switching regressions employed for **usdtry** predictive variable. I have not included any statistics for the non-switching components since I am strictly looking if estimation models for predictability across different regimes. NA indicates that there exists a singular covariance which does not allow a regression estimation. The statistical results for the regime switching models are presented in the table above. We can say that there are three models where statistical significance of variables change across states at 5% confidence interval and four models if we extend the confidence interval to 10%. Hence, the estimation results suggest that models to predict stock returns change within long time periods. With one model resulting in singular covariance, one can say that the majority of the models prove to add value to use regime switching regressions over linear models when **usdtry** is used as the predictive variable.

*3.1.4 2 Regime Models with **svar** Predictive Variable*

Table 3: Statistical Significance Results Table of Markov Switching Regressions for svar Variable

Switching Components	Regime 1			Regime 2		
	α_0	β_0	σ^2_0	α_1	β_1	σ^2_1
α	0.0000	-	-	0.0058	-	-
α and β	0.0064	0.4297	-	0.0000	0.0025	-
α, β and σ^2	0.0003	0.1449	0.0000	0.0029	0.2814	0.0000
σ^2 and α	0.0037	-	0.0000	0.0009	-	0.0000
β	NA	NA	NA	NA	NA	NA
β and σ^2	-	0.2466	0.0000	-	0.1233	0.0000
σ^2	-	-	0.0000	-	-	0.0000

The table shows p-values of all the switching regressors, for each of regime switching regressions employed for **svar** predictive variable. I have not included any statistics for the non-switching components since I am strictly looking if estimation models for predictability across different regimes. NA indicates that there exists a singular covariance which does not allow a regression estimation. The statistical results for the regime switching models are presented in the set above. We can say that the only model in which the statistical significance differs across regimes is when the switching components are α and β, in which, while the predictive variable is insignificant in regime one it becomes significant in regime two. In other models, we generally observe that the coefficients of the regressors differ between regimes which indicates that returns should be estimated in accordance with the state of the economy. Yet, we also see that in most cases, the coefficients only change slightly, about which one can say that estimating a regime switching model does not add a lot of value. Therefore, we can say that for **svar** as the predictive variable, employing regime switching models, while in some cases it adds limited value due to observed minor changes, result in a better fit than simple linear models.

3.2 Forecasting Analysis

To evaluate the forecasting performance of regime switching predictive regression relative to simple linear predictive regression models, we have selected some of the models from the previous estimation. We have selected the models, for which the estimation results proved statistically significant differences for the predictive variables per the state of the economy. This means that we have selected models where **infl, usdtry,** or **svar** were significant in one regime but were not significant in the other. We have limited the analysis to two regime models, since employing three regime models were found to be significant for analyses with the given period and variables. The selected regressions are therefore, the models where; the predictive variable is **infl** and switching components are the slope and intercept (β and α), and just the slope (β); the predictive variable is **usdtry** and the switching components are the intercept and slope parameters (α and β), and the variance and the slope parameter (σ^2 and β); the predictive variable is **svar** and switching components are the intercept and slope parameters (α and β).

*3.2.1 Out of Sample Results of Models with **infl** as Predictive Variable*

Statistical Image 1: Statistical results for prediction with infl as the predictive variable

Forecast Evaluation
Date: 01/04/21 Time: 19:03
Sample: 2019M01 2020M10
Included observations: 22
Evaluation sample: 2019M01 2020M10
Number of forecasts: 3

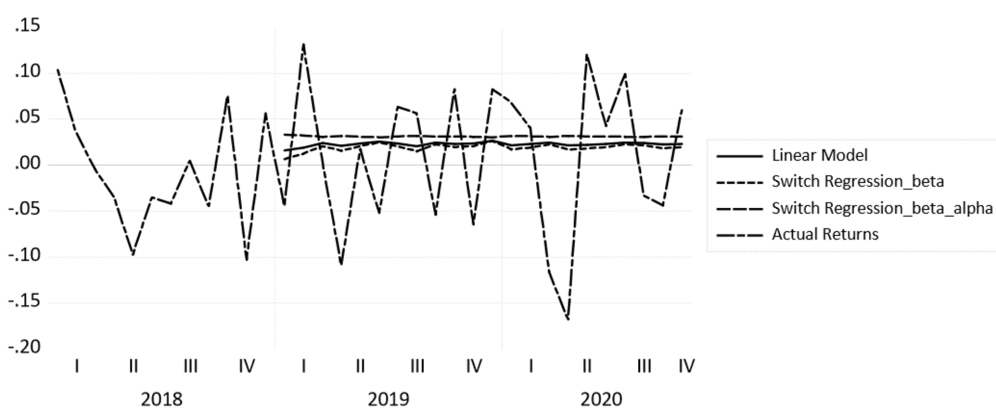
Combination tests
Null hypothesis: Forecast i includes all information contained in others

Equation	F-stat	F-prob
BASEINFLFORE	0.095548	0.9093
SWITCHREGINFLBE	0.106693	0.8993
SWITCHREGINFLBE	0.263522	0.7711

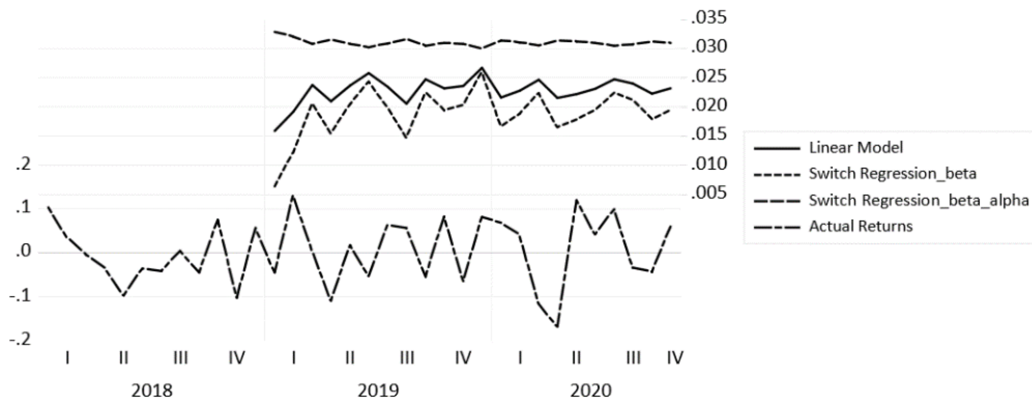
Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
BASEINFLFORE	0.081180	0.068617	110.1435	141.5742	0.793342	1.103700
SWITCHREGINFLBE	0.080816	0.068631	107.4971	145.6816	0.809322	1.069592
SWITCHREGINFLBE	0.084604	0.068353	125.8720	124.2327	0.726890	1.247361

Graph 2: Forecast Comparison Graph For infl as the Predictive Variable



Graph 3: Forecast Comparison Graph For infl as the Predictive Variable with Adjusted Scales



The statistical results for out-of-sample forecasting with **infl** as a predictive variable are presented above. From the results in statistical image 1 above, one can say that according to any error statistic, the regime switching predictive regression model performs better in predicting stock returns than a simple linear regression. However, when we look at the forecast comparison graph 2 presented above, we can say that neither of the models performs well in predicting the returns out-of-sample. Still, one can argue that when scales are adjusted, see graph 3, the regime switching model provides a predictive value. We can see that the general trends for the forecast and the regime switching models are comparable, yet the amplitude of the movements are not well represented in forecasts, which one can argue that volatility information is missing in all predictive models estimated. However, from the evaluation statistics and the graphs, we can say that the regime switching predictive regressions seem to perform better than the linear predictive models employed.

*3.2.2 Out of Sample Results of Models with **usdtry** as Predictive Variable*

The statistical results for out-of-sample forecasting with **usdtry** as a predictive variable are presented below in statistical image 2. From this statistical table, one can see that according to any error statistic, the regime switching predictive regression model performs better in predicting stock returns than a simple linear predictive regression. However, when one looks at the forecast comparison graph presented, one can say that neither of the models perform well in out-of-sample predicting the returns. Perhaps the observations we can make through graph 5 is that the trends of the forecasted models and the actual returns differ marginally. One can see that the error terms for the forecasted regressions carry more of the information than forecasted regimes themselves.

Statistical Image 2: Statistical results for prediction with usdtry as the predictive variable

Forecast Evaluation
Date: 01/04/21 Time: 19:13
Sample: 2019M01 2020M10
Included observations: 22
Evaluation sample: 2019M01 2020M10
Number of forecasts: 3

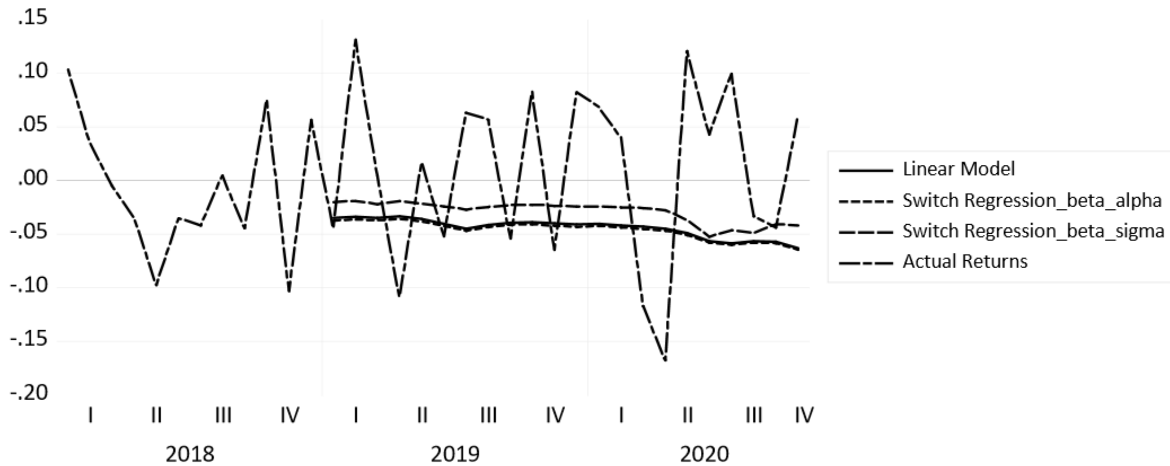
Combination tests
Null hypothesis: Forecast i includes all information contained in others

Equation	F-stat	F-prob
BASEUSDFORE	1.480560	0.2526
SWITCHREGUSDBE	0.875193	0.4329
SWITCHREGUSDCB	1.211395	0.3198

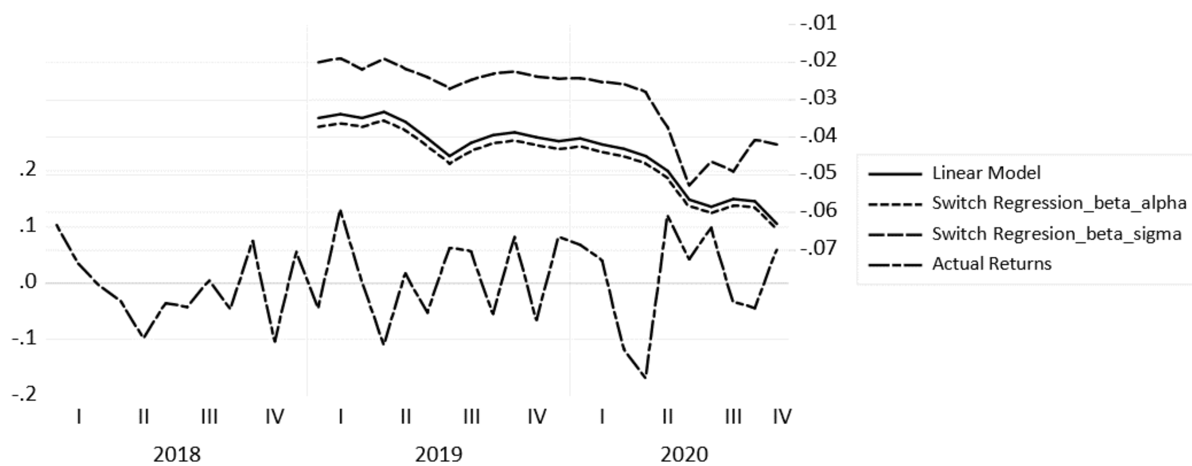
Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
BASEUSDFORE	0.097155	0.082531	158.5000	141.7442	0.774783	0.689370
SWITCHREGUSDBE	0.091976	0.079091	137.0736	149.7793	0.796095	0.781008
SWITCHREGUSDCB	0.099497	0.084162	166.3392	139.7543	0.768457	0.661389

Graph 4: Forecast Comparison Graph for usdtry as the Predictive Variable



Graph 5: Forecast Comparison Graph for usdtry as the Predictive Variable with Adjusted Scales



*3.2.3 Out of Sample Results of Models with **svar** as Predictive Variable*

The statistical results for out-of-sample forecasting with **svar** predictive variable are presented below in statistical image 3. From the statistical table, one can say that according to error statistics, the linear model predicts the returns better than the regime switching model. Yet, graph 7 shows that the linear model and the switch regression are highly correlated. Additionally, the Diebold-Mariano test included in the results presented in statistical image 3 suggest that linear and switch regression share the same accuracy in forecasting. Hence, in the given timeframe, we could not establish a decisive argument regarding the forecasting performance of the regime switching predictive regression model and the linear predictive regression model.

Statistical Image 3: Statistical results for prediction with svar as the predictive variable

Forecast Evaluation
Date: 01/04/21 Time: 19:19
Sample: 2019M01 2020M10
Included observations: 22
Evaluation sample: 2019M01 2020M10
Number of forecasts: 2

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Equation	F-stat	F-prob
BASESVARFORE	2.615981	0.1215
SWITCHREGSVARC	3.568034	0.0735

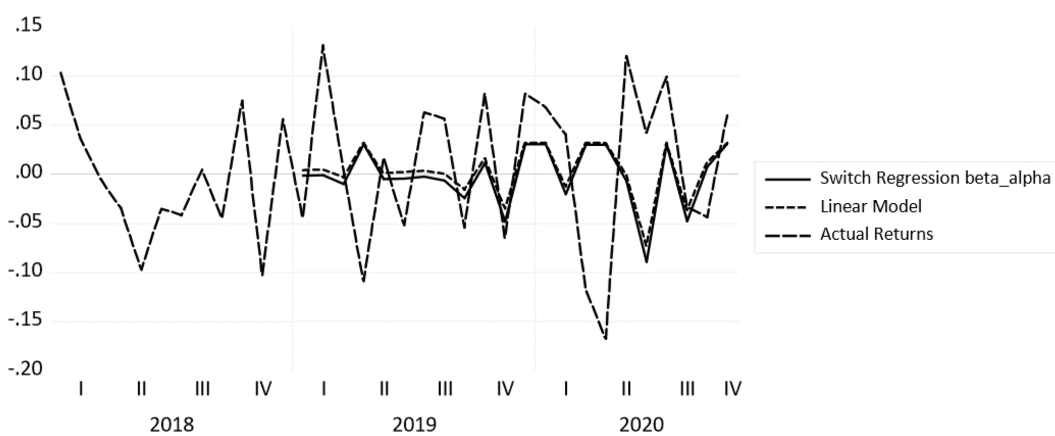
Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-1.327257	0.1987	0.0993	0.9007
Sq Error	-1.485751	0.1522	0.0761	0.9239

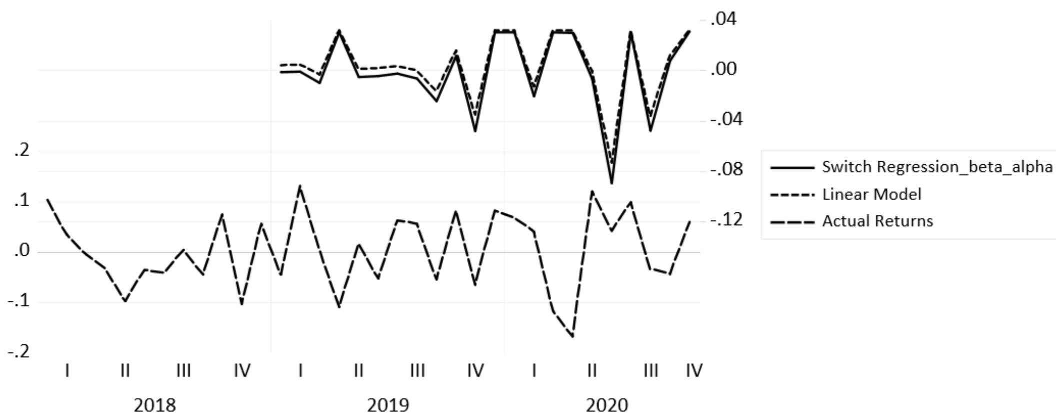
Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
BASESVARFORE	0.085195	0.069111	100.3666	153.2896	0.793260	1.199163
SWITCHREGSVARC	0.087461	0.071252	113.0934	153.4813	0.780943	1.191854

Graph 6: Forecast Comparison Graph for svar as the Predictive Variable



Graph 7: Forecast Comparison Graph for svar as the Predictive Variable with Adjusted Scales



4 Conclusions

In this work project, I have employed several linear and regime switching predictive regression models to analyse the time varying predictability of the stock returns in XU100 index. Fundamentally, I compared the historically followed linear predictive approach which tracks long term predictability of returns to the regime switching model, which divide the dataset into different stages of the economy.

With the in-sample analysis, we could argue that for any predictive variable selected, governing a regime switching predictive regression model performs better than a linear predictive regression model. Upon observing different statistical significance over different regimes one can say that regime switching models successfully reflect the arbitrage opportunity for investors. On the other hand, there were no strong observations in the out-of-sample analysis which suggested that the regime switching model outperforms the linear model. We can explain this in two different ways. First is that inefficiency only happens instantaneously, and the market corrects itself too quickly for regimes to establish a predictive model itself. This was also obvious when we analysed the scaled forecast graphs and have observed a high correlation between the linear and regime switching predictive regressions despite, the in-sample analysis showing significance in using regime switching models. Hence, we can say that the regime switching predictive regression models also follow closely the behaviour of a linear model except in times of market inefficiency. Secondly, the period of analysis, that is between 1986 and 2020, was a stable period and therefore there was no need for an established second regime which, one would employ to predict the returns when there is heterogeneity in the state of economy in long periods.

All in all, we can argue that regime switching models are more preferable over linear regressions as they allow more flexibility in states of the economy where an opportunity for abnormal returns is possible as well as in the normal states of economy.

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