

Master thesis

Historical performance of different asset classes (among stock, bonds) during different periods of stock market cycles.

By

Tatsiana Kiryienka

The master thesis is carried out as a part of the education at the University of Agder and is therefore approved as such. However, this does not imply that the University answers for the methods that are used or the conclusions that are drawn.

Supervisor:

Valeri Zakamouline

The University of Agder, Kristiansand

1st June, 2010

Acknowledgements

I want to express my greatest gratitude to my supervisor Valeri Zakamouline for his patience and wisdom guiding me through this process. Writing the thesis was not easy, but rather challenging and interesting.

Tatsiana Kiryienka
Kristiansand, 2010

Abstract

This thesis was carried out as the final assignment of the Master of Business Administration Program at University of Agder, in the Faculty of Economics and Social Sciences.

The subject of the thesis is the relative performance of different asset classes during different phases of the rhythmic cycles. Different phases of the stock market cycle have been searched for and analyzed. The historical experience is used to make the analysis.

Table of contents

Acknowledgements	2
Abstract	3
Table of contents	4
List of tables and figures	5
Introduction	6
1. Long Cycles in the U.S. Stock Market.....	10
1.1. Determination and Measuring the Long Market Cycle in the Stock Market.....	10
1.2. Cyclical Dynamics as Explanation of the Long- Term Reversal.....	14
1.3. Turning Points and Summary Statistics of Market Upswings and Downswings...	16
2. Performance of the Asset Classes During the Business Cycles.....	20
2.1 Classification of the Asset Classes. The Bond Market and Equity Securities.....	20
2.2. Investigation of Performance of Value and Growth Stocks.....	22
2.3 The Performance of Bonds.....	27
2.4 Investigation of Performance of 30 Industries.....	30
Conclusions	34
Literature and references	35

List of tables and figures

Table 1. Market swings with turning points	17
Table 2. Descriptive statistics of monthly returns during periods of upswings and downswings. Here the returns are standard returns, not log returns	18
Table 3. Performance of 6 portfolios during bull versus bear markets.....	27
Table 4. Book-to-market equity (BE/ME) quintiles.....	28
Table 5. Performance of 30 industry during bull versus bear markets.....	32
Figure 1. Panel (a) reports the results of the estimation of the first-order autocorrelations for $k=1, \dots, 25$ year periods. Panel (b) shows a scatter plot of $r_{t,t+17}$ versus $r_{t-17,t}$. In addition, a regression line is fit through these data points.....	11
Figure 2. The compounded log market return over 1926-2009 years together with a fitted linear trend line.....	12
Figure 3. Panel (a) reports the results of the spectral analysis using the residuals from the linear fit. Panel (b) reports the results of the harmonic analysis. In particular, this panel plots the residuals from the linear fit as well as the best fit to the harmonic functions.....	13

Introduction

This paper analyzes the historical performance of different asset classes during different periods of stock market. The aim of the master's thesis is to analyze previous studies on the dynamics of economic activity and to show that there is a long-term interrelated cyclical behavior of the stock market. The type of dynamics is broadly termed as "business cycles" or "economic cycles". Owen (1817) and Sismondi (1819) seem to be the first to present a systematic exposition of periodic economic cycles. The first part of the twentieth century exhibited widespread acceptance in the economics profession of the cyclical nature of capitalist development, including long periods of upswings and downswings. The most known economic cycles are the Kitchin inventory cycles of 3-5 years, the Juglar fixed investment cycles of 7-11 years, the Kuznets infrastructural investment cycles of 15-25 years, and the Kondratiev long technological cycles of 45-60 years.

Burns and Mitchell (1946), the founders of the modern business cycle literature, defined business cycles as follows: *"Business cycles are a type of fluctuations found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own."*

Obviously, economic theory moved towards the study of economic fluctuations rather than cycles, and the term "business cycle" lost its original meaning. To the macroeconomics point of view on the dynamics of many aggregate economic indicators, modern finance theory considers the dynamics of the aggregate stock market as completely random without any cyclicity in behavior. The efficient market hypothesis of modern finance is associated with the idea of a "random walk", which loosely says that the returns of risky assets are unpredictable. The (simple) random walk model for the returns of risky assets has gained widespread acceptance in finance from the mid of 1960s. However, during the late 1980s there appeared a series of papers where the authors challenged the random walk hypothesis, Fama and French, Lo and MacKinlay, and Poterba and Summers. In particular, these authors considered the time series properties of some economic indicators at increasing horizons up to 10 years and found the indications of mean-reversion, a significant temporary component, and some return predictability at 4-5 year horizons.

In the aftermath of the U.S. stock market crash of 2000 many financial analysts and practitioners began to speak about the existence of regular 18-year stock market cycles (if measured from peak to trough; 36-year cycles if measured from peak to peak). Using a simulation experiment we demonstrate that the stock market cycles are highly statistically significant that allows us to reject the hypothesis that the stock market returns follow a simple random walk. We then divide the total historical period into subperiods of stock market upswings and downswings and present the descriptive statistics of upswings and downswings.

The existence of long regular stock cycles in the recent history of the U.S. stock market raises several important questions. Do these cycles really exist or is it just a rare singular coincidence, a result of data-snooping? Are these cycles really of regular nature such that long bull and bear markets alternate every 18 years or so? The problem is as follows. If they are regular, then they are predictable which probably contradicts the absence of arbitrage argument and the efficient market hypothesis. Finally, what causes these cycles and which is the performance of different asset classes during different periods of the business cycles? One of the contributions of this paper is to try to provide some answers to these questions. Having studied the long cyclical behavior of many macroeconomic indicators during the same historical period, we believe that the answers lie in the dynamics of different industries.

Industries differ in their sensitivity to the business cycle. More sensitive industries tend to be those producing high-priced durable goods for which the consumer has considerable discretion as to the timing of purchase. Examples are automobiles or consumer durables. Other sensitive industries are those that produce capital equipment for other firms. Operating leverage and financial leverage increase sensitivity to the business cycle.

The idea of the thesis is to show that different industries should perform differently across stages of the stock market cycle. One way that we think about the relationship between industry analysis and the business cycle is the notion of industry or sector rotation. Sector rotation is an investment strategy involving the movement of money from one industry sector to another in an attempt to beat the market.

There are four stages in market cycle: market bottom, bull market, market top, and bear market. Bull market begins as the market rallies from the market bottom; bear market is the precursor to the next market bottom. The use of "bull" and "bear" to describe markets comes from the way the animals attack their opponents. A bull thrusts its horns up into the air while a bear swipes its paws down. These actions are metaphors for the movement of a market. If the trend is up, it's a bull market. If the trend is down, it's a bear market.

We also demonstrate that the size and value premiums widely documented in the literature have basically counter-cyclical behavior with respect to the stock market cycles. The both the size and value premiums are statistically significant only during the periods of stock market downswings. From one side, this result may tell that the size and value premiums can hardly be considered as the investors' compensation for bearing the risk because these premiums are generated in "bad times". From the other side, we also find that small size and high book-to-market ratio stocks do appear to be more risky, as compared with the rest of the market, during the periods of stock market downswings. However, the equity premiums generated by these stocks during market downswings seem to be much higher than a sort of "fair" compensation for bearing the risk.

There are several strands of the literature are related to our paper, and our findings together with interpretations allow to present a unified explanation of many empirical phenomena. This stands are: literature on return predictability; literature on the stock market; literature on conditional estimation and time-varying returns and risk factors; literature on observed cycles and asset classes. Studies of the link between the stock market and macroeconomics provided by Fama and French (1989) reveal that the stock returns seem to be higher at business cycle troughs than they are at peaks. Also several studies report (Harvey (1989b)) that the conditional mean-variance frontier of risky assets changes through time with a business cycle pattern. That is, these findings can be interpreted as the indication that the stock returns exhibit a counter-cyclical behavior to the business cycles. In contrast to these studies, in this paper we consider cycles that are longer than those reported by the NBER. Moreover, we find that the stock market cycles are not really counter-cyclical to the cycles in real economy, but the real economy leads the stock market and sometimes the lag between the economic growth and the stock market growth can be very substantial.

Another strand of literature emphasizes that on long horizons the stationarity of stock returns and SMB and HML Fama/French factors does not hold and these processes should be considered as either time-varying or regime-switching. Zhang (2010) demonstrate that the value premium is time-varying. When investors foresee a high economic growth in the near future, there are more willing to invest in this firms. Similarly, when investors foresee an economic recession, they fear of bad performance of these firms and require a high risk premium.

This thesis is mainly based on the data from the library of Fama and French. The portfolios include all NYSE, AMEX, and NASDAQ firms with the necessary data. During the

analysis of the relative performance of different asset classes the empirical performance of the Sharpe were used.

1 Long Cycles in the U.S. Stock Market

1.1 Determination and Measuring the Long Market Cycle in the Stock Market

To determine the Long Market Cycles we estimate the trend and the best fit to sine and cosine functions. In our research we analyze the behavior of the aggregate, the whole, market which consists of individual stocks. We use monthly and annual (nominal) returns on the market index for the period from July 1926 to December 2009 obtained from the data library of Kenneth French.¹

The market index represents the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (from Center for Research in Security Prices (CRSP)). Monthly and annual market index returns are transformed to log returns. Then we regress multi-period returns $r_{t,t+k}$ on lagged multi-period returns $r_{t-k,t}$. In particular, we run the following regression

$$r_{t,t+k} = \alpha_k + \gamma_{1k} r_{t-k,t} + \varepsilon_{t,t+k}.$$

Observe that the slopes of the regression, γ_{1k} , are the estimated autocorrelations of k -period returns.

Panel (a) in Figure 1 reports the estimated γ_{1k} for $k=1, \dots, 25$ year periods. Observe that the graph in this panel shows a significant negative autocorrelation (down to -0.2) for 3-4 years returns. These findings are consistent with those reported by Fama and French (1988) who studied the autocorrelation up to 10 years period. Surprisingly, we detect also an extremely high negative autocorrelation (down to almost -0.75) for 17-18 years returns. Recall that the standard model which is the mixture of a random walk with constant drift and a stationary transitory component cannot in principle produce (under reasonable parameters) autocorrelations below -0.5.

Panel (b) in Figure 1 presents a scatter plot of $r_{t,t+17}$ versus $r_{t-17,t}$. In addition, a regression line is fit through these data points.

¹ See http://www.mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

The scatter plot shows a strong tendency for the 17-years returns to predict future 17-years returns. The regression line has a strongly negative slope, and R^2 statistics is 72%. The estimated regression line

$$r_{t,t+17} = 3.09 - 0.74r_{t-17,t}.$$

Apparently, these results indicate that there is a long-term cyclical component in the market returns. The approximate period of this cyclical component is 17-18 years if we measure it from peak to trough, or 34-36 years if we measure it from peak to peak.

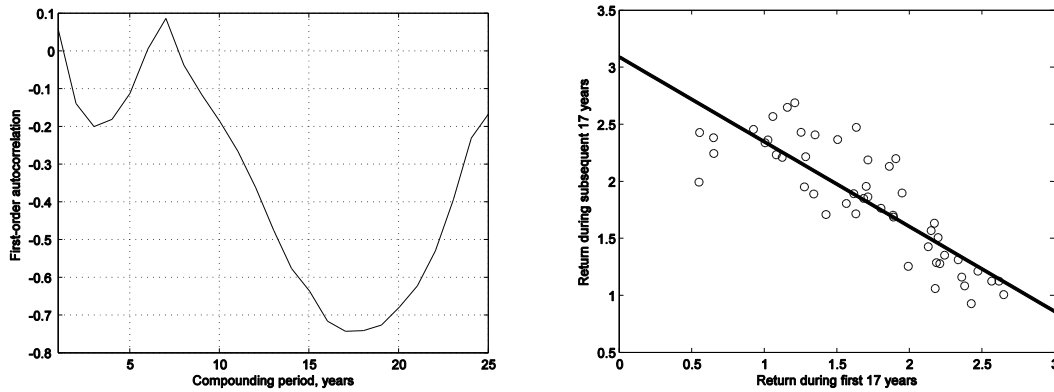


Figure 1. Panel (a) reports the results of the estimation of the first-order autocorrelations for $k=1, \dots, 25$ year periods. Panel (b) shows a scatter plot of $r_{t,t+17}$ versus $r_{t-17,t}$. In addition, a regression line is fit through these data points.

Our conceptual framework in this section is that a given time series y_t represents the sum of a trend (or growth) component g_t , a cyclical component c_t , and a noise ε_t . That is

$$y_t = g_t + c_t + \varepsilon_t.$$

The g_t represents a function that varies “smoothly” over time. The c_t are deviations from g_t and over long time periods their average is near zero.

First of all, we want to separate out the trend component g_t . There are several possible ways to do this. The simplest way is to assume that the trend is linear. The other most often used way is to employ some smoothing routines such as moving-averages, moving differences, moving medians, or more elaborate methods as, for example, in Hodrick and Prescott (1997). It is worth noting that the use of a proper detrending method is very crucial

for detection of long cycles. In particular, to find a trend one usually uses some smoothing filter on data. To detect a long-term trend one needs to tune correctly the smoothing filter in order to pass a specific range of low frequencies. In other words, such a filter should omit the middle-range and higher frequencies. Figure 2 plots the compounded log market return, $y_t - y_0$, over 1926-2009 years together with a fitted linear trend line. R^2 statistics for this line amounts to 98.2%. Such a high goodness of fit motivates us to consider the log of the aggregate stock market value as repeated fluctuations about its long-term linear trend. Observe that the detrending using a linear trend is a filtering method that removes only zero frequency and passes all other frequencies. To control whether this simple detrending works well, we use a spectral analysis and check that there are no pronounced peaks in spectral density in the range of very low frequencies (periods of 60 years or more).

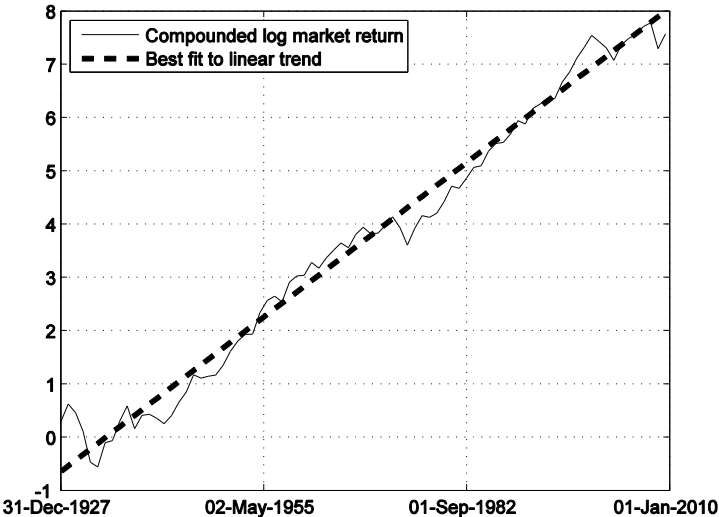


Figure 2. The compounded log market return over 1926-2009 years together with a fitted linear trend line.

Second, our goal is to separate out the cyclical component. The empirical analysis presented in the previous section motives us to look for a fixed-length cycle. We perform a spectral analysis using the residuals from the linear fit and the results are presented in Figure 3, Panel (a). In particular, we convert the time series $y_t - g_t$ into a frequency domain using a discrete Fourier transform. We remind the reader that the Fourier transform decomposes a function of time into the sum of a (potentially infinite) number of sine wave frequency components. The “spectrum” of frequency components is the frequency domain representation of the signal. Observe that the spectrum of the residuals has a strongly

pronounced peak in the spectral density at 35.4 years which suggests that a 35.4-year cycle is present in the data. The peak value is 232.4.

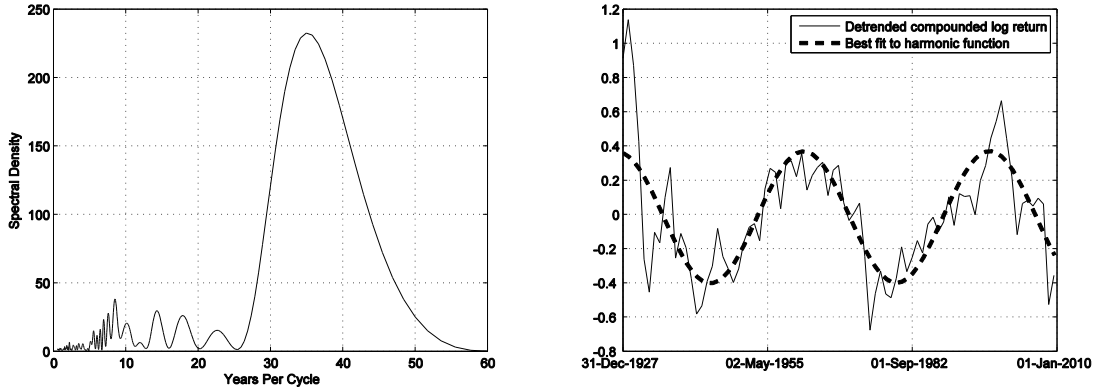


Figure 3. Panel (a) reports the results of the spectral analysis using the residuals from the linear fit. Panel (b) reports the results of the harmonic analysis. In particular, this panel plots the residuals from the linear fit as well as the best fit to the harmonic functions.

We can arrive at the same result using a harmonic analysis. In particular, we estimate the following model using the monthly (or annual) data

$$y_t - g_t = \alpha + \beta_1 \cos\left(\frac{2\pi t}{p}\right) + \beta_2 \sin\left(\frac{2\pi t}{p}\right) + \varepsilon_t,$$

where t is a time index set to 1 in the initial month and is incremented by 1 unit each subsequent month, and p is a fixed-length periodicity of the cycle. The value of p is determined by maximizing the R^2 statistics of the linear regression above. This analysis again produces the length of the cycle of $p=425$ months or $p=35.4$ years (with a half-period of 17.7 years). At this period the value of the R^2 statistics is 61.3% (using the annual data). Figure 3, Panel (b) shows the residuals and the best fit to the harmonic functions.

The “usual” hypothesis is that the log market return follows a random walk. Our findings presented in this section suggest another hypothesis, namely that the log value of the aggregate stock market growth smoothly over time, with fluctuations that consist of a cyclical and an uncertain component. Whereas it is difficult to test the latter hypothesis, it is relatively easy to test the former one. The idea is that in principle a realization of a pure random walk can also produce a clearly pronounced linear trend and a cycle. The question is, what are the chances of getting such an evidently defined pattern? These chances can be easily estimated using a simulation analysis. (Zakamouline, 2010)

We perform the simulation analysis using two distinct methods. The first method consist in bootstrapping the historical market returns. In particular, we use the historical observations of the market returns and construct a number of resamples of the market returns (of equal length to the historical data series), where each of them is obtained by random sampling with replacement from the original dataset. Implicitly, this method assumes that the returns are independent and identically distributed. In the second method we explicitly assume that the log market returns are normally distributed. Then we estimate the mean and standard deviation of the log market returns and simulate a number of possible realizations of market returns where the length of each realization equals to the length of the historical data series. We find that these two methods produce practically identical results.

We perform 25,000 simulations and answer the following set of questions. First, what is the probability that a realization of a random walk produces a goodness of fit to a linear trend of better than 98%? This probability amounts to 17%, which is not an extremely rare event. We cannot reject the hypothesis (that the underlying process is a pure random walk) at conventional significance levels of 5% or 1%. Yet, we are 83% sure that the dynamics of the log market index is not a random walk. Second, what is the probability that a realization of a random walk produces a goodness of fit to a harmonic cycle of better than 61%. Here to find a harmonic with the highest power in the spectrum (we limit the length of the cycle by 41,5 years since the length of our dataset is 83 years; the idea is that we should observe at least 2 full cycles) we perform a discrete Fourier transform. This probability equals to 3,7% which is quite a rare event. Third, what is the probability that a realization of a random walk produces a goodness of fit to a linear trend of better than 98% and the same time a goodness of fit to a harmonic cycle of better than 61%. This probability is 0,5%, which is an extremely rare event. If we, in addition, require that the peak value of the harmonic with the highest power must be at least 232, then this probability reduces further to 0,3%. (Zakamouline, 2010)

To summarize, our simulation experiments allow us to reject the random walk hypothesis with a very high degree of confidence.

1.2 Cyclical Dynamics as Explanation of the Long- Term Reversal

Financial literature documents short-term momentum and long-term reversal in stock prices. Usually both these effects are considered as pricing anomalies that contradict the

efficient market hypothesis. A standard model that can generate these effects is as follows (see, for example, Summers (1986), Campbell and Mankiw (1987), Fama and French (1988), Lo and MacKinlay (1988), and Poterba and Summers (1988)). Denote by Y_t the value of a stock market index at time t . Denote by y_t the log of the index, that is, $y_t = \log(Y_t)$. In this model the index value is composed of two components: a permanent component which is a random walk, and a transitory component which is a stationary process

$$y_t = q_t + z_t. \quad (1)$$

In particular, the process q_t is a random walk

$$q_t = q_{t-1} + \mu + e_t,$$

where μ is expected drift and e_t is white noise. z_t is any zero-mean stationary process. The common interpretation is that q_t is the “fundamental” component that reflects the efficient market value, and z_t reflects a deviation from the efficient market value q_t , implying the presence of “fads” or “bubbles”. The compounded return from t to $t+k$ is

$$r_{t,t+k} = y_{t+k} - y_t = (q_{t+k} - q_t) + (z_{t+k} - z_t).$$

Denote the first-order autocorrelation of compounded k -period returns by

$$\gamma_{1k} = \frac{\text{Cov}(r_{t,t+k}, r_{t-k,t})}{\text{Var}(r_{t,t+k})}.$$

Fama and French (1988) showed that whereas the random walk component produces white noise in returns, the stationary component causes negative autocorrelation in returns. This result does not depend on any particular parameterization of z_t . Moreover, Fama and French (1988) also showed that the value of the first-order autocorrelation of compounded k -period returns is limited below by -0.5.

To illustrate the aforesaid, suppose that z_t is an ARMA(1,1) process

$$z_t = \varphi z_{t-1} + w_t + \theta w_{t-1},$$

where w_t is white noise, and φ and θ are some constants. Using the standard logic, the derivation of the expression for γ_{1k} yields

$$\gamma_{1k} = \frac{\varphi^{k-1}(2-\varphi^k)(\varphi+\theta)(1+\varphi\theta) - (1+2\varphi\theta+\theta^2)}{k(1-\varphi^2)\left(\frac{\sigma_e}{\sigma_w}\right)^2 + 2((1+2\varphi\theta+\theta^2) - \varphi^{k-1}(\varphi+\theta)(1+\varphi\theta))}, \quad (2)$$

where σ_e and σ_w are the standard deviations of e_t and w_t respectively. The reasonable value of φ should be close to but less than 1.0, and the value of θ should be close to 0.0. Otherwise, the presence of ARMA(1,1) components could be easily detected by looking at the plots of sample autocorrelation and partial correlation functions of $r_{t,t+1}$. The examination of the possible shapes of γ_{1k} given by (2) (for φ in $[0.8, 1.0)$ and θ in $[-0.2, 0.2]$) reveals that the value of γ_{1k} is constrained to lie above the lowest limit of -0.5, and this limit can be attained as k goes to infinity only when $\sigma_e=0$. That is, the first-order autocorrelation of compounded k -period returns can decrease to the value of -0.5 only if the log of the market index represents the sum of a constant drift plus a temporary component. In other words, when the “fundamental” market value is completely deterministic, which, according to all canons, is totally unrealistic.

1.3 Turning Points and Summary Statistics of Market Upswings and Downswings

A closer look at Panel (b) in Figure 3 reveals that the 35.4-year cycle is more an average than an accurate, regularly repeating cycle. In other words, the market does not cycle through consequent periods of upswings and downswings every 35.4 years with Swiss-timepiece accuracy. To determine more or less accurately the periods of market upswings and downswings, we employ the method of a trend detection widely used in technical analysis. In particular, in technical analysis one interprets a chart as a series of highs and lows, and it is the movement of the highs and lows that constitutes a trend. For example, an uptrend is classified as a series of higher highs and higher lows, while a downtrend is one of lower lows and lower highs.

We apply this definition of uptrends and downtrends to the detrended accumulate log market returns while trying to find the turning points as close as possible to the minima and maxima of the harmonic function that produces the best fit. We need to determine only 5 turning points. Whereas two of them are pretty easy to define (the market crash of 1929 and the beginning of the Great Depression; and the crash of 2000 of the Dot-com bubble), the determination of other three is not so obvious. Our results are reported in Table 1.

Direction of a swing	Start date	End date	Swing length
Upswing	?	September 1929	?
Downswing	October 1929	April 1942	150 months, 12.5 years
Upswing	May 1942	November 1961	234 months, 19.5 years
Downswing	December 1961	February 1978	194 months, 16.2 years
Upswing	March 1978	March 2000	264 months, 22.0 years
Downswing	April 2000	?	?

Table 1: Market swings with turning points. (Zakamouline, 2010)

It is worth emphasizing that we determine upswings and downswings using the detrended compounded log market returns, that is, using the residuals from the best fit of the log market index to a linear function. Thus, we denote these periods as market upswings and downswings, not market uptrends and downtrends. Observe that our dataset contains only two complete periods of upswings and downswings. The average market upswing lasted 249 month/20.75 years, whereas the average market downswing lasted 172 months/14.3 years. The ratio of the average market upswing to the average market downswing amounts to 1.46. Next we divide our total dataset of market returns into two separate subsets, where the first one consist of all periods of upswings and the second one consists of all periods of downswings (as determined in Table 1).The total lengths of all market downswings in our sample is 463 months (38.6 years),and the total length of all market upswings is 539 month (44.9 years). The descriptive statistics of these two subsets is presented in Table 4. Observe that a good statistical characterization of the market dynamics during upswing and downswing periods may require some notion of *regime switching*. Indeed, not only the mean return during downswings is much smaller than during upswings, but also periods of downswings are much more volatile than periods of upswings. In particular, both the standard deviation and kurtosis of return distribution during downswings are almost two times higher than those during upswings. Moreover, note that the skewness of return distribution during downswings is positive, whereas the skewness during upswings is negative. This means that during periods of market downswings there were observed many extremely high positive returns (attempts of market recovery?), while during periods of market upswings there were observed many extremely high negative returns (attempts of market correction?). Finally

observe that during periods of the stock market downswings the mean stock return is approximately equal to the mean return on the money market account.

Statistics	Upswings	Downswings
Mean, market return, %	1.49	0.24
Sdt. Deviation, market return, %	4.03	6.69
Skewness, market return	-0.70	0.53
Kurtosis, market return	5.64	9.44
Mean, T-bill return, %	0.35	0.24

Table 2: Descriptive statistics of monthly returns during periods of upswings and downswings. Here the returns are standard returns, not log returns. (Zakamouline, 2010)

The efficient market hypothesis is associated with the idea of a “random walk”, which loosely says that the returns of risky assets are unpredictable. More formally, a random walk process like that given by equation (2) consists of a deterministic drift μ and an unpredictable change e_t . In the simplest case the value of μ is constant through time and the unpredictable change is an outcome of a time-stationary random process. Our findings advocate that the stock market returns cannot be described by a simple random walk. One probably needs to use a non-stationary process where both the drift and volatility are uncertain. Better yet, the stock market returns could be modelled as a regime-switching process.

When it comes to the discovered long-term pattern in the stock market returns, it is probably impossible to either predict this pattern or exploit this pattern to achieve greater returns that could be obtained by holding a randomly selected well-diversified portfolio of individual stocks. First, we believe that the stock market cycles are of different lengths. Second, to exploit this pattern one needs to know the phase of the cycle. However, one is never sure in what phase of the cycle one is, until the cycle has been completed; and one is never sure that a given cycle is completed until the next cycle has definitely begun. Third, even if one happens to invest in the stocks during a market upswing, there is no guarantee that the return will be positive: each long stock market upswing can be described as alternating shorter periods of upturns and downturns. Fourth, if the long stock market cycles were predictable, then no one rational investor would hold the stocks during market downswings as

the equity premium is practically zero. Thus, we believe that long stock market cycles do not contradict the efficient market hypothesis at all.

We will use the result of the chapter 1 during the following research.

2 Performance of the Asset Classes during the Business Cycles

2.1 Classification of the Asset Classes. The Bond Market and Equity Securities

The money market consists of very short-term debt securities. Among them are:

1) Treasury Bills (T-bills, or bills. The most marketable of all money market instrument. T-bills represent the simplest form of borrowing: The government raises money by selling bills to the public. Investors buy the bills at a discount from the stated maturity value. At the bill's maturity, the holder receives from the government a payment equal to the face value of the bill. The difference between the purchase price and ultimate value constitutes the investor's earnings).

2) Certificates of Deposit (It is a time deposit with a bank. Time deposits may not be withdrawn on demand).

3) Commercial Paper (Large, well-known companies often issue their own short-term unsecured debt notes rather than borrow directly from banks. Commercial paper maturities range up to 270 days).

4) Bankers Acceptances (It starts as an order to a bank by a bank's customer to pay a sum of money at a future date, typically within 6 months).

5) Eurodollars (There are dollar-denominated deposits at foreign banks or foreign branches of American banks. Most Eurodollar deposits are for large sums, and most are time deposits of less than 6 month's maturity).

6) Repos and Reverses (It is a form of short-term, usually overnight, borrowing. The dealer sells government securities to an investor on an overnight basis, with an agreement to buy back those securities the next day at a slightly higher price).

7) Federal Funds (Funds in the bank's reserve account).

8) Brokers' Calls (Individuals who buy stocks on margin borrow part of the funds to pay for the stock from their broker. The broker in term may borrow the funds from a bank, agreeing to repay the bank immediately if the bank request it).

In our research we will use the bond market and equity securities.

The bond market is composed of longer-term borrowing or debt instruments than those that trade in the money market. This market includes:

1) Treasury notes and bonds (T-note maturities range up to 10 years, whereas bonds are issued with maturities ranging from 10 to 30 years. Both are used in denominations of \$1,000

or more. Both notes and bonds make semiannual interest payments called coupon payments, a name derived from precomputer days, when investors would literally clip coupons attached to the bond and present a coupon to receive the interest payment).

2) Corporate bonds (The means by which private firms borrow money directly from the public. These bonds are similar in structure to Treasury issues-they typically pay semi-annual coupons over their lives and return the face value to the bondholder at maturity. They differ most importantly from Treasury bonds in degree of risk).

3) Municipal bonds (Issued by state and local governments. They are similar to Treasury and corporate bonds except that their interest income is exempt from federal income taxation. The interest income also is exempt from state and local taxation in the issuing state. They are basically two types- general obligation bonds and revenue bonds).

4) Mortgage securities (These securities have become a major component of the fixed-income market).

5) Federal agency debt (Some government agencies issue their own securities to finance their activities. These agencies usually are formed to channel credit to a particular sector of the economy that Congress believes might not receive adequate credit through normal private sources).

Bonds – the set of dependent variables used in the time-series regressions includes the excess returns on two government and five corporate bond portfolios. The government bond portfolios (from CRSP) cover maturities from 1 to 5 years and 6 to 10 years.

Common stocks, also known as equity securities or equities, represent ownership shares in a corporation. The two most important characteristics of common stock as an investment are its residual claim and limited liability features.

Residual claim means that stockholders are the last in line of all those who have a claim on the assets and income of the corporation. In a liquidation of the firm's assets the shareholders have a claim to what is left after other claimants such as the tax authorities, employees, suppliers, bondholders, and other creditors have been paid.

Limited liability means that the most shareholders can lose in the event of failure of the corporation is their original investment.

Each share of common stock entitles its owner to one vote on any matters of corporate governance that are put to a vote at the corporation's annual meeting and to a share in the financial benefits of ownership.(Bodie, Kane, and Marcus (2008)

In our investigation we analyze large and small stocks, long-term corporate and government bonds, inter-term government bonds and treasury bills.

2.2 Investigation of Performance of Value and Growth Stocks

We can explain the performance of different asset classes using the returns on stocks and bonds. Eugene F. Fama and Kenneth R. French (1993) identifies five common risk factors in the returns on stocks and bonds. There are three stock-market factors and two bond-market factors, related to maturity and default risks.

As a reaction to the failure of the CAMP to explain important asset market regularities Fama and French propose a three-factor model to explain broad trends in stock markets including the value premium.

A three-factor model is essentially a statistical model aiming at summarizing regularities in US stock market returns. The model was thought of as a risk based model in which the factors are supposed to capture unobserved systematic risk factors. (Risager, p.67)

The systematic factors in the Fama-French model are firm size and book-to-market ratio as well as the market index. Fama and French propose measuring the size factor in each period as the differential return on small firms versus large firms. This factor is usually called SMB (for “small minus big”). Similarly, the other extra-market factor is typically measured as the return on firms with high book-to-market ratios minus that on firms with low ratios, or HML (for “high minus low”). Therefore, the Fama-French three-factor asset-pricing model is $E(r_i) - r_f = a_i + b_i(E(r_M) - r_f) + s_i E(\text{SMB}) + h_i E(\text{HML})$.

The coefficients b_i, s_i , and h_i are the betas of the stock on each of the three factors, often called the factor loadings. According to the arbitrage pricing model, if this are the relevant factors, excess returns should be fully explained by risk premiums due to these factor loadings. In other words, if this factors fully explain asset returns, the intercept of the equation should be zero.

To create portfolios that track the size and book-to-market factors, Davis, Fama, and French sort industrial firms by size (market capitalization or market “cap”) and book-to-market (B/M). Their size premium, SMB, is constructed as the difference in returns between the smallest and largest third of firms. Similarly, HML in each period is the difference in returns between high and low book-to-market firms. They use a broad market index, the value-weighted return on all stocks traded on U.S. national exchanges (NYSE, AMEX, NASDAQ) to compute the excess return on the market portfolio relative to the risk-free rate, taken to be the return on 1-month Treasury bills.

To test the three-factor model, Davis, Fama, and French form nine portfolios with a range of sensitivities to each factor. They construct the portfolios by sorting firms into three-size groups (small, medium, and big; or S, M, B) and three book-to-market groups (high, medium, and low; or H, M, L). The nine portfolios thus formed are labeled in the following matrix; for example, the S/M portfolio is comprised of stocks in the smallest third of firms and the middle third of book-to-market ratio.

If the three-factor model holds, the intercept should not be statistically different from zero. This hypothesis can be tested by a conventional t-test. When portfolios are formed on price-earnings multipliers, price-cash flow ratios, and past sales growth, the three-factor model is able to explain broad variation in returns.

The time-series regressions are also convenient for studying two important asset-pricing issues:

1) One of our central themes is that if assets are priced rationally, variables that are related to average returns, such as size and book-to-market equity, must proxy for sensitivity to common (shared and thus undiversifiable) risk factors in returns. The time-series give direct evidence on this issue. In particular, the slopes and R^2 values show mimicking portfolios for risk factors related to size and size and book-to-market capture shared variation in stock and bond returns not explained by other factors.

2) The time-series regressions use excess returns (monthly stock or bond returns minus the one-month Treasury bill rate) as dependent variables and either excess returns or returns on zero-investment portfolios as explanatory variables. In such regressions, a well-specified asset-pricing model produces intercepts that are indistinguishable from 0. The estimated intercepts provide a simple return metric and a formal test of how well different combinations of the common factors capture the cross-section of average returns. Moreover, judging asset-pricing models on the basis of the intercepts in excess-return regressions imposes a stringent standard. Competing models are asked to explain the one-month bill rate as well as the returns on longer-term bond and stocks. (Fama and French (1993))

Cooper et al. (2008) test whether the three-factor model can explain the variation in US returns when stocks are sorted according to asset growth. Thus, stocks first sorted into deciles according to their past asset growth, and next the three-factor model is estimated for each asset growth category. By running three-factor regressions- one for each asset growth deciles

Cooper discover important information on the validity of the model. Thus, the results show that low growth firms have a monthly constant term (alpha) that equals 0,24 percent. The high growth stocks have a constant that equal to -3,84, which means that it is highly significant. In other words, the three-factor model has difficulties in explaining the cross sectional return patterns in the sense that there is more than 8 percent annual return difference between low and high growth companies that is left unexplained. The explanation of the strong performance of companies with low growth is therefore something that goes beyond the three factors.

Another striking argument against the risk based view also offered by Cooper et al. (2008) is the simple observation that over the 35 year period they study, the return on the stock portfolio with the highest asset growth is below the risk free interest rate. Thus, over the period 1968-2003 the mean annual return (value-weighted) on the portfolio with the highest asset growth equals 5,2 percent, whereas the average risk free rate equals 6,3 percent. If the negative equity premium was a short lived phenomenon one could better have argued that this is a temporary phenomenon that should not disturb us. However, when we observe such a phenomenon over a long time period it is clear that returns reflect other things than risk. Moreover, if fast growing companies, which are much more risky than T-Bills, persistently produce returns that are lower than the risk free rate, the efficient market view is seriously challenged. (Risager,68)

Our research proceeds as follows. First our tests based on six portfolios formed on size and P/B. The data are from the Center for Research in Security Prices (CRSP) and Compustat, supplemented by the book equity data for NYSE stocks in Davis, Fama, and French (2000). As in Fama and French (1993), we sort stocks into two size groups, S (small, that is, NYSE, Amex (after 1962), and (after 1972) Nasdaq stocks with market capitalization below the NYSE median) and B (big, market cap above the NYSE median), and three price-to-book groups, G (growth stocks, that is, NYSE, Amex, and Nasdaq stocks in the top 30% of NYSE P/B), N (neutral, middle 40% of NYSE P/B), and V (value, bottom 30% of NYSE P/B). The intersection of these independent sorts produces six portfolios, refreshed at the end of June each year, where SG and BG are small and big growth portfolios, SN and BN are small and big neutral portfolios, and SV and BV are small and big value portfolios.

To measure risk-adjusted performance of different asset classes during different periods of business cycles we used the Sharpe ratio. The Sharpe Ratio is designed to measure the expected return per unit of risk for a *zero investment strategy*. The difference between the

returns on two investment assets represents the results of such a strategy. The Sharpe Ratio does not cover cases in which only one investment return is involved.

Clearly, any measure that attempts to summarize even an unbiased prediction of performance with a single number requires a substantial set of assumptions for justification. In practice, such assumptions are, at best, likely to hold only approximately. Certainly, the use of unadjusted historic (ex post) Sharpe Ratios as surrogates for unbiased predictions of ex ante ratios is subject to serious question. For a number of investment decisions, ex ante Sharpe Ratios can provide important inputs. When choosing one from among a set of funds to provide representation in a particular market sector, it makes sense to favor the one with the greatest predicted Sharpe Ratio, as long as the correlations of the funds with other relevant asset classes are reasonably similar. When allocating funds among several such funds, it makes sense to allocate funds such that the selection (residual) risk levels are proportional to the predicted Sharpe Ratios for the selection (residual) returns. If some of the implied net positions are infeasible or involve excessive transactions costs, of course, the decision rules must be modified. Nonetheless, Sharpe Ratios may still provide useful guidance.

Whatever the application, it is essential to remember that the Sharpe Ratio does not take correlations into account. When a choice may affect important correlations with other assets in an investor's portfolio, such information should be used to supplement comparisons based on Sharpe Ratios.

All the same, the ratio of expected added return per unit of added risk provides a convenient summary of two important aspects of any strategy involving the difference between the return of a fund and that of a relevant benchmark. The Sharpe Ratio is designed to provide such a measure. Properly used, it can improve the process of managing investments.

The Sharpe ratio is calculated by subtracting the risk-free rate from the rate of return for a portfolio and dividing the result by the standard deviation of the portfolio returns. The Sharpe ratio formula is:

$$S = \frac{R - R_f}{\sigma}$$

where:

R - the expected portfolio return,

R_f - the risk free rate,

σ - the portfolio standard deviation.

The Sharpe ratio tells us whether a portfolio's returns are due to smart investment decisions or a result of excess risk. This measurement is very useful because although one portfolio or fund can reap higher returns than its peers, it is only a good investment if those higher returns do not come with too much additional risk. The greater a portfolio's Sharpe ratio, the better its risk-adjusted performance has been. A negative Sharpe ratio indicates that a risk-less asset would perform better than the security being analyzed.

Using the monthly data of 6 portfolios formed on size and book-to-market² we calculated the Sharpe ratio for every portfolio. The firms in the portfolios sorted into two-size groups (small and big; or S and B) and three book-to-market groups (high, medium, and low; or H, M, L).

After that we ranked every of 6 portfolios during the bull and bear periods. Bull market begins as the market rallies from the market bottom; bear market is the precursor to the next market bottom. Another words, if the trend is up, it's a bull market. If the trend is down, it's a bear market. According to the researches in chapter 1 we define 3 bull and 3 bear market periods during the period of July 1926- December 2009.

The bull periods are following:

- 1) July 1926 - September 1929;
- 2) May 1942 – November 1961;
- 3) October 1974 – March 2000.

The bear periods are following:

- 1) October 1929 – April 1942;
- 2) December 1961 – September 1974;
- 3) April 2000 – December 2009.

² See http://www.mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. 6
Portfolios Formed on Size and Book-to-Market (2*3).

The rank for every portfolio are determined in table 3.

Portfolios	Bull		Bear	
	Sharpe ratio	Rank	Sharpe ratio	Rank
Small Size - Low Book-to-Market	0,186	6	0,0135	4
Small Size - Medium Book-to-Market	0,2715	4	0,0558	2
Small Size - High Book-to-Market	0,2846	1	0,0658	1
Big Size - Low Book-to-Market	0,2562	5	-0,0238	6
Big Size - Medium Book-to-Market	0,2825	2	-0,0032	5
Big Size - High Book-to-Market	0,2792	3	0,0368	3

Table 3 : Performance of 6 portfolios during bull versus bear markets.

The best performance during the bull and bear market according to the Sharpe ratio belongs to Small Size - High Book-to-Market portfolio with Sharpe ratio 0,2846 (Rank 1). Another place during the bull market takes Big Size - Medium Book-to-Market portfolio with Sharpe ratio 0,2825 (Rank 2). According to the analysis the worst performance during the bull market belongs to Small Size - Low Book-to-Market portfolio with Sharpe ratio 0,186 (Rank 6). In contrast, during the bear market first rank belongs to Small Size - High Book-to-Market portfolio with Sharpe ratio 0,0658. The worst performance during the bear market belongs to Big Size - Low Book-to-Market portfolio with Sharpe ratio -0,0238. The relative performance of 6 different portfolios during different phases of the business cycles is supposed to be different.

2.3 The Performance of Bonds

During the investigation of the performance of bonds we have two analyze bond-market factors. One common risk in bond returns arises from unexpected changes in interest rates. Our proxy for this factor, TERM, is the difference between the monthly long-term government bond return (from Ibbotson Associates) and the one-month Treasury bill rate measures at the end of the previous month (from the Center for Research in Security Prices, CRSP). The bill rate is meant to proxy for the general level of expected returns on bonds, so that TERM proxies for the deviation of long-term bond returns due to shifts in interest rates.

For corporate bonds, shifts in economic conditions that change the likelihood of default give rise to another common factor in returns. The proxy for this default factor, DEF, is the difference between the return on a market portfolio of long-term corporate bonds (the Composite portfolio on the corporate bond module of Ibbotson Associates) and the long-term government bond return. (Fama and French (1993))

Table 4 shows that, used along as the explanatory variables in the time-series regressions, TERM and DEF capture common variation in stock and bond returns. The 25 stock portfolios produce slopes on TERM that are all more than five standard errors above 0; the smallest TERM slope for the seven bond portfolios is 18 standard errors from 0. The slopes on DEF are all more than 7.8 standard errors from 0 for bonds, and more than 3.5 standard errors from 0 for stocks.

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	m					t(m)				
Small	0,93	0,9	0,89	0,86	0,89	5,02	5,5	5,95	6,08	6,01
2	0,99	0,96	0,99	1,01	0,98	5,71	6,32	7,29	8,34	6,92
3	0,99	0,94	0,94	0,95	0,99	6,25	7,1	7,8	8,5	7,6
4	0,92	0,95	0,97	1,05	1,03	6,58	7,57	8,53	9,64	7,83
Big	0,82	0,82	0,8	0,8	0,77	7,14	7,6	8,09	8,26	6,84
	d					t(d)				
Small	1,39	1,31	1,33	1,45	1,52	3,96	4,27	4,73	5,45	5,45
2	1,26	1,28	1,35	1,38	1,41	3,84	4,47	5,28	6,05	5,29
3	1,21	1,19	1,25	1,24	1,21	4,05	4,74	5,49	5,89	4,88
4	0,96	1,01	1,13	1,21	1,22	3,65	4,28	5,25	5,89	4,92
Big	0,78	0,73	0,78	0,83	0,89	3,59	3,6	4,18	4,56	4,15
	R ²					s(e)				
Small	0,06	0,08	0,09	0,1	0,1	7,5	6,57	6	5,68	5,95
2	0,08	0,1	0,13	0,17	0,12	6,97	6,09	5,45	4,87	5,69
3	0,1	0,12	0,15	0,17	0,14	6,38	5,35	4,86	4,48	5,28
4	0,11	0,14	0,17	0,21	0,15	5,63	5,04	4,57	4,39	5,31
Big	0,13	0,15	0,16	0,17	0,12	4,61	4,33	4	3,89	4,55

Table 4: Book-to-market equity (BE/ME) quintiles.

The slopes on TERM and DEF allow direct comparisons of the common variation in stock and bond returns tracked by the term-structure variables. Interestingly, the common variation captured by TERM and DEF is, if anything, stronger for stocks than for bonds. Most of the DEF slopes for stocks are bigger than those for bonds. The TERM slopes for stocks (all close to 1) are similar to the largest slopes produced by bonds.

The fractions of return variance explained by TERM and DEF are higher for bonds. In the bond regression, R^2 ranges from 0.49 for low-grade corporate to 0.97 and 0.98 for high-grade corporate. In contrast, R^2 ranges from 0.06 to 0.21 for stocks. Thus, TERM and DEF clearly identify shared variation in stock and bond returns, but for stocks and low-grade bonds, there is plenty of variation left to be explained by stock-market factors.

There is an interesting pattern in the slopes for TERM. The slopes increase from 0.45 to 0.72 for 1-to 5-year and 6- to 10-year government, and then settle at values near 1 for four of the five long-term corporate bond portfolios. (The low-grade portfolio LG, with a slope of 0.81, is the exception). As one would expect, long-term bonds are more sensitive than short-term bonds to the shifts in interest rates measures by TERM. What is striking, however, is that the 25 stock portfolios have TERM slopes like those for long-term bonds. This suggests that the risk captured by TERM results from shocks to discount rates that affect long-term securities, bonds and stocks, in about the same way.

There are interesting parallels between the TERM slopes observed here and our earlier evidence that yield spreads predict bond and stock returns. In Fama and French (1989), we find that a spread of long-term minus short-term bond yields (an ex ante version of TERM) predicts stock and bond returns, and captures about the same variation through time in the expected returns on long-term bonds and stocks. We conjectured that the yield spread captures variation in a term premium for discount-rate changes that affect all long-term securities in about the same way. The similar slopes on TERM for long-term bonds and stocks observed here seem consistent with that conjecture.

The pattern in the DEF slopes in table 4 is also interesting. The returns on small stocks are more sensitive to the risk captured by DEF than the returns on big stocks. The DEF slopes for stocks tend to be larger than those for corporate bonds, which are large than those for governments. DEF thus seems to capture a common “default” risk in returns that increases from government bonds to corporate, from bonds to stocks, and from big stocks to small stocks. Again, there is an interesting parallel between this pattern in the DEF slopes and similar pattern observed in Fama and French in time-series regressions of stock and bond returns on an ex ante version of DEF (a spread of low-grade minus high-grade bond yields).

Given the negative relation between size and the slopes on DEF in table 6, it is easy to say why the DEF slopes work well in cross-section return regressions for size portfolios.

Our time-series regressions suggest, that DEF cannot explain the size effect in average stock returns. In the time-series regressions, the average premium for a unit of DEF slope is the mean of DEF, a tiny 0.02% per month. The average TERM returns is only 0.06% per month. As a result, we shall see that the intercepts in the regressions of stock returns on TERM and DEF leave strong size and book-to-market effects in average returns. We shall also find that when the stock market factors are added to the regressions, the negative relation between size and the DEF slopes in table 4 disappears.

2.4 Investigation of Performance of 30 Industries

Industry analysis is important in the investigation of market cycles. Performance can vary widely across industries. Industry groups exhibit considerable dispersion in their stock market performance.

Although we know what we mean by an “industry”, it can be difficult in practice to decide where to draw the line between one industry and another. There is a substantial variation within this group by size, focus, and region, and one might well be justified in further dividing the industries into distinct subindustries.

Three factors will determine the sensitivity of a firm’s earnings to the business cycle. First is the sensitivity of sales. Necessities will show little sensitivity to business conditions. Examples of industries in this group are food, drugs, and medical services. Other industries with low sensitivity are those for which income is not a crucial determinant of demand. Tobacco products are an example of this type of industry. Another industry in this group is movies, because consumers tend to substitute movies for more expensive sources of entertainment when income levels are low. In contrast, firms in industries such as machine tools, steel, autos, and transportation are highly sensitive to the state of the economy. (Bodie, Kane, and Marcus (2008, page 586)

The second factor determining business cycle sensitivity is operating leverage, which refers to the division between fixed and variable costs. (Fixed costs are those the firm incurs regardless of its production levels. Variable costs are those that rise or fall as the firm produces more or less product.) Firms with greater amounts of variable as opposed to fixed

costs will be less sensitive to business conditions. This is because in economic downturns, these firms can reduce costs as output falls in response to falling sales. Profit for firms with high fixed costs will swing more widely with sales because costs do not move to offset revenue variability. Firms with high fixed costs are said to have high operating leverage, as small swings in business conditions can have large impacts on profitability. (Bodie, Kane, and Marcus (2008, page 587)

One way that we think about the relationship between industry analysis and the business cycle is the notion of sector rotation or industry rotation. The idea is to shift the portfolio more heavily into industry or sector groups that are expected to outperform based on one's assessment of the state of the business cycle. Near the peak of business cycle, the economy might be overheated with high inflation and interest rates, and price pressures on basic commodities. This might be a good time to invest in firms engaged in natural resource extraction and processing such as minerals or petroleum.

Following a peak, when the economy enters a contraction or recession, one would expect defensive industries that are less sensitive to economic conditions, for example, pharmaceuticals, food, and other necessities, to be the best performers. At the height of the contraction, financial firms will be hurt by shrinking loan volume and higher default rates. Toward the end of the recession, however, contractions induce lower inflation and interest rates, which favor financial firms.

At the trough of a recession, the economy is poised for recovery and subsequent expansion. Firms might thus be spending on purchases of new equipment to meet anticipated increases in demand. This, then, would be a good time to invest in capital goods industries, such as equipment, transportation, or construction.

Finally, in an expansion, the economy is growing rapidly. Cyclical industries such as consumer durables and luxury items will be most profitable in this stage of the cycle. Banks might also do well in expansions, since loan volume will be high and default exposure low when the economy is growing rapidly.

Using the monthly data of 30 industry portfolios we calculated the Sharpe ratio for every portfolio. The rank for every portfolio are determined in table 5.

Industry	Bull		Bear	
	Sharpe ratio	Rank	Sharpe ratio	Rank
Food	0,2664	7	0,0187	13
Beer	0,2377	10	0,0273	9
Smoke	0,2029	19	0,0819	3
Games	0,2076	15	0,0042	20
Books	0,2681	6	-0,0595	30
Household	0,2168	14	0,0058	18
Clothes	0,1631	25	0,0147	16
Health	0,2502	8	0,0161	15
Chemicals	0,2072	16	0,0334	6
Textiles	0,159	26	0,0251	10
Constructions	0,2003	20	0,0014	21
Steel	0,1663	24	0,0175	14
Fabric Production	0,1982	21	0,031	7
Electronic Equipment	0,2454	9	0,0087	17
Automobiles	0,2066	17	0,022	12
Carry	0,1975	22	0,0307	8
Minerals	0,1071	30	0,0764	4
Coal	0,1384	29	0,0821	2
Oil	0,2054	18	0,05	5
Utilities	0,2957	1	-0,0319	28
Telecommunication	0,2925	2	-0,0491	29
Services	0,2771	3	-0,0245	27
Bus Equipment	0,2744	4	-0,0212	26
Paper	0,2197	13	0,0232	11
Transportation	0,1757	23	0,127	1
Wholesale	0,1568	28	-0,0024	24
Retail	0,2333	11	-0,0006	23
Meals	0,2199	12	0,0049	19
Finance	0,2734	5	-0,0146	25
Other	0,1577	27	0,0006	22

Table 5. Performance of 30 industry during bull versus bear markets.

Following the data of the table 5 the best performance during the bull markets belongs to Utilities, Telecommunication, Services, Bus Equipment and Finance with Sharp ratios 0,2957; 0,2925; 0,2771; 0,2744 and 0,2734 accordantly (Rank1, Rank 2, Rank 3, Rank 4, Rank 5). At the same time, during the bear markets the leading positions takes following industries: Transport, Coal, Smoking production, Minerals and Oil production with Sharpe ratios 0,127; 0,0821; 0,0819; 0,0764 and 0,05 accordantly (Rank 1, Rank 2, Rank 3, Rank 4, Rank 5). The worst performances during bull markets belongs to Coal and Minerals industries

with meaning of Sharpe ratios 0,1384 and 0,1071 accordantly (Rank 29, Rank 30). We can see, that during bear market these industries have their best performance.

The worst performances during bear markets go to Utilities, Telecommunication and Books industries with sharp ratios -0,0319; -0,0491 and -0,0595 accordantly (Rank 28, rank 29, Rank 30). It is like the best performance during bull markets.

According to the research of the performance of 30 industries of the U.S. market the best performance of several industries during the bull markets equal to the worst performance during the bear markets and, in contrast, the worst performance during the bull markets equal to the best performance during the bear markets.

We can also see, that such industries as Constructions, Games, Housholdes, Meals and others leaves on the same rank during bull and bear markets.

Conclusions

During the research the author demonstrated the historical performance of different asset classes during different periods of stock market (bull and bear markets). Previous studies on the dynamics of economic activity were analyzed during the investigation. Using the dataset of stock market returns during 1926-2009 we found a rather strong regularity in the length of the cycle. It was determined and measured so called “business cycles” and found turning points of market upswings and downswings during the period of 1926-2009. The start date of the first downtrend is October 1929 and the end date of the downtrend is April 1942; the start date of the first uptrend is May 1942 and the end date is November 1961; the start date of the second downtrend is December 1961 and the end date is September 1974; the start date of the second uptrend is October 1974 and the end date is March 2000.

In chapter 2 the investigation of different asset classes during the period from 1926 to 2009 took place. During the research we used the data from the library of Fama and French, the portfolios include all NYSE, AMEX, and NASDAQ firms with the necessary data. We then divide the total historical period into subperiods of stock market upswings and downswings and present the descriptive statistics of upswings and downswings.

During the analysis of the relative performance of different asset classes the empirical performance of the Sharpe and the three-factor model were used.

One way that we think about the relationship between industry analysis and the business cycle is the notion of industry or sector rotation. Sector rotation is an investment strategy involving the movement of money from one industry sector to another in an attempt to beat the market.

Literature and references

- Bodie, Z., Kane, A. and Marcus, A. J. (2008). *Investments*. 8-th edition. New York.
- Burns, A. and Mitchell, W. (1946). *Measuring Business Cycles*. New York: National Bureau of Economic Research.
- Chan, L. K. and Lakonishok, J. (2004). "Value and Growth investing: Review and Update", *Financial Analysts Journal*, 60(1), 71-86.
- Chen, L. and Zhang, L (2010). "A Better Three-Factor Model That Explains More Anomalies", *Journal of Finance*, 65(2), 653-594.
- Fama, E.F. and French, K. R. (1989). "Business Conditions and Expected Returns on Stock and Bonds." *Journal of Financial Economics*, 25 (1), 23–49.
- Fama, E. F. and French, K. R. (1993). "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics*, 33 (1), 3-56.
- Fama, E.F. and French, K. R. (2005). "The Anatomy of Value and Growth Stock Returns", CRSP working paper.
- Harvey, C. R. (1989b). "Time-Varying Conditional Covariances in Tests of Asset Pricing Models", *Journal of Financial Economics*, 24, 289-317.
- Hodrick, R. J. And Prescott, E. C. (1997). "Postwar . U. S. Business cycle: An Empirical Investigation", *Journal of Money, Credit, and Banking*, 29(1), 1-16.
- Michael A. Alexander. (2000), *Stock Cycles. Why Stocks Won't Beat Money Markets Over the Next Twenty Years*.
- Owen, R. (1817). *Report to the Committee of the Association for the Relief of the Manufacturing Poor*. London.
- Risager, O. (2009), *Investing in Value Stocks*, working paper. Copenhagen.
- Sismondi, J. C. L. (1819). *Nouveaux Principes D'economie Politique*. Paris.
- Zakamouline, V. (2010), *Are There Long Cycles in the U.S. Stock Market?*, working paper. University in Agder.

www.bea.gov

www.nbear.gov