# Detecting the Long Term Cyclical Behaviour of the Turkish Stock Market by Means of Spectral Analysis

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# Detecting the Long Term Cyclical Behaviour of the Turkish Stock Market by Means of Spectral Analysis

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**Abstract**

This paper explores long term cycles in Turkish stock market returns. Weekly data for five indices (ISE-100, Industrial Index, Financial Index, Services Index and Technology Index) in the Istanbul Stock Exchange were examined using a spectral analysis during the period of February 1986-March 2010. The results illustrate that the 40 month (Kitchin) cycle is the dominant long term cycle for the investigated indices.

**Keywords:** Spectral analysis, stock returns, long term cycles
**JEL Classification Codes:** G12, G14

## 1. Introduction

A time series can be analysed by using two common approaches: (1) time domain analysis and (2) frequency domain analysis. Time domain analysis generally uses autocorrelation and partial autocorrelation functions to explain time series behaviours, while frequency domain analysis (also called spectral analysis) explains fluctuations in a time series in terms of sine and cosine functions at various frequencies (Wei, 1993:206).

The long term cyclical behaviour of a financial time series can best be described by a frequency domain analysis because cycles are more explicitly observed and represented in the frequency domain (Wang, 2008). While the frequency domain is a powerful tool for analysing time series in economics/finance, it has not been used frequently in the literature because of the computational burden. Some examples are written by Granger (1966); Rausser and Cargill(1970); Murphy(1987); King and Rebelo(1993); Thoma(1994); Garcia-Ferrer and Queralt(1998); Hong(1999); Bjornland(2000); Coshall(2000); Sayan and Sayan(2002); Breitungand and Candelon (2006); Orlov(2006); Wong and McAleer(2009).

Financial time series, especially stock returns, may exhibit a cyclic regularity. The most popular long term cycles include the January Effect, Kitchin Cycle, Juglar Cycle and Kondratieff Cycle. The January effect, also known as the turn-of-the year effect, is a calendar-related anomaly illustrating stocks rising during the first month of the year. The Kitchin Cycle is a 40 month cycle. The Juglar Cycle is the most widely known economic cycle; it illustrates boom and bust waves every 9 years. The

Kondratieff Cycle is a long term cycle which lasts about 54 years. In the study, Kondratieff Cycle cannot be explored, since there is not enough data available (Korotayev and Tsirel, 2010; Wong and McAleer, 2009).

The aim of this study is to examine the long term cyclical behaviour of the Turkish Stock Market by means of a spectral analysis. To detect the cycles, weekly data from the ISE-100 Index, ISE-Industrial Index, ISE-Services Index, ISE-Financial Index and ISE-Technology Index of Istanbul Stock Exchange are analysed in the frequency domain.

The rest of this paper is organized as follows. Section 2 presents the related literature. Section 3 introduces the terminology and logic of spectral analysis. Section 4 presents the data used. The empirical results from the frequency domain analysis in the Turkish Stock Market are presented in Section 5. Section 6 discusses the conclusions.

## 2. Literature Review

Many studies have examined the cyclical behaviour of stock market returns. Sarantis (2001) investigates the stock price growth rates of seven major industrial countries (G-7) by using a smooth transition autoregressive (STAR) model. According to the results, United States stock prices have a 4 month cycle in the middle regime and 9 month cycle in other regimes. On the other hand, German, United Kingdom (UK) and Canadian stock prices have an average 5 month cycle in the upper regime and long period cycles in the lower regime (5 years for Canada, 2 years for UK and 1 year for Germany). Edwards et al. (2003) focused on the emerging markets and included four Latin American and two Asian countries in their study. They report that cycles in emerging markets have a shorter duration than those of developed countries. Their results also indicate that, in contrast to Asian markets, Latin American stock markets have behaved more similarly to developed markets after financial liberalization. Yan at al. (2007) identified bull and bear market cycles in the Chinese stock market and found the average duration of bull markets to be 15.13 months for the Shanghai Stock Exchange and 16.86 months for the Shenzhen. The average duration of bear markets is 10.14 months for Shanghai and 11.83 months for Shenzhen.

Many studies have also examined stock markets using spectral analysis. Granger and Morgenstern (1963) analysed the New York Stock Market prices and found weakly significant cycles. Bertoneche (1979) examined the weekly European stock returns and was not able to detect any significant cycles. Giudici and Simpson (2009) proposed that by using weekly data, one can detect a two week cycle. For this reason, they sampled the Standard and Poor's 100 Index (S&P100) data within the daily, weekly and monthly subsets every 5 minutes. In this way, they were able to observe intraday cycles.

McCullough (1995) investigated 20 stocks from the New York Stock Exchange (NYSE) by spectral analysis and concluded that stock price changes are not white noise. Praets (1979) proposed two tests to detect whether stock price changes are white noise by using indices in the Melbourne Stock Exchange. He found that 9 indices were not white noise and 8 indices weakly deviated from white noise. Wong ve McAleer (2009) investigated the impact of the presidential election cycle on stock prices by using S&P data. According to the empirical results, stock prices in the United States of America (USA) exhibited a 200 week (about 4 year) Presidential Election Cycle.

Orlov (2006) examined the link between capital controls and stock market volatility in the frequency domain. Uebele and Ritschl (2009) explored the co-movement between stock markets and various indicators of real investment in Germany before World War I. Smith (2001) studied the co-movements among the Pacific Rim markets in the period of the pre and post 1987 crash. The results showed that the co-movements increased among the markets during the post crash period. Sato (2008) and Giampaoli et al. (2009) used spectral methods to analyse high frequency financial data.

The numbers of studies that have analyzed the Turkish stock market by using frequency domain analysis are very limited. Sayan and Sayan (2002) showed that the joint Time-Frequency Representation (TFR) techniques can be used in the analysis of stock market data. They analyzed the

ISE-100 Index of the Istanbul Stock Exchange by using various TFR techniques and compared their performance.

## 3. Univariate Spectral Analysis

The univariate spectral analysis is used to identify periodic behaviour in a time series. It detects significant cycles within a single time series by estimating dominant sinusoidal components. Any stationary time series, with a sample of t observations, $y_0, \ldots\ldots y_{t-1}$, can be modelled by an expression in the following form:

$$y_t = \sum_{j=0}^{n} \alpha_j \cos(w_j t) + \beta_j \sin(w_j t) + \varepsilon_t \tag{1}$$

Where: $w_j$ is the angular frequency and $\varepsilon_t$ is the error term. $\phi$ is the phase that $\alpha_j = A_j \cos\phi$ , $\beta_j = -A_j \sin\phi$ and $A_j$ is the amplitude. The expression (1) is also called the Fourier decomposition of $y_t$ (Wong and McAleer, 2009).

The periodogram is a plot which illustrates the contribution of $w_j$ to the total sum of squares. For the periodogram analysis, the coefficients $\alpha_j, \beta_j$ and $A_j$, can be estimated by the least squares method. In order to determine the $\alpha_j, \beta_j$ coefficients, equation (2) is minimized.

$$\pi(\alpha_j, \beta_j) = \sum_{j=0}^{n} (y_t - \alpha_j \cos(w_j t) - \beta_j \sin(w_j t))^2 \tag{2}$$

After estimating the numerical values of $\alpha_j$ and $\beta_j$ at any period, the squared amplitude at a period of interest can be computed by equation (3).

$$A_j^2 = \alpha_j^2 + \beta_j^2 \tag{3}$$

According to Harvey (1993), the peridogram is an unbiased estimator of the cyclical properties of the time series, but it is not consistent. This problem can be overcome by smoothing the periodogram values by a weighted moving average transformation. Smoothing eliminates the background noise from the periodogram and allows the underlying form to be more insulated. The most commonly used smoothers are Daniel, Tukey-Hamming, Parzen, Bartlett, Kaiser-Bessel and Welch windows. In this study, Tukey-Hamming Window is used for smoothing.[1]

## 4. Data

The data for this study consists of weekly time series data from Istanbul Stock Exchange 100 Index (ISE-100) and 4 sector indices (Industrial Index, Services Index, Financial Index and Technology Index). The sample periods begin in February 1986 for the ISE-100; January 1991 for the Industrial Index; January 1991 for the Financial Index, January 1997 for the Services Index; and July 2000 for the Technology Index; all continue up through March 2010. The observations are taken from the Electronic Data Delivery System of the Central Bank of the Republic of Turkey. Since the stock market prices are a non-stationary series, we transform the data by calculating the logarithmic difference of the stock market index;

$$r_t = \log(P_t) - \log(P_{t-1}) \tag{4}$$

Where, $r_t$ is the weekly logarithmic return and $P_t$ is the index at time $t$.

Table 1 illustrates the basic statistics for the return series. The mean returns are all positive, but close to zero. The returns for the Financial and Technology indices are negatively skewed. The returns

[1] The choice of window width affects the results. But there is no exact way of selecting width. In this study window width is selected by trial and error method.

for all indices are leptokurtic. According to the Jarque-Bera normality test, all stock return series are not normally distributed. The spectral analysis requires that a series be stationary. If the series is not stationary, it will cause leakage problems in the spectral analysis. A leakage is a problem that occurs when the respective frequency will leak into the neighbouring frequencies. The Augmented Dickey Fuller (ADF) tests for the unit root in which the Akaike Information Criterion (AIC) is used to determine the lag length and shows that all returns are stationary.

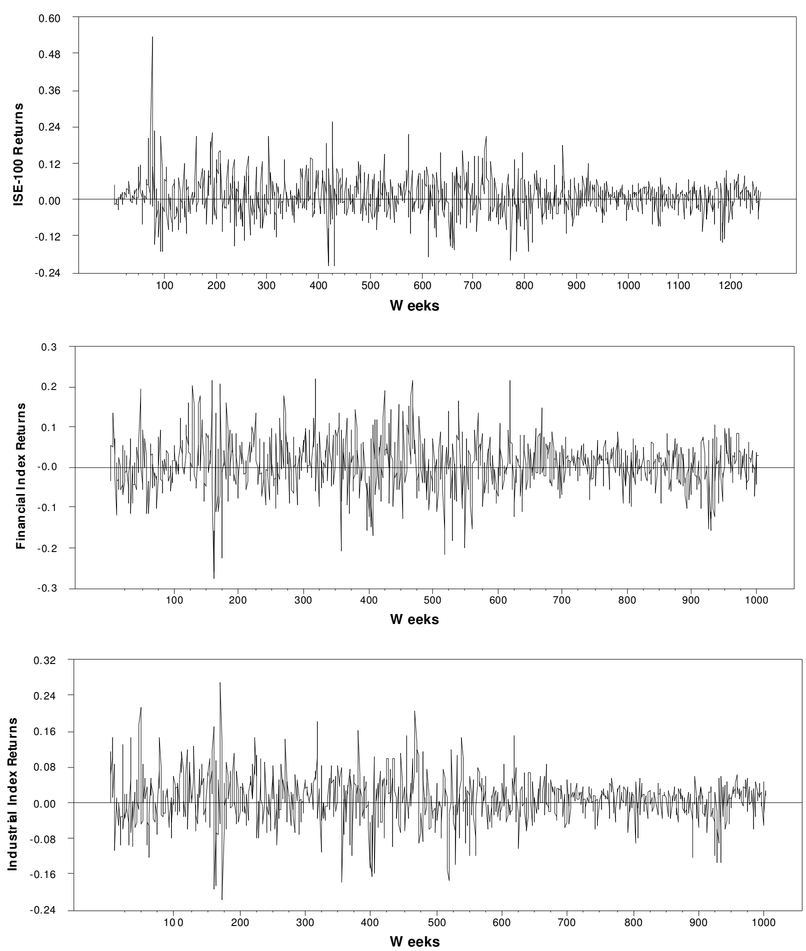
**Table 1:** Basic statistics for stock returns

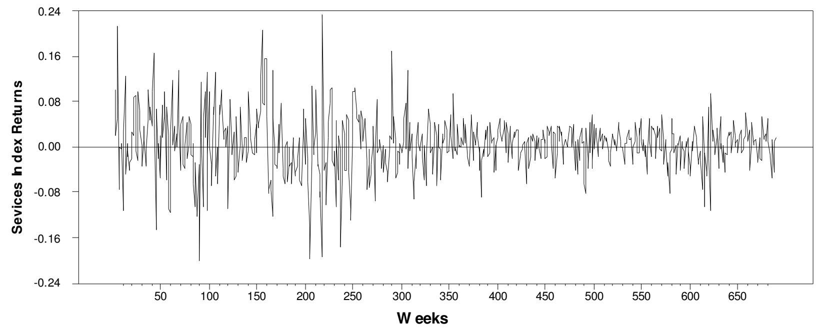
| | ISE-100 | Industrial | Financial | Services | Technology |
|---|---|---|---|---|---|
| **Sample size** | 1257 | 1001 | 1001 | 688 | 506 |
| **Mean** | 0.0080 | 0.00751 | 0.0078 | 0.0051 | 0.0001 |
| **Std. Deviation** | 0.059 | 0.051 | 0.062 | 0.051 | 0.052 |
| **Maximum** | 0.534 | 0.269 | 0.218 | 0.234 | 0.177 |
| **Minimum** | -0.221 | -0.219 | -0.274 | -0.201 | -0.230 |
| **Skewness** | 0.655 | 0.005 | -0.036 | 0.056 | -0.692 |
| **Kurtosis** | 9.185 | 5.546 | 4.851 | 5.832 | 5.557 |
| **J-B Normality** | 2093.328* | 270.317* | 143.114* | 230.230* | 178.186* |
| **ADF** | -26.807 | -23.621* | -23.981* | -21.426* | -16.876* |

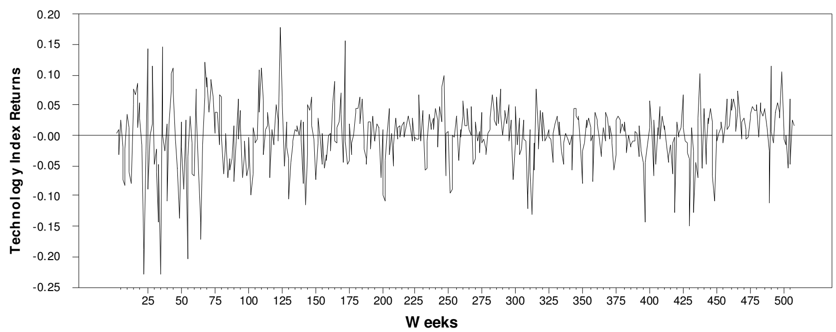
*: significant at %5 ADF: Augmented Dickey-Fuller Test for stationarity

A plot of the weekly returns series are shown in Figure 1. Figure 1 shows that the stock return variance has been oscillating with alternating periods of high and low volatility. Thus, it can be suggested that stock returns may exhibit a cyclical pattern.

**Figure 1:** Logarithmic returns






## 5. Empirical Results

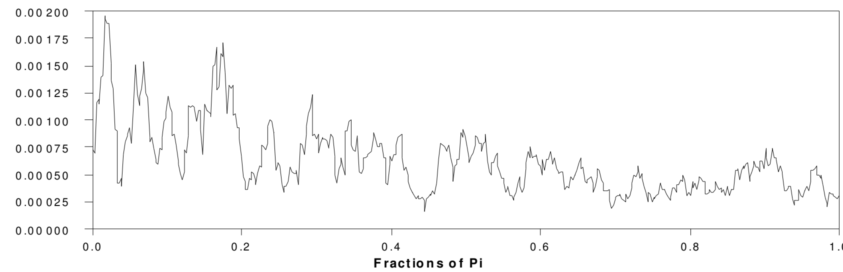
Figure 2 plots periodograms of weekly returns on the stock market indices. The vertical axis shows the contribution of a particular frequency (or period of time) to the total sum of squares. The horizontal axis represents time in terms of the fraction of $\pi$. According to Figure 2, there are significant peaks in the region of 160 weeks, 52 weeks and 26 weeks for the ISE-100 Index return. These results suggest that the Kitchen cycle, January effect and 6 month cycle are dominant cycles for the ISE-100 Index returns.[2]

The Kitchin cycle and January effect can also be observed for the Industrial and Financial indices, but there is no significant peak in the region of 6 months. The periodograms for services and technology indices are a little bit different than the other indices. Two year significant cycles are detected for the services and technology indices. Furthermore, a 1.5 year significant peak occurs for the technology index returns. The Kitchin cycle can also be observed in the services index returns.

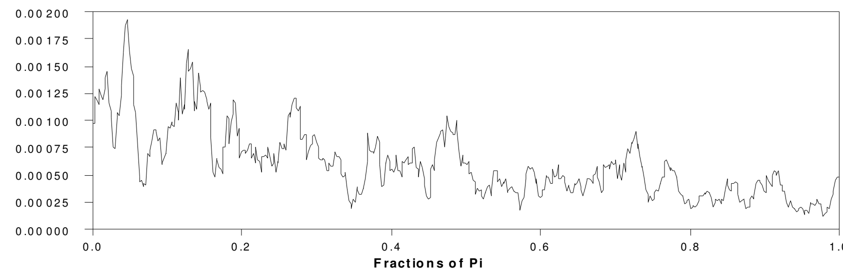
As a result of the study, we don't find any evidence of the existence of the Juglar cycle for any indices. In the literature, some studies explore the presidential election cycles on the stock returns. According to law, elections have to occur every 4 years in Turkey, but in the sample period, this is not the case. Many times elections are made before 4 years were completed. Therefore, we expect no president election cycle in the stock returns. The periodograms also show that the presidential election cycle does not exist in the Turkish stock market.

[2] The significance of peaks are analyzed by using the Coshall(2000)'s methodology.

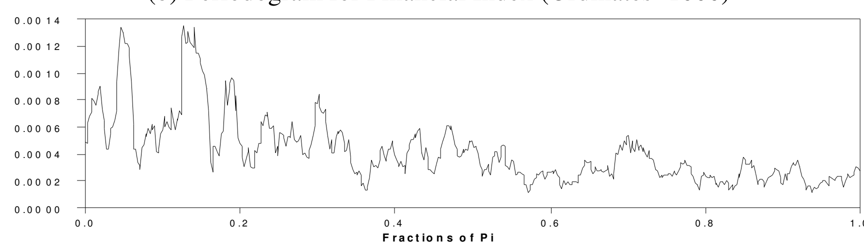
**Figure 2:** Periodograms for Returns



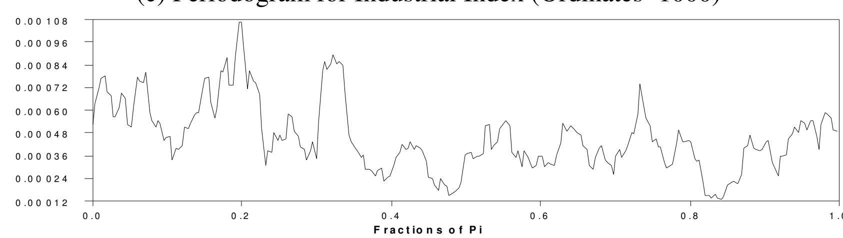

(a) Periodogram for ISE-100 Index(Ordinates=1000)



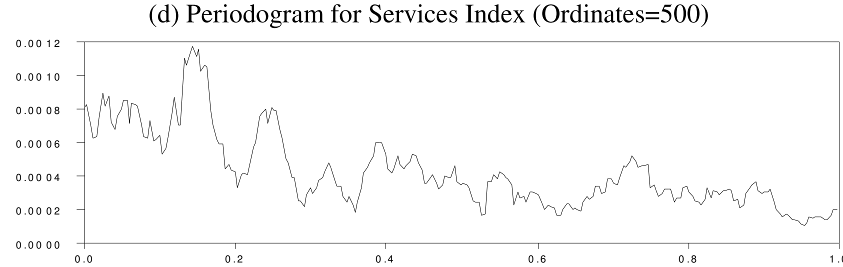

(b) Periodogram for Financial Index (Ordinates=1000)




(c) Periodogram for Industrial Index (Ordinates=1000)




(d) Periodogram for Services Index (Ordinates=500)




(e) Periodogram for Technology (Ordinates=500)

## 6. Conclusions

In this study, the long term cyclical behaviour of the Turkish stock market was investigated. The results illustrate that 160 weeks, 52 weeks, 2 years and 1.5 year cycles were detected for the various indices. This information can be useful for long term Turkish stock investors. The results also provide information about the differences in the cycles for the various sectoral indices.

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