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景氣循環、通貨膨脹衡量及聯邦資金利率期貨三論

Three Essays on Business Cycles,
Inflation Measurement and Fed Funds Rate Futures

顏承暉

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中文摘要

研究總體時間序列資料並據以提供其實務上的應用及意涵是總體經濟學家的重要工作。然而，和其他領域實證研究相較，景氣循環在投資組合上的應用、Kitchin、Juglar 以及 Kuznets 循環間的交互作用、通貨膨脹衡量以及聯邦資金利率期貨對美國貨幣政策的預測能力等方面的研究在文獻中屬於相對少數。基於此原因，本論文將針對這些實務上重要的總體經濟議題從實證的角度分析，並據此提出其意涵。

本論文第一章應用頻譜分析（spectral analysis）來探討景氣循環以及資產價格的循環現象。第一節將介紹頻譜分析如何應用在景氣循環研究上。第二節則探討景氣循環對不同類別資產價格的意涵。首先，本節將利用 Canova (1996)所提出的檢定方法驗證債券市場、股票市場、商品市場是不是具有相似的循環現象。其次，本節還應用 Fuller (1996)的檢定方法，透過交叉頻譜分析驗證各資產價格與景氣循環的領先落後關係。研究顯示：(1) 債券、股票以及商品市場具有和景氣循環相似的循環週期，週期介在 3.5~7.5 年間；(2)債券、股票、景氣循環以及商品市場間存在四個具統計上顯著的領先或落後的關係：分別是景氣循環領先商品市場，然而卻同時落後債券市場以及股票市場，又債券市場領先商品市場。此外，本節還透過實際的資料指出，應用這樣的領先落後關係，在不同景氣循環階段持有相對強勢的資產類別，有助於增加投資組合的獲利。

第三節則更進一步分析九大類的共同基金報酬是否也具備有循環上的關連性。研究結果指出：(1) 不同種類的基金類別的確也存在類似的循環現象；(2) 其中存在三種領先或落後的關係，分別是債券型基金領先股票型基金、股票型基金領先能源型基金；債券型基金領先科技型基金、科技型基金領先能源型基金；貨幣型基金領先地產型基金。

第四節將利用 1870 至 2008 年 15 個 OECD 國家的資料，並應用 Canova (1996)所提出的檢定方法證明，除了大家所熟悉的 3~5 年 Kitchin 循環外，這段期間大多數的 OECD 國家同時也經歷具有規律性的 7~11 年之 Juglar 循環，以及 15~25 年的 Kuznets 循環。除此之外，本節還比對歷次 OECD 所認定的景氣循環高峰與谷底日期以及其所處 Juglar 循環以及 Kuznets 循環的該當階段發現，當經濟同時處於 Juglar

及 Kuznets 循環的上升階段時，OECD 所認定的循環擴張期通常會比較長。而當經濟同時處於 Juglar 及 Kuznets 循環的下降階段時，OECD 所認定的短循環景氣收縮期通常會較長。值得注意的是，這一節還指出 Kitchin、Juglar 及 Kuznets 循環同時進入收縮期是造成 1930 年經濟大蕭條以及 2008 年全球金融海嘯的共同原因之一。

鑑於通貨膨脹是總體經濟學的重要議題，而近年來各電子及平面媒體經常出現官方公布之通貨膨脹與一般民眾生活經驗顯不相當的輿論。因此本論文的第二章將探討如何衡量消費者物價指數（CPI）的可靠度。本章試圖建構一個新的迴歸模型，透過模型的估計結果來衡量 CPI 的可靠性。更進一步來說，該模型是文獻上指數隨機方法（the stochastic approach to index numbers）的擴充。本文認為，傳統上的指數隨機方法中關於相對價格間系統性改變的機制應該要隨時間作改變。因此，在這一章的模型中，將加入一般通貨膨脹率以及景氣循環階段等虛擬變數來解決文獻上的不足。而這樣的延伸也更能夠回答凱因斯對於指數隨機方法的批判。此外，本章還應用澳洲以及美國的資料，比對本論文與傳統設定方法的實證差別，結果顯示，這一章的設定較傳統的方法更合適用來衡量 CPI 的可靠度。

聯邦資金利率期貨是否具有未來聯邦資金利率走勢的預測能力是文獻上重要的議題之一，然而過去的研究對於這個議題大多以量化的預測能力來衡量，對於質化（方向性）預測能力的討論則相對有限。但從 1989 年起聯邦資金利率的變動即以 0.25%及其倍數的幅度調整，因此傳統文獻上的量化預測能力評估並不適當。有鑑於此，本論文第三章將應用 Pesaran 及 Timmermann (1992, 1994)所提出的無母數一般化 Henriksson-Merton (H-M)檢定驗證聯邦資金利率期貨對未來聯邦資金利率走向是否具有方向性預測能力。主要實證結果表明，聯邦資金利率期貨對於 (1) 貨幣政策緊縮、寬鬆或中立，或(2)目前貨幣政策升息或降息循環的轉折點至少在 1 週之前就具有預測能力。此外，本章亦驗證，隨著 1994 年 2 月美國貨幣政策制定過程更趨透明化，聯邦資金利率期貨的預測能力是否有所改善。結果顯示，利率期貨的預測能力的確隨著聯準會政策制定過程的更為透明化而有所增進。

英文摘要

Macroeconomists carry the duty of providing insights and creating application value for practitioners based on studying macroeconomic time series data. However, compared with empirical studies in other areas, application of the business cycle concept on investment portfolios, the interplay between the Kitchin, Juglar and Kuznets cycles, the measurement of inflation rates, and the predictability of Fed Funds futures on U.S. monetary policy are all relatively underrepresented in literature. To bridge the gap in literature, this dissertation aims to study these practically important issues with a formal statistical procedure.

The first chapter applies the spectral analysis to discuss the cyclical patterns of business cycles and asset prices. Section 1 briefly introduces the application of spectral analysis on the study of business cycles. Section 2 uses spectral analysis to discuss the implication of the business cycle concept on the investment of multiple asset classes. In this section, Canova's (1996) test is applied to test whether if the bonds market, stock market and commodities market have similar cyclical features as the business cycle. Moreover, the test in Fuller (1996) is applied to verify if lead or lag relationships exist between asset prices of the three markets, respectively, and the business cycle with cross spectrum analysis. Empirical results indicate that (1) Bond, stock and commodity markets all have similar cyclical patterns as the business cycles, which are about 3.5~7.5 years in length. (2) There are four statistically significant pairs of lead or lag relationships among the bonds, stock and commodities market, respectively, and the business cycle, they are: the business cycle leads the commodities market, and lags both the bonds markets and stock market, respectively, and the bonds market leads the commodities market. In addition, we have verified through actual data that applying such lead or lag relationship to hold the relative stronger asset class in each corresponding phase of the business cycle can help improve the returns of a portfolio.

Then, section 3 analyzes whether 9 types of mutual funds also possess similar connections in their cyclical patterns. Empirical results indicate that (1) These mutual fund types exhibit similar cyclical patterns. (2) Among them, there are three types of lead or lag relationships, in which bond funds lead stock market funds, stock market

funds lead energy funds; bond funds lead technology funds, technology funds lead energy funds; and money market funds lead real estate funds.

Section 4 uses data from 15 OECD countries from 1870 thru 2008 and apply Canova's (1996) test to prove that, other than the well recognized 3~5 year Kitchin cycle, most OECD countries have experienced regular 7~11 year Juglar cycles and 15~25 year Kuznets cycles as well during the same period. In addition, as we compare the business cycle peaks and troughs dates recognized by the OECD with the Juglar cycle and Kuznets cycle patterns identified in our model, we found that when the economy is in the upswing of Juglar and Kuznets cycles, the expansions of the short cycle identified by the OECD are usually longer. Also, when the economy is in the downswing of Juglar and Kuznets cycles, the contractions of the short cycle identified by the OECD are usually longer. This section further points out that the joint downswing of the Kitchin, Juglar and Kuznets cycle is one of the common causes of the 1930 Great Depression and the 2008 global financial crisis.

Inflation has always been a core issue in macroeconomics. Recent media highlighted the issue that the official inflation rates may not match public experience. Therefore in Chapter II, we shall discuss the measurement of the reliability of CPI. Here we try to construct a new regression model that can measure the reliability of CPI, which model is an extension of the stochastic approach to index numbers. Therefore, the mechanism of systematic change in relative prices in the literature of stochastic approach to index numbers is allowed to vary with time in this chapter. Then we included inflation rate and phases of business cycle dummies in our model to allow for time varying. Such an extension can answer the Keynes's critic on stochastic approach to index numbers. Moreover, we used US and Australian data, and compared the results from our setting with those from the traditional setting, and further confirmed that our setting was more appropriate than the conventional.

Whether the Fed Funds rate futures have the ability to predict future Fed Funds rates is a significant issue in literature. However, most past researches evaluate predictive ability with quantitative measurements, while its qualitative (directional) accuracy was less emphasized. Since changes in Fed Funds rates were in multiples of 0.25% since 1989, therefore the quantitative evaluation used in traditional literature may not be adequate. Hence in Chapter III, the non-parametric generalized Henriksson-Merton (H-M) test proposed by Pesaran and Timmermann (1992, 1994) is applied to verify the directional predictive ability of FF futures on FF rates. The major empirical results are (1) predicting the tightening, easing, or maintaining of monetary policy (2) when the monetary policy reaches a probable turning point, the futures based predictors are reliable for at least one week. In this chapter, we also investigate the effects of practice changes of the US monetary policy process made in February 1994. The results show that the reliability of futures based predictors have improved since then, which was marked a time when the FOMC decisions were made more open and transparent.

目　錄

中文摘要 2
英文摘要 4
目　錄 7
圖目錄 10
表目錄 11
Introduction 13
Chapter 1
Dissecting of Business Cycles: Applications of Spectral Analysis 16
I. Introduction to the Spectral Analysis on Analyzing Business Cycle 16
1.1 Introduction 16
1.2 Univariate Spectral Analysis 17
1.2.1 Detrending and Signal Extraction 17
1.2.2 Testing for Business Cycle 18
1.3 Multivariate Spectral Analysis 20
II. An Intermarket Investigation and its Implications to Portfolio Reallocation 21
2.1. Introduction 21
2.2. Rationales and Empirical Verification of the Existence of Intermarket Relationships 23
2.2.1. Rationales of the intermarket relationships 23
2.2.2. Data 26
2.2.3. The existence of cyclical behavior 27
2.2.4. Lead-lag relationship between markets 29
2.3. Portfolio Return within Business Cycles 31
2.4. Conclusions and Remarks 35
III. Cycle and Performance of Mutual Funds. 37
3.1 Introduction 37
3.2 Data and methodology 37
3.2.1 Data 37
3.2.2 Uni-spectral analysis 38
3.2.3 Cross-spectral analysis 39

3.3 Empirical results 40
IV. Interplay among Business Cycles Reconsidered: Implications for the 2008 Global Recession. 43
4.1. Introduction 43
4.2. Early Inquiry of Interplay Between Business Cycles 44
4.3. Data 47
4.4. The Existence of Kitchin, Juglar, and Kuznets Cycles 48
4.5. Phases of the Kitchin, Juglar, Kuznets, and Kondratieff Cycle 52
4.5.1. Interplay Between Business Cycles 52
4.5.2. Experience in the Great Depression and the Most Recent Global Recession 56
4.6. Concluding Remarks 59
Appendix 1.1 60
Chapter 2
Measuring CPI's Reliability: the Stochastic Approach to Index Numbers Revisited 64
I. Introduction 64
II. Specification of the Full model 66
III. Empirical Evidence 69
IV. Concluding Remarks 77
Appendix 2.1: Estimated Standard Errors of CPI of Australia and US by Crompton's Method 78
Appendix 2.2: Estimated Standard Errors of CPI of Australia and US by Adding Economic Environment Dummies 80
Chapter 3
An Application of Henriksson-Merton Test: Are Fed Funds Rate Futures Valuable in Predicting US Monetary Policy? 82
I. Introduction 82
II. A Review of Earlier Studies 84
2.1. Rationality Testing and Forecasting Accuracy Evaluation 84
2.2. Importance of Directional Accuracy 85
2.3. Monetary Policy Cycle 86
2.4. Changes in FOMC Disclosure Practices 86
III. Silent Features of the FF Future Rate 87

IV. Usefulness of Futures for Predicting Fed Funds Rate 90
V. Concluding Remarks 95
Appendix 3.1. Contingency tables regarding "tighten, ease or unchanged" 96
Appendix 3.2. Contingency tables regarding the turning point of the monetary policy cycle 99
References 102

圖目錄

Figure 1.1 An idealized diagram of how bond, stock and commodity interact during a typical business cycle 21
Figure 1.2 Spectral density, S&P500, 10 years gov. bond, RJ/CRB, industrial production 27
Figure 1.3 Filtered series of 10-years gov. bond, S&P 500, industrial productions and commodity futures... 29
Figure 1.4 The significant lead/lag relations between different markets........................ 30
Figure 1.5 The partition of each fund for X category funds 39
Figure 1.6 The lead/lag relations of monthly data 42
Figure 1.7 Spectrum density of aggregate GDP, yearly data 51
Figure 1.8 Spectrum density of advanced countries industrial production, quarterly data 51
Figure 1.9 CF-filter decomposition of World GDP cycles, 1870-2008, yearly data....... 52
Figure 1.10 CF-filter decomposition of World IP cycles, Q1/1961-Q1/2009, quarterly data 52
Figure 2.1 Estimated standard errors of Crompton's method and the absolute difference values between the inflation rate at time t with general inflation mean, Australia 71
Figure 2.2 Estimated standard errors of Crompton's method and the absolute difference value between the inflation rate at time t with the general inflation mean, US 71
Figure 2.3 Estimated standard errors after adding dummies and the absolute difference values between the inflation rate at time t with general inflation mean, Australia 75
Figure 2.4 Estimated standard errors after adding dummies and the absolute difference values between the inflation rate at time t with the general inflation mean, US... 76
Figure 3.1 1995~2007 Average FF futures Open Interests 88
Figure 3.2 Forecast and actual change of FF target rate 91
Figure 3.3 Forecast and actual change of policy cycle turning point............................. 93

表目錄

Table 1.1 Univariate spectral statistic 28
Table 1.2 Square coherence and average lead/lad time 30
Table 1.3 Average annual return of portfolio (May, 1960－December, 2007) 33
Table 1.4 Portfolio return over individual business cycles 35
Table 1.5 Numbers of funds in each category 37
Table 1.6 Univariate spectral statistic, monthly data 40
Table 1.7 Summary of lead/lag relations, monthly data 41
Table 1.8 Canova test for short, medium and long term Cycle 50
Table 1.9 Matching the OECD business cycle reference dates and Kitchin cycle turning points 53
Table 1.10 Average duration of expansion and contraction during long cycle upturn and downturn (quarters) 54
Table 1.11 Nearest turning points of each cycles before the Great Depression of 1930 57
Table 1.12 Nearest turning points before the 2008 World Recession 58
Table A.1.1 Reference business cycle date of 15 OECD countries 60
Table 2.1 Number of months with high standard errors during different business cycle phases of Australia using Cromptom (2000)'s method 73
Table 2.2 Number of months with high standard errors during different business cycle phases of US using Cromptom (2000)'s method 73
Table 2.3 The total number of months where "high standard errors of estimated CPI" occurred in different business cycle phases in the US after adding dummies 76
Table 2.4 Summary statistic results before and after the inclusion of dummies 77
Table A.2.1 Estimated standard errors of CPI of Australia by Cromptom (2000)'s method 78
Table A.2.2 Estimated standard errors of CPI of US by Cromptom (2000)'s method ... 79
Table A.2.3 Estimated standard errors of CPI of Australia by adding dummies 80
Table A.2.4 Estimated standard errors of CPI of US by adding dummies 81
Table 3.1 Market timing statistics of FF futures rates 92
Table 3.2 Market timing statistics of policy cycle turning points 94
Table A.3.1 Forecast and actual change regarding "tighten, ease or unchanged" (full range) 96

Table A.3.2 Forecast and actual change regarding "tighten, ease or unchanged" (pre 1994/2 97
Table A.3.3 Forecast and actual change regarding "tighten, ease or unchanged" (after 1994/2) 98
Table A.3.4 Forecast and actual change of policy cycle turning point (full range) 99
Table A.3.5 Forecast and actual change of policy cycle turning point (pre 1994/2)..... 100
Table A.3.6 Forecast and actual change of policy cycle turning point (after 1994/2) .. 101

Introduction

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Chapter 1.

Dissecting of Business Cycles: Applications of Spectral Analysis

This chapter will apply the spectral analysis to discuss the cyclical pattern of business cycles and asset prices.

I. Introduction to the Spectral Analysis on Analyzing Business Cycle

1.1 Introduction

Among the numerous instruments developed by econometricians, spectral analysis is the most proper analytical tool for identifying cyclical patterns and verifying whether lead-lag relationships exist between two different series. Following its promotion by Granger (1966, 1969) and Granger and Hatanaka (1964), the method has gradually been widely applied to the research of cyclical patterns in financial and macroeconomic variables. In which, univariate spectral analysis can formally picture the cycles in the variable of interest (Baxter and King, 1999; Christiano and Fitzgerald, 2003)[1] and cross-spectral analysis has turned out to be the crucial tool for verifying whether there are lead or lag relationships between pairs of variables. There are also numerous formal statistical tests for spectral analysis that can verify cyclical lead or lag relationships between variables (Fuller, 1996; Canova, 1996). Even though spectral analysis is not a tool for forecasting, it can portray the relationships between cycles in asset prices and business cycles. This kind of information is potentially helpful for investors as it may help improve their performance.

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[1] For example, if different economic time series followed a common cyclical pattern, say 4~6 years, one can separate out the 4~6 years cyclical patterns via spectral filters such as Baxter and King filter (1999) and Christiano and Fitzgerald filter(2003). Furthermore, by analyzing the filtered series, one can detect relationships between the different economic time series.

Therefore, in this section, we will introduce how to apply the spectral analysis technique on the analysis of business cycles.

1.2 Univariate Spectral Analysis

1.2.1 Detrending and Signal Extraction

One of the major aims of this thesis is to verify the existence of the Kitchin, Juglar and Kuznets cycles. However, verifying them is statistically difficult, since economic fluctuations as a whole involve various forces. That is, a time series can be perceived as a linear sum of signals as the following.

$$\text{Time Series} = \text{Signal 1} + \text{Signal 2} + ... + \text{Signal N} + ... \quad (1)$$

Thus, the analysis of cycles requires the elimination of the non-cyclical components, such as trend and noise. Earlier literature took care of this using two-sided moving average with varying time windows to single out cyclical components (Shinohara (1990), Dujim (1985)). However, it is now well known that such treatments may generate statistical artifacts (Bird et al., 1965) and hence were rarely used in more recent studies. In this thesis, we will use a more generalized method in the trend-cycle decomposition of our data in order to offer a better description of historical fluctuations.

Discussions in this thesis focus on specific economic cycles, i.e. Kitchin, Juglar and Kuznets cycles or some specific union of frequencies. Therefore, the statistical procedure that we use not only can identify possible existing trends and cycles, but also extract signals belonging to specific cycle frequencies from a given time series. To satisfy dual requirements of trend removal and preserving fluctuations of different frequencies in economic time series over time, we apply the band pass filter proposed by Christiano and Fitzgerald (2003) and Baxter and King (1999) to decompose our time series data sample. The so called band-pass filter is derived from the "Spectral Representation Theorem", according to which any time series within a broad class can be decomposed into different frequency components. Thus, such theory provides a tool for extracting signals from a specific frequency by eliminating signals from all other frequencies.

More specifically, we can perceive the longer cycle as the trend of a time series and shorter fluctuations as random noise. For example, in section IV of this chapter, as we didn't intend to discuss the 40~60 years Kondratieff cycle, all oscillations ranging from infinity to 40 years is treated as trend in this section. And, fluctuations under frequencies of 2 years are often regarded as seasonal patterns or random noise. Consequently, the oscillations ranging from 2 to less than 40 years are defined as possible cyclical frequencies that we will consider in section IV. Therefore a filter that allows time series components with periodic fluctuations between 2 and 40 years to pass through while removing components of higher and lower frequencies will be applied in the next section. We can also obtain specific spans of frequency that we desire in a series, such as 3~5 years, 7~11 years and 15~25 years.

However, since the exact band-pass filter is a moving average of infinite order, an approximation is necessary for practical application. In literature, the Baxter-King band-pass filter (Baxter and King, 1999, the BK filter in abbreviation) and the Christiano-Fitzgerald full sample asymmetric filter (Christiano and Fitzgerald, 2003, the CF filter in abbreviation) are the most commonly used to deal with this problem.

During our choice of filtering technique, we have also considered other trend-cycle filters, such as the Hodrick-Prescott (H-P) filter (Hodrick and Prescott, 1997) and the unobserved components (UC) structural model of time series decomposition (Harvey, 1985, 1989). The H-P filter, which has been widely employed recently in the business cycle literature, was not considered appropriate as it is incapable of separating cycles with different frequencies. On the other hand, the reason not to employ the UC structural model is mainly due to our perception that each of the cycles is a quasi-periodic oscillation.

1.2.2 Testing for Business Cycle

The conventional test for the existence of cycles is Fisher's *g*-test for the significance of the highest peak in the periodgram (Warner, 1998). However, the test is not suitable in this chapter for two reasons. First, our intention is to verify the aforementioned traditional views to the business cycle, which is the coexistence of multiple kinds of cycles, namely, the Kitchin, Juglar and Kuznets cycles. But, the *g*-test is for the identification of peaks in the spectrum, not for verifying cycles in pre-specified frequencies. Second, we consider cyclical fluctuations as quasi-periodic, which mean cycles occur in some union of frequencies and not at a particular frequency. That is, we are not searching for peaks in the spectrum, but for cyclical components over bands of periods (3~5 years, 7~11 years and 15~25 years). Therefore, for our special purpose, we shall apply the third test statistic proposed by Canova (1996) to test for the existence of cycles.

According to his work, define $\Omega \in [0, \pi]$ to be the union of the intervals of frequencies that we have interest to verify the existence of cycles, Ω_1 and Ω_2 are subsets of Ω such that $\Omega_1 \cap \Omega_2 = \varnothing$ and $\Omega_1 \cup \Omega_2 = \Omega$. Let $\|\cdot\|$ denote the Lebesque measure and $h(\omega)$ the spectral density of a stochastic process. Then the null hypothesis of no cycles within Ω can be defined as:

$$H_0 = \frac{\int_{\Omega_1} h(\omega) d\omega}{\|\Omega_1\|} = \frac{\int_{\Omega_2} h(\omega) d\omega}{\|\Omega_2\|} \tag{2}$$

The test derived from Canova (1996) takes the form

$$D = \frac{\sum_{\omega \in F(\Omega_1)} I_N(\omega) / \|\Omega_1\|_F}{\sum_{\omega \in F(\Omega_2)} I_N(\omega) / \|\Omega_2\|_F} \tag{3}$$

where $I_N(\omega)$ is the sample periodogram estimate at frequency ω as defined in Priestley (1981), $F(\Omega_i)$ is the set of all Fourier frequencies in Ω_i for $i = 1$ and 2, while $\|\Omega_i\|_F$ is the number of Fourier frequencies in Ω_i. Canova (1996) has shown that, under H_0, D is asymptotically distributed as $\chi^2(2\|\Omega_1\|_F)$. However, the statistic is a large sample test, but the time series used in this thesis are very short, where for smaller samples, the distribution of the test statistics would be very different than its asymptotic form. To deal with this problem, we follow the procedures of Reiter and Woitek (1999) to derive the small sample distribution of the test statistics that satisfy the null hypothesis of no cycles at business cycle frequencies by Monte-Carlo experiment.

1.3 Multivariate Spectral Analysis

Cross-spectrum analysis is the generalization of the power spectrum to the two series case and provides an advanced method for interpreting the relationship between a pair of series. The cross-spectrum is a complex valued function of the frequency ω:

$$f_{jk} = c_{jk}(\omega) - iq_{jk}(\omega)\,, \tag{4}$$

where $c_{jk}(\omega)$ refers to $\frac{1}{2}\sum_{\tau=-\infty}^{\infty}\Gamma_{jk}(\tau)\cos(\omega\tau)$ and $q_{jk}(\omega)$ refers to $\frac{1}{2}\sum_{\tau=-\infty}^{\infty}\Gamma_{jk}(\tau)\sin(\omega\tau)$ and $\Gamma_{jk}(\tau)$ is the covariance between *j* and *k* series. Note that (4) is quite difficult to interpret, and therefore it is usual to define two further functions that are much easier to interpret, phase shift ($\phi_{jk}(\omega)$) and squared coherency ($sc_{jk}(\omega)$), where

$$\phi_{jk}(\omega) = -\arctan(q_{jk} / c_{jk}(\omega)) \tag{5}$$

$$sc_{jk}(\omega) = \frac{\left| f_{jk}(\omega)\right|^2}{f_{jj}(\omega) f_{kk}(\omega)} \tag{6}$$

The “phase shift” measures the change in lead or lag relationships and squared coherency the correlation between the two series at frequency ω. A positive phase shift shows that the second series lags the first series and vice versa. According to Fuller (1996), the lead or lag relationships of two series have meaning only if the square coherence is significantly above zero. A test of the hypothesis that $sc_{jk}(\omega) = 0$ is given by the statistic

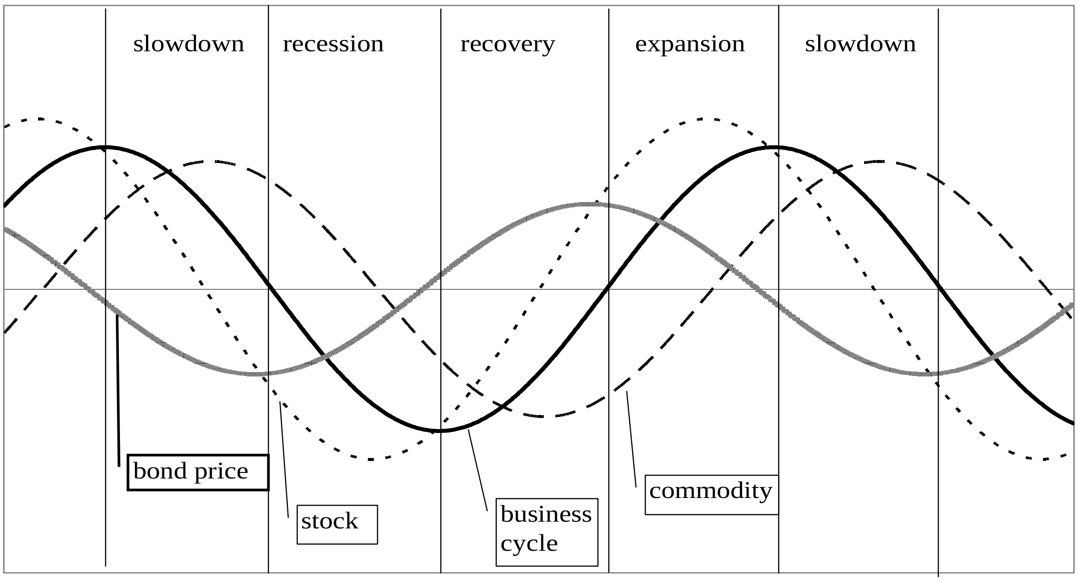
$$F_{4d}^2 = \frac{4d sc_{jk}(\omega)}{2[1 - sc_{jk}(\omega)]} \qquad (7),$$

where *d* is the parameter to construct a smoothed estimator of spectrum density, where in this thesis, *d* is 5. Therefore, any $sc_{jk}(\omega)$ larger than 0.349 indicates the two series are not independent in frequency ω.

II. An Intermarket Investigation and its Implications to Portfolio Reallocation

2.1. Introduction

Figure 1.1 An idealized diagram of how bond, stock and commodity interact during a typical business cycle



Intermarket analysis is the study of multiple asset classes in an integrated manner. Such an analytic framework has been widely used by finance practitioners and has been recognized as useful[2]. The main reason why intermarket analysis can help investors enhance their profit is that peaks and troughs of a particular asset price cycle possesses a time lead or lag relationship corresponding to business cycle. In addition, the lead or lag relationships can be arranged orderly in a time sequence. Typically, in expansions, bond prices peak and then stock prices peak, followed by the peak of business cycle and then finally the peak of commodity prices, while also bottoming in the same order during contractions as well (Pring, 1992, 2002; Murphy, 2004)[3]. This stylized sequence is

[2] The Journal of Technical Analysis (Summer-Autumn 2002) had asked the membership of the Market Technicians to rate the relative importance of technical disciplines for an academic course on technical analysis. Of the fourteen disciplines included in the poll, intermarket analysis ranked fifth, while the cycle analysis ranked sixth (Charlton and Earl, 2006).

[3] For example, the 10 years government bond prices and S&P 500 has reached its peak in March and

shown in Figure 1.1. By understanding this rotation chronology via intermarket analysis, an investor can have the bigger picture and would be able to see significant market and economic changes earlier than other investors only with a single market focus.

Notwithstanding the contributions many earlier researches have made on this significant issue, they have only discussed it in a restricted manner. For example, Ayres (1939), Pring (1992, 2002) and Murphy (2004) have shown the intermarket relationships between bonds, stocks and commodities markets with the business cycle through graphic analysis, but they failed to include statistical analysis. Moore (1975, 1990) and Oppenlander (1997) have verified the lead or lag relationships between stock prices and the business cycle and also between bond prices and the business cycle by investigating simple accumulated returns on stocks and bonds, with the reference business cycle turning points recognized by National Bureau of Economic Research (NBER), but they failed to link all that to the commodity prices. There are also many researches on the applicability of the intermarket concept, such as Brocato and Steed (1998)[4], Siegel (1991)[5] and Gorton and Rouwenhorst (2006)[6]. While their discussions were also in restricted manner with only the stock market and the bond market (Brocato and Steed, 1998; Siegel 1991), some were also presented with only basic statistic

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September, 2007 that is nine and three months before the business cycle peak recognized by NBER. Besides, the RJ/CRB commodity price index has reached its peak in June, 2008, which is six months after the business cycle peak.

4 Brocato and Steed (1998) indicated that cyclically reallocating the portfolio consisted of equity and bond considering the business cycle can improve the return to risk ratio and make the portfolio more efficient.

5 As demonstrated by Siegel (1991), common stock returns can be significantly enhanced by a strategy that relies on correctly forecasting the turning points of the business cycle and reacting to it before the formal announcement of business cycle peaks and troughs by NBER.

6 Based on basic statistical analysis, Gorton and Rouwenhorst (2006) had illustrated the negative correlation between commodity returns and equity and bond returns as probably due to the different price behavior of bond, equity and commodity assets throughout the business cycle. Therefore, inclusion of commodity assets as an option can enhance the efficiency of investment portfolios.

operations (Gorton and Rouwenhorst 2006)[7].

A more rigorous way to address this significant issue would require verifying such rotational sequence of business cycle and different markets in an integrated manner and also validate its applicability on asset allocation. Therefore, to resolve the aforementioned incompleteness in literature, a through analysis of the issue is necessary and should include: (1) detecting cyclical behavior in each of the asset prices; (2) find out the time lead or lag relationships between different markets and the business cycle; (3) demonstrate the applicability of the intermarket framework. Moreover, one should use more sophisticated and up to date time-series econometric techniques throughout the issue, especially in the verification of cyclical relationships, with formal statistical testing.

The main purpose of the section is to apply the spectral analysis to detect cyclical behaviors in bond, stock and commodity markets and the business cycle and find out the lead or lag relationships among them. We will also demonstrate the applicability of the intermarket analysis with the result of our spectral analysis.

2.2. Rationales and Empirical Verification of the Existence of Intermarket Relationships

2.2.1. Rationales of the intermarket relationships

In order to get a better handle on this concept, we will explain how and why these relationships exist and how the business cycle influences market activities. Among the different markets and the business cycle of our interest in this section, the business cycle is the focal point of the intermarket chain (Moore, 1990; Harvey, 1989; Stock and

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[7] They use NBER business cycle dates to divide the business cycle into four phases—early expansion, late expansion, early recession and late recession. Phases are identified by dividing the number of months form peak to trough (trough to peak) into equal halves to indicate early recession and late recession (early expansion and late expansion). Hence, they compare average returns of different assets over these four business cycle phases.

Watson, 1999). If we separate a complete business cycle into four phases－expansion, slowdown, recession and recovery phases just as Schumpeter (1939) did, we will find out lead or lag relationships of these three markets in relation to the business cycle are due to their different behaviors in each business cycle phase. As illustrated in Figure 1.1, the horizontal line is the potential growth path that separate positive output gap and negative output gap of economic activity. The curved line labeled business cycle shows the economy activity during alternating periods of expansion, slowdown, recession and recovery phases. When the curve line is above the horizontal line but increasing (decreasing), the economy is in its expansion (slowdown) phase. While the curve line is below the potential growth path but decreasing (increasing), the economy is in its recession (recovery) phase.

In the expansion phase, utilization rate of the economy is high, with booming investment activities and inflation pressure. In such circumstances, central banks would tighten their monetary policies and cause interest rates to rise, making bond markets bearish. In addition, commodity prices will rise at this phase due to strong demand induced by flourishing investment activities. Even stock markets would be bullish with huge profit, though stock markets usually peak at the end of this phase, as increases in interest rates are likely to have an unfavorable effect on stock price (Moore, 1983; Pring, 1992, 2002; Murphy, 2004). The higher the yield on bonds, the more attractive they become as an alternative to holding stocks. Furthermore, higher interest rates and the accompanied reduce on availability of credit may diminish the propensity of investors to borrow money for buying stocks. Moreover, higher interest rates increase the cost of doing business, notably the cost of holding inventory, and hence may adversely affect profit margins even at a time the economy is still in its expansion phase (Moore, 1975).

In the slowdown phase, inflation remains high at beginning of this phase and utilization rate starts to deteriorate from its highest level. Profit margins of corporations shrink as economic growth slows down, making stock markets bearish. However, commodity markets may remain prosperous at the start of this stage despite economic activities are slowing down for two reasons. First, commodity demands are usually closely related to investment activities. Even when the economy has started to slowdown, since investments take time to build, it may prove difficult for involved parties to discontinue investment projects halfway, which will in order keep demand for commodities on a plateau. Second, commodity suppliers have time lags in their response to commodity price changes. Hence, despite the initiating economic downturn, suppliers have yet fully responded to the strong commodity demand, creating an elongated period of excess demand. Eventually, weaker economic performance finally form the peak of the commodity markets and the economy enters a low inflation environment in most cases, implying that interest rates may be falling, which will lead to bullish bond markets at the end of this stage,.

Regarding the recession phase, low inflation rates keeps interest rates low and makes the bond markets stay bullish. However, when nearing the end of this stage, the fall in interest rates helps the market for stocks, and if the customary early upturn in profits also occurs, optimism among investors in common stocks is doubly justified even though business activity is still depressed and sliding downwards (Moore, 1983). Notably, with the slack utilization rate of the economy, investment demand is low at this stage, keeping the commodity markets bearish.

As for the recovery phase, stock markets are still bullish due to improvement of profit and low interest rates. On the other hand, the low utilization rate keep firms reluctant to invest, which further keeps the commodity markets bearish at the beginning of this stage. Nevertheless, since economic recovery has took place for a period of time, forward looking central banks starts to initiate tightening monetary policies that directs interest rates to climb, which makes bond prices to reach its peak at the end of this stage.

In sum, the peaks (troughs) of the stock market usually occur at the end of expansion (end of recession phases), which all lead the turning points of the business cycle. The peaks (troughs) of the bond markets usually occur at the end of recovery (end of slowdown phases), which not only lead the turning points of the business cycle but also lead the corresponding turning points of the stock markets. However, the peaks (troughs) of the commodity markets usually come at the end of the slowdown (end of the recovery) phase, which not only lags behind the turning points of the business cycle but also the corresponding points of the other two markets.

2.2.2. Data

The data we use in this section includes the 10 year US Treasury bond prices, industrial production index (both downloaded from FRB St. Louis), S&P 500 stock price index (from the Bloomberg terminal), and the equally-weighted index of commodity futures (from NBER)[8], covering data from May, 1960 thru December, 2007. In order to compare the performance of multiple assets, we transform the three market indexes into total return indexes.

To satisfy the stationary requirement of spectral analysis, our data is processed by the Baxter-King band-pass filter (Baxter and King, 1999, the BK filter in abbreviation), so that the frequencies 18~180 months remain[9]. Furthermore, previous studies about the lead or lag relationships between asset prices and economic activity often use the accumulated return (or annual growth rate) of assets and reference business cycle dates to interpret their relationships. However, such comparison is statistically inappropriate, since reference dates of business cycles in practice is the date where absolute decline in the level of either the reference series or the detrended reference series initiate. However, the peak of growth rate in such reference series may have already been passed. Therefore, even if previous literatures have verified the lead or lag relationships between asset prices and economic activity, the relationship may be an artifact. But we can avoid the aforementioned drawback by filtering the economic series and asset prices with the same BK filter.

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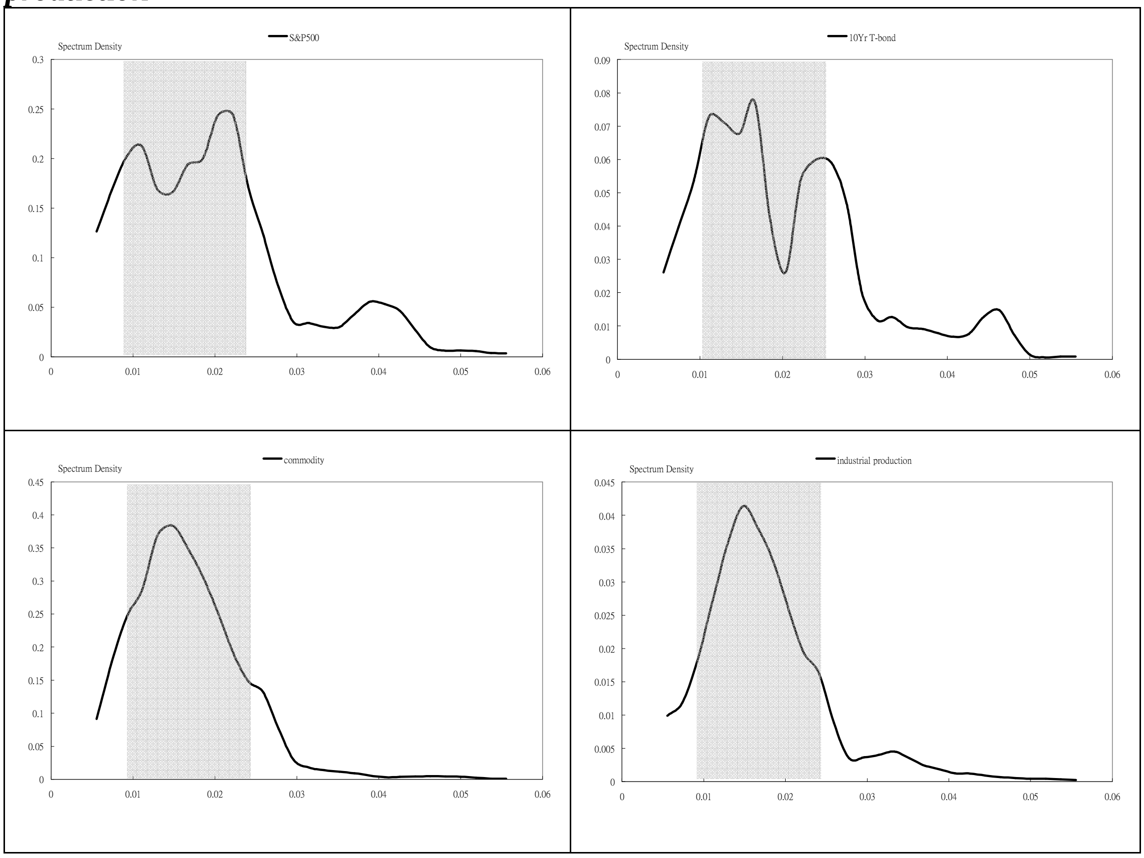
[8] The total return index of the equally-weighted index of commodity is constructed by Gorton and Rouwenhorst (2008). It is available on the website at http://www.nber.org/data-appendix/w10595/EqWtdTR_Jan_2008.xls.

[9] Since the original series is only 52 years and 7 month in length and thus insufficient to discuss the 15-25 year Kuznets cycle and the 40-60 year Kondratieff cycle, all oscillations ranging from infinity to 15 years are treated as trends in this paper. Furthermore, fluctuations under 18 months are often regarded as seasonal patterns or random noise. Consequently, the oscillations ranging from less than 15 to 1.5 years are defined as possible cyclical lengths of the cycles that we discuss in this section.

2.2.3. The existence of cyclical behavior

The characteristics of the cycles in each of the markets are first analyzed individually. Our aim is to find out whether all these markets display the same propensity for cyclical fluctuations, and also whether they share the same regularity in those fluctuations. We apply the third test statistic proposed by Canova (1996) to test for the existence of cycles.

Figure 1.2 Spectral density, S&P500, 10 years gov. bond, RJ/CRB, industrial production



Note: Shaded areas cover the frequencies $(\frac{2\pi}{90}, \frac{2\pi}{41})$

The results from spectral analysis show that the spectral density of S&P 500 is enlarged between two cyclical components, a shorter one at cycle length of 45 months, and another longer one with cycle length of 90 months. As for the 10 year Treasury bond, spectral density also magnify between two cyclical components, each with cycle lengths of 41.5 months and 90 months. Spectral densities of Commodity futures and industrial production, respectively, enlarge around the peaks in their spectrum density at 67.5 months (see Figure 1.2 and column 2 and 3 of Table 1.1). In other words, the four series seems to have similar cyclical behaviors, respectively.

Whether the four series share the similar cyclical pattern in statistical sense is of interest and will be tested as follows. Define $(\frac{2\pi}{90},\frac{2\pi}{41.5})$ as Ω_1 which is the union of frequencies with cycles, while $(\frac{2\pi}{180},\frac{2\pi}{90})\cup(\frac{2\pi}{41.5},\frac{2\pi}{18})$ is Ω_2. Applying the Canova test, the corresponding D statistics are shown on the column 4 of Table 1. To be sure, $(\frac{2\pi}{90},\frac{2\pi}{41.5})$ is significant at 99% confidence, which means the four markets follow similar cyclical mechanisms in the span of 3.5 years to 7.5 years. In fact, the short cycle peaks of 41.5 months in the S&P 500 and 10 years Treasury bond, and 67.5 months in commodity futures and industrial production are interesting, since these frequencies are within the range of the well known 3~5 year Kitchin cycle (Kitchin, 1923). Besides, the long cycle peaks of 90 months in S&P 500 and Treasury bond all are within the frequencies of 7~11 year Juglar cycle (1862). Such results also provide evidence for the existence of Kitchin cycles and Juglar cycles in those markets.

Table 1.1 Univariate spectral statistic

	Peak Freq.	Peak. Duration (months)	D
IP	0.0148	67.5	7.557^{***}
SP	0.0111 & 0.0222	90 and 45	3.702^{***}
Gov	0.0111 & 0.0241	90 and 41.5	3.208^{***}
Com	0.0148	67.5	6.828^{***}

Note: 1.Industrial production, S&P 500, 10 years government bond and commodity are named by IP, SP, Gov and Com respectively.

2. Sig. Freq and Sig. of Duration refers to frequency and corresponding duration of peak of spectrum.

3. *, **, *** denote the 90%, 95% and 99% of significant.

In summary, we use Canova (1996)'s test to verify the existence of the cycles in various markets. It has especially shown that the frequency peaks of the power spectrum in these markets are rather coincident. It further hints that there are common relationships behind the scenes that link the seemingly independent markets altogether. This finding will strengthen the results of our cross-spectral analysis.

2.2.4. Lead-lag relationship between markets

Before statistically verifying the lead or lag relationships between different markets, let's take a look at the cyclical behavior in each of the markets. Figure 1.3 shows the filtered series of these markets with frequencies $(\frac{2\pi}{90}, \frac{2\pi}{41.5})$. The arrows of Figure 1.3 show quite clearly that the momentum of the bond prices leads the stock prices, the stock prices lead the industrial production, and the commodity futures lag behind all of them for most of the time.

Figure 1 Filtered series of 10-years gov. bond, S&P 500, industrial productions and commodity futures

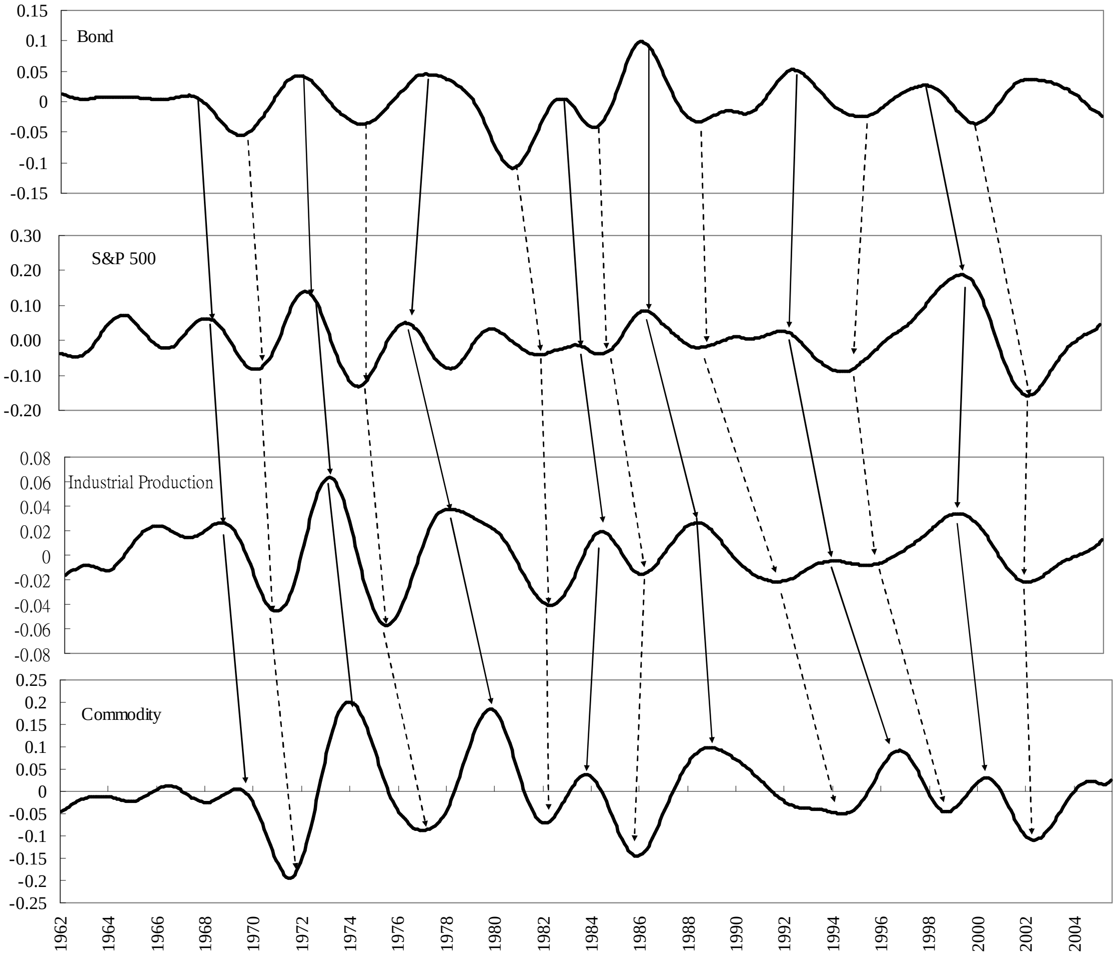


Table 1.2 and Figure 1.4 is the summary of the cross-spectrum within the

frequency of $(\frac{2\pi}{90}, \frac{2\pi}{41.5})$. Instead of SP/Gov and SP/Com failing to have significant lead or lag relationship, the other four square coherences are all above the 0.349 mark, indicating significant lead or lag relationship in these four cases. Among them, industrial production has significant lead or lag relationships with the other three markets, in which it leads commodities for an average of 7.97 months and lags behind S&P 500 and treasury bonds for an average of 9.42 and 17.49 months, respectively. This result indicates that economic fluctuation does influence financial markets. On the other hand, government bonds also lead commodities for 24.25 months. Noteworthy, the relationship between stock markets and economic activity and the relationship between bond markets and economic activity are similar to the results of Moore (1978), where he found that, on average, stock price peaks lead business cycle peaks for 5 months, while bond price peaks lead business cycle peaks for 14 months within the sample period 1943-73.

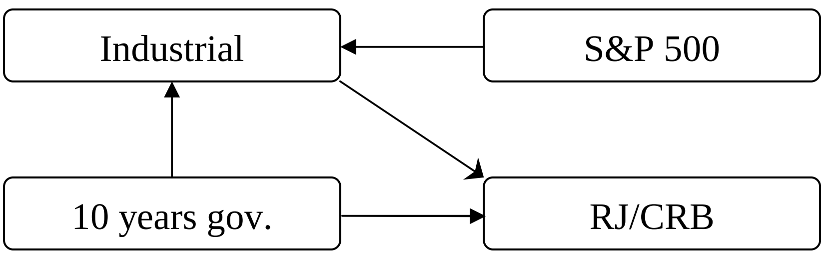
Table 1.2 Square coherence and average lead/lad time

	IP	SP	GOV	CRB
IP	–	–	–	–
SP	0.42(9.04)	–	–	–
Gov	0.50(17.49)	0.17(6.15)	–	–
Com	0.49(-7.97)	0.21(-19.12)	0.53(-24.25)	–

Note: 1.Industrial production, S&P 500, 10 years government bond and commodity are named by IP, SP, Gov and Com respectively.

2. Outside of parenthesis are the square coherence, in parenthesis are the average lead time of the row element on the column element

Figure 2 The significant lead/lag relations between different markets



Note: Arrows point to the lagging market

Nevertheless, although we cannot find significant lead or lag relationships between the S&P 500 index and government bond prices, and between the S&P 500 index and commodities, by indirect inferring the lag time of industrial production with S&P 500 and with government bonds, we can find a weak support that bond prices lead the stock prices for roughly 8 months, which is similar to Moore's (1975) results of 11 month lead. As for S&P 500 and commodities, even though the relationships are insignificant, we can also find a weak support that S&P 500 lead the commodities by indirectly inferring their individual lead or lag relationships with industrial production.

In summary, through the study of cross spectrum analysis, we verified that the commodities lag behind the other three markets, while the stock and bond markets, even tough their relationship with each other is ambiguous, both lead industrial production and commodities. Thus, our results give some evidence to Murphy (2004) and Pring's (2006) idea that the order of lead or lag relationships among these four markets is bond market, equity market, economic activity and commodity market. Besides, the result can also reinforce the conclusion of Gorton and Rouwenhorst (2004).

2.3. Portfolio Return within Business Cycles

Are investors capable to increase their returns by implementing the aforementioned cyclical sequence among those markets? Actually, the implication of the cyclical sequence assumes investors can perfectly gauge their position in business cycles, where they should increase their stock positions before the economy reaches the trough, then switch to commodity assets before the economy reaches the peak, and then to bonds throughout most of the recession. If the investor can only choose between stocks and bonds, then the strategy is to increase stock positions before the trough and then reallocate to bonds nearing the peak. Noteworthy, the strategy with only stock and bond is similar to Siegel (1991), who has shown that portfolio returns can be enhanced significantly by switching between bonds and stocks before turning points in the business cycle.

Table 1.3 is the summary results about whether commodity assets are a proper asset choice in the reallocation strategy based on the stages of business cycles. The first nine rows of Table 1.3 shows the summarized data of the US business cycle and the average annual return from investing in stocks, bonds and commodities over the business cycle. Over the entire period of May 1960 to December 2007, the seven recessions averaged 10.71 months in length, and expansions averaged 70.76 months in length, so that almost one-eighth of the time the economy in a recession.

From May 1960 thru December 2007, the average annual nominal return from investing in the stock market is 11.42%, while the average return is 7.59% and 12.36% from investing in 10-year Treasury bonds and the commodity index, respectively. The risk-adjusted return, the "benchmark" or "traditional asset class" return, is defined as the weighted average return with only stocks and bonds in the portfolio for the period and weighted according to the time the economy is in expansion (for stocks) and recession (for bonds), is 10.92%.

The column labeled "without Com" in the lower part of Table 1.3 is the return of reallocating only between stock and bond assets throughout the business cycle. The slot labeled "concurrent" reports returns from being 100% long in equities during economic expansion and 100% long in Treasury bonds during economic contractions. The returns calculated in "*h*-month lead" assumes an investor who leads the business cycle peaks for *h*-months in switching from stocks to bonds in business cycle expansions and leads the business cycle troughs also for *h*-months in switching from bonds to stocks in recessions. In contrast, an investor who lags the business cycle turning points to switch out of, and then into stocks an equal number of months after the peak and trough of the business cycle are labeled "*h*-month lag". Actually, the results in the column labeled "without Com" is the similar to Siegel (1991), that investors can increase their returns by switching into bonds before the peak of the business cycle and into stocks before the trough of the business cycle.

The remaining part of Table 1.3 shows whether investors can increase returns by including commodity assets in their portfolio in some stages of the business cycle. Noteworthy, as previous subsections have shown, bull commodity markets can go on even after the economy has passed its peak. Therefore, the investor can switch from stock assets to commodity assets before the peak of the business cycle and switch to bond assets some time after the peak. The rows of lower-right part of Table 1.3 define when the investor switches its stock assets into commodity assets. The row labeled "concurrent" means the investor becomes 100% long in commodity assets at the business cycle peak. *g*-month lead/lag means the investor shifts to commodity assets *g* months before/after the business cycle peak. The column part denotes the investor switches its commodity assets into bond assets *K*-months after the business cycle peak. Note that, we still assume investors switch their bonds into stock assets *h* months before/after the business cycle trough.

Table 1.3 Average annual return of portfolio (May, 1960 —December, 2007)(bps)

(1) Average length of recession (months)	10.71
(2) Average Length of Expansion	70.67
(3) Average Length of Business cycle	81.38
(4) % of Time Economy in Recession	13.17
(5) % of Time Economy in Expansion	86.83
(6) Average Annual Return for Stock (%)	11.42
(7) Average Annual Return for Bonds (%)	7.59
(8) Benchmark Returns (6) X (5)+(7)X(4) (%)	10.92
(9) Average Annual Return for Com	12.36
(10) Average Returns of Portfolio (%)	

	Without Com	With Com						
		0-month	1-month	2-month	3-month	4-month	5-month	6-month
6-month lead	14.01	15.35	15.71	16.16	15.64	15.19	15.47	15.67
5-month lead	13.85	14.93	15.47	15.93	15.26	14.82	14.96	15.02
4-month lead	14.31	14.66	15.21	15.45	14.78	14.38	14.53	14.59
3-month lead	14.22	14.34	14.89	15.13	14.37	13.97	13.91	13.97
2-month lead	14.69	14.60	15.15	15.39	14.63	14.14	14.08	13.99
1-month lead	13.54	14.05	14.59	14.83	14.08	13.59	13.52	13.43
concurrent	12.65	—	13.19	13.43	12.68	12.20	12.13	12.25
1-month lag	12.00	—	—	12.23	11.49	11.02	10.95	11.06
2-month lag	11.29	—	—	—	10.55	10.08	10.02	10.13
3-month lag	10.88	—	—	—	—	10.40	10.34	10.45
4-month lag	10.21	—	—	—	—	—	10.15	10.26
5-month lag	9.72	—	—	—	—	—	—	9.84
6-month lag	9.82	—	—	—	—	—	—	—

Still, if investors can perfectly gauge the future movement of the business cycle and switch their stock assets into commodity assets before the economy reaches the peak, then switch into bonds some time after the peak, and then switch their bond assets into stock assets before the trough, they can earn more return than when their response lags the turning points of the business cycle. Besides, we can see that over most rows, investors can gain more return by switching into commodity assets before the peak of the business cycle and then switch into bond assets several months after the peak compared to the column labeled “without Com”, the case where investors only invests in stocks and bonds. The additional gains from holding commodity assets for until two months after the business cycle peak compared to the column labeled “without Com” ranges from 23 basis points to 215 basis points per year in the span May, 1960 to December, 2007. These results reinforce that the sequential relationship among cycles in different markets do exist during the period May 1960 to December 2007. Besides, these results also echo Gorton and Rouwenhorst (2006) that the inclusion of commodities can enhance portfolio performance.

However, with the recent extraordinary spikes in commodity prices, whether this outperformance mentioned above is due to the instable hikes or the regular intermarket sequential relationship of cycles is an issue facing scrutiny and would have to be addressed. Table 1.4 is the average return of different portfolios over each business cycle since May 1960 to December, 2007[10]. We can see that, in five out of seven business cycles since May 1960, investors would have enhanced their returns had they switched into commodity assets before the peak of the business cycle and then switch into bonds some time after the peak. The greatest addition in gains by such strategy is 1,026 basis points in the business cycle from December 1973 to January 1980. The largest additional loss of that strategy is -534 basis points at the business cycle from February 1980 to July 1981, the time just few months after the second oil crisis. During October 1978 to January 1980, cumulated rise in commodity prices reached 55.36%. Such a extraordinary rise in commodity prices was not due to business cycles but supply shocks, thus after the crisis, even though the economic environment would favor commodity assets, the price of commodities were still falling. The other occasion that including commodity assets would result in negative additional gains was in the business cycle from August 1990 to March 2003. In fact, though the average return of including commodity assets in the portfolio cannot exceed the average returns of portfolios with only traditional asset classes, the average returns of the two are similar. In summary, the additional gains from properly allocating commodities into the portfolio were fairly stable since May 1960.

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[10] We defined a complete business cycle is from peak to peak. Thus, since May 1960, there are 7 times complete business cycle.

Table 1.4 Portfolio return over individual business cycles (bps)

	Benchmark (1) [a]	Reallocation without commodity (2) [b]	Reallocation with commodity (3) [c]	Gain (3)-(2)
1960/5~1969/12	9.18	9.81	11.21	1.41
1970/1~1973/11	6.30	13.35	16.69	3.34
1973/12~1980/1	8.18	11.84	22.10	10.26
1980/2~1981/7	12.93	12.25	6.91	-5.34
1981/8~1990/7	17.68	20.50	21.22	0.72
1990/8~2001/3	15.04	19.99	19.87	-0.12
2001/4~2007/12	6.19	6.24	6.88	0.64

[a] *"Benchmark" denotes the average annualized return defined as the weighted average of the stock and bond return for the period and weighted by the share of time the economy is in an expansion (for stocks) and a recession (for bonds).*

[b] *"Reallocation without commodity" denotes the average annualized return in which investors switch out of stocks 6 months before the peak of the business cycle expansion and switches into stocks the same number of months before the trough of the recession.*

[c] *"Reallocation with commodity" denotes the average return in which investors switch to commodities 6 months before the peak of business cycle, and then switch into bonds 2 month after the peak, and then switch into bonds 6 months before the trough.*

2.4. Conclusions and Remarks

This section has examined the cyclical behavior of the bond market, stock market, economic activity and the commodity market. We show that: (1) The fluctuations of these four markets are governed essentially by the shorter 3~5 year Kitchin cycle and the longer 7~11 year Juglar cycle; (2) The four markets have four significant lead or lad relationships, in which economic activity leads the commodity market and lags behind both the bond market and the equity market, while the bond market leads the commodity market. The results are useful for investors to optimize their portfolio in different phases of the business cycle, and more so as we expand our discussion to include commodity markets, which is rarely discussed in previous literature. Through the empirical study by this section, readers can better understand the cyclical sequence among multiple markets. The implication of our results is straightforward and is helpful for investors to enhance their gains by incorporating such an "intermaket framework".

Besides, the results not only can apply to asset allocation, but also on gauging business cycle turning points. For most policy makers, market participants and business managers, future economic performances are important. However, the prediction of turning points is indeed one of the most challenging aspects of economic forecasting in general, even with large-scale macroeconometric models. Zarnowitz (1992) had shown that, in history, the largest forecasting errors are all associated with business cycle turning points. Therefore, in order to overcome this challenge, forecasters should include some leading indicators in their forecasting model, as did the Wharton model (Adams and Klein, 1972; Adams and Duggal, 1974). For market participants, even though they might not be familiar with the sophisticated econometric models, they can use some kind of rule of thumb to gauge future economic movements by leading financial indicators, such as stock prices and bond prices. For example, Siegel (1991) has pointed out that, out of the forty-one recessions from 1802 through 1990, thirty-eight of them, which is 93%, have been preceded (accompanied) with declines of 8% or more (based on monthly average) in stock total return indexes. As for lagging indicators, such as commodity prices, it not only can be used to reaffirm the turning points in economic activity that precedes those of the lagging indicator's, but its inverse can also be treated as long leaders of the next business cycle turning point.

For upcoming researchers, spectral analysis is also a possible tool for market timing decisions. Indeed, there are many markets left out of this section, such as the corporate bond market, that are grounds where later researchers can further study with spectral analysis.

III. Cycle and Performance of Mutual Funds.

3.1 Introduction

Many researchers have even applied the spectral analysis to financial economics, e.g. Turhan-Sayan and Sayan (2001) studied the stock market and Wilson and Zurbruegg (2003) the real estate market. Nevertheless, only a few literatures have applied the spectral approach to fund investment. In order to fill the gap in the literature, we will use cross-spectral analysis to find out the lead or lag relationships among various categories of funds from the data of 2,135 funds covering nine categories, namely equity funds (Eds), energy funds (ENds), currency funds (Cds), finance funds (Fds), technology funds (Tds), balanced funds (Bds), medical service funds (Mds), bond funds (BOds) and real estate funds (Rds) from 1997 to 2008, and incorporate the lead or lag relationships as a reference for investors to establish their investment portfolios.

3.2 Data and methodology

3.2.1 Data

Table 1.5 Numbers of funds in each category

	Source	Daily data	Monthly data
Eds	1035	559	251
ENds	34	21	7
Cds	56	39	19
Fds	15	11	7
Tds	75	53	32
Bds	171	51	25
Mds	41	26	11
BOds	673	329	118
Rds	35	12	5

Note: We delete some data so that the funds of each category have to be the same starting and ending time, e.g. the source numbers of equity funds are 1,035, and, by deleting 784 numbers, 251 numbers of monthly data are left, and so forth. The number of daily data is the same as that of monthly data.

Our data (including dividends information) comes from four websites, FundDJ, FortunEngine, E-fund and cnYES with a total of 2,135 funds. They are grouped into nine categories, namely Eds, ENds, Cds, Fds, Tds, Bds, Mds, BOds and Rds. The data covers the eight years of 2001 through 2008.

For the subsequent spectral analysis, the monthly data shows the accumulated returns compiled from daily returns. The definition of returns and compound accumulated returns are defined as follows:

$$X_{i,t} = \frac{NAV_{i,t} - NAV_{i,t-1} + q_{i,t}}{NAV_{i,t-1}}$$

where $X_{i,t}$ is the daily return of the ith fund on day t, $NAV_{i,t}$ is the net asset value of the ith fund on day t, and $q_{i,t}$ represents the dividend of the ith fund distributed on day t. The compound accumulated return of the ith fund in a given period $[1,T]$, is $TX_i = \left[\prod_{t=1}^{T}\left(1+X_{i,t}\right)\right]-1$.

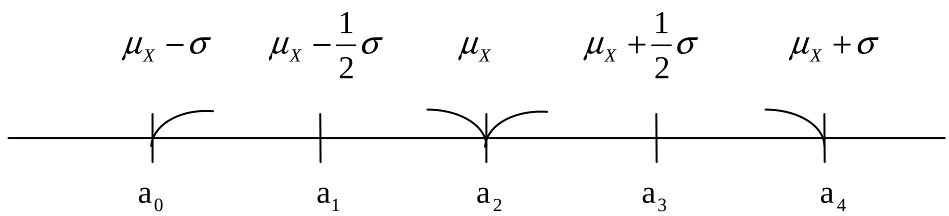
3.2.2 Uni-spectral analysis

Prior to the cross-spectral analysis, we used uni-spectral analysis to verify if individual funds have cyclical phenomenon. Noteworthy, cross-spectral analysis is only meaningful in finding the lead or lag relationships when individual funds have the cyclical phenomenon. In order to verify this prerequisite, we applied the test proposed by Canova (1996). I define Ω_A as the average frequency of the peak of power spectrum among funds in a fund category, plus/minus a standard deviation of their peak frequencies, and Ω_R is the range beyond the cycle of Ω_A. At the same time, $\bar{D}$ is defined as the average of D over each fund in a given category. In conclusion, we may determine whether if significant cyclical phenomenon exists in an interval for a specific fund category, and then we use cross-spectral analysis to verity the lead or lag relationship between specific fund categories.

3.2.3 Cross-spectral analysis

Since massive data is required in calculation when conducting cross-spectral analysis for any pair of funds, we use the following procedures in attempt to reduce computation complexity. According to uni-spectral analysis, we have a number of frequencies of power spectrum peaks for each fund category (e.g., X fund category) and average and standard deviation of frequency of power spectrum peaks calculated from X fund category is named μ_X and σ_X, respectively. The likelihood, $[\mu_X - \sigma_X, \mu_X + \sigma_X]$, is regarded as a maximum interval (ignoring extreme value) of frequency of power spectrum peaks of funds in X fund category. We partition $[\mu_X - \sigma_X, \mu_X + \sigma_X]$ into four intervals, $[a_0,a_1]$, $[a_1,a_2]$, $[a_2,a_3]$ and $[a_3,a_4]$, the first, second, third and fourth intervals, respectively:

Figure 3 The partition of each fund for X category funds



Assuming that X and Y are any two fund categories, we select all funds in the first interval of Y fund category and all funds in the fourth interval of X fund category; all funds in the forth interval of Y fund category and all funds in the first interval of X fund category to conduct cross-spectral analysis. We find the maximum and minimum frequency which is one to one period of cross-spectral and all lead or lag relations between X and Y fund categories will be contained in the interval in which is consists of maximum and minimum period. Without loss of generality, the procedure can help us to reduce calculation to 1/16. Notice that I define the X fund category leads Y fund category if the funds in the first interval of X lead the funds in the fourth interval of Y, and the funds in the fourth interval of X lead the funds in the first interval of Y at the same time.

3.3 Empirical results

Tables 1.6 shows the empirical results of my univariate spectral analysis. The $\bar{D}$ column of the Tables 1.6 present that, the $\bar{D}$ of all fund categories are all greater than 1. In other words, it illustrates that most fund categories have the cyclical phenomenon. In addition, the average period of power spectrum peaks almost emerges somewhere between the 17 and 22 months, which is equivalent to 1.5 – 1.8 years, a period obviously beyond 12 months. It implies that, other than the seasonal factors (Granger and Morgenstern, 2001) as often referred to in literature, there is another longer regular cycle. In fact, the cycle of 17 – 22 months is very interesting. It is equivalent to half of the 3 – 5 years Kitchin Cycle. It means that on average, each short business cycle contains two bull markets and two bear markets.

In summary, we use Canova (1996)'s statistic to verify the existence of the cyclical phenomenon amid various categories of funds. It especially shows that the average frequency of power spectrum peaks amid different categories of funds is rather concentrated. It further signifies a common relationship behind the scenes to make the cycle phenomenon of the various fund categories so close. This finding will strengthen the results of my cross-spectral analysis.

Table 1.6 Univariate spectral statistic, monthly data

	Ave. Freq.	Std. Freq.	Ave. Period	Std. Period	$\bar{D}$
Rds	0.058317	0.002594	17.174630	0.755685	1.090291
Fds	0.055397	0.003457	18.260952	1.121108	4.361164
Bds	0.053106	0.004141	18.935106	1.406434	1.868759
Cds	0.048867	0.020240	19.32595	5.30494	1.635437
Tds	0.054641	0.006403	18.490468	1.706582	5.088025
Mds	0.045363	0.003559	22.170533	1.773675	1.272006
ENds	0.054275	0.006537	18.687441	2.628904	3.634304
BOds	0.055547	0.010426	18.963197	5.563634	2.471326
Eds	0.055194	0.004070	18.223430	1.451083	2.215471

Note 1: Average and standard deviation frequency of power spectrum is named by Ave. Freq. and Std. Freq. respectively.

2. Average and standard deviation period of power spectrum is named by Ave. Period and Std. Period, respectively

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Given that Bds can be regarded as the investment portfolio made of equity funds and bond funds, which cannot represent any specific industry or market, and there is no unified definition for Mds among the various websites, we will not consider Bds and Mds in my cross-spectral analysis.

Corresponding to maximum and minimum frequency of the cross-spectra, we have the maximum and minimum period which is the maximum and minimum of lag or lead's time. Table 1.7 is the summary of monthly data's cross-spectrum, in which I define that X category funds leads Y category funds if lead time of X category funds exceeds more than one month, vice versa; otherwise, they are simultaneous. Out of the summary, more than one month of the lead or lag relations neither exists between Fds and all other categories of funds, nor between Eds and Tds. The ones without indicating the lead/lag relations all fall in simultaneity.

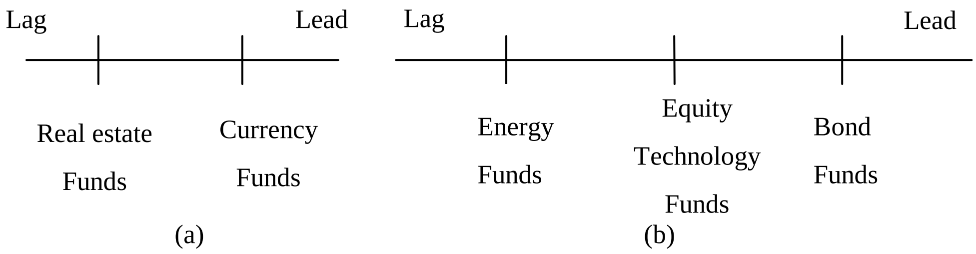
I further infer another three kinds of monthly relations (see Figure. 1.6), in which the first is BOds leading Eds and Eds leading ENds (Figure. 1.6 (b)) – the result is consistent with section II; the second is BOds leading Tds and Tds leading ENds (Figure. 1.6 (b)) – hence, ENds are the lagging indicator in the three kinds of funds and bond funds are the leading indicator; the third kind is Cds leading Rds (Figure. 1.6(a)).

Table 1.7 Summary of lead/lag relations, monthly data

	Interval[1]	Lead/lag of the latter [1]
Rds vs Cds	〔1.095，1.314〕	Lag
Tds vs ENds	〔0.279，1.063〕	Lead
Tds vs BOds	〔0.968，1.463〕	Lag
ENds vs BOds	〔1.044，1.604〕	Lag
ENds vs Eds	〔0.036，1.087〕	Lag
BOds vs Eds	〔0.599，1.212〕	Lead

[1] The figures in 3rd column of the table are presented in a way of X related to Y, e.g. real estate lagging behind currency and technology leading energy, etc., and the minimum period of real estate lagging behind currency is 1.09 months, while the maximum period is 1.31 months.

Figure 4 The lead/lag relations of monthly data



IV. Interplay among Business Cycles Reconsidered: Implications for the 2008 Global Recession.

4.1. Introduction

Business cycles are no fresh phenomenon. Many recognized scholars have paid serious attention to the discussion of business cycles, among them even some of the best all-time in Schumpeter (1939), whom marked a concluding effort for the ages before his time. However, as the Keynesian school attained a more dominating position, mainstream macroeconomics has come to prefer a more analytical framework on economic growth analysis. In this paradigm shift, business cycle discussions were more tied to analytic modeling, and were mostly part of the issue than the issue itself.

However, business cycles are sill important for many. Governments and politicians wish for prolonged expansions and brief contractions, and official agencies of many nations and prominent agencies regularly release reference dates for their nation’s business cycles, such as the National Bureau of Economic Research (NBER) in the U.S. and the Economic Planning Agency of Japan, in order to provide information for decision making in both public and business realms. But still, that is not enough. Most of the spotlight is still concentrated on the short term inventory cycle, and that is basically what these agencies actually identify. Even the term “business cycle” meant strictly the short term cycle in daily and business vocabulary. All this is understandable, short cycles are easily and swiftly recognized, but there are times when good times are too good and bad times too bad that apparently exceed the scope of short cycles. Therefore, we need to further understand the longer cycles, as they are the underlying trends for the shorter cycles that have our lives embedded within.

Therefore, the study for cycles longer than the short-term is aimed to provide insight on a larger scope. This has become more important than ever, as during the process of writing this thesis, we were just coming through the most server recession since the World War II. Particularly, including the current recession, the world faces a deeper recession about every 10 years over the past 30 years, for example the second oil crisis of 1980, Savings and Loan crisis of the US and the Lost Decade of Japan of 1990, the Dotcom bubble of 2001 and the Subprime crisis of 2008. With more information of the various cycles and how they interact, along with the scope and length of the cycles, policy makers may more easily find our position in the downturn, and eventually make decisions that best fit with where we are positioned in the waves of time.

The purpose of this section is to draw attention back to the organic mechanism of the economy which seems to have escaped the attention of economic analysis thus far. By analyzing the cyclical dynamism of the advanced economies since 1870, it is the relative position of long-term and short-term economic cycles (or waves or swings) that lead to the many remarkable booms and busts throughout history, especially one as significant as the current global recession and the Great Depression of 1930.

4.2. Early Inquiry of Interplay Between Business Cycles

It is a long debate on whether business cycles have empirical regularities. With respect to these empirical regularities, there is a significant difference between the view of modern business cycle researchers and that of their classical predecessors. In the classical tradition, the business cycle is an endogenous mechanism where fluctuations were seen as a recurrent phenomenon with characteristic periodicities. An important aspect of the classical view is that cycles of different frequencies can be found in economic series. This tradition originated in the 19th century with the work of Juglar (1862) and has continued until the 1950s, inspiring among many others, the works of Kitchin (1923), Kuznets (1930), Kondratieff (1926) and Schumpeter (1939).

In contrast, the perception of most modern macroeconomists, whom were deeply influenced by Burns and Mitchell (1946), is that the mechanism of business cycle is exogenous, where economic time series typically do not have a pronounced regular cyclical pattern. According to the modern view, the only defining property of business cycles is the strong coherence of many important economic time series, i.e., their tendency to move together (Sargent, 1987). Therefore, researches about modern views, eager to find out the determinant of the relationships of different economic variables, lead to theoretical explanations such as literature of the real business cycle (RBC). They believed the business cycle is a random process; only exogenous shocks can generate the business cycle phenomenon. For example, Kehoe and Prescott (2002) use the RBC framework to explain the episodic ‘‘Great depressions’’.

However, even the modern view has offered a more comprehensive framework than the traditional view to analyze the interplay of different economic variables over the business cycle, it is still insufficient. Since the general perception is that recessions exist because there were expansions before it, therefore, boom and bust should be considered together with a holistic framework. Though the modern view can explain the cause and consequence of the recession, it is incapable to holistically consider the boom and burst together.

On the other extreme, famous researchers have established plenty explanation for the recurrent boom and bust through the traditional view—periodic and coexistence of different types of cycles. The theoretical driving forces of different kinds of cycles are regular fluctuations of investment activities: the Kitchin with inventory investment, the Juglar with investment in machinery and equipment, the Kuznets with building or transportation investment and then the Kondratieff with the construction of basic capital goods which is lead by clusters of innovations such as railways and canals in the sense of investment. The different cycle lengths are each associated with the particular form of investment, determined by the durability of the investment and the time lags between movements in final demand and the completion of the invested capital good (Duijn, 1983).

Noteworthy, considerable debates about such regularity of business cycles have always been there, since their lengthy durations always accompany institutional and economic structural change (Abramovitz, 1968; Solomou, 1998; Maddison, 1991). Thus, past experience might not yield value to the future. Particularity, Abramovitz (1968) had argued that the Kuznets cycle has disappeared since the Trans-Atlantic migration ended. Besides, insufficiency of data is another reason against the traditional view. Burns and Mitchell had noted in their comprehensive work *Measuring Business Cycles* (1946) that since their own data only extend to the 1930s, which is too brief a span to determine whether building cycles (Kuznets cycles) and Kondratieff cycles were a continuing feature of the modern economy. Becker in his presidential address of American Economic Association (AEA) in 1987 echoed Burns and Mitchell’s consideration. “If long cycles of the Kondratieff or Kuznets type exist, we will need another 200 years of data to determine whether they do exist or are just a statistical figment of an overactive imagination".

However, if we look into the theoretical cause, most the mechanisms of business cycles of different frequencies still validate. Even if the amplitudes and frequencies of these different cycles are not stable due to varying economic environment and structure; their forces still work in modern economies. Therefore, the length of the cycle and also the amplitude to some extent are variable, however, their variations taking place within limits (Frisch, 1933; Hillinger, 1992). Especially to answer doubts if the Kuznets cycle had vanished, Easterlin (1987) asserted that even the Trans-Atlantic migration has waned, interplay of inter generations may still make the Kuznets cycles vivid.

Past researches also provide plenty of evidence to support the traditional view. It was Kondratieff (1926) who first conceived the coexistence of shorter- and longer-term cycles and the corresponding effect of their interplays. He argued that during the rise of the long waves, years of prosperity are more numerous, whereas during the downswing, years of depression predominate. Dujim (1985) used the industrial production data of UK, US, West Germany, France, and Japan and Shinohara (1996) used post war Japanese data to confirm such concept. In addition, Schumpeter (1936) not only echoed the coexistence of short and long cycles, but formally distinguished them as Kitchin cycles (3~5 years), Juglar cycles (7~11 years), Kuznets cycles (15~25 years) and Kondratieff cycles (40~60 years). In this respect, Reiter and Woitek (1999) used data of 15 OECD countries and found that a large number of their covered countries experienced regular Kitchin and Juglar cycles in the period 1960~1993. Berry (1991) used real and nominal series data of the US and UK and also validated the regularity of Kuznets and Kondratieff cycles.

Furthermore, earlier researches also used the idea of coexisting cycles to explain the deep recessions in economic history. Schumpeter (1936) pointed out that deep recessions in the period covered by his material, namely 1825~1830, 1873~1878 and 1929~1934, all came in times when all cycles were in their downward phases. Similar arguments of coincidence in the downturn of two or more cycles (among Kitchin, Juglar, Kuznets and Kondratieff cycles) have also been suggested by Berry (1991) on the Great

Depression of US and Sen (1997) on the 1990s Russia and Shinohara (1996) on the 1990s Japan.

Therefore, even if the interplay between business cycles is not fully agreed among the research community, however, in the description of economic evolution, it is inadequate to dismiss the force of different types of cycles in understanding the process of the economy. Besides, we have 70 more years of data than what was available to Burns and Mitchell; therefore we are in a better position to discuss the regularity of cycles in the traditional view than they once were.

4.3. Data

The data we use in this section comes from two sources; one is the International Financial Statistics (IFS) database, where we take the quarterly industrial production data of 15 OECD countries and aggregate advanced economies from first quarter 1961 thru first quarter 2009. The 15 nations are: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, UK and the USA. The other source is the real GDP data of the aforementioned countries and their aggregate from 1870 thru 2006 edited by Madisson (2009), where we merged it with IFS data to obtain the real GDP data of major countries and their aggregate from 1870 thru 2008.

The reason why we use two types of data to examine the interplay of different cycles is due to several considerations. First, the cycles discussed in this section include the 3~5 year Kitchin, 7~11 year Juglar and 15~25 year Kuznets, though high frequency quarterly data contain more information, as the duration of the cycle type being verified increases, the time length of the data set might not satisfy the basic requirements of spectral analysis. For instance, the industrial production data we use is only 48 years plus 1 quarter in length, which may span over eight to fourteen 3~5 year Kitchin cycles, and four to six 7~11 year Juglar cycles, but it only covers two 15~25 year Kuznets cycles and one Kondratieff cycle at best. However, some scholars consider the length of data necessary for applying spectral analysis must at least cover three cycles (Klotz and Neal, 1974), some others thought seven cycles were the minimum requirement (Granger and Hatanaka, 1964), while still a few suggest at least ten cycles (Soper, 1975) worth of data were needed to perform spectral analysis

Thus, even with the more relaxed demands of Klotz and Neal (1974), quarterly industrial production data is not long enough to discuss the 15~25 year Kuznets cycle and the 40~60 year Kondratieff Cycle. But by merging the Maddison (2009) and IMF data, we can obtain a 139 year series for real GDP, which covers seven to nine Kuznets cycles, and satisfies both Klotz and Neal (1974) and Granger and Hatanaka's (1964) requirements. However, even with annual GDP, the data length is still incapable of analyzing the 40~60 year Kondratief cycle, the reason why in verifying the existence of cycles in this section, we will mainly focus on the Kitchin, Juglar and Kuznets cycles.

4.4. The Existence of Kitchin, Juglar, and Kuznets Cycles

Empirical results in this section comes from two data types－quarterly data and yearly data. According to the preceding discussion, yearly GDP data can be used to verify the existence of Kitchin, Juglar and Kuznets cycle by applying Canova's test. In each of these three cases, Ω_2 can be defined as $(\frac{2\pi}{40},\frac{2\pi}{25})\cup(\frac{2\pi}{15},\frac{2\pi}{11})\cup(\frac{2\pi}{7},\frac{2\pi}{5})\cup(\frac{2\pi}{3},\frac{2\pi}{2})$. For the test on the Kitchin cycle, $\Omega_1=(\frac{2\pi}{5},\frac{2\pi}{3})$, while for the Juglar and Kuznets cycle, Ω_1 is $(\frac{2\pi}{11},\frac{2\pi}{7})$ and $(\frac{2\pi}{25},\frac{2\pi}{15})$, respectively. The corresponding test statistics are in column 2, 5 and 7 of Table 1.8. The results strongly support the presence of classical business cycles in the 15~25 year range. The test statistic is highly significant in all cases for the CF-filtered data. However, the results are less supportive of Kitchin and Juglar cycles. Only for Germany, Spain and Switzerland do we find robust Juglar cyclical structure. But, though the evidence to Juglar cycles was less supportive, the D statistics for 13 out of 15 countries, while insignificant still exceed one. As for Kitchin cycles, each of the statistics were not only insignificant, but far below unity, which implies no evidence for regular Kitchin cycle in the yearly data.

For the above problem, Granger (1966) had asserted that the insignificancy of Kitchin and Juglar cycles may be due to the typical spectral shape of economic time series, which is the negative slope across frequency. The existence of a typical spectral shape suggests that the amplitude of the longer wave is greater than the amplitude of the shorter cycles. Therefore in the superimposition of different cycles, the effects of the shorter cycles become negligible; hence the insignificance of the Kitchin and Juglar cycle in the above tests does not imply short cycles do not exist. Take aggregate GDP as example (Figure 1.7), though the existence of Juglar cycles was not significant, but the spectral density did pick up in the union frequency of Juglar cycle[11]. Therefore, we should further verify the existence of Kitchin and Juglar cycles by inspecting the frequencies of shorter cycles. We again apply Canova's test on our quarterly industrial production data in the remainder of this section. Without the effect of the longer Kuznets cycle, we verify the existence of Kitchin and Juglar cycles. In other words, Ω_2 is defined as $(\frac{2\pi}{15},\frac{2\pi}{11})\cup(\frac{2\pi}{7},\frac{2\pi}{5})\cup(\frac{2\pi}{3},\frac{2\pi}{2})$, with results shown in columns 3 and 6. The results strongly support the presence of 7~11 years Juglar cycles. The test statistic is highly significant in 13 out of 15 OECD countries. For Netherlands and Switzerland, though the statistics are insignificant they still exceed one.

However, as for Kitchin cycle, the statistic is insignificant again. But by visualizing the spectral density of industrial production in advanced countries (Figure 1.8), they do pick up at spectral densities within the union of frequency of Kitchin cycles. Therefore, the insignificance of Kitchin cycle is partially due to the typical shape of spectrum. For this regard, we eliminate the effect of Juglar and Kuznets cycles and focus on the existence of Kitchin cycles in the frequency span $(\frac{2\pi}{7},\frac{2\pi}{2})$, with results shown in column 4 of Table 1.8, the results are weakly supportive for the existence of the Kitchin cycle in the frequency span $(\frac{2\pi}{7},\frac{2\pi}{2})$ with 13 out of 16 statistics exceeding one and four of them are significant.

In summary, by verifying the regularity of Kitchin, Juglar and Kuznets cycles with

[11] Most countries have similar shape of spectrum of aggregate GDP.

yearly GDP data and quarterly industrial production data, we found strong support for the existence of longer cycles (Juglar and Kuznets) and some weak evidence of the regular Kitchin cycle.

Table 1.8 Canova test for short, medium and long term Cycle

	Kitchin cycle (3~5)[a]	Kitchin cycle (3~5)[b]	Kitchin cycle (3~5)[c]	Juglar Cycle (7~10)[a]	Juglar Cycle (7~10)[b]	Kutznet Cycle (15~20)[a]
Austria	0.34	0.60	0.81	1.10	4.53[d]	4.11[d]
Belgium	0.30	0.74	1.03	1.07	3.63[d]	7.34[d]
Denmark	0.42	0.89	1.26	1.12	2.26[e]	6.60[d]
Finland	0.18	0.42	0.77	1.23	4.60[d]	3.45[d]
France	0.05	1.21	1.94[f]	1.07	4.67[d]	5.61[d]
Germany	0.37	1.28	2.14[f]	0.94	4.38[d]	5.17[d]
Italy	0.58	0.95	1.14	1.78[e]	3.22[d]	6.08[d]
Japan	0.35	1.09	1.62	1.10	3.71[d]	6.52[d]
Netherlands	0.35	0.76	0.92	1.72[e]	1.72[f]	5.38[d]
Norway	0.48	0.86	1.18	2.29[e]	2.44[e]	10.70[d]
Spain	0.72	1.14	2.36[e]	1.76[f]	4.73[d]	7.51[d]
Sweden	0.23	1.39	1.44	1.07	1.69	4.75[d]
Switzerland	0.65	1.09	2.63[e]	1.85[e]	6.25[d]	10.67[d]
UK	0.26	0.79	1.15	0.99	3.48[d]	3.19[d]
USA	0.26	0.78	1.05	2.06[e]	3.35[d]	10.58[d]
Advanced countries	0.31	1.29	1.63	1.30	3.79[d]	4.31[d]

[a] *Yearly data with* $\Omega_2 = (\frac{2\pi}{60}, \frac{2\pi}{25}) \cup (\frac{2\pi}{15}, \frac{2\pi}{11}) \cup (\frac{2\pi}{7}, \frac{2\pi}{5}) \cup (\frac{2\pi}{3}, \frac{2\pi}{2})$

[b] *Quarterly data with* $\Omega_2 = (\frac{2\pi}{15}, \frac{2\pi}{11}) \cup (\frac{2\pi}{7}, \frac{2\pi}{5}) \cup (\frac{2\pi}{3}, \frac{2\pi}{2})$

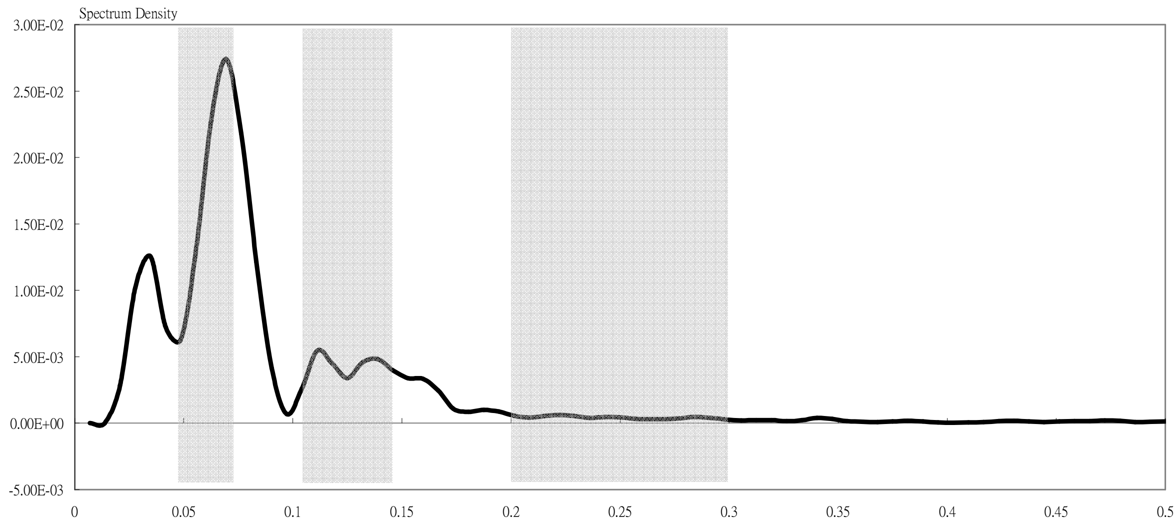
[c] *Quarterly data with* $\Omega_2 = (\frac{2\pi}{7}, \frac{2\pi}{5}) \cup (\frac{2\pi}{3}, \frac{2\pi}{2})$

[d] *Average spectral density in the business cycles frequency range is significantly higher than the other frequency, 1 percent significant level.*

[e] *Average spectral density in the business cycles frequency range is significantly higher than the other frequency, 5 percent significant level.*

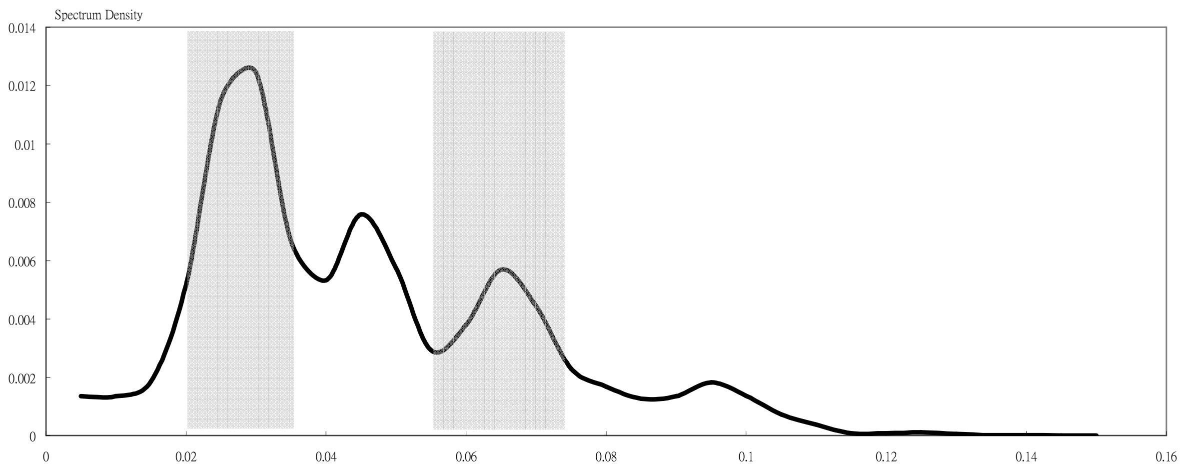
[f] *Average spectral density in the business cycles frequency range is significantly higher than the other frequency, 10 percent significant level.*

Figure 5 Spectrum density of aggregate GDP, yearly data



Note: Shade areas are in turn to Kuznets, Juglar and Kitchin cycle from left.

Figure 6 Spectrum density of advanced countries industrial production, quarterly data



Note: Shade areas are in turn to Juglar and Kitchin cycle from left.

4.5. Phases of the Kitchin, Juglar, Kuznets, and Kondratieff Cycle

4.5.1. Interplay Between Business Cycles

The preceding section verified the existence of the Juglar and Kunznets cycles, with also some weaker evidence of the existence of the Kitchin cycle. In this section, we will apply the CF filter to portray the path of economic development by means of interplay between business cycles. The cyclical components of the fifteen countries aggregate GDP by filtering is displayed in Figure 1.9. A more recent decomposition of industrial production is displayed in Figure 1.10.

Figure 7 CF-filter decomposition of World GDP cycles, 1870-2008, yearly data

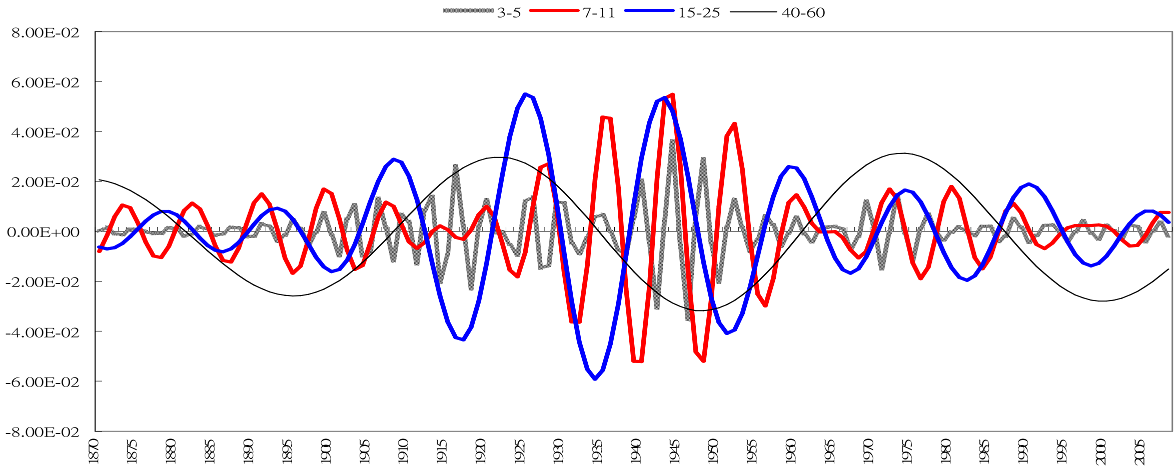


Figure 8 CF-filter decomposition of World IP cycles, Q1/1961-Q1/2009, quarterly data

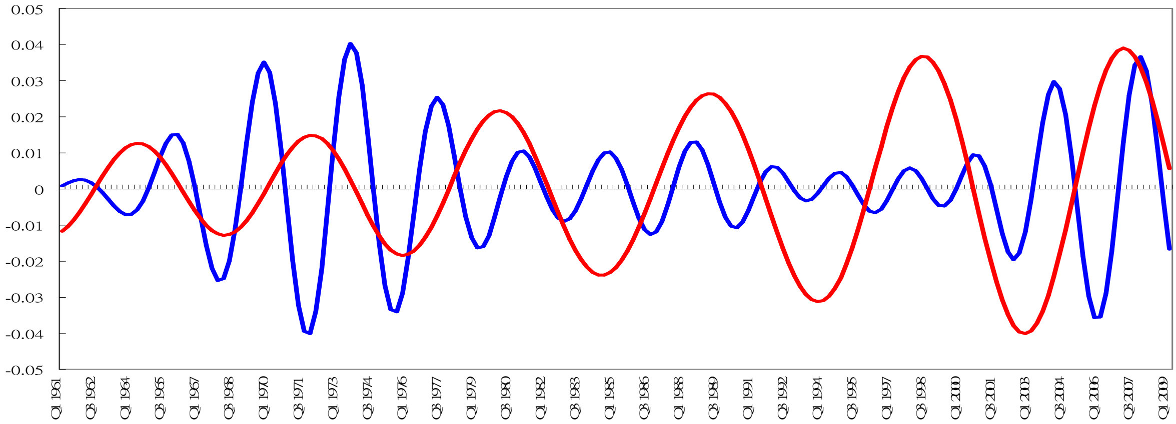


Table 1.9 Matching the OECD business cycle reference dates and Kitchin cycle turning points

	0[a]	1[a]	2[a]	3[a]	4[a]	U[b]	R[b]
Austria	5	7	0	3	2	6	73.9%
Belgium	3	8	5	2	1	4	82.6%
Denmark	1	5	5	2	2	1	93.8%
Finland	5	11	2	1	3	1	95.7%
France	3	7	4	3	4	4	84.0%
Germany	5	5	6	4	2	1	95.7%
Italy	4	4	4	5	1	5	78.3%
Japan	3	9	4	1	0	4	81.0%
Nederland	2	8	5	6	2	0	100.0%
Norway	2	2	3	2	0	14	39.1%
Spain	4	5	4	2	1	7	69.6%
Sweden	3	6	5	2	2	4	81.8%
Switzerland	8	7	5	0	2	3	88.0%
UK	2	10	4	1	1	3	85.7%
USA	3	10	1	3	2	3	85.7%
Advanced countries	3	12	2	0	0	6	73.9%

[a] 0 denotes the turning points of business cycles dates of OECD and Kitchin cycle coincede, while 1, 2, 3, 4 denotes the two turning points are 1, 2, 3, and 4, quarters apart in time.

[b] U denotes the number of turning points of OECD cycles dates that cannot be matched by Kitchin cycle turning points.

How did the Kitchin, Juglar and Kuznets cycles fluctuated over the last fifty years? Columns labeled R in Appendix 1.1 shows the peaks and troughs of business cycles in terms of business cycle reference dates recognized by the OECD. While the columns labeled Ki, Ju, Ku are the business cycle turning points of the Kitchin, Juglar and Kuznets cycles under the recognition of CF filter. Generally, the reference dates was always deemed as Kitchin cycles in literature. In Table 1.9, we compared the reference dates by the OECD and the turning points of our Kitchin cycles, and we found that within one year before and after OECD reference dates of peak and trough, 73.9% we can find a corresponding Kitchen cycle turning point. As for each of the countries discussed in this section, they are still highly in parallel between reference dates by OECD and our Kitchin cycles. However, the turning points of Kitchin cycles do not always have corresponding reference dates recognized by OECD. For example, in most of the 15 countries, there were a contraction phase of the Kitchin cycle in the period 2004~2005, but it has been recognized by the OECD as business cycle turning points in only a few countries. The reason for this was due to the interplay between shorter- and longer-term cycles.

Table 1.10 Average duration of expansion and contraction during long cycle upturn and downturn (quarters)

	Upturn		Downturn	
	Expansion	Contraction	Expansion	Contraction
OECD	16.0	7.3	3.0	8.6
Austria	11.0	4.0	7.0	10.0
Belgium	12.0	6.0	5.0	4.5
Denmark	11.0	7.0	4.0	13.0
Finland	8.0	5.0	NA	6.0
France	7.0	7.5	5.0	11.5
Germany	10.7	5.0	6.0	8.5
Italy	8.0	6.5	5.0	14.0
Japan	19.7	NA	NA	8.5
Netherlands	11.7	10.0	9.0	9.7
Norway	12.0	6.0	NA	6.5
Spain	11.8	7.0	4.0	9.3
Sweden	9.3	10.0	NA	14.0
Switzerland	11.5	4.0	6.0	8.0
UK	10.7	4.5	7.0	13.3
USA	13.7	8.0	7.3	6.4
Average	11.5	6.5	5.7	9.5

In the remainder of this subsection, we will discuss the effects of interaction between these cycles. For the convenience of discussion, we only discuss the incidents of joint upturns and downturns of all Kitchin, Juglar and Kuznets cycles and set aside the cases where one of the three cycles is in the downturn (or upturn) phase and the other two are in the other phase. The following are the brief summaries of the conclusions of Table 1.10.

(1) Generally, when the Juglar and Kuznets cycles are in their upturn phase based on our identification, the upturn of the reference cycle defined by OECD countries always lasts longer. This can be seen in last row in Table 1.10: expansions during the simultaneous upturn of Juglar and Kuznets cycles last for an average of 11.5 quarters, is longer than the average expansion of 5.7 quarters when Juglar and Kuznets cycles are in simultaneous downturn. Besides, during these circumstances, expansion periods are longer than the contraction periods, which are 11.5 quarters and 6.5 quarters,

respectively.

Below we shall take the aggregate OECD and the US as examples. The durations of expansions that started at Q4/86 and Q4/01 of OECD were 14 and 25 quarters, and they all lie in simultaneous upturn of Juglar and Kuznets cycles. In the US, there were also longer expansions when Juglar and Kuznets cycles are in their upturn phases, especially the expansion starting Q4/01, the expansion of US lasted 25 quarters. In addition to the US, Germany and Japan both experienced the longest expansion of the postwar era as recognized by the OECD in the first decade of the 21st century at the time with simultaneous upturns of Juglar and Kuznets cycles. It should be noted that, the contraction phase of Kitchin cycle did occur during 2004~2005, as shown in Appendix 1.1. However, literature has deemed slowdowns in that time as "mid-cycle pause", which may strongly suggest that even with a Kitchen downturn, if the longer cycles are in the stronger parts of their upturn, the Kitchen downturn could be completely mitigated.

(2) In the simultaneous downturn of Juglar and Kuznets cycles, the duration of expansion is shorter and there could easily be two contractions within a brief time span. The average period of contractions with simultaneous downturns of Juglar and Kuznets cycles is 9.5 quarters, which is longer than the average of 5.7 quarters of expansion periods when Juglar and Kuznets cycles are in simultaneous downturns. Besides, it is also longer than the average contraction period with simultaneous upturns of Juglar and Kuznets cycles which is 6.5 quarters. Take the OECD aggregate as example, during the period of Q1/64 thru Q3/67, the expansion that started at Q3/65 only lasted 3 quarters and it was sandwiched by two contractions during a span of merely less than four years. With regard to contractions that started at Q4/79 and Q2/90, they lasted 13 quarters each and were the lengthier recessions in the post war era. Noteworthy, there were also double dips in the recession periods Q1/91~Q3/96 of Austria, Q1/80~Q2/83 of Belgium, Q2/89~Q2/93 of Spain, and Q1/79~Q4/82 of the US, and they were at a time when downturns of Juglar and Kuznets cycles coincide. In addition to the current financial crisis, which is no doubt a long recession, lengthy contractions have been experienced in Q2/64~Q4/67 and Q4/00~Q3/03 of Austria, Q4/88~Q2/91 and Q4/00~Q4/04 of Denmark, Q4/91~Q1/95 of Finland, Q4/00~Q2/03 of France, Q1/80~Q4/82 of Germany, Q4/89~Q3/93 of Italy, Q1/91~Q4/93 of Japan, Q1/80~Q1/83 of the Netherlands,

Q2/98~Q1/02 of Spain, Q2/74~Q1/78 of Sweden and Q4/88~Q2/92 of UK. Consistent to our thesis results, they all occurred at times when the Juglar and Kuznets cycles were both in downturn.

In summary, the durations of upturns and downturns in the reference cycle of OECD were affected by the direct impact of medium- and longer-term waves. The observations presented above provide clear evidence for the existence of both medium- and longer-term cycles in the post war economy in the scope of the countries discussed in this section.

4.5.2. Experience in the Great Depression and the most Recent Global Recession

Before the World War II, due to the lack of officially recognized business cycle reference dates, as was available in discussions of the above subsection, we cannot discuss the issue in the same manner. However, there was a well known worldwide recession that is similar to the recent global financial crisis that can be used to discuss the interplay between business cycles, the Great Depression of 1930. Table 1.11 shows the nearest turning points of the three cycles before the start of the Great Depression of the 1930s. When the turning point before the outbreak of Great Depression is a peak, it means that the Great Depression occurred in the contraction phase of the corresponding cycle. Otherwise, it means that the Great Depression occurred in the expansion phase of the corresponding cycle

From Table 1.11, 13 out of 15 countries we discussed in this section were already in the contraction phase of the Kuznets cycle before the start of the Great Depression. Meanwhile, 8 countries were also in the contraction phase of the Juglar cycle and 12 countries were in the contraction phase of the Kitchin cycle. Due to the coincidence of Kitchin, Juglar and Kuznets cycle downturns across a majority of countries at the time, the severity of the recession is not surprising in the view of interplay between business cycles.

Table 9 Nearest turning points of each cycles before the Great Depression of 1930

	Kitchin Cycle	Juglar Cycle	Kuznets Cycle
Austria	Peak (1930)	Trough (1926)	Peak (1925)
Belgium	Trough (1928)	Peak (1930)	Peak (1929)
Denmark	Peak (1930)	Trough (1922)	Peak (1922)
Finland	Peak (1929)	Peak (1929)	Peak (1928)
France	Peak (1929)	Peak (1930)	Trough (1922)
Germany	Trough (1927)	Peak (1928)	Peak (1923)
Italy	Peak (1928)	Trough (1929)	Trough (1927)
Japan	Peak (1929)	Trough (1929)	Trough (1930)
Nederland	Peak (1929)	Peak (1930)	Trough (1921)
Norway	Peak (1930)	Trough (1925)	Peak (1924)
Spain	Trough (1927)	Trough (1929)	Peak (1929)
Sweden	Peak (1930)	Peak (1929)	Peak (1929)
Switzerland	Peak (1929)	Peak (1929)	Peak (1917)
UK	Peak (1930)	Trough (1930)	Peak (1917)
USA	Peak (1930)	Peak (1928)	Peak (1925)
Advanced countries	Peak (1928)	Peak (1925)	Peak (1922)

[a] Turning point dates are in the parentheses.

As for the current financial crisis, Table 1.12 is the nearest turning points before the start of this current recession. The aggregate OECD has passed the peak of the Kuznets cycle in 2006, and the peaks of Kitchin and Juglar in 2007. Therefore, when this worldwide recession started, it was in the downturn phases of all Kitchin, Juglar and Kuznets cycles. As previously discussed, there were only 7 incidents of simultaneous downturns of all Kitchin, Juglar and Kuznets, where 6 of them experienced severe recessions, with the current financial crisis one of them. In respect to country specific data, 14, 8 and 13 countries of the 15 have passed the Kitchin, Juglar and Kuznets cycle peaks before 2008, respectively, the outbreak year of the recent crisis, which mirrors the Great Recession of 1930. The quarterly data also confirmed such observation.

What are the implications when the economy in the joint downturns of Kitchin, Juglar and Kuznets cycles? From the discussions above, the implications are:

(1) The recession is probably longer than average.

(2) Recessions could be double-dipped even though recoveries have begun.

Thus, even when it seems to be signs of recovery in the second half of 2009, from the discussion of this section, the path to full recovery is likely to be long, hard and uncertain.

Table 10 Nearest turning points before the 2008 World Recession

	Kitchin Cycle	Juglar Cycle	Kuznets Cycle
Austria	Peak (2007)	Peak (2007)	Peak (2004)
	Peak (Q4/2007)	Peak (Q4/2007)	
Belgium	Peak (2007)	Trough (2004)	Peak (1999)
	Peak (Q4/2007)	Peak (Q2/2007)	
Denmark	Peak (2007)	Trough (2003)	Peak (2001)
	Peak (Q3/2007)	Peak (Q3/2007)	
Finland	Peak (2007)	Peak (2007)	Peak (2004)
	Peak (Q4/2007)	Peak (Q1/2007)	
France	Peak (2007)	Trough (2006)	Peak (2001)
	Peak (Q4/2007)	Peak (Q2/2007)	
Germany	Peak (2007)	Trough (2005)	Peak (2005)
	Peak (Q4/2007)	Peak (Q3/2007)	
Italy	Peak (2007)	Peak (2001)	Peak (2003)
	Peak (Q4/2007)	Peak (Q1/2007)	
Japan	Peak (2007)	Peak (2005)	Trough (1998)
	Peak (Q4/2007)	Peak (Q4/2006)	
Nederland	Peak (2007)	Trough (2004)	Peak (2000)
	Peak (Q2/2008)	Peak (Q3/2008)	
Norway	Trough (2007)	Peak (2007)	Peak (2000)
	Trough (Q4/2007)	Trough (Q4/2007)	
Spain	Peak (2007)	Peak (2007)	Peak (2007)
	Trough (Q3/2007)	Trough (Q4/2006)	
Sweden	Peak (2007)	Peak (2007)	Peak (2005)
	Peak (Q4/2007)	Peak (Q2/2007)	
	Trough (2006)	Trough (2005)	Trough (2001)
Switzerland	Peak (Q4/2007)	Peak (Q1/2008)	
UK	Peak (2007)	Peak (2007)	Peak (2007)
	Peak (Q4/2007)	Peak (Q1/2007)	
USA	Peak (2007)	Trough (2003)	Peak (2005)
	Peak (Q4/2007)	Peak (Q2/2007)	
Advanced countries	Peak (2007)	Peak (2007)	Peak (2006)
	Peak (Q4/2007)	Peak (Q1/2007)	

[a] Turning point dates are in the parentheses.

4.6. Concluding Remarks

In concluding this section, we would like to re-emphasis the observations in this section: business cycles are not of the short-term type alone. The exercise in this section illustrates the importance of considering shorter- and longer-term cycles together, while interplay is essential to a comprehensive understanding of the process of the world economy.

Appendix 1.1

Table A.11 Reference business cycle date of 15 OECD countries

		OECD				Austria				Belgium				Denmark			
		R	Ki	Ju	Ku	R	Ki	Ju	Ku	R	Ki	Ju	Ku	R	Ki	Ju	Ku
60-63	P	1/60	1/62			4/60	3/61	3/63			3/61						
	T	1/63				1/63	2/63				2/63				1/63		61
64-65	P	**1/64**		3/64		**2/64**	3/65				3/65	1/64			1/65	2/64	
	T	**3/65**	1/64										63				
66-68	P	**2/66**	1/66														
	T	**3/67**	4/67	2/68	67	***4/67***	1/68	4/67	66		1/68	1/68			4/67	2/68	
69-72	P	*2/69*	4/69	4/71		*4/70*	1/70	4/72		*3/69*	4/69	2/72			3/69	1/72	70
	T	*3/71*	4/71			*4/71*	4/71			*2/71*	4/71				3/71		
73-75	P	**4/73**	3/73		74	**1/74**	4/73		75	**1/74**	3/73		73		2/73		
	T	**2/75**	3/75			**3/75**	3/75			**3/75**	2/75			1/75	1/75	3/75	
76-78	P		2/77			1/77	1/77			4/76	1/77			2/76	4/76		
	T			1/76		1/78	4/78	2/76		4/77	3/78	2/76			3/78		78
79-80	T													1/79			
	P	**4/79**		1/80		**1/80**	4/80	4/80		**1/80**	1/80	4/80		4/79	1/80	1/79	
	T		1/79														
81-83	T	**1/83**	1/81		82	**4/82**				**1/81**	3/81			*1/83*	3/81	1/83	
	P		4/82				4/82			**2/82**	2/83				4/82		
	T									**2/83**							
84-85	P	*4/84*	3/84			3/85	3/85			*4/85*				*4/85*			84
	T			3/84					84			1/85	84		3/84		
86-87	P														1/86	1/87	
	T	*4/86*	4/86			*4/87*	3/87	2/86		*1/87*	2/87			**4/87**	3/87		
88-89	P		3/88	1/89							4/88	4/89		**4/88**	2/89		
	T																
90-91	P	**2/90**			90	*1/91*	2/91	1/91	91	*1/90*							
	T		2/90							3/91	3/90			**2/91**	4/90	1/91	
92-94	P		1/92							2/92	2/92				1/92		
	T	**3/93**	2/93	4/93		**2/93**	1/93			3/93	4/93	2/94			2/93		92
	P														4/94		
94-96	P	1/95	4/94			**1/95**	1/95			*2/95*	1/95			*1/95*			
	T	2/96	2/96			*3/96*	4/96	2/95		*1/96*	3/96			*4/96*	3/96		
97-99	P	4/97	4/97	2/98		*2/98*	3/98	3/99		*2/98*	2/98	3/98		*3/98*	2/98	1/99	
	T	1/99	2/99		98	1/99			97	1/99	4/99			2/99			
00-02	T			4/02			1/00								1/00		
	P	*3/00*	4/00			4/00	1/01			**4/00**	1/01		00	**4/00**	4/01		01
	T	*4/01*	2/02				3/02			**4/01**	2/02				4/02		
03-06	P		1/04		05		4/04		04		1/04				1/04		
	T		4/05			3/03	1/06	4/03			1/06	1/03		**4/04**	4/05	2/03	
07-08	P	1/08	4/07	1/07		1/08	4/07	4/07		1/08	4/07	2/07		4/06	3/07	3/07	
	T																

Table A.1.1. (cont.)

		Finland				France				Germany				Italy			
		R	Ki	Ju	Ku	R	Ki	Ju	Ku	R	Ki	Ju	Ku	R	Ki	Ju	Ku
60-63	P	2/61	2/61			4/60				1/61	3/61	2/63		3/63	3/63		
	T	1/63				*1/63*	1/62		63	1/63	3/63						
	P						4/63										
64-65	P	2/65		3/64		*1/64*		1/64		**1/65**	3/65					4/64	
	T		1/64		64	1/65	2/65							1/65	2/65		65
66-68	P		2/66			3/66	3/66							1/67	1/67		
	T	*3/68*	2/68	3/68		3/67	2/68	2/68		**2/67**	4/67	2/67	67	*1/68*	4/68	1/68	
69-72	P	*2/70*	2/70	3/72	72	*2/69*	1/70	3/72		*1/70*	4/69	3/71		*1/69*	2/70	1/72	
	T	4/71	1/72			*2/71*	4/71			*4/71*	3/71			*2/71*	4/71		
73-75	P	**3/74**	1/74			**2/74**	3/73		73	2/73	3/73			*4/73*	3/73		75
	T	**4/75**	4/75			**3/75**	2/75			2/75	2/75	3/75		3/75	2/75		
76-78	P	4/76	1/77			4/76	1/77			1/77	1/77		76	4/76	1/77		
	T	2/78	3/78	3/76		4/77	4/78	3/76		2/78	4/78			1/78	4/78	2/76	
79-80	P	2/80	3/80	4/80		3/79	1/80	4/80		**1/80**	3/80	4/79		**1/80**	3/80	2/80	
	T				79												
81-83	P																
	T	*4/82*	3/82			**4/82**	3/81		83	**4/82**	1/82			**2/83**	3/82		
	P						1/83				4/82						
84-85	P	*1/85*	4/84			1/84								**3/84**	2/85		
	T			4/84			4/84	2/85			2/84	4/84	84	4/85		4/84	
	P									*4/85*	4/85						
86-87	P				87		3/86										
	T	*2/86*	2/87			*1/87*					1/87				1/87		
88-89	P		4/89	1/89				4/89			3/88		89	**4/89**	4/88	2/89	
	T									*1/88*							
90-91	P	**1/90**				*1/90*						3/90					
	T	**4/91**					1/90				1/90				3/90		
	P						4/91			**1/91**	4/91						
92-94	P														1/92		
	T		2/92	2/93		3/93	2/93	3/94		**2/93**	2/93			**3/93**	3/93	4/93	93
	P		2/94							**4/94**							
94-96	P	1/95				*1/95*	1/95				1/95			*4/95*	1/95		
	T	*2/96*	2/96		96	*4/96*	3/96			**1/96**	4/96	1/95	96	*4/96*	4/96		
97-99	P	*2/98*	2/98	1/98		*2/98*	2/98	4/98		*2/98*	3/98	2/99		*4/97*	2/98	1/98	
	T	3/99				1/99				*1/99*	4/99			1/99			
00-02	T			3/02			1/00										
	P	4/00				**4/00**	2/01		01	4/00	1/01			4/00			
	T		2/02				4/02				3/02				2/02		
03-06	P		1/04		04		2/04				2/04		05		1/04		03
	T	3/03	1/06			**2/03**	1/06	1/03		3/03	3/06	3/03		*1/05*	4/05	3/02	
07-08	P	1/08	4/07	1/07		1/08	4/07	2/07		1/08	4/07	3/07		2/08	4/07	1/07	
	T																

Table A.1.1. (cont.)

		Japan				Netherlands				Norway				Spain			
		R	Ki	Ju	Ku	R	Ki	Ju	Ku	R	Ki	Ju	Ku	R	Ki	Ju	Ku
60-63	P	4/61		1/63		4/60	2/61	4/63		4/60				*4/61*	2/62		
	T	4/62	3/62			1/63	2/63		63	*1/63*	1/63	2/62	63			3/61	61
64-65	P	**2/64**	2/64			4/64	2/64			*2/65*	4/65					4/65	
	T	**4/65**												*3/63*	2/64		
66-68	T		1/66	1/67	66			4/67			4/67						
	P		2/67									2/66		*2/66*	1/66		
	T		3/68			*2/67*	1/68							2/68	1/68		
69-72	P	*2/70*	1/70	3/71		*3/69*	1/70	4/71			4/69			2/69	4/69		
	T	1/72	4/71			*1/72*	1/72			*1/69*	2/71	2/70		*2/71*	4/71	4/69	
	P										3/72						
73-75	P	**4/73**	3/73		73	**1/74**	4/73		73	*2/74*		2/73		*1/74*	3/73	1/74	73
	T	**1/75**	3/75	4/75		**3/75**	3/75	4/75		4/75	1/74				3/75		
76-78	P	4/76	2/77			3/76	2/77			*4/76*	1/76				2/77		
	T	3/77				3/77				*2/78*	1/78	2/76		**1/76**		4/77	
79-80	T		1/79				1/79								3/79		
	P	**1/80**	4/80	3/80		**1/80**	4/80	4/79		*4/79*	1/80	4/79		**3/79**			
	T									4/80							
81-83	T				81									**3/82**			83
	P									**1/82**			81	**4/83**	4/82	3/81	
	T	**1/83**	3/82			**1/83**	3/82			**2/83**	1/82						
84-85	P	4/84	4/84			**2/85**	2/84				4/83						
	T			3/85				1/84	86			1/84		*2/85*	3/84	2/85	
86-87	P							4/87		3/86							
	T	*1/87*	4/86			*3/87*	4/86			3/88	1/86						
88-89	P		3/88				1/89			**4/89**	4/89	1/88		*2/89*	1/88	2/89	
	T														4/89		
90-91	T												90	**1/91**			
	P	*1/91*		1/90	90	*3/90*								**4/91**	3/91		90
	T		2/90				2/90			**4/91**	1/91						
92-94	P		2/92				4/91			*4/94*	3/93						
	T	**4/93**		2/94		4/93	3/93					2/92		**2/93**	2/93	4/93	
94-96	P					4/94	3/95					2/96		1/95	1/95		
	T		1/96							*4/95*	2/95			3/96	4/96		
97-99	P	2/97	3/97	3/98						3/98	1/97			**2/98**	3/98	1/98	
	T	4/98	1/99		98	*1/97*	2/97	2/97			1/99						
00-02	P	4/00	4/00			*3/00*	4/00	1/01	00		1/01		00				
	T	*4/01*	2/02	3/02			3/02			3/00		2/00		**1/02**	1/02	3/02	01
	P									2/02							
03-06	T					**2/03**		4/04			3/03						
	P		1/04	4/06		2/04	3/04				4/05	1/04		*2/04*	4/03	4/06	
	T		1/06			1/06	2/06			1/04				1/05	4/05		
07-08	T										4/07	1/08					
	P	*1/08*	4/07			1/08	2/08	3/08		2/08				3/07	3/07		07
	T																

Table A.1.1. (cont.)

		Sweden				Switzerland				UK				USA			
		R	Ki	Ju	Ku	R	Ki	Ju	Ku	R	Ki	Ju	Ku	R	Ki	Ju	Ku
60-63	P					4/61	4/61	4/63		**1/60**			61	1/62	2/62		63
	T	*1/63*	3/62	2/61						**1/63**	4/62	1/62					
64-65	T													1/64	1/64		
	P	*1/65*		3/65						**1/65**	4/64	4/65		**3/66**	4/65	2/65	
	T						4/64										
66-68	T					1/66		4/67									
	P		1/66			*4/66*	4/66										
	T	1/68	2/68			*1/68*	3/68			**3/67**	3/67			**3/67**	4/67		
69-72	P	2/70	1/70		71	*2/70*	2/70	1/72	71	**2/69**	4/69			**2/69**	3/69		
	T	1/72	1/72	1/70		**2/72**	1/72			1/72	4/71		69	**4/70**	3/71		
73-75	P	**2/74**	4/73	4/74		**2/74**	4/73			2/73	4/73			**4/73**	3/73		
	T					**2/75**	3/75			*3/75*	4/75	1/75		**2/75**	3/75	4/74	
76-78	P					3/77	3/77								3/77		
	T	**1/78**	1/78					2/76									
79-80	P	*1/80*	2/80					3/80		*2/79*	1/79	3/79		**1/79**		1/79	
	T			3/79	80	1/79	2/79							**3/80**	3/79		
81-83	T								81	*1/81*	2/81	3/83				4/83	81
	P			4/83		**1/80**	2/81			*4/83*	1/83			**2/81**	2/81		
	T	*4/82*	2/82			*4/82*	2/83							4/82	1/83		
84-85	P	*2/85*	2/84				2/85							*3/84*	4/84		
	T							1/85		*3/84*	1/85						
86-87	P					*2/86*											
	T	*1/87*	3/86	4/87		*2/87*	1/87							*3/86*	3/86		
88-89	P				89	*1/89*	4/88			*4/88*	1/89	1/88	89	*4/88*	2/88	2/88	
	T					*4/89*											
90-91	T						1/90							**2/91**	2/90		
	P	*1/90*	3/90	1/91		**1/91**	3/91	2/90	91								90
	T									**2/92**	1/91						
92-94	T	**2/93**	3/92	4/94		**2/93**	2/93					3/92				2/93	
	P		2/94				4/94			4/94	3/93			4/94	1/94		
	T																
94-96	P	1/95				2/95											
	T	4/96	2/96			3/96	3/96	1/95			1/96			1/96	4/95		
97-99	P	4/97	1/98	4/98		1/98	1/98	3/99			4/97	2/97			4/97	1/98	
	T	2/99			97	1/99	2/99			**1/99**	3/99		98		2/99		98
00-02	P	3/00				**4/00**	4/00			4/00	4/00			2/00	3/00		
	T	*3/02*	2/02				3/02		01	*2/03*	2/02	2/02		4/01	1/02		
03-06	T			1/03		**3/03**		4/03								2/04	
	P	*2/04*	1/04		05		2/04			*2/04*	1/04				4/03		05
	T	2/05	4/05				1/06			*4/05*	1/06				4/05		
07-08	P	4/07	4/07	1/07		*3/07*	4/07	1/08		*1/08*	4/07	1/07	07	1/08	4/07	2/07	
	T																

Chapter 2.

Measuring CPI's Reliability: the Stochastic Approach to Index Numbers Revisited

In this chapter, we shall discuss the measurement of the reliability of CPI. Here we will try to construct a new regression model that can measure the reliability of CPI, which model is an extension of the stochastic approach to index numbers. We allow for the mechanism of systematic change in relative prices in the literature of stochastic approach to index numbers to vary with time. Therefore, our model includes inflation rate and phases of business cycle dummies to allow for time varying. Such an extension can answer the Keynes's critic on stochastic approach to index numbers. Moreover, we used US and Australian data, and compared the results from our setting with those from the traditional setting, and further confirmed that our setting was more appropriate than the convention.

I. Introduction

Price indexes play a vital role in economic and business decision-making. The Consumer Price Index (CPI) is inarguably the most commonly cited and eye-catching among them. However, as Manchau (2007) pointed out recently, "… prices were rising everywhere, yet the price index gives the illusion of price stability," which signaled the CPI growth rate has become less reliable now in its measure of inflation. Therefore, searching for a better means in gauging the reliability of the CPI is not only theoretically an attractive topic, but also essentially important. To this end, this chapter focuses on providing a new regression specification that can better help detect whether or not the CPI can be depended upon.

Essentially, we seek to provide new insights to the following familiar problem in the stochastic approach to index numbers (Bowley; 1907, 1911, 1919, 1926, 1928; Edgeworth, 1888; Jevons, 1863, 1865, 1869; Liang and Chen, 2000; Mills, 1927; Selvanathan and Rao, 1994). Given the inflation rate of *n* goods in $t = 1, 2, ..., T$ periods $Dp_{11}...Dp_{n1}, Dp_{12}...Dp_{n2}, ..., Dp_{1T}...Dp_{nT}$, how should we use this information to measure the general inflation rate, which represents the proportionate change in the general price level?

The conventional approach to this problem was proposed by Clements and Izan (1987) and Crompton (2000). The basic assumption of their regression models was that an individual commodity's inflation rate at time t is driven by an unknown central tendency, along with a time-invariant individual price trend of each respective n commodity. Consequently, by applying the panel estimation technique to the n individual commodities' inflation rate data during the time period T, they obtained the estimates of the two corresponding sets of parameters, i.e., their central tendencies and individual price trends, as well as their corresponding estimated standard errors. Based on the stochastic approach to index numbers, the central tendency estimates were utilized to calculate the general inflation rates of $t = 1, 2, ..., T$, while the corresponding estimated standard errors could represent the reliability of the estimated general inflation rates (Selvanathan and Rao, 1994).

Yet, the models proposed by Clements and Izan (1987) and Crompton (2000) were incomplete, since the aforementioned time-invariant assumption in fact contradicted with Mill's (1927) proposition that specific individual price trends would vary in different price levels and business cycle phases. In the absence of addressing these concerns, the estimated standard errors of the general inflation rate may correlate with the inflation rate levels (Chang and Cheng, 2000; Debelle and Lamount, 1997; Fielding and Mizen, 2000; Parsley, 1996; Vining and Elwertowsky, 1976) and business cycle phases (Reinsdorf, 1994). As a result, the estimators of the standard errors of the estimated inflation rates obtained from Clements and Izan (1987), as well as Crompton's (2000) regression models, can be subjected to the biased statistical problem.

We thus propose a resolution by relaxing the time-invariant assumption of the individual price trend by adding two sets of dummy variables representing different inflation rate levels and business cycle phases. Based on this framework, we try to estimate the general inflation rates and their corresponding standard errors in avoiding the statistical problems caused by the model misspecification, due to the omitted variables. Through our new regression, the estimated inflation rates are still computed by an expenditure-share-weighted average of the n commodities, which means its corresponding standard errors can still be interpreted as a reliability measure of the CPI. Using Australian and US data spanning between September 1990 to March 2009 and January 1990 to December 2008, respectively, and comparing with the results of Crompton (2000), our research shows that the estimated standard errors of the estimated inflation rates have a weaker correlation with the inflation rate levels and business cycle phases in our specification. This implies that Clements and Izans' (1987) and Crompton (2000)'s models were indeed incomplete. Without the unrealistic time-invariant assumption imposed on the inflation rates of individual commodity groups, this study takes a step further in addressing the "Keynes' (1930) critic" regarding the stochastic approach to index numbers.

II. Specification of the Full model

During earlier research of the stochastic approach to index numbers (Edgeworth, 1888; Mills, 1927), researchers assumed the data generating process was given by

$$Dp_{it} = \alpha_t + \mu_{it} \quad (1)$$

where Dp_{it} represents the inflation rate in each commodity group at time t; α_t is the general inflation rate at time t and μ_{it} denotes the independent error term. Using (1), we can obtain not only a set of point estimates of the inflation rate at time *t*, but also their corresponding standard errors (Edgeworth, 1888; Mills, 1927; Selvanathan and Rao, 1994; Liang and Chen, 2000).

However, (1) does not permit peculiar changes in the prices of different commodity groups. Such weakness in the model was previously criticized by Keynes (1930)[12]. To

[12] "The hypothetical change in the price level, which would have occurred if there had been no changes in relative prices, is no longer relevant if relative prices have in fact changed -- for the change in relative prices has in itself affected the price level.

I conclude, therefore, that the unweighted (or rather he randomly weighted) index number of prices -- Edgeworth's 'indefinite' index number -- ...has no place whatever in a rightly conceived discussion of the problems of price levels."

Keynes (1930, p. 30)

rectify this problem, Clements and Izan (1987) introduced a "new stochastic approach" to index numbers by allowing for a systematic change in relative prices, which were the specific price trends for each commodity group. This was achieved by adding a commodity dummy to (1):

$$Dp_{it} = \alpha_t + \beta_i + \mu_{it} \tag{2}$$

where β_i denotes the constant systematic change in the relative price of commodity *i*. Conceptually, these systematic changes can be interpreted as the expectation of the deviation change of the *ith* relative price from the general price level.

Clearly, Clements and Izan (1987) made great progress in the stochastic approach to index numbers. Nevertheless, there is still room for improvement in their procedure. Due to stringent restrictions on the OLS error term, one of the key downsides was that it may yield a biased estimator of the standard errors of the estimated general inflation rate. This subsequently led to Crompton (2000) reformulating and extending (2) by deriving a variance estimator that was robust enough to unknown forms of heteroscedasticity.

However, due to the omitted variables problem, even Cromption's (2000) procedure was still inadequate in modeling the system of separate inflation rates for each commodity group that varied with time. It should be noted that, β_i in (2) is time-invariant. Mill (1927, p. 76) noticed that the relative position between the specific price trends of each commodity group could change throughout the cyclical swings of commodity prices: "During the major cyclical swings of commodity prices there are pronounced differences in the movements of individual commodities."

"Pronounced difference" means the specific individual price trend deviation from the general price trend should not be constant with time. The reason is that the prices of every individual commodity group are not equally affected by the effects of the general inflation levels and business cycle phases. Some individual commodity prices are rendered relatively inert by contracts or customized agreements, while others are peculiarly sensitive to a general price-raising or price-lowering force (Mill, 1927, p. 240). At times, some specific prices may vary with the business cycles phases, while the prices of some commodity groups may be constant or insensitive over time. To be certain, Vining and Elwertowsky (1976), Parsley (1996), Debelle and Lamount (1997) and Chang and Cheng (2000) have illustrated that the variance of the estimated inflation is positively correlated with the general inflation rate, thereby revealing the regression model (2) could be incorrectly specified, as it ignored the inflation effect. Moreover, Reinsdorf (1994) found a negative relationship existed between the variance and the inflation level over the recession periods in US data, an indication that the possible misspecification of the model may also stem from the ignorance of the business cycle phase effects.

Taking into account Mill's (1927) arguments and the aforementioned empirical findings, we modify the model proposed by Crompton (2000) by introducing two sets of dummies, which represent the business cycle phases as well as the high and low inflation levels in acquiring the systematic changes in the relative prices of the different commodity groups in such a circumstance. Specifically, the full model is set as follows:

$$Dp_{it} = \alpha_t + \beta_i + \sum_J \gamma_{ji} D_{jt} + \mu_{it} \tag{3}$$

where the inflation rate of each commodity group at time t (Dp_{it}) originates from the inflation rate of general prices (α_t) at time t (could be taken as CPI), which is independent from the influence of individual commodities, the long-term systematic change in relative commodity prices i (β_i), and short-term systematic change in relative commodity prices i ($\sum_J \gamma_{ji} D_{jt}$). Notably, the first two terms are exactly the same as in Clements and Izan (1987) and Crompton (2000), but here we introduce the $\sum_J \gamma_{ji} D_{jt}$ term, where D_{jt} for j from 1 to J are dummies of the business cycle phases and inflation levels at t, and γ_{ji} is the corresponding difference in the price trend for the *jth* dummy. Additionally, μ_{it} denotes the error term, with $\operatorname{var}\mu_{it} = \varepsilon_{it}^2$, $\operatorname{cov}(\mu_{is}, \mu_{jt}) = 0$ for $i \neq j$, $s \neq t$. Regarding the variance of the error term in (3), we adopt the assumption from Crompton (2000), which contains an unknown form of heteroscedasticity. Noteworthy, γ_{ji} in (3) would change as the sample is in different inflation levels and business cycle phases. Consequently, by adding $\sum_{J} \gamma_{ji} D_{jt}$ in (3), we can further answer the "Keynes (1930) critic."

Following Cropmton's (2000) procedure, it is possible to obtain the estimated inflation rate in general price ($\hat{\alpha}_t$) as the expenditure weighed (w_i) average of the n inflation rates over the n commodities by multiplying (3) with $(w_i)^{1/2}$, yielding

$$y_{it} = \alpha_t x_i + \beta_i x_i + \sum_{J} \gamma_{ji} D_{jt} x_i + v_{it}, \tag{4}$$

where $y_{it} = Dp_{it}(w_i)^{1/2}$, $x_i = (w_i)^{1/2}$ and $v_{it} = \mu_{it}(w_i)^{1/2}$ and $\text{var}(v_{it}) = \varepsilon_t^2 w_i$. However, (4) remains unidentified since an increase in α_t for each t and a decrease of β_i and/or γ_{ji} for each i has no effect on the righthand terms. Accordingly, by imposing the restrictions $\sum_{i=1}^{n} w_i \beta_i = 0$ and $\sum_{i=1}^{n} w_i \gamma_{ji} = 0$ for *j* from *1* to *J*, (4) can be estimated using the constrained LS approach and a corrected heteroscedasticity in v_{it} with White's heteroscedasticity consistent covariance matrix estimator (White, 1980). Noteworthy, $\hat{\alpha}_t = \sum_{i=1}^{\infty} w_i Dp_{it}$ shares the same form with the official price index. The associated sampling variance of $\hat{\alpha}_t$, corrected for heteroscedasticity is $Var(\hat{\alpha}_i) = \sum_{i=1}^{n} w_i v_{it}^2$, which is the weighed average of the sum of squared residuals over the *n* commodities.

III. Empirical Evidence

To validate our findings, we first estimated the consumer price index (CPI) using quarterly data from Australia spanning between 3Q 1990 to 1Q 2009[13] and monthly

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[13] Crompton (2000) illustrated the stochastic approach by estimating quarterly Australian consumer inflation rates using price series from the categories, which included food, clothing, housing, household equipment and operation, transportation, tobacco and alcohol, and health and personal care.

data from the US covering from January 1990 to December 2008 via the approach proposed by Crompton (2000). There were ten sub-components in Australia's CPI (*n*=10), which encompassed food, alcohol and tobacco, clothing and footwear, housing, household contents and services, health, transportation, communication, recreation and education. Meanwhile, there were eight sub-components in the US CPI (*n*=8), which included food and beverages, housing, apparel, transportation, medical care, recreation, education and communication and other goods and services[14]. After the data was pooled, it yielded 750 observations in the Australian sample and 1,824 observations in the US sample. It was arranged in a way, where the first 75 (228) observations or the first column of the Australia (US) sample are the log price changes from the previous year of the first sub-component series, which is food (food) in the Australia (US) sample. The second 75 (228) observations or the second column is the alcohol and tobacco (housing) log price change series. The same logic can be applied to the subsequent observations or columns. The estimated results are provided in Appendix 2.1.

Figure 2.1 and Figure 2.2 depict the relationships between the estimated standard errors of the estimated inflation rate by Crompton's (2000) method and the respective absolute difference value between the inflation rate at time t and average inflation rate in Australia and the US. The R^2 of the fitted lines in Figure 2.1 and Figure 2.2 is 0.33 and 0.19, respectively, and are both significant at 99% confidence. The results indicate the standard errors estimated with Crompton's method indeed varies with the inflation levels, which suggests for a noteworthy misspecification in Crompton's (2000) model.

[14] The price data and corresponding expenditure weights were obtained from Australian Bureau Statistics (*www.abs.gov.au*) and Bureau of Labor Statistics of the US (*www.bls.gov*).

Figure 9 Estimated standard errors of Crompton's method and the absolute difference values between the inflation rate at time t with general inflation mean, Australia

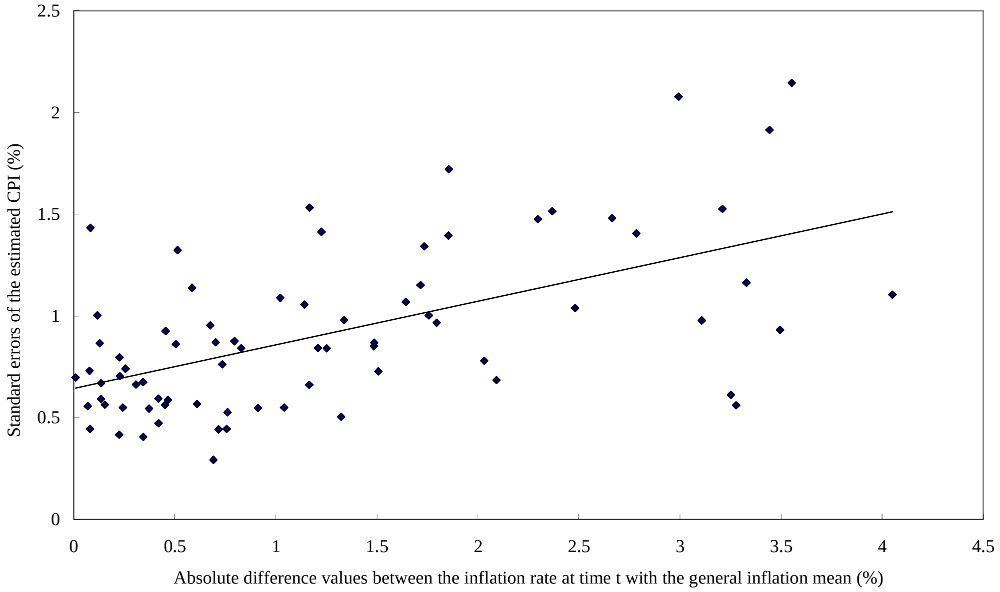
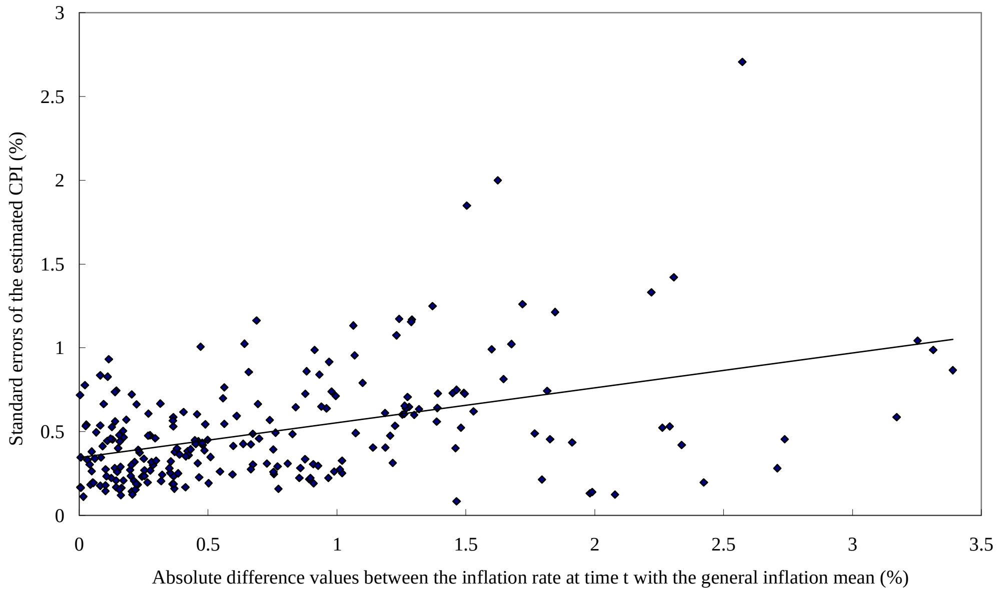


Figure 10 Estimated standard errors of Crompton's method and the absolute difference value between the inflation rate at time t with the general inflation mean, US



Further examination of the estimated standard errors of the monthly estimated CPI inflation in the US sample reveals that the lifted estimated standard errors of the estimated CPI inflation were detected in 1990, 1998, 2001 and 2007~2008. These particular years all occurred roughly during the business cycle peaks of the US[15]. In other words, the standard errors of the CPI inflation estimated by Crompton's (2000) method may also vary among the different phases of the business cycle.

To investigate this conjecture, we used a Christiano-Fitzgerald (2003) full sample asymmetric filter (hereafter, CF filter)[16] on the GDP of Australia and industrial production index on the US[17] to distinguish the different business cycle phases with time, which include expansion, slowdown, recession and recovery. Each cycle ranged between 3~10 years[18]. Based on the results listed in Table 2.1 and 2.2, we can examine the relationship between the estimated standard errors of the estimated inflation rate and business cycles phases. Specifically, we found that the high standard errors of the estimated Australian inflation rates occurred more frequently in the slowdown and recession phases, with the corresponding ratios reaching 56.5% and 66.7%, respectively. It was more infrequent during the expansion and recovery phases, where the corresponding ratios reached 44% and 25%, respectively. As for the US, they occurred less often when the economy was in the recovery phase, rendering a ratio of 14.04%.

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[15] National Bureau Economic Research (NBER) dated July 1990, March 2001 and December 2007 as business cycle peaks of the US. The Economic Cycle Research Institute (ECRI) dated January 1998 as a growth cycle peak of the US.

[16] Note that the CF filter is applied, due to its generality in which the weights on the leads and lags are allowed to differ. Specifically, the band-pass filter is a linear filter that calculates a two-sided weighted moving average of the data wherein the cycles are in a "band," given by a specified lower and upper bound. They are "passed" through or extracted, and the remaining cycles are "filtered" out. Furthermore, the filter is time-variant, with the weights depending on both the data and the changes in each observation.

[17] The Australia CPI is quarterly-based data; the US CPI is monthly-based data. In the literature, among those using quarterly data, the GDP series is the most commonly used in the study of business cycles; while among those using monthly data, the industrial production series is the most commonly used. Therefore, in order to match the frequencies of the CPI data used in Australia and the US in the identification of business cycle phases, we shall use the Australian quarterly GDP and the US monthly industrial production series with CF filter to identify the phases of business cycle in each nation.

[18] Since Kitchin cycles range between 3~5 years, and Juglar cycles range between 7~10 years (Duijn, 1983), the period of 3~10 years that we choose includes the two most frequent periods of cyclic fluctuation.

Meanwhile, it was relatively frequent when the economy was in the expansion, slowdown and recession phases, where the ratios were 60%, 67.5% and 60.66%, respectively.

Table 12 Number of months with high standard errors during different business cycle phases of Australia using Cromptom (2000)'s method

	expansion[b]	slowdown[b]	recession[b]	recovery[b]	Total
No. High[a]	11	13	10	3	37
No. Low[a]	14	10	5	9	38
total	25	23	15	12	75
ratio (%)	44.00	56.52	66.67	25.00	49.33

[a] No. High (No. Low) denotes the number of high standard errors for the estimated CPI, where high standard errors are defined by the first (last) 50% quintiles of standard errors.

[b] Phases of business cycles are derived by CF filter.

Table 13 Number of months with high standard errors during different business cycle phases of US using Cromptom (2000)'s method

	expansion[b]	slowdown[b]	recession[b]	recovery[b]	Total
No. High[a]	42	27	37	8	114
No. Low[a]	28	13	24	49	114
total	70	40	61	57	228
ratio (%)	60	67.5	60.66	14.04	50

[a] No. High (No. Low) denotes the number of high standard errors for the estimated CPI, where high standard errors are defined by the first (last) 50% quintiles of standard errors.

[b] Phases of business cycles are derived by CF filter.

Statistically, to validate whether the standard errors of inflation correlates with the revolving business cycles, we applied the Pearson independent χ^2 test (Agresti, 2002) during months with high standard errors and business cycle phases. The corresponding χ^2 statistic of the Australia and US sample was 2.74 and 19.98, respectively. The US statistic was significant at 99% confidence, while the statistic of Australia was insignificant at 90% confidence.

In summary, based on Crompton's (2000) approach, our calculated standard errors of the inflation rates revealed a statistically significant relationship between the estimated standard errors of the estimated inflation rates and the level of inflation in

Australia. In the US, we found that the calculated standard errors of the estimated inflation rates were not only statistically significantly correlated to the level of inflation, but also to the business cycle phases. These results evidently indicated possible misspecification in Crompton (2000)'s model since it only included α_t and β_i in (2). Under his framework, if there are different systematic changes in different phases throughout the business cycle during varying inflation levels, the estimated standard errors of the estimated inflation rates will increase sharply, as the systematic changes in some business cycle phases or a certain inflation level becomes significantly distant from the long-term systematic change. In other words, some of the extremely high standard errors acquired by Cromptom (2000)'s method simply reflect the misspecification, where the effects of different business cycle phases and inflation levels were ignored. To resolve these shortcomings, we introduce the dummies into (3), as shown below.

For the cycle dummies, let C_t be the cycle component derived from the CF filter, we denote

$$D_t^E = 1, \text{ if } C_t \geq 0 \text{ and } C_t \geq C_{t-1}, \ D_t^E = 0 \text{ if otherwise;}$$

$$D_t^S = 1, \text{ if } C_t \geq 0 \text{ and } C_t < C_{t-1}, \ D_t^S = 0 \text{ if otherwise;}$$

$$D_t^R = 1, \text{ if } C_t < 0 \text{ and } C_t < C_{t-1}, \ D_t^r = 0 \text{ if otherwise;}$$

where D_t^E, D_t^S and D_t^R are dummies of expansion, slowdown and recession, respectively.

As for high and low inflation dummies, we let the high (low) inflation dummy equal to 1 if the inflation rate of period *t* is higher (lower) than the average general inflation rate plus (minus) one standard deviation of the general inflation rate. In other words,

$$D_t^{HI} = 1, \text{ if } DP_t > mean(DP) + stdev(DP), \ D_t^{HI} = 0 \text{ if otherwise;}$$

$$D_t^{LI} = 1, \text{ if } DP_t < mean(DP) - stdev(DP), \ D_t^{LI} = 0 \text{ if otherwise.}$$

where D_t^{HI} (D_t^{LI}) is the dummy of high (low) inflation, DP_t is the general inflation rate at time *t*, $mean(DP)$ and $stdev(DP)$ are the mean and standard deviation of the general inflation, respectively.

Based on the aforementioned empirical findings, we add the inflation dummies into the estimation of Australia's inflation rates, while both the inflation and cycle dummies are included in the estimation of the US inflation rates. The results after the inclusion of dummies are presented in Appendix 2.2. Figure 2.3 and Figure 2.4 depict the relationships of the estimated standard errors after the addition of dummies with the respective absolute difference values between the inflation rate at time *t* and the mean general inflation in Australia and the US. Although the slope of the fitted line in Australia is still significant, the R^2 of the fitted line, however, decreased to 0.19 from 0.33. As for the US, the slope of the fitted line in Figure 2.4 is insignificant at 90% confidence and the R^2 of the fitted line decreased from 0.19 to 0.004. Both slopes in Figure 2.3 and Figure 2.4 fell as well.

Figure 11 Estimated standard errors after adding dummies and the absolute difference values between the inflation rate at time t with general inflation mean, Australia

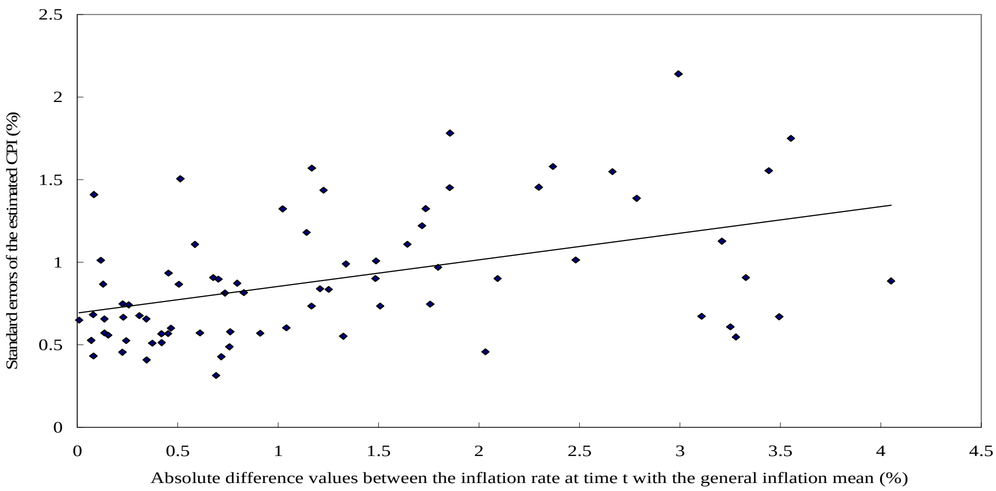
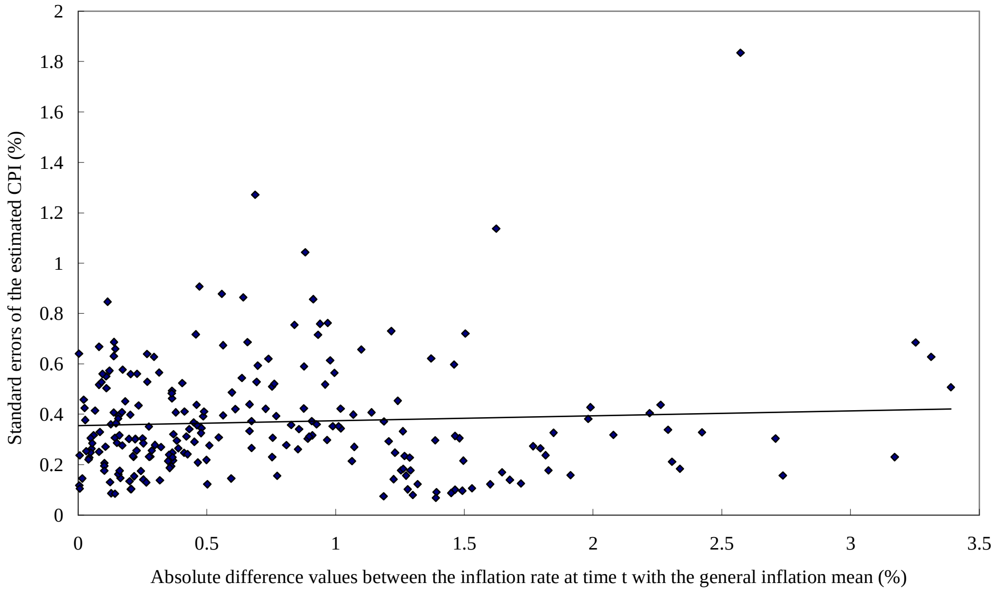


Figure 12 Estimated standard errors after adding dummies and the absolute difference values between the inflation rate at time t with the general inflation mean, US



As for the business cycle phases in the US, the occurrence ratios of high standard errors appeared to be more balanced across the different economic environments in Table 2.3 compared to Table 2.2. The corresponding χ^2 statistic of the cycle phases and the estimated standard errors of the estimated CPI also fell from 19.98 to 8.58 after the inclusion of additional dummies.

Table 14 The total number of months where "high standard errors of estimated CPI" occurred in different business cycle phases in the US after adding dummies

	expansion[b]	slowdown[b]	recession[b]	recovery[b]	total
No. High[a]	35	25	38	16	114
No. Low[a]	35	15	23	41	114
total	70	40	61	57	228
ratio (%)	50	62.5	62.30	28.07	50

[a] *No. High (No. Low) denotes the number of high standard errors for the estimated CPI, where high standard errors are defined by the first (last) 50% quintiles of standard errors.*

[b] *Phases of business cycles are derived by CF filter.*

Table 15 Summary statistic results before and after the inclusion of dummies

	Austrilia			US		
	slope[a]	R^2 [b]	χ^2 [c]	*slope*[a]	R^2 [b]	χ^2 [c]
before	0.21 (5.98)	0.33	2.74	0.21 (7.19)	0.19	19.98
after	0.16 (4.26)	0.19	-	0.02 (0.91)	0.004	8.58

[a] *"Slope" denotes the fitted slope of the standard errors of the estimated inflation rate to the absolute difference values between the inflation rate at time t with the general inflation mean. t-statistics are in parentheses.*

[b] *"R^2" denotes the corresponding R-square of the fitted line of the standard errors of estimated inflation rate to the absolute difference values between the inflation rate at time t with the general inflation mean.*

[c] *χ^2 denotes the chi-square statistic Number of months with high standard errors and phases of business cycle.*

In summary, our new findings validates the value of adding different general inflation rate level and business cycle phase dummies into the regression specification, based on the stochastic approach to the index numbers.

IV. Concluding Remarks

This chapter centers on providing a new regression specification that can help better gauge the CPI's reliability. Specifically, we argue that based on the stochastic approach to index numbers, the conventional approach to the systematic changes in relative prices should be made time variant. We thus propose a more comprehensive regression specification by including additional dummies that represent different general inflation rate levels and business cycle phases. Under this framework, we can avoid possible misspecification of the regression equation as was found in Clements and Izan (1987), while also further addressing the "Keynes' critic" on the stochastic approach to index numbers. The empirical results of Australia and the US evidently validate the merit of our specification. Future researchers may also work on finding other possible factors that have not yet been considered in past research or in this chapter in further improving the reliability measurement of the estimated CPI.

Appendix 2.1: Estimated Standard Errors of CPI of Australia and US by Crompton's Method

Table A.16 Estimated standard errors of CPI of Australia by Cromptom (2000)'s method

%	Q1	Q2	Q3	Q4		Q1	Q2	Q3	Q4
1990			0.93	1.01	2000	1.00	0.93	1.16	0.98
1991	0.68	0.87	1.32	1.41	2001	0.61	0.56	0.56	0.86
1992	1.53	1.72	1.51	1.48	2002	0.66	0.74	0.57	0.41
1993	1.15	0.76	0.47	0.53	2003	0.44	0.70	0.73	0.80
1994	0.50	0.55	0.45	0.59	2004	0.95	0.70	0.54	0.67
1995	1.34	1.48	1.41	1.04	2005	0.67	0.55	0.56	0.44
1996	0.55	0.42	0.29	0.85	2006	0.59	0.87	0.98	0.88
1997	1.39	2.08	2.15	1.91	2007	0.56	0.59	0.84	0.87
1998	1.53	0.78	0.73	0.66	2008	0.84	0.84	1.00	1.14
1999	1.07	0.97	1.06	1.09	2009	1.43			

Table A.17 Estimated standard errors of CPI of US by Cromptom (2000)'s method

%	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nob	Dec	Ave
1990	0.52	0.53	0.42	0.45	0.52	0.49	0.44	0.28	0.59	0.87	0.99	1.04	0.59
1991	0.45	0.20	0.13	0.14	0.12	0.21	0.08	0.19	0.45	0.78	0.83	0.84	0.37
1992	0.66	0.45	0.27	0.27	0.35	0.44	0.37	0.21	0.11	0.14	0.22	0.17	0.31
1993	0.23	0.30	0.28	0.20	0.12	0.16	0.16	0.17	0.32	0.32	0.27	0.34	0.24
1994	0.24	0.23	0.21	0.23	0.26	0.25	0.29	0.34	0.38	0.23	0.25	0.38	0.27
1995	0.41	0.45	0.47	0.46	0.56	0.54	0.28	0.16	0.19	0.15	0.20	0.28	0.35
1996	0.15	0.18	0.18	0.12	0.15	0.21	0.20	0.18	0.18	0.26	0.33	0.40	0.21
1997	0.23	0.19	0.19	0.31	0.46	0.43	0.39	0.31	0.29	0.33	0.49	0.60	0.35
1998	0.63	0.62	0.73	0.73	0.61	0.60	0.53	0.65	0.75	0.73	0.64	0.71	0.66
1999	0.64	0.65	0.47	0.25	0.22	0.25	0.22	0.26	0.38	0.44	0.45	0.59	0.40
2000	0.57	0.72	1.02	0.54	0.53	0.85	0.59	0.32	0.43	0.39	0.42	0.39	0.57
2001	0.49	0.41	0.74	0.53	0.42	0.56	0.74	0.66	0.48	0.67	0.99	1.07	0.65
2002	0.99	1.02	0.73	0.61	0.81	0.74	0.40	0.31	0.56	0.31	0.30	0.35	0.59
2003	0.61	0.93	0.72	0.31	0.33	0.26	0.22	0.16	0.24	0.22	0.27	0.28	0.38
2004	0.30	0.40	0.41	0.28	0.50	0.48	0.33	0.19	0.17	0.50	0.76	0.67	0.41
2005	0.30	0.35	0.40	0.62	0.24	0.19	0.53	1.01	1.85	1.17	0.43	0.36	0.62
2006	0.64	0.49	0.36	0.54	0.84	0.79	0.74	0.49	1.16	1.25	0.65	0.35	0.69
2007	0.65	0.60	0.26	0.46	0.39	0.47	0.70	0.86	0.30	0.55	1.17	0.95	0.61
2008	1.15	1.13	0.92	0.73	0.71	1.26	1.42	1.33	1.21	0.57	2.00	2.71	1.26

Appendix 2.2: Estimated Standard Errors of CPI of Australia and US by Adding Economic Environment Dummies

Table A.18 Estimated standard errors of CPI of Australia by adding dummies

%	Q1	Q2	Q3	Q4		Q1	Q2	Q3	Q4
1990			0.67	0.89	2000	1.01	0.93	0.91	0.67
1991	0.90	0.90	1.50	1.44	2001	0.61	0.55	0.56	0.87
1992	1.57	1.78	1.58	1.55	2002	0.68	0.74	0.57	0.41
1993	1.22	0.81	0.51	0.58	2003	0.43	0.65	0.68	0.75
1994	0.55	0.60	0.49	0.57	2004	0.91	0.67	0.51	0.66
1995	1.32	1.45	1.39	1.01	2005	0.66	0.53	0.57	0.43
1996	0.57	0.45	0.31	0.90	2006	0.60	1.01	0.99	0.87
1997	1.45	2.14	1.75	1.55	2007	0.53	0.57	0.82	0.87
1998	1.13	0.46	0.73	0.73	2008	0.84	0.84	0.75	1.11
1999	1.11	0.97	1.18	1.32	2009	1.41			

Table A.19 Estimated standard errors of CPI of US by adding dummies

%	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nob	Dec	Ave
1990	0.44	0.34	0.18	0.18	0.31	0.27	0.16	0.30	0.23	0.51	0.63	0.68	0.35
1991	0.16	0.33	0.38	0.43	0.32	0.26	0.31	0.32	0.22	0.46	0.50	0.52	0.35
1992	0.30	0.09	0.14	0.30	0.33	0.39	0.43	0.31	0.14	0.10	0.13	0.12	0.23
1993	0.17	0.26	0.21	0.13	0.10	0.10	0.15	0.08	0.23	0.23	0.23	0.30	0.18
1994	0.27	0.28	0.23	0.21	0.31	0.30	0.32	0.32	0.30	0.25	0.24	0.32	0.28
1995	0.53	0.55	0.58	0.57	0.69	0.67	0.41	0.22	0.19	0.16	0.14	0.21	0.41
1996	0.15	0.26	0.25	0.18	0.20	0.28	0.26	0.23	0.18	0.25	0.28	0.41	0.24
1997	0.27	0.28	0.30	0.44	0.59	0.54	0.51	0.42	0.39	0.42	0.27	0.18	0.39
1998	0.12	0.11	0.10	0.09	0.07	0.08	0.14	0.10	0.10	0.09	0.07	0.16	0.10
1999	0.23	0.18	0.29	0.31	0.30	0.34	0.26	0.23	0.31	0.36	0.37	0.49	0.31
2000	0.45	0.56	0.86	0.38	0.36	0.69	0.42	0.19	0.29	0.34	0.35	0.39	0.44
2001	0.52	0.49	0.66	0.46	0.44	0.48	0.63	0.56	0.35	0.53	0.86	0.25	0.52
2002	0.12	0.14	0.22	0.33	0.17	0.24	0.60	0.73	0.30	0.37	0.27	0.28	0.31
2003	0.53	0.85	0.64	0.28	0.42	0.35	0.30	0.16	0.15	0.31	0.35	0.34	0.39
2004	0.36	0.37	0.41	0.33	0.41	0.38	0.25	0.23	0.25	0.41	0.67	0.57	0.39
2005	0.22	0.24	0.29	0.52	0.13	0.12	0.42	0.91	0.72	0.45	0.33	0.27	0.39
2006	0.52	0.37	0.24	0.41	0.72	0.66	0.61	0.36	1.27	0.62	0.76	0.41	0.58
2007	0.76	0.72	0.36	0.63	0.56	0.64	0.88	1.04	0.40	0.40	0.18	0.40	0.58
2008	0.23	0.21	0.76	0.59	0.56	0.13	0.21	0.40	0.33	0.62	1.14	1.83	0.58

Chapter 3.

An Application of Henriksson-Merton Test: Are Fed Funds Rate Futures Valuable in Predicting US Monetary Policy?

In this chapter, we apply the non-parametric generalized Henriksson-Merton (H-M) test proposed by Pesaran and Timmermann (1992, 1994) to verify the directional predictive ability of Federal Funds futures on Federal Funds rates.

I. Introduction

The Federal Reserve implements monetary policy by making discrete adjustments[19] to its target for the Federal Funds (FF) rate. Changes in the FF rate triggers a chain of events that affect other short-term interest rates, foreign exchange rates, long-term interest rates, the volume of money and credit and, ultimately, a range of economic variables including employment, output and prices of goods and services. Therefore, how well markets anticipate the FF rate is a topic of great interest to financial market participants and policymakers alike[20].

It is not surprising that a vast body of research have already studied the behavior of the FF rate and proposed empirical models designed to have it explained. The literature has suggested that several variables can explain FF rate movements: inflation and output gap (e.g. Taylor, 1993, Clarida, Gali, and Gertler, 1998, 2000), FF futures rates (e.g. Krueger and Kuttner, 1996, Robertston, and Thornton, 1997, Poole, and Rasche, 2000,

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[19] Changes in the FF target rate are limited to multiples of 25 basis points since August 1989 (Poole and Rasche, 2003).

[20] Although the Fed lowered the Fed Funds rate to 0~0.25% at 12/16/2008, giving up the Fed Funds rate as an operation target of monetary policy and shifted to unconventional operation targets, as the US economy bottoms and recovers, the Fed inevitably shall resume using the Fed Funds rate as operation targets of monetary policy. Therefore, understanding the predictability of FF futures on Fed Funds rate are still valuable.

Owen, and Webb, 2001, S¨oderstr¨om, 2001, Poole, and Rasche, 2003, Lange, Sack, and Whitesell, 2003) and other short or long term interest rate (e.g. Enders and Granger, 1998, Hansen and Seo, 2002, Sarno and Thornton, 2003, Clarida et al., 2006).

Among which, the FF futures rates were the most frequently used indicator to predict future FF rate movements, since its pricing information is widely available in a timely fashion while being recognized as essentially public and market-based forecasts of future interest rates of Federal Funds. The closing prices of each trading day are quoted on the financial pages of most major newspapers the next day. Moreover, real time quotes are available on the Internet with the CBOT's website. Besides, the FF futures rates are better than the Treasury bond yields, another high frequency variable, as a predictor of monetary policy movement. Since the FF futures rates, unlike long and short term interest rates that are affected by other factors of demand (risk appetite) and supply (government deficit) in the market, the FF futures market is most affected by market expectation on future monetary policy.

Although vast many literature have studied the prediction power of FF futures rates on future FF rate movements, most researches focus only on quantitative accuracy instead of qualitative (directional) accuracy. But changes in the FF target rate are discrete; therefore a conventional quantitative accuracy test, such as MSE and MAPE based criterions, may not be a proper application. Furthermore, for most people, directional movement (raise, no change and cut) of the FF rate is important as well, since it represents the FOMC's tendency of monetary policy (tighten, neutral and ease). On the other hand, the U.S. monetary policy have became more "gradualism" (Lange, Sack and Whitesell, 2003) in late 1990's, which means the monetary policy cycle of the US has become more obvious and prolonged since then. Therefore, the predicting power of the FF futures near the turning point of the monetary policy cycle is important as well.

In addition, market participants use the FF futures to foresee future U.S monetary policy as well, but few papers have discussed how many periods ahead are FF futures valuable in the sense of Henriksson and Merton (1981) in predicting future FF target rate movements[21]. Furthermore, reviewing literatures associated with FF futures, many papers have discussed the effects of the change in FOMC disclosure practice made at 1994/2, but qualitative measurements about this topic were rare.

Here we apply the non-parametric generalized Henriksson-Merton test proposed by Pesaran (1992) and Pesaran and Timmermann (1994) to fill these gaps in literature. The remainder of this chapter is organized as follows. In section 2, we briefly discuss some earlier studies about the prediction of FF rate by FF futures. In section 3, we introduce the Federal Futures market and illustrate how market participants use FF futures rates to anticipate the future FF rate. In section 4, we apply the generalized non-parametric Henriksson-Merton test on FF futures rates to predict future FF rates. The last section is concluding remarks.

II. A Review of Earlier Studies

Many literatures have discussed the relationship between FF futures rates and the FF rate. We first review the rationality testing and forecasting accuracy evaluation, and then we discuss the importance of directional accuracy. Behavior of FF futures rates related to the monetary policy cycle and changes in the FOMC disclosure practice will then be discussed.

2.1. Rationality Testing and Forecasting Accuracy Evaluation

The first paper to examine the rationality of FF futures rates in explaining future FF rate

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[21] Henriksson and Merton (1981) applied Merton's (1981) theory with Bayesian statistical methods to derive a test that could measure for the user whether the prediction for a variable by a model is meaningful and valuable. Straightforwardly, Merton's (1981) argument could be summarized as follows: Firstly, user of forecast (investors) may already have a prior view on a variable's future value (expected return on stocks). These views may be based on a combination of prior distribution. Secondly, after a forecasting agency releases their forecast, the messages become part of the sample information collected by the forecast user. Finally, after receiving these sample information, if the posterior distribution formed by it may not only be different but also adjust to a more accurate direction than the aforementioned prior distribution, then that message is said to be valuable and useful for the user.

movements is Krueger and Kutter (1996). They use monthly data from June, 1989 through November, 1994 by regressing the futures-based forecast errors (denoted as $\overline{f}_t^{t+k} - \overline{r}_{t+k}$) on a variety of economic indicators (denoted as x_{t-1}),

$$\overline{f}_t^{t+k} - \overline{r}_{t+k} = a + \theta(L)x_{t-1} + u_{t+k} \qquad (1).$$

They found that the coefficients for economic indicators were rarely significant, which indicated that when information from futures is included, there may only be slight improvement, if at all, using economic indicators. Krueger and Kutter also examined the forecasting accuracy evaluation between futures based forecasts and naïve[22] forecasts by comparing out of sample forecasting MSE (MSFE).

Besides, Swason (2006) updated the sample period of earlier studies to include data since mid-2000 and found that despite a upswing in private sector forecast errors and uncertainty in 2001, an overall improvement in private sector interest rate forecasts with FF futures rate appears to be a robust feature of the data.

2.2. Importance of Directional Accuracy

Robertson and Thornton (1997) is the pioneer of directional accuracy on FF futures research studies. They used -9 and +21 basis points as the cut point to separate market expectation on the difference between futures rates and current target rate into two groups, —change and no change.[23] They used hit ratio[24] as a measure of forecasting accuracy and found that the accuracy of one month ahead forecast is 70 percent. However, their procedures are rough, since they did not consider the dates of FOMC meetings and they did not apply a formal test procedure.[25]

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[22] The “naïve” forecast means forecaster would predict FOMC would always not change FF target rate in the future meetings. Krueger and Kuttner (1996) found that futures-rate-based forecasts are significantly more accurate than the “no change” forecast at one- and two-month horizons.

[23] A spread between futures rate and current target rate that is outside the interval indicate an expected target change.

[24] Hit ratio: the percentage of times that were accurately forecasted, which is the number of accurate forecasts divided by the number of total observations.

[25] Although Hit Ratio is a numeric measure, it provides only an ordinal ranking of competing forecasts.

2.3. Monetary Policy Cycle

Carlson and McIntire (1995) found that predictive accuracy is the lowest around policy cycle turning points. Nosal (2001) found that futures rates on average over predicts the FF rate, and, over different phases of the business cycle, it may systematically over or under predict the eventual fed funds rates. Their research raises the question about the predictive power of FF futures around the turning points of the monetary cycle.

2.4. Changes in FOMC Disclosure Practices

Poole and Rasche (2000, 2003) lead the study on effects of changes in FOMC's disclosure practice by using daily frequency data to test the predictive power of FF futures rates on future FF rates. In their research, one-month-ahead FF futures rate changes were defined "large", which represent surprise in monetary policy change, if a daily change in the futures rate exceeded five basis points. They found that the frequency of large changes in the futures rates have decreased over the decade, particularly after the February 1994 introduction of public announcements of changes in the intended funds rate at the conclusion of FOMC meetings. It indicates an improved understanding within the market of the information processed by the FOMC in reaching its policy decisions. Although their procedure was not delicate, their conclusions were of great value since they found that such institutional change can have huge impact on the transparency of monetary policy.

There were many advanced empirical researches that shared Poole and Rasche (2000)'s spirits to test the predictive power of FF futures rates post 1994. Owens and Webb (2001) examined whether the forecast extracted from futures prices accurately predicts the policy action thirty days later by estimating the following regression equation

$$\Delta i_t^T = \alpha + \beta(i_{t-30}^f - i_{t-30}^T) + \varepsilon_t \tag{2}$$

where i_t^T is the FOMC's target for the federal funds rate at the end of date t, Δ is

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There is no way of knowing, from the Hit Ratio measure alone, whether a value of 0.68 is "good" or how much better 0.78 is than 0.75. (McIntosh and Dorfman, 1992) the difference operator, i^{f}_{t-30} is the value of the federal funds rate target at date t anticipated by market participants thirty days earlier. Besides, they have also used probit analysis to estimate the following equation

$$I\Delta i^{T}_{t} = \alpha + \beta \Pr \Delta i^{T}_{t-30} + e_{t} \tag{3}$$

where $I\Delta i^{T}_{t}$ is an indicator variable that takes the value of one if the FOMC changes target rate in its meeting at date t, and zero if it chooses no change in target rate, $\Pr \Delta i^{T}_{t-30}$ is the implicit probability that the FOMC will change the federal funds rate target in the next thirty days. However, their data processing had a significant drawback, since the settlement price of FF futures rates is the daily average of effective federal funds rate. The time when FOMC meeting take place is important[26]. Therefore, S¨oderstr¨om (2001) modified equation (2) of Owens and Webb (2001) as follows

$$\Delta i^{T}_{t+1} = \alpha + \beta (i^{e}_{t} - i^{T}_{t}) + \varepsilon_{t+1} \tag{4}$$

where i^{e}_{t} is the futures-based funds rate expectation at date t considering the date of FOMC meeting take place.

III. *Silent Features of the FF Future Rate*

The 30-day Federal Funds Futures contracts started trading on the floor of the Chicago Board of Trade since October 3, 1988. The contracts are for the interest paid on overnight federal funds held for the contract month with a principal of $5 million and are priced on the basis of 100 minus the overnight federal funds rate for the delivery month. At maturity, the contract is compared with the daily average of effective FF rate as reported by the Federal Reserve Bank of New York. However, though FF futures are

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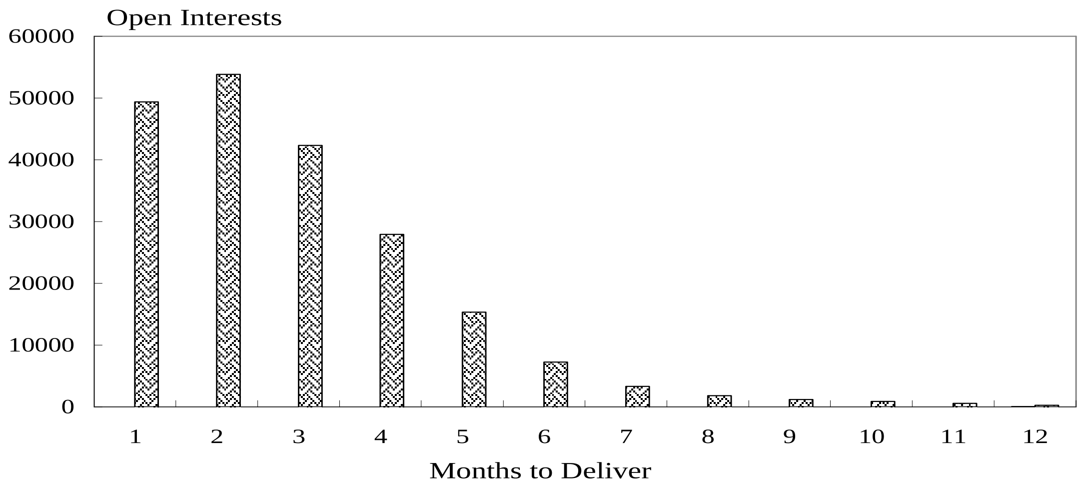
[26] Since settlement price of FF futures rate are average daily federal funds effective rate, one basis point change on FF futures rate imply more propensity change on FF target rate when FOMC meeting take place late of the month. Therefore, equal weighting on different FF futures rate inferring propensity of target rate change is not proper.

traded for the current month and for 23 future months, the effective contract is only about five months out (figure 3.1)[27].

Figure 13 1995~2007 Average FF futures Open Interests



Source: Bloomberg

There are several studies about extracting the expectation of monetary policy from FF futures rates over time (S¨oderstr¨om, 2001, Owens and Webb, 2001, Sack, 2004). Here we introduce the most commonly used procedure for extracting information from FF futures. Since there are four months of each year in which the FOMC doesn't meet, the contract prices represent the expected federal funds target rate previously announced by the FOMC. Then, for each of the eight months in which the FOMC meets, calculating the expected FF rate is slightly more complicated. Since a FF futures rate is simply equal to the average of expected effective funds rate for the contract month, therefore

$$i_{t,h}^{f} = \sum_{\tau=1}^{m} \frac{1}{m} E_t i_{t+h,\tau}^{ef} \tag{5}$$

where $i_{t,h}^{f}$ is the FF futures rate at time *t* for *h* periods ahead, $i_{t+h,\tau}^{ef}$ is the effective funds rate on day τ of month $t+h$. Assume the market always forecasts the average funds rate to coincide with the average target, i.e.

[27] Since average FF futures open interest exceed 10,000 only for 5 months out.

$$E(i_{t+i}^{ef} - i_{t+i}^{T}) = 0 \tag{6}$$

where i_{t+i}^{T} is the target rate for month $t+i$. Therefore, in the months with FOMC meetings, the average expected FF rate for the period represents a weighted average of the FF target rate before the FOMC meeting and the expected rate for days after the meeting. When rates are expressed in percentages, this is equivalent to:

$$i_{t,h}^{f} = \frac{ki_{i+h}^{T} + (m-k)i_{i+h}^{\hat{T}}}{m} \tag{7}$$

where i_{t+h}^{T} is the expected FF target rate leading up to the FOMC meeting day, which is *k* days into the month, $i_{t+h}^{\hat{T}}$ is the estimate of the target funds rate after the meeting, and there are *m* days in the month with the FOMC meeting.

The expected target FF rate after the FOMC meeting can be derived as:

$$i_{i+h}^{\hat{T}} = \frac{mi_{t,h}^{f} - ki_{t+h}^{T}}{m-k} \tag{8}$$

It is often useful to convert this forecast to an anticipated probability that the FOMC changes its target rate. Then by definition:

$$i^{\hat{T}} = p(i^{T} + \Delta i^{T}) + (1-p)i^{T} \tag{9}$$

where Δi^{T} is the expected change in the target rate and p is the anticipated probability that the FOMC changes its target. This can solve for p, yielding

$$P = \left| \frac{100(i^{\hat{T}} - i^{T})}{\Delta i^{T}} \right| \tag{10}$$

This calculation thus extracts the probability of a target change that is implied by the futures quote.

IV. *Usefulness of Futures for Predicting Fed Funds Rate*

In this section, we will use daily frequency data and the forecasts made at a number different days in prior to the FOMC meeting to see the usefulness of futures for predicting directional change of FF rate by applying generalized H-M test. Because a press statement describing policy action is released immediately at the conclusion of any FOMC meeting at which an action was undertaken since February 1994, market participants regard the day as a milestone of FOMC decisions becoming more open and transparent. In order to see whether prediction power indeed greatly improved, we separated my sample into two groups of prior 1994/2 and after 1994/2. The following are procedures we applied for the empirical part of the chapter.

Because changes in the FF target rate are limited to multiples of 25 basis points since August 1989 (Poole and Rasche, 2003), and 56 of 78 times (72 percent) changes in target rates are 25 basis points. Therefore if the market participants anticipate FOMC will change the target rate, the magnitude will usually be 25 basis points. On the other hand, since we are only interested in directional change of target FF rate and the minimum change of target FF rate is 25 basis points, no matter what the magnitude is, changes of FF target rate are a multiple of 25 basis points, the probability of eq. (10) under these circumstances will remain the same by replacing Δi^T with 25 basis points. By replacing Δi^T with 25 basis points I can get

$$P = \left| \frac{100(i^{\hat{T}} - i^T)}{0.25\%} \right| \tag{10'}$$

The economists might have some “rule of thumb” that anticipate target rate will be changed if $P > 0.5$ and $0 < P \leq 0.5$ implies market anticipate target rate will be unchanged. In other words, for example, if $P > 0.5$ and $i^{\hat{T}}_{t+h} > i^T_{t+h}$ means the market anticipates the target rate will be raised. Therefore, with consideration to the actual FOMC movement, we can group my data into a 3 by 3 contingency table of predictions on different days prior to an FOMC meeting as:

Figure 14 Forecast and actual change of FF target rate

		Forecast		
		Raised	unchanged	Cut
Actual	raised	n_{11}	n_{12}	n_{13}
	Unchanged	n_{21}	n_{22}	n_{23}
	Cut	n_{31}	n_{32}	n_{33}

Then the market timing statistics, s_n which is proposed by Pesaran and Timmermann (1992, 1994)[28], can be computed from the cell frequencies in this table

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[28] When actual and predicted values fall in n categories the null hypothesis of no market timing can be written as

$$H_0 : \sum_{i=1}^{m} (P_{ii} - P_{io}P_{oi}) = 0 .$$

This hypothesis state that the proportion of correct predictions is equal to the proportion we would expect under the null of independence of the distribution of realized and predicted values across the categories. To derive the asymptotic distribution of S_n, let $P' = (P_{11}, P_{12}, ..., P_{1m}; P_{21}, P_{22}, ...; P_{m1}, P_{m1}, ..., P_{mm})$ and using familiar results on the ML estimator of P_{ij} 's, note that

$$\sqrt{n}(\hat{P} - P_0) \underset{\sim}{a} N(0, \Psi_0 - P_0 P_0')$$

where P_0 is the true value of P and Ψ_0 is an $m^2 \times m^2$ diagonal matrix which has P_0 as its diagonal elements. The test of H_0 can be based on the statistic

$$S_n = \sum_{i=1}^{m} (\hat{P}_{ii} - \hat{P}_{io}\hat{P}_{oi}) ,$$

where $\hat{P}_{ij} = n_{ij} / n$, $\hat{P}_{io} = n_{io} / n$, $\hat{P}_{oj} = n_{oj} / n$ and n is the total number of observations. Now using the result that, under H_0,

$$\sqrt{n}S_n \overset{a}{\sim} N(0, V_s) ,$$

which turned out to be:

Table 20 Market timing statistics of FF futures rates

days prior to FOMC meeting	Pre 1994/2	After 1994/2	Full range
1d	3.35 (0.00080)***	16.55 (0)***	13.13 (0)***
2d	3.40 (0.00067)***	14.92 (0)***	11.95 (0)***
3d	2.28 (0.02261)***	15.16 (0)***	11.96 (0)***
4d	3.50 (0.00047)***	12.82 (0)***	10.44 (0)***
1w	2.63 (0.00854)***	11.52 (0)***	10.24 (0)***
2w	2.00 (0.04550)***	11.23 (0)***	9.65 (0)***
3w	2.30 (0.02145)***	10.65 (0)***	9.16 (0)***
4w	1.27 (0.20408)*	10.44 (0)***	8.65 (0)***
5w	1.71 (0.08727)*	9.52 (0)***	8.40 (0)***
6w	1.74 (0.08186)*	7.92 (0)***	7.31 (0)***
2m	-0.74 (1)	4.60 (0)***	3.57 (0.00044)***
3m	0.63 (0.52869)	1.89 (0.05876)*	1.79 (0.07345)*
4m	-1.60 (1)	-0.087 (1)	0.15 (0.88076)

** 90% **95% ***99%*

Note: z-statistic (p-value)

We see that market timing statistics are significant at 99% confidence level for at least 2 months prior to FOMC meetings and 90 % confidence level for at least 3 months prior to FOMC meetings of 1989/8 to 2008/3, which means FF futures rates are of great value to market participants. However, the market timing statistics increases as days approach the FOMC meeting, indicating improvement in the prediction power as more information become accessible to market participants. Comparing the columns labeled “pre 1994/2” and “after 1994/2”, we see that the market timing statistics are much smaller in the “pre 1994/2” period. Besides, the market timing statistics are significant

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where

$$V_s = \left(\frac{\partial f(P_0)}{\partial P}\right)'(\Psi - P_0 P_0')\left(\frac{\partial f(P_0)}{\partial P}\right),$$

and

$$\begin{aligned}\frac{\partial f(p)}{\partial P_{ij}} &= 1 - P_{0i} - P_{i0}, \quad \text{for } i = j \\ &= -P_{j0} - P_{0i} \qquad \text{for } i \neq j\end{aligned}$$

at 99% level for only 3 weeks prior to FOMC meetings in the “pre 1994/2” period, but are significant for at least 2 months prior to FOMC meetings in the “after 1994/2” period. The results indicate that there is an important shift that occurred during the early 1990s in the ability for financial markets to better anticipate monetary policy actions. Through most of the pre 1994/2 period, market prices have had predictive power for policy actions only about 6 week ahead. More recently, however, market quotes have became much better predictors of monetary policy moves as good as several months ahead.

However, some may question that such improvement in predicting ability may not come from a more transparent monetary policy process but from the change in the philosophy of FOMC monetary operation. Since monetary policy has become more “gradualism” in late 1990’s, it means that interest rate increases tend to be followed by additional increases and, after a turning point, decreases by additional decreases. Therefore, the predictive accuracy is lowest around policy cycle turning points (Carlson and McIntire, 1995). In order to see whether the predictive power also improved at policy cycle turning points, we adopt the following empirical study.

We define the policy cycle turning points as whenever a direction of target rate change is different with the previous FOMC decision, which means if the previous FOMC decision is ease and current decision is no change then the current meeting is the policy cycle turning point. In other words, if previous FOMC decision is ease and current decision is ease then the current meeting is not a policy cycle turning point. Then we can define the following 2 by 2 contingency table as follows:

Figure 15 Forecast and actual change of policy cycle turning point

		Forecast	
		Turning point	Not turning point
Actual	Turning point	n_{11}	n_{12}
	Not turning point	n_{21}	n_{22}

Then the market timing statistics, s_n, computed from the cell frequencies in the table turned out to be:

Table 21 Market timing statistics of policy cycle turning points

days prior to FOMC meeting	Pre 1994/2	After 1994/2	Full range
1d	2.4928 **(0.0127)	8.1076*** (0)	9.1858*** (0)
2d	2.7412*** (0.0061)	7.3632*** (0)	8.5203*** (0)
3d	2.4492** (0.0143)	7.2050*** (0)	8.3861*** (0)
4d	1.5945 (0.1108)	6.5090*** (0)	7.0814*** (0)
1w	1.8297* (0.0673)	5.7950*** (0)	6.4626*** (0)
2w	1.0833 (0.2787)	5.6960*** (0)	6.0938*** (0)
3w	0.3006 (0.7637)	5.7095*** (0)	5.1879*** (0)
4w	0.0922 (0.9266)	5.3008*** (0)	5.2664*** (0)
5w	1.5649 (0.1177)	4.7937*** (0)	5.7886*** (0)
6w	1.2388 (0.2154)	3.6836*** (0.0002)	4.4844*** (0)
2m	-0.2681 (1)	2.8506*** (0.0044)	3.0113*** (0.0026)
3m	1.1779 (0.2388)	1.3450 (0.1786)	2.2025** (0.0276)
4m	-0.8011 (1)	0.4470 (0.6549)	0.2784 (0.7807)

** 90% **95% ***99%*

Note: z-statistic (p-value)

Going down the column of Table 2 labeled “full range”, The results reinforce my points mentioned above. Going down the column of Table 3 labeled “full range”, the results are similar to Table 3.2 that market timing statistics are significant at 99% confidence level for at least 2 months prior to FOMC meetings and 95 % confidence level for at least 3 months prior to FOMC meetings of 1989/8 to 2008/3. Furthermore, the market timing statistics also increase as dates approach the FOMC meeting. Comparing the columns labeled “pre 1994/2” and “after 1994/2”, we again see that market timing statistics are much smaller in the “pre 1994/2” period, with the market timing statistics significant at 90% level only 1 week prior to the FOMC meeting in the “pre 1994/2” period, but are at least 2 months prior to the FOMC meeting in the “after 1994/2” period.

V. *Concluding Remarks*

The Federal Funds rate plays a key role in the financial and economic environment facing individuals, businesses and economists, which make accurately forecasting the rate valuable. This chapter verified the directional forecasting ability of the FF futures rates on the FF target rate. We found that the futures as proxies of predictors were of value to the user. However, the accuracy of the FF futures rates prediction generally decreases with the increase in forecast horizon. Besides, the futures based predictors were more valuable since 1994/2, the time when FOMC decisions became more open and transparent.

Appendix 3.1. Contingency tables regarding "tighten, ease or unchanged"

Table A.22 Forecast and actual change regarding "tighten, ease or unchanged" (full range)

days prior to FOMC meeting	n_{11}	n_{21}	n_{31}	n_{12}	n_{22}	n_{32}	n_{13}	n_{23}	n_{33}
1d	35	14	4	0	83	15	0	0	30
2d	33	11	4	2	86	18	0	0	27
3d	34	12	4	1	84	18	0	1	27
4d	33	16	6	2	80	20	0	1	23
1w	32	16	6	3	78	18	0	3	25
2w	33	18	5	2	77	22	0	2	22
3w	33	18	7	2	75	22	0	4	20
4w	33	19	5	2	74	24	0	4	20
5w	32	20	4	3	75	26	0	2	19
6w	32	19	5	3	71	28	0	7	16
2m	26	31	5	9	58	34	0	8	10
3m	18	32	11	13	57	32	0	8	6
4m	14	41	15	17	46	32	0	9	2

Table A.23 Forecast and actual change regarding "tighten, ease or unchanged" (pre 1994/2

days prior to FOMC meeting	n_{11}	n_{21}	n_{31}	n_{12}	n_{22}	n_{32}	n_{13}	n_{23}	n_{33}
1d	4	8	3	0	24	13	0	0	7
2d	4	6	4	0	26	15	0	0	4
3d	4	8	4	0	23	14	0	1	5
4d	4	11	5	0	20	14	0	1	4
1w	4	9	5	0	21	12	0	2	6
2w	4	11	5	0	19	13	0	2	5
3w	4	9	6	0	19	13	0	4	4
4w	4	10	5	0	18	14	0	4	4
5w	3	8	3	1	23	16	0	1	4
6w	3	8	3	1	21	14	0	3	6
2m	1	13	4	3	15	15	0	4	4
3m	0	12	10	0	18	11	0	2	2
4m	0	16	11	0	10	11	0	5	1

Table A.24 Forecast and actual change regarding “tighten, ease or unchanged” (after 1994/2)

days prior to FOMC meeting	n_{11}	n_{21}	n_{31}	n_{12}	n_{22}	n_{32}	n_{13}	n_{23}	n_{33}
1d	31	6	1	0	59	2	0	0	23
2d	29	5	0	2	60	3	0	0	23
3d	30	4	0	1	61	4	0	0	22
4d	29	5	1	2	60	6	0	0	19
1w	28	7	1	3	57	6	0	1	19
2w	29	7	0	2	58	9	0	0	17
3w	29	9	1	2	56	9	0	0	16
4w	29	9	0	2	56	10	0	0	16
5w	29	12	1	2	52	10	0	1	15
6w	29	11	2	2	50	14	0	4	10
2m	25	18	1	6	43	19	0	4	6
3m	18	20	1	13	39	21	0	6	4
4m	14	25	4	17	36	21	0	4	1

Appendix 3.2. Contingency tables regarding the turning point of the monetary policy cycle

Table A.25 Forecast and actual change of policy cycle turning point (full range)

days prior to FOMC meeting	n_{11}	n_{21}	n_{12}	n_{22}
1d	106	15	13	46
2d	108	13	16	43
3d	109	12	17	42
4d	103	18	19	40
1w	104	17	22	37
2w	99	22	21	38
3w	94	27	21	38
4w	94	27	22	37
5w	90	31	18	41
6w	85	36	21	38
2m	60	61	16	43
3m	49	69	15	44
4m	37	81	17	41

Table A.26 Forecast and actual change of policy cycle turning point (pre 1994/2)

days prior to FOMC meeting	n_{11}	n_{21}	n_{12}	n_{22}
1d	20	11	9	18
2d	22	9	10	17
3d	21	10	10	17
4d	19	12	11	16
1w	21	10	12	15
2w	17	14	11	16
3w	15	16	12	15
4w	13	18	11	16
5w	14	17	7	20
6w	14	17	8	19
2m	6	25	6	21
3m	9	19	5	22
4m	5	23	7	19

Table A.27 Forecast and actual change of policy cycle turning point (after 1994/2)

days prior to FOMC meeting	n_{11}	n_{21}	n_{12}	n_{22}
1d	86	4	4	28
2d	86	4	6	26
3d	88	2	7	25
4d	84	6	8	24
1w	83	7	10	22
2w	82	8	10	22
3w	79	11	9	23
4w	81	9	11	21
5w	76	14	11	21
6w	71	19	13	19
2m	54	36	10	22
3m	40	50	10	22
4m	32	58	10	22

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