6-19-2015

Business Cycle Effects on US Sectoral Stock Returns

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DOI: 10.25148/etd.FIDC000087

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BUSINESS CYCLE EFFECTS ON US SECTORAL STOCK RETURNS

A dissertation submitted in partial fulfillment of

the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Keran Song

2015

To: Dean Michael R. Heithaus
College of Arts and Sciences

This dissertation, written by Keran Song, and entitled Business Cycle Effects on US Sectoral Stock Returns, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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Date of Defense: June 19, 2015

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ACKNOWLEDGMENTS

I sincerely thank my advisor and committee chair Dr. Prasad Bidarkota for his continuous guidance, patience and support on my dissertation writing and academic progress.

I sincerely thank my committee members, Dr. Hakan Yilmazkuday, Dr. Jesse Bull, and Dr. Xiaoquan Jiang for their insightful advice and kind encouraging words.

I also want to express my gratitude to Dr. Cem Karayalcin and Dr. Mihaela Pintea for their administrative support.

I would like to thank all other professors in the Economics Department for sharing their precious knowledge and intelligence.

ABSTRACT OF THE DISSERTATION

BUSINESS CYCLE EFFECTS ON US SECTORAL STOCK RETURNS

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My dissertation investigated business cycle effects on US sectoral stock returns.

The first chapter examined the relationship between the business cycle and sectoral stock returns. First, I calculated constant correlation coefficients between them. Then, I employed the DCC GARCH model to estimate time-varying correlation coefficients for each pair of them. Finally, I ran regression of sectoral returns on dummy variables designed to capture the four stages of the business cycle. I found that though sectoral stock returns were closely related to the business cycle, they did not share some of its main characteristics.

The second chapter developed two models in order to discuss possible asymmetric business cycle effects on US sectoral stock returns. One was a GARCH model with asymmetric explanatory variables and the other one was an ARCH-M model with asymmetric external regressors. I found that some sectors changed their cyclicities from expansions to recessions. Negative shocks to business cycles had most power to influence sectoral volatilities. Positive and negative parts of business cycle risk had same effects on some sectors but had opposite effects on other sectors. A general conclusion of both

models was that business cycle had stronger effects than own sectoral effects in driving sectoral returns.

The third chapter discussed Chinese business cycle effects on US sectoral stock returns at two horizons. At a monthly horizon, the third lag of Chinese IP growth rate had positive effects on most sectors. The second lag of US IP growth rate had positive effects on almost all sectors. At a quarterly horizon, besides the extensive positive effects of the first lag of Chinese IP growth rate, the third and fourth lags also had effects on some sectors. The US IP growth rate had the same pattern, namely positive first and fourth lag effects and negative third lag effects. Using a 5-year rolling fixed window, I found that these business cycle effects were time-varying. The major changes in parameters resulted from the elimination of quota on textiles by WTO, the terrorist attacks on the US, and the 2007 financial crisis.

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CHAPTER 1

SECTORAL US STOCK RETURNS OVER THE BUSINESS CYCLE

1.1 Introduction

How to reduce the market risk is still an open area. A great many efforts have been made to answer this question. Diversification is a proven method that can dramatically decrease nonsystematic risk. Thus, diversification becomes the main strategy for investors to manage portfolios. Creating a portfolio depends on characteristics of stocks and economic conditions. However, it is difficult to describe the characteristics of a single stock, for the stock can be affected by many random factors hard to identify. While considering several stocks, the description may be more feasible since some common features will appear from the cluster. These common features may expose systematic risk which is easy to avoid, or they may uncover latent nonsystematic risk which can be solved by diversification. As a consequence, some researchers start to seek proper approaches to combine related stocks and discover their common traits. One effective approach is to analyze sectoral stock returns. Early attempts on sectoral stock returns can be traced back to Wei and Wong (1992). They introduce 19 industry stock returns to examine their relations to inflation and find that the expected inflation positively associates with sectoral stock returns. They also find that the sensitivity of the association affirmatively depends on the level of real assets and inversely depends on the debt ratio of the corresponding sector. Therefore, investors can adjust portfolios following the trend of inflation.

Another paper, by Berdot, Goyeau, and Leonard (2006), takes the business cycle into consideration and introduces exchange rate to analyze sectoral stock return problems. By using French sectoral stock returns and the US business cycle data, they inspect the exchange rate effects on these French sectors. They calculate covariations between the US business cycle and each sectoral stock returns and obtain the cyclicities of sectors as a function of the significant lags/leads length to the business cycle. These results are then employed to provide some investment suggestions at different stages of the business cycle. Related analyses can be found in Choi and Zeghal (2002), Fouquin, Sekkat, Mansour, Mulder and Nayman (2001), and Koutmos and Martin (2007).

Because of the important role of oil and oil related products, oil prices also become a variable to discuss in relation to sectoral stock returns. Arouri (2011) investigates effects of crude oil price fluctuations on 12 Europe sectoral stock indexes and national index. By broadening the perspective from aggregated level to disaggregated sectoral level, he compares the sensitivity of sectoral stock returns and the whole market returns to oil price changes. The results from his paper show that choosing stocks across sectors is more efficient than within sectors, which confirm that investors should consider sector level portfolio diversification. Similar research can be found in Arouri, Jouini and Nguyen (2011, 2012), Arouri and Nguyen (2010), Nandha and Faff (2008), which all pay attention to the relationship between the oil price and sectoral stock returns, as well as confirm the importance of sectoral analysis.

There are some other aspects to investigate sectoral stock returns. For example, Julie Salaber in her 2009 paper demonstrates empirically that some sectors may be less risky than other sectors whatever the whole market is. The sectoral stocks in her paper are called sin stocks, i.e., stocks of tobacco, alcohol, and gaming industry, which have abnormal risk-adjusted returns compared to similarly characteristic industries, and always outperform the overall market in recession. Meric, Ratner and Meric (2008) use principal analysis and Granger causality test to show the co-movement of sectoral indexes and benchmark market index in bull and bear markets. They find that in the bull market global diversification is better than sector diversification, which means investing in different countries in the same sector is better than investing in different sectors within the same country. However, in the bear market, the sector diversification is much better. Balli and Balli (2011) show that in Euro area, the stock returns of financial sector is much likely affected by overall Euro stock index, while basic industry sectors such as basic sources, food & beverage, oil and gas and so on are less dependent on the whole market behavior.

Literature mentioned above shows important relationships between sectoral stock returns and some macroeconomic variables, including some specific characteristics of the sectors. In the present paper, I try to discuss the relationship between sectoral stock returns and the business cycle. It is a general belief that economic conditions will affect average stock returns. However, since departments of an economy have different properties and operation systems, also since the economic conditions vary themselves, the business cycle may have different effects on departmental stock returns. For example, when the economy goes into a recession, the government may use some fiscal policies and monetary policies, such as increasing government spending, decreasing interest rate, and so on, to boost the economy. The companies which satisfy government demand may have better performances in this period and the companies in financial related sector may behave weakly. As a result, the stock returns of the former companies will increase and those of the latter companies will decrease reflecting the changes of their performances. On the other hand, investors may also wonder whether the stock returns of above two kinds of companies will reverse during a booming economy. Essentially, these questions concern the sectoral stock returns over business cycles. If we can describe the movements of sectoral stock returns along the time horizon, investors will have more choices to reduce risk and investments will become more profitable.

Using the information of the US stock market, I apply three methods to investigate the relationships between sectoral stock returns and business cycles. For the first two methods, I use the GDP to represent business cycles, and use correlation coefficients to represent the relationships. The constant correlation coefficient between GDP growth rate and each sector is calculated first. The coefficients reveal close positive relationships between sectoral returns and business cycles. I then estimate the time-varying correlation coefficient by the DCC GARCH model. In the DCC GARCH model, the time-varying correlation is captured by the conditional correlation coefficients, which will demonstrate the short term changes of the dependence between GDP growth rate and sectoral returns. The changes are more meaningful when considering the investment, because whatever the long term value is, investors can always find profitable chances in the short term. For the third method, I use dummy variables to represent business cycles and use regression to disclose the relationships between business cycles and sectoral returns. The signs of the estimated parameters tell the directions of the effects of business cycles on sectoral stock returns, and the statistical significance of the parameters provides reliable suggestions for investment.

The rest of this paper is organized as follows. Section 2 discusses the constant correlation between business cycles and sectoral returns. Section 3 searches time-varying correlation coefficients between them. Section 4 regresses sectoral stock returns on dummy variables of business cycles. Section 5 concludes.

1.2 Constant Correlation Coefficient

Stock market activity is closely related to economic conditions. Obviously, the stock market flourishes during a booming period and withers during a recession. Because of various characteristics, however, sectoral stock markets may have different processes when co-moving with economic conditions. In this section I verify this point by analyzing the relationships between sectoral stock returns and the business cycle. Dow Jones Sectoral Indexes system divides the whole stock market into 10 sectors: basic materials, consumer goods, consumer services, financials, health care, industrials, oil & gas, technology, telecommunication, and utilities. The system abbreviates them as BM, NC, CY, FN, HC, IN, EN, TC, TL, and UT[1]. I follow the abbreviations and use them in the rest of this paper. I also include the whole US market stock index to compare the difference between aggregated and disaggregated market levels.

Figure 1.1 illustrates the relationship between GDP growth rate, representing the business cycle, and sectoral stock returns. Each panel of this figure draws stock returns of one sector[2] together with GDP growth rate. Sectoral stock returns are indicated by solid red lines and GDP growth rate is indicated by dashed blue lines. In figure the GDP growth rate fluctuates moderately around zero, with an apparent drop in 2008. While, the stock returns of each sector fluctuates vigorously around GDP growth rate and presents sharp decreases in 2008, according to the recession of US economy in that year. The vertical axis of each panel ranging from -60% to 30% indicates the value of sectoral stock returns and GDP growth rate. Consistent measurement of the vertical axis is very helpful to show the

[1] Please refer to Table 1.1 for the sectors and their corresponding abbreviations.

[2] Sometimes we will add the whole US market on the top of sectors and mention them together as “eleven sectors”.

differences among sectoral stock returns. For instance, sector US, NC, and HC are less volatile than others; 2008 recession has strong effects on US, BM, FN, IN, EN, and TC; and the business cycle has opposite effects on sectoral stock returns at some times.

Though GDP growth rate fluctuates moderately but sectoral stock returns fluctuate vigorously, co-movements between them are easy to observe. Table 1.2 shows the correlation coefficients between stock returns of each sector and GDP growth rate. The US whole market has the largest correlation coefficient, which is 55 percent. Industrials also has a high correlation coefficient over 50 percent. There are 7 sectors whose correlation coefficients are higher than 40 percent. The lowest coefficients occur in TL and UT but they still exceed 30 percent. In consequence, we can confirm that, from the aspect of quarterly data, all sectors have close relationships with the business cycle.

One problem of the constant correlation coefficient is that the largest correlation coefficient occurs on US whole market. Since the US whole market stock index is an average of the sectors, its returns should reflect the average level of them. But in Table 1.2 the correlation coefficient between US whole market and GDP growth rate is the highest, rather than an average. The reason for this result simply lies in the calculation of the correlation coefficient. In Table 1.3, I display the covariances between GDP growth rate and the sectors. The average of covariance of all sectors is 0.00025, which is very close to the covariance of the US whole market, 0.00026. The covariance reveals that the whole market index reflects the average level without any ambiguity. However, the comparatively low standard deviation of the whole market boosts its correlation coefficient. The standard deviation of the US whole market is 0.07 which is lower than the average level, 0.09. Three sectors, NC, HC and UT, have smaller standard deviations than the US whole market, but they also have smaller covariances. Other sectors all have larger standard deviations, while their covariances are either smaller than US whole market or not large enough to generate a higher correlation coefficient. The covariances and the correlation coefficients together reveal that the US whole market reflects the average level of the sectors and it also has the closest connection with the business cycle.

Another problem of the constant correlation coefficient is that it reflects a relationship for a long time. Because both GDP growth rate and sectoral stock returns change over time, we need to know the time-varying pattern of the correlations between them. The time-varying correlations are useful in that investors can form investment strategies by diversifying their choices in short time. The DCC-GARCH model can help us find the dynamic correlation coefficients.

1.3 Dynamic Conditional Correlation Coefficient

1.3.1 The DCC-GARCH Model

Engle (2002) provides a multivariate GARCH model to calculate the time-varying correlation coefficients between two time series. The GARCH model is developed from constant conditional correlation model established by Bollerslev (1990). If each of two random variables follows a univariate GARCH process, then their conditional covariance can be described by their conditional variances times a correlation coefficient: $h_{12t} = \rho_{12}\sqrt{h_{11t}h_{22t}}$. The DCC-GARCH model enables correlation coefficient ρ_{12} to change over time: $h_{12t} = \rho_{12t}\sqrt{h_{11t}h_{22t}}$.

Preliminary analysis for ACF of sectoral stock returns indicates that their autoregressive order is one:

$$r_{it} = c_{im} + a_i r_{it-1} + \varepsilon_{it}$$

1)

The subscript i indicates different sectors, which are US, BM, NC, CY, FN, HC, IN, EN, TC, TL, UT, and the subscript m indicates that the parameter is used for mean equation. GDP growth rate is also an AR (1) process:

$$r_{gt} = c_{gm} + a_g r_{gt-1} + \varepsilon_{gt}$$

2)

The subscript m has the same meaning and the subscript g indicates GDP growth rate.

Residuals of sectoral stock returns and GDP growth rate are assumed to follow GARCH (1,1) processes, and conditional covariance of each sector and GDP growth rate is described by the DCC-GARCH model:

$$\varepsilon_{it} = v_{it}\sqrt{h_{it}}, \varepsilon_{gt} = v_{gt}\sqrt{h_{gt}}$$

3)

$$h_{it} = c_{iv} + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1}$$

4)

$$h_{gt} = c_{gv} + \alpha_g \varepsilon_{gt-1}^2 + \beta_g h_{gt-1}$$

5)

$$h_{igt} = \rho_{igt}\sqrt{h_{it} h_{gt}}$$

6)

Where v_{it} and v_{gt} follow i.i.d. standard normal distributions and h_{it} and $h_{gt}$are conditional variance of ε_{it} and ε_{gt}. We can find the conditional covariance between ε_{it} and ε_{gt} given that these two disturbances are correlated. The time-varying correlation coefficients ρ_{igt} are generated from $\rho_{igt} = h_{igt}/\sqrt{h_{it}h_{gt}}$. The problem arises from finding the conditional covariance h_{igt}. Following Engle (2002), I use a smoother to estimate it:

$$q_{ljt} = (1 - \lambda_1 - \lambda_2)\overline{s_{lj}} + \lambda_1 s_{lt-1}s_{jt-1} + \lambda_2 q_{ljt-1}\, , l = i, g, j = i, g$$

7)

The standardized residuals, $s_{it} = \widehat{\varepsilon_{it}}/\widehat{h_{it}^{0.5}}$, are estimates of v_{it} in equation (3), and the standardized residuals, $s_{gt} = \widehat{\varepsilon_{gt}}/\widehat{h_{gt}^{0.5}}$ are estimates of v_{gt}. $\overline{s_{lj}}$ is the unconditional correlation between s_{it} and s_{gt}. Confining non-negative λ_1 and λ_2 and $\lambda_1 + \lambda_2 < 1$ assures that the correlations matrix are positive definite and converge to unconditional correlation matrix. Then, the DCCs can be calculated as:

$$\rho_{igt} = q_{igt}/\sqrt{q_{iit}q_{ggt}}$$

8)

1.3.2 Estimation of the Parameters

As in Engle (2002), I can use two step estimation to find the parameters in my models. The log-likelihood function of a bivariate GARCH model can be written as:

$$\mathrm{L} = -\frac{1}{2}\sum_{t}(2ln(2\pi) + ln|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t)$$

Where ε_t is a vector of the residuals such that $\varepsilon_t = (\varepsilon_{gt}, \varepsilon_{it})'$, and H_t is the conditional covariance matrix of ε_t. Decomposing H_t to a diagonal matrix D_t and a symmetric matrix R_t allows the log-likelihood function to be estimated by two steps. The conditional covariance matrix H_t can be written as $H_t = D_t R_t D_t$ where $D_t = \begin{pmatrix} h_{gt}^{0.5} & 0 \\ 0 & h_{it}^{0.5} \end{pmatrix}$ is a diagonal matrix with square root of conditional variances on its diagonal and zeroes otherwise, and $R_t = \begin{pmatrix} 1 & \rho_{igt} \\ \rho_{igt} & 1 \end{pmatrix}$ is the symmetric correlation matrix such that $\rho_{igt} = h_{igt}/(h_{gt}^{0.5} h_{it}^{0.5})$. Then the third part of the log-likelihood function can be written as $\varepsilon_t' H_t^{-1} \varepsilon_t = \varepsilon_t' D_t^{-1} R_t^{-1} D_t^{-1} \varepsilon_t = v_t' R_t^{-1} v_t$ where v_t is a vector of the standardized residuals such that $v_t = \left(v_{gt}, v_{it}\right)' = (\varepsilon_{gt}/h_{gt}^{0.5}, \varepsilon_{it}/h_{it}^{0.5})'$. Therefore, I can write the log-likelihood function as:

$$\mathrm{L} = -\frac{1}{2} \sum_{\mathrm{t}} (2ln(2\pi) + ln|D_t R_t D_t| + v_t' R_t^{-1} v_t)$$

$$\mathrm{L} = -\frac{1}{2} \sum_{\mathrm{t}} (2ln(2\pi) + 2ln|D_t| + ln\,|R_t| + v_t' R_t^{-1} v_t)$$

$$= -\frac{1}{2} \sum_{\mathrm{t}} (2ln(2\pi) + 2ln|D_t|) - \frac{1}{2} \sum_{\mathrm{t}} (ln\,|R_t| + v_t' R_t^{-1} v_t)$$

$$\mathrm{L} = \mathrm{L}_1 + \mathrm{L}_2$$

Using L_1 and L_2 to represent the two parts of above equation, I find that L_1 is a function of parameter θ_1 which only contains parameters of the mean and variance equations of GDP growth rate and sectoral stock returns. L_2 is a function of θ_1 and θ_2 where θ_2 only contains parameters of the correlation coefficient equations. Since L_1 does not depend on θ_2, I can estimate L_1 first and then estimate L_2. Adding $v_t' v_t$ into L_1 makes L_1 the sum of two univariate GARCH likelihoods

$$\mathrm{L}_1 = -\frac{1}{2} \sum_{t} (2ln(2\pi) + 2ln|D_t| + v_t' v_t)$$

and subtracting $v_t' v_t$ from L_2 keeps L unchanged

$$\mathrm{L}_2 = -\frac{1}{2} \sum_{\mathrm{t}} (ln\,|R_t| + v_t' R_t^{-1} v_t - v_t' v_t)$$

The first step is to estimate L_1. Since GDP growth rate and sectoral stock returns do not depend on each other, L_1 can be estimated as two separate univariate GARCH models. A little more deduction for L_1 gives us

$$\mathrm{L}_1 = -\frac{1}{2}\sum_t \left(2ln(2\pi) + 2l\,n\left(h_{gt}^{0.5}\right) + 2l\,n\left(h_{it}^{0.5}\right) + \varepsilon_{gt}^2/h_{gt} + \varepsilon_{it}^2/h_{it}\right)$$

$$\mathrm{L}_1 = -\frac{1}{2}\sum_t (ln(2\pi) + 2\,ln\left(h_{gt}^{0.5}\right) + \varepsilon_{gt}^2/h_{gt}) - \frac{1}{2}\sum_t (ln(2\pi) + 2\,ln\left(h_{it}^{0.5}\right) + \varepsilon_{it}^2/h_{it})$$

$$\mathrm{L}_1 = \mathrm{L}_{1g} + \mathrm{L}_{1i}$$

Thus, I break the bivariate log-likelihood function into two parts: a univariate log-likelihood function of the GDP growth rate and a univariate log-likelihood function of sectoral stock returns. Specifically, L_{1g} is a function of θ_{1g} , where $\theta_{1g} = (c_{gm}, a_g, c_{gv}, \alpha_g, \beta_g)$; L_{1i} is a function of θ_{1i}, where $\theta_{1i} = (c_{im}, a_i, c_{iv}, \alpha_i, \beta_i)$. Because L_{1g} does not depend on θ_{1i} and L_{1i} does not depend on θ_{1g}, I can estimate L_{1g} and L_{1i} as two univariate GARCH process to obtain θ_{1g} and θ_{1i}.

The second step is to estimate L_2. L_2 is a function of θ_1 and θ_2 where $\theta_1 = (\theta_{1g}, \theta_{1i})$ and $\theta_2 = (\overline{s_{lj}}, \lambda_1, \lambda_2)$. Smoother equation (7) and results from L_1 enable me to estimate θ_2 and derive the smoothers q_{ljt} by maximizing L_2. Then, placing the smoothers q_{ljt} into equation (8) I can find time-varying correlation coefficients ρ_{igt}.

1.3.3 Empirical Results

The first column in Table 1.4 contains estimated values of the constant term c_{im} in equation (1). Six of them are significant including US whole market. Parameters for AR(1) terms are in the second column. A dash for NC and HC indicates their AR(1) parameters are restricted to zero in searching for a converged maximum log-likelihood. For the rest sectors, AR(1) parameters are positive and have approximate magnitudes. Columns three to five are parameters for the variance equation. Most of the ARCH(1) and GARCH(1) parameters are significant. In order to obtain a converged maximum log-likelihood, I restrict GARCH(1) parameters for FN and EN to zeros. For some sectors, like NC, the ARCH(1) parameter is small and the GARCH(1) parameter is large. Thus, for these sectors, a shock from last period has a small effect on current volatility but this effect will last for a long time. On the other hand, for some other sectors, like BM, the ARCH(1) parameter is large and the GARCH(1) parameter is small. Thus, for these sectors, a shock from last period has a strong effect on current volatility, but this effect will decay fast.

Last two columns are estimates of DCC parameters λ_1 and λ_2 in equation (7). These two parameters should be positive and their sum should be in unit circle to ensure the conditional covariance converging to its long run unconditional level. These two parameters enable sectoral stock returns to accumulate previous shocks and dynamic effects and make the conditional covariance fluctuate along the horizon. The closer the sum of the parameters to unity and the larger the parameter λ_2, the greater the conditional covariance persists. The closer the sum to zero, the faster the conditional covariance converges to its long run value-the unconditional covariance. The larger the parameter λ_1, the greater the conditional covariance fluctuates. In my results, the sum of λ_1 and λ_2 is close to one for BM, NC, CY, FN and TL. These sectors also have a large parameter λ_2. Therefore, these sectors will have more persistent conditional covariance. The sum of these two parameters is only 0.2 for the sector HC, so the conditional covariance of HC will be closer to its unconditional covariance than other sectors. US, IN, EN and UT have a large parameter λ_1 and their conditional covariances are more volatile than other sectors.

In Figure 1.2, I plot the estimated DCC for each sector in 11 panels along with their constant correlation coefficients. In each panel, a horizontal line is also drawn to indicate the zero value of correlation coefficient. There are some common features of each sector's DCCs. First, it is easy to see that those DCCs fluctuate around their long run unconditional correlation coefficient, and all of them have a tendency to converge to that. Some sectors have more volatile DCCs, like the US whole market, IN, EN and UT, in observing the large estimates of λ_1. The largest difference between the DCCs and the constant coefficient occurs on IN, when a negative correlation exits between the economy and stock returns. Second, whether volatile or not, there is a trend in each DCC curve such that the dynamic correlation has continued to increase over the past 20 years. The increasing process reveals that connections between the economic conditions and sectoral stock returns become stronger and stronger. Third, though generally sectoral stock returns are positively and increasingly related to economic conditions, occasionally some sectors are found negatively moving along with economic conditions. Comparing to the zero correlation line, negative dynamic correlation coefficients appear on US, BM, IN, EN, TC, TL and UT. During the periods when negative coefficients are observed, diversifications within sectors will benefit investors.

From above analysis, I can confirm that constant correlation is not enough when considering portfolio construction. Dynamic correlation is a more effective method to cope with conditional risk. Some statistics of the estimated DCCs are presented in Table 1.5.

1.4 Variation of Sectoral Stock Returns over Business Cycles

1.4.1 Outlook of Monthly Sectoral Stock Returns over Business Cycles

In this section, I investigate the relationship between sectoral stock returns and business cycles through a regression model. I want to add some new evidence to the existing literature, which shows how different sectors move asymmetrically over the business cycles. Since the Dow Jones only has recent 20 years of sectoral stock indexes data, I focus on the nearest 20 years business cycles. Specifically, the NBER determines three peaks and three troughs in these years, as in Table 1.6[3]. The lengths of contractions and expansions are also provided in the same table. As denoted by the NBER, a contraction is a period between a peak and the next trough, and an expansion is between a trough and the next peak.

In Figure 1.3, I plot monthly sectoral stock returns, along with the business cycle information listed in Table 1.6. Without the data restriction of GDP, which is only available at quarterly frequency, I can use monthly stock returns for all sectors. The shadows in each panel indicate two contractions in recent 20 years. The shadows also divide the rest portions into three parts, which are expansions in business cycles. It is apparent that each series falls under the zero horizon line in the two contractions, especially in the second one. Although there are some negative observations in the expansion periods, most of them are positive. Furthermore, even if being negative, the returns bounce back to positive quickly during expansions. However, the negative values of returns during contraction are more persistent.

[3] The data come from NBER website at: http://www.nber.org/cycles/cyclesmain.html.

Although the sectors share common features, some of them have their own properties. For example, some sectors, like FN and TC, have more variation in the first expansion than in the second one, while, some other sectors do not have much difference in these two periods, like BM and EN. Some sectors have local minimum value in 1999, like the US and FN, but sector BM has a maximum value in the year. Moreover, some sectors, like US and CY, fluctuate more vigorously around the first contraction, but some sectors show the opposite. One interesting sector is Technology, which experiences dramatically volatility from 1999 to 2003. This may arise from the computational innovation during that time. As a consequence, different behaviors of sectors demonstrate the fact that diversification of investment among sectors may be profitable.

1.4.2 Average Behavior of Sectoral Stock Returns over Business Cycles

Now consider a regression of each sector on business cycles. Expansions and contractions are defined by NBER, as in Table 1.6. Then, by using the middle point of the time span, I divide an expansion into two stages, which are stage I and stage II, and divide a contraction into two stages too, which are stage III and stage IV. Please refer to Figure 1.4 for more details. This method has been used in other papers, like in DeStefano (2004). Table 1.7 presents the period of time and the lasting length of each stage of business cycles. From the table we can see the four stages jointly form an entire business cycle.

I then define four dummy variables corresponding to the four stages as follows:

$$D_j = \begin{cases} 1, if\ the\ month\ belongs\ to\ stage\ j \\ 0, otherwise \end{cases}, \qquad j = 1, 2, 3, 4$$

For example, D_2 is the dummy variable for stage II. Referring to Table 1.7, D_2 has value 1 during April 1996 to March 2001 and December 2004 to December 2007, and has value 0 for other periods. Thus, each dummy variable has the same length as the sample period. A regression model is set up to investigate varying performance of sectoral stock returns over business cycles:

$$SR_{i,t} = c_{i1}D_1 + c_{i2}D_2 + c_{i3}D_3 + c_{i4}D_4 + \varepsilon_{i,t}$$

9)

where D_1 to D_4 are dummy variables for four stages and c_i are parameters related to them. Through the regression on dummy variables, I can separate variation of sectoral stock returns according to different stages.

Table 1.8 presents the regression results on four dummy variables of business cycles. Every sector has positive parameters in stage I and stage II, and negative parameters in stage III and stage IV. Therefore, generally speaking, sectoral stock returns and business cycles have positive relationship in expansions and negative relationship in contractions.

Specifically, four sectors, NC, FN, IN and EN, have significant estimated parameters in Stage I ranging from 0.0079 to 0.0107. Also four sectors, US, HC, EN and UT, have significant estimated parameters in Stage II ranging from 0.0081 to 0.0137. Rest sectors, BM, CY, TC and TL, are not significantly affected by these two stages of business cycles. It is apparent that in Stage II sectoral stock returns have better performance than in Stage I.

Only two sectors, TL and UT, have significant parameters in Stage III which are -0.028 and -0.0266. Five sectors, US, FN, IN, EN and UT, have significant parameters in Stage IV ranging from -0.0266 to -0.0426, in absolute value. It is also clear that Stage IV have worse effects on sectoral stock returns than Stage III. Significant parameters are not observed on BM, NC, CY, HC and TL. One interesting conclusion from these results is that business cycles tend to have stronger effects on sectoral stock returns when approaching to peaks and troughs.

From the aspect of the stages of business cycles, stage IV significantly affects five sectors, which is the most compared to other stages. Therefore, exiting in stage IV will guarantee the profit at a higher determinate level. Stage I and II affect four significant sectors, hence entering in this stage may also be profitable. Stage III only significantly affects two sectors, so no clear guideline will be produced in this stage.

From the aspect of sectors, EN and UT have the most reliable results. Business cycle effects on them are quite important because both of them have three significant parameters. Therefore, selecting these two sectors in a portfolio will ensure a stable profit. On the other hand, BM, CY and TC have no significant estimated parameters at all. Thus, when using business cycle information to forecast stock returns, investors need to pay close attentions on them. All other sectors have one or two significant stages in business cycles.

In Table 1.9 I re-list the regression results according to parameter values of each dummy variable. All the parameters are sorted by decreasing order of absolute values. Thus, sequences of sectors in columns one and three express the profitability of sectors in Stage I and Stage II; while, sequences of sectors in columns five and seven express the risk of sectors in Stage III and Stage IV. On the basis of the order of sectors, in Table 1.10 I make some suggestions on diversifying portfolios through business cycles.

Investors should enter the sectors in Stage I and Stage II following the order of columns two and three, or diversify a portfolio by including more upper sectors. In Stage III and Stage IV, investors should exit the sectors as the order of columns four and five, or change a portfolio by excluding more upper sectors. The stars after sectors indicate that the parameters of the stage dummy variables are significant. These sectors, which will guarantee more reliable results, may be preferred by a risk averse investor.

1.5 Conclusion

In this paper I use three methods to investigate the relationship between US business cycle and US sectoral stock returns. For the first two methods, I use GDP as a proxy of the business cycle. For the third one, I use dummy variables to represent the business cycle. The conclusion is very clear that the business cycle and sectoral stock returns have close relationships.

The constant correlation coefficients between GDP growth rate and sectoral stock returns range from 32% to 55%. The dynamic correlation coefficients between them converge to their constant coefficients and generally have an upward trend. The dynamic correlation coefficients are stable on some sectors but are quite volatile on some other sectors. The largest dynamic coefficient is 97% on IN and the smallest one is -64% on EN. The empirical results of the second method reveals that constant correlation coefficient has its disadvantage in diversifying portfolios.

Regressions of sectoral stock returns on business cycles show that all sectors have positive parameters in expansions and negative parameters in contractions. Considering a four stage classification, I find that sectors have varying performance through business cycles. Some sectors are influenced intensely by business cycles but some sectors are not affected at all. The multifarious behaviors of sectors provide some possibilities to diversify portfolios among sectoral stock markets.

Table 1.1: Basic Sectors and their Abbreviations

Abbreviation	Full name	Abbreviation	Full name
US	US whole market	BM	Basic materials
NC	Consumer goods	CY	Consumer service
FN	Financials	HC	Health care
IN	Industrials	EN	Oil & gas
TC	Technology	TL	Telecommunication
UT	Utility		

Note: The abbreviations for sectors follow the convention of Dow Jones.

Table 1.2: Constant Correlation Coefficients (ρ) between Sectoral Stock Returns and GDP Growth Rate

Sectors	US	BM	NC	CY	FN	HC	IN	EN	TC	TL	UT
ρ	0.55	0.43	0.43	0.49	0.48	0.45	0.55	0.45	0.45	0.32	0.35

Note: 1. The abbreviations are the same as in Table 1.1.
2. The numbers under the abbreviations are the correlation coefficients between the stock returns of corresponding sectors and GDP growth rate.

Table 1.3: Correlation (ρ) and Covariance between GDP Growth Rate and Each Sector

	ρ between GDP growth rate and sectoral stock returns	Covariance between GDP growth rate and sectoral stock returns	Standard deviation of each sector
US	0.55	0.00026	0.07
BM	0.43	0.00030	0.11
NC	0.43	0.00017	0.06
CY	0.49	0.00025	0.08
FN	0.48	0.00032	0.1
HC	0.45	0.00019	0.07
IN	0.55	0.00030	0.08
EN	0.45	0.00025	0.09
TC	0.45	0.00035	0.12
TL	0.32	0.00019	0.09
UT	0.35	0.00016	0.07
Ave	0.44	0.00025	0.09

Note: The quarterly data and the abbreviation are the same with Figure 1.1.

Table 1.4: Estimated Parameters of DCC-GARCH Model between GDP Growth Rate and Each Sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sectors	c_{im}	a_i	c_{iv}	α_i	β_i	λ_1	λ_2
US	0.019*	0.15	0.0007	0.36*	0.57*	0.26	0.41
	(0.007)	(0.14)	(0.0007)	(0.16)	(0.23)	(0.17)	(0.42)
BM	0.007	0.29*	0.004*	0.42*	0.29	0.1	0.84*
	(0.01)	(0.13)	(0.0023)	(0.17)	(0.23)	(0.09)	(0.09)
NC	0.018*	-	0.0013	0.12	0.55*	0.03	0.95*
	(0.007)	-	(0.0011)	(0.09)	(0.29)	(0.14)	(0.06)
CY	0.007	0.25*	0.001	0.16	0.7*	0.04	0.92*
	(0.009)	(0.12)	(0.001)	(0.17)	(0.18)	(0.06)	(0.07)
FN	0.01	0.22*	0.0046*	0.52*	-	0.02	0.93*
	(0.01)	(0.12)	(0.0013)	(0.3)	-	(0.03)	(0.06)
HC	-0.01	-	0.0015*	0.09	0.61	0.09	0.11
	(0.01)	-	(0.0019)	(0.12)	(0.41)	(0.13)	(0.42)
IN	0.022*	0.2	0.0013	0.49*	0.46*	0.57*	0.06
	(0.008)	(0.14)	(0.0014)	(0.21)	(0.27)	(0.17)	(0.15)
EN	0.021*	0.25*	0.0051*	0.37*	-	0.36*	0.52*
	(0.008)	(0.1)	(0.0011)	(0.19)	-	(0.14)	(0.18)
TC	0.026*	0.27*	0.0027*	0.28*	0.52*	0.16	0.17
	(0.012)	(0.12)	(0.0015)	(0.16)	(0.18)	(0.13)	(0.48)
TL	0.013	0.32*	0.0037*	0.3*	0.14	0.05	0.92*
	(0.009)	(0.11)	(0.0019)	(0.16)	(0.34)	(0.06)	(0.05)
UT	0.019*	0.14	0.0009	0.17	0.62*	0.24*	0.44*
	(0.009)	(0.13)	(0.0006)	(0.13)	(0.15)	(0.12)	(0.16)

Note: 1. Parameters followed by a star are significant at ten percent level. 2. Numbers in parentheses are standard deviations. 3. Parameters of GDP growth rate are not listed. 4. Some of the maximum log-likelihood iterations do not converge, so I put a few restrictions on several parameters to obtain the DCC: restrict GDP growth rate to an AR(1)-GARCH(1,1) without constant for sectors BM, CY, FN, HC and EN; restrict GDP growth rate to a random walk GARCH(1,1) process for HC and UT; restrict stock returns on NC and HC to random walk GARCH(1,1) processes; restrict stock returns on FN and EN to ARCH(1) processes. A dash in columns a_i or β_i means the parameter for AR(1) or GARCH(1) is restricted to zero. I also find that HC has a converged DCC GARCH process when using GARCH (1,2) for its stock return.

Table 1.5: Statistics of Dynamic Conditional Correlation for Each Sector

	Max	Min	Mean	STD
US	0.89	-0.20	0.41	0.22
BM	0.80	-0.08	0.32	0.23
NC	0.52	0.01	0.22	0.15
CY	0.59	0.01	0.31	0.15
FN	0.32	0.01	0.15	0.08
HC	0.74	0.42	0.57	0.06
IN	0.97	-0.63	0.40	0.34
EN	0.93	-0.64	0.29	0.39
TC	0.74	-0.11	0.37	0.13
TL	0.54	-0.17	0.12	0.19
UT	0.85	-0.32	0.24	0.25

Note: The first column is the maximum value of DCCs for each sector. The second column is the minimum value. The third column is the mean. The fourth column is the standard deviation.

Table 1.6: The NBER Business Cycle Information from July 1990 to June 2009

Peak	Trough	Contraction	Expansion
July 1990	March 1991	8	92
March 2001	November 2001	8	120
December2007	June 2009	18	73

Table 1.7: Four Stages of Business Cycles

Stages	Periods	length: in month
Stage I	1992/02-1996/03, 2001/12-2004/11, 2009/07-2011/12	109
Stage II	1996/04-2001/03, 2004/12-2007/12	97
Stage III	2001/04-2001/07, 2008/01-2008/09	13
Stage IV	2001/08-2001/11, 2008/10-2009/06	13

Note: Because my sector stock returns data start from 1992 and end at 2011, I define the four stages complying with that time. However, the division points are still the same with in Table 1.6.

Table 1.8: Regression Results of Each Sector Stock Returns on Four Dummy Variables of Business Cycles

Sectors	c_1	c_2	c_3	c_4
US	0.0072	0.0081*	-0.0136	-0.0226*
	(0.0041)	(0.0045)	(0.0124)	(0.0124)
BM	0.0091	0.0037	-0.0161	-0.0219
	(0.0061)	(0.0067)	(0.0182)	(0.0182)
NC	0.0079*	0.0055	-0.006	-0.0168
	(0.0036)	(0.0039)	(0.0106)	(0.0106)
CY	0.0083	0.0076	-0.0051	-0.0209
	(0.0047)	(0.0051)	(0.0139)	(0.0139)
FN	0.0107*	0.0078	-0.0199	-0.0426*
	(0.0056)	(0.0061)	(0.0166)	(0.0166)
HC	0.0042	0.0108*	-0.006	-0.0093
	(0.004)	(0.0044)	(0.012)	(0.012)
IN	0.009*	0.0064	-0.0133	-0.0297*
	(0.0049)	(0.0053)	(0.0146)	(0.0146)
EN	0.0095*	0.0137*	-0.0179	-0.0287*
	(0.0052)	(0.0057)	(0.0156)	(0.0156)
TC	0.0089	0.0114	-0.0163	-0.0088
	(0.0073)	(0.008)	(0.0219)	(0.0219)
TL	0.0032	0.0063	-0.028*	-0.0223
	(0.0054)	(0.0059)	(0.016)	(0.016)
UT	0.004	0.0089*	-0.0266*	-0.0282*
	(0.0039)	(0.0043)	(0.0117)	(0.0117)

Note: The first row for each sector lists the estimated parameters of the dummy variables. The numbers with parentheses are standard deviations. A * means the parameter is significant at 10 percent.

Table 1.9: Business Cycle Effects on Sectoral Stock Returns: Sorted by Magnitude of Coefficients

Sector	c_1	Sector	c_2	Sector	c_3	Sector	c_4
FN	0.0107*	EN	0.0137*	TL	-0.028*	FN	-0.0426*
EN	0.0095*	TC	0.0114	UT	-0.0266*	IN	-0.0297*
BM	0.0091	HC	0.0108*	FN	-0.0199	EN	-0.0287*
IN	0.009*	UT	0.0089*	EN	-0.0179	UT	-0.0282*
TC	0.0089	US	0.0081*	TC	-0.0163	US	-0.0226*
CY	0.0083	FN	0.0078	BM	-0.0161	TL	-0.0223
NC	0.0079*	CY	0.0076	US	-0.0136	BM	-0.0219
US	0.0072	IN	0.0064	IN	-0.0133	CY	-0.0209
HC	0.0042	TL	0.0063	HC	-0.006	NC	-0.0168
UT	0.004	NC	0.0055	NC	-0.006	HC	-0.0093
TL	0.0032	BM	0.0037	CY	-0.0051	TC	-0.0088

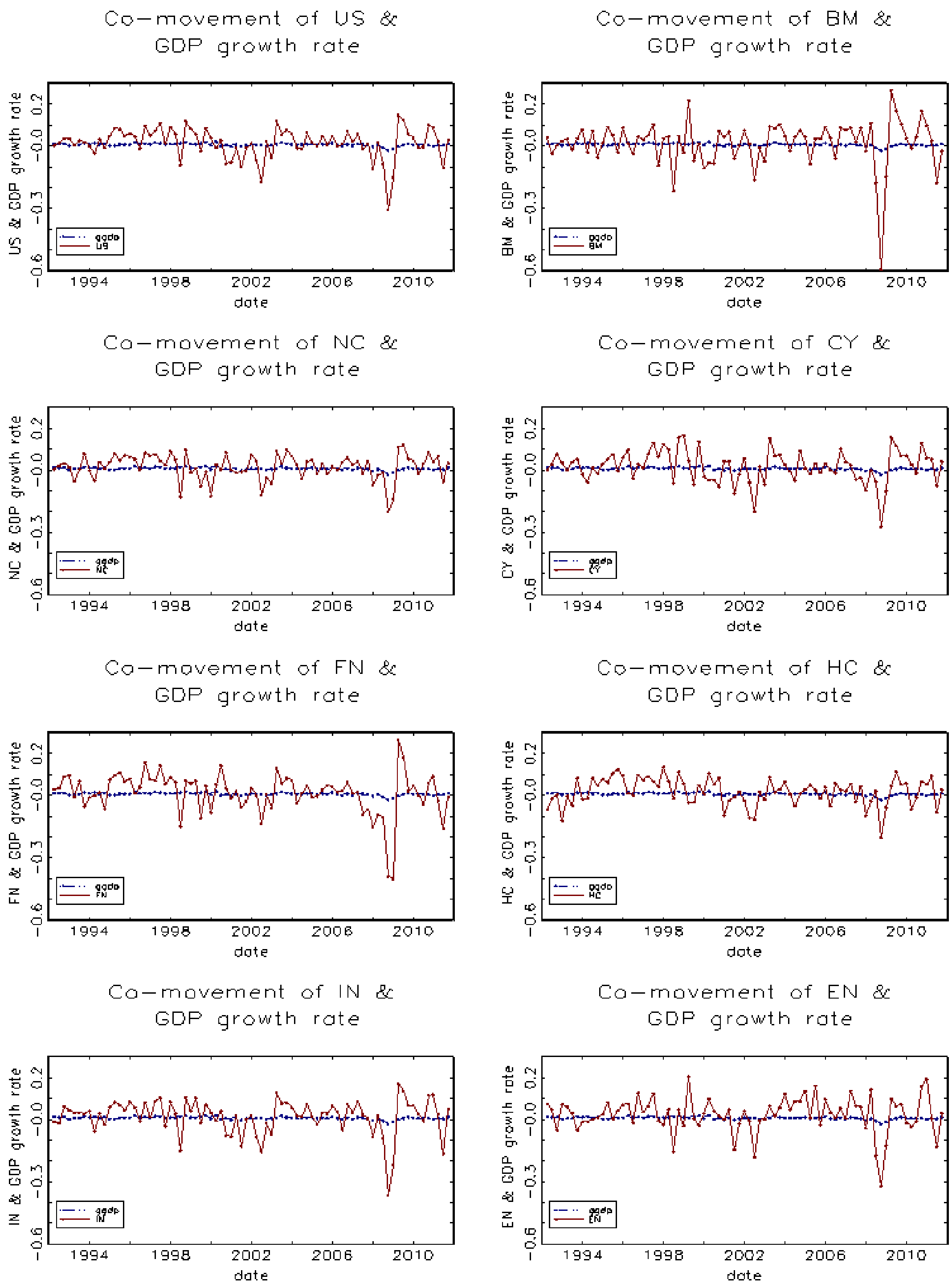
Note: c_1 to c_4 indicate the parameters of each dummy variable of business cycles corresponding to each sector. All parameters are ordered by the absolute value.

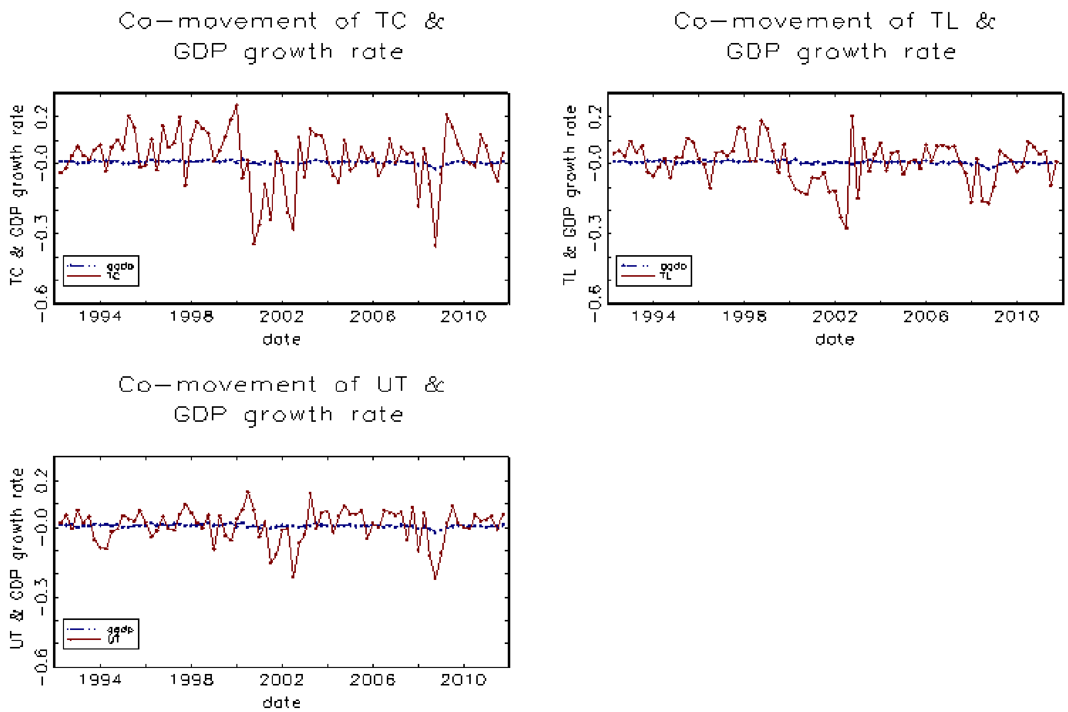
Table 1.10: Suggestions for Portfolio Management

	Stage I	Stage II
Enter	Financials *	Oil & gas*
	Oil & gas*	Technology
	Basic materials	Health care*
	Industrials*	Utilities*
	Technology	US whole market*
	Consumer service	Financials
	Consumer goods*	Consumer service
	US whole market	Industrials
	Health care	Telecommunication
	Utilities	Consumer goods
	Telecommunication	Basic materials
	Stage III	Stage IV
Exit	Telecommunication*	Financials*
	Utilities*	Industrials*
	Financials	Oil & gas*
	Oil & gas	Utilities*
	Technology	US whole market*
	Basic materials	Telecommunication
	US whole market	Basic materials
	Industrials	Consumer service
	Consumer goods	Consumer goods
	Health care	Health care
	Consumer service	Technology

Note: 1.Depending on the signs of dummy variable parameters, investors should enter in Stage I and Stage II and exit in Stage III and Stage IV. 2. The sectors listed under each stage are ordered according to the magnitude of the dummy variable parameters. 3. A * indicates the parameter of the sector is significant.

Figure 1.1: Co-movement of Sectoral Stock Returns and GDP Growth Rate, Quarterly Data



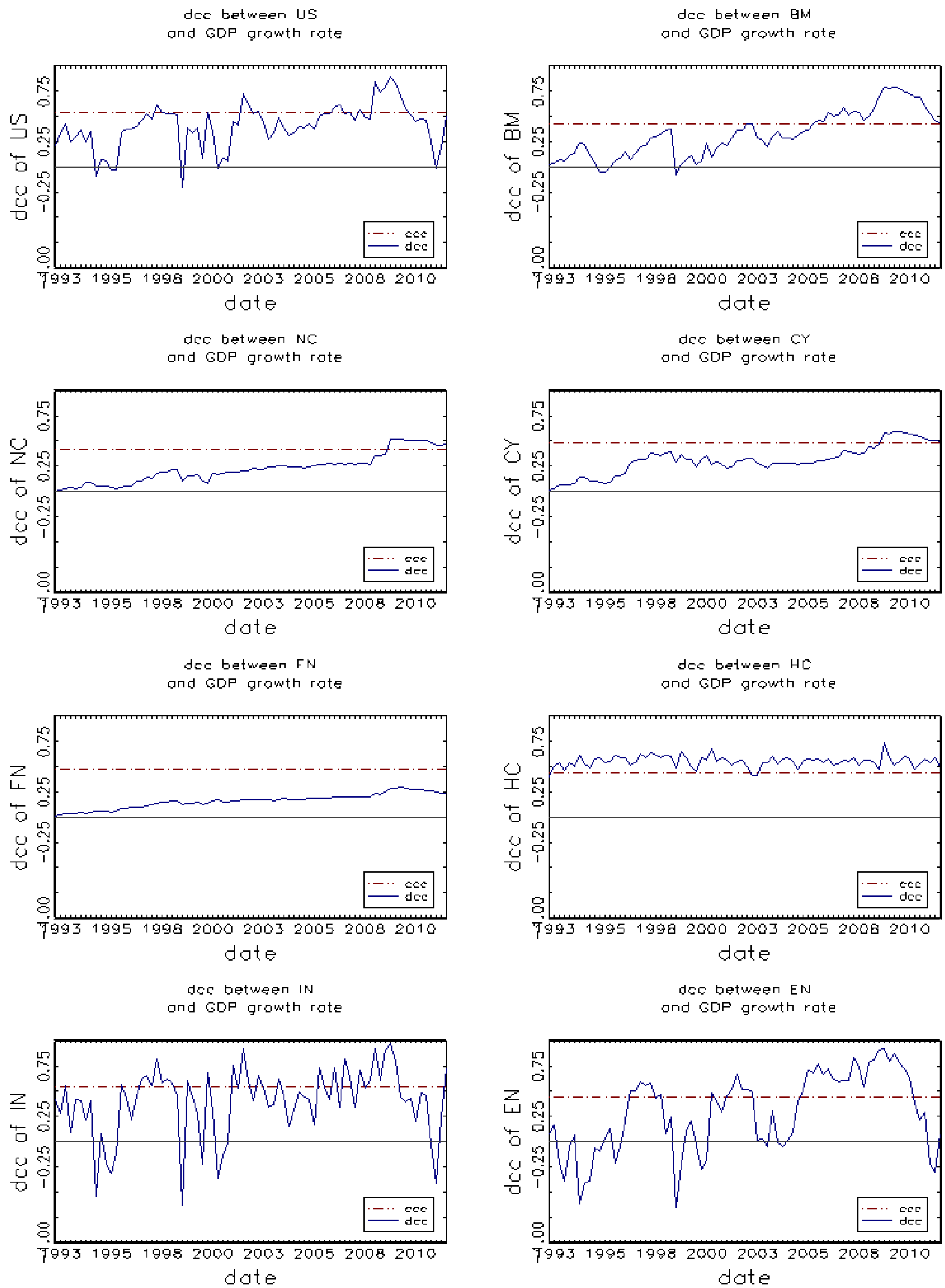


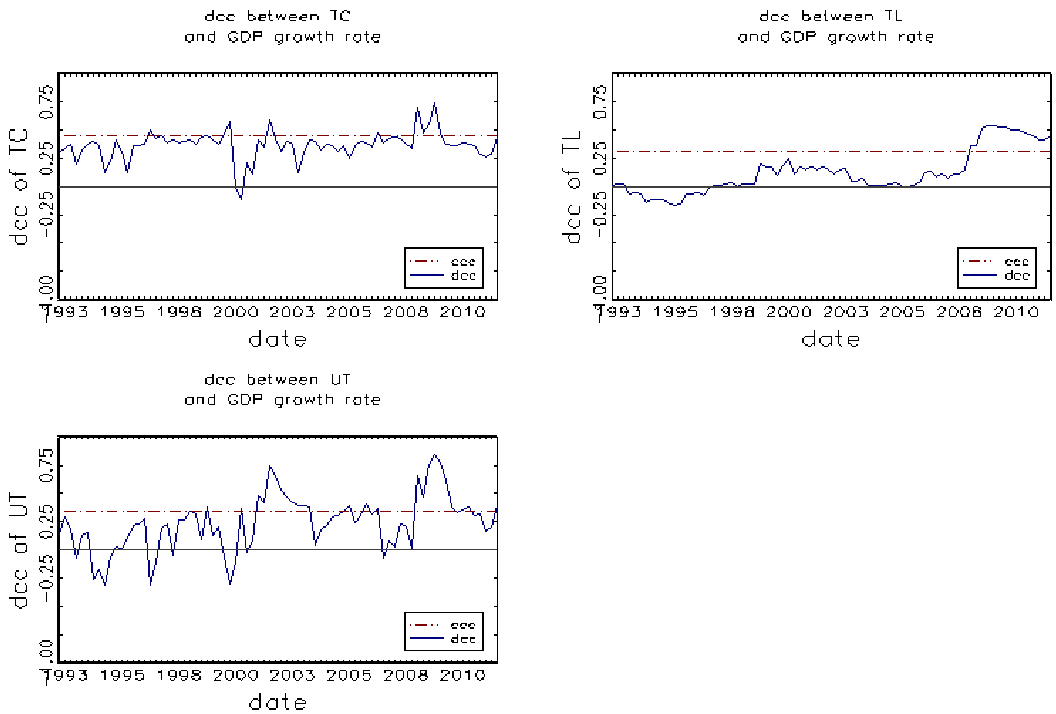
Note: 1. Quarterly GDP data come from the BEA website[4]. Quarterly sectoral stock returns data are calculated from quarterly sectoral stock prices, which are the average of daily stock prices. All the sectoral stock data come from the Dow Jones website[5]. All the data are from the second quarter of 1992 to fourth quarter of 2011. The GDP growth rate is calculated by the formula: $ggdp_t = ln(GDP_t/GDP_{t-1})$, and the stock returns is calculated by the formula: $SR_{i,t} = ln(SP_{i,t}/SP_{i,t-1})$, where ggdp means growth rate of GDP, SR means stock returns, and SP means stock price. 2. Abbreviations for sectors are defined as in Table 1.1. 3. The Dow Jones does not provide stock returns data for sector of Technology for year 1998, therefore, I use interpolation to estimate the four quarterly data in 1998 by using the 1997 last quarter data and the 1999 first quarter data.

[4] The website address is http://www.bea.gov/iTable/iTable.cfm?ReqID=9&step=1

[5] The website address is http://www.djindexes.com/investable-products/?assetclass=equity&tab=globalindexes.

Figure 1.2: Dynamic Conditional Correlation Coefficient between GDP Growth Rate and Each Sector





dcc between TC
and GDP growth rate
dcc of TC
date
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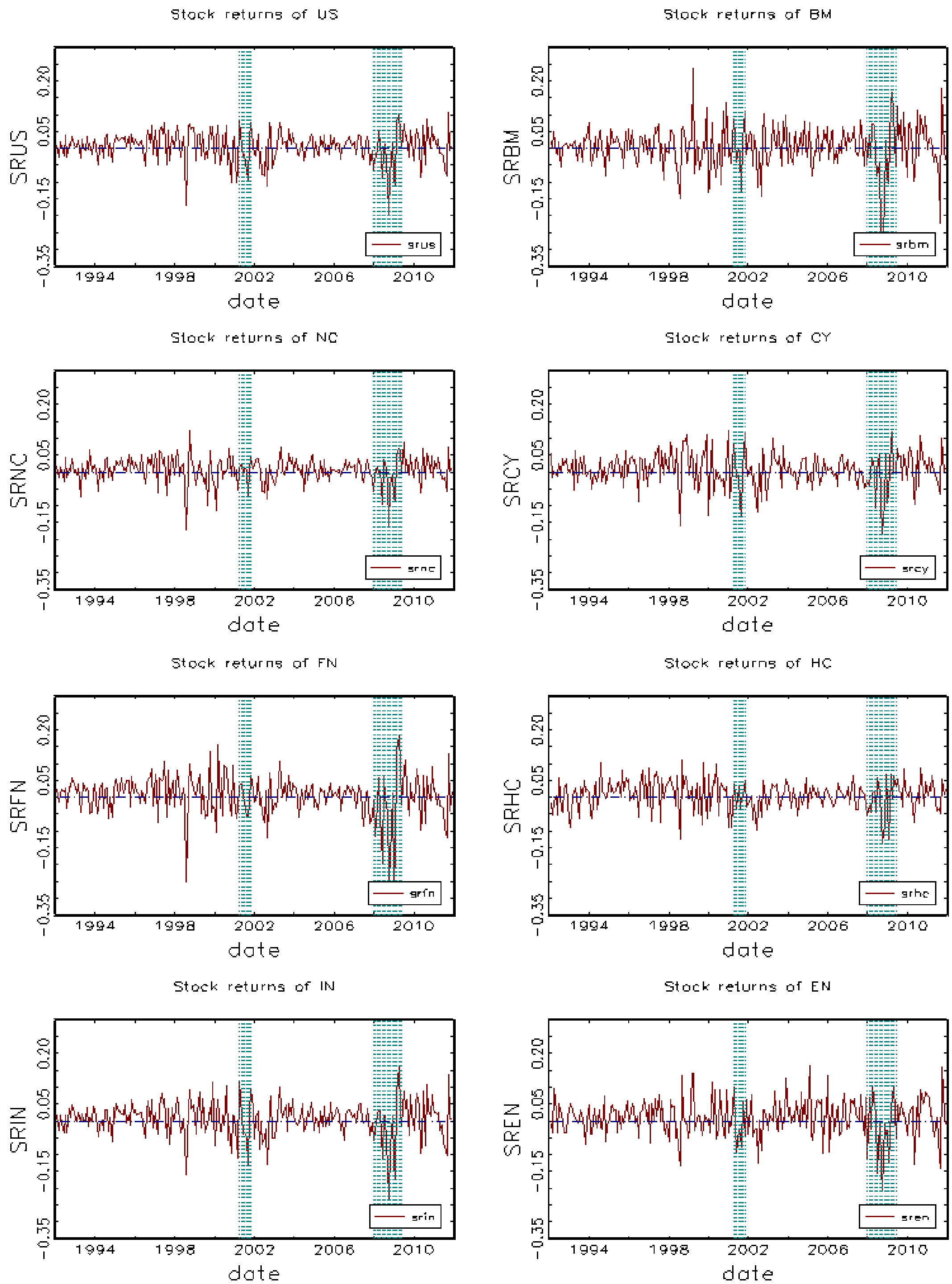
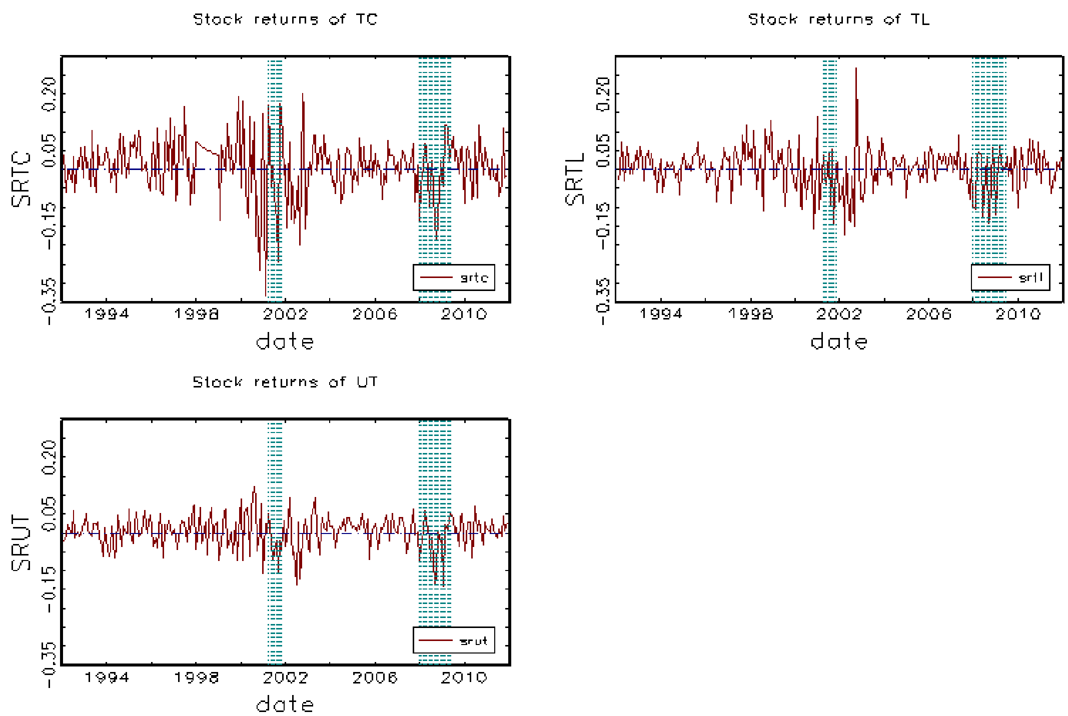
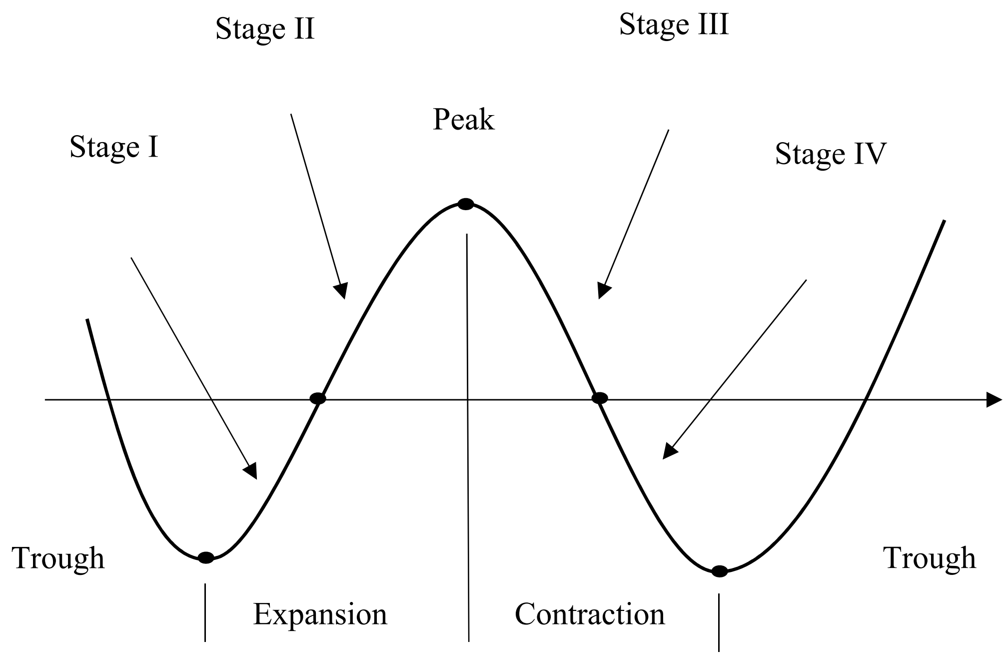
Figure 1.3: Sectoral Stock Returns over Business Cycles





Note: Red line in each panel is sectoral stock returns, from 1992 February to 2011 December. Shadowed areas in each panel indicate economic depressions.

Figure 1.4 Four Stages of a Business Cycle



Not
e:
A full business cycle is from a trough to the next trough. An expansion is from a trough to the next peak. A contraction is from a peak to the next trough. The middle point of an expansion divides it into two parts, Stage I and Stage II. The middle point of a contraction divides it into two parts two, Stage III and Stage IV.

CHAPTER 2

ASYMMETRIC BUSINESS CYCLE EFFECTS ON US SECTORAL STOCK RETURNS

2.1 Introduction

To describe and predict stock return is an interesting but difficult assignment. Though many theories and models are devoted to this task, it is still an unsolved problem. For example, Arbitrage Pricing Theory (APT) assumes that there are n factors which may affect a firm's stock returns. But it does not tell us what these n factors are. Most commonly accepted factors are the Fama and French (1989) three factors: dividend yield, default premium, and term premium. However, Campbell and Diebold (2009) use a well-established database to demonstrate that, actually, these three factors have power to predict stock returns only because they contain information about business conditions. Their result reinforces Daniel and Torous (1991) who also claim that the default premium and the term premium are qualified to predict stock returns only because they possess business cycle information. As a consequence, the business cycle sometimes replaces macroeconomic and financial variables to describe and predict stock returns directly.

There are numerous papers that investigate the business cycle effect on stock returns, but they all concentrate on the whole market. Among those papers, Fama and French (1989) show that dividend yield, default spread, and term spread are inversely related to business conditions (the business cycle) and positively related to expected stock returns. The opposite directions imply a negative relationship between stock returns and the business conditions. Similarly, Campbell and Diebold (2009) confirm the same negative relationship using seven different proxies of the business cycle.

An interesting phenomenon is that, although the whole market is negatively related to the business cycle, sectoral stock markets show mixed comovements with the business cycle. It is widely accepted that sectoral stock returns behave as pro-cyclical, counter-cyclical, or acyclical. This is equivalent to express that sectoral stock returns are positively related to, negatively related to, and not related to the business cycle. Needless to say, the aggregated market stock index cannot reflect the different relationships between the business cycle and sectoral stock indices. Reasons for distinct reactions of sectors to the business cycle are straightforward. Sectors are composed of different enterprises which will be influenced by many factors, such as organization structures, labor quality, production cost, transaction cost, information transmission channel, sensitivity to macroeconomic variables, and so on. All these factors affect the operation of an enterprise, and make the behavior of the enterprise different from that of others. Discrepancy of operation and behavior among enterprises will finally be reflected in their market value. When I categorize all enterprises into some sectors, the individual specific characteristics will be absorbed by those sectors. The categorization produces two results: first, being a collection of enterprises, a sector shall contain the common properties of its belongings, and reflect these properties in its stock index. Second, each sector will have its own qualities which are different from others' and manifested by the stock index. Hence, sectoral level research is valuable and necessary.

Broadly speaking, research on a specific sector, or some related sectors, can be regarded as sectoral research. Such sectors always have important connections with the whole economy, or reveal very diverse traits compared to other sectors. Among these sectors, financials is the most frequently studied. There is a huge amount of literature that discusses the financials sector and its subsectors, like banks, real estates, insurance companies, and so on. For detailed literature reviews, one can refer to Agbloyor, Abor, Adjasi, and Yawson (2012), and Lee, Chien, and Lin (2012). Besides the financial sector, some real sectors have also been considered, such as high technology sector (Han and Shen (2007)), basic materials (Kutan, Muradoglu, and Sudjana (2012)), oil and gas (Mohanty, Nandha, and Bota (2010)), and a subsector called sin sector, which involves tobacco, alcohol and gaming (Salaber (2007)). Papers mentioned above provide valuable results for sectoral stock returns.

However, for my particular purpose, I need to encompass all sectors. I follow previous literature in classifying the stock market into ten sectors: basic materials, consumer goods, consumer service, financials, health care, industrials, oil & gas, technology, telecommunication, and utility. For simplicity, I abbreviate them to BM, NC, CY, FN, HC, IN, EN, TC, TL, and UT. This classification has been used by Dow Jones Global Index, Thomson Reuters Datastream Sector Index, FTSE Sector Index, and some other major indexes.

Literature has already described some unique features of different sectors. Arouri (2011) investigates effects of crude oil price fluctuations on 12 Europe sectoral stock indices and national index. By broadening the perspective from aggregated level to disaggregated sectoral level, he compares the sensitivity of sectoral stock returns and the whole market returns to oil price changes. Results from his paper show that strength of the association between oil price change and stock returns varies greatly across sectors. Similar works can be found in Arouri, Jouini and Nguyen (2011, 2012), Arouri and Nguyen (2010), and Nandha and Faff (2008), which all pay attention to the relationship between the oil price and sectoral stock returns. There are also some papers that examine the effect of exchange rates on sectoral stock returns. Jayasinghe and Tsui (2008) start from three aspects to test the influence of exchange rate exposure on sectoral stock returns in Japan: sensitivity of sectoral returns to changes in exchange rate of the yen; sensitivity of the conditional volatility of sectoral returns to changes in exchange rate of the yen and its possible asymmetric effect; and the correlation between sectoral returns and exchange rate changes. Their results are fruitful in that they present different sensitivities of sectors and distinct time varying processes of correlations between sectors and exchange rate exposure.

One major concern on sectoral stock research is the comovement of disaggregate market and aggregate market. The direct approach for this consideration is to investigate the relationship between aggregate index and sectoral indexes. For example, Balli and Balli (2011) introduce ten sectors and some subsectors to test the existence of the structural change effect of the EMU's emergence. They find that the aggregate Euro equity index affects many sectoral indices, especially the financials sector. However, some non-financial sectors, like basic resources, food and beverages, health-care, retail services, oil & gas, and utility show less dependence on the aggregate Euro equity index. Sehgal and Jain (2011) introduce ten sectoral indices as well as aggregate index, the BSE-500, of Indian stock market to explain the reasons for success of the momentum trading strategy. Their research shows that a large part of stock momentum profits is captured by sectoral factors. They conclude that sectoral momentum accounts for a major part of aggregate momentum.

The comovement of disaggregate market and aggregate market is closely related to the relationship between sectoral stock returns and the business cycle. The business cycle is a main representation of an economy, which intrinsically relates to the aggregate market behavior. Therefore, the business cycle becomes a good variable to analyze sectoral stock returns. Berdot, Goyeau, and Leonard (2006)) take the business cycle into consideration and introduce exchange rate to analyze sectoral stock returns. Using French sectoral stock returns and US business cycle data, they inspect exchange rate effects on the sectors. They calculate covariations between US business cycle and French market sectoral stock returns. Then they estimate significant lags/leads length to the business cycle for each sector. With this information, they classify the French sectoral stock indices as early sectors, lagging sectors, and concurrent sectors. Their final results show that the whole market and the sectoral markets are divergent, and reveal that the aggregate level index may average out different feedbacks of sectoral returns to business conditions. Related analysis can be found in Choi and Zeghal (2002) and Koutmos and Martin (2007).

Above evidence asserts that sectors follow different stochastic processes which cannot be identified by aggregate index data. Early literature has demonstrated that the actual power of explanatory factors stems from their inherent business cycle information. Therefore, in the present paper, I follow these previous research results to use the business cycle to explain and predict sectoral stock returns.

I intend to address two issues in discussing business cycle effects on sectoral stock returns. In the first part I want to discern the relationship between the business cycle and sectoral stock returns in two channels simultaneously: business cycle effects on the mean of sectoral stock returns and business cycle shocks' effects on the volatility of sectoral stock returns. Mean and volatility are two major characteristics of stock returns. However, up to now, there is no such research which considers effects of the business cycle on both of them. Thus, one purpose of this paper is to discuss both mean and volatility effects. A GARCH model is developed for this purpose. In the second part, where an ARCH-M model will be applied, I want to detect possible relationships between risk of the business cycle and returns of sectoral indexes. Square root of the conditional variance of the business cycle series will be used as the risk measure which will exert its explanatory power on sectoral stock returns. This square root appears like an "exogenous ARCH term", resembling own ARCH term of sectoral stock returns. I try to use this exogenous term to illustrate the risk-return relationship between the business cycle and sectoral stock returns. Thus, with the first model, I can capture the parallel business cycle effect on the first and second moments of sectoral stock returns, and with the second model, I can capture the cross effect of the second moment of the business cycle on means of sectoral stock returns.

One important consideration is that the impact of the business cycle may be asymmetric. The asymmetry is widely documented and accepted in the literature. For example, comparing sectoral stock indices and US economic peaks and trough from 1973 to present, one can note that stock prices always drop earlier than the business cycle's troughs, excepting the trough in November 2001, while movements of stock prices around the peaks are mixed where a lot of concurrences exist. Therefore, I split the business cycle into positive and negative parts to model this asymmetric impact. A benchmark symmetric model will be set up and evaluated first, and then an asymmetric model will be introduced and estimated. As a result, the asymmetry I mentioned in this paper has two layers: the first is the asymmetric effect of the business cycle on stock returns of different sectors of an economy; the second is the asymmetric effect of the different periods of the business cycle, the expansion and the recession, on sectoral stock returns.

The rest of this paper is organized as follows. Section two elaborates on data issues, mainly regarding the data sources and selection of the proxy for the business cycle; section three sets up the models, namely the symmetric and asymmetric parallel business cycle effect model, and the symmetric and asymmetric cross business cycle effect model; section four provides empirical results; section five concludes.

2.2 Data

According to Federal Reserve Bank's release H.15, annualized discount yield on 3-month Treasury bill is used as interest rate. I use this variable as the risk-free asset return in the paper. All other data are obtained from Datastream. The ten sectors studied along with the abbreviations used to refer to them are summarized in Table 2.1. I also analyze returns on the aggregate US stock market index. For simplicity, the ten sectors along with the aggregate US market index are referred to as eleven sectors in the rest of this paper.

There are two potential proxies for the business cycle, GDP and Industrial Production. GDP is the most comprehensive, and therefore contains most information about the business cycle. However, it is only measured at a quarterly frequency which is not suitable for my purposes. Studying quarterly stock returns will not enable us to answer some of the questions being addressed here, such as the business cycle's volatilities effects on sectoral indices' volatilities, and the business cycle's risk effects on sectoral indices' returns. Answering these questions requires us to use models being able to analyze volatilities. High-frequency data with GARCH effects better satisfies my purposes. Therefore, Industrial Production (IP) is chosen as a proxy for the business cycle. It is measured on a monthly basis.

One problem of using IP is that its release date lags behind its occurrence. For example, IP index in January 2014 is released on February 14th. Consequently, January's IP growth rate will affect stock market staring from February 15th. Its effect will end on March 17th when February's IP index is released. The release process reminds us to calculate monthly stock returns depending on release dates rather than on calendar dates. Table 2.2 displays release dates of IP index and implied time correspondence between IP and stock market. My data span the period from February 1973 through February 2014.

Using information in Table 2.2, I compute monthly sectoral stock indices sp_t as an average of daily stock indices over that month (Note, the "month" here is different from the calendar month.) Let sr_t denote monthly sectoral stock returns at time t. These are obtained as: $sr_t = ln(sp_t) - ln(sp_{t-1})$. Monthly IP growth rate (clearly calendar month) is defined by the same formula. Then, for easier interpretation, monthly sr_t and IP growth rate are annualized into percent per year. Some main statistics of the variables are summarized in Table 2.3 and Table 2.4.

Table 2.3 displays the minimum and maximum values for returns, along with their dates of occurrences. Two features are worth noting. First, all sectors, excepting TL and UT, have their minima during the stock market crash of 1987. However, for all other sectors, maxima occur in different months of different years. Second, the range of minima is greater than the range of maxima. The lowest return is -395 percent per year on CY. Other minima range from –394 to -201. The highest return is 251 on FN. Other maxima range from 135 to 229.

Table 2.4 displays other main statistics. During the period studied, average return on US whole market is 7 percent per year. Among individual sectors, the highest average return is 9 percent per year on HC and the lowest is 3.4 on UT. Average returns on NC, TL and UT are lower than average interest rates, which is 5.2 percent per year. The third column lists standard deviations. Standard deviations of sectoral stock returns are much higher (about 13 times to 21 times) than that of interest rates. Columns 4 and 5 provide skewness and kurtosis of each series. The negative numbers on skewness and large magnitudes on kurtosis tell us that stock returns are left skewed and have higher modes and fatter tails than a normal distribution.

2.3 The Econometric Model

Generally, I can write expected stock returns $E_{t-1}(r_t)$ as a function of business conditions at time t-1:

$$E_{t-1}(r_t) = F(X_{t-1})$$

where X_{t-1} denotes business conditions at t-1. This function indicates that, based on the information about business conditions at t-1, investments made at t-1 expect to get returns at t.

Explicit forms of the function and specific variables for X_{t-1} vary according to the models. With a focus on asymmetric business cycle effects on sectoral stock returns, I set up two econometric time series models: parallel business cycle effect model and cross business cycle effect model. Different components of the IP growth rate are employed as X_{t-1} in these models. Specifically, in the parallel effect model, I use the IP growth rate to explain sector returns and its shocks to explain sector conditional variances. In the cross effect model, I use square root of conditional variance of IP growth rate to explain sector excess returns.

2.3.1 Parallel Business Cycle Effect

2.3.1.1 Symmetric Parallel Business Cycle Effect

My major concerns are asymmetric effects. Before discussing asymmetric effects, I set up a symmetric model to reveal the general effect of the business cycle and to provide the basis for evaluating the asymmetric effects. Frameworks of the symmetric model and the asymmetric model are the same. The difference between them is just the component of the explanatory variable X_{t-1}.

With the parallel model I aim at two points: the business cycle's effects on mean of sectoral stock returns, and spillover effects from the business cycle's volatilities to volatilities of sectoral stock returns. A GARCH model enables us to discuss these two problems simultaneously. The first order lag of IP growth rate is included in the mean equation of sectoral stock returns. Though stock returns always have strong tendency to be autoregressive, some other factors may also have powerful explanatory role on the mean of them. Besides, since different sectors are composed of different enterprises, these factors may have distinct effects from sector to sector. By including the lag of IP growth rate, I hope to verify the variation of business cycle effect over sectors' means. Then, the first order lag of squared residuals from autoregression of IP growth rate, which designate shocks to the business cycle, are inserted into the GARCH processes of sectoral stock returns. Its parameters can reveal the discrepancy of spillover effects of the business cycle on sectors.

The mean equations of IP growth rate is given by:

$$r_{gt} = c_{gm} + a_{g1}r_{gt-1} + a_{g2}r_{gt-2} + a_{g3}r_{gt-3} + \varepsilon_{gt} \tag{1}$$

The subscript g indicates that the parameter is used for growth rate of IP and the subscript m indicates that the parameter is used for mean equation. I assume that IP growth rate is a function of its own lags. Preliminary analysis for the ACF of IP growth rate indicates that the order of autoregressive process should be set to three. The residual of equation (1) ε_{gt}, is assumed to follow a GARCH (1, 1) process:

$$\varepsilon_{gt} = v_{gt}\sqrt{h_{gt}} \tag{2}$$

$$h_{gt} = c_{gv} + \alpha_g \varepsilon_{gt-1}^2 + \beta_g h_{gt-1} \tag{3}$$

The conditional variance, h_{gt}, is described by equation (3). It depends on its own lag and the squared shock from last period. The subscript v indicates the parameter is used for variance equation. v_{gt} in equation (2) is a white noise process, such that $v_{gt} \sim \text{iid N}(0,1)$. Therefore the IP growth rate is an AR (3) – GARCH (1, 1) process.

Equation (4) is the mean equation of sectoral stock returns with symmetric business cycle effect.

$$r_{it} = c_{im} + a_i r_{it-1} + f_i r_{gt-1} + \varepsilon_{it} \tag{4}$$

I assume that all sectors share the same mean and variance equation. The subscript *i* indicates different sectors of an economy, which are US, BM, NC, CY, FN, HC, IN, EN, TC, TL, UT[6]. Other subscripts have the same meanings as in previous equations. The parameter f_i captures different business cycle effects on each sector. The residuals of the mean equation also follows a GARCH (1, 1) process:

[6] Please refer to Table 2.1 for sectors and their abbreviations.

$$\varepsilon_{it} = v_{it}\sqrt{h_{it}} \tag{5}$$

$$h_{it} = c_{iv} + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1} + \varphi_i \varepsilon_{gt-1}^2 \tag{6}$$

In equation (5), v_{it}~iid $\mathrm{N}(0,1)$ and is independent of v_{gt}. The conditional variance of ε_{it} depends on its own lag, square of its shock from last period, and the square of business cycle shock from last period. The parameter φ_i measures the spillover effect from the business cycle on volatility of each sector. As φ_i appears in the variance equation, it must have a positive value. Therefore, I can only compare the different business cycle effects on sectoral stock returns volatility from the magnitude of φ_i rather than the sign of it.

Because GARCH process for IP growth rate does not depend on any information of sectoral stock returns, I can first estimate equation (1), (2), and (3) to obtain ε_{gt} and h_{gt}, and then use them to estimate equation (4), (5), and (6). Thus, for this model I just need to estimate two separate GARCH processes.

2.3.1.2 Asymmetric Parallel Business Cycle Effect

Progressing to an asymmetric model, positive and negative portions of the business cycle's mean and variance need to be included in the mean and variance equation of sectoral stock returns, respectively. Developed from the symmetric model, the asymmetric model is as follows.

$$r_{gt} = c_{gm} + a_{g1} r_{gt-1} + a_{g2} r_{gt-2} + a_{g3} r_{gt-3} + \varepsilon_{gt} \tag{1}$$

$$r_{it} = c_{im} + a_i r_{it-1} + f_i^p r_{gt-1}^+ + f_i^n r_{gt-1}^- + \varepsilon_{it} \tag{7}$$

Equation (1) is the mean equation of IP growth rate which is exactly the same as the symmetric model. Equation (7) is the mean equation of sectoral stock returns which is a function of its first-order lag and asymmetric business cycle effects. In those subscripts, p indicates that the parameter is used for positive asymmetric term, and n indicates that the parameter is used for negative asymmetric term. The rest subscripts have the same meaning as before. Thus, f_i^p measures business cycle effects on the sectors in expansions and f_i^n measures effects in recessions. Both the sign and magnitude of f_i^p and f_i^n tell us the asymmetric business cycle effects. The asymmetric term r_{gt-1}^+ and r_{gt-1}^- are defined as:

$$r_{gt-1}^+ = \begin{cases} r_{gt-1}, & if\ r_{gt-1} \geq 0 \\ 0\ \ , & if\ r_{gt-1} < 0 \end{cases}$$

$$r_{gt-1}^- = \begin{cases} 0\ \ , & if\ r_{gt-1} \geq 0 \\ r_{gt-1}\ , & if\ r_{gt-1} < 0 \end{cases}$$

The residuals of the mean equations are still assumed to follow GARCH (1, 1) processes, namely:

$$\varepsilon_{gt} = v_{gt}\sqrt{h_{gt}}\ , \qquad \varepsilon_{it} = v_{it}\sqrt{h_{it}} \qquad (2), (5)$$

Where $v_{it}, v_{gt} \sim \text{iid N}(0,1)$ and v_{it} and v_{gt} are independent.

The conditional heteroskedasticities are as follows:

$$h_{gt} = c_{gv} + \alpha_g \varepsilon_{gt-1}^2 + \beta_g h_{gt-1} \qquad (3)$$

$$h_{it} = c_{iv} + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1} + \varphi_i^p \varepsilon_{gt-1}^{2+} + \varphi_i^n \varepsilon_{gt-1}^{2-} \qquad (8)$$

Equation (3) is the same as the previous model. Equation (8) is the variance equation of sectoral stock returns. The asymmetric term ε_{gt-1}^{2+} and ε_{gt-1}^{2-} are defined as:

$$\varepsilon_{gt-1}^{2+} = \begin{cases} \varepsilon_{gt-1}^2, & if\ \varepsilon_{gt-1} \geq 0 \\ 0\ \ , & if\ \varepsilon_{gt-1} < 0 \end{cases}$$

$$\varepsilon_{gt-1}^{2-} = \begin{cases} 0 \quad , & if\ \varepsilon_{gt-1} \geq 0 \\ \varepsilon_{gt-1}^{2}, & if\ \varepsilon_{gt-1} < 0 \end{cases}$$

Adding these two ARCH terms into the variance equation of sectoral stock returns can help us to detect possible asymmetric spillover effects of business cycle shocks. However, since the parameters φ_i^p and φ_i^n are both positive, I can only compare the asymmetric effect from their magnitudes.

Estimation strategy is the same as in the symmetric model.

2.3.2 Cross Business Cycle Effect

2.3.2.1 Symmetric Cross Business Cycle Effect

The ARCH-M model provides a good environment to comprehend the relationship between risk and return. Holt and Aradhyula (1998) introduce a multivariate generalized ARCH-M model to identify the feasible endogenous risk of US broiler industry under the CCC-GARCH framework. Polasek and Ren (2000) develop a VAR-GARCH-M model to verify possible feedback of exchange rates on their returns among US, Germany, and Japan. For my specific purpose, the second target of this paper is to find the effects of business cycle risk on sectoral stock returns.

The mean equation and the variance equation for the IP growth rate remain the same:

$$r_{gt} = c_{gm} + a_{g1}r_{gt-1} + a_{g2}r_{gt-2} + a_{g3}r_{gt-3} + \varepsilon_{gt} \tag{1}$$

$$\varepsilon_{gt} = v_{gt}\sqrt{h_{gt}} \tag{2}$$

$$h_{gt} = c_{gv} + \alpha_g \varepsilon_{gt-1}^2 + \beta_g h_{gt-1} \tag{3}$$

The new mean equation and variance equation for sectoral stock returns are:

$$r_{it} = c_{im} + \theta_i\sqrt{h_{it}} + \delta_i\sqrt{h_{gt}} + \varepsilon_{it} \tag{9}$$

$$\varepsilon_{it} = v_{it}\sqrt{h_{it}} \tag{5}$$

$$h_{it} = c_{iv} + \alpha_i\varepsilon_{it-1}^2 + \beta_i h_{it-1} \tag{10}$$

The residuals follow GARCH (1, 1) processes, where v_{it}, v_{gt}~iid $\mathrm{N}(0,1)$ and v_{it} and v_{gt} are independent. In the mean equation (9), the left hand side is the excess returns of a sectoral index. The excess return is calculated by subtracting the risk-free asset return from the sectoral stock returns. Here I use the monthly interest rate of the three month Treasury bill as the risk free asset return. On the right hand side, there are two risk factors: one is the risk of the sectoral index itself indicated by square root of its own conditional variance; the other one is the risk of the business cycle indicated by square root of the conditional variance of IP growth rate. Therefore, I can investigate the risk premium of a sectoral index under its own risk and risk of the business cycle.

2.3.2.2 Asymmetric Cross Business Cycle Effect

To explore potential asymmetric effects of good and bad news about the business cycle on the means of sectoral stock indices, I construct another model derived from the previous one. The new mean equation for sectoral stock returns is:

$$r_{it} = c_{im} + \theta_i\sqrt{h_{it}} + \delta_i^p\sqrt{h_{gt}}^{+} + \delta_i^n\sqrt{h_{gt}}^{-} + \varepsilon_{it} \tag{11}$$

The asymmetric terms $\sqrt{h_{gt}}^{+}$ and $\sqrt{h_{gt}}^{-}$ are defined as follows:

$$\sqrt{h_{gt}}^{+} = \begin{cases} \sqrt{h_{gt}}, & if\ \varepsilon_{gt-1} \geq 0 \\ 0 \quad , & if\ \varepsilon_{gt-1} < 0 \end{cases}$$

$$\sqrt{h_{gt}}^{-} = \begin{cases} 0 \quad , & if\ \varepsilon_{gt-1} \geq 0 \\ \sqrt{h_{gt}}, & if\ \varepsilon_{gt-1} < 0 \end{cases}$$

The parameters δ_i^p and δ_i^n can help us capture the positive and negative business cycle risk effects on the mean of sectoral stock returns. Because these two parameters are not constrained to be positive, both their signs and magnitudes will show asymmetric effects of the business cycle. The conditional variance of sectoral stock returns is still a GARCH (1,1) process and is the same as equation (10):

$$h_{it} = c_{iv} + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1} \tag{10}$$

2.4 Empirical Results

2.4.1 Symmetric Parallel Business Cycle Effect

Estimation results of the symmetric parallel business cycle effect model are summarized in Table 2.5. Estimated parameters for monthly growth rate of IP are at the bottom of the table. It is clear that r_{gt} follows a significant AR(3)-GARCH(1,1) process. All three lags have positive effects. The ARCH parameter is slightly bigger than the GARCH parameter showing that exogenous shocks affect IP growth rate to some extent but these effects do not persist for long.

Columns 1 to 3 in Table 2.5 are estimates of the parameters in equation (4). All intercepts and the first order autoregressive terms are significant. Slopes of the first order lags are comparatively stable: through all sectors, the slopes range from 0.149 to 0.315. But effects of IP growth rate vary from sector to sector. Two points are worth noting. First, all sectors bear a positive relationship with IP growth rate implying that all sectors are pro-cyclical. Second, for all sectors but NC, parameter for IP growth rate is bigger than that for sector's own lag. The biggest difference between these two parameters is on EN, where IP growth rate brings 4.9 times more changes than EN's own effect. The difference is especially important for US, IN, EN and UT whose parameters are significant. I can learn from this result that business cycle effects are consistently stronger than sectors' autoregressive effects.

Columns 4 to 7 in Table 2.5 are estimates of the parameters in equation (6). The ARCH effect and GARCH effect are significant for all sectors. Their parameters lie in 0.092 on EN to 0.443 on NC and in 0.167 on NC to 0.861 on EN. Most sectors, like BM, HC, IN, EN, TC, TL, and UT, have a small ARCH parameter and a large GARCH parameter. For these sectors, a temporary shock from last period has a small effect on current conditional variance, but this small effect will last for a long time. Sector NC has a large ARCH parameter and a small GARCH parameter. Thus, past shocks to NC have important but short effects on its current conditional variance.

The last column of Table 2.5 discloses the impact of IP growth rate shocks on volatilities of sectoral stock returns. The IP growth rate shocks almost do not affect volatilities of US, BM, HC, EN, TC, and TL. The estimated parameters for these sectors are displayed as 0s since they are smaller than 0.00001. However, for other sectors, IP growth rate shocks disturb their stability even more than their own shocks do. For example, one unit of shock to IP growth rate increases NC's volatility by 0.987 times and FN's volatility by 0.946 times, while one unit of shock to NC and FN only increases their volatility by 0.443 times and 0.336 times.

From above I can see that first order and second order moment of the business cycle have different effects over sectoral stock returns, and the differences are large from sector to sector.

2.4.2 Asymmetric Parallel Business Cycle Effect

Table 2.6 summarizes the estimated parameters of the asymmetric parallel business cycle effect model. Parameters of sectors' own factors are listed in columns 1-2 and columns 5-7. These estimation results almost replicate the results of the symmetric effect model. First, the autoregressive terms and the intercepts tend to have same algebraic signs and similar magnitudes, especially so for the autoregressive terms. The maximum AR parameter is 0.315 which occurs for sector CY and the minimum is 0.145 which occurs for sector EN. Second, the ARCH parameters and the GARCH parameters follow the pattern in previous model. For most sectors, effects of temporary shocks are small but last for a long time. While for NC, effects of shocks are strong but vanish quickly.

Columns 3 and 4 are estimated parameters for the asymmetric business cycle effects on means of sectoral stock returns. Generally, negative business cycle effects are stronger than positive ones. The smallest parameter for negative effects is 0.579 on BM while the largest parameter for positive effects is 0.335 on EN. The comparison strongly demonstrate that business cycle effects are asymmetric. We can use the asymmetric effects to explain the phenomenon why stock market crashes rapidly during depressions but flourishes moderately during expansions. Besides, negative business cycle effects are even stronger than the business cycle effects in symmetric model, referring to Table 2.5. Obviously, symmetric model will underestimate business cycle effects.

Comparing to sectors' own lag effects, negative business cycle effects are greater. Parameters for autoregressive terms range from 0.145 on EN to 0.315 on CY, while the smallest parameter for negative business cycle effects is 0.579. On the other hand, positive business cycle effects are greater for only two sectors, IN and EN. As a consequence, sectoral stock returns flourish during expansions mainly on the basis of their own momentum, but they are impaired primarily by the force of business cycle during depressions.

Though all sectors has a positive parameter for symmetric business cycle effect, BM, TC, and TL has a negative parameter for positive business cycle effect. Parameter signs reveal two categories of cyclical behavior of sectors, which is invisible under symmetric model: consistent behavior and reverse behavior. Sectors like US, NC, CY, FN, HC, IN, EN, and UT follow consistent behavior: they are pro-cyclical no matter during an expansion or a depression. Sectors like BM, TC, and TL follow reverse behavior: they are counter cyclical during an expansion and pro-cyclical during a depression. Given that business conditions is already known my conclusion will provides more accurate prediction for stock returns.

Figure 2.1 compares observed values of sectoral stock returns and their fitted values from the asymmetric parallel model. The pink solid curves and the black dotted curves indicate them, respectively. The figure shows that my model can predict stock returns to some extent. Since my model has a first order autoregressive term in the mean equation of sectoral stock returns, I use Figure 2.2 to compare fitted values between AR (1) model and my model. The gold solid curves are one step ahead forecast by AR (1). I still use the black dotted curves to indicate the one step ahead forecast by my model. Figure 2.2 shows that, for extreme values, my model has better forecast than AR (1). For example, my forecasts go deeper around troughs of 1974 and 2009, which are much closer to observed values than forecasts of AR (1). For EN and UT, my forecasts are constantly closer to observed values through the observation period. For NC and CY, the positive part of my forecasts approaches nearer to observed values. For other sectors, there is no obvious difference between my model and AR (1), excluding the mentioned extreme values.

Columns 8 and 9 are estimated parameters for asymmetric business cycle effects on volatilities of sectoral stock returns. As in the symmetric model, some estimates are smaller than 0.00001 and displayed as 0. Combining the estimation results from symmetric model, the sectors can be distinguished as four groups. For the first one, shocks to business cycle do not have spillover effects on them under both symmetric and asymmetric settings. The US whole market, BM, EN, TC, and TL fall into this group. For the second one, shocks to business cycle only have spillover effects in the symmetric model. This group contains UT and NC. For the third one, spillover effects only emerge in the asymmetric model, especially the negative side of the asymmetry. Health care is the unique sector in this group. For the last one, spillover effects exist in both models. Rest sectors, CY, FN, and IN are in this group. Among these three, FN is the sole sector which is affected by both positive and negative shocks. CY and IN are affected unilaterally by negative shocks.

The most sensitive spillover effect occurs on CY. The parameter for negative shocks to the business cycle is 2.636 on CY, comparing to 1.476 on FN, 0.253 on HC, 0.744 on IN, and 0.533 on FN for positive shocks. The result is similar to the symmetric model, external shocks have stronger impact than sector's own shocks. Parameters for ARCH terms are 0.349 on CY, 0.327 on FN, 0.093 on HC, and 0.161 on IN. All of them are smaller than the parameters for their corresponding external shocks. Moreover, since the GARCH parameters of these sectors are large, these external effects will last for a long time.

Figure 2.3 illustrates relationship between sectoral stock returns and asymmetric shocks to IP growth rate. Red dotted curves indicate sectoral volatilities. Gold solid curves and black solid curves are squared positive shocks and squared negative shocks, respectively. For easy viewing, I mirror squared negative shocks to the opposite direction. But keep in mind that their values are still positive. Since I use annualized data, difference of magnitude between second moments of IP growth rate and sectoral stock returns is quite large. Maxima of sectoral volatilities ranges from 8181 to 59111, but maxima of squared positive shocks and negative shocks to IP growth rate is only 899 and 2367. Therefore, when I draw these three series together, most points of the asymmetric shocks shrink to the horizontal axis. The discrepancy of the ranges makes it hard to detect the relationship between sectoral volatilities and the asymmetric shocks. However, we can still notice that two peaks of squared negative shocks strongly influence sectoral volatilities.

To summarize, business cycle has strong asymmetric effects on sectoral stock returns. Negative business cycle effects are generally stronger than the sectors' autoregressive effects. Negative shocks to the business cycle have strong spillover effects on CY, FN, HC, and IN. Good news on business cycle does not enhance existing sectoral stock volatilities, excepting for FN.

2.4.3 Symmetric Cross Business Cycle Effect

Table 2.8 summarizes estimation results of symmetric cross business cycle effect model. My major interest falls on the estimated parameters of the risk items in the mean equation (9). Their estimates are listed in columns 2-3. In column 2, I find that some sectors exhibit a negative relationship between their returns and risk, like NC, CY, HC, IN, EN, and UT. The negative relationship is quite different from the literature and contrary to economic theories. If an asset has risk, investors do not want to hold it unless it provides a risk premium. Risk and premium should have positive relationship, since only high premium can compensate for high risk. Otherwise, no investor will consider a risky asset for investment purposes.

One reason for negative parameters for ARCH-M term may lie in the low frequency of the data. When averaging daily stock index to generate monthly data, volatility of the series diminishes largely. Meanwhile, value of excess return will increase as it is accumulated during a month. Since the two variables develop toward opposite directions, the original positive relationship may reverse at some critical points.

Another reason for negative parameters for ARCH-M term may rest in the definition of risk. Generally, I use the second moment of a series to indicate its risk. However, when time of holding one asset increases, risk on the asset will enlarge. As a consequence, when frequency of a series falls, time of holding the asset should also be considered as a component of risk. In my model, time is not introduced as an explanatory variable, which will blur the relationship between risk and returns and produce some unusual phenomenon. However, since my interest focuses on business cycle effects, I will not cover the discussion about the time risk effect.

Column 3 lists the estimated parameters of business cycle risk for each sector. It turns out that business cycle risk will augment excess returns for some sectors, like BM, NC, CY, FN, and IN, but reduce them for other sectors, like US, HC, EN, TC, TL, and UT. Understanding the different effects can help us to predict sectoral excess returns when business cycle risk occurs. For example, one unit of business cycle change will increase CY's excess returns 2.367 times, but decrease UT's excess returns 1.403 times.

It is clear that business cycle risk has stronger effect on excess returns than sectors' own risk effect. For each sector, absolute value of δ_i is greater than absolute value of θ_i. However, business cycle risk does not always has the same direction with sectors' own risk. For BM and FN both risk has positive effect. For HC, EN, and UT, both risk has negative effect. For the rest sectors, they influence excess returns oppositely. Therefore, business cycle risk can boost sector's own risk effect when they are toward the same direction but dominate sector's own risk effect when they are contrary.

2.4.4 Asymmetric Cross Business Cycle Effect

Table 2.9 summarizes the estimation results of asymmetric cross effect model. Parameters for sectoral stock returns' own risk terms, which are listed in column 2, still have same signs and magnitudes compared with symmetric model.

Columns 3 reports estimates of positive business cycle risk parameters δ_i^p. Positive risk has positive effects on US, BM, NC, CY, FN, IN, and EN, and has negative effects on HC, TC, TL, and UT. Positive effects range from 0.048 on EN to 2.393 on CY. Negative effects range from -0.401 on HC to -1.27 on UT. Except US and EN, positive business cycle risk has stronger effects in absolute value than sector's own risk.

Columns 4 reports estimates of negative business cycle risk parameters δ_i^n. Negative risk has positive effects on BM, CY, FN, and IN, and has negative effects on US, NC, HC, EN, TC, TL, and UT. Positive effects range from 0.112 on BM to 1.689 on CY. Negative effects range from -0.455 on NC to -1.785 on UT. Except BM, negative business cycle risk has stronger effects in absolute value than sector's own risk.

Obviously, business cycle risk effect is asymmetric, both in direction and magnitude. Some sectors are more sensitive to positive business cycle risk, like BM, NC, CY, FN, IN. Remaining sectors, like US, HC, EN, TC, TL, and UT, are more sensitive to negative business cycle risk. Both positive risk and negative risk have positive effects on BM, CY, FN and IN. Both of them have negative effects on HC, TC, TL, and UT. They have opposite effects on US, NC, and EN, while negative risk effects are negative and dominate positive risk effects which are positive. If combining all these asymmetric effects together, I can get similar symmetric effects as in part 2.4.3.

Shocks to business cycle can exert their effects on sectoral stock returns through different channels. In parallel models, a shock to business cycle from last period plays a role in sectors' current volatilities. It appears in conditional variance equations and affects the second moment of sectoral stock returns directly. While in cross model, a shock to business cycle from last period first is transformed into current business cycle risk which then performs its function on current excess returns. In consequence, if there is a shock to business cycle, it can have spillover effects through sectors, it also can affect sectors' excess returns, depending on specific settings of a model.

Figure 2.4 illustrates one step ahead forecast under asymmetric cross business cycle effect model. Forecasted values can mimic observed values to some extent, especially for some extreme values. For US, BM, and FN, positive forecast values are better. For NC, HC, EN, TC, TL, and UT, negative forecast values are better. For CY, two forecasts have equal quality. Thus, if a shock to business cycle occurs, investors can predict its effects on next period sectoral excess returns and make appropriate adjustment.

2.5 Conclusions

In this paper, I use two models to discuss the asymmetric business cycle effects on US sectoral stock returns. Several conclusions can be drawn.

First, business cycle has asymmetric effects on mean of sectoral stock returns. Under symmetric parallel model, all sectors are pro-cyclical. After introducing asymmetric effects, I find basic materials (BM), technology (TC), and telecommunication (TL) are pro-cyclical during depressions but are counter cyclical during expansions.

Second, shocks to business cycle has asymmetric spillover effects. Not all sectors, but consumer goods (NC), consumer service (CY), financials (FN), industrials (IN), and utility (UT) have their volatilities influenced by business cycle shocks. Moreover, spillover effects of business cycle mainly from negative shocks. Positive shocks to business cycle only spill over FN.

Third, business cycle risk has asymmetric effects on excess returns on sectoral stock indices. Positive risk and negative risk have positive effects on BM, CY, FN, and IN, have negative effects on health care (HC), TC, TL, and UT, and have opposite effects on US, NC, and oil & gas (EN). Focusing on absolute value, positive risk has stronger effects on BM, NC, CY, FN, and IN, while negative risk has stronger effects on US, HC, EN, TC, TL, and UT.

Fourth, business cycle effects are generally stronger than own sectoral effects. Whether they are effects on means of sectoral stock returns, effects on volatilities of sectoral stock returns, if any, or effects on excess sectoral returns, whether they are symmetric or asymmetric, they almost always possess larger estimated parameters compared to corresponding sectoral effects.

Finally, shocks to business cycle influence sectoral indices through two channels. In the parallel effect model, business cycle shocks exert their effect directly on the volatility of sectoral stock returns. In the cross effect model, business cycle shocks first are passed on to conditional variances, which in turn play a role in affecting excess sectoral stock returns through their square root.

Some questions also emerge in this practice. For example, why do the ARCH-M terms in cross effect model have negative parameters, and how will the ARCH-M terms affect the excess sectoral returns if conditional variances of sectoral indices are influenced by business cycle shocks. I will follow up these questions in future research.

Table 2.1: Basic Sectors and their Abbreviations

Abbreviation	Full name	Abbreviation	Full name
US	US whole market	BM	Basic materials
NC	Consumer goods	CY	Consumer service
FN	Financials	HC	Health care
IN	Industrials	EN	Oil & gas
TC	Technology	TL	Telecommunication
UT	Utility		

The abbreviations for sectors follow the convention of Datastream.

Table 2.2: Calendar Time & Corresponding Time Period in Models

IP index release date	Time Period of IP	Time of influenced stock market
1973.1.15	1972.12	1973.1.16 - 1973.2.16
1973.2.16	1973.1	1973.2.17 - 1973.3.16
1973.3.16	1973.2	1973.3.17 - 1973.4.16
⋮	⋮	⋮
⋮	⋮	⋮
2014.1.17	2013.12	2014.1.18 - 2014.2.14
2014.2.14	2014.1	2014.2.15 - 2014.3.17
2014.3.17	2014.2	-

Source of IP index release date: Federal Reserve Bank.
Website: http://www.federalreserve.gov/releases/g17/.

Table 2.3: Minima and Maxima

	Min Occurrence Date	Min Value	Max Occurrence Date	Max Value
RUS	1987.10.17 - 1987.11.16	-296.83	2009.3.17 - 2009.4.15	135.11
RBM	1987.10.17 - 1987.11.16	-393.91	2009.3.17 - 2009.4.15	210.11
RNC	1987.10.17 - 1987.11.16	-371.90	1982.10.16- 1982.11.16	158.35
RCY	1987.10.17 - 1987.11.16	-395.14	1975.1.16 - 1975.2.13	175.39
RFN	1987.10.17 - 1987.11.16	-286.48	2009.3.17 - 2009.4.15	251.27
RHC	1987.10.17 - 1987.11.16	-260.78	1974.10.16 - 1974.11.15	165.19
RIN	1987.10.17 - 1987.11.16	-364.56	2001.4.18 - 2001.5.14	167.74
REN	1987.10.17 - 1987.11.16	-275.15	1980.1.17 - 1980.2.15	166.94
RTC	1987.10.17 - 1987.11.16	-372.16	1975.2.14 - 1975.3.14	204.47
RTL	2008.9.16 - 2008.10.16	-200.73	2002.10.18 - 2002.11.15	229.04
RUT	2009.2.19 - 2009.3.16	-210.23	1975.1.16 - 1975.2.13	155.97
RIP	2008.9.16 - 2008.10.16	-51.64	1998.8.15 - 1998.9.16	25.19
INT	2011.9.16 - 2011.10.17	0.010	1981.5.16 - 1981.6.16	16.30

1. Units of Min and Max values are percent per year.
2. R denotes returns. For example, RUS denotes stock returns on entire US market index, RBM indicates stock returns on the sector referenced by BM (Basic materials), and so forth. The only exception is RIP, which denotes the growth rate of IP (Industrial production).
3. INT denotes interest rate on 3-month T-bill.

Table 2.4: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
	Mean	Median	Std.	Skewness	Kurtosis
RUS	7.00	12.40	46.95	-1.17	7.86
RBM	6.69	11.31	65.90	-1.11	8.57
RNC	4.58	10.39	57.21	-1.10	7.60
RCY	7.55	12.40	58.31	-1.07	8.29
RFN	7.07	12.93	61.65	-0.75	6.17
RHC	8.99	11.28	46.11	-0.73	6.04
RIN	8.14	14.90	58.04	-1.12	7.95
REN	7.65	12.05	54.92	-0.72	5.18
RTC	7.30	8.72	71.57	-0.65	5.55
RTL	4.39	7.72	50.47	-0.51	4.92
RUT	3.41	7.80	44.03	-0.85	5.94
RIP	2.04	2.84	8.83	-1.33	8.73
INT	5.15	5.09	3.40	0.51	3.37

1. All variables are measured monthly, in percent per year.
2. Annualized discount yield on 3-month Treasury bill, reported in Federal Reserve Bank's release H.15, is used as interest rate.

Table 2.5: Estimation Results of Symmetric Parallel Business Cycle Effect Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	c_{im}	a_i	f_i	c_{iv}	α_i	β_i	φ_i
RUS	8.996*	0.258*	0.46*	199.144	0.264*	0.674*	0
	(2.429)	(0.051)	(0.254)	(129.908)	(0.093)	(0.121)	(0.617)
RBM	6.894*	0.203*	0.218	332.903*	0.101*	0.82*	0
	(3.532)	(0.05)	(0.374)	(166.476)	(0.035)	(0.053)	(0.965)
RNC	9.244*	0.304*	0.297	1236.438*	0.443*	0.167*	0.987
	(2.998)	(0.048)	(0.288)	(252.436)	(0.089)	(0.099)	(1.328)
RCY	10.962*	0.315*	0.41	557.717*	0.358*	0.49*	0.69
	(3.017)	(0.048)	(0.307)	(267.061)	(0.08)	(0.132)	(1.233)
RFN	11.334*	0.287*	0.34	537.068*	0.336*	0.517*	0.946
	(3.043)	(0.047)	(0.305)	(215.065)	(0.087)	(0.114)	(1.096)
RHC	9.032*	0.262*	0.336	146.899	0.096*	0.831*	0
	(2.638)	(0.046)	(0.246)	(94.774)	(0.034)	(0.067)	(0.356)
RIN	9.719*	0.236*	0.578*	358.381*	0.183*	0.717*	0.141
	(3.069)	(0.05)	(0.325)	(209.993)	(0.071)	(0.106)	(0.781)
REN	6.507*	0.149*	0.728*	140.552*	0.092*	0.861*	0
	(2.764)	(0.049)	(0.303)	(74.749)	(0.029)	(0.04)	(0.694)
RTC	8.328*	0.246*	0.397	285.381*	0.11*	0.831*	0
	(3.769)	(0.048)	(0.36)	(118.017)	(0.03)	(0.041)	(0.751)
RTL	4.853*	0.202*	0.32	117.321*	0.125*	0.826*	0
	(2.495)	(0.049)	(0.247)	(48.61)	(0.03)	(0.037)	(0.431)
RUT	4.465*	0.23*	0.545*	101.572*	0.161*	0.776*	0.259
	(2.169)	(0.049)	(0.226)	(39.893)	(0.036)	(0.041)	(0.392)
	c_{ipm}	a_{ip1}	a_{ip2}	a_{ip3}	c_{ipv}	α_{ip}	β_{ip}
RIP	2.957*	0.172*	0.141*	0.171*	29.11*	0.321*	0.218
	(0.598)	(0.059)	(0.05)	(0.045)	(6.689)	(0.079)	(0.132)
Significance level: 0.1 '*'							

Numbers in braces are standard deviations. Some estimates are displayed as 0 since they are smaller than 0.00001.

Table 2.6: Estimation Results of Asymmetric Parallel Business Cycle Effect Model-Mean Equations

	(1)	(2)	(3)	(4)	(5)
	c_{im}	a_i	f_i^p	f_i^n	c_{iv}
RUS	10.916*	0.262*	0.141	0.951*	174.918
	(3.034)	(0.051)	(0.399)	(0.524)	(138.952)
RBM	8.579*	0.206*	-0.031	0.579	320.933*
	(4.576)	(0.05)	(0.58)	(0.763)	(184.073)
RNC	10.428*	0.305*	0.159	0.58	1235.3*
	(3.848)	(0.049)	(0.434)	(0.593)	(265.368)
RCY	12.272*	0.315*	0.235	0.741	552.493*
	(3.865)	(0.049)	(0.465)	(0.711)	(287.265)
RFN	12.238*	0.288*	0.199	0.625	537.127*
	(3.878)	(0.047)	(0.466)	(0.678)	(225.313)
RHC	11.082*	0.264*	0.031	0.735	152.037
	(3.432)	(0.047)	(0.4)	(0.496)	(101.034)
RIN	11.145*	0.235*	0.308	0.955	334.239
	(3.976)	(0.051)	(0.536)	(0.679)	(210.328)
REN	9.154*	0.145*	0.335	1.272*	138.508*
	(3.72)	(0.049)	(0.483)	(0.598)	(79.907)
RTC	11.307*	0.249*	-0.038	0.906	276.98*
	(4.999)	(0.048)	(0.599)	(0.675)	(117.866)
RTL	7.38*	0.201*	-0.025	0.801	118.557*
	(3.319)	(0.049)	(0.386)	(0.492)	(49.664)
RUT	7.783*	0.234*	0.123	1.391*	101.061*
	(2.862)	(0.049)	(0.326)	(0.539)	(40.79)

Note: 1. Numbers in braces are standard deviations. Some estimates are displayed as 0 since they are smaller than 0.00001.

2. Estimation results of IP growth rate are the same as in symmetric parallel model and therefore are not listed here.

Table 2.7: Estimation Results of Asymmetric Parallel Business Cycle Effect Model-Variance Equations

	(6)	(7)	(8)	(9)
	α_i	β_i	φ_i^p	φ_i^n
RUS	0.25*	0.698*	0	0
	(0.095)	(0.128)	(0.994)	(0.933)
RBM	0.1*	0.824*	0	0
	(0.04)	(0.052)	(2.045)	(1.282)
RNC	0.451*	0.183*	0	0
	(0.09)	(0.104)	(1.454)	(0.354)
RCY	0.349*	0.485*	0	2.636
	(0.079)	(0.142)	(1.639)	(2.294)
RFN	0.327*	0.522*	0.533	1.473
	(0.09)	(0.12)	(1.766)	(1.806)
RHC	0.093*	0.826*	0	0.253
	(0.036)	(0.073)	(0.79)	(0.6)
RIN	0.161*	0.737*	0	0.744
	(0.07)	(0.101)	(1.492)	(1.415)
REN	0.093*	0.861*	0	0
	(0.031)	(0.039)	(1.427)	(0.907)
RTC	0.108*	0.834*	0	0
	(0.031)	(0.04)	(1.627)	(0.873)
RTL	0.126*	0.825*	0	0
	(0.031)	(0.037)	(1.067)	(0.686)
RUT	0.168*	0.779*	0	0
	(0.038)	(0.039)	(0.781)	(0.394)
Significance level: 0.1 '*'				

Note: 1. Numbers in braces are standard deviations. Some estimates are displayed as 0 since they are smaller than 0.00001.
2. Estimation results of IP growth rate are the same as in symmetric parallel model and therefore are not listed here.

Table 2.8: Estimation Results of Symmetric Cross Business Cycle Effect Model

	(1)	(2)	(3)	(4)	(5)	(6)
	c_{im}	θ_i	δ_i	c_{iv}	α_i	β_i
RUS	0.752	0.134	-0.168	159.045	0.226*	0.731*
	(9.201)	(0.153)	(1.047)	(104.883)	(0.071)	(0.087)
RBM	-9.43	0.155	0.375	382.687*	0.111*	0.803*
	(17.8)	(0.273)	(1.552)	(211.718)	(0.034)	(0.063)
RNC	21.462*	-0.361*	0.497	1780.467*	0.524*	0
	(10.89)	(0.172)	(1.353)	(243.659)	(0.094)	(0.054)
RCY	5.867	-0.297	2.367	1452.697*	0.451*	0.161
	(13.383)	(0.259)	(1.5)	(677.54)	(0.087)	(0.233)
RFN	-6.956	0.068	1.554	853.702*	0.412*	0.396*
	(12.95)	(0.187)	(1.353)	(272.144)	(0.105)	(0.124)
RHC	11.803	-0.077	-0.506	153.55	0.092*	0.837*
	(18.216)	(0.382)	(0.996)	(94.648)	(0.032)	(0.061)
RIN	6.212	-0.098	0.728	308.541*	0.198*	0.732*
	(12.181)	(0.175)	(1.315)	(159.69)	(0.058)	(0.069)
REN	18.299	-0.231	-0.401	153.018*	0.108*	0.845*
	(12.913)	(0.225)	(1.263)	(74.008)	(0.03)	(0.039)
RTC	9.961	0.052	-1.207	339.163*	0.115*	0.819*
	(17.713)	(0.221)	(1.418)	(139.057)	(0.03)	(0.043)
RTL	4.142	0.074	-0.869	120.242*	0.134*	0.819*
	(10.865)	(0.197)	(0.982)	(51.543)	(0.032)	(0.038)
RUT	19.008*	-0.188	-1.403	117.655*	0.168*	0.772*
	(9.237)	(0.182)	(0.923)	(42.356)	(0.038)	(0.043)
Significance level: 0.1 '*'						

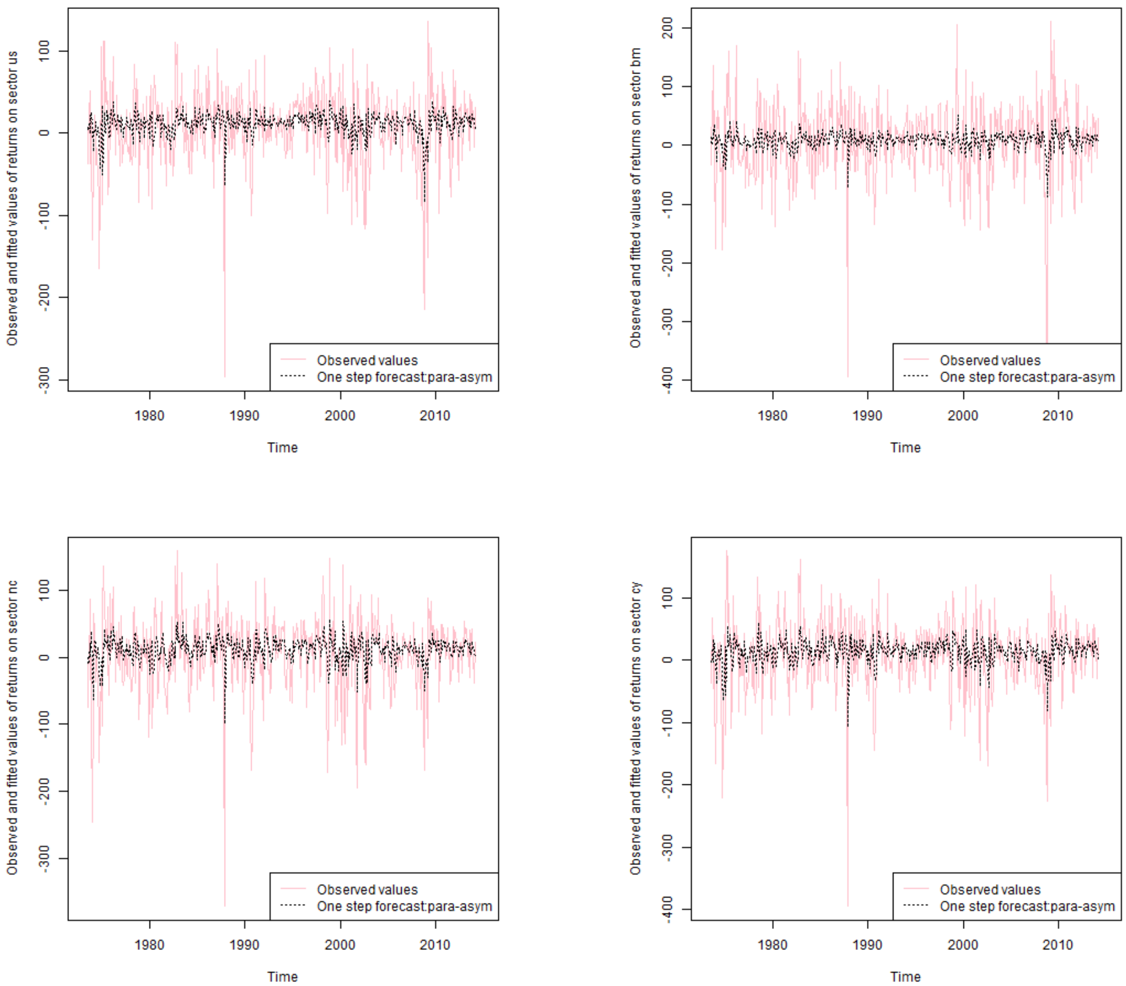
Note: 1. Numbers in braces are standard deviations. Some estimates are displayed as 0 since they are smaller than 0.00001.
2. Estimation results of IP growth rate are the same as in parallel models and therefore are not listed here.

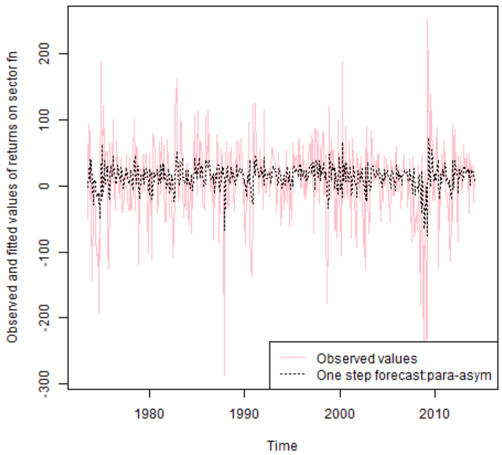
Table 2.9: Estimation Results of the Asymmetric Cross Business Cycle Effect Model

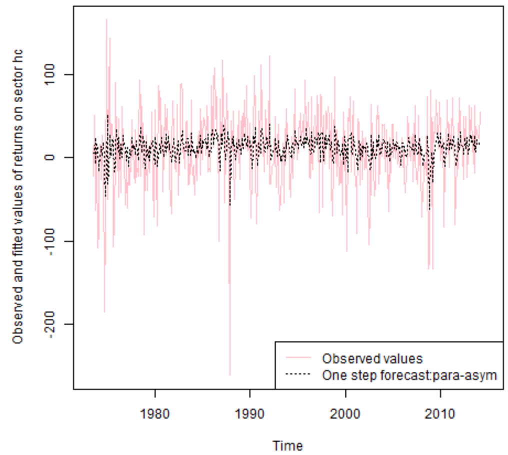
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	c_{im}	θ_i	δ_i^p	δ_i^n	c_{iv}	$_i$	$_i$
RUS	0.491	0.169	0.101	-0.663	222.942	0.264*	0.671*
	(9.412)	(0.158)	(1.083)	(1.118)	(147.531)	(0.092)	(0.122)
RBM	-10.684	0.181	0.582	0.112	397.985*	0.11*	0.8*
	(18.175)	(0.281)	(1.584)	(1.613)	(222.865)	(0.035)	(0.066)
RNC	22.27*	-0.322*	0.617	-0.455	1705.481*	0.541*	0.006
	(10.532)	(0.163)	(1.283)	(1.364)	(215.776)	(0.094)	(0.043)
RCY	4.333	-0.224	2.393	1.689	1281.754*	0.448*	0.218
	(13.247)	(0.284)	(1.813)	(1.944)	(773.048)	(0.088)	(0.276)
RFN	-7.777	0.081	1.81	1.336	853.83*	0.416*	0.392*
	(13.008)	(0.188)	(1.408)	(1.413)	(267.709)	(0.105)	(0.123)
RHC	11.842	-0.077	-0.401	-0.612	153.109	0.092*	0.837*
	(18.078)	(0.379)	(1.026)	(1.027)	(95.669)	(0.032)	(0.062)
RIN	5.088	-0.056	1.079	0.158	369.938*	0.204*	0.707*
	(12.524)	(0.187)	(1.34)	(1.381)	(191.817)	(0.061)	(0.083)
REN	15.569	-0.166	0.048	-0.989	166.642*	0.105*	0.841*
	(13.443)	(0.243)	(1.296)	(1.318)	(82.192)	(0.031)	(0.043)
RTC	8.302	0.078	-0.854	-1.518	353.538*	0.118*	0.813*
	(17.647)	(0.22)	(1.473)	(1.461)	(145.549)	(0.031)	(0.045)
RTL	3.743	0.083	-0.716	-1.033	121.062*	0.132*	0.819*
	(10.949)	(0.199)	(1.013)	(1.018)	(51.821)	(0.032)	(0.038)
RUT	20.116*	-0.189	-1.27	-1.785*	116.696*	0.171*	0.77*
	(9.276)	(0.181)	(0.936)	(0.983)	(41.882)	(0.039)	(0.043)
Significance level: 0.1 ‘*’							

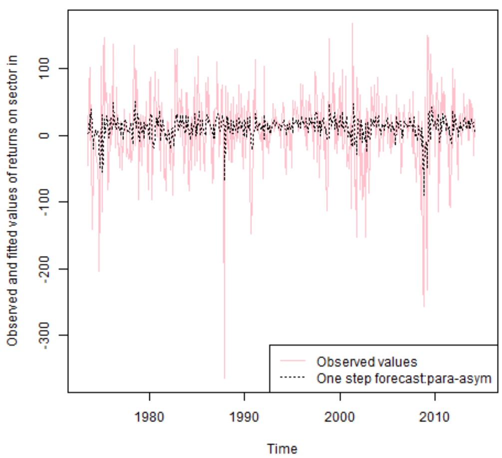
Note: 1. Numbers in braces are standard deviations. Some estimates are displayed as 0 since they are smaller than 0.00001.
2. Estimation results of IP growth rate are the same as in parallel models and therefore are not listed here.

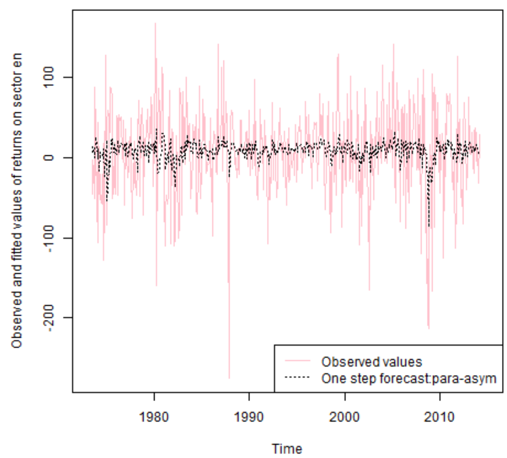
Figure 2.1: Observed Sectoral Stock Returns and Fitted Values from Parallel Asymmetric Model

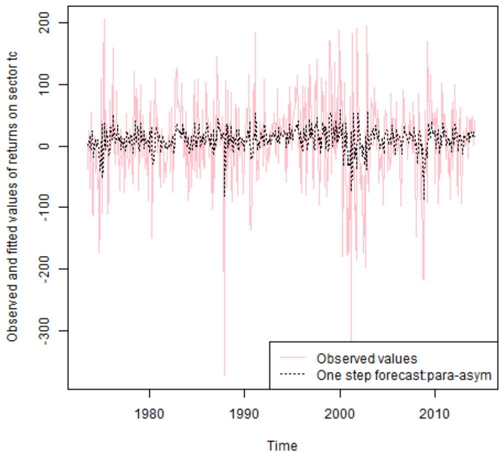


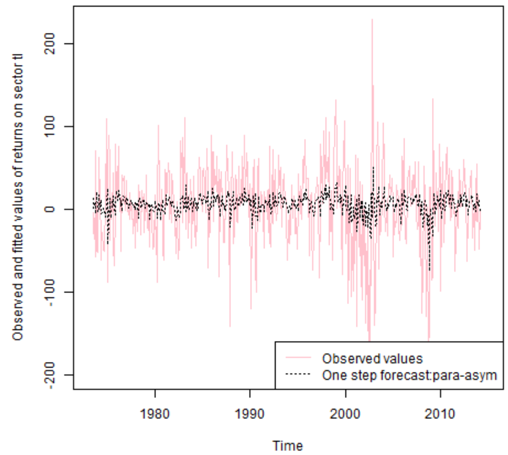

Observed and fitted values of returns on sector fn
Observed values
One step forecast:para-asym
Time


Observed and fitted values of returns on sector hc
Observed values
One step forecast:para-asym
Time


Observed and fitted values of returns on sector in
Observed values
One step forecast:para-asym
Time


Observed and fitted values of returns on sector en
Observed values
One step forecast:para-asym
Time


Observed and fitted values of returns on sector tc
200
100
0
-100
-200
-300
Observed values
One step forecast:para-asym
1980
1990
2000
2010
Time


Observed and fitted values of returns on sector tl
200
100
0
-100
-200
Observed values
One step forecast:para-asym
1980
1990
2000
2010
Time

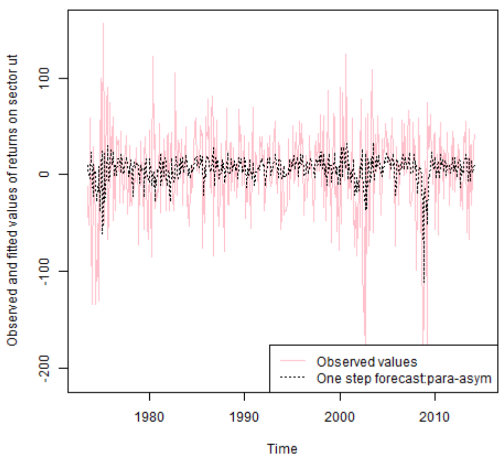
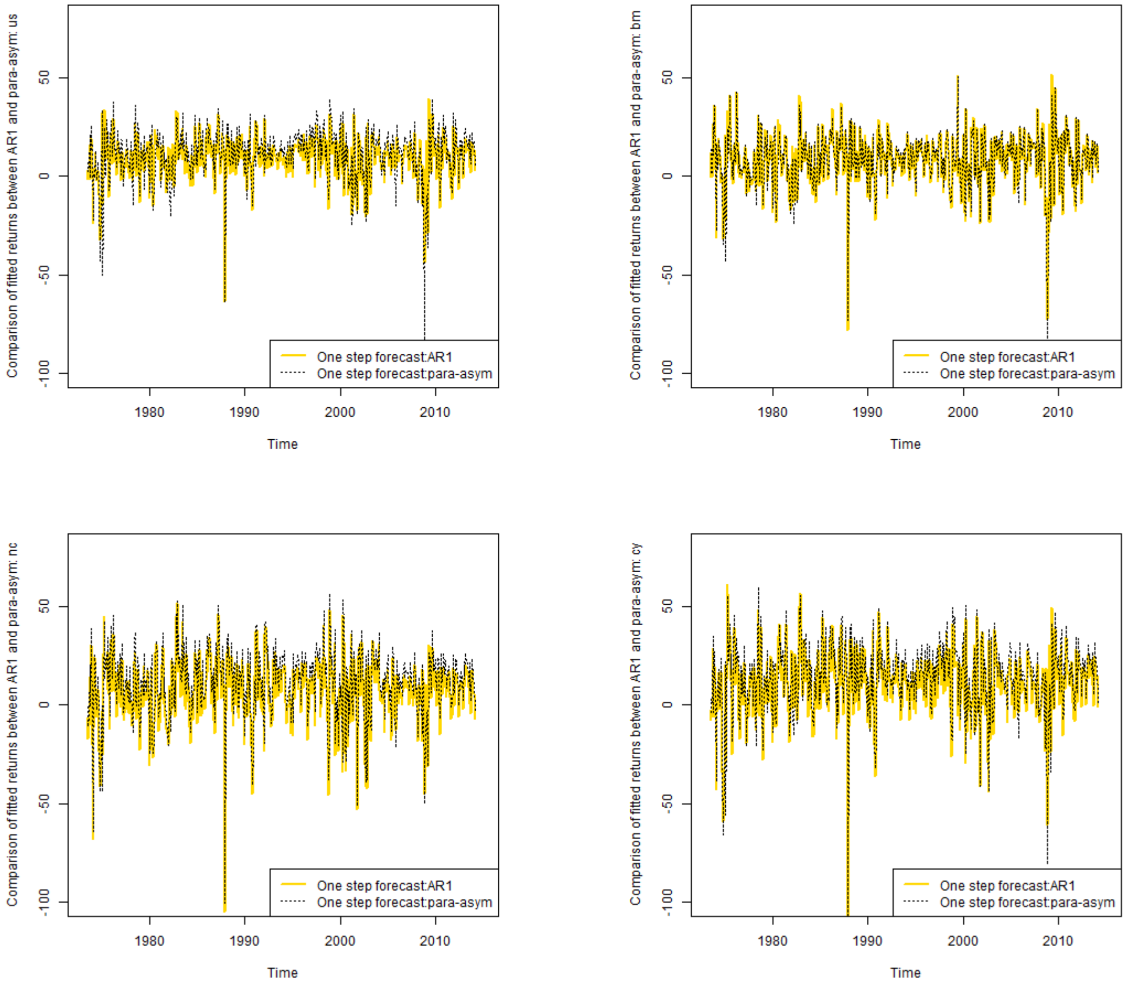
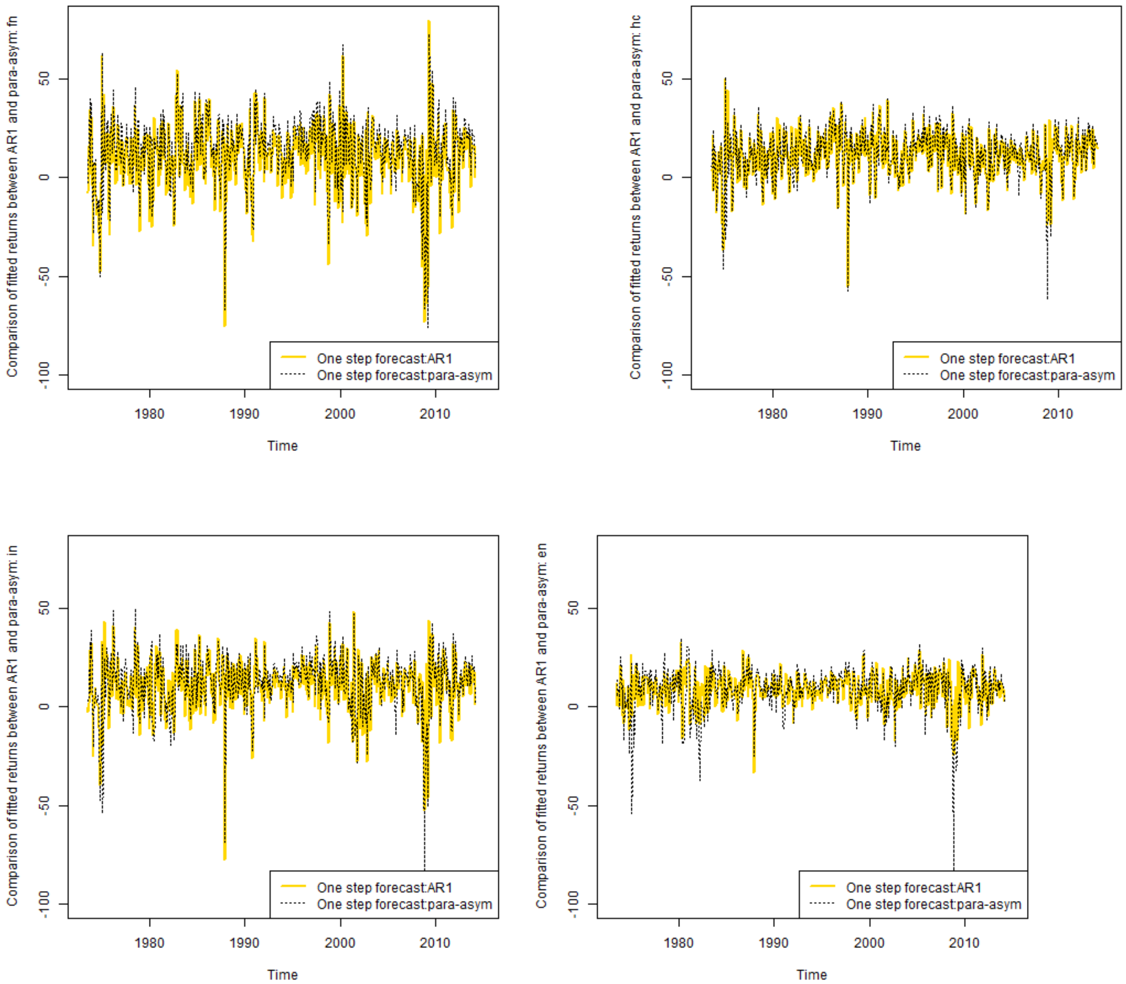
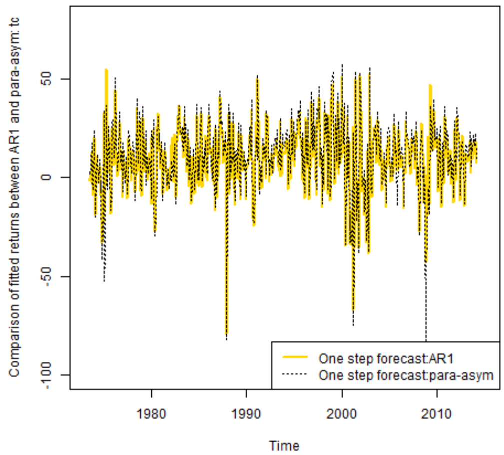
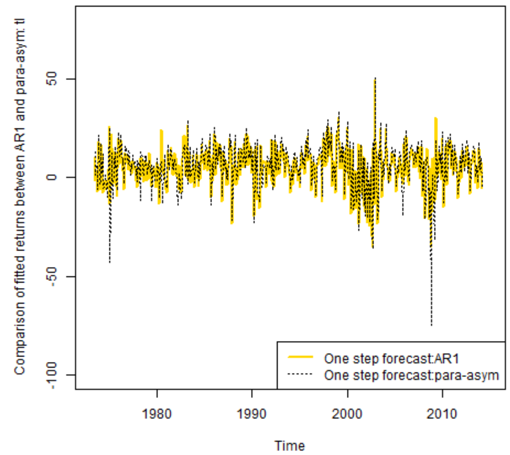

Observed and fitted values of returns on sector ut
100
0
-100
-200
Observed values
One step forecast:para-asym
1980
1990
2000
2010
Time

Figure 2.2: Comparison of Fitted Sectoral Stock Returns between AR(1) and Parallel Asymmetric Model




Comparison of fitted returns between AR1 and para-asym: fn
Comparison of fitted returns between AR1 and para-asym: hc
Comparison of fitted returns between AR1 and para-asym: in
Comparison of fitted returns between AR1 and para-asym: en
-100
-50
0
50
1980
1990
2000
2010
Time
One step forecast:AR1
One step forecast:para-asym


Comparison of fitted returns between AR1 and para-asym: tc
-100
-50
0
50
1980
1990
2000
2010
Time
One step forecast:AR1
One step forecast:para-asym


Comparison of fitted returns between AR1 and para-asym: tl
-100
-50
0
50
1980
1990
2000
2010
Time
One step forecast:AR1
One step forecast:para-asym

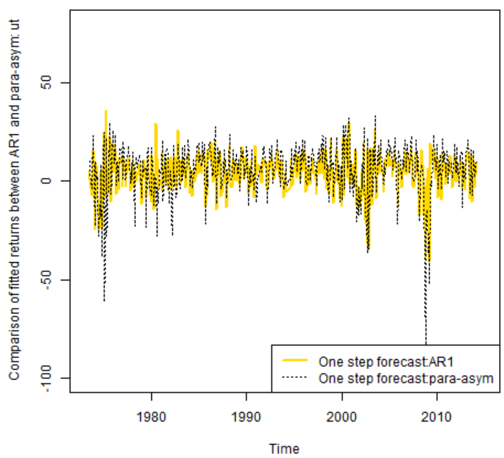
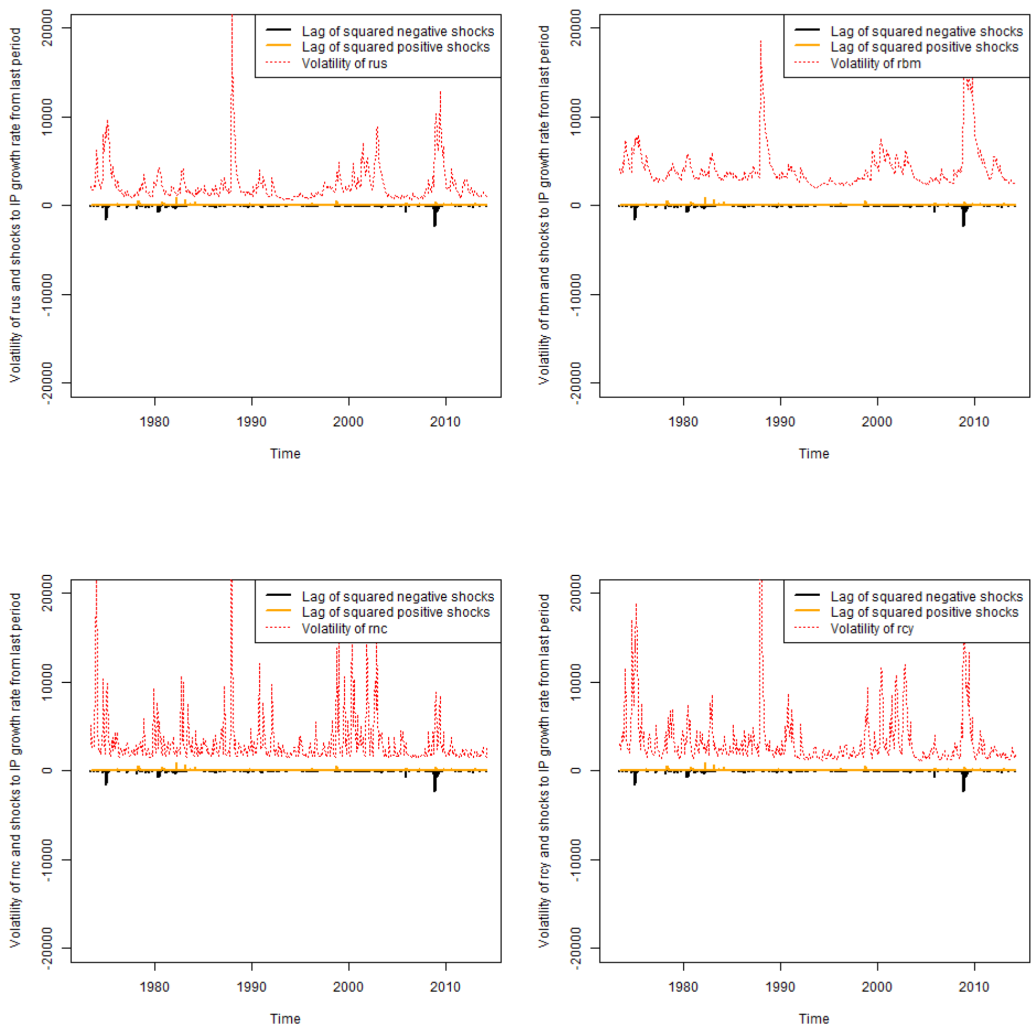
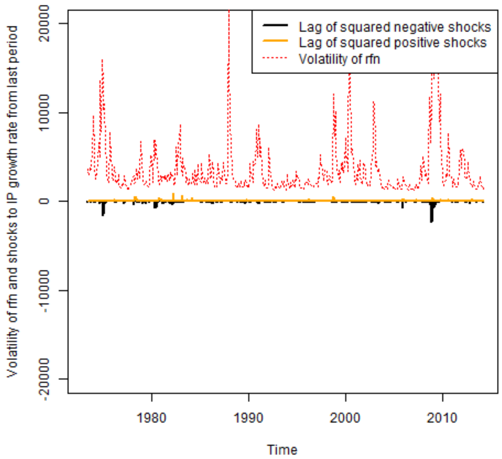
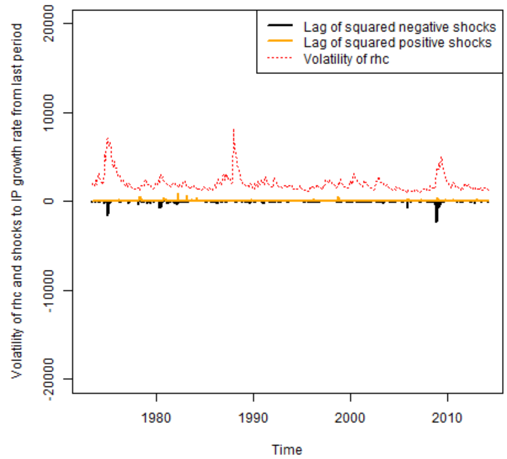
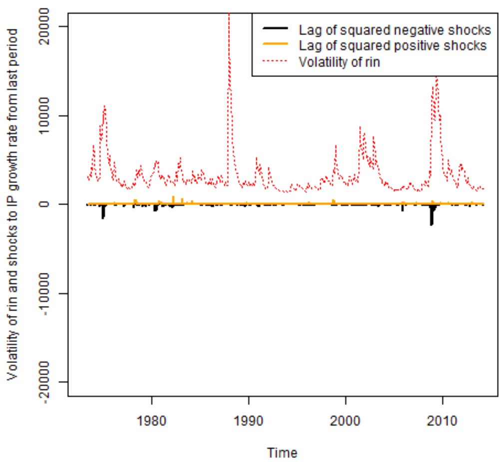

Comparison of fitted returns between AR1 and para-asym: ut
-100
-50
0
50
1980
1990
2000
2010
Time
One step forecast:AR1
One step forecast:para-asym

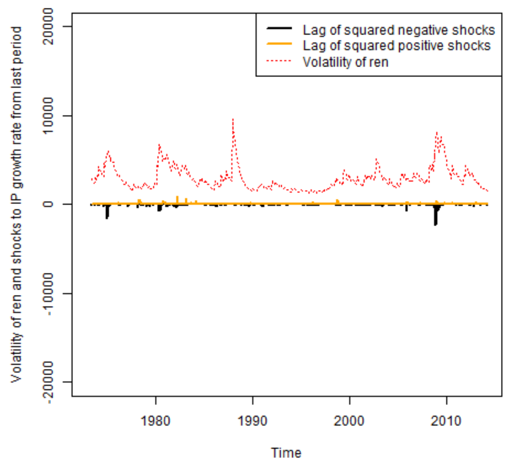
Figure 2.3: Plots of Sectoral Volatilities and Asymmetric Shocks to IP Growth Rate

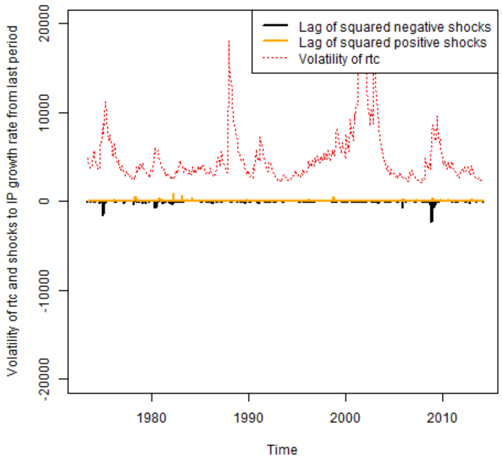



Lag of squared negative shocks
Lag of squared positive shocks
Volatility of rfn
Volatility of rfn and shocks to IP growth rate from last period
Time

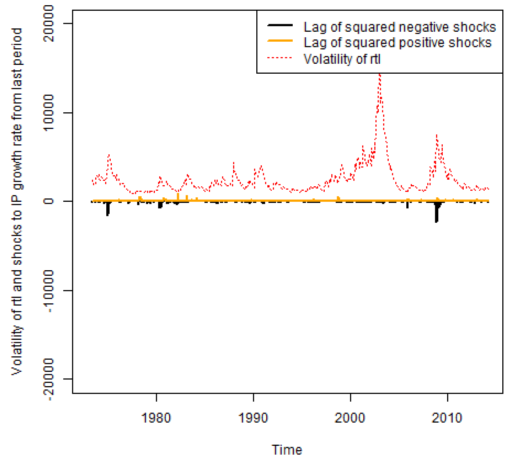

Lag of squared negative shocks
Lag of squared positive shocks
Volatility of rhc
Volatility of rhc and shocks to IP growth rate from last period
Time


Lag of squared negative shocks
Lag of squared positive shocks
Volatility of rin
Volatility of rin and shocks to IP growth rate from last period
Time

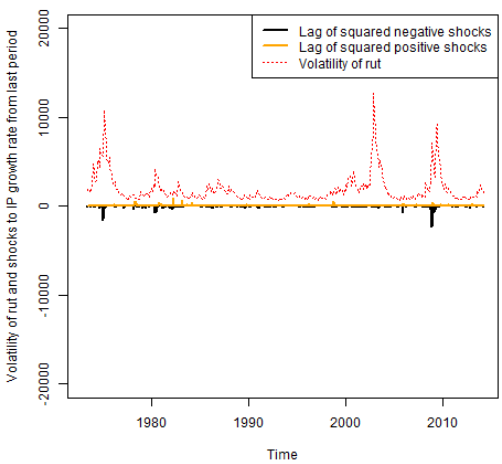

Lag of squared negative shocks
Lag of squared positive shocks
Volatility of ren
Volatility of ren and shocks to IP growth rate from last period
Time



Lag of squared negative shocks
Lag of squared positive shocks
Volatility of rtc
Volatility of rtc and shocks to IP growth rate from last period
20000
10000
0
-10000
-20000
1980
1990
2000
2010
Time

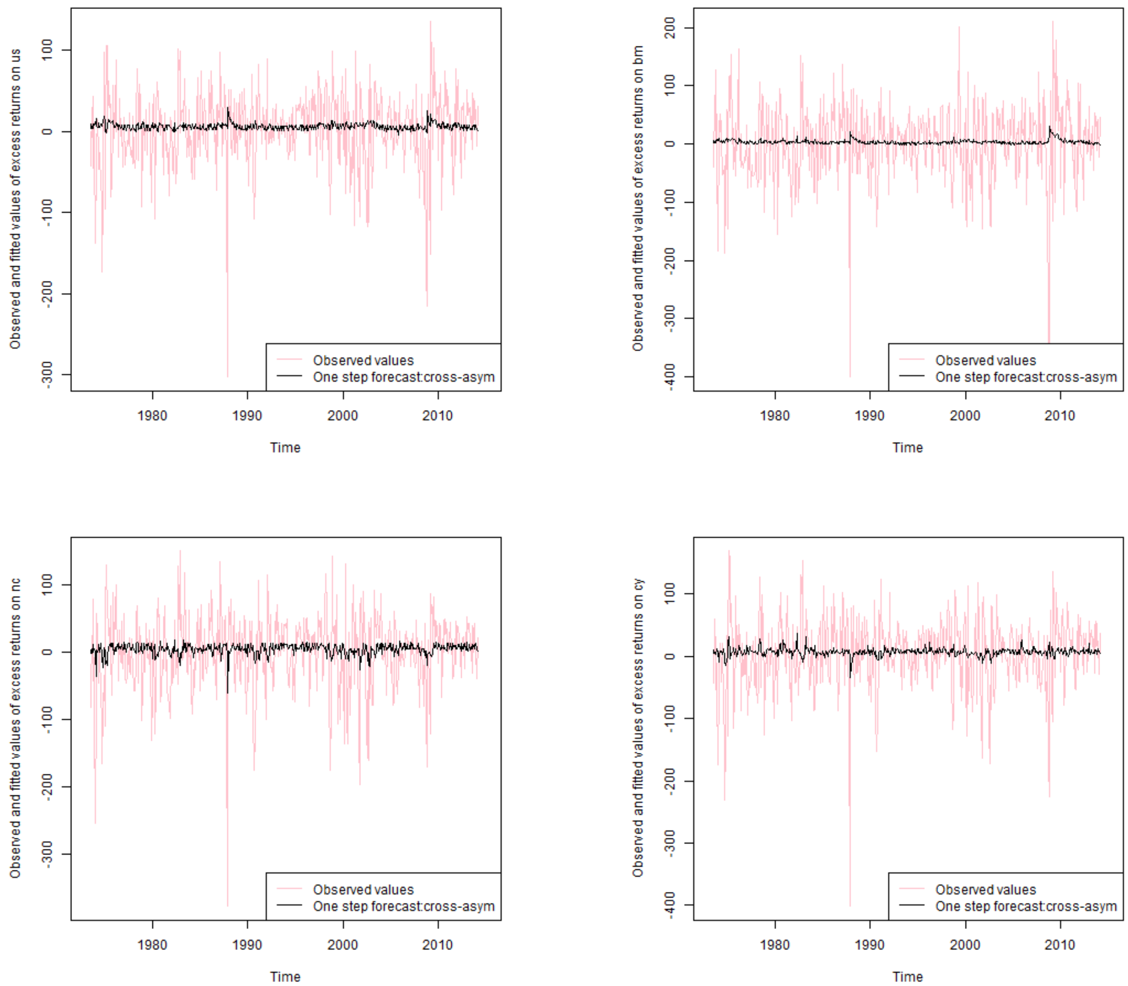


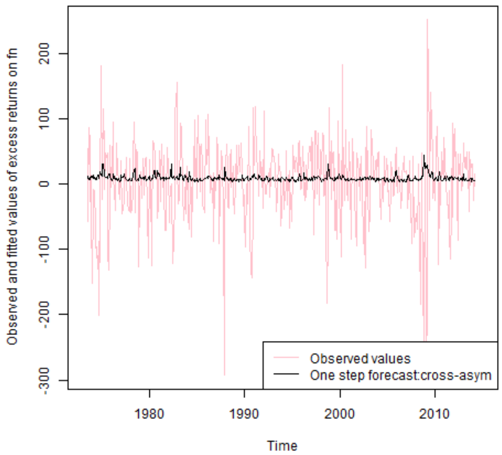
Lag of squared negative shocks
Lag of squared positive shocks
Volatility of rtl
Volatility of rtl and shocks to IP growth rate from last period
20000
10000
0
-10000
-20000
1980
1990
2000
2010
Time

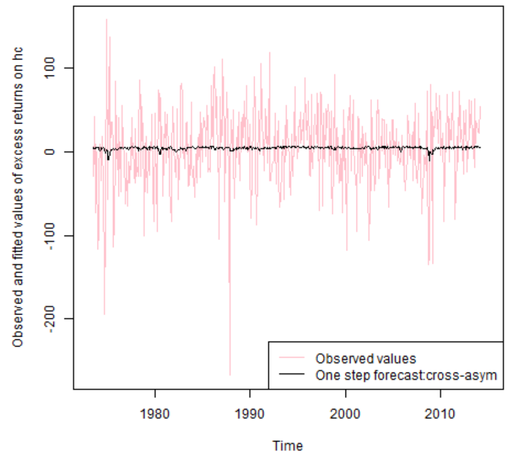


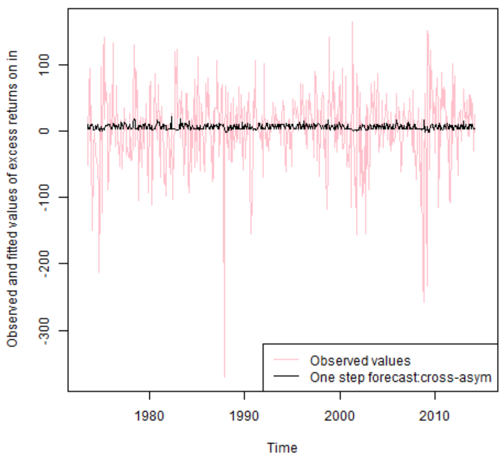
Lag of squared negative shocks
Lag of squared positive shocks
Volatility of rut
Volatility of rut and shocks to IP growth rate from last period
20000
10000
0
-10000
-20000
1980
1990
2000
2010
Time

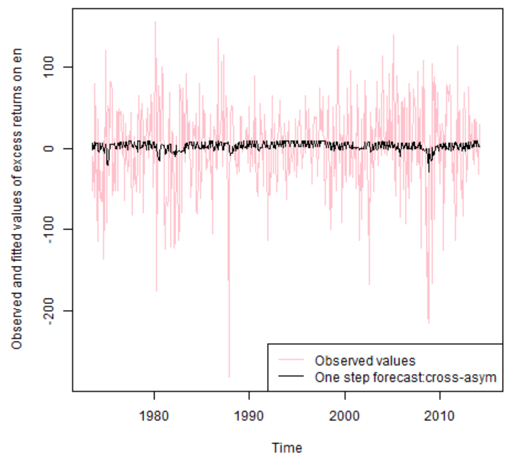
Figure 2.4: Fitted Values of Excess Sectoral Returns from Asymmetric Cross Business Cycle Effect Model

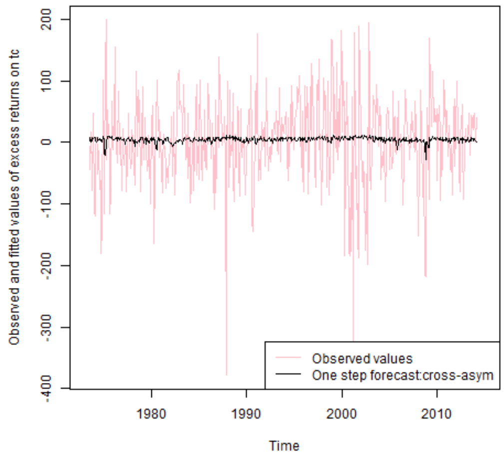


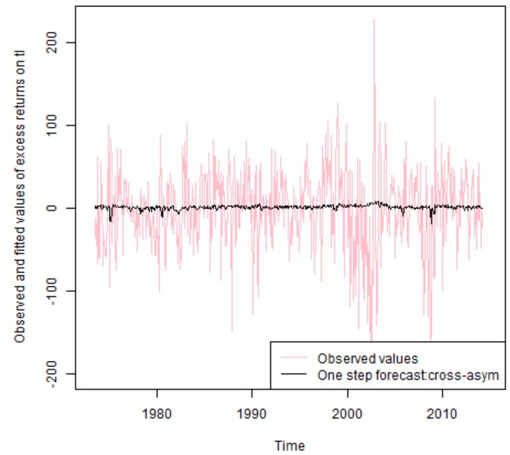

Observed and fitted values of excess returns on fn
200
100
0
-100
-200
-300
1980
1990
2000
2010
Time
Observed values
One step forecast:cross-asym

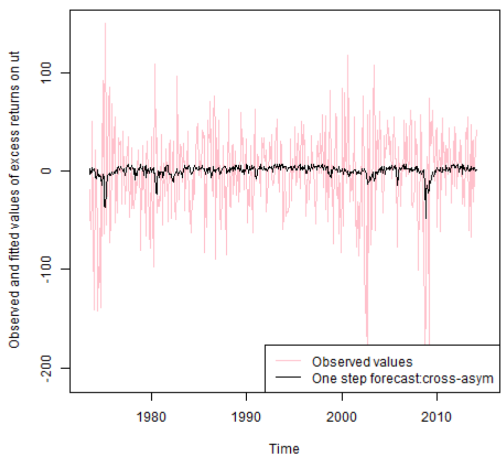

Observed and fitted values of excess returns on hc
100
0
-100
-200
1980
1990
2000
2010
Time
Observed values
One step forecast:cross-asym


Observed and fitted values of excess returns on in
100
0
-100
-200
-300
1980
1990
2000
2010
Time
Observed values
One step forecast:cross-asym


Observed and fitted values of excess returns on en
100
0
-100
-200
1980
1990
2000
2010
Time
Observed values
One step forecast:cross-asym


Observed and fitted values of excess returns on tc
Observed values
One step forecast:cross-asym
Time


Observed and fitted values of excess returns on tl
Observed values
One step forecast:cross-asym
Time


Observed and fitted values of excess returns on ut
Observed values
One step forecast:cross-asym
Time

CHAPTER 3

CHINESE BUSINESS CYCLE EFFECTS ON US SECTORAL STOCK RETURNS

3.1 Introduction

Early research on financial inter linkages focuses on the direction of influence from one market to another. For instance, Berben and Jansen (2005) investigate stock market linkages among German, the UK, the US and Japanese markets at both the aggregate level and sector levels. Similar studies can be found for country groups or regional unions like G7, OECD, BRIC, and NAFTA, to name a few.

This sort of research naturally extends to the discussion about the influence from mature markets to some lower level markets. Narayan and Narayan (2012) explore the impact of US macroeconomic conditions on stock markets of seven Asian countries. They find that the US short-term interest rates and exchange rates have significant effects on returns for all countries in the short run. By dividing the research sample into a pre-crisis period and a crisis period, they also find that the financial crisis in 2007 has actually weakened the influence of US macroeconomic conditions on Asian stock markets. Nitschka (2014) uses GDP gaps of G7 countries as proxies for their business cycle dynamics to assess the developed markets' influence on ten emerging markets' stock returns. Their findings confirm the predictive power of business cycle dynamics on stock market excess returns, though the predictability for the emerging markets is weaker than for the G7 countries.

With the development of emerging markets and international economic integration, studies about the influence from emerging markets to mature markets have been initiated in the literature. For example, both Xu and Hamori (2012) and Syriopoulos, Makram and Boubaker (2015) examine and verify the interaction of US stock market and BRIC countries stock markets. Xu and Hamori (2012) discover that US stock market significantly affects the stock markets of Russia, India and China while China is the only country in BRIC that in turn affects the US. They also detect a volatility spillover from the US to India. Adding South Africa into BRIC and changing focus from aggregate market to disaggregate markets, Syriopoulos, Makram and Boubaker (2015) find volatility spillovers from the US to Brazil, Russia, India and South Africa for both industrials and financials sectors. On the other hand, Brazil and Russia have volatility spillover effects on US industrials sector and financials sector, respectively. Though there is no strong evidence of spillover effect from the US to China, the effects in the opposite direction indeed exist for both sectors.

Among those emerging markets, China is the one attracting great attentions. Evidence in the literature shows that Chinese stock market affects not only its peer countries, but also some developed countries. Allen, Amram and McAleer (2013) use two multivariate GARCH models to examine the volatility spillovers from Chinese stock market to its neighbors and trading partners, namely Australia, Hong Kong, Singapore, Japan and the United States. They also estimate the time varying correlations between Chinese stock market and other markets. They conclude with strong evidence of the spillover effect from China to the other countries and non-constant correlations between China and the other countries. In another paper, Zhou, Zhang and Zhang (2012) develop a model based on generalized forecast error variance decomposition to measure volatility spillovers between China and some Asian and western countries, including Hong Kong, Taiwan, India, Japan, Korea, Singapore, the United Kingdom, the United States, France and Germany. They find that the volatility of Chinese stock market has had a significantly positive impact on other markets since 2005, while the volatility interactions among China, Hong Kong and Taiwan are more remarkable. They point out that, stemming from the restrictions on foreign direct investment, the linkages of the stock markets of China and other countries weaken during the financial crisis.

As the two largest individual economies in the world, the United States and China are forming a close and firm economic relationship. Research on their financial interaction occupies an increasing portion in the literature. Chow, Liu and Niu (2011) model the relationship between Shanghai and New York Stock markets by a time-varying regression. The dynamic patterns of the parameters reveal that the effect of stock returns of New York on Shanghai increases after the 1997 Asian financial crisis and turns positive and significant after China entered WTO in 2002. On the other hand, the stock returns of Shanghai start to have positive and significant impact on New York after 2002. However, Ye (2014) fail to find a significant influence of Chinese stock market on US stock market. Employing a nonparametric approach, Ye (2014) presents that daily returns on the S&P500 and other benchmark US stock indexes significantly forecast returns on Chinese stock indexes, namely the SSEC and SZCI. Nonetheless, the impact of Chinese stock market on US stock market was weak in the observed period.

As the debate on the integration between China and the United States continues, I intend to provide more evidence in this paper. Because of the predictive power of macroeconomic variables and rapidly growing magnitude of the Chinese economy, I use Chinese business cycle information as a predictor in explaining US stock market.

Moreover, since the connection between China and US markets varies across economic sectors, I focus on the predictability of US sectoral stock returns. To the best of my knowledge, my paper is the first to consider Chinese business cycle effects on US sectoral stock returns. Moreover, I also consider dynamic of international economic relationships using a framework of time-varying parameter model.

The rest of this paper is as follows. Section 2 describes data and methods for the empirical research. Section 3 discusses estimated results for different models. Section 4 concludes.

3.2 Data and Methods

Monthly US sectoral stock indexes from April 1999 to December 2014 are obtained from Thomson Reuters. Other major databases, like Dow Jones, DataStream and FTSE, also provide sectoral stock indexes. As stated in Chow, Liu and Niu (2011), significant effects from China to the US appear after 2002 when China entered WTO. Hence, I choose data from Thomson Reuters which most closely matches the significant period. The ten sectors are basic materials, cyclical consumer goods and services, non-cyclical consumer goods and services, financials, health care, industrials, energy, technology, telecommunication, and utilities. This classification is also employed by other major databases. To distinguish different effects between aggregate market and disaggregate markets, I also include the US whole market index into my discussion and sometimes refer them together as eleven sectors. For simplicity, the sectors are abbreviated as US, BM, CY, NC, FN, HC, IN, EN, TC, TL and UT. Table 3.1 provides corresponding abbreviations for each sector.

I use industrial production (hereafter IP) as the surrogate for business cycle for both China and the US. In all the models described below, IP growth rates of both countries are used to explain US sectoral stock returns. Monthly returns are obtained as $r_{it} = ln(p_{it}) - ln(p_{it-1})$, where r_{it} and p_{it} indicate monthly stock returns and stock indexes on sector i at time t. Monthly IP growth rate of the US is obtained as $r_{ut} = ln(ip_{ut}) - ln(ip_{ut-1})$ and monthly IP growth rate of China is obtained as $r_{ct} = ln(ip_{ct}) - ln(ip_{ct-1})$. Subscript u and c refer to the US and China, respectively.

Table 3.2 summarizes the main statistics of monthly sectoral stock returns and IP grow rates. During the studied period, average return on US whole market is about 3.9 percent per year. Among individual sectors, the highest average return is 7.1 percent per year on EN and the lowest is -1.9 on TL. Average IP growth rate of the US is around 1.2 percent per year while Chinese IP growth rate experiences a low and negative average for the observing period. It appears that extreme values of sectoral stock returns are mostly negative, as their medians of them are larger than their means, excepting BM. The third column lists standard deviations. These range from 44 on CY to 97 on TC. Chinese IP growth rate is about four time more volatile than US IP growth rate. Columns four and five provide minimum values and maximum values for these variables. There is clear evidence that, other than sector BM and Chinese IP growth rate, all variables are left skewed.

3.2.1 Chinese Business Cycle Effects

It has been shown that stock returns can be predicted by both domestic and foreign macroeconomic variables, like interest rate, exchange rate, unemployment rate, and so on. Chinese economy has opened up and flourished for more than thirty years. This has prominently enhanced Chinese economic influence internationally. The economic connection between China and the United States has strengthened steadily during this period. Currently, the United States is the most important Chinese international trade partner and China is also one of the most important international trade partners of the United States[7]. In addition to international trade, foreign direct investment (FDI) between these two countries has also increased dramatically[8]. Thus, it is very meaningful to research the interaction between them. In the literature, much effort has been devoted to discussing how the United States business conditions affect China (see Goh, Jiang, Tu and Wang (2013) as an example). Here, I try to explore whether Chinese macroeconomic conditions possess useful information in explaining US stock returns. I consider both aggregate market and disaggregate markets to shed light on Chinese effects on different sectors of the United States.

The first model examines Chinese business cycle effects on monthly US sectoral stock returns.

$$r_{it} = c_i + \sum_{j=1}^{l} a_{ij} r_{ct-j} + \sum_{j=1}^{k} b_{ij} r_{ut-j} + \varepsilon_{it} \qquad 1)$$

r_{it} indicates monthly stock returns on sector *i*, representing one of the eleven sectors, namely US, BM, CY, NC, FN, HC, IN, EN, TC, TL and UT. This model defines monthly sectoral stock returns as a function of past IP growth rates of two countries. r_{ct-j} is Chinese IP growth rate at time *t-j*, *j* from 1 to *l*. r_{ut-j} is IP growth rate of the US at time *t-j*,

[7] For 2012 and 2013, The United States is the biggest international trade partner of China and China is the third biggest international trade partner of the United States. Data sources: UNCTAD website, http://unctadstat.unctad.org/CountryProfile/156/en156GeneralProfile.html and http://unctadstat.unctad.org/CountryProfile/842/en842GeneralProfile.html.

[8] For 2012, the United States is the top 1 FDI outflow country from China and top 6 FDI inflow country to China. In 2013, the rank of the Unite State change to top 2 for FDI outflow and top 5 for FDI inflow. Data sources: National Bureau of Statistics of China, http://www.stats.gov.cn/tjsj/ndsj/2014/indexch.htm.

j from 1 to k. a_{ij} and b_{ij} are corresponding parameters which capture business cycle effects of both countries at different lags. ε_{it} is the residual term and is assumed to follow a GARCH(1,1) process:

$$\varepsilon_{it} = v_{it}\sqrt{h_{it}} \tag{2}$$

$$h_{it} = \gamma_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1} \tag{3}$$

I set the lengths of l and k to 3. Thus, lagged monthly IP growth rates up to a quarter impact US stock returns. For various reasons such as geographical distance, international transportation, and differences in economic systems, the influence from one country to another country may appear after several months. On the other hand, since US IP for a given month is released in the middle of next month, business cycle effects of the US will appear after the first month.

Considering possible business cycle effects on a longer horizon, I employ a model to test the effects on quarterly sectoral stock returns.

$$r_{it}^q = c_i^q + \sum_{j=1}^{l} a_{ij}^q r_{ct-j}^q + \sum_{j=1}^{k} b_{ij}^q r_{ut-j}^q + \varepsilon_{it}^q \qquad 4)$$

The superscript q indicates the variables are quarterly data, which are obtained from monthly data. Specifically, quarterly IP growth rates are sums of monthly data and quarterly sectoral stock returns are averages of monthly data. All the subscripts have the same meaning as in the first model, namely i indicates sectors, c indicates variables for China and u indicates variables for the US. Here, I set the lengths of l and k to 4. Thus, lagged quarterly IP growth rates up to a whole year impact US stock returns. Parameters a_{ij}^q and b_{ij}^q measure possible quarterly effects at different lags. Because of the low frequency of the quarterly data, squares of residual terms ε_{it}^{q} are not correlated. Thus there are no GARCH effects for the quarterly business cycle effect model.

3.2.2 Time-Varying Predictability

Economic conditions and financial markets fluctuate dramatically. For many situations, a constant parameter linear model is not suitable enough to describe a statistical relationship. A time-varying model better characterizes of a relationship under various conditions. It also better reflects the reactions of the relationship to different events. Guidolin, McMillan and Wohar (2013) estimate a 5-year rolling fixed window model on monthly US sectoral stock returns. They find that the predictability of dividend yield on US sectoral stock returns is time-varying, and this time-variation is closely connected to US business cycle.

In the present paper, I add Chinese business cycle into the analysis. I expect stronger predictability of US sectoral stock returns. Following Guidolin, McMillan and Wohar (2013), I extend the 5-year rolling fixed window model from one lag to three lags of monthly data to capture effectively any international influences that may exist.

$$r_{it}^{\tau} = c_i^{\tau} + \sum_{j=1}^{l} a_{ij}^{\tau} r_{ct-j}^{\tau} + \sum_{j=1}^{k} b_{ij}^{\tau} r_{ut-j}^{\tau} + \varepsilon_{it}^{\tau} \tag{5}$$

The superscript τ indicates the variables and the parameters are for rolling period τ. The residual terms ε_{it}^{τ} are assumed to follow standard normal distributions[9]. I estimate the model over the period from May 1999 to April 2004 to obtain the first set of parameters. Then rolling the period one month forward to June 1999 to May 2004 I estimate the model

[9] LM test reveals that averagely around 73% of the rolling periods do not have GARCH effect.

again to obtain the second set of parameters. This process marches through the sample period producing 129 estimates for each parameter. Generally, I expect to find an increasing trend for the parameters of US whole market based on the development of US-China economic relationship. However, there are no ex-ante imaginations for trends of the sectors.

3.3 Empirical Results

3.3.1 Chinese Business Cycle Effects on Monthly US Sectoral Stock Returns

Table 3.3 and Table 3.4 display the estimated results for Chinese business cycle effects on monthly US sectoral stock returns. Columns two to four in Table 3.3 are parameters for Chinese IP growth rate lags. The first lag of Chinese IP growth rate has a significant negative effect on stock returns on TL and the second lag has a significant positive effect on TC. Chinese economic conditions formed three months earlier have most important effects on US sectoral stock returns. They positively affect the US whole market and sector BM, NC, IN, EN and TC, and negatively affect sector UT. One unit change in Chinese IP growth rate three months earlier increases 0.2 units of stock return on US aggregate market. The effects on sectors are even stronger, excepting on UT. The significant positive parameters for sectors range from 0.32 on BM to 0.51 on EN. However, CY, FN and HC are not influenced by Chinese economic conditions. These three sectors do not have significant parameters for all three lags of Chinese IP growth rate.

Columns five to seven in Table 3.3 are estimates of parameters for IP growth rate lags of the US. Compared to China, the US has stronger monthly effects on its own stock market. The estimated parameters for US IP growth rate are generally larger than the estimated parameters for China IP growth rate. The economic condition of the US in last month does not have many effects on its sectoral stock returns, which is the same as China. However, the second lag of US IP growth rate has positive and significant effects on almost all sectors. This result complies with the release procedure of US IP data. Since US IP data for a given month are released in the middle of the next month, any business cycle effect on stock returns will not appear until the next month. This effect has also been observed in Cooper and Priestley (2008). The third lag of US IP growth rate only has significant effects on FN and HC.

Generally, business cycles have important influences on US sectoral stock returns, though these influences do not emerge immediately. There are two differences between Chinese business cycle effects and the US business cycle effects. The first is that Chinese business cycle effects occur later than and are smaller than the US business cycle effects. The second is that Chinese business cycle has a smaller effect on the US whole market compared to sectoral markets, while the US business cycle has an average effect on the US whole market.

Column eight to ten in Table 3.4 are estimated parameters for the GARCH processes. Sector NC does not have a significant GARCH parameter and sector CY does not have a significant ARCH parameter. All other sectors have significant GARCH effects. Excepting NC, HC and EN, all other sectors have Small ARCH parameters and larger GARCH parameters. This result explores that for most sectors, the shock from last period has a small impact on their current stock returns but this impact will last for a long time.

Columns eleven and twelve in Table 3.4 list F statistics and R-squared values for the mean equations. The numbers in parentheses under the F statistics are their corresponding P-values. Both R-squared and adjusted R-squared are provided for all sectors. The

R-squared for FN is reported as zero since it is negative. This situation sometimes happens when calculating R-squared for the mean equation of a GARCH model. Therefore, the adjusted R-squared and F statistics for FN are zeros too.

3.3.2 Comparison of the Model only Contains US Business Cycle Effects

In order to find out how better Chinese business cycle can help predicting US sectoral stock returns, I estimate another model that only contains US business cycle effect.

$$r_{it} = c_i + \sum_{j=1}^{k} b_{ij} r_{ut-j} + \varepsilon_{it} \tag{6}$$

$$\varepsilon_{it} = v_{it}\sqrt{h_{it}} \tag{7}$$

$$h_{it} = \gamma_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1} \tag{8}$$

Table 3.5 and Table 3.6 lists the estimated results for this model. The magnitudes, signs and significances for corresponding parameters almost replicate the results in Table 3.3 and Table 3.4. Sector FN has a negative R-squared value. Thus, its F statistics, R-squared value and adjusted R-squared value are reported as zeros. In column ten of Table 3.6, I merge the adjusted R-squared values from Table 3.4. For both columns nine and ten, I round the adjusted R-squared values to three decimal places for comparison.

By employing Chinese business cycle, the adjusted R-squared values increase on six sectors including US, NC, IN, EN, TC and TL. For the US whole market, the change is small. However, for the sectors, the changes are considerable, from 28% on IN to 850% on TL. Thus, it is reasonable to believe that Chinese business cycle has an important role in explaining stock returns on these sectors.

On the other hand, three sectors experience a dropping adjusted R-squared value. However, the extent of the decreases is comparatively small, from 11% on HC to 28% on

UT. Thus, when using Chinese business cycle to explain and predict monthly US sectoral stock return, we need to pay close attention on these sectors.

3.3.3 Robustness Test

To prevent potential problems from using a specific data source, I perform a robustness test by re-estimating equations (1) to (3) on data from DataStream for the same sample period. The estimation results are presented in Table 3.7 and Table 3.8. Almost all parameters for IP growth rates of China and the US sustain the same magnitudes, signs, and significances. The third lag of Chinese IP growth rate become weak in explaining stock returns on UT but become strong on CY, compared to the results from using Thomson Reuters data. The first lag of US IP growth rate still fails to significantly affect sectoral stock returns, but the second lag does hold its explanatory power on the returns. For the variance equations, all parameters for ARCH and GARCH terms are significant and their magnitude are very close to previous results. The F statistics and R-squared values also keep their characteristics as in section 3.3.1.

3.3.4 Chinese Business Cycle Effects on Quarterly US Sectoral Stock Returns

Estimated parameters for four lags of Chinese quarterly IP growth rate are listed in the first four columns in Table 3.9. In parentheses, corresponding standard deviations are put under the estimates. Last period Chinese IP growth rate has positive and significant effects on quarterly stock returns on most US sectors, including the US whole market. Two sectors, TC and TL, do not have significant estimates. The significant parameters range from 0.53 on HC to 1.03 on FN. The second lag of Chinese quarterly IP growth rate has no effect on US sectoral stock returns. But the third lag has negative and significant effects on four sectors, US, FN, IN and EN, and the fourth lag has positive and significant effects on two sectors, BM and EN.

For CY, FN and HC, Chinese business cycle does not have monthly effects on their returns. However, at a longer horizon their returns are affected by Chinese business cycle. On the contrary, a longer horizon blurs Chinese business cycle effects on two sectors, TC and TL, whose monthly stock returns are evidently impacted by Chinese business cycle.

Chinese business cycle effects last a long time on quarterly US sectoral stock returns. For some sectors, more than one lag of Chinese quarterly IP growth rate have effects on their returns. For US whole market, FN, IN and EN, the first lag and the third lag of Chinese IP growth rate have positive and negative effects on their quarterly returns, respectively. For BM and EN, both the first lag and the third lag have positive effects on their returns. Also, EN is the only sector that is influenced by three lags of Chinese quarterly IP growth rate.

Estimated parameters for lags of US IP growth rate are listed in columns five to eight in Table 3.9. US business cycle effects have a similar pattern with Chinese effects. First lag of US IP growth rate has positive and significant effects of all sectors. Except UT, the second lag has no effect on sectors. The third lag has negative and significant effects on six sectors while the fourth lag goes back to positive effects on eight sectors.

Though US business cycle has strong and extensive effects on its sectoral stock returns, it does not explain all the variations of the returns. Chinese business cycle adds some useful information besides US business cycle. Moreover, for some sectors, Chinese business cycle even has stronger effects at the longer horizon, like CY, FN, and UT.

Columns nine and ten are F statistics and R squares for all sectors. Under F statistics and R-squared values are P-value and adjusted R-squared values, respectively. At ten percent significance level, the F tests reveal that the estimate parameters are jointly non-zero excepting sector TL. TL also has a low R-squared value, compared to other sectors.

3.3.5 Time-Varying Predictability on Monthly US Sectoral Stock Returns

I use 5-year rolling fixed window to estimate equation (5) for 129 times and obtain corresponding time-varying parameters for four lags of both Chinese and US's IP growth rate. Based on the significance of the estimated parameters in section 3.3.1, I present two figures. One is for China including parameters for the first lag on TL and third lag on remaining sectors. The other one is for US containing parameters for the second lag on all sectors. In both figures, I color the significant estimates in red.

In Figure 3.1, time-varying parameters on the third lag of Chinese IP growth rate express a moderate increasing trend. This verifies my supposition at the beginning. Because of a closer economic relationship between China and the US, Chinese economic conditions have an expanding influence on US whole market. This increasing trend also appears on most sectors.

Most estimated values are positive but sectors TL and UT do have negative values for a long period. Parameters for most sectors experience remarkable shifts during the sample period. Excluding CY, HC and UT, parameters for all other sectors increase sharply around the 60th rolling period and drop back around the 75th rolling period. I suspect the reason for the increase is the ending of WTO international trade quota on textile starting from 2005 and the negotiation on Chinese textile export to the US during 2005. Almost all sectors have a local minimum around the 100th rolling period, in observing the financial crisis in 2007. Though having an increasing trend, the parameters for CY only rise moderately at the time when parameters for other sectors jump up. Parameters for HC and UT are the most erratic. Parameters for HC seem to meander around zero while parameters for UT have a diminishing tendency.

Parameters for the second lag of US IP growth rate also fluctuate during the sample period, as plotted in Figure 3.2. Because of the terrorist attack in 2001, parameters for almost all sectors decrease to their local minimum values and many of them become negative. Then after the US economy warms back, the parameters experience steady high values for a long time. Similar to Figure 3.1, all sectors have a peak around the 60th rolling period. The 2007 financial crisis has effects on all sectors shifting down the parameters around the 100th rolling period. The crisis continues to exert its effects in 2009 and generates the deepest declines occurring around the 120th rolling period.

Comparing the parameters among sectors, I find that TC and TL are affected more by terrorist attack and less by financial crisis than other sectors. Sector CY has the smallest range of parameter change while sector FN has the largest one.

3.4 Conclusion

In this paper, I use business cycle information from China and the US to explain US sectoral stock returns at two horizons. I find that the third lag of monthly Chinese IP growth rate has significant positive effects on monthly stock returns on US, BM, NC, FN, IN, EN, and TC. The first lag of monthly Chinese IP growth rate has significant negative effect only on TL. The second lag only has significant positive effect on TC. Chinese IP growth rate has no effect on monthly returns on CY, FN and HC. On the other side, the second lag of US IP growth rate have significant positive effects on all monthly sectoral returns, excepting FN. The first lag of US IP growth rate has positive effects only on BM and the third lag has opposite effects on FN and HC.

By examining an alternative model that only possess US business cycle variables I confirm the existence of Chinese business cycle effects. Re-estimating the monthly model using another database verifies the robustness of my results.

Chinese business cycle has stronger effects on quarterly US sectoral stock returns than monthly returns. The first lag of quarterly Chinese IP growth rate has significant positive effects on US, BM, NC, CY, FN, HC, IN, EN and UT. For CY, FN, IN and UT, the first lag of quarterly Chinese IP growth rate even has stronger effects than that of the US. The third lag has negative effects on US, FN, IN and EN and the fourth lag has positive effects on BM and EN. Five sectors, US, BM, FN, IN and EN, are affected by more than two lags of quarterly Chinese IP growth rate. US business cycle effects and Chinese business cycle effects have the same pattern on quarterly sectoral stock returns, namely positive first lag and fourth lag effect and negative third lag effect.

The parameters are time-varying. Parameters for the third lag of monthly Chinese IP growth rate have increasing trends and shift remarkably for most sectors. Parameters for the second lag of monthly US IP growth rate also fluctuate dramatically during the sample period. The major changes in the parameters occur at times marking the ending of international trade quota on textiles, terrorist attack on the US, and the global financial crisis.

Table 3.1: Basic Sectors and their Abbreviations

Abbreviation	Full name	Abbreviation	Full name
US	US whole market	BM	Basic materials
NC	Non-cyclical consumer goods and services	CY	Cyclical consumer goods and services
FN	Financials	HC	Health care
IN	Industrials	EN	Energy
TC	Technology	TL	Telecommunication
UT	Utilities		

The abbreviations for sectors follow the convention of Thomson Reuters.

Table 3.2: Summary Statistics of Monthly Data

	(1)	(2)	(3)	(4)	(5)
	Mean	Median	Std.	Minimum	Maximum
RUS	3.89	10.06	58.99	-222.99	176.15
RBM	5.84	2.71	79.01	-290.51	264.32
RNC	5.07	5.64	69.64	-272.43	206.09
RCY	5.19	10.02	44.41	-170.28	110.35
RFN	2.04	12.87	81.46	-393.24	276.24
RHC	5.31	7.11	53.86	-203.37	147.32
RIN	5.19	9.99	71.73	-290.42	203.04
REN	7.14	11.6	78.38	-251.62	220.7
RTC	2.5	8.01	97.43	-332.3	267.78
RTL	-1.93	5.7	68.29	-173.88	311.72
RUT	5.98	14.41	53.48	-215.08	138.12
RCIP	-0.07	-1.07	34.18	-172.73	181.46
RUIP	1.24	1.62	8.41	-51.59	18.58

1. All variables are measured monthly, in percent per year.
2. RUS indicates stock returns on US whole market, RBM indicates stock returns on the sector of basic materials, and so forth. RCIP and RUIP indicate IP grow rates of China and the US, respectively.

Table 3.3: Estimated Parameters for Monthly US Sectoral Stock Returns – Parameters for Lags of IP Growth Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	c_i	a_{i1}	a_{i2}	a_{i3}	b_{i1}	b_{i2}	b_{i3}
RUS	3.8	−0.06	0.11	0.2*	0.08	1.39*	−0.11
	(3.5)	(0.11)	(0.14)	(0.1)	(0.36)	(0.41)	(0.48)
RBM	6.73	−0.05	0.12	0.32*	1.07*	1.63*	−0.84
	(4.95)	(0.18)	(0.21)	(0.16)	(0.56)	(0.65)	(0.66)
RNC	5.81	0.01	0.22	0.38*	−0.42	1.02*	0.15
	(4.74)	(0.14)	(0.16)	(0.14)	(0.44)	(0.58)	(0.6)
RCY	4.5	0	−0.04	0.09	−0.21	1.14*	0.34
	(3.12)	(0.1)	(0.12)	(0.1)	(0.45)	(0.37)	(0.44)
RFN	6.71	−0.07	0.06	−0.02	0.71	0.51	−0.92*
	(4.13)	(0.12)	(0.16)	(0.12)	(0.49)	(0.46)	(0.53)
RHC	5.96*	−0.02	0	0.16	−0.12	1.03*	0.94*
	(3.4)	(0.12)	(0.12)	(0.1)	(0.41)	(0.39)	(0.52)
RIN	3.6	−0.04	0.1	0.37*	0.4	1.64*	0.23
	(4.34)	(0.14)	(0.15)	(0.13)	(0.51)	(0.55)	(0.58)
REN	4.96	0.14	0.16	0.51*	−0.51	1.9*	0.67
	(5.39)	(0.18)	(0.21)	(0.17)	(0.71)	(0.72)	(0.78)
RTC	5.57	0.18	0.54*	0.47*	0.06	1.21*	0.04
	(5.21)	(0.2)	(0.25)	(0.19)	(0.57)	(0.62)	(0.78)
RTL	1.7	−0.25*	−0.05	0.12	0.31	1*	0.16
	(4.3)	(0.15)	(0.18)	(0.15)	(0.53)	(0.58)	(0.54)
RUT	2.63	0.01	−0.16	−0.18*	0.06	1.6*	0.55
	(3.61)	(0.11)	(0.13)	(0.11)	(0.51)	(0.47)	(0.49)

1. Numbers in parentheses for estimated parameters are their standard deviations.
2. Numbers in parentheses for F statistics are the corresponding P-values.
3. In column twelve, R^2 for each sector is listed first and adjusted R^2 is listed under it.
4. The parameters followed by a star are significant at 10 percent level.
5. Numeric subscripts of the parameters represent orders of lags of IP growth rates. For example, a_{i1} is the parameter of the first lag of China IP growth rate on sector i, and b_{i2} is the parameter of the second lag of the US IP growth rate on sector i.

Table 3.4: Estimated Parameters for Monthly US Sectoral Stock Returns – Parameters for GARCH Processes, F Tests, and Coefficients of Determination

	(8)	(9)	(10)	(11)	(12)
	γ_i	α_i	β_i	F-Stat	R^2&$\overline{R^2}$
RUS	77.11	0.23*	0.76*	2.14	0.066
	(79.98)	(0.08)	(0.08)	(0.05)	0.035
RBM	974.51*	0.27*	0.54*	0.70	0.023
	(473.43)	(0.09)	(0.14)	(0.65)	−0.010
RNC	1238.35*	0.4*	0.32	1.93	0.060
	(615.28)	(0.14)	(0.22)	(0.08)	0.029
RCY	207.95	0.1	0.78*	2.12	0.066
	(217.03)	(0.07)	(0.16)	(0.05)	0.035
RFN	79.97	0.26*	0.74*	0#	0#
	(73.39)	(0.07)	(0.05)	(1.00)	0#
RHC	812.23*	0.31*	0.38*	2.60	0.079
	(334.18)	(0.13)	(0.18)	(0.02)	0.049
RIN	548.45	0.27*	0.6*	3.61	0.107
	(503.54)	(0.11)	(0.21)	(0.00)	0.077
REN	2543.82*	0.14*	0.38*	2.89	0.088
	(1125.8)	(0.08)	(0.23)	(0.01)	0.057
RTC	455.29	0.29*	0.66*	1.12	0.036
	(356.42)	(0.14)	(0.15)	(0.35)	0.004
RTL	184.81	0.19*	0.77*	1.47	0.046
	(134.89)	(0.06)	(0.07)	(0.19)	0.015
RUT	201.62	0.17*	0.76*	1.78	0.056
	(148.78)	(0.09)	(0.11)	(0.11)	0.024

1. Numbers in parentheses for estimated parameters are their standard deviations.
2. Numbers in parentheses for F statistics are the corresponding P-values.
3. In column twelve, R^2 for each sector is listed first and adjusted R^2 is listed under it.
4. The parameters followed by a star are significant at 10 percent level.
5. Numeric subscripts of the parameters represent orders of lags of IP growth rates. For example, a_{i1} is the parameter of the first lag of China IP growth rate on sector *i*, and b_{i2} is the parameter of the second lag of the US IP growth rate on sector *i*.
#: R^2 is reported as zero since a negative value is generated for sector FN. In consequence, $\overline{R^2}$ and F statistics are reported as zeros too.

Table 3.5: Estimated Parameters for US IP Growth Rate on Monthly US Sectoral Stock Returns – Parameters for Lags of US IP Growth Rate

	(1)	(2)	(3)	(4)
	c_i	b_{i1}	b_{i2}	b_{i3}
RUS	3. 65	0. 1	1. 32*	0. 01
	(3. 54)	(0. 37)	(0. 42)	(0. 49)
RBM	6. 49	1. 07*	1. 62*	−0. 71
	(5. 03)	(0. 57)	(0. 67)	(0. 68)
RNC	4. 78	−0. 34	0. 99*	0. 29
	(4. 84)	(0. 48)	(0. 58)	(0. 61)
RCY	4. 21	−0. 18	1. 11*	0. 36
	(3. 11)	(0. 44)	(0. 37)	(0. 44)
RFN	5. 83	0. 72	0. 51	−0. 82
	(4. 13)	(0. 52)	(0. 47)	(0. 55)
RHC	5. 33	−0. 17	0. 94*	1. 05*
	(3. 47)	(0. 42)	(0. 4)	(0. 51)
RIN	4. 36	0. 33	1. 61*	0. 38
	(4. 31)	(0. 5)	(0. 54)	(0. 59)
REN	4. 43	−0. 45	1. 85*	0. 98
	(5. 65)	(0. 71)	(0. 7)	(0. 72)
RTC	4. 85	0. 24	1. 2*	0. 2
	(5. 49)	(0. 59)	(0. 63)	(0. 76)
RTL	1. 94	0. 3	0. 85	0. 27
	(4. 33)	(0. 53)	(0. 57)	(0. 56)
RUT	3. 12	−0. 06	1. 64*	0. 48
	(3. 61)	(0. 5)	(0. 48)	(0. 5)

1. Numbers in parentheses for estimated parameters are their standard deviations.
2. Numbers in parentheses for F statistics are the corresponding P-values.
3. In column nine, R^2 for each sector is listed first and adjusted R^2 is listed under it.
4. The parameters followed by a star are significant at 10 percent level.
5. Column ten is copies from Table 3.3b and rounded to three decimal places for better comparison.
6. Numeric subscripts of the parameters represent orders of lags of IP growth rates.

Table 3.6: Estimated Parameters for US IP Growth Rate on Monthly US Sectoral Stock Returns – Parameters for GARCH Processes, F Tests, and Coefficients of Determination

	(5)	(6)	(7)	(8)	(9)	(10)
	γ_i	α_i	β_i	F-Stat	R^2&$\overline{R^2}$	$\overline{R^2}$ from Table 3.3b
RUS	79.26	0.22*	0.77*	3.07	0.048	
	(73.45)	(0.07)	(0.06)	(0.03)	0.032	0.035
RBM	778.57	0.23*	0.62*	0.78	0.013	
	(516.53)	(0.08)	(0.15)	(0.51)	−0.004	−0.010
RNC	722	0.32*	0.53*	2.41	0.038	
	(475.56)	(0.11)	(0.17)	(0.07)	0.022	0.029
RCY	175.1	0.1*	0.8*	3.79	0.058	
	(183.15)	(0.06)	(0.14)	(0.01)	0.043	0.035
RFN	100.32	0.26*	0.74*	0#	0#	
	(80.63)	(0.07)	(0.05)	(1.00)	0#	0#
RHC	761.47*	0.26*	0.44*	4.61	0.070	
	(363.32)	(0.11)	(0.2)	(0.00)	0.055	0.049
RIN	185.49	0.19*	0.78*	4.96	0.075	
	(146.31)	(0.07)	(0.07)	(0.00)	0.060	0.077
REN	8.86	0	1*	3.55	0.055	
	(45.8)	(0.01)	(0)	(0.02)	0.039	0.057
RTC	358.51	0.25*	0.71*	1.21	0.019	
	(256.95)	(0.09)	(0.1)	(0.31)	0.003	0.004
RTL	174.67	0.18*	0.78*	0.90	0.015	
	(132.78)	(0.06)	(0.07)	(0.44)	−0.002	0.015
RUT	181.34	0.15*	0.79*	3.12	0.048	
	(138.52)	(0.07)	(0.09)	(0.03)	0.033	0.024

1. Numbers in parentheses for estimated parameters are their standard deviations.
2. Numbers in parentheses for F statistics are the corresponding P-values.
3. In column nine, R^2 for each sector is listed first and adjusted R^2 is listed under it.
4. The parameters followed by a star are significant at 10 percent level.
5. Column ten is copies from Table 3.3b and rounded to three decimal places for better comparison.
6. Numeric subscripts of the parameters represent orders of lags of IP growth rates.

#: R^2 is reported as zero since a negative value is generated for sector FN. In consequence, $\overline{R^2}$ and F statistics are reported as zeros too.

Table 3.7: Estimated Parameters for Monthly US Sectoral Stock Returns from DataStream – Parameters for Lags of IP Growth Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	c_i	a_{i1}	a_{i2}	a_{i3}	b_{i1}	b_{i2}	b_{i3}
RUS	3.51	−0.03	0.17	0.19*	0.27	1.47*	−0.15
	(3.48)	(0.11)	(0.13)	(0.1)	(0.39)	(0.42)	(0.46)
RBM	18.31*	−0.17	0.06	0.33*	−0.18	1.15*	−1.29*
	(4.62)	(0.17)	(0.22)	(0.18)	(0.79)	(0.63)	(0.68)
RNC	3.77	0.06	0.24*	0.36*	−0.31	1.43*	0.29
	(3.52)	(0.12)	(0.13)	(0.12)	(0.47)	(0.42)	(0.48)
RCY	5.7	0.04	0.23	0.33*	0.07	0.93*	−0.03
	(4.16)	(0.13)	(0.14)	(0.14)	(0.47)	(0.51)	(0.55)
RFN	7.93*	−0.12	−0.01	−0.04	0.2	0.69	−0.68
	(4.47)	(0.12)	(0.17)	(0.13)	(0.53)	(0.53)	(0.58)
RHC	4.48	−0.01	−0.03	0.07	−0.21	1.06*	0.59
	(3.43)	(0.11)	(0.12)	(0.1)	(0.42)	(0.43)	(0.48)
RIN	3.04	−0.05	0.14	0.28*	0.52	2.11*	0.3
	(4.13)	(0.14)	(0.16)	(0.13)	(0.5)	(0.55)	(0.56)
REN	7.54	0.18	0.11	0.42*	−0.6	1.81*	0.65
	(4.87)	(0.16)	(0.19)	(0.15)	(0.74)	(0.71)	(0.72)
RTC	6.47	0.24	0.68*	0.4*	0.17	1.44*	−0.15
	(5.11)	(0.2)	(0.24)	(0.19)	(0.59)	(0.67)	(0.71)
RTL	0.31	−0.14	−0.03	0.08	0.39	1.27*	−0.06
	(4.47)	(0.16)	(0.18)	(0.15)	(0.54)	(0.6)	(0.6)
RUT	1.94	0	−0.14	−0.16	−0.05	2.16*	0.73
	(3.46)	(0.11)	(0.12)	(0.1)	(0.47)	(0.45)	(0.46)

1. Numbers in parentheses for estimated parameters are their standard deviations.
2. Numbers in parentheses for F statistics are the corresponding P-values.
3. In column twelve, R^2 for each sector is listed first and adjusted R^2 is listed under it.
4. The parameters followed by a star are significant at 10 percent level.
5. Numeric subscripts of the parameters represent orders of lags of IP growth rates.

Table 3.8: Estimated Parameters for Monthly US Sectoral Stock Returns from DataStream – Parameters for GARCH Processes, F Tests, and Coefficients of Determination

	(8)	(9)	(10)	(11)	(12)
	γ_i	α_i	β_i	F-Stat	R^2&$\overline{R^2}$
RUS	90.73	0.25*	0.74*	2.16	0.067
	(91.81)	(0.08)	(0.08)	(0.05)	0.036
RBM	1192.22*	0.66*	0.34*	0#	0#
	(492.82)	(0.23)	(0.13)	(1.00)	0#
RNC	206.43	0.25*	0.69*	1.73	0.054
	(153.38)	(0.1)	(0.12)	(0.12)	0.023
RCY	929.37*	0.4*	0.37*	1.53	0.048
	(482.82)	(0.13)	(0.19)	(0.17)	0.017
RFN	166.59	0.35*	0.65*	0#	0#
	(142.8)	(0.09)	(0.08)	(1.00)	0#
RHC	340.62	0.17*	0.69*	2.08	0.065
	(223.03)	(0.08)	(0.14)	(0.06)	0.033
RIN	181.45	0.19*	0.77*	3.68	0.109
	(127.09)	(0.06)	(0.07)	(0.00)	0.079
REN	2112.06*	0.24*	0.31*	2.68	0.082
	(713.01)	(0.11)	(0.18)	(0.02)	0.051
RTC	353.27	0.26*	0.7*	0.72	0.023
	(264.41)	(0.11)	(0.12)	(0.63)	−0.009
RTL	149.46	0.16*	0.81*	1.12	0.036
	(110.72)	(0.05)	(0.05)	(0.35)	0.004
RUT	167.94*	0.22*	0.73*	1.94	0.060
	(100.77)	(0.07)	(0.08)	(0.08)	0.029

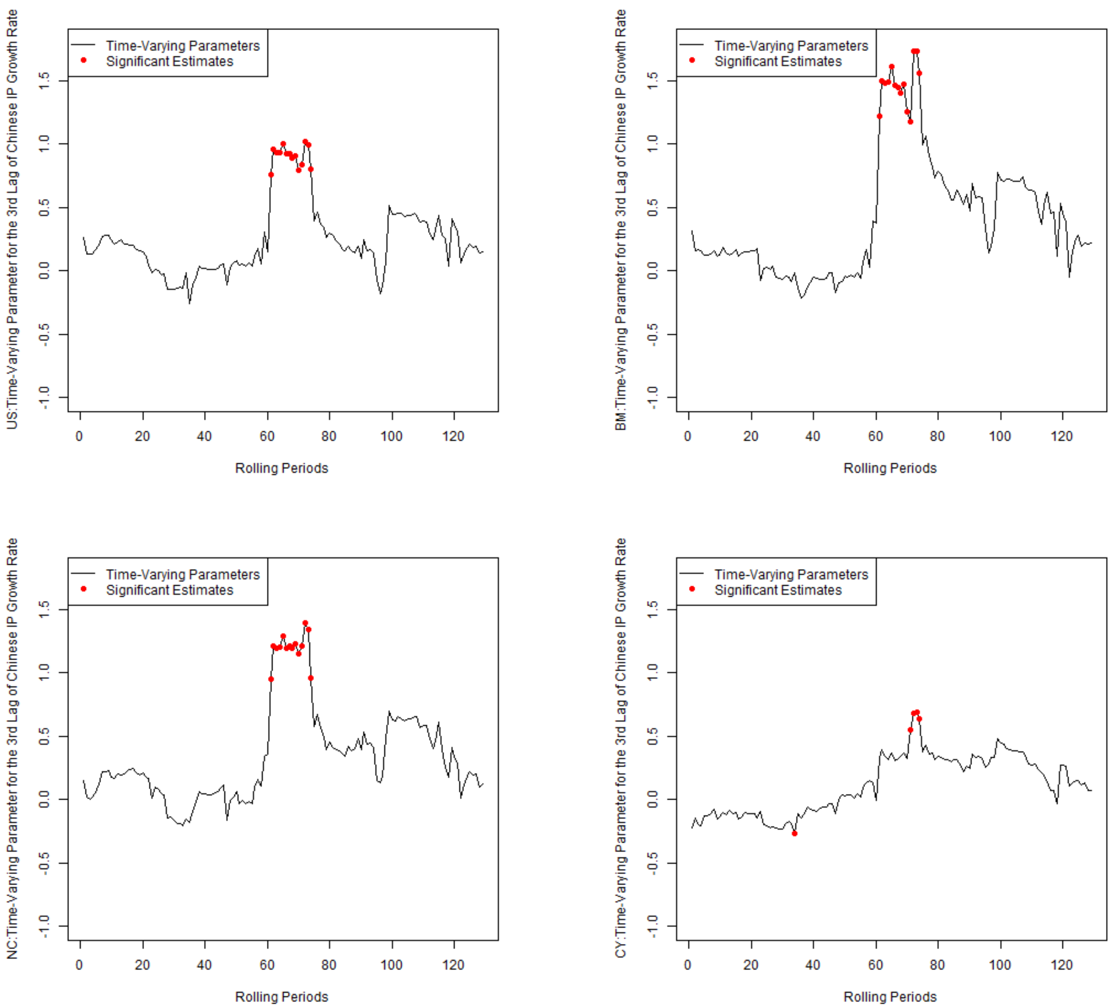
1. Numbers in parentheses for estimated parameters are their standard deviations.
2. Numbers in parentheses for F statistics are the corresponding P-values.
3. In column twelve, R^2 for each sector is listed first and adjusted R^2 is listed under it.
4. The parameters followed by a star are significant at 10 percent level.
5. Numeric subscripts of the parameters represent orders of lags of IP growth rates.
#: R^2 is reported as zero since a negative value is generated for sector BM and FN. In consequence, $\overline{R^2}$ and F statistics are reported as zeros too.

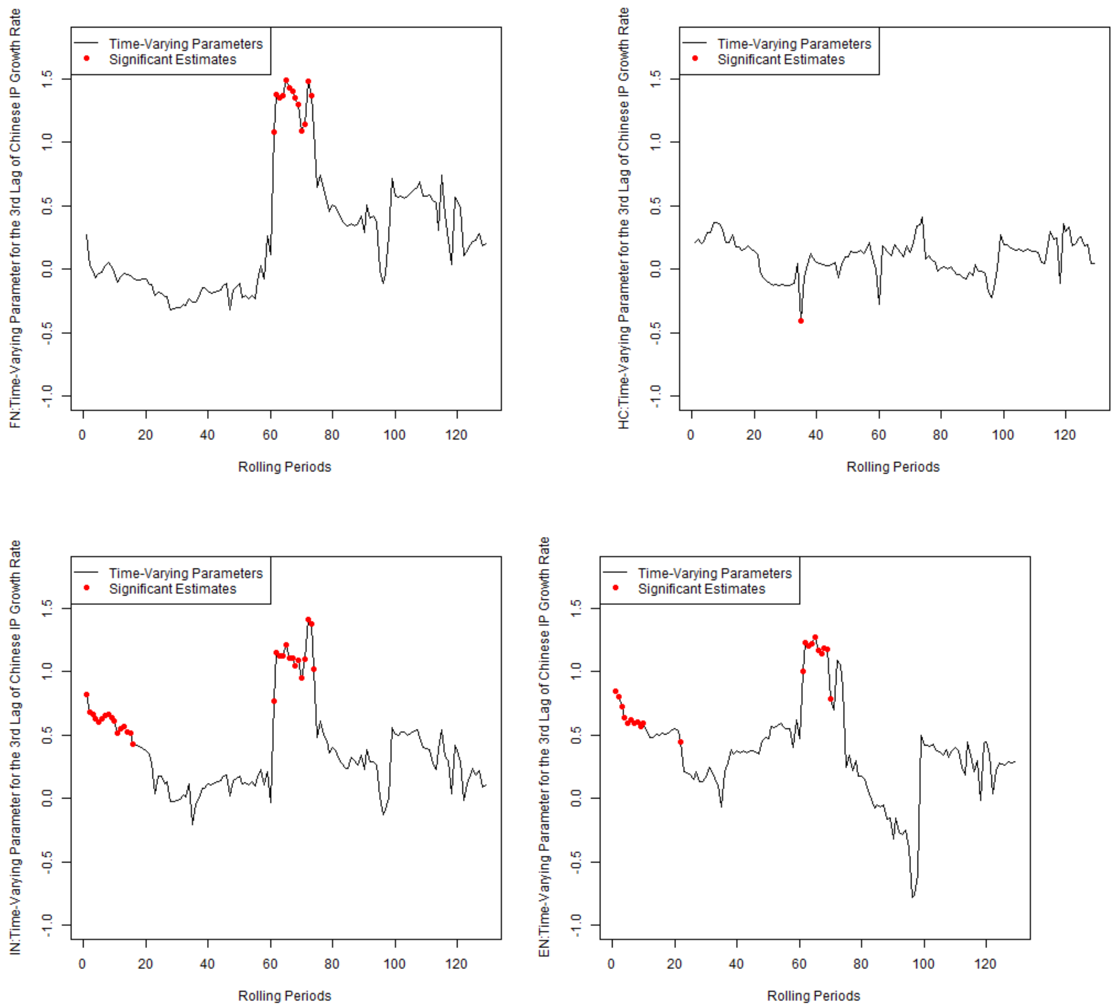
Table 3.9: Estimated Parameters for Quarterly US Sectoral Stock Returns

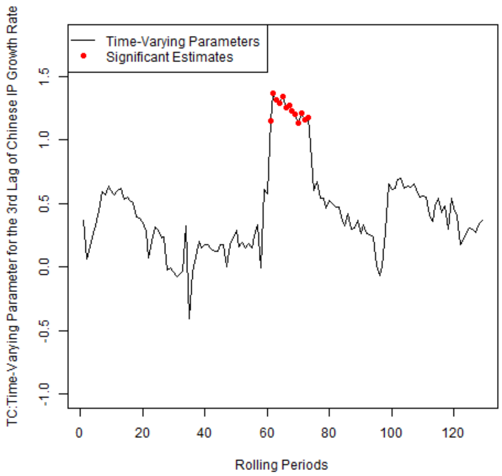
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	a_{i1}^q	a_{i2}^q	a_{i3}^q	a_{i4}^q	b_{i1}^q	b_{i2}^q	b_{i3}^q	b_{i4}^q	F-Stat	R^2& $\overline{R^2}$
RUS	0.6*	-0.23	-0.46*	0.19	1.06*	-0.24	-0.63*	0.53*	4.78	0.41
	(0.25)	(0.24)	(0.22)	(0.22)	(0.27)	(0.32)	(0.31)	(0.3)	(0)	0.33
RBM	0.87*	-0.23	-0.26	0.58*	1.27*	-0.64	-1.23*	1.07*	4.62	0.41
	(0.33)	(0.32)	(0.3)	(0.3)	(0.36)	(0.43)	(0.42)	(0.41)	(0)	0.32
RNC	0.59*	-0.33	-0.41	0.42	1.03*	-0.28	-0.86*	0.44	3.95	0.37
	(0.29)	(0.28)	(0.26)	(0.26)	(0.32)	(0.37)	(0.36)	(0.35)	(0)	0.28
RCY	0.56*	-0.12	-0.08	-0.02	0.43*	-0.17	-0.38	0.47*	2.58	0.28
	(0.2)	(0.2)	(0.18)	(0.18)	(0.22)	(0.26)	(0.26)	(0.25)	(0.02)	0.17
RFN	1.03*	-0.1	-0.59*	0.31	0.85*	-0.1	-0.93*	0.78*	4.47	0.4
	(0.33)	(0.32)	(0.29)	(0.29)	(0.36)	(0.42)	(0.41)	(0.4)	(0)	0.31
RHC	0.53*	-0.19	-0.3	-0.15	0.75*	-0.25	-0.22	0.51*	3.47	0.34
	(0.22)	(0.21)	(0.2)	(0.2)	(0.24)	(0.28)	(0.28)	(0.27)	(0)	0.24
RIN	0.93*	-0.13	-0.48*	0.3	1.06*	0.01	-1.04*	0.86*	5.78	0.46
	(0.29)	(0.28)	(0.26)	(0.26)	(0.32)	(0.38)	(0.37)	(0.36)	(0)	0.38
REN	0.99*	-0.25	-0.48*	0.55*	1.11*	-0.34	-0.86*	1.19*	6.34	0.48
	(0.29)	(0.28)	(0.26)	(0.26)	(0.31)	(0.37)	(0.36)	(0.35)	(0)	0.41
RTC	0.33	-0.43	-0.6	0.01	1.46*	-0.38	-0.33	0.02	1.82	0.21
	(0.45)	(0.43)	(0.4)	(0.4)	(0.49)	(0.58)	(0.56)	(0.55)	(0.09)	0.1
RTL	0.3	-0.47	0.06	-0.13	0.74*	-0.11	-0.1	0.25	1.3	0.16
	(0.31)	(0.29)	(0.27)	(0.27)	(0.33)	(0.4)	(0.39)	(0.37)	(0.26)	0.04
RUT	0.75*	-0.01	-0.09	0.17	0.69*	-0.51*	-0.23	0.81*	3.85	0.36
	(0.22)	(0.21)	(0.19)	(0.2)	(0.24)	(0.28)	(0.27)	(0.27)	(0)	0.27

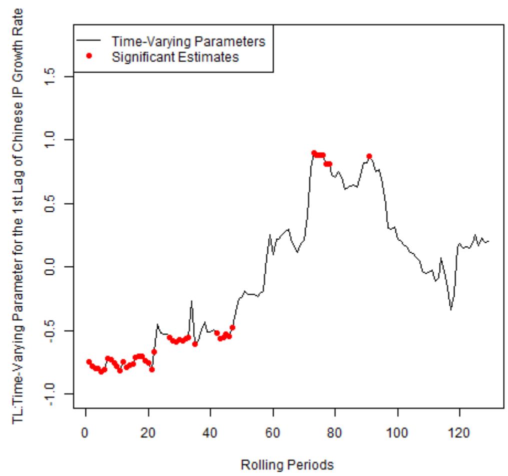
1. Numbers in parentheses for estimated parameters are their standard deviations.
2. Numbers in parentheses for F statistics are the corresponding P-values.
3. In column twelve, R^2 for each sector is listed first and adjusted R^2 is listed under it.
4. The parameters followed by a star are significant at 10 percent level.
5. Numeric subscripts of the parameters represent orders of lags of IP growth rates.
6. Since my major concerns are on the parameters for IP growth rate, the estimates of the constant terms are not listed.

Figure 3.1: Time-Varying Parameters for the Third Lag of Chinese IP Growth Rate




Time-Varying Parameters
Significant Estimates
FN:Time-Varying Parameter for the 3rd Lag of Chinese IP Growth Rate
HC:Time-Varying Parameter for the 3rd Lag of Chinese IP Growth Rate
IN:Time-Varying Parameter for the 3rd Lag of Chinese IP Growth Rate
EN:Time-Varying Parameter for the 3rd Lag of Chinese IP Growth Rate
Rolling Periods
-1.0
-0.5
0.0
0.5
1.0
1.5
0
20
40
60
80
100
120


Time-Varying Parameters
Significant Estimates
TC:Time-Varying Parameter for the 3rd Lag of Chinese IP Growth Rate
Rolling Periods


Time-Varying Parameters
Significant Estimates
TL:Time-Varying Parameter for the 1st Lag of Chinese IP Growth Rate
Rolling Periods

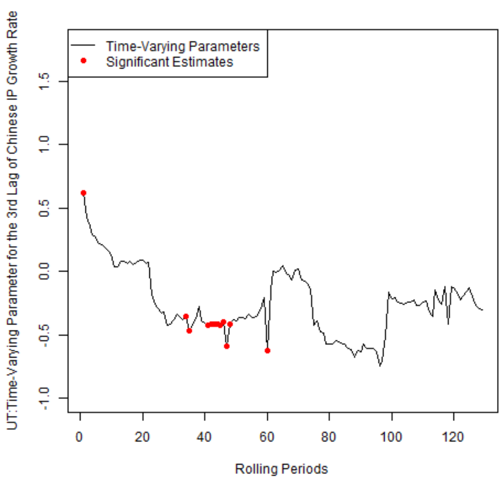
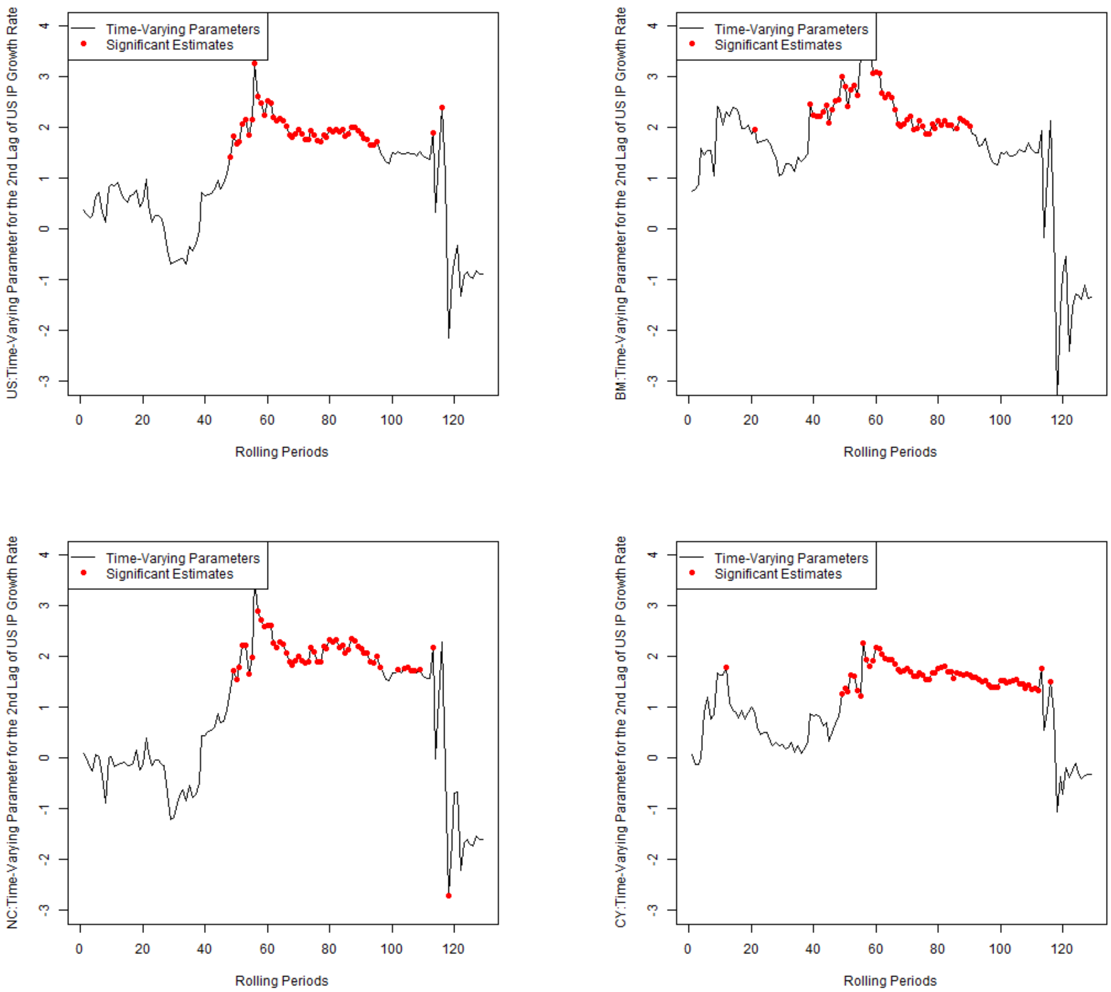
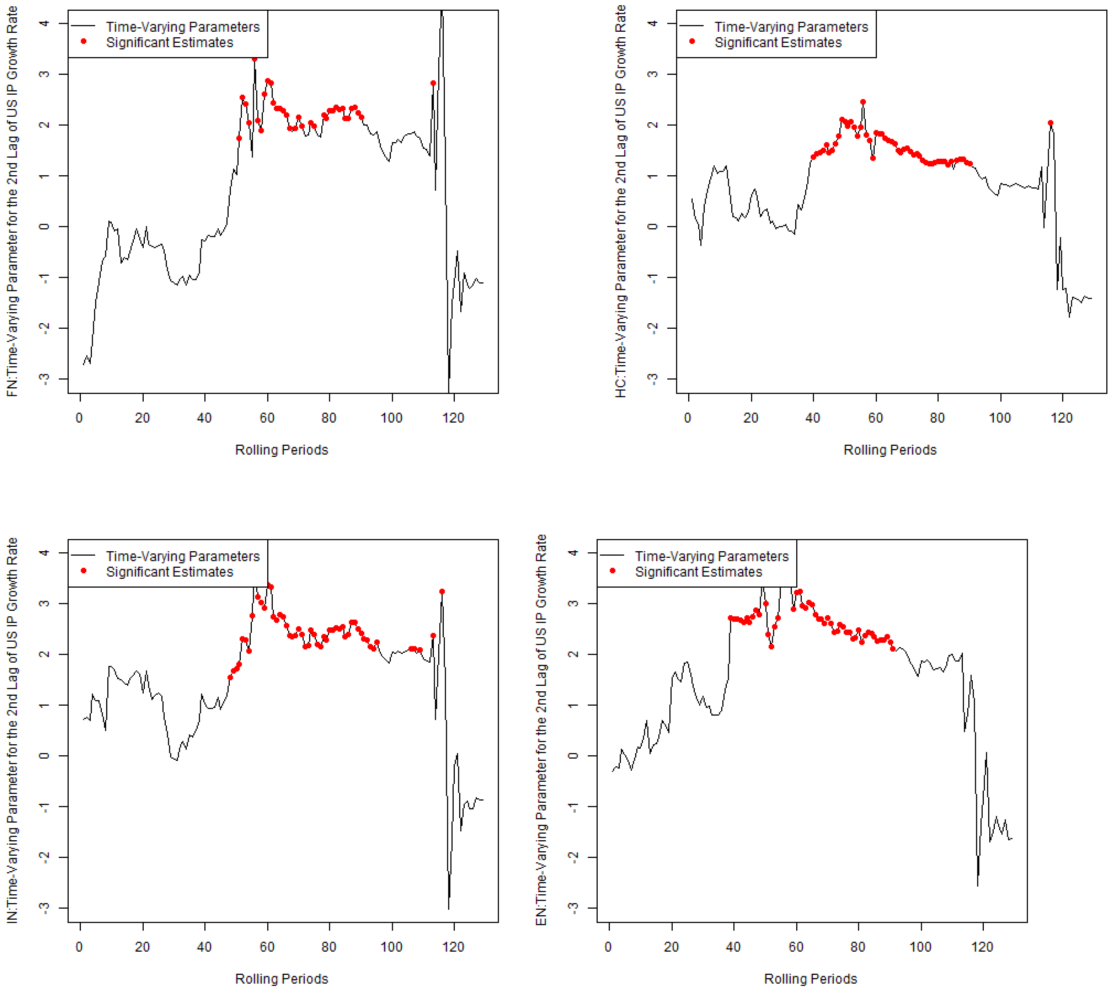
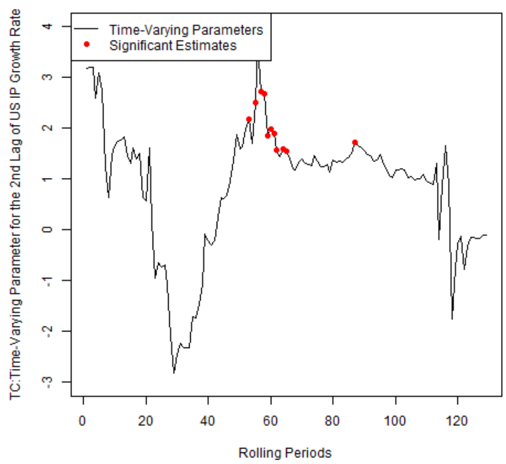
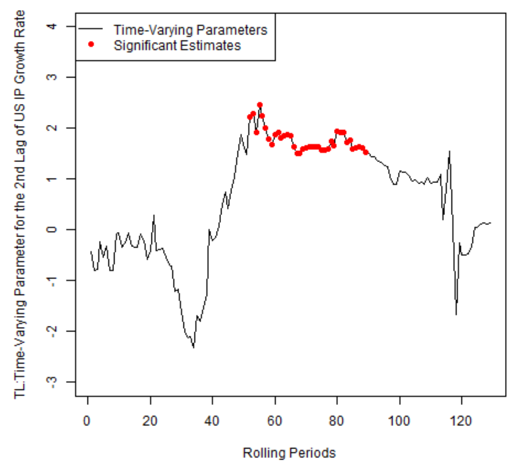

Time-Varying Parameters
Significant Estimates
UT:Time-Varying Parameter for the 3rd Lag of Chinese IP Growth Rate
Rolling Periods

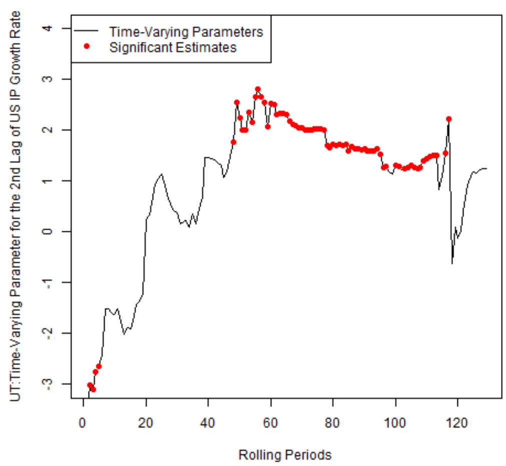
Figure 3.2: Time-Varying Parameters for the Second Lag of US IP Growth Rate




Time-Varying Parameters
Significant Estimates
FN:Time-Varying Parameter for the 2nd Lag of US IP Growth Rate
Rolling Periods
HC:Time-Varying Parameter for the 2nd Lag of US IP Growth Rate
IN:Time-Varying Parameter for the 2nd Lag of US IP Growth Rate
EN:Time-Varying Parameter for the 2nd Lag of US IP Growth Rate


Time-Varying Parameters
Significant Estimates
TC:Time-Varying Parameter for the 2nd Lag of US IP Growth Rate
Rolling Periods


Time-Varying Parameters
Significant Estimates
TL:Time-Varying Parameter for the 2nd Lag of US IP Growth Rate
Rolling Periods


Time-Varying Parameters
Significant Estimates
UT:Time-Varying Parameter for the 2nd Lag of US IP Growth Rate
Rolling Periods

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