THE PREDICTIVE POWER OF REGIME-SWITCHING MODELS FOR STOCK MARKET RETURNS

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Thesis
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Introduction

- The behavior of stock market returns is a subject of study that concerns a wide range of people
- Many have tried to estimate and predict stock markets
- Linear and nonlinear models are applied
- The economic environment is volatile and many factors affect the stock markets
- It is difficult to find an appropriate model for accurate predictions
- We employ a regime-switching model, we estimate it and we investigate its out-of-sample forecasting performance for three stock markets
- We examine whether the nonlinear regime-switching model improves predictions compared to linear models

Literature Review

We consider studies with nonlinear models and especially those with threshold and regime-switching models.

- McMillan (2001) observes a nonlinear relationship between the US stock market returns and interest rates. He finds that threshold models outperform the linear ones.
- Schaller and Van Norden (1997) show that switching behavior exists in the US stock market. Stock market returns are predicable from economic variables. The returns react asymmetrically to these variables.
- Zhu and Zhu (2013) identify two regimes in the US stock market which are correlated with the business cycle. The low variance regime is related to economic growth, while the high variance regime is connected with economic decline.

- Some researchers examine and predict stock market volatility and some others stock market trend
- There are studies that forecast stock market returns using neural networks (NN).

- ➢ Stock markets are often described by asymmetry
- ➢ They are sometimes correlated with the business cycle
- ➢ Stock markets can be predicted by macroeconomic and financial variables
- ➢ A good estimated model does not guarantee a consistent performance out-of-sample
- ➢ Switching behavior exists in the markets
- ➢ Regime-switching, threshold and generally nonlinear models forecast more accurately than linear models
- ➢ Nonlinearity is necessary for better results

Dataset

Data

- We investigate three stock market indices:
  - **S&P/TSX composite Index** (Canada)
  - **FTSE 100 Index** (the United Kingdom)
  - **S&P 500 Index** (the United States)
- We have weekly data from January 3, 2000 to November 16, 2015
- The observations for S&P/TSX and FTSE is 829 and for S&P 500 is 828
- We divide the sample into in-sample(2/3) and out-of-sample(1/3)
- We generate the returns: $y_t = \log(x_t) - \log(x_{t-1})$

Descriptive statistics

We depict some features of the data and their distribution.

Descriptive Statistics

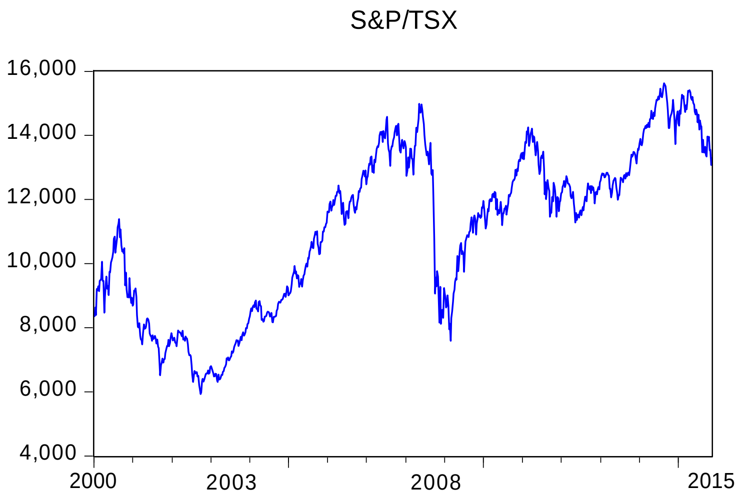
	S&P/TSX	FTSE	S&P500
Mean	0,0006	-6.84E-05	0,0004
Median	0,0031	0,0019	0,0017
Maximum	0,1282	0,1258	0,1136
Minimum	-0,1754	-0,2363	-0,2008
Std. Dev.	0,0249	0,0250	0,0254
Skewness	-0,9443	-1,0831	-0,8182
Kurtosis	9,9712	14,8240	9,8838
Jarque-Bera	1799,7	4985,2	1725,2
Probability	0,0000	0,0000	0,0000

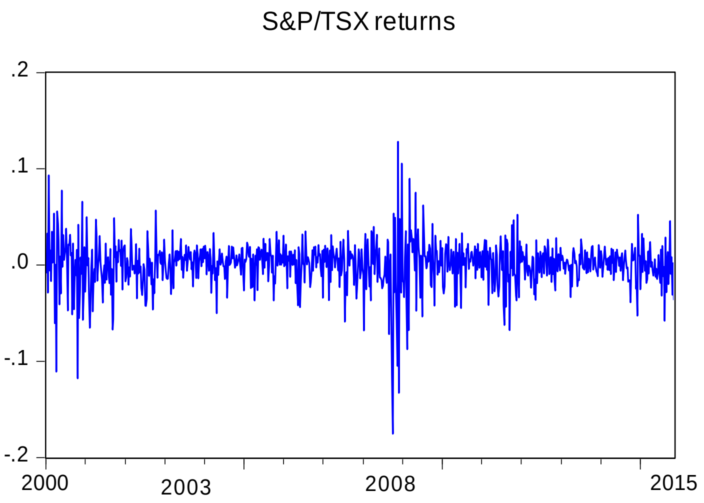
Table 1

Graphs

The graphs of the stock markets give us some information about their behavior.

Graphs of levels and returns





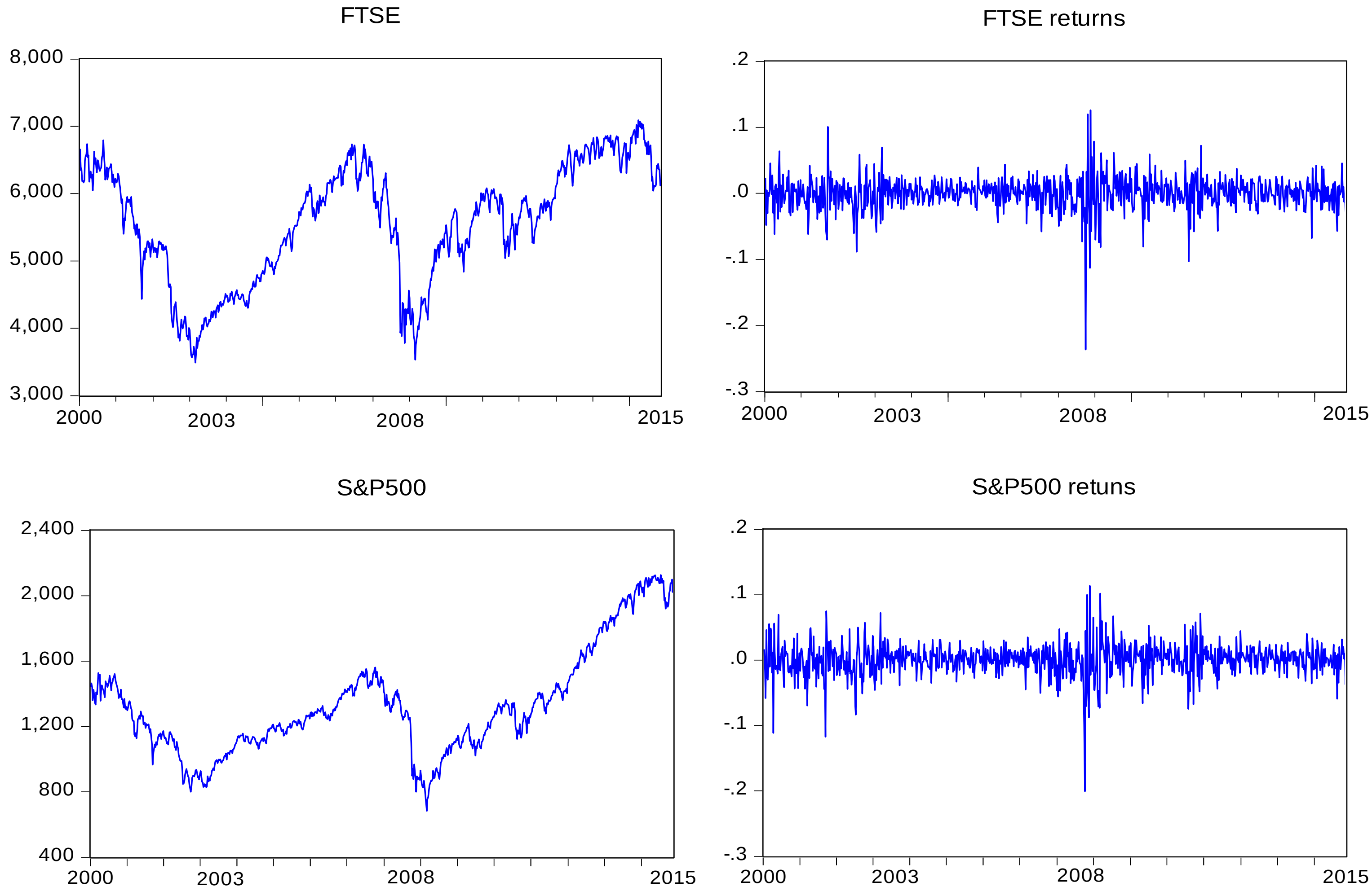


Figure 1

Their movement is in general smooth. Only in 2008 we observe steep recession at the stock markets. This happens probably due to the global financial crisis.

Unit root test

We test the stationarity of the series with Augmented Dickey-Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.

Unit root tests

	ADF t-statistic		KPSS LM-stat	
	Logs	Returns	Logs	Returns
S&P/TSX	-1,657	-9,084***	2,379***	0,058
FTSE	-1,824	-8,217***	0,969***	0,122
S&P500	-0,637	-17,850***	1,404***	0,253

Table 2

Both tests reach the same inference. All our series are I(1).

The models

Regime-switching model

- We apply a first order Markov regime-switching model with two states, introduced by Hamilton (1989)
- The model is nonlinear and moves through time from one regime to the other abruptly based on a probability law
- The probability of being in a regime depends on the previous state, is constant and is described by a Markov chain
- The model allows for different specification in the conditional mean of each regime and for different variances
- Our model is:

$$y_t = \begin{cases} c_0 + c_1 y_{t-1} + u_t, u_t \sim iidN(0, \sigma^2) \\ c_0^{'} + c_1^{'} y_{t-1} + u_t, u_t \sim iidN(0, \sigma^{'2}) \end{cases}$$

Autoregressive model and random walk

- In order to evaluate the regime-switching model we also consider an autoregressive model of order 1 and a random walk without drift
- AR(1): $y_t = c_0 + c_1 y_{t-1} + v_t$
- Random walk: $y_t = y_{t-1} + \varepsilon_t$
- Both are linear contrary to the regime-switching model that is nonlinear.

Full sample estimation results

Estimation of the model

- We estimate the regime-switching model for our three stock market indices taking into account the whole sample

Full sample estimation

	S&P/TSX	FTSE	S&P500
c_0	-0,0057 (0,0031)*	-0,0086 (0,0042)**	-0,0050 (0,0032)
$c_{0'}$	0,0024 (0,0007)***	0,0017 (0,0008)**	0,0024 (0,0008)***
c_1	-0,1853 (0,0722)**	-0,1342 (0,0879)	-0,0494 (0,0893)
$c_{1'}$	-0,0334 (0,0455)	-0,0661 (0,0444)	-0,1299 (0,0452)***
log(sigma)	-3,1913 (0,0659)***	-3,1121 (0,0813)***	-3,1800 (0,0789)***
log(sigma')	-4,1793 (0,0465)***	-4,0792 (0,0448)***	-4,1085 (0,0444)***

Table 3

- The high volatility regime for all three stock indices is the first one, while the low volatility regime is the second one
- **For all three stock markets high volatility is associated with negative returns while low volatility is associated with positive returns**

Transition probabilities

- The probabilities that the process moves from one regime to the other are constant and characterized by a Markov chain
- These probabilities are called constant Markov transition probabilities

Markov transition probabilities

	1→2	2→1
S&P/TSX	0,068	0,024
FTSE	0,119	0,028
S&P500	0,057	0,020

Table 4

Expected durations

	Regime 1	Regime 2
S&P/TSX	14,807	41,882
FTSE	8,377	35,774
S&P500	17,410	50,965

Table 5

- When the model is at one state, the probability of changing state is very low
- The model remains for long periods at each regime and does not have the tendency to change regime frequently
- All three indices spend more time at the low volatility state

Regime classification measure

- According to Ang and Bekaert (2002), we can calculate a measure to assess the quality of regime classification
- This measure is called Regime Classification Measure (RCM) and the formula for a model with two regimes is the following:

$$RCM = 400 \times \frac{1}{T} \sum_{t=1}^{T} p_t (1 - p_t)$$

- If p_t is close to 1 or 0, the regime-switching model is ideal
- Low RCM implies good regime classification, $0 \le RCM \le 100$
- In our analysis we find:

Regime classification measure

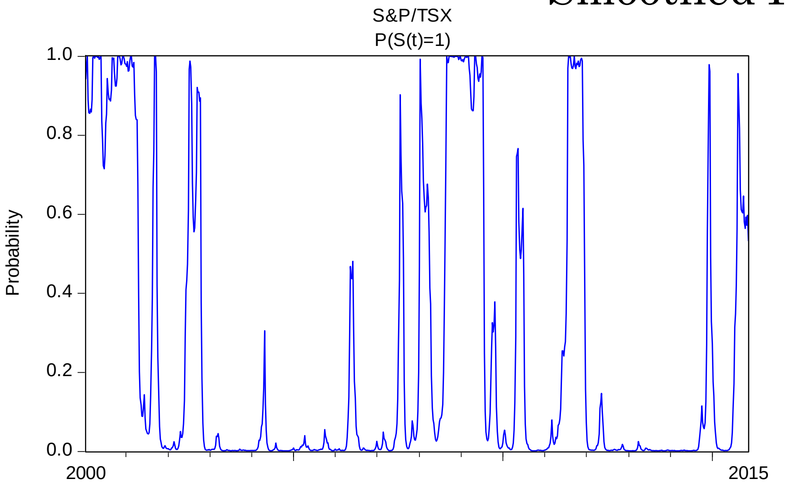
	RCM
S&P/TSX	19,640
FTSE	21,332
S&P500	19,982

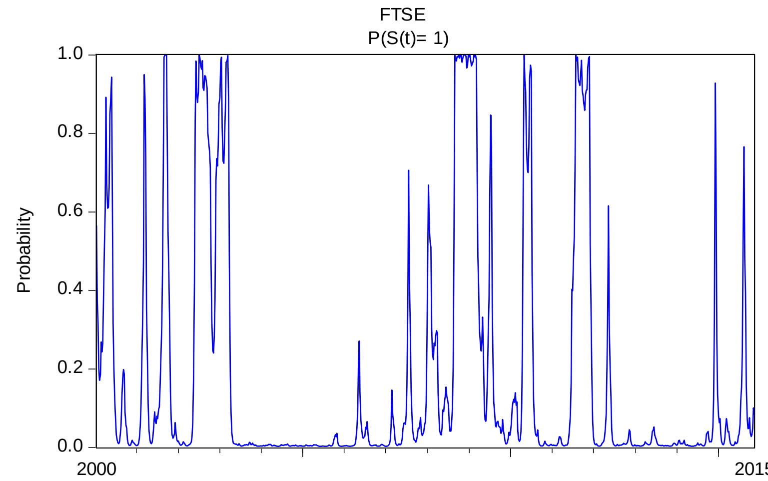
Table 6

- We have good regime classification for the model in all three cases

- The smoothed regime probabilities(p_t) indicate in which regime the market is throughout the period under scrutiny
- Figure 2 shows the smoothed probabilities of the high volatility regime for the three stock market returns

Smoothed Regime Probabilities





All three stock markets stay longer at the low volatility regime.

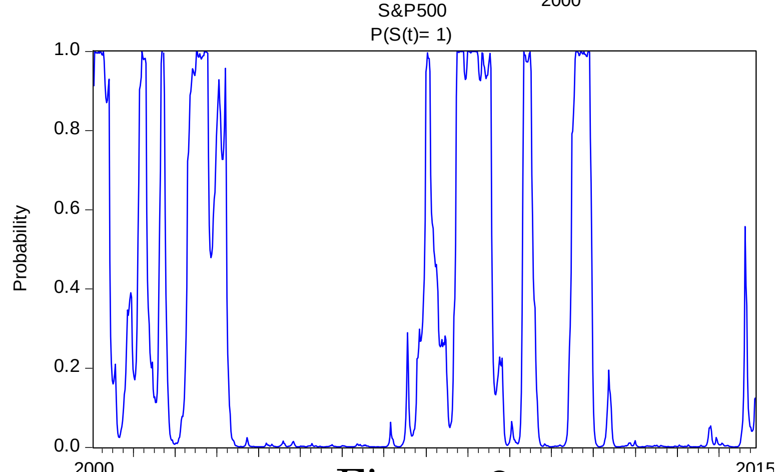


Figure 2

Out-of-sample forecast evaluation

- We want to investigate whether the regime-switching model can provide more accurate forecasts than the simple AR(1) model and the random walk model
- We divide the sample in two parts, in-sample and out-of-sample
- We follow the recursive method and we perform one-step-ahead forecasts out-of-sample

Recursive method

- Our sample has T observations and T=R+P
- The first R observations are used to estimate the models and the last P are used for forecast purposes
- In the beginning, we estimate the models for the first T-P observations and we find the forecast for the T-P+1 observation
- We estimate again the models for the T-P+1 observations and the forecast for the T-P+2 observation is derived
- Each time we increase the in-sample observations by one, we estimate the models for these observations and we get the next one-step-ahead forecast
- When we estimate the models for the T-1 observations we finally take the last forecast
- In the end we have P forecasts

Error criteria

- In order to evaluate the predictive accuracy of the models we employ two criteria, the Mean Squared Error (MSE) and the Mean Absolute Error (MAE):

$$MSE = \frac{1}{p}\sum_{t=1}^{p}\left(f_t - y_t\right)^2 \quad \text{and} \quad MAE = \frac{1}{p}\sum_{t=1}^{p}\left|f_t - y_t\right|$$

- The smaller their value is, the larger the forecasting strength of the model
- To compare the models we take the ratios of the values of the measures
- We use the regime-switching model as benchmark
- If the ratio is less than unity, the regime-switching model outperforms the other model

Forecasting performance of the models

		S&P/TSX	FTSE	S&P500
MSE	RS/AR	0,983	0,985	0,983
	RS/RW	0,433	0,448	0,444
MAE	RS/AR	0,991	0,994	0,990
	RS/RW	0,661	0,684	0,655

Table 7

- According to both criteria, RS has stronger predictive power than the other two models for all three stock market indices
- However, the difference between models is not big
- We need to examine whether the differences are statistically significant
- We perform the Diebold and Mariano (1995) test

Diebold and Mariano test

- Taking into account Diebold and Mariano (1995), we consider the time series $\{y_t\}_{t=1}^{P}$ and two forecasts for this series, $\{f_{it}\}_{t=1}^{P}$ and $\{f_{jt}\}_{t=1}^{P}$
- The forecast errors are $\{e_{it}\}_{t=1}^{P}$ and $\{e_{jt}\}_{t=1}^{P}$
- The loss differential is $d_t = [g(e_{it}) - g(e_{jt})]$
- We have two loss functions, the one refers to the squared errors and the other to the absolute errors
- Diebold and Mariano (1995) recommend a test with null hypothesis H_0: $E[g(e_{it})] = E[g(e_{jt})]$ or $E[d_t] = 0$
- $\bar{d}$ is the sample mean loss differential and $\bar{d} = \frac{1}{P}\sum_{t=1}^{P}[g(e_{it}) - g(e_{jt})]$
- For large samples, $\bar{d}$ approaches the normal distribution with mean μ and variance V/P

- The large-sample statistic that follows the standard normal distribution and tests the null hypothesis is $DM = \frac{\bar{d}}{\sqrt{\hat{V}}}\sqrt{P}$, where is a consistent estimator of the variance V

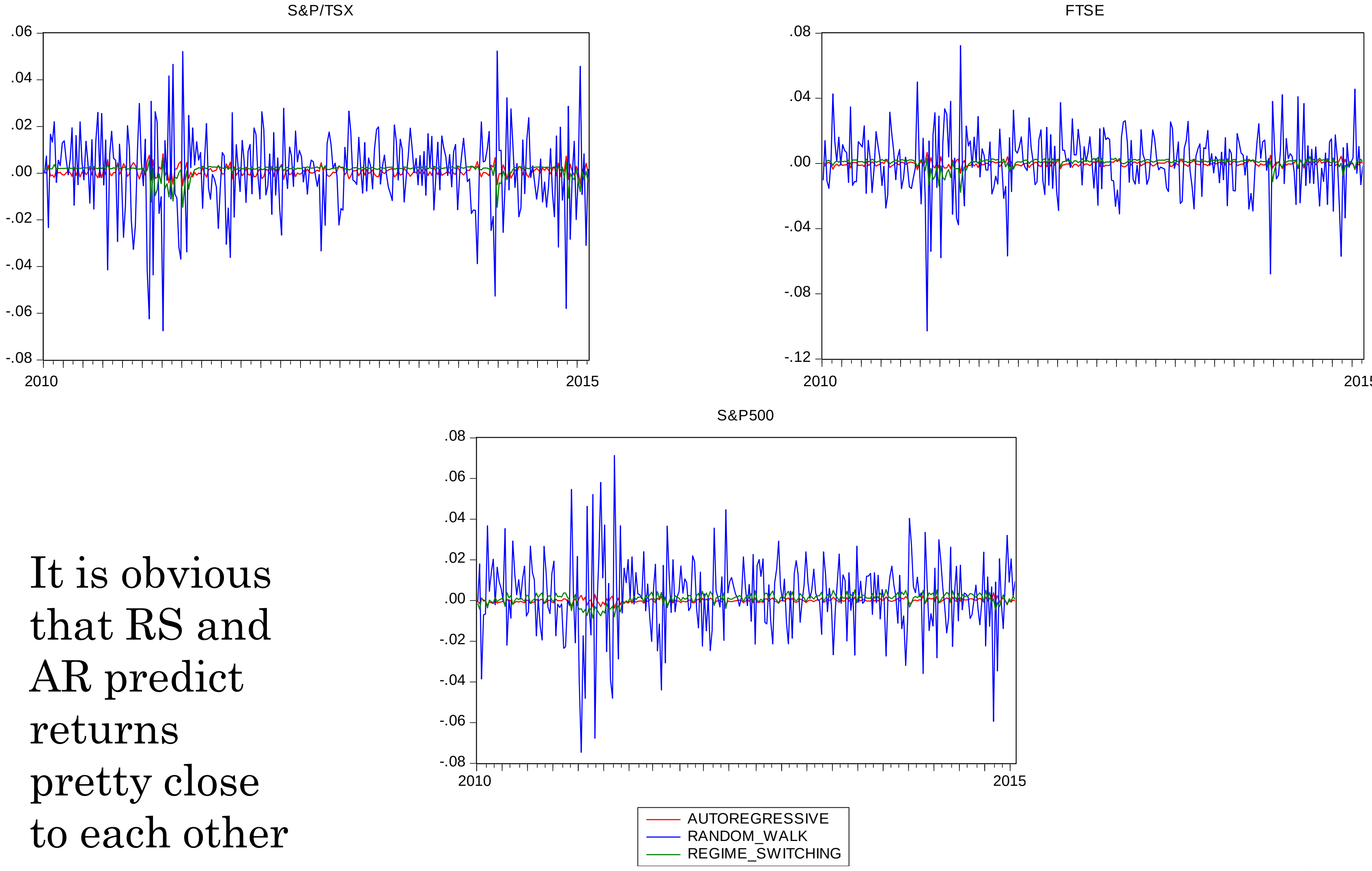
DM-test statistic

	S&P/TSX		FTSE		S&P500	
	DM-test	p-value	DM-test	p-value	DM-test	p-value
RSvsAR (MSE)	-0,7378	0,230303	-0,6318	0,263770	-0,8103	0,208875
RSvsRW (MSE)	-5,6033	1,05E-08	-5,4505	2,51E-08	-6,1011	5,27E-10
RSvsAR (MAE)	-0,7620	0,223037	-0,6182	0,268238	-1,0774	0,140641
RSvsRW (MAE)	-7,3750	8,22E-14	-6,5506	2,86E-11	-8,2917	1,11E-16

Table 8

- We take a 5% significance level
- We can reject the null hypothesis when |DM|>1,96 and we cannot reject it when |DM|<1,96
- When we compare RS with AR, we cannot reject the null hypothesis of equal predictive accuracy
- When we compare RS with RW, we reject the null hypothesis

Forecasted returns of the models



It is obvious that RS and AR predict returns pretty close to each other contrary to RW.

Figure 3

Robustness Test

- Now we proceed with a robustness check regarding the way we split our sample
- The forecasting analysis conducted above is based on 276 out-of-sample observations
- We increase and decrease the out-of-sample observations by 70
- We investigate the forecasting performance of our models
- We check if the results will remain qualitatively the same
- **The results are robust to the break-point of the sample**

Forecasting performance of the models (206 out-of-sample observations)

		S&P/TSX	FTSE	S&P500
MSE	RS/AR	0,9934	0,9899	0,9820
	RS/RW	0,4296	0,4403	0,4130
MAE	RS/AR	0,9962	0,9908	0,9835
	RS/RW	0,6674	0,6843	0,6327

Table 9

Forecasting performance of the models (346 out-of-sample observations)

		S&P/TSX	FTSE	S&P500
MSE	RS/AR	**1,0004**	**1,0033**	**1,0039**
	RS/RW	0,4336	0,4703	0,4634
MAE	RS/AR	0,9985	0,9982	**1,0006**
	RS/RW	0,6689	0,6979	0,6723

Table 10

CONCLUSION

- Our regime-switching model predicts better than the random walk, but has equal predictive ability to the simple AR(1) model
- Although the regime-switching model has a relatively good fit in-sample, the out-of-sample predictions are not satisfactory
- The literature supports nonlinear models
- Thus, further research should be done and more parameters have to be considered for a more effective model to be generated

THANK YOU FOR YOUR ATTENTION

ANY QUESTIONS?