경제학석사학위논문

Stock Return Autocorrelation under Stages of Business Cycle: An Empirical Evidence

경기 순환 단계별 주식 수익률의 자기상관에 관한 실증 분석

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국문초록

이 논문에서 1954년부터 2011년까지 월별, 일별 주식 수익률의 자기상관의 형태를 경기순환의 단계에 따라 분석하였다. 경기 순환은 여섯 개의 단계인 저점, 확장I, 확장II, 고점, 수축I, 수축II로 정의하였다. 각 단계에서 주식 수익률의 자기상관을 분석하여, 월별 수익률은 경기 수축기에, 일별 수익률은 경기 확장기에 자기상관이 존재하는 것을 밝혀냈다. 이러한 자기상관을 이용한 투자전략을 세웠는데, 자기상관이 존재하는 기간 내에서 전기 주식수익률이 양수일 경우 주식을 사서 1기간 보유하고, 전기 주식수익률이 음수일 경우 공매도하는 방식의 전략을 테스트해보았다. 결과적으로, 이러한 전략은 월별 데이터에 사용하였을 경우 시장 수익률보다 낮았으며, 일별 데이터에 적용한 경우 높게 나타났다. 일별 수익률에 전략을 적용하였을 경우의 높은 수익률은 규모가 작은 회사들에 기인한 것일 수 있음을 보였다. 다른 투자전략을 테스트해 본 결과, 월별 수익률의 자기상관은 경기가 저점일 경우 연속되는 양의 수익률, 수축II 단계일 경우 연속되는 음의 수익률에 영향을 받았을 가능성이 있음을 보였다.

주요어 : 주식 수익률, 자기상관, 경기순환, 투자전략

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Abstract

Stock Return Autocorrelation under Stages of Business Cycle :An Empirical Evidence

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In this paper, I investigate monthly and daily stock return autocorrelation behaviors from 1954 to 2011 under different stages of the business cycle. Business cycles is defined as six consecutive stages of Trough, Expansion I, Expansion II, Peak, Contraction I, and Contraction II. By examining autocorrelation in stock returns on each stage, I find out that there exist monthly stock return autocorrelations on the periods of economic contraction, while daily stock return autocorrelations were found on the periods of economic expansion. Using this autocorrelations, I test a trading strategy that buys stocks and hold it for one period if return on last period was positive, and short stock and settle the trade after one period if last period return was negative on each period where autocorrelations exist. The results show that monthly returns from this strategy are lower than the market return and daily returns yield higher than the market return. I also suggest that appearances of daily autocorrelations on stages of economic expansion may arise from the autocorrelations in returns from small firms. Also by testing another trading strategy, I show that consecutive positive returns on Trough and negative returns on Contraction II could be an explaining factor of the monthly returns autocorrelations.

keywords : Stock Return, Autocorrelation, Business Cycle, Trading Strategy

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1. Introduction

Since the efficient market hypothesis was developed by Eugene Fama in 1960s, it gradually have become a prevailing theory in financial economics. In his famous paper *Efficient Capital Markets* (1970), Fama distinguishes types of efficient markets, including weak form, semi-strong form, and strong form. Although different range of information is defined on these three forms of efficient markets, the theory suggested that investors who are willing to yield excess returns using any information would fail, since capital prices adjust instantaneously right after the arrival of the new information. On the other hand, another mainstream of financial economics have risen after 1990s. The efficient market hypothesis have contributed a lot on intuitions and techniques of financial economics, however, there still exist many phenomena that are not explained by existing theories, which are called financial market anomalies. One of the well-known anomalies is a phenomenon of momentum, the observed tendency of consecutive asset price rising, or consecutive falling. While De Bondt and Thaler (1985) shows stock return reversal such that stocks that performed poorly for more than past three to five years achieves higher return for next 3 to five years, Jegadeesh and Titman (1993) states on their paper as follows:

> *…strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant positive returns over 3- to 12-month holding periods. We find that the profitability of these strategies are not due to their systematic risk or to delayed stock price reactions to common factors.*

In their paper they shows that trading using stock prices momentum yields excessively higher returns. The existence of stock price momentum in a short and mid run is a contradiction of the weak form of efficient market, since traders are able to yield higher return than the market return using earlier information of stock returns. Even though momentum itself does not mean positive autocorrelation, of course, stock momentum is closely related to the returns autocorrelations, as Lo and MacKinlay (1990) show that stock return autocorrelations could be a source of the momentum.

Other studies on stock returns argue that stock returns have distinct features on different business conditions. Investigating stock and bond returns pattern on business condition, Fama and French (1989) states as follows:

> *The dividend yield*[1] *and the default spread capture similar variation in expected bond and stock returns. The major movements in these variables, and in the expected return components they track, seem to be related to long-term business episodes that span several measured business cycles. The dividend yield and the default spread forecast high returns when business conditions are persistently weak and low returns when conditions are strong.*

As they show, it is commonly accepted that stock returns have a pattern that follows business condition, which oscillates following the path of contraction and expansion. Then, how do autocorrelations in stock returns differ under business condition? If stock market shows a consecutive positive returns when business condition is weak and consecutive negative returns when business condition is good, autocorrelations of stock returns would appear under some business conditions.

From these motive, I investigate the autocorrelations of the monthly and daily stock returns on each stages of business cycle. In this paper, I first define business cycle and

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[1] Here, they use dividend yield as a measure of stock returns.

decompose quarterly GDP data from the first quarter of 1954 to the second quarter of 2011 into 6 different stages of business cycle, using Hodrick-Prescott filter. Six stages are composed of consecutive stages including Trough, Expansion I, Expansion II, Peak, Contraction I, and Contraction II. Then, stock returns autocorrelations are estimated on each stages of business cycle, on both monthly and daily basis. The data shows that there exist stock returns autocorrelations on Contraction II and Trough on a monthly level, while autocorrelations appear on Expansion I, Expansion II, and Peak on a daily level. Focusing on the stages where the autocorrelations are observed, I construct trading strategy implementing the features of autocorrelations. That is, I construct a trading strategy that buy stock if last period return was positive, and short stocks if last period return was negative. On a monthly level, this strategy is a failure, while it yields about two times higher return on a daily level. I also test to find out the source of the monthly and daily returns autocorrelations. It is shown that monthly level autocorrelation may be driven from the consecutive positive signs of returns for Trough, while consecutive negative returns may arise autocorrelations on Contraction II. On a daily level, I build portfolios that are grouped by U.S firms' market capitalization. The returns of the strategy on these portfolios demonstrate that return autocorrelations of small firms could be an explaining factor of daily basis stock return autocorrelations.

The rest of this paper is as follows. Section II describes datasets used in this paper, which include business cycle data and stock return data. It also explains the measure of business cycle, and decomposition of business cycle into six different stages. In section III, monthly return autocorrelations on each stages of business cycle are analyzed. This section investigates on which stages of business cycle the autocorrelations in returns exist, and possible sources of the autocorrelations. Section IV do the similar analysis with section III, but on a daily level. Section V concludes.

2. Data

This section explains overall dataset used in this paper. Six stages of business cycle is defined using Hodrick-Prescott filter, and stock return data is briefly explained.

2.1 Business Cycle Data

This paper focuses on the movements of stock return under different stages of business cycle. Therefore, how to define and estimate business cycle are crucial. There have been many researches investigating the measurement of business cycle after Burns and Mitchell(1946) defined business cycle as follows:

> *Business cycles are a type of fluctuation 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; in duration, business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar characteristics with amplitudes approximating their own.*

In their definition of business cycle, properties of fluctuating states of an economy and repeating cycles of expansions and contractions are well described. However, although this definition of business cycle characterized the essential aspect of business cycle, the method of estimating detailed phases of the fluctuation inside the business cycle have changed. Methods of estimating business cycle by Baxter and King(1994) and Hodrick and Prescott(1997) are widely accepted and used these days. Basically, quarterly reported GDP data is mainly composed of 3 different component, that is, trend component, cyclical component, and irregular noise. Baxter-King band pass filter(BK filter) and Hodrick-

Prescott filter(HP filter) capture these components of output data, and suggest techniques to isolate cyclical component from other two components. Although specific techniques of isolating cyclical component from GDP data differs between these two filters, these two filters shows almost same results when estimating cyclical components. Since BK filter sacrifices first and last data points, I used HP filter to classify business cycle.

Hodrick and Prescott(1997) proposed the technique that decomposes time series data as a smoothly varying trend component and cyclical component. Thus, detrending log output enables isolating cyclical component from other two components. Following the notation of Hodrick and Prescott(1997), I denote log output $\mathrm{y_t} = g_t + c_t$ where g_t refers to a growth component and c_t refers to a cyclical component. Cyclical component c_t is determined after g_t is determined through following programming problem:

$$Min_{\{g_t\}_{t=-1}^{T}} \left\{ \sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=1}^{T} [(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2 \right\}.$$

Data in consideration is quarterly reported GDP data. λ is a value which penalizes a variability of growth components. I used the same penalty scheme, 1600 for quarterly data following Ravn and Uglig(2002), and Kaiser and Maravall(2005). From calculated cyclical components $c_t = y_t - g_t$, I use following criteria to decompose business cycle into six different stages[2]:

[2] While decomposing c_t into six different stages, similar methodology with Ahn Dong Hyun and Byoung Kyu Min, Bo Hyun Yoon(2013) is applied

(i) Trough (t-1, t, t+1)

$c_t \leq c_l$, t-1=Contraction II, $\Delta c_{t-1} < 0, \Delta c_{t+1} > 0$,

(ii) Expansion I (t)

$c_l < c_t \leq 0$, t-1=Trough,

(iii) Expansion II (t)

$0 < c_t \leq c_h$, t-1=Expansion I,

(iv) Peak

$c_h \leq c_t$, t-1=Peak, $\Delta c_{t-1} > 0, \Delta c_{t+1} < 0$,

(v) Contraction I (t)

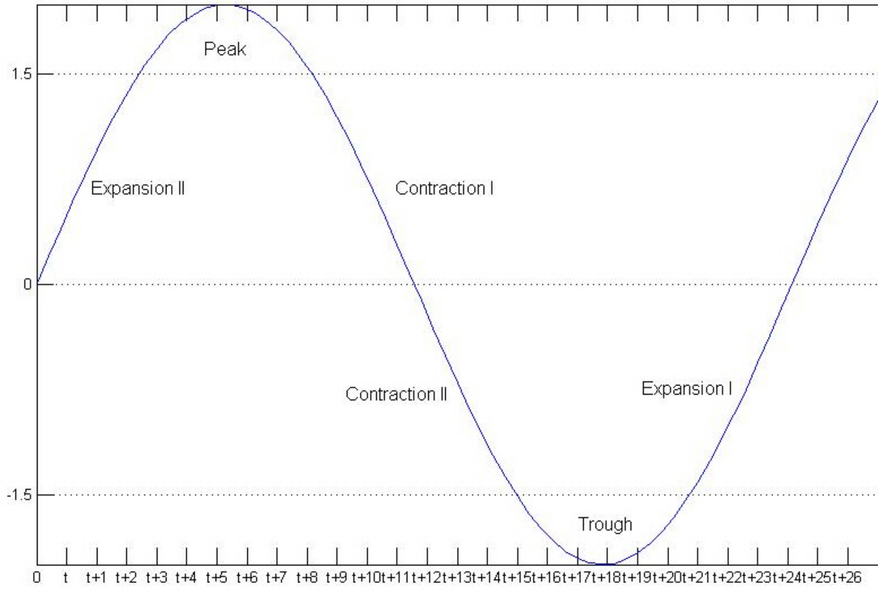
$c_t \leq c_h$, t-1=Peak,

(vi) Contraction II (t)

$c_l < c_t \leq 0$, t-1=Contraction I.

Figure 1 briefly shows this definition of 6 stages of business cycle. Expansion I and Expansion II refer to periods where aggregate economic condition is continuously expanding, therefore, $\Delta c_t > 0$. Likewise, Contraction I and Contraction II represent lower economic conditions that $\Delta c_t < 0$. For close overview of stock return behaviors under extreme status of business cycle, Peak and Trough are defined. c_h and c_l determine the size of periods of these two business conditions. Following Ahn and Min(2011, working paper), I set $c_h = 1.5$ and $c_l = -1.5$ since the absolute value of the standard deviation of the cyclical component is about 1.5. Since Peak and Trough are less frequently observed, their periods are extended to t-1 and t+1 if t=Peak or Trough.

Figure 1. Decomposition of the Business Cycle



From total 230 quarters, from the first quarter of 1954 to second quarter of 2011, 10 business cycles appear and the 11^{th} cycle is ongoing. Average length of cycle is 22 quarters. Table 1 shows basic properties of six stages of business cycle, from the first to tenth cycle.

Table 1. Properties of Six Stages of Business Cycle(by Quarter)

	Trough	Expansion I	Expansion II	Peak	Contraction I	Contraction II
Appearance	24	63	56	33	24	20
Average Length	2.4	6.3	5.6	3.3	2.4	2.0

2.2 Stock Return Data

In this paper, three different stock returns data are used to investigate the pattern of stock return autocorrelation. First return data is risk premium, which is also called the excess return $r_m - r_f$, that denotes the market return minus risk free interest rate. The market return here is a value weighted return of all CRSP firms in U.S. which are listed on the NYSE, AMEX, and NASDAQ stock markets, and risk free rate is the one-month Treasury bill rate. Second return data is a simple market return r_m, which is composed of CRSP firms' value weighted returns, equal weighted returns, and S&P 500 returns. All of two returns data is used on both monthly and daily level analyses. Even though these two types of aggregate returns differ by risk free rate r_f, the similar result is observed. Also, daily individual stock return data of CRSP listed U.S. firms is used for more detailed analysis of daily stock return autocorrelation. Table 2 shows summary statistics of monthly excess returns under six different stages of business cycle.

Table 2. Summary Statistics of Monthly $r_m - r_f$ under Six Stages of Business Cycle

	Trough	Expansion I	Expansion II	Peak	Contraction I	Contraction II
Mean	0.0298901	0.01234	0.005769	-0.001901	-0.013075	-0.017335
s.d	0.0449165	0.0338342	0.0428414	0.0390301	0.0494387	0.0554605
Max	-0.1012	-0.08	-0.2314	-0.1178	-0.1323	-0.1854
Min	0.1605	0.1243	0.1044	0.0954	0.0812	0.077

As Fama and French(1989) stated, expected returns are lower when economic conditions are strong and higher when conditions are weak. This table shows that average stock return decreases monotonically from Trough to Contraction II, while stock returns are positive on Trough, Expansion I, and Expansion II, and negative on Peak, Contraction I, and Contraction II. In section 3, different trading strategies are induced on a monthly level from the fact that stock returns differ under each stage of business cycles.

3. Monthly Level Analysis

In this section, I first investigate on which stages monthly stock return autocorrelations exist. Then I implement two trading schemes to see whether trading using autocorrelation yields higher returns compared to the market returns.

3.1 Autocorrelation in Monthly Stock Return

In this section, monthly stock returns data from January 1954 to June 2011 is used. First, coefficient $\rho$of AR(1) process $R_t = \rho R_{t-1} + \epsilon_t$,which has monthly excess returns $R_t = r_{m,t} - r_{f,t}$ as a dependent variable and lagged monthly excess returns $R_{t-1} = r_{m,t-1} - r_{f,t-1}$ as an independent variable, are estimated under six different stages to see how autocorrelations differ on each stage of business cycle. Since certain stage of cycles usually appears with gaps that is composed of other 5 stages, every first observations of each stage of a cycle are sacrificed. Table 3 shows estimated ρ and p-value of this process.

From Table 3, it is shown that autocorrelation coefficients ρ are significant only on two stages, Trough and Contraction II, where $\rho = 0.2977$ on Trough and $\rho = 0.4205$ on Contraction II. Contraction II and Trough are last two of three stages where overall economic activity is relatively decreasing, and furthermore, c_t is negative only in these two stages among the stages of economic downturn. Therefore, the result could be interpreted that monthly stock return shows positive autocorrelation in the periods of severe economic downturn.

The results that positive autocorrelations exist only in stages Contraction II and Trough is somewhat notable. To search more detailed aspect of these autocorrelations in economic downturns, I construct a trading strategy using the characteristic of autocorrelations to test whether this strategy yields higher average return compared to the market return.

Table 3. Estimation of ρ in AR(1) Process $R_t = \rho R_{t-1} + \epsilon_t$, on Monthly Level

Stage	Coef.	P>|z|
Trough	0.2976	0.004
Expansion I	0.1056	0.218
Expansion II	0.0895	0.209
Peak	-0.1314	0.313
Contraction I	0.1124	0.477
Contraction II	0.4204	0.004

3.2 Implementation of Trading Strategy on Monthly Level

If stock returns show positive autocorrelation, the probability of returns being positive when last month return was positive would be high. Likewise, the probability of returns being negative when last month return was negative would be relatively high. Accordingly, it is expected that implementing trading strategy using this aspect of autocorrelation could yield returns higher than the market return, on average. Here, I establish trading strategy named Strategy A which has a trading scheme as follows:

Strategy A

If t-1=Contraction II or Trough,

Buy stock at t-1 and hold it for 1 month,	if $R_{t-1} > 0$,
short sell stock at t-1 and settle the trade after 1 month,	Otherwise.

Using excess stock return data of Contraction II and Trough from 1954 January to 2011 June, I implement Strategy A and test a difference between returns of Strategy A and market returns. Table 4 shows the results.

Table 4. Mean and Standard Deviation of Excess Returns of the Market and Excess Returns of Strategy A

	$R_{m,1}$	R_A
Mean	0.0115	0.0089
s.d.	0.0517	0.0523

$R_{\mathrm{m},1}$ refers to the market return, and R_A refers to the return using Strategy A. On this table, Average monthly market return on Contraction II and Trough is 0.0115, while average return using Strategy A is 0.0089 in the same trading periods. Standard deviations of these two returns do not differ a lot. The result contradicts to the expectation that trading using the autocorrelation would yield higher returns compared to the market return. Does this result mean that trading using the feature of autocorrelation has no effect on yielding higher return? Table 2 shows that average stock returns are shown to be differ in Trough and Contraction II, where it is the highest and positive on average on Trough, while it is the lowest with negative sign on Contraction II. Since these two stages have stock returns that differ most in their first order moment among total six stages, it is suspected that the autocorrelation features on these two stages would be also distinct. From this evidence that stock returns have a tendency of decreasing as business cycle proceeds, another trading strategy is designed, named Strategy B, which has asymmetric trading schemes on different stages as follows:

Strategy B

If t-1= Trough,

Buy stock at t-1 and hold it for 1 month,	if $R_{t-1} > 0$,
do nothing,	Otherwise.

If t-1=Contraction II,

do nothing,	if $R_{t-1} > 0$,
short sell stock at t-1 and settle the trade after 1 month,	Otherwise.

Strategy B has a similar feature with Strategy A, but trading scheme of Strategy A is applied only in one-sided sign of past return and asymmetrically on two different stages. From the evidence that average stock return on stage of Trough is positive with 0.1398, Strategy A is applied only for positive past return. Strategy B, therefore, buys stock and hold it for one period when last month return was positive on Trough. On the other hand, it does nothing if last month return was negative. On Contraction II, asymmetrically, Strategy B short sell stock and settle the trade after 1 month if last month return was negative, and do nothing otherwise. Table 5 shows average returns and standard deviations of yield implementing Strategy B.

Table 5. Mean and Standard Deviation of Excess Returns of the Market and Excess Returns of Strategy A, B

	$R_{m,1}$	R_A	$R_{m,2}$	R_B
Mean	0.0115	0.0089	0.0115	0.0200
s.d.	0.0517	0.0523	0.0501	0.0474

Strategy B, and 0.0200 is an average return in period where trades occur. By definition of trading strategy B, there does not exist trade if last month market return was negative on Trough, and similarly, there is no trade if last return was positive on Contraction II. Since trade does not occur in some periods, $R_{m,2}$ is calculated to match the periods where trades occur. Nevertheless, $R_{m,1}$ and $R_{m,2}$ are almost similar in their mean and standard deviation values, while it is shown that average return of Strategy B R_B is nearly two times greater than the market returns, $R_{m,1}$ and $R_{m,2}$.

Table 6. Mean and Standard Deviation of Value Weighted Returns of the Market and Value Weighted Returns on Strategy A, B

	$R_{v,1}$	$R_{v,A}$	$R_{v,2}$	$R_{v,B}$
Mean	0.0121	0.0091	0.0118	0.0197
s.d.	0.0515	0.0521	0.0499	0.0474

Table 7. Mean and Standard Deviation of Equally Weighted Returns of the Market and Equally Weighted Returns of Strategy A, B

	$R_{e,1}$	$R_{e,A}$	$R_{e,2}$	$R_{e,B}$
Mean	0.0240	0.0220	0.0257	0.0334
s.d.	0.0656	0.0655	0.0638	0.0593

Table 8. Mean and Standard Deviation of S&P 500 Returns of the Market and S&P 500 Returns of Strategy A, B

	$R_{s,1}$	$R_{s,A}$	$R_{s,2}$	$R_{s,B}$
Mean	0.0112	0.0068	0.0125	0.0175
s.d.	0.0508	0.0516	0.0478	0.0462

I also implement Strategy A and Strategy B on CRSP value weighted returns, equally weighted returns, and S&P 500 returns and compare it to the market returns. The results are interesting, because Strategy A, which applied the characteristic of autocorrelation on trading, is proved to be worse than the market, at the same time Strategy B that employed the feature of autocorrelation partially according to the stages' average return shows considerably higher return compared to that of the market. Can it be an evidence that the autocorrelations arise as a result of consecutive positive returns on Trough and consecutive negative returns on Contraction II? To find out the source of the autocorrelations, I investigate the relations between R_{t-1} and R_t, the lagged excess return and excess return. The distribution of R_{t-1} and R_t on Contraction II and Trough are as follow:

Table 9. Distributions of R_{t-1} and R_t on Trough and Contraction II

Trough	$R_t > 0$	$R_t < 0$	Contraction II	$R_t > 0$	$R_t < 0$
$R_{t-1} > 0$	49	14	$R_{t-1} > 0$	10	14
$R_{t-1} < 0$	14	4	$R_{t-1} > 0$	16	20

Figure 2. Scatter Plot of R_{t-1} and R_t on Trough

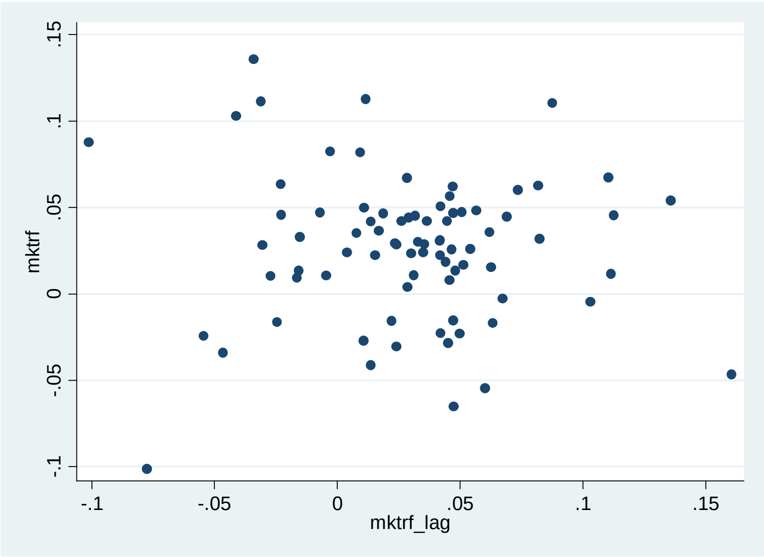


Figure 3. Scatter Plot of R_{t-1} and R_t on Contraction II

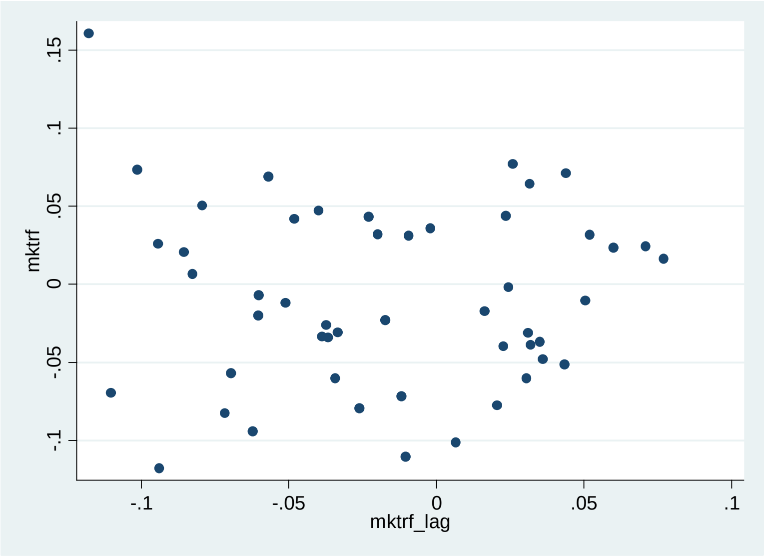


Figure 2 and 3 graphically show distribution of R_{t-1} and R_t on Contraction II and Trough, and table 9 shows total counts of this distribution. Among 81 observations of return distributions on Trough, 77.78% of them have a negative past returns. Of 63 return distributions that have $R_{t-1} < 0$, 49 of next month return R_t's are positive which have a probability of 0.78. On Contraction II, 36 of 60 observations have negative R_{t-1}'s, and the probability of $R_t > 0$ when $R_{t-1} < 0$ is 0.56. From the results above, it could be suggested that the autocorrelation appears on Trough by cause of consecutive positive returns, while the autocorrelation arises on Contraction II due to successive negative returns.

Finally, I tested another trading scheme called Strategy C to see the benchmark of asymmetric trading between Contraction II and Trough. Strategy C has a trading scheme as follows:

Strategy C

Buy stock at t-1 and hold it for 1 month, if t-1=Trough

short stock at t-1 and settle after 1 month, if t-1=Contraction II

I implement Strategy C on excess return data. Using Strategy C, average return is turned out to be 0.0192, with standard deviation of 0.04738. The average return of Strategy C is similar to that of Strategy B, which has 0.02001 on average. Standard Deviations of both strategies do not differ much. Comparison between Strategy B and Strategy C indicates that monthly returns when last month return was negative on Trough and last month return was positive on Contraction II are almost zero. Therefore, this result provides another evidence that monthly stock return autocorrelations could be explained by consecutive positive signs on Trough and consecutive negative signs on Contraction II.

In this section, I investigate the feature of monthly stock return autocorrelation. The positive autocorrelations appear on stages, Contraction II and Trough among six stages. I construct trading scheme called Strategy A and Strategy B using the feature of the autocorrelations and average returns on each stage, and test if these two trading strategies yield higher return than market returns. Strategy A shows lower return than the market return in all samples including excess return, CRSP value weighted and equally weighted returns, and S&P 500 return, while Strategy B is successful in all. I check the sign distributions of all observations on Trough and Contraction II and find out that asymmetric consecutive signs of returns in these two stages could be a probable source of the autocorrelations. Next section does the similar investigation on autocorrelation, but on a daily basis.

4. Daily Level Analysis

This section explains the feature of autocorrelation on a daily basis. Similar analysis is conducted as of section 3. First, I investigate on which stages the autocorrelations are significant.

4.1 Autocorrelation in Daily Stock Return

Like monthly autocorrelations are estimated following AR(1) process, daily autocorrelation is estimated under process $R_t = \rho R_{t-1} + \epsilon_t$ using excess return. The sample returns data include all available daily returns from January 1st, 1954 to June 30th, 2011. The results are as follows:

Table 10. Estimation of ρ in AR(1) Process $R_t = \rho R_{t-1} + \epsilon_t$, on Daily Level

Stage	Coef.	P>|z|
Trough	-0.0011	0.004
Expansion I	0.0913	0.218
Expansion II	0.0446	0.209
Peak	0.0641	0.313
Contraction I	0.0138	0.477
Contraction II	0.0052	0.004

In Contrast to monthly level autocorrelation, coefficient ρ's are significant on stages Expansion I, Expansion II, and Peak. It is shown that p value of the estimated coefficients ρ is almost zero in these three periods, while the autocorrelations on other stages are shown to be insignificant. The autocorrelation coefficient is the highest on Expansion I with 0.0912 while it is the lowest on Expansion II with 0.0446. Three stages have positive autocorrelations, where the autocorrelation coefficient is 0.0641 on Peak.

The result is somewhat startling because the autocorrelations are significant in almost exactly different stages of business cycle using month and daily level excess returns. While monthly autocorrelations exist on the consecutive two stages Contraction II and Trough among three stages of economic downturn, daily autocorrelations exist on all three periods of economic expansion.

4.2 Implementation of Trading Strategy on Daily Level

In section 4.1, it is found that there exist significant positive daily stock return autocorrelations on economic expansions, that is, on stages Expansion I, Expansion II, and Peak. With the same expectation as the one in monthly analysis that trading strategy using positive autocorrelation would yield higher return, I construct Strategy D which corresponds with Strategy A on a monthly level. The properties of Strategy D are as follows:

Strategy D

If t-1=Expansion I, Expansion II, or Trough

Buy stock at t-1 and hold it for 1 day,	if $R_{t-1} > 0$,
short sell stock at t-1 and settle the trade after 1 day,	Otherwise.

Strategy D does not differ with Strategy A except that it is implemented on the daily stock returns and the range of time that strategy is implemented. It is expected that Applying Strategy D on daily return data, yields on strategy D would be higher than the market returns. Table 11 shows the comparison of mean and standard deviation between daily excess return $R_t = r_{m,t} - r_{f,t}$ and return using Strategy D.

Table 11. Mean and Standard Deviation of Excess Returns of the Market and Excess Returns of Strategy D

	$R_{m,1}$	R_D
Mean	0.00034	0.00084
s.d.	0.00824	0.00820

The table shows that average daily market excess return is 0.00034 and standard deviation is 0.00824 on Expansion I, Expansion II, and Peak. At the same time, average daily return using strategy D is 0.0008r, with almost same standard deviation. The result is somewhat surprising. Unlike Strategy A on monthly level return, Strategy D using daily autocorrelation is shown to yield competently high return, about 2.5 times higher, compared to its benchmark, market excess return. For more reliable result, I also test to see if Strategy D is still effective on another dataset.

Table 12. Means and Standard Deviations of Value Weighted Return, Equally Weighted Return, S&P 500 Return of the Market, and Corresponding Returns of Strategy D

	R_v	$R_{v,D}$	R_e	$R_{e,D}$	R_s	$R_{s,D}$
Mean	0.0004	0.0009	0.0007	0.0015	0.0004	0.0005
s.d.	0.0081	0.0081	0.0068	0.0066	0.0087	0.0087

In table 12, R_v, R_e, and R_s refer to the CRSP value weighted return, equally weighted return, and S&P 500 return on Expansion I, Expansion II, and Peak, from the first trading day of 1954 to June 30 2011. $R_{v,D}$, $R_{e,D}$, and $R_{s,D}$ indicate the corresponding returns using Strategy D. Strategy D demonstrates more than two times higher return than each of market value weighted return, market equally weighted return. Strategy D using CRSP value weighted return yield 0.0009 on average, while average market return is 0.0004. For equally weighted return, Strategy D shows 0.0015, while market return is 0.0007. Though this strategy is not very successful when it is tested using S&P 500 return, it still yields higher return than the market return on average. These results from table 12 coincide with the result from table 11 that returns using the feature of the autocorrelation are higher than the market returns on stages of Expansion I, Expansion II, and Peak.

Thus, for more than 57 years, investors could yield excessively higher daily return in the periods of economic expansion if they knew that the economy is expanding. Considering that there has been a lot of improvement on researches estimating the business cycle, this outcome does not go along with the efficient market hypothesis stating that investors cannot yield return higher than the market return on average using information from the past. Then, why does this excessively high return exist? Comparing the average returns from table 12, equally weighted return using Strategy D is the highest while return on S&P 500 using Strategy D is the lowest. S&P 500 index indicates returns of top U.S. enterprises, and that the weight of small firms is the largest in equally weighted return index. Therefore, separating returns of big and small firms may lead to an answer. In section 4.3, viabilities of Strategy D is tested on portfolio level where firms are grouped by size to find out where the daily autocorrelation comes from and why the Strategy D shows different level of yield on value weighted, equally weighted return, and S&P 500 return.

4.3 Portfolio Analysis of Daily Autocorrelation

In this section, I implement Strategy D in section 4.3, but on an individual stock level. First, Strategy D is applied on individual stocks and corresponding daily return is calculated on Expansion I, Expansion II, and Peak. Next, firms are sorted by their size of market capitalization, and then grouped according to their rank. Finally, four portfolios composed of top 10%, top 25%, bottom 10%, and bottom 25% rank of market capitalization are composed, and corresponding return without the strategy are calculated.

Stock return data of all available CRSP firms listed in NYSE, AMEX, and NASDAQ stock market is used in this analysis. The table 13 shows the result.

Table 13. Returns of Portfolios of Firms Sorted by Market Capitalizations and Corresponding Returns using Strategy D

	R_v	$R_{v,D}$	R_e	$R_{e,D}$
All Stocks	0.0005	0.0007	0.0010	-0.0017
Top 10%	0.0039	-0.0092	0.0051	-0.0105
Top 25%	0.0017	-0.0055	0.0027	-0.0071
Bottom 10%	0.0004	0.0007	0.0005	0.0009
Bottom 25%	0.0004	0.0007	0.0005	0.0008

Table 13 shows normal returns and returns using Strategy D of value weighted and equally weighted portfolios, where portfolios are composed of top 10%, 25% and bottom 10%, 25% of market capitalization firms. All return data is from the periods of Expansion I, Expansion II, and Peak. The result is straightforward. That is, returns using Strategy D are lower than the normal returns for top 10% and 25% market capitalization portfolios. Strategy D yields -0.0092 and -0.0105 for value weighted and equally weighted portfolio, while normal return is 0.00387 and 0.00511 for top 10% market capitalization firms. For top 25%, value weighted and equally weighted portfolio yield -0.0055 and -0.0071 using Strategy D, but normal returns are 0.00173 and 0.00271. On contrast, for bottom 10% and 25% market portfolios, average yields using Strategy D is about two times higher for both value weighted and equally weighted portfolios. For bottom 10% market capitalization, returns using Strategy D are 0.00075 and 0.00086, while normal returns for two portfolios are lower than these, that is, 0.00043 and 0.00045. Similar results hold for bottom 25% market capitalization firms' portfolios. Even though this test is not rigorous and it is lack of theoretical backgrounds, this test still suggests that the source of the daily autocorrelations on stages Expansion I, Expansion II, and Peak may arise or be driven from the small size firms autocorrelation. That is, stocks with low market capitalization may be a source of explaining daily level autocorrelation in the periods of economic expansions.

In section 4, I first show that there exist positive daily level autocorrelations on three stages of business cycles, Expansion I, Expansion II, and Peak. I test whether trading using these autocorrelations on these three stages could yield higher return than the market return, by constructing trading scheme called Strategy D. Strategy D corresponds with Strategy A of the monthly level, which has a trading scheme such that buy stock and hold it for a day if the return of the last trading day was positive and short sell stock and settle the trade after a day if the return of the last trading day was negative. Using this strategy, I show that the performances of Strategy D for all returns data including excess return, CRSP value weighted return, equally weighted return, and S&P 500 return is successful, yielding about two times higher returns compared to the corresponding normal market returns. Finally, I investigate the portfolios of the individual stocks grouped by their market capitalizations to find out where these successful trading arises. By investigating these portfolios, I point out that tracing returns of firms with low market capitalization could exhibit the source of the daily autocorrelations in the periods of economic expansions, though more rigorous and theory based research is required.

5. Conclusion

In this paper, I investigate monthly and daily stock return autocorrelation behaviors under different stages of the business cycle, using three types of return data from 1954 to 2011. Business cycles is defined as six consecutive stages of Trough, Expansion I, Expansion II, Peak, Contraction I, and Contraction II. By examining return autocorrelations on each stage, I find out that there exist monthly stock return autocorrelations on Contraction II and Trough, while daily stock return autocorrelations are found on stages of Expansion I, Expansion II, and Peak.

Anticipating that these monthly and daily autocorrelations would yield higher returns than the markets, I design a simple trading strategy, which buys stocks and hold it for one period if last period return was positive, and short sells stock and settles the trade after one period if last period return was negative. Monthly returns from this strategy are lower than the market return on Contraction II and Trough, while daily returns are higher than that of the market on Expansion I, Expansion II, and Peak.

For a monthly level analysis, by considering that there exists a wide gap between average returns on Contraction II and Trough, I compose another strategy that trades asymmetrically on different stages of business cycles. That is, this alternative strategy only buys stock for the one with past positive returns on Trough, on the other hand it only short sell stock for the one with past negative returns on Contraction II. This alternative strategy shows about two times higher returns than that of the market for all returns data. By exploiting distributions of the returns and the lagged returns, it is shown that successive positive returns could be a source of monthly return autocorrelation on Trough, while successive negative returns may arise monthly return autocorrelation on Contraction II.

Strategy using daily return autocorrelations on Expansion I, Expansion II, and Peak is successful. Therefore, I investigate different portfolios of stocks which are grouped by firms' market capitalizations to find out the origin of the autocorrelations. Using all available returns data of U.S. CRSP firms listed on NYSE, AMEX, and NASDAQ stock markets, I construct four portfolios that are sorted by firms' market capitalizations. The test shows that returns where the strategy is implemented on portfolios composed of firms with high market capitalizations are lower than the market returns, while returns using strategy on low market capitalization firms' portfolio are higher than the market return. This test suggests that daily stock return autocorrelations on the periods of economic expansion may be driven from small firms. However, even though I find out that there exist monthly and daily stock return autocorrelations on asymmetric stages of business cycle and suggest the sources of these autocorrelations, more rigorous research is still required to find out exactly where the autocorrelations come from.

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