Detecting Predictable Non-linear Dynamics in Dow Jones Islamic Market and Dow Jones Industrial Average Indices using Nonparametric Regressions

Marcos Álvarez-Díaz[*], Shawkat Hammoudeh[**] and Rangan Gupta[***]

Abstract

This study performs the challenging task of examining the forecastability behavior of the stock market returns for the Dow Jones Islamic market (DJIM) and the Dow Jones Industrial Average (DJIA) indices, using non-parametric regressions. These indices represent different markets in terms of their institutional and balance sheet characteristics. The empirical results posit that stock market indices are generally difficult to predict accurately. However, our results reveal some point forecasting capacity for a 15-week horizon at the 95 per cent confidence level for the DJIA index, and for nine- week horizon at the 99 per cent confidence for the DJIM index, using the non-parametric regressions. On the other hand, the ratio of the correctly predicted signs (the success ratio) shows a percentage above 60 per cent for both indices which is evidence of predictability for those indices. This predictability is however statistically significant only four-weeks ahead for the DJIM case, and twelve weeks ahead for the DJIA as their respective success ratios differ significantly from the 50 percent, the expected percentage for an unpredictable time series. In sum, it seems that the forecastability of DJIM is slightly better than that of DJIA. This result on the forecastability of DJIM adds to its other findings in the literature that cast doubts on its suitability in hedging and asset allocation in portfolios that contain conventional stocks.

Keywords: C58; G11

JEL Classification: Islamic and conventional equity markets; forecasting; nonparametric regressions; point prediction; success ratio

1. Introduction

One of the most challenging topics in Finance has been the attempt to predict accurately the dynamic future evolution of stock market returns. The financial markets are usually characterized by complex, unpredictable and apparently erratic dynamics

[*]Department of Economics, University of Vigo, Galicia, Spain. Email: marcos.alvarez@uvigo.es.
[**]Corresponding author. LeBow College of Business, Drexel University, Philadelphia, United States. Email: hammousm@drexel.edu.
[***]Department of Economics, University of Pretoria, Pretoria, South Africa. Email: rangan.gupta@up.ac.za.

(Hsieh, 1991). This fact, well-known as efficient market hypothesis, does not support stock market predictability. According to this hypothesis, the price of a financial asset reflects all information which can be obtained from its own past values (Fama, 1970). The acceptation of this hypothesis implies that past information does not explain current market activity and, therefore, the dynamics of financial prices can be well approximated by a random walk. Financial returns are assumed to be independent and behave as a white noise process and, consequently, it is not possible to obtain accurate predictions or devise a profitable investment strategy from past values of the returns.

In spite of the general acceptance of the efficient market hypothesis, some empirical evidence has questioned the adequacy of this hypothesis. Specifically, there exist considerable studies showing that the dynamics of the stock returns include some nonlinear deterministic component (Hsieh, 1989; Brooks, 1996; Serletis and Gogas, 2000; Kocenda, 2001; Ajmi et al. 2014). These studies all conclude that if the nonlinear component is important and captured, it would be possible to improve significantly the forecasting accuracy using nonlinear methods. Moreover, other studies have gone one-step further and have demonstrated that stock returns are to some extent predictable (see for example, Lo and MacKinlay, 1988; Guidolin and Timmermann, 2007; Chen and Hong, 2010; Dangl and Halling, 2012).

Most of the research accomplished until now is carried out using data from well-established conventional stock markets or well-known conventional financial indices (Leung *et al.*, 2000; Chen *et al*, 2003). However, an open question which is of great interest for academics and practitioners is whether it is possible to investigate the existence of non-linear predictable structures, using data for less well-established and unconventional financial indices or stock markets. These markets and their indices have been growing in importance in recent years and are expected to continue to gather momentum in the future as more countries and institutions accept them. One of those financial markets is the global Islamic stock market which is better represented by the Dow Jones Islamic Market index, the DJIM index.

The Islamic equity markets are seemingly different from the well-known and well-established conventional markets in the United States and other developed countries. These markets are not well-known in the financial literature and have different characteristics which may make them more or less difficult to model and forecast than their conventional counterparts. They prefer investments in growth and small capitalization stocks, which are not as liquid as the conventional standard stocks. They also restrict speculative financial transactions such as financial derivatives because they have no underlying real transactions. These derivatives include futures and options, government debt issues with a fixed coupon rate, and hedging by forward sale, interest-rate swaps and any other transactions involving items not physically in the ownership of the seller (e.g., short sales).

Studies have also shown that restricting leverage, which is defined as the percentage of debt in the total assets or market capitalization, like in the Islamic finance industry, reduces liquidity (Frieder and Martell, 2006). The issues of liquidity and presence of a second trading market, or the lack thereof, in the world of Islamic finance have also been a matter of continuing debate.[1] Moreover, the tax laws do not accommodate Islamic finance transactions where there can be a double charge. The differences of opinions among Islamic scholars regarding the acceptability of certain transaction structures make investors shy away from the secondary market trading because of lack of clarity.

[1]The Islamic bonds known as *sukuks* have no secondary market and are held to maturity because asset managers may not be able to find other Islamic investment alternatives to invest in.

These unusual characteristics may affect the forecastability behavior of the global Islamic stock market. Barring the recent (working) paper by Gupta *et al.*, (2013), no studies have attempted to forecast the returns of this global unconventional market. Gupta *et al.*, (2013) use a wide variety of linear and nonlinear predictive regression models, based on a large number of predictors, to indicate that these models cannot outperform the (benchmark) autoregressive model in forecasting the DJIM returns. These authors posit that, in addition to the above-mentioned characteristics of the Islamic stock markets, the prohibition of interest rates in the Islamic finance industry possibly shuts off the channels that connect market returns with economic activity, which in turn complicates the attempts to forecast the Islamic stock returns. This paper thus suggests that future research should be aimed at analyzing whether the performance of the linear autoregressive model can be improved by using nonlinear versions of the univariate autoregressive model due to wide evidence on the existence of nonlinear data-generating process for the asset returns (see for example Guidolin *et al.*, 2009, 2010, and references cited therein).[2]

Against this backdrop, the objective of this paper is to forecast the returns of the global Islamic stock market as represented by the Dow Jones Islamic Market index, and compare the forecast with that of the Dow Jones Industrial Average, using a non-linear forecasting method called the nearest neighbor (NN) approach. This method is one of the most popular techniques in non-linear time series forecasting. It is also attractive for its simplicity and ability to predict complex non-linear behaviors.

[2]Note that in the nonlinear (time-varying) models used by Gupta *et al.*, (2013), nonlinearity is only captured between the DJIM returns and the predictors. That paper does not specifically model the DJIM returns as nonlinear originating from a nonlinear data- generating process.

The remainder of this study is organized as follows. Section 2 discusses the data and presents the non-linear forecasting method. Section 3 discusses the results and Section 4 concludes.

2. Empirical investigation

2.1. Preliminary data analysis

The data used in our study are the Dow Jones Islamic Market (DJIM) Index and the Dow Jones Industrial Average (DJIA) Index, which are sourced from Bloomberg. The DJIM index is the most comprehensive Islamic equity index and embraces a global universe of investable equities that have been screened for Sharia compliance. The companies in this index pass the industry and financial ratio screens which are set forth by the Sharia scholars. The DJIM includes Sharia-compliant stocks from 44 countries and its regional allocation is classified as follows: 60.14% for the United States; 24.33% for Europe and South Africa; and 15.53% for Asia (Hammoudeh *et al*., 2013). The analysis is based on weekly data spanning the period from January 1996:W1to July 2013:W1, having a total of 923 observations. The range of the data sample is constrained by the data availability. The adoption of a weekly frequency allows one to have sufficient information to reflect accurately the dynamics of the series (Yao and Tan, 2000). Additionally, this periodicity helps alleviate possible biases related to the daily frequency such as, for example, the weekend effect or the day-of-the-week effect. To be precise, each series captures the value of the financial index during a representative day of the week, usually Wednesday. However, as it is very common in the financial literature, if a particular Wednesday happens to be a non-trading day, then either Tuesday or Thursday is retained (Lo and MacKinlay, 1988; Diebold and Nason, 1990; Hu, Zhang and Patuwo, 1999; Darrat and Zhong, 2000).

Given the presence of trends in the evolution of the two series, the variables are transformed to their growth levels to ensure stationarity[3]. This transformation eases interpretation since the log-difference of variables is usually understood as returns. According to this transformation, given the series DJIA (Y_t) and the DJIM (X_t), their respective returns can be approximated by $y_t = \log(Y_t) - \log(Y_{t-1})$ and $x_t = \log(X_t) - \log(X_{t-1})$. Nevertheless, some linear deterministic structures still remain in the time series after taking differences (i.e. seasonal components). Therefore, the series y_t and x_t must be filtered again using some linear forecasting technique. Many authors have recommended the use of autoregressive models to bleach the time series (Katz, 1988a, 1988b; Theiler and Eubank, 1993). In our study, we consider the autoregressive models.

$$y_t = \alpha_0 + \alpha_1 \cdot y_{t-1} + ... + \alpha_p \cdot y_{t-p} + yresidual_t \quad (1)$$
$$x_t = \mu_0 + \mu_1 \cdot x_{t-1} + ... + \mu_p \cdot x_{t-q} + xresidual_t \quad (2)$$

where $\{\alpha_i\}_{i=0}^{p}$ and $\{\mu_j\}_{j=0}^{q}$ are the linear coefficients. These coefficients are estimated by a least-squares fit which minimizes the variance of the residuals. The orders of the autoregressive models p and q are selected by minimizing the following generalization of the Akaike Information Criterion (AIC)

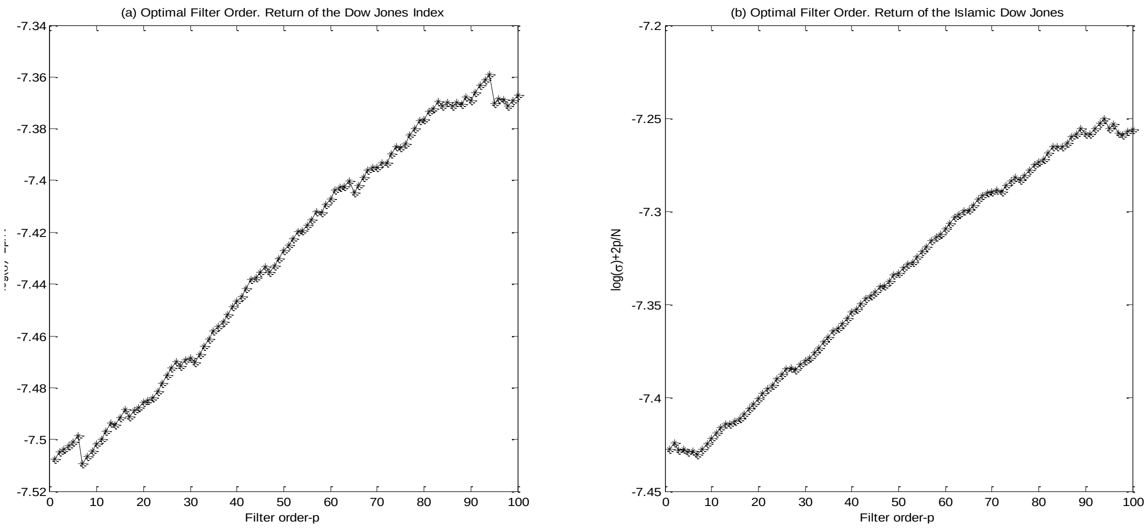
$$\text{AIC}(r) = \ln\left(\sigma_e^2(r)\right) + 2 \cdot \frac{r}{N} \quad (3)$$

where N is the sample size, r is the number of coefficients and $\sigma_e^2(r)$ is the estimated variance of the errors. This generalization of the AIC criterion has been widely used to select the order of the autoregressive model when bleaching time series (Cañellas *et al.*,

[3] The unit root tests have not been reported to save space, but the details are available upon request from the authors.

2005; Álvarez-Díaz e*t al. 2*010, among others). It is important to note that the term $2 \cdot \frac{r}{N}$ is included to penalize the use of extra coefficients that do not reduce significantly the error.

Figure 1. Choice of the Optimum *p*-order of the Autoregressive for the Time Series



As depicted in Figure 1, we retain the optimal order of the autoregressive model of seven for both series (*p*=7 and *q*=7) based on the AIC criterion.[4] The filtered series are the residuals of Equations (1) and (2): *yresiduals* and *xresiduals*. Figure 2 displays the time evolution of the filtered time series. In turn, Figure 3 shows the sample autocorrelation function for both series, as well as their respective intervals of confidence empirically constructed by means of the surrogate method (Theiler *et al.*, 1992). As we can observe in this figure, none of the sample autocorrelation coefficients

[4] Other possible choices for the model order selection include the Schwarz Criterion or the Hannah Quinn Criterion. The use of these criteria also confirms the optimal choice of *p*=7 and *q*=7. It is at these lags where these criteria are minimized and the estimated errors are uncorrelated.

Figure 2. Time evolution of the filtered time series

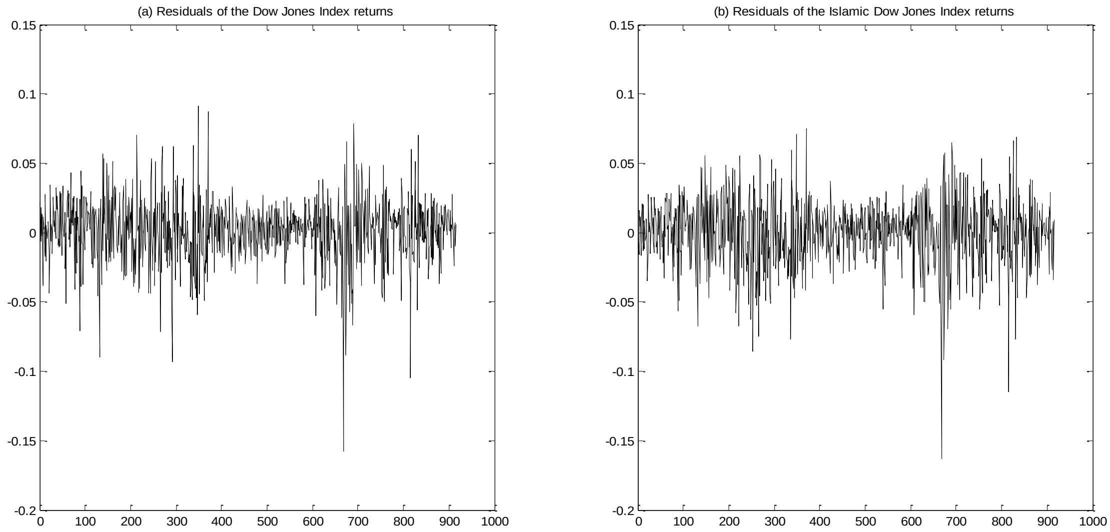
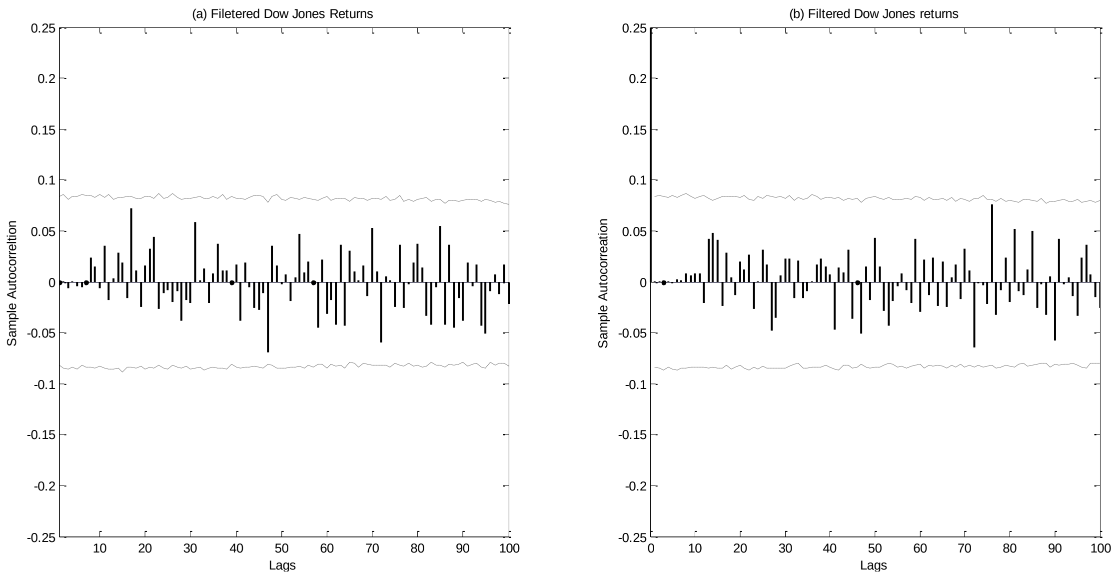


Figure 3. Sample autocorrelation function (ACF) of the filtered time series



Note: The confidence intervals are constructed using the surrogate method with a 99 percent significance level.

is statistically significant. Therefore, the autocorrelation analysis points to the absence of a linear structure for both the residuals of the DJIM returns and the residuals of the DJIA returns. This result is also corroborated by the Ljung-Box test and the Breusch-Godfrey LM test since the null hypothesis for uncorrelated behavior cannot be rejected for any lag. As a consequence, there seems to be no linear deterministic signals in the residuals. This characteristic guarantees that our autoregressive models do approach quite well to the best linear predictor (Theiler and Eubank, 1993).

We also test for the existence of non-linear structures by using the BDS statistic proposed by Brock *et al.* (1996). The BDS statistic tests the null hypothesis that the residuals of the autoregressive model behave as an independent and are identically distributed random variables (*i.i.d.*, in short). However, an important problem that arises at this point is that the possible existence of linear dependence in the conditional second moments could lead to the rejection of the *i.i.d.* hypothesis, using the BDS test. If this is the case, the rejection of this hypothesis will not imply the presence of non-linear structures in the mean.

Table 1: The ARCH Test for the Original and the Standardized Residuals

	ARCH TEST			ARCH TEST	
Lags	**Residuals of the Islamic Dow-Jones**	**Standardized Residuals of the Islamic Dow-Jones**	**Lags**	**Residuals of the Dow-Jones**	**Standardized Residuals of the Dow-Jones**
1	33.35***	1.55	1	33.35***	0.01
2	35.67***	2.90	2	35.67***	0.88
3	44.21***	3.73	3	44.21***	3.76
4	47.16***	4.66	4	47.16***	3.80
5	56.19***	4.74	5	56.19***	4.06
6	56.07***	5.00	6	56.07***	5.50
7	60.55***	5.00	7	60.55***	5.89
8	61.38***	6.12	8	61.38***	6.69
9	61.97***	7.06	9	61.97***	6.66
10	62.77***	7.96	10	62.77***	8.34

Note: The asterisks *, ** and *** represent the rejection of the null hypothesis H_0: conditional homoskedasticity at the 10, 5 and 1 percent significance levels, respectively.

Table 1 shows the results of the ARCH test for the residuals of the DJIM returns and the residuals of the DJIA returns. These results allow one to confirm whether there is a linear dependence in the conditional variance or not, which if confirmed is not useful if we want to improve our predictive ability. It is for this reason that we have applied the BDS test to test for the non-linearity of the standardized residuals

$$Z_t = \frac{u_t}{\hat{h}_t}$$

where Z_t is the standardized residuals, u_t is the series *yresidual*$_t$ or *xresidual*$_t$, and $\hat{h}_t^2$ is the conditional variance which is estimated using the GARCH(1,1) model

$$\hat{h}_t^2 = \alpha_0 + \alpha_1 \cdot u_{t-1}^2 + \beta_1 \cdot h_{t-1}^2$$

As one can see also in Table 1, the values of the Arch test reveal that the standardized residuals do not have any structure in the variance. Table 2 displays the results of the BDS test applied to the standardized residuals. The BDS statistics reject the null of no nonlinearity in the standardized residuals of the DJIA and the DJIM indices. This finding provides evidence that each of these series has a statistically nonlinear dependency. The basic problem to be solved now is to determine if these non-linear signals are strong enough to improve significantly our predictions.

Table 2: The BDS results for the standardized residuals

Embedding Dimension	**BDS Test Statistics Standardized Residuals of the Islamic Dow-Jones**	**BDS Test Statistics Standardized Residuals of the Industrial Dow-Jones**
2	1.03	0.87
3	1.26	1.33
4	1.41	1.42*
5	1.88*	1.89*
6	2.35**	1.88**
7	2.20**	1.98**
8	1.87*	2.26**
9	1.65*	2.53**
10	0.83	2.05**

Note: The asterisks *, ** and *** represent the rejection of the null hypothesis H_0: *no nonlinearity* at the 10, 5 and 1 percent significance levels, respectively. The BDS is implemented assuming ε as a fraction of the standard deviation.

2.2. The non-linear forecasting method: local regression

To accomplish the goal pursued in our study, we use a specific non-linear forecasting method known as the nearest neighbor (NN) as indicated earlier. This method is one of the most popular techniques in non-linear time series forecasting. It has been widely employed in different fields such as physics, biology and medicine. Some examples of its applications in economics and finance can be found in Diebold and Nason (1990), Meese and Rose (1991), Fernández-Rodríguez *et al.* (1999), Álvarez-Díaz and Álvarez (2008) and Álvarez-Díaz (2010). The explanation of this popularity in forecasting research is due to the multiple advantages it offers in comparison with other forecasting methods. First, it reduces the possibility of model misspecification and provides a versatile method of exploring for a general functional relationship between the variables (Barkoulas *et al.*, 2003). Second, it has shown an important ability to predict complex dynamics (Farmer and Siderovich, 1987; Casdagli, 1989). Finally, it requires a minimum prior treatment of the series and behaves quite well when analyzing the series that are affected by some type of noise (Aparicio *et al.*, 2002).

In our study, we use a specific nearest neighbor method known as the local regression. This general procedure can be explained by using matrix algebra. Specifically, given any time series $\{x_t\}_{t=1}^{T}$, it is possible to construct the matrix:

$$M_{T-m+1xm} = \begin{pmatrix} M^1 \\ M^2 \\ . \\ . \\ . \\ M^{T-m+1} \end{pmatrix} = \begin{pmatrix} x_1 & x_2 & . & . & . & x_m \\ x_2 & x_3 & . & . & . & x_{m+1} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ x_{T-m+1} & x_{T-m+2} & . & . & . & x_T \end{pmatrix}$$

which is the *trajectory matrix* of the time series. This matrix represents the dynamics of the time series from a spatial perspective. Each row of the trajectory matrix is a vector

$$M^{i} = (x_i, x_{i+1}, ..., x_{m+i-1})$$

whose dimension (m) is called the *embedding dimension*. The next step is to select the past dynamics which are similar to the recent behavior of the time series. Following Cleveland and Devlin (1988) and Yakowitz (1987), we look for the K vectors $M^{i} \in \Re^{m}$ which minimize the Euclidean distance from the vector that represents the present dynamics (M^{T-m+1}). Formally, we consider that the K closest neighbors are the vectors that minimize the function

$$dista(M^{i}, M^{T-m+1}) = \left\| M^{i} - M^{T-m+1} \right\| = \left(\sum_{l=1}^{m} \left(\left(x_{l,1} - x_{l,T-m+1} \right)^{2} \right) \right)^{\frac{1}{2}}$$

Based on the calculation of the distances, we can then build both the N matrix with the K vectors closest to M^{T-m+1} as well as the *Ematrix* that reflects the value to which each of the K vectors evolves τ periods-ahead

$$N_{Kx(m+1)} = \begin{pmatrix} N^{1} \\ N^{2} \\ . \\ . \\ . \\ N^{K} \end{pmatrix} = \begin{pmatrix} k11 & k12 & . & . & . & k1m \\ k21 & k22 & . & . & . & k2m \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ kK1 & kK2 & . & . & . & kkm \end{pmatrix}; \qquad E_{Kx1} = \begin{pmatrix} E^{1} \\ E^{2} \\ . \\ . \\ . \\ E^{K} \end{pmatrix}$$

The predicted value of the future returns ($\hat{x}_{T+\tau}$) from the vector M^{T-m+1} will be determined by the regression model:

$$\hat{x}_{T+\tau} = b_0 + b_1 \cdot x_{T-m+1} + b_2 \cdot x_{T-m+2} + ... + b_m \cdot x_T$$

where the coefficients b_i have been estimated by the ordinary least squares, using the matrices N and E ($b = (N'N)^{-1} N'E$). Other authors have formulated weighting schemes that give greater weights to nearby observations in estimating the local regression. However, as Jaditz and Riddick (2000) point out, the weighted regression is computationally slower and usually provides worse forecasts than the un-weighted local regression.

An important question for the application of the local regression is to choose correctly the embedding dimension (*m*) and the number of nearest neighbors (*K*). An appropriate selection of these technical parameters is of great importance for the success of the predictive exercise. In our case, we follow the recommendations proposed in the literature, and we select *K* and *m* at the same time using a trial-and-error process (Casdagli, 1992). Specifically, we start by dividing our sample into three sub-periods: Training, Selection and Out-of-Sample (Yao and Tan, 2000). The first one, which is composed by the first 571 observations, is reserved as history of the time series. In this sub-period, we apply different local regression models by assuming a number of the nearest neighbors between 10% of all observations up to 90%, increasing in steps of 10%. For the case of the embedding dimension, we consider values from 2 to 20 (Hsieh, 1991). The selection period, which covers the 213 following observations, is used to determine the optimal combination of *K* and *m* that optimizes a given fit criterion in this specific sub-sample. Finally, the last 130 observations form the out-of-sample set, and the value of the accuracy measure obtained in this sub-sample is employed to validate our predictive ability.

There are different accuracy measures to evaluate the forecasting accuracy. In our study, we use two different criteria depending on whether our goal is to predict the exact value of the time series (point prediction), or if it is to anticipate the direction of the sign movements (sign prediction). For the point prediction, we consider the *Normalized Mean Square Error* (NMSE)

$$NMSE = \frac{\sum\left[x_x - \hat{x}_t\right]^2}{\sum\left[x_t - mean(x_t)\right]^2}$$

The basic idea of this fit criterion is to compare the errors of the forecasting method with those obtained by assuming the sample mean as a naive predictor. Consequently, a NMSE value lower than/equal/higher than one would imply a forecasting ability better than/equal to/worse than the mean as a predictor. This criterion has been recommended in the literature (Casdagli, 1989) and has been traditionally used in financial forecasting (Elms, 1994; Yao *et al.,* 1999, among many others).

On the other hand, for the sign prediction we use the ratio of correctly predicted signs (*Success Ratio*) defined by the expression

$$SR = \frac{\sum_{t=1}^{T} I\left[x_t \cdot \hat{x}_t > 0\right]}{T} \times 100$$

where *SR* is the success ratio and $I(\cdot)$ is an indicator function that takes the value one if $x_t \cdot \hat{x}_t > 0$ and zero otherwise. This criterion gives us the percentage of the correct predictions of an appreciation or depreciation of the financial indices considered in our analysis. The sign prediction is extremely important for empirical financial purposes since it affects a trader's decision to buy or sell a financial asset. A financial trader must always keep in mind that even the smallest forecast errors in the point prediction can cause important losses if the direction of the forecast is mistaken (Tenti, 1996; Walczak, 2001).

3. Empirical results

A total of 130 out-of-sample forecasts are made for the weekly period from January 2011:W1 to July 2013:W1. The predictive analysis used here is based on the approach introduced by Sugihara and May (1990) and empirically applied in economics by Finkenstädt and Kuhbier (1995) and Agnon *et al.* (1999), among others. Specifically, this approach is based on analysing the out-of-sample predictability of a series over different forecast horizons. In our specific case, we assume a forecast horizon from 1 to 20 weeks ahead of the residuals of the DJIM returns ($xresidual_t$), and the residuals of the DJIA returns ($yresidual_t$). If these series are unpredictable, we would observe that the NMSE obtained by our nonlinear forecasting method would fluctuate around a value of one (the accuracy of applying the mean as the naïve predictor) regardless of the considered forecast horizon. For the sign prediction, we would expect to observe a fluctuation in the percentage of correct forecasts about 50 percent (the predictions obtained by chance throwing a coin) regardless of how far into the future one tries to predict. On the other hand, there would be evidence of predictability if we observe that for some forecast horizons the value of the NMSE is statistically lower than one, or the Success Ratio is statistically higher than 50 percent.

One important question is how to determine the statistical significance of the predictions made for each forecast horizon. This is a very important matter since our study is basically based on discovering time horizons where our predictions are statistically significant. In order to do this, we construct empirical confidence intervals by using a nonparametric technique called the surrogate data method (Theiler *et al.* 1992). Any NMSE or SR inside the empirical interval would be considered as the result of the application of the nonlinear method on a random and unpredictable time series. Alternatively, if the NMSE is below the lower bound or the SR is above the upper bound of the interval, then there would be evidence of a significant predictive ability. As a consequence, we would verify that the residuals of the DJIM returns and the residuals of the DJIA returns have non-linear signals that are strong enough to improve significantly our predictions.

Table 3: Point prediction of the DJIA for different periods ahead.

Forecasting Periods	Out-of-Sample NMSE	Empirical Confidence Intervals		
		at 90 percent	at 95 percent	at 99 Percent
1	1.010	(0.977, 1.062)	(0.971, 1.073)	(0.955, 1.092)
2	0.994	(0.980, 1.028)	(0.975, 1.034)	(0.966, 1.045)
3	1.013	(0.982, 1.022)	(0.978, 1.027)	(0.967, 1.042)
4	1.025	(0.976, 1.046)	(0.969, 1.053)	(0.954, 1.072)
5	1.072	(0.979, 1.082)	(0.971, 1.092)	(0.956, 1.118)
6	0.997	(0.977, 1.033)	(0.970, 1.039)	(0.957, 1.048)
7	0.999	(0.979, 1.033)	(0.971, 1.038)	(0.962, 1.049)
8	0.985	(0.982, 1.027)	(0.977, 1.031)	(0.967, 1.045)
9	0.996	(0.979, 1.032)	(0.974, 1.039)	(0.959, 1.063)
10	0.987	(0.979, 1.081)	(0.968, 1.094)	(0.951, 1.125)
11	0.982*	(0.985, 1.086)	(0.971, 1.114)	(0.944, 1.169)
12	0.972*	(0.984, 1.080)	(0.971, 1.102)	(0.951, 1.140)
13	0.982*	(0.983, 1.044)	(0.968, 1.062)	(0.955, 1.102)
14	0.973*	(0.982, 1.044)	(0.972, 1.061)	(0.960, 1.104)
15	0.963**	(0.983, 1.066)	(0.971, 1.089)	(0.954, 1.134)
16	0.988	(0.984, 1.027)	(0.977, 1.059)	(0.967, 1.082)
17	1.029	(0.984, 1.028)	(0.977, 1.041)	(0.964, 1.067)
18	1.020	(0.981, 1.054)	(0.973, 1.075)	(0.965, 1.110)
19	0.998	(0.984, 1.053)	(0.971, 1.073)	(0.957, 1.115)
20	0.998	(0.983, 1.047)	(0.973, 1.064)	(0.959, 1.127)

Note: The symbols *, **, *** means rejection of the null hypothesis that there is no forecasting capacity at the 10, 5 and 1 percent significance level, respectively. The empirical confidence intervals were constructed using the surrogate method.

Tables 3 and 4 show the results of the point prediction for different forecasting periods. These tables also display the surrogate empirical intervals with confidence levels at 90, 95 and 99 percents. For the case of the residuals of the DJIA index, all point predictions are inside the 99 percent confidence interval. The NMSE values move always above the lower bound and fluctuate around a value of one, indicating that there is no evidence of a predictive capacity. Nevertheless, if we are less demanding and

Table 4: Point prediction of the DJIM for different periods ahead.

Forecasting Periods	Out-of-Sample NMSE	Empirical Confidence Intervals		
		at 90 percent	at 95 percent	at 99 Percent
1	1.002	(0.979, 1.021)	(0.975, 1.025)	(0.961, 1.030)
2	0.989	(0.979, 1.019)	(0.976, 1.024)	(0.966, 1.040)
3	1.016	(0.977, 1.062)	(0.969, 1.071)	(0.959, 1.090)
4	0.990	(0.978, 1.062)	(0.969, 1.075)	(0.954, 1.090)
5	1.018	(0.979, 1.076)	(0.969, 1.085)	(0.953, 1.100)
6	0.992	(0.978, 1.074)	(0.969, 1.084)	(0.946, 1.120)
7	1.003	(0.980, 1.079)	(0.971, 1.090)	(0.945, 1.110)
8	0.991	(0.980, 1.071)	(0.973, 1.081)	(0.962, 1.110)
9	0.944^{***}	(0.977, 1.071)	(0.970, 1.084)	(0.947, 1.110)
10	0.970^{**}	(0.980, 1.041)	(0.975, 1.051)	(0.965, 1.060)
11	0.983	(0.978, 1.041)	(0.974, 1.049)	(0.962, 1.080)
12	0.996	(0.978, 1.042)	(0.972, 1.051)	(0.962, 1.080)
13	0.972^{*}	(0.975, 1.052)	(0.967, 1.069)	(0.956, 1.090)
14	0.995	(0.979, 1.042)	(0.972, 1.048)	(0.961, 1.070)
15	0.980	(0.973, 1.060)	(0.967, 1.070)	(0.953, 1.110)
16	1.012	(0.977, 1.030)	(0.975, 1.039)	(0.965, 1.060)
17	1.018	(0.980, 1.022)	(0.977, 1.028)	(0.969, 1.050)
18	1.019	(0.977, 1.043)	(0.971, 1.054)	(0.960, 1.100)
19	0.986	(0.972, 1.087)	(0.962, 1.107)	(0.950, 1.150)
20	1.014	(0.980, 1.029)	(0.966, 1.059)	(0.966, 1.060)

Note: The symbols *, **, *** means rejection of the null hypothesis that there is no forecasting capacity at the 10, 5 and 1 percent significance level, respectively. The empirical confidence intervals were constructed using the surrogate method.

consider the 95 percent confidence interval, we observe that there could be a certain degree of predictability for 15 periods ahead. A similar predictive behavior can be observed for the case of the residuals of the DJIM index. However, it is much more clear here the existence of a predictable pattern for the Islamic returns. As we can see, the NMSE for nine-periods-ahead is below the lower bound of the 99 percent confidence interval. This fact is a clear indication that there is a statistical significant predictive capacity at this horizon for the DJIM. In general, this predictive result seems to be consistent with other studies already published in the literature on different markets and, specifically, with those that examine the close relationship among liquidity, efficiency and forecasting capacity. Hubert (1997), for example, analyzes the Austrian market and concludes that the more mature (liquid) a market becomes, the more the dynamics of its prices approach constitute random walk. Yao *et al.* (1999) study the Malaysian financial market and find little evidence of randomness in the dynamics of the returns. Darrat and Zhong (2000) discover an apparent predictability in the Chinese financial market, which is probably attributed to its low liquidity and the existence of asymmetric information. It seems, therefore, that in our study the liquidity (or lack thereof) and the specific institutional characteristics of the Islamic stock market could be responsible for the higher forecastability of DJIM compared to that of DJIA.

Table 5: Sign prediction of the DJIA for different periods ahead.

Forecasting Periods	**Out-of-Sample Success Ratio (%)**	**Empirical Confidence Intervals**		
		at 90 percent	**at 95 percent**	**at 99 Percent**
1	51.91	(47.33, 61.07)	(46.56, 61.83)	(43.51, 64.12)
2	51.91	(45.80, 59.54)	(44.27, 61.07)	(41.98, 63.36)
3	52.67	(48.85, 61.07)	(48.09, 62.60)	(45.80, 64.12)
4	59.54	(48.85, 61.07)	(48.09, 61.83)	(45.04, 64.12)
5	59.54*	(45.80, 59.54)	(44.27, 61.07)	(41.98, 64.12)
6	58.02	(46.56, 60.31)	(45.04, 61.07)	(41.98, 63.36)
7	54.96	(44.27, 59.54)	(43.51, 60.31)	(39.69, 62.60)
8	52.67	(44.27, 59.54)	(42.75, 60.31)	(39.69, 63.36)
9	57.25	(45.04, 60.31)	(42.75, 61.07)	(41.22, 63.36)
10	54.96	(45.80, 60.31)	(44.27, 61.07)	(40.46, 63.36)
11	58.02	(47.33, 61.07)	(45.04, 62.60)	(42.75, 64.89)
12	63.36***	(45.80, 60.31)	(44.27, 61.07)	(41.98, 62.60)
13	56.49	(49.62, 61.07)	(48.85, 61.83)	(47.33, 63.36)
14	56.49	(46.56, 60.31)	(45.04, 61.83)	(41.98, 64.12)
15	51.15	(48.85, 61.83)	(48.09, 62.60)	(45.04, 64.12)
16	55.73	(47.33, 61.07)	(46.56, 61.83)	(44.27, 63.36)
17	55.73	(48.85, 61.07)	(48.09, 61.83)	(45.80, 64.89)
18	50.38	(49.62, 61.07)	(48.09, 61.83)	(45.80, 63.36)
19	52.67	(41.98, 60.31)	(41.98, 60.31)	(39.69, 61.83)
20	48.09	(43.51, 61.07)	(43.51, 61.07)	(40.47, 63.36)

Note: The symbols *, **, *** means rejection of the null hypothesis that there is no forecasting capacity at the 10, 5 and 1 percent significance level, respectively. The empirical confidence intervals were constructed using the surrogate method.

Tables 5 and 6 present the results of the sign prediction for the different forecasting horizons considered in our study. In the case of the residuals of the DJIA index, the most remarkable finding is the high predictive accuracy of twelve periods ahead. The success ratio obtained for DJIA using the local regression gives a value of 63.33 percent. This percentage of correct predictions is above the upper bound of the 99 percent confidence interval. It thus implies that DJIA is predictable because its success ratio is statistically higher than 50 percent (the expected value of the success ratio for an unpredictable time series).

Table 6: Sign prediction of the DJIM for different periods ahead.

Forecasting Periods	Out-of-Sample Success Ratio (%)	Empirical Confidence Intervals		
		at 90 percent	at 95 percent	at 99 Percent
1	49.62	(42.75, 57.25)	(41.22, 58.78)	(38.93, 61.07)
2	54.96	(42.75, 57.25)	(41.98, 58.78)	(38.93, 60.31)
3	58.78**	(41.98, 56.49)	(41.22, 58.02)	(38.17, 61.07)
4	60.31***	(42.75, 57.25)	(41.22, 58.78)	(38.17, 60.31)
5	56.49	(42.75, 57.25)	(41.98, 58.02)	(38.17, 61.07)
6	49.52	(42.75, 56.49)	(41.22, 58.02)	(38.17, 60.31)
7	52.67	(42.75, 57.25)	(41.22, 58.02)	(38.93, 62.60)
8	52.67	(41.98, 57.25)	(40.46, 58.02)	(37.40, 60.31)
9	58.78*	(42.75, 57.25)	(41.98, 59.54)	(39.69, 61.83)
10	52.67	(42.75, 57.25)	(41.22, 58.02)	(37.40, 62.00)
11	54.20	(42.75, 57.25)	(41.98, 58.78)	(38.93, 60.31)
12	46.56	(42.75, 57.25)	(41.22, 58.02)	(38.93, 61.07)
13	48.85	(42.75, 57.25)	(40.46, 58.78)	(38.93, 61.83)
14	47.33	(42.75, 57.25)	(41.98, 58.78)	(40.46, 61.07)
15	50.38	(42.75, 57.25)	(41.22, 58.02)	(38.93, 60.31)
16	45.04	(43.71, 57.25)	(41.98, 58.02)	(39.69, 61.07)
17	45.80	(42.75, 56.49)	(41.98, 58.02)	(38.93, 60.31)
18	55.73	(42.75, 57.25)	(41.22, 58.78)	(37.40, 61.07)
19	54.02	(42.75, 56.49)	(41.98, 58.02)	(38.93, 60.31)
20	52.67	(42.75, 58.02)	(41.22, 58.78)	(38.17, 61.83)

Note: The symbols *, **, *** means rejection of the null hypothesis that there is no forecasting capacity at the 10, 5 and 1 percent significance level, respectively. The empirical confidence intervals were constructed using the surrogate method.

For the case of the dynamic predictive behavior for the residuals of the DJIM, the result shows a predictable capacity of four-periods-ahead. At this predictive horizon, the success ratio reflects a value of 60.31 percent, which is also greater than the 50 percent value for unpredictability, and which is almost outside the upper bound of the 99 percent confidence interval as shown in Table 6. These sign prediction results are in accordance with the stylized fact observed in financial forecasting that provides evidence of the difficulties of getting a success ratio higher than 60 percent (Lequarré, 1993).

4. Conclusion

It is acknowledged in the financial literature that predicting stock market returns is usually challenging because these markets are characterized by complex and erratic dynamics. In fact, the literature is mixed on such predictability, ranging from those that support no predictability based on the efficient market hypothesis to those who demonstrate that stock returns are to some extent predictable. Some theoretical and empirical results seem to support the growing belief that the behaviour of financial returns could include some nonlinear deterministic component. If these nonlinear structures are important, then it would be possible to improve significantly our forecasting capacities by using nonlinear forecasting methods.

Most of the research on the stock returns predictability has been conducted on well-established conventional stock markets or well-known financial indices for developed and developing countries. Despite the growing importance of Islamic finance, no published research has looked into the forecastibility of the returns of the seemingly different Islamic stock markets as represented by DJIM in comparison to that of their conventional counterparts represented by DJIA. In addition to their growing importance, the Islamic markets are different from their conventional counterparts due to their compliance with the Sharia rules which may make them different to forecast, compared to conventional markets. They are also different from the conventional stocks in terms of the characteristics of their ownership and balance sheets and their implications for liquidity. This makes forecasting the Islamic stock market returns useful and interesting.

Since the presence of a non-linear deterministic component in the conventional stock returns is considered a reason behind the forecasting challenge, we also consider this component to be present in the Islamic stock returns. In fact, this study verifies this nonlinearity in the Dow Jones Islamic Market (DJIM) index which represents the global Islamic stock market. The use of the BDS test reflects the existence of a non-linear component both in the DJIM and in the DJIA indices. The great question that we have to answer is whether the non-linear structure in those indices is strong enough to improve significantly our predictions.

A priori, the anecdotal evidence on the institutional characteristics of the DJIM stocks makes us believe that these stocks are relatively less efficient and may be more predictable than the conventional counterparts. But this conjuncture is not well supported in the empirical literature. It is for this reason we compare the forecastability of the DJIM with DJIA indices. For this purpose, we make use of a non-linear forecasting method to get accurate predictions known as the nearest neighbor method (NN). This method has been shown to have an important ability to predict complex dynamics

We also check the statistical significance of these predictions by means of the surrogate method. Our results show no evidence of a strong predictive capacity for the two indices under consideration. Nevertheless, we observe that there could be a certain degree of predictability for the DJIA. Specifically, we have found that it is possible to achieve statistically significant forecasts 15 periods ahead for the point prediction, and 12 periods ahead for the sign prediction. A similar pattern is observed for the DJIM returns but, in this case, they have a higher predictive capacity than the DJIA returns. The nine-period ahead forecasts for the point prediction are highly significant, while for the sign prediction we detect a predictable pattern of a four-period ahead forecast. It seems therefore that the characteristics of less liquidity and unconventional institutional structure of the Islamic stock market could be responsible for this higher forecastability of DJIM compared to DJIA.

The forecastability finding in this study adds to the results of other studies which find that the Islamic markets to be causal and interactive with conventional markets and also do not perform much better than the conventional markets during crises. The forecastability of the DJIM provides new evidence on the characteristics of this unconventional equity index which has not discussed in the literature. It implies that the Islamic equity markets may not be good candidates as risk diversifiers in asset allocations and hedgers against risk exposures.

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