Studies of UK Director Trading:

In Aggregate and by Director Role

Submitted by Xingzhou LIU to the University of Exeter
as a thesis for the degree of
Doctor of Philosophy in Finance
In October 2013

I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

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Abstract

The topic of insider/director trading raises interesting questions and has generated much attention from researchers, market participants and regulators. The purpose of this thesis is to investigate the long-run director trading performance in the UK market. It examines relationship between aggregate director trading and indicators of the UK macroeconomy focus on the macro-aspects in Chapter 4 and 5. The extant empirical literature on aggregate director trading can be categorized into two parts: the first is the relationship between director trading and the stock market; and the second is the link between stock returns and future aggregate economic activities. Having examined the macro-picture, it goes to examine a more micro-picture. Chapter 6 examines long-run relationship between director trading and market reactions.

This thesis is organized around three research studies which are presented in Chapters 4, 5 and 6 and which examine long-run director trading activities in the UK. Chapters 4 and 5 together investigate the evidence for director trading activities and the macroeconomy. There is little literature on aggregate director trading and the macro-economy: therefore Chapter 4 examines the relationship between aggregate director trading and future market excess returns. Empirical evidence is presented which demonstrates that the returns on stock market are significantly correlated to future economic growth. Chapter 5 then examines whether the forecasting ability can be improved by adding aggregate director trading as a measurement of business confidence into the forecasting model. Chapter 6 examines the long-run performance of market reaction to director roles.

In order to examine the relationship between aggregate director trading and the macro-economy, the link between aggregate director trading and future market excess returns is investigated. This thesis considers the importance of the seasonality issue in UK director trading and employs a number of alternative seasonality adjustments to adjust the raw data on aggregate director trading. The positive correlation between aggregate director trading and future market

excess returns is confirmed and evidence is provided that indicates directors are contrarian: in aggregate they purchase (sell) their own-company stock prior to general stock market increases (decreases). In the long-run, the empirical work demonstrates that aggregate director trading has forecasting power in terms of predicting future stock market excess returns. Additional findings are that aggregate director trading in large firms has a positive significant predictive ability for identifying future excess returns of large firms and aggregate director trading of some industries has positive significant forecasting ability for future excess returns of these industries.

Having confirmed the relationship between aggregate director trading and future market movement, this thesis turns to examine the link between aggregate director trading and future UK economic growth. It measures economic growth of future real economic activity by the change in gross domestic product (GDP) and it documents a strong correlation between past aggregate director trading and future real economic activity. The predictability of future economic growth increases with both the length of forecasting horizon and past net number of director trading. In a multivariate regression analysis this thesis finds that aggregate director trading retains predicting power with respect to future GDP growth even after including popular business cycle variables (dividend yield of FTSE All share, growth rate of industrial production and term spread) as explanatory variables. This finding suggests that aggregate director trading captures things related to changes in real activity but not captured by market factors (Fama-French 3 factors: SMB, HML and RMRF) and business cycle variables.

After examining the relationship between aggregate director trading, market returns and changes in GDP, the last empirical Chapter of the thesis concentrates director trading on the micro-aspects of director trading and stock movement. It examines the stock market reaction to director trading with firm characteristics and the effects of director trading pattern. Using long-run calendar-time abnormal returns (CTAR) methodology with Fama-French 3-factor model, evidence is presented that directors do have more valuable information allowing them to make significant abnormal returns than other market participants, the performance of CFOs supports the information hierarchy hypothesis in 1- and 6-month post-purchase trading time, and the director trading with firm characteristics has a significant effect on stock abnormal returns.

Acknowledgements

I wish to express my sincere gratitude to a number of people who have directly and indirectly contributed to the successful completion of this thesis. Foremost among them is my first supervisor, Professor Ian Tonks, whose invaluable guidance, suggestions, comments and references have made this challenging progress an enjoyable and deeply intellectually stimulating experience. I also would like to thank my second supervisor, Professor Alan Gregory for his guidance and suggestions. I am sincerely thankful to both these professors for their contribution in greatly improving my understanding of the field of finance in general, and particularly of the area that is the focus of this thesis.

I am thankful to the participants at the annual PhD student conference held in the school for several helpful suggestions. I also wish to thank my colleagues with whom I have shared an office over the last three years for their support, encouragement and for some very interesting discussions on several aspects of my thesis.

In addition I would like to thank the staff at the University of Exeter Business School, the IT officers and the librarians for their help in many different ways throughout my research.

My time at Exeter was made colourful and enjoyable in large part due to many friends and groups that have become a part of my life - thank you.

Lastly, and most importantly, I would like to thank my family for all their love, understanding and encouragement. To my parents, who raised me with a love of science and have been a constant source of support, I dedicate this thesis.

Contents

List of Tables

List of Figures

List of Abbreviations

AMEX	American Stock Exchange
ANP	Aggregate Net Number of Director Purchases
AP	Aggregate Number of Purchases Transactions
AS	Aggregate Number of Sales Transactions
BHAR	Buy and Hold Abnormal Returns
BHER	Buy and Hold Excess Returns
CAAR	Cumulative Average Abnormal Return
CAR	Cumulative Abnormal Return
CER	Cumulative Excess Return
FSA	Financial Services Authority
FSMA	Financial Services and Markets Act
GDP	Gross Domestic Product
GNP	Gross National Product
HS	Hemscott Company Guru Academic
i.i.d.	Independent and Identically Distributed
ICB	Industry Classification Benchmark
ISIN	International Securities Identification Number
ITSFEA	Insider Trading and Securities Fraud Enforcement Act
LBS	London Business School
LSE	London Stock Exchange
LSPD	London Share Price Data
MAD	Market Abuse Directive
NBER	National Bureau of Economic Research
NPR	Net Number of Director Purchase Ratio
NYSE	New York Stock Exchange
OECD	Organisation for Economic Cooperation and Development
ONS	Office for National Statistics
PR	Purchase Ratio
RIS	Regulatory Information service
RNS	Regulatory News Service
RPI	Retail Prices Index
SANP	Standardized Aggregate Net Number of Purchases
SAP	Standardized Aggregate Number of Purchases Transactions
SAS	Standardized Aggregate Number of Sales Transactions
SEC	Securities and Exchange Commission
SEDOL	Stock Exchange Daily Official List
SOX	Sarbanes-Oxley Act
SR	Sales Ratio

Chapter 1 Introduction

1.1 Introduction

It has long been established that insiders/directors (corporate executives or company directors) are able to trade profitably in their own companies' stock in the market, and that outsiders following these trading strategies can also earn significant and abnormal returns.

The reasons that director trade are first, director are contrarian. They tend to buy stocks with poor past performance and cheap according to measures such as B/M (Seyhun, 1988, 1990, 1992; Lakonishok and Lee, 2001; Gregory et al., 2013). Second, director trading could make profit. Directors have many reasons to sell shares, but the main reason to buy shares is to make money. That is why most of empirical works find director purchase is useful signal, while sales are not (Gregory et al., 1997; Lakonishok and Lee, 2001; Fidrmuc at al., 2006).

Most of the previous literature has focused on the share price reaction of aggregate insider/director trading in terms of individual company effect, but this thesis focuses on aggregate director trading activities. The existing empirical literature uses two approaches to measure the effect of insiders/directors information on share prices. One strand of the literature argues that price reaction is via the long-run abnormal returns earned over the 6 to 12 months after a transaction. The existence of significant abnormal returns over this period is interpreted as proof of superior insiders/directors information (for example, Jaff, 1974; Seyhun, 1992; Gregory et al., 1994; Gregory et al., 1997; Lakonishok and Lee, 2001; Gregory et al., 2012; Gregory et al., 2013). The second strand of the literature assumes that stock markets are (to some degree at least) informationally efficient and that share prices adjust rapidly to insiders/directors trades. These studies measure the abnormal return on the date of announcement of the insider/director trade (Jaffe, 1974; Friederich et al., 2002; Fidrmuc et al., 2006; Gregory et al., 2012). In other words, these empirical works are based on event studies.

Economic theory suggests that stock prices reflect expectations about future corporate earnings. Corporate profits are an important part of gross domestic product (GDP) and also are likely to be correlated with its components, including consumption and investment. The forward-looking nature of stock prices would imply that stock prices should be valuable as leading indicators of economic activity.

Previous studies conducted in the US (Moore 1983, Fama 1981, Fischer and Merton 1984, Barro 1990, Vassalou 2003, Reilly and Brown, 2006) have found that the relationship between stock returns and future real activity is strong, which indicates that stock prices are a leading indicator of economic activity. International evidence including that from the UK market, is consistent with the US finding. Studies by Klein and Moore (1985), Aylward and Glen (2000), Liew and Vassalou (2000), Gregory et al. (2003) showed that stock markets returns are significant correlated to future economic growth.

Seyhun (1992) established the cash flow hypothesis which postulates that corporate insiders can predict the future cash flows in their own firms before other market participants. To the extent that the changes in cash flows are due to the future economy-wide activity, insiders in all firms will also observe similar signals in their own firms and also trade in their own firms in the same direction. After a while, as changes in economy-wide cash flows become recognized by other market participants, the stock prices of all firms will tend to adjust. Consequently, aggregate insider trading can predict the future real activity and future stock returns. Seyhun's (1992) empirical work presents the results of growth rates of gross national product (GNP), the Index of Industrial Production, and after-tax corporate profits and demonstrates these are consistent with the cash flow hypothesis: aggregate insider trading is positively correlated with all of these three measures of real activity 12 to 20 months in the future. Moreover, aggregate insider trading follows an increase in future real activity albeit with a 6 to 12-month lag.

Although there is some existing literature on aggregate insider/director trading, it is not very extensive. Therefore, this thesis will demonstrate relationship between aggregate director trading and future aggregate macroeconomic activities. In order to link the connection, it establishes correlation between aggregate director trading and future market excess, and correlation between future economic growth and market returns. Also, it examines whether aggregate director trading is a good measure of business confidence.

Besides investigating long-run director trading with regard to the macro-aspects, the thesis also concentrates on the micro-aspects. It examines long-run performance of market reaction to director trading patterns.

The information hierarchy hypothesis postulates that the information content of transactions depends on the type of director who trades (Seyhun, 1986). According to this hypothesis, directors who are familiar with the day-to-day operations of the company trade on more valuable information. This may be reflected in the returns to their trade, if and when they trade. In other words, if directors trade based on their information access, the abnormal returns depend on the type of director that makes the trade, which should follow the order by category of director: CEO, CFO, other executive directors and other non-executive directors.

Some the US and UK studies supports the information hypothesis (Seyhun, 1986; Lin and Howe, 1990; Gregory et al., 2012). In contrast, some empirical works do not support or do not find any evidence of information hierarchy (Jeng et al., 1999; 2003; Fidrmuc et al., 2006). Hence, the thesis will investigate long-run performance of market reaction to director trading patterns in the UK market.

1.2 Research Questions

In generally, previous studies have confirmed the relationship between future economic growth and stock returns using evidence from the US and internationally. Some research has identified a relationship between aggregate insider trading and future economic growth in the US but this has not yet been demonstrated in the UK. Thus, it is essential to investigate the link between aggregate UK director trading and future economic growth. Second, as mentioned in Section 1.1, the thesis will examine long-run director trading study to study the information hierarchy hypothesis in the UK. Specifically, this research addresses the following questions:

1. Is aggregate director trading activity a useful component in predicting future economic activity?

2. Is aggregate director trading a leading, coincident or lagging indicator?
3. Do UK director trading patterns support the information hierarchy hypothesis?

Answering questions 1 and 2, firstly requires examining the evidence as to whether aggregate director trading is significantly correlated to future market excess returns, this is presented in Chapter 4. Chapter 5 carries out an investigation into the relationship between aggregate director trading and future economic growth. Meanwhile, Chapter 6 examines the information hierarchy hypothesis to try to solve question 3 through a long-run study.

1.3 Contribution of this Thesis

This thesis examines aggregate director trading activity in the UK in a long-run study. It confirms that aggregate director trading has a positive significant relationship with the future excess returns of market portfolios, and has predictive power for future excess stock returns. A further study confirms that aggregate director trading is a leading indicator that has a forecasting ability for future economic movements. The major contributions of this thesis are:

- The first and also the most important contribution is that this thesis finds evidence that aggregate director trading (also CBI industrial trends survey data, CBI business confidence) is a leading indicator that has a positive significant forecasting ability of future economic growth. This finding covers gap of academic research literature between director trading and macroeconomic activities in the UK.
- Another important contribution is this thesis constructs seasonality methods to measure UK aggregate director trading activities. Three seasonal adjustments are applied: month dummy, seasonality adjustments based on trading assumptions, and based on real companies' fiscal-year ends. Furthermore, it also checks the month-of-the-year effect on market returns and trading volume in order to minimize other unexpected factors that may affect relationship between aggregate director trading and future market excess returns.

- This thesis tests a firm's characteristics and the information hierarchy hypothesis using director trading patterns. By categorizing directors into six non-overlapping groups (CEOs, CFOs, executive chairmen, non-executive chairmen, other executives and other non-executives), it is shown in the long-run study that this hypothesis can be rejected within the UK market.
- In addition to the seasonality adjustments, several measurements of director trading transactions are also applied. This thesis employs traditional net number of purchase transactions, the net purchase ratio, the difference of net purchase ratio, the difference of net purchase transaction, and the growth rate of net purchases in order to check the performance of aggregate director trading.
- Finally, 23 years with 276 calendar months of director trading are included within the range of January 1986 to December 2008. This is the longest time period employed in studies of UK aggregate director trading to date.

1.4 Structure of the Thesis

The thesis is organized as follows: Chapter 1 is an introductory chapter, whilst Chapter 2 provides an overview of the relevant literature and the US and UK regulation framework related to insiders/directors trading.

Chapter 3 provides details of director trading data for the UK, and the data filter employed and sample characteristics are described. Due to the various fiscal-year ends of UK-listed companies and UK regulation requirements, director trading has to address the issue of seasonality. Thus, in Chapter 3 one important aspect is the construction of seasonality adjustments for UK director trading.

Chapter 4 examines the relationship between aggregate director trading and future market excess returns. The methods of Seyhun (1988, 1992) and Lakonishok and Lee (2001) using long-run cumulative excess returns (CERs) and buy and hold excess returns (BHERs) are applied with the constructed seasonality adjustment. Several measurements of director trading activities are also introduced. This chapter also includes robustness check for director trading with firm size control and examining subsample industry performance.

Chapter 5 tests the relationship between aggregate director trading and future macroeconomic movement. A sensitivity test is employed to indicate the performance of the relationship between aggregate director trading and future economic growth. The multivariate regression method of Liew and Vassalou (2001) is applied to link director trading and future economic change by controlling for the performance of the stock market and business cycle.

Chapter 6 details the performance of market reaction to director trading through firm characteristics and the information hierarchy hypothesis in a long-run study in the UK. Fama-French 3-factor and Carhart 4-factor models with calendar time abnormal returns are applied to examine whether director trading with firm characteristics affects the performance of abnormal returns and whether performance of post-trading activities of director trading patterns supports the information hypothesis.

Finally, Chapter 7 summarizes the major finds of this thesis and addresses the limitations of the research and suggests some future studies.

Chapter 2 Literature Review and Regulatory Framework

2.1 Literature Review

Two terms need to first be clarified; that of who are insiders and who are directors. Generally speaking, the term ‘insiders’ is applied in US studies while the term ‘directors’ is employed in UK studies. In the US, The Securities and Exchange Act of 1934 defines insiders as officers, directors, and shareholders of 10% or more of any equity class of securities. Directors in the UK are members of the board of directors (both executives and non-executives), and therefore the use of this term excludes other key employees and large shareholders.

2.1.1 Director Trading and Future Market Return

Early investigations into the relationship between director trading activity and market performance are well documented in US studies; Jaffe (1974) and Finnerty (1976) reported significant abnormal returns associated with directors’ trading activity. Seyhun (1986) found that significant abnormal returns associated with insiders’ transactions were inversely correlated with firm size, and claimed that since small companies have wide spreads it would not be possible for outsiders to earn abnormal returns by following insiders’ transactions. Seyhun (1988) reported that aggregate insider trading is positively correlated to future market returns for the 1975-1981 period. He found an increase in current aggregate insider trading was associated with an increase in future excess market returns to risk-free rate 2-month ahead. A later paper by Seyhun (1990) reported on the transactions of insiders following the 1987 stock market crash. Although insiders were neither heavy buyers nor sellers in the period leading up to the crash, heavy purchasing activity followed it. This led Seyhun to conclude that the fall in share prices at least in part, represented an overreaction by the markets, resulting in moving share prices away from their fundamental values. He also concluded that insiders used additional information in forming their purchasing decisions rather than relying upon ‘a naïve mean reversion strategy’ (pp.1381-83) Seyhun (1992) extended his findings on the predictive ability of aggregate insider trading by examining the forecasting ability of multi-month aggregate insider trading and the variables that are associated with business conditions and fundamental values. He documented the predictability of stock returns increasing with the length of forecasting horizon, the number of months of past insider trading. Insider trading retains its marginal explanatory power when future real activity is included as an additional explanatory variable. Moreover, other predictors of time series variation in stock returns, such as past stock returns, dividend yields, and term and default spreads, do not attenuate the predictive power of aggregate insider trading. The evidence suggests that aggregate insider trading captures a component of stock returns not related to movement in future real activity, dividend yields, past stock returns, and term or default spreads.

Insider transactions are consistent with a well-informed contrarian approach to stock investing (Rozeff and Zaman, 1998; Lakonishok and Lee, 2001; Jenter, 2005, Jiang and Zaman, 2010).

Lakonishok and Lee (2001) examined insider trading activities for all the companies traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ during the 1975-1995 period. They found only small stock price responses to the reporting announcement of the trade to the US Securities and Exchange Commission (SEC). They found that insiders in aggregate trading are contrarian investors, but that they predict market movements better than simple contrarian strategies. They also found that the limited stock price reaction is more apparent for smaller firms on the buying side, but there is no response on the selling side. Only insider purchases appear to be useful, while sales are not associated with low returns, ‘insiders have many reasons to sell shares, but the main reason to buy shares is to make money’ (Lakonishok and Lee 2001, p.109).

Meanwhile, empirical works documenting dollar volume and large firm performance have failed. Jaffe (1974) examined large dollar volume of trading by insiders, but concluded that this was not related to the value of insider information. Seyhun (1986) found that the coefficient of dollar volume trading is insignificantly different from zero, which suggests that the dollar value of insider trading is not related to the value of insider information. His finding is similar to those of Jaffe (1974) and Scholes (1972) who also failed to find a relationship between dollar volume of trading and value of insider information. Lakonishok and Lee (2001) noted that insider trading based on dollar volume of trading contained less information, possibly because it might be influenced by a few very large transactions.

For the insider performance of large firms, Seyhun (1986) found that insiders in large firms and large shareholders in all firms trade on less valuable information. He explained the lack of information content of the large dollar volume transactions as probably being due to the fact that the large dollar volume of transactions are proxies for large firms and large shareholders: insiders in large firms and large shareholders in all firms who happen to trade the large dollar volume transactions, also trade on less valuable information. Lakonishok and Lee (2001) found that large companies are priced more efficiently than small companies and consequently, insiders have a relative advantage in timing an index of small stocks than an index of large stocks.

In the UK, the earliest investigation of the impact of directors' trading was by King and Roell (1988). Using a filtered sample obtained from the transactions of directors published weekly in the financial times for 1986 to 1987, they found that significant and very large positive abnormal returns were associated with directors' purchases, but insignificant negative abnormal returns followed directors' sales. The finding of Pope et al. (1990) contradict the results of King and Roell, showing that in two of the three sub-periods examined it is the negative abnormal returns following directors' sales which are significant. Gregory et al. (1994) demonstrated that both directors' purchases and directors' sales can produce significant abnormal returns when measured by a 'conventional' event study methodology. However, when a size effect is controlled for, only directors' purchases indicate significant abnormal returns, the magnitude of which is considerably reduced. Using as a signal the monthly net volume of directors' trades, Gregory et al. (1997) documented a similar conclusion to Gregory et al. (1994), that monthly abnormal returns following a purchase signal are small but significantly positive for up to 24 months. The returns for the sale signal, though always negative and insignificant, can be statistically insignificant in the longer term.

Recent UK studies have mainly concentrated on the event study of director trading activities. Friederich et al. (2002) used daily data to analyze trades by UK directors for the period 1986-1994 and found annualized abnormal returns were significantly negative (-2.85%) in the 20 days before a purchase, and then the abnormal returns are significantly positive (1.96%) for the 20 days after the directors' trade. Fidrmuc et al. (2006) reported similar results for directors' trades in UK companies over the period 1991-1998, and also considered the trade size on the CARs. They investigated the market's reaction to UK director transactions and analyzed whether the reaction depended upon a firm's ownership. They found that ownership by directors and outside shareholders did have an impact on the abnormal returns. In addition, they tested the hypothesis of information hierarchy and found no evidence that returns from trading differed across categories of director. Andriosopoulos and Hoque (2011) investigated aggregate director trading activity in the UK and identified relationship between directors' market timing and market sentiment as measured by bull (bear) periods. They provided evidence that directors used market sentiment as a platform to act like contrarians. However, a limitation of their study was that they did not allow for seasonalities in monthly UK aggregate director trading, due to UK regulation requirements which impose constraints on when directors can trade before earnings announcements. Since companies' earnings announcement tends to be clustered around certain times of the year, this will cause seasonal patterns in aggregate director trading. These seasonalities need to be allowed for in interpreting the predictive power of aggregate director trading. Gregory et al. (2013) found evidence that UK directors are contrarians; they bought value stocks and sold glamour stocks during a long-run study. This confirmed that directors' trading signals clearly generate significant positive abnormal returns on the buy side and smaller but typically insignificant negative returns on the sell side, which is consistent with previous insider/director studies.

To summarize, short-term and long-run studies of insider/director trading all find evidence that this has the ability to forecast future market movement.

2.1.2 Market Return and Future Economic Growth

Economic theory suggests that stock prices reflect expectations about future corporate earnings. Corporate profits are an important part of GDP and also are likely to be correlated with its components, including consumption and investment. The forward-looking nature of stock prices would imply that stock prices should be valuable as leading indicators of economic activity.

Previous studies conducted in the US have shown that the relationship between stock returns and future real activity is strong, which indicates that stock prices are leading indicators of economic activity.

Fama (1981) documented the presence of a positive and statistically significant relationship between the market factor and future economic growth in the US. He found evidence that real stock returns are positively related to measures of real activity, such as capital expenditures, the average real rate of return on capital and output. By using production growth rate as a real activity variable during the time period 1953-1987, Fama (1990) suggests that a large fraction of the variation of stock returns can be explained primarily by time-varying expected returns and forecasts real activity.

Moore (1983) examined the evidence for stock prices as a business cycle indicator for the period 1873-1975 and found that stock prices led the business cycle for much of that period and were better predictors of timing points than were business failures.

Fischer and Merton (1984) built upon this evidence and found that for the period 1950 -1982 stock price changes were the best predictor of future growth in GNP from among the group of financial variables that they tested. Furthermore, they found that stock prices led growth in both investment and consumption, and they traced the link between the stock market and consumption and investment. They also noted the extensive use that has been made of stock prices as leading indicators by academics, governments, and business analysts.

Barro (1990) examined the link between stock prices, investment and GNP in more detail. Using data for the period 1891-1987, he also demonstrated that lagged stock price changes have a significant predictive power for both investment and GNP and similar findings have been documented for the Canadian market. In addition, for the US market, Barro noted that stock prices outperform Tobin's (1969) q as a leading indicator of investment activity.

Pesaran and Timmermann (1995) examined the robustness of the evidence for the predictability of the US stock market. In order to simulate the historical process through which an investor may attempt to forecast stock returns, they established the type of variables an investor is likely to consider when modelling stock returns: dividend yield, earnings-price ratio, 1-month T-bill rate, 12-month T-bond rate, year-on-year rate of inflation, year-on-year rate of change in industrial output, and year-on-year growth rate in the narrow money stock. They also considered time lags between the changes in the business cycle variables and stock returns. They confirmed the importance of predicable components in stock returns related to the business cycle. They also found that the only variable to be included in the forecasting models throughout the entire sample period of 1960-1992 was the one-month lagged value of the one-month T-bill rate.

Vassalou (2003) showed that news related to future GDP growth is an important factor for explaining the cross-section of book-to-market and size portfolios. The Fama-French factors HML and SMB appear to contain mainly news related to future GDP growth.

Reilly and Brown (2006) mentioned the cyclical indicator approach. The National Bureau of Economic Research (NBER) examines the behaviour of hundreds of economic time series in relation to past business cycles and groups various economic series into three major categories based on their relationship to the business cycle. Leading indicators include economic series that usually reach peaks or troughs before corresponding peaks or troughs in aggregate economic activity. Coincident indicators include economic time series that have peaks and troughs that roughly coincide with the peaks and troughs in the business cycle. Lagging indicators include series that experience their peaks and troughs after those of the aggregate economy. In their book, Reilly and

Brown (2006) note that the NBER figures the index of 500 common stock prices is a leading indicator to aggregate economic activity in the US.

For international evidence, Klein and Moore (1985) examined measurements of leading, coincident and lagging indicators in 10 developed countries (the US, Canada, UK, West Germany, France, Italy, Belgium, Netherlands, Sweden and Japan) within the Organization for Economic Cooperation and Development (OECD), and confirmed that the stock price index is a leading indicator of business cycle.

Aylward and Glen (2000) investigated the link between stock changes and subsequent economic activity (GDP, consumption and investment) in 23 countries (include the UK) during most of the post-war period. They found evidence that stock price changes lead GDP, consumption and investment in most countries. The results were stronger for the G7 countries than for the emerging markets, both in the percentage of markets where the stock market has a predictive power and in the economic significance of the predictability.

Using data from 10 countries (including the UK), Liew and Vassalou (2000) found that the Fama-French factor HML and SMB contained significant information about future GDP growth. This information is to a large degree independent of that in the market factor. Even in the presence of popular business cycle variables, HML and SMB retain their ability to predict future economic growth in some countries. However, little evidence is found to support such an explanation in the case of WML (winners minus losers, or Momentum factor).

Consistent with Liew and Vassalou (2000), Gregory et al. (2003) found both HML and SMB were positively correlated with future GDP growth using UK data from July 1980 to December 1998.

There has been some discussion concerning the relationship between director trading and future economic growth. Seyhun (1988) investigated the information content of aggregate trading by corporate insiders in their own firms. His hypothesis is if the mispricing observed by insiders in their own firms is strictly due to firm-specific information, then no relationship between insider trading and changes in economy-wide activity would be expected. However, if part of the mispricing observed by insiders in their own firms is caused by changes in economy-wide activity that are not yet fully reflected in security prices, then a positive relationship between aggregate insider trading activity and subsequent market returns would be expected. However, Seyhun (1988) did not identify the economy-wide factors that lead to the predictive ability of aggregate insider trading, although he extrapolated from his work that net aggregated insider trading activity can be a useful component of the leading indicators of future economic activity.

In a further study by Seyhun (1992), he established the cash flow hypothesis which postulates that corporate insiders can predict the future cash flows in their own firms before other market participants. To the extent that the changes in cash flows are due to the future economy-wide activity, insiders in all firms will also observe similar signals in their own firms and also trade in their own firms in the same direction. After a while, as changes in economy-wide cash flows become recognized by other market participants, the stock prices of all firms will tend to adjust. Hence, aggregate insider trading will predict the future real activity and future stock returns. Empirical work has shown that the results of growth rates of GNP, the Index of Industrial Production, and after-tax corporate profits are consistent with the cash flow hypothesis. Therefore, aggregate insider trading is positively correlated with all these three measures of real activity between 12 to 20 months in the future. Moreover, aggregate insider trading follows increases in future real activity with a 6- to 12-month lag.

Generally speaking, the previous studies confirm the relationship between future economic growth and stock returns by providing evidence from the US and other international markets. The relationship between aggregate insider trading and future economic growth has been proven in the US but not for the UK or other international markets. Thus, it is essential to investigate aggregate director trading and future economic growth in the UK.

2.1.3 Director Role and Market Reaction of Director Trading

The information hierarchy hypothesis postulates that the information content of transactions depends on the type of director who trades (Seyhun, 1986). According to this hypothesis, directors who are familiar with the day-to-day operations of the company trade on more valuable information. In other words, the abnormal returns depend on the type of director that makes the trade, which should follow the order by category of director: CEOs, CFOs, other executive directors and other non-executive directors.

Seyhun (1986) investigated the determinants of insiders' superior predictive ability using event study by applied daily cumulative abnormal returns (CARs) of estimate insider trading as dependent variable and used independent variables as dummy variables for types of insiders. He found that it appeared that insider information arises as a result of insiders' association with a firm, since insiders who are closer to day-to-day decision-making trade on more valuable information. Seyhun grouped all insiders into five categories: officers, directors, officer-directors, chairmen of the board of directors, and large shareholders. Officers traded most frequently, followed by directors, large shareholders, officer-directors, and chairmen of the boards of directors. Further tests determined that the coefficient of the officer-director group was significantly positive at the 1% level, suggesting that on average, officer-directors trade on more valuable information than officers. Insiders in large firms and large shareholders in all firms account for most of the dollar value of trading, although insiders in large firms and large shareholders in all firms trade on less valuable information. Differences between all insiders are significant at the 5% level. These tests indicate insiders who are more familiar with the overall operations of a firm trade on more valuable information.

Lin and Howe (1990) expected insiders who are more familiar with the operations of a firm to trade on more valuable information, and examined whether an information hierarchy exists among insiders, as suggested by Baesel and Stein (1979), Scholes (1972), and Seyhun (1986). Lin and Howe (1990) followed Seyhun's (1986) procedure and classified insiders in the same manner. Instead of the daily CARs, they applied monthly CARs as a dependent variable. They found that there was a positive relationship between abnormal returns and insider roles. The chairmen of the board, directors, officer-directors, and officers possess a greater amount of information than large unaffiliated shareholders. This finding is consistent with previous evidence from the US that information hierarchy exists among insiders. Specifically, insiders close to the operations of a firm (chairmen of the board, directors, officer-directors, and officers) trade on more valuable information than large shareholders.

Seyhun (1986) and Lin and Howe (1990) both partially confirmed this hypothesis using US data. The differences between these two studies are that Seyhun (1986) measured the market reaction to insider trades by the CARs covering the first 50 and 100 days, respectively, following the day of the trade, whilst Lin and Howe (1990) used 6 and 12-month CARs.

In contrast, some empirical studies do not support or do not find any evidence of information hierarchy. Jeng et al. (1999, pp.30-31) questioned whether insiders can benefit from their information advantage:

> Some insiders are more 'inside' than others. The chief executive, for example, is likely to have better information about the firms' prospects than lesser officers. Since the CEO's trades are likely to be carefully scrutinized, both by shareholder and by regulators, he may be more reluctant to trade on his informational advantage. The net effect of these considerations on the profitability of insider trading is an empirical question.

Jeng et al. (1999) concluded that insiders benefit 'handsomely' from their informational advantage, especially from their purchases. However, they did not find any support for the information hierarchy hypothesis, as they reported that CEOs acquire lower abnormal returns, although not significantly lower, than other officers and directors.[1]

Jeng et al. (2003) tested the information hierarchy hypothesis and distinguished between three categories of corporate insiders as defined by job-title. They grouped insiders into three categories: 'top-executives' are those corporate

[1] The results of Seyhun (1986) and Lin and Howe (1990) are not directly comparable to those of Jeng et al. (1999) given the different methodologies they used in calculating the returns.

officers that hold the title of chief executive, chairman of the board and president; ‘officers’ includes all corporate officers except for top executives; and ‘directors’ are members of the corporate board who are not also officers. Unlike Seyhun (1998), these categories do not overlap and cover all trades in their sample. Jeng et al. (2003) found no evidence that the top executives earned higher abnormal returns than other categories of insiders. They found that the portfolios based on the officer purchases and the director purchases yield point estimates of the abnormal returns that were significant and of a similar order of magnitude to the overall purchase portfolio results. In contrast to Seyhun (1986), they found insignificant returns for the top-executive purchase portfolios. However, they noted that the purchases of the top-executives tended to be twice as large as the other categories, and since they also found that abnormal returns to large purchases were no larger than the returns to medium-sized trades, they were able to reconcile their results with Seyhun’s (1986).

By investigating gender differences in insider trading behaviour of senior corporate executives in the US between 1975 and 2008, Bharath et al. (2009) found that both male and female insiders earned economically and statistically significant positive returns on average; males earned greater returns than females and traded more frequently than females. This difference is particularly notable in terms of the value of the trades. These gender differences exist across the firm among officers, board directors, top executives, and surprisingly, even CEOs and CFOs. They suggested that male executives trade more and earn more than their female counterparts which is consistent with the notion that males possess an informational advantage over females within firms; however, no explanations was proffered as to the potential source(s) of this advantage. Instead, exploration of the possibility that the findings are an indication of males’ superior communication networks was stated as likely to be more fruitful.

All the above research was based on US data. Fidrmuc et al. (2006) tested the information hierarchy hypothesis using UK data and utilised the Stock Exchange Yearbooks to classify directors into five categories: CEOs (including joint CEO-chairmen), other executive directors (the deputy CEO and the financial officer), chairman (non-executives in more than 90% of the cases), other incumbent directors (both executive and non-executive directors not included in the previous categories) and former directors who traded were traced for up to 2 months after the end of the financial year during which they left the company. It tested the information hierarchy hypothesis in two ways: first, they compared the cumulative average abnormal returns (CAARs) earned after trades by each of the individual categories of directors; and second, they performed a multivariate regression analysis using 2-day CARs as the dependent variable and with dummy variables representing the individual categories as explanatory variables. The results of the CAARs analysis showed CEO and other directors do make significant profit in post-event time. However, there was no support for the information hierarchy hypothesis as the differences between the 2-day CAARs for the different categories of directors were not statistically significant. The results of the cross-sectional multivariate regressions with CARs for purchases and sales did not support the information hierarchy either. Fidrmuc et al. (2006) concluded that although CEOs are assumed to have the best knowledge about their company's prospects, the information content of their trades is lower than that of other directors' trades. The most plausible explanation for this result is that the Financial Services Authority (FSA) and the market may follow CEO transactions more closely, which causes CEOs to trade more cautiously and at less informative moments.

Recently, Gregory et al. (2012) re-examined the information hierarchy hypothesis, but focused on only two categories of directors (executive and non-executive) on the basis that this more natural classification encompasses the idea that executive directors are involved in the day-to-day management of a company and therefore have access to more private information than non-executives. Furthermore, they tested performance of gender stereotypes. Unlike the conclusions of Bharath et al. (2009) who found that women were informationally disadvantaged, in the UK sample the returns to female executive trades were in fact significantly greater than the male trades in post-trade (10 days or more) after controlling for firm- and trade-related characteristics.

Generally speaking, evidence for the information hypothesis in the US and UK show that directors have superior information which they can utilise to make significant abnormal returns; however, the different classification of directors and gender employed in studies using US and UK data give different results.

2.2 The Regulatory Framework of Directors' Trades in the US and UK

2.2.1 The Regulatory Framework of Directors' Trades in the US

In the US Insiders are defined as officers, directors, other key employees, and shareholders holding more than 10% of any equity class (Lakonishok and Lee, 2001) and insider trading is regulated by the SEC with the 1934 Securities and Exchange Act and its amendments imposing restrictions on insider trading. The essence of the US rules on insider trading is that insiders must either abstain from trading on undisclosed information or release this information to the public before they trade (Hu and Noe, 1997).

In the US insiders only have to report their holdings within the first 10 days of the month following the month of the trade (Persons, 1997). Insider transactions are published in the SEC's online Insider Trading Report. Chang and Suk (1998) noted that trades normally appear in the online report the same day that the SEC is informed, then shortly afterwards the information is published in the Wall Street Journal and other publications.

In the US the Insider Trading and Securities Fraud Enforcement Act (ITSFEA) of 1988 raised the maximum fine for insider trading to $1 million and 10 years imprisonment in response to frequent violations of the existing insider regulations. The Act also placed the liability for illegal insider trading by any of the company's employees with the top management.

The Sarbanes-Oxley Act of 2002 (hereafter SOX) constitutes a far-reaching federal law aimed at improving the reliability of corporate governance and the financial reporting process in the US. Until August 2002 the reporting requirements consisted of filing a Form 4 to the SEC within 10 days after the close of the calendar month in which the transaction occurred, which could result in a delay of up to 40 days. Section 403 of SOX amends this provision of Section 16(b) of the Exchange Act of 1934 as of August 29, 2002 by requiring insiders to file their Form 4 to the SEC within 2 business days of the transaction date. Furthermore, effective from June 30, 2003, Form 4 must be filed electronically, and companies with websites are required to post information online about the trades the day after they are filed with the SEC.

2.2.2 The Regulatory Framework of Directors' Trades in the UK

Director trading in the UK is regulated by The Companies Act 1985, The Criminal Justice Act 1993 (Part V), The Financial Services and Markets Act 2000 and the Listing Rules for publicly listed companies on the London Stock Exchange (LSE).

Under the Criminal Justice Act 1993, when a director has inside information acquired by virtue of his/her employment, office or profession, he/she is prohibited from dealing in any securities that are affected by that information. Inside information, broadly defined, is specific or precise information about particular securities or an issuer that has not been made public and would be likely to have a significant effect on the price of those securities if it were made public. Directors must also not disclose inside information, except in the proper performance of their job. Breach of the Criminal Justice Act is a criminal offence punishable by imprisonment or a fine or both.

The Companies Act 1985 specifies that a director is obliged to disclose to the company any interests in its securities. They must notify the company of all changes in those interests and of dealings connected with them within five business days. The company must keep a register of the interests notified, which must be kept available for inspection. Under the listing rules for companies trading on the LSE, the company must notify a regulatory information service (RIS) of interests and changes in those interests before the end of the next business day following receipt of the information from the director. Guidance for companies and directors is available in the Continuing Obligations Guide and the Price Sensitive Information Guide which can be obtained from the FSA. From 15 April 2002 a new mechanism for disseminating regulatory information became effective, allowing listed companies the choice of which RIS to use to disclose their regulatory information to the market. The RIS providers include: Business Wire Regulatory Disclosure, Newslink Financial, PimsWire, PR Newswire Disclose, and the Regulatory News Service (RNS) provided by the LSE.

Listing rules also require that listed companies must have a code of dealing in securities that meets the minimum standards set out in the model code. Directors must not deal on considerations of a short-term nature, or during a two-month 'close period' before the announcement or publication of the annual report, the half-yearly (or quarterly) results, or when the director is in possession of unpublished price-sensitive information about the company's listed securities, or before receiving clearance from the company chairman or other designated director that the proposed dealing may proceed. The model code requirements are more extensive than the prohibitions on insider dealing in the Criminal Justice Act 1993.

The Financial Services and Markets Act 2000 (FSMA) provides the statutory framework for the new UK market abuse regime, which became effective on 1 December 2001. Under the market abuse regime introduced by the FSMA, the FSA can impose penalties on companies or individuals. These may comprise either an appropriate financial penalty or a public censure.

The FSA may also apply to the court for injunctions or restitution orders in cases of market abuse. Market abuse is widely defined and includes behaviour by a person in relation to securities traded on the LSE that amounts to misuse of information, the creation of a false or misleading impression, or market distortions.

Since July 2005, the FSA has implemented the market abuse directive (MAD). The MAD is an important part of the EU financial services action plan, which aims to introduce a common approach to prevent and detect market abuse, including insider trading. The MAD is the Directive of the European Parliament and of the Council of 28 January 2003 on insider dealing and market manipulation (market abuse) (No. 2003/6/EC). The existing UK regime is generally considered to be more extensive than the MAD and therefore the MAD regime has been superimposed over the existing UK structure. However, the MAD insider dealing provisions are more specific than the UK regime. The revised definition of inside information is that it is information of a precise nature which, is not generally available, relates directly or indirectly to one or more issuers of qualifying investments or to one or more of the qualifying investments and would, if generally available, be likely to have a significant effect on the price of the qualifying investments or on the price of related investments (e.g. derivatives). The MAD requires an issuer and persons working on its behalf to draw up a list of those persons working for them who have access to insider information relating to the issuer on a regular or occasional basis. If requested, the issuer must provide this list to the FSA. The list must identity each person who has access to inside information, the reason why such person is on the insider list and the date on which the list was created and updated.

In summary, there are substantial differences between the US and UK regulatory framework on insider/director trading. Among these, a very important difference within the UK regulatory regime is that unlike the US, 'insiders' are more broadly defined, and in particular include large shareholders, who are subject to the same reporting requirements as company officers and directors. The UK also discloses director trading information to the public more quickly than the US system, even after the execution of SOX.

Chapter 3 Data, Sample Characteristics and Seasonality Adjustment

3.1 Data and Data Filter

The director's dealing data was obtained from two databases: Directus, which covers the trading period 1986-1993, and Hemscott Company Guru Academic (HS), which covers 1994-2008. Thus, combining these two datasets, the sample covers January 1986 to December 2008, in total 276 calendar months.

The original file from Directus contains 46,984 entries and includes information on company names, LBS number, transaction and announcement dates, price, transaction value, and security classes (89 different types).[2]

The HS contains 488,671 original transaction records and provides information on company names, directors' names, directors' shareholdings, directors' positions on the board, transaction and announcement dates, number of shares traded, price, transaction types (13 different types)[3] and transaction descriptions (27 different types).[4]

From the earlier research (Seyhun, 1988; 1990; 1992; 1998) it is expected that directors' open market sales and purchases are more likely to represent actions taken as a result of special director information. Other empirical studies (Seyhun, 1990; Gregory et al., 1994; Fidrmuc et al., 2006) indicated that the option-related trade by directors contained lower information and were insignificantly related to post-signal abnormal returns. Therefore, in line with these studies only open market purchases and sales by directors from 1986 to 2008 are analysed in this study. This means that the sample data is all for ordinary shares or common shares. All other types of directors' transactions,

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[2] The 89 security types include ordinary shares, restricted voting shares, options, warrants, trust, etc.

[3] Transaction types consist of purchase, sale, exercise of option, sale of option shares, in lieu of dividend, rights taken up, sale of rights, received on conversion, transfer in between holdings, transfer out, n/a, and B&B purchase and sale.

[4] Transaction descriptions capture any relevant additional information relating to the transaction. They include ADRs, ISA, trust, warrants, etc.

such rights taken up, exercises of options, shares acquired through a plan and so forth are excluded.[5]

Following the above adjustments, the sample covers 25,668 directors' transaction records with respect to 3,114 firms from 1986 to 1993, and 60,300 directors' transaction records with respect to 1,086 firms from 1994 to 2008.

One thing need to be mentioned: Among 60,300 directors' transactions during 1994 to 2008, they contain company information of AIM (Alternative Investment Market, LSE). But there are only 4,979 records of AIM. The rest is still listed on main UK market. Therefore, the market index is used in Chapters are index of FTSE All Share.

Throughout this thesis the sample firms are classified into three size equity groups. To form the three size groups, 10 size portfolios were initially created based upon the market capitalisation at the end of each September.[6] The cut-off points for the 10 size portfolios are based on market capitalisation for all the listed firms each year. Firms in the top three size deciles are defined as large firms, those in the next four size deciles as medium-size firms, and the remainder in the smallest three deciles as small firms.

The data of Monthly/Quarterly FTSE All Share returns, 90-day UK Treasury Bill rate (as risk-free interest rate), and firm market capitalisation were obtained from the files of the London Share Price Data (LSPD) and DataStream.

3.2 Summary Characteristics of Sample

Table 3.1 lists the summary statistics for aggregate director trading for all the firms, large firms and small firms. Panel A of Table 3.1 shows that the overall sample data contains 55,262 number of transactions by director purchases and 30,706 by directors sales are from January 1986 to December 2008, with more

[5] Numerous consistency checks on dates, prices, and shares were performed to eliminate approximately 10,400 transaction records containing apparent data errors.

[6] Because of diversified fiscal-end year of UK listed companies, Agarwal and Taller (2008). 'Does financial distress risk drive the momentum anomaly?' Financial Management **37**(3): 461-484.and Gregory et al Gregory, A., R. Tharyan, et al. (2009). 'Stock market patterns around directors' trades: effects of director category and gender on market timing' suggest using market capitalisation on September 30 of each year as benchmark for these companies. At this step, the data check via LSPD deletes companies that have zero or negative market values or do not have any value at the end of September of that year.

than 25 billion shares of director trading in total. Number of shares based on monthly director purchases is greater than the sales (54,172,253 vs. 38,384,047), whilst the average number of shares purchased per transaction is equal to 270,557, which is smaller than the sales (345,014).

Panel B of Table 3.1 describes the sample data for the large firms and includes 28,128 transactions of purchases and 17,794 of sales, with approximately 12.55 billion trading shares in total. Mean shares of purchases trading are slightly greater than the sales (23,404,857 vs. 22,065,584). Similarly to Panel A, the average number of shares purchased per transaction is equal to 229,655, which is also smaller than the sales (342,256).

Panel C presents the sample data of small firms and includes 12,228 transactions of purchases and 5,094 of sales, with more than 5.7 billion total numbers of trading shares. Mean shares of purchases trading are dramatically greater than the sales (15,149,699 vs. 5,623,450). Unlike Panels A and B, the average number of shares purchased per transaction is greater than the sales (341,946 vs. 304,686).

In generally, it can be seen that number of shares based on monthly purchases trading (mean), total number of shares of director purchases, and total number of director transactions are all higher than the sales among all samples and firm segmentation, although for small firms it is more apparent. However, for average shares per transactions, sales are greater than purchases (except small firms). It also can be seen that trading volume and trading transactions of big firms are higher and more frequent than small firms.

3.3 Seasonality Adjustment

3.3.1 Director Trading Adjustment

A recent study of UK aggregate director trading (Andriosopoulos and Hoque, 2011) did not make any allowance for seasonality in monthly UK aggregate director trades. As described in Section 3.1, due to diversified fiscal year-end date and the UK regulations, a seasonality adjustment for UK directors' transactions is required. Figure 3.1 shows the fiscal year-end of FTSE indices for 1986, 1996 and 2008. It can be seen that approximately 25% and 50% of fiscal year-ends are in March and December, respectively. The remainder are random and the number of companies is small.

As requirement of listing rules of the LSE, a company will be required to publish annual and semi-annual reports including consolidated financial information for the relevant period, together with an accompanying review of the company's business for that period, within four months and two months respectively of the relevant financial period. "However, there is a longer delay to the announcement of the final earnings report (approximately 12 weeks) than the interim announcement (approximately 9 weeks)." (Hiller and Marshall, 2002)。

Due to no forced reporting time and no academic paper to clarify what financial announcement date should be, Therefore, in this Chapter, based on my assumption, it supposes companies listed in LSE release their earnings two months (8 weeks) after fiscal year-end and for half year-end.

Furthermore, a regulatory requirement in relation to UK director trading is that the directors of companies traded on the LSE cannot trade during the two months preceding a preliminary, final, or interim earnings announcement (Fidrmuc et al., 2006), and companies typically report earnings twice a year (half year report and annual report), with earnings being typically released two months after the fiscal year-end. Therefore, for the December year-end there should be substantially less directors trading in January, February, July and August, with the same situation occurring in April, May, October and November for March year-end companies. The regulations on directors' trades induce seasonality into the reported trades and hence, seasonality adjustment one is applied, as in Table 3.2.

The methodology of seasonality adjustment two is a more advanced approach of seasonality adjustment one. The purpose of the measurement is to investigate seasonality performance using all available firms' fiscal year-end data.

The layout structures of the two datasets from Directus and HS are total different which made the procedure for output fiscal year-end complicated, especially for data taken from Directus. Directus has no Stock Exchange Daily Official List (SEDOL) or International Securities Identification Number (ISIN) ticker number which can be recognised by DataStream; instead it contains

London Business School (LBS) company identity number. In order to solve this problem London Share Price Data (LSPD) is required. The reason for applying the LSPD to the dataset is that it provides the link between LBS number and SEDOL number for each company listed on the LSE.

However, solving this problem caused another; unlike the LBS number which is unique for every single company no matter whether it is acquired, merged or placed, etc., the SEDOL number of a company changes over time as a result of acquisition, merger etc.[7] Therefore to solve this new problem, the LBS number and SEDOL number were cross-checked in both Directus and the LSPD to investigate how many SEDOL numbers correspond to each LBS number for the period 1986-1993. In the worst case, LBS number 6353, the company has 11 different SEDOL numbers during its life time! This method uses the start and finish date of a SEDOL number in File N to check the LSPD. The start date of a company should not be later than 1994 (one year forward) and the end date should not be earlier than 1985 (one year backward). The results in fiscal year-end data for all the available companies via DataStream. This new file linking the Directus data can then be utilised to determine the real number of sample companies which had March and December fiscal year-ends.

This problem is absent from the HS data because there is an ISIN ticker number in the original file and the data is more recent (time range is from 1994 to 2008). Another positive is HS data can be manipulated by employing the Industry Classification Benchmark (ICB) ten industry classifications. It was not possible with the Directus data because ICB classification began in 1994.

After applying these adjustments, the final results show that there are 280 companies which had either a March or December year-end out of a total number of 367 companies for which fiscal year-end data could be obtained during the period 1986- 1993; and 560 companies had either a March or December year-end out of a total number of 959 companies for which fiscal year-end data could be obtained during the period 1994-2008.

[7] For more detailed reasons for the new SEDOL, please check Source File G and N records of the LSPD dataset

The next stage is to gather the new seasonal director trading data. This involves separately recording the transaction numbers for companies which had a December/March fiscal year-end month by month. Similar to seasonality adjustment one, for a December year-end there should be substantially less directors trading in January, February, July and August, and the same situation should occur in April, May, October and November for transactions of companies with a March year-end.

The second step is to determine the monthly seasonality transactions. The first step is to calculate the average monthly transaction number of companies with a December fiscal year-end without data from January, February, July and August. The second step is to add the average transaction number to the original transaction number data for the calendar months January, February, July and August in order to achieve new seasonal adjust transaction data adjusted for a December fiscal year -end. A similar process must be applied for companies with a March fiscal year-end: calculate the average number of monthly transactions excluding the data for April, May, October and November, then add this to data for April, May, October and November to obtain the final seasonally adjusted transaction data.

Seasonality adjustment three establishes the month dummy variables to test the effect of the under-estimated trading months. As can be seen in Table 3.2, for December year-end companies the performance of director trading activities in January and July should be similar, because these two months are all one month after the fiscal year-end and half-year end, whilst February and August are both two months later. Similarly, for March year-end companies the performance in April and October, May and November, respectively, should be similar. Therefore, the calculation treats every January and July of the year in the sample as 1 and the remainder as 0; treat February and August as 1, the remainder as 0; treat April and October as 1, the remainder as 0; and treat May and November as 1, and the remainder as 0. Table 3.3 illustrated how this calculation works.

3.3.2 Trading Volume Adjustment

Another possible method to detect seasonality is to track trading volume. The trading volume of the FTSE100 from November 1986 to December 2008 can be found through DataStream.

In order to test the existence of seasonality via trading volume a non-parametric method is required (Gultekin and Gultekin, 1983).

Kruskal and Wallis (1952, henceforth K-W) developed a non-parametric test: consider an arrangement of monthly trading volume as a T*12 matrix, $V=[v_{tm}]$, with rows of R representing the years and each column representing the month of a year. Each element, v_{tm}, of the matrix V, is therefore the trading volume per month m of the year t. The K-W procedure can then be used to test the hypothesis that all 12 samples (i.e., columns of V) are drawn from the same population. Specifically, it tests the hypothesis that the 12 months have identical means.

The basic model of trading volume is:

$$v_{tm} = \mu + \tau_m + \varepsilon_{tm} \qquad t=1, 2, \ldots, T_m, \quad m=1, 2, \ldots, 12, \quad (1)$$

Where μ is the unknown overall mean, τ_m is the unknown month m effect and $\sum_{m=1}^{12} \tau_m = 0$. This assumes that the error terms for trading volume of every month, ε_{tm}, are independent of the other error terms of other months trading volume. Moreover, all of the error terms for trading volume are drawn from the same continuous distribution.

For trading volume, it tests the null hypothesis that:

$$H_0: \tau_1 = \tau_{2=} \ldots = \tau_{12} = 0,$$

Against the alternatives that all τs are not equal. A rejection of the null hypothesis implies that the trading volume exhibits seasonality.

The K-W test first ranks the M observations ($M = \sum_{m=1}^{12} T_m$) jointly from least to greatest. Let x_{tm} denote the rank of v_{tm} in this joint ranking; the test statistic is:

$$H = \frac{12}{M(M+1)} \sum_{m=1}^{12} T_m (\overline{X}_m - \overline{X}.)^2, \text{ (2)}$$

Where $\overline{X}_m$ is the average rank received by the trading volume in the mth month such that:

$$\overline{X}_m = \frac{1}{T_m} \sum_{t=1}^{T_m} x_{tm}, \text{ (3)}$$

Where $\overline{X}. = \frac{M+1}{2}$ is the average rank of all *M* observations. When H_0 is true, the statistic *H* has an asymptotic chi-square distribution with 11 degrees of freedom. The appropriate *α*-level test is:

$$\text{Reject } H_0 \text{ if } H_0 \geq \chi^2(11, \alpha),$$

Where $\chi^2(11, \alpha)$ is the upper α percentile point of a χ^2 distribution with 11 degrees of freedom.

Since this procedure uses the rankings of the observations it is not sensitive to outliers. Furthermore, the K-W test requires no distributional assumptions about the trading volume; therefore it is less restrictive than parametric tests.[8] Table 3.4 shows that the critical value does not reject the null hypothesis and that there is no difference among monthly trading volumes. Therefore, there is no seasonality effect with regard to trading volume.

3.3.3 Month-of-the-Year Effort

After checking the seasonality movements in director trading, the next stage is to investigate the existence of seasonality within the capital markets. Seasonality, as in the other studies (Fama 1965; Malkiel and Fama 1970; Rozeff and Kinney, 1976; Kendall, 1953; Officer 1975; Richards 1979; Gultekin and Gultekin 1983), implies that there are significant differences in the month-to-month mean returns. To test the month-of-the-year effect the K-W test will be applied.

It can be seen that the critical value of K-W test in Table 3.5 does not reject the null hypothesis that there is no month-of-the-year effect. This indicates that the UK stock market returns do not exhibit a month-of-the-year effect and the 12

[8] See Hollander and Wolfe, 1973, pp.114-120 for more details

months of FTSE indices have identical means. Consequently, only the seasonality of director trading needs to be considered.

Figure 3.1 Fiscal year-end of FTSE 100, 250 and 350 on the year 1986, 1996 and 2008

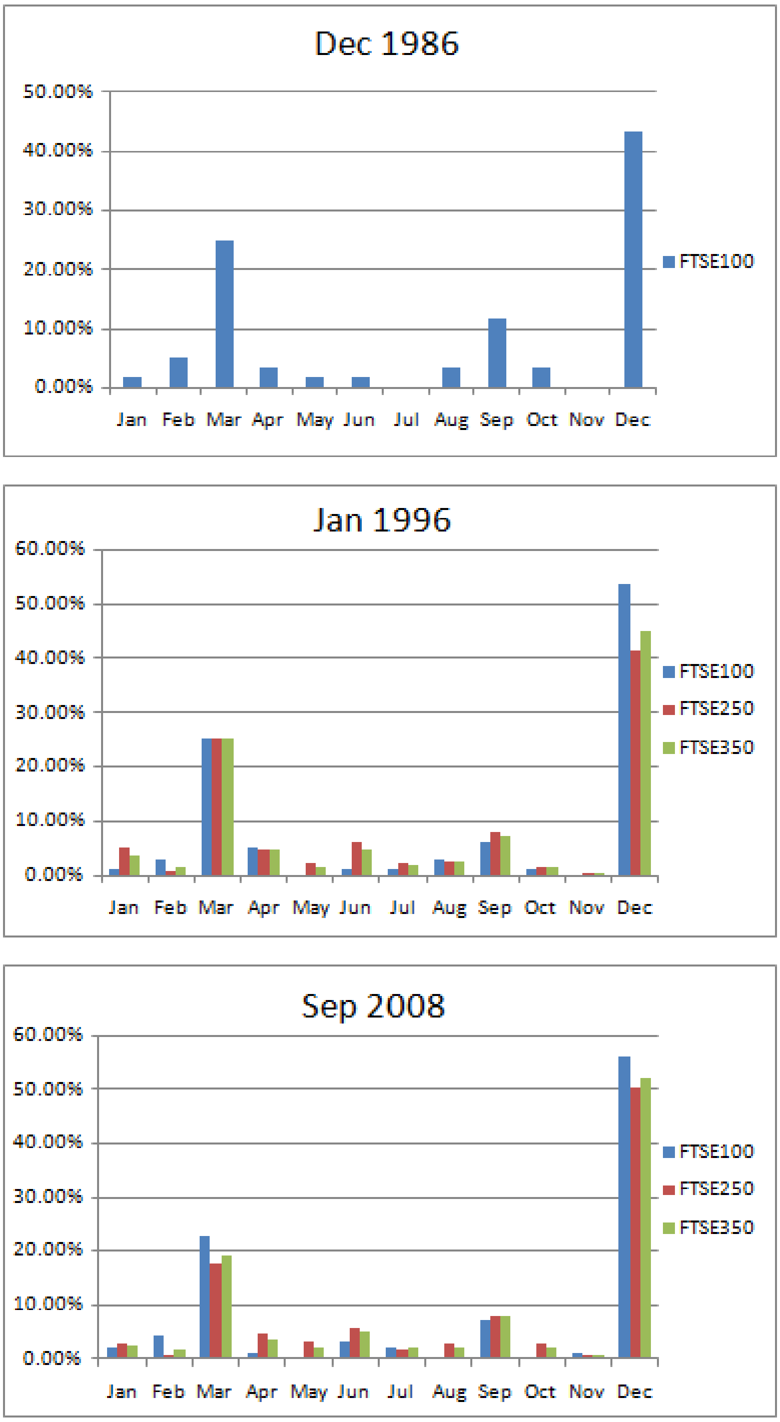

Table 3.1 Sample Characteristics of Directors Trading From January 1986 to December 2008

Panel A: Director Trading Transaction of Overall Sample

	Purchases	*Sales*
No. of Shares Based on Monthly Trading	54,172,253	38,384,047
Standard Deviation	95,383,620	50,479,984
Total No. of Shares	14,951,541,746	10,593,996,956
Total No. of Trading Transactions	55,262	30,706
Average Shares*	270,557	345,014
Total No. of Month	276	276

Panel B: Director Trading Transactions of Large Firms

	Purchases	*Sales*
No. of Shares Based on Monthly Trading	23,404,857	22,065,584
Standard Deviation	62,883,994	39,081,469
Total No. of Shares	6,459,740,464	6,090,101,200
Total No. of Trading Transactions	28,128	17,794
Average Shares*	229,655	342,256
Total No. of Month	276	276

Panel C: Director Trading Transactions of Small Firms

	Purchases	*Sales*
No. of Shares Based on Monthly Trading	15,149,699	5,623,450
Standard Deviation	36,999,111	8,779,765
Total No. of Shares	4,181,316,850	1,552,072,062
Total No. of Trading Transactions	12,228	5,094
Average Shares*	341,946	304,686
Total No. of Month	276	276

* The average shares in Panels A, B and C are per transaction.

Table 3.2 Fiscal year-end of UK Director Trading Data & Seasonlity Adjust One

Month		Under-Estimated	No-change
March (25%)	Fiscal-year end Announcement	April	March
		May	
	Half-term Announcement	October	September
		November	
December (50%)	Fiscal-year end Announcement	January	December
		February	
	Half-term Announcement	July	June
		August	

This is calculated using the following assumption:

January	Data/(1-0.5)
February	Data/(1-0.5)
March	Data
April	Data/(1-0.25)
May	Data /(1-0.25)
June	Data
July	Data /(1-0.5)
August	Data /(1-0.5)
September	Data
October	Data /(1-0.25)
November	Data /(1-0.25)
December	Data

As discussed in Section 3.3.1, 25% of companies have March year-end and 50% of companies have December year-end, and according to my fiscal year-end assumption, director trading in April, May, October, November, January, February, July and August is under-estimated; director trading in March, September, December and June is unchanged. Therefore, the detailed seasonality would be: director trading in January, February, July and August is $\frac{Real\ Trading\ Data}{(1-0.5)}$; trading in April, May, October and November is $\frac{Real\ Trading\ Data}{(1-0.25)}$; in the rest months (March, June, September and December), the seasonality is what real trading data is.

Table 3.3 Demonstration of Month Dummy

Month	Jan/Jul	Feb/Aug	Apr/Oct	May/Nov
Jan	1	0	0	0
Feb	0	1	0	0
Mar	0	0	0	0
Apr	0	0	1	0
May	0	0	0	1
Jun	0	0	0	0
Jul	1	0	0	0
Aug	0	1	0	0
Sep	0	0	0	0
Oct	0	0	1	0
Nov	0	0	0	1
Dec	0	0	0	0

Table 3.4 Kruskal-Wallis equality-of-populations rank test of FTSE 100 Trading Volume from November 1986 to December 2008

FTSE 100 Trading Volume		
Month	Obs	Rank Sum
January	22	2353
February	22	3237
March	22	3016
April	22	3131
May	22	2668
June	22	2900
July	22	2953
August	22	3071
September	22	2761
October	22	3101
November	23	3214
December	23	3106
chi-squared = 4.959 with 11 d.f. probability = 0.9332		
chi-squared with ties = 4.959 with 11 d.f. probability = 0.9332		

Table 3.5 Month-to-Month Mean Stock Market Returns and the Tests of Equality of Mean Returns January 1986 to December 2008; FTSE Indices

													K-W tests[b]	
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Stat.	Prob.
FTSEAll Monthly Return[a]	0.00880	0.01479	0.00595	0.01845	0.00569	-0.00530	0.00323	0.00098	-0.01677	-0.00102	0.00486	0.02479	13.104	0.2866
FTSE100 Monthly Return[a]	0.00571	0.01174	0.00494	0.01848	0.00472	-0.00465	0.00438	0.00091	-0.01493	0.00114	0.00543	0.02510	13.820	0.2431
Excess Return of FTSEAll Monthly[a]	0.00310	0.00914	0.00039	0.01294	0.00025	-0.01086	-0.00239	-0.00466	-0.02234	-0.00648	-0.00054	0.01939	13.301	0.2741
Excess Return of FTSE100 Monthly[a]	0.000001	0.00610	-0.00062	0.01297	-0.00072	-0.01020	-0.00124	-0.00473	-0.02051	-0.00432	0.00003	0.01970	13.526	0.2604

[a]Number of observations is 23 for each month.
[b]The Kruskal-Wallis test statistic is approximately distributed as chi-square with 11 degrees of freedom. It tests the null hypothesis that month-to-month mean returns are equal against the alternative that they are not. The critical values for the chi-square distribution with 11 degrees of freedom at 10%, 5%, and 1% significant level are 17.275, 19.675, and 24.725, respectively. The probability value is the probability that a chi-square statistic is at least as large as the one reported would be obtained if the null hypothesis is true, i.e. mean returns are equal.

Chapter 4 Aggregate Director Trading and Market Excess Returns

4.1. Introduction

As discussed in Chapter 2, this study investigates the information content of aggregate trading by company directors in their own firms. It follows the earlier stated hypothesis that director trading that is information-related trading by company directors is in response to factors that affect security returns, i.e., firm-specific, industry-wide, or economy-wide factors; therefore, analysis of director trading can potentially uncover the sources of these factors not currently reflected in security prices.

Section 4.2 describes the data and the seasonality methodology. The time period of director trading is from January 1986 to December 2008 and three seasonality adjustments are discussed and applied.

Section 4.3 describes the methodology. Several measurements of aggregate director trading, methods of calculating market excess returns and econometrics tests which could avoid potential statistical problems are discussed. To describe director trading activities, the aggregate net number of director purchases (ANP), net number of director purchase ratio (NPR), difference of aggregate net purchase ratio (ΔNPR), difference of aggregate net purchase (ΔNP) and change of aggregate net number of director purchases (NPGR) are employed. To measure excess returns, cumulative excess returns (CERs) and buy and hold abnormal returns (BHERs) are introduced into the model. To avoid potential econometric issues, a serial correlation test, the Newey-West t-test (Newey and West, 1987) and the White test (White, 1980) are applied.

Section 4.4 presents the empirical results and analyses the relationship between aggregate director trading and market returns in different ways. A time-series method is applied to investigate the performance of the aggregate director in the short-term and long-run. The size effect is noted in other empirical studies and is also considered, the model controls for firm-size and industry.

Finally, Section 4.5 summarises the results and concludes Chapter 4.

4.2 Data and Seasonality

The aggregate director trading data is from January 1986 to December 2008 and is taken from two datasets (Directus and HS). By following the data filtering methods of previous studies, the final sample covers 25,668 directors' transaction records with respect to 3,114 firms from 1986 to 1993, and 60,300 directors' transaction records with respect to 1,086 firms from 1994 to 2008.

Due to diversified fiscal year-end dates and the UK regulations, seasonality adjustments for director trading are applied. Three seasonality adjustment measurements are used. Seasonality adjustment one is based on December and March fiscal year-end assumptions, seasonality adjustment two is based on December and March fiscal year-end observations, and seasonality adjustment three employs month dummies based on December and March fiscal year-ends to test the effect of the under-estimated trading months. Details of the data, sample characteristics and seasonality adjustment measurements of director trading are fully described and discussed in Chapter 3.

The data for Monthly FTSE All Share returns, 90-day UK Treasury Bill rate (as risk-free interest rate), and dividend yield of FTSE All Share can be obtained from the files of the LSPD and DataStream dataset. The firm capitalisation and book-to-market values can be obtained from both LSPD and DataStream.

For macro-economy variables, the majority of the UK data can be accessed from the Office for National Statistics (ONS, http://www.ons.gov.uk/ons/index.html). From the official ONS website the monthly retail prices index (RPI) and monthly seasonal adjusted index of total production industries can be obtained.

Data of money supply measured by UK notes and coins in circulation outside of the Bank of England (M0, the narrow definition) and spot price of oil (both WTI and Brent) are also available from DataStream.

4.3 Methodology

Seyhun (1988; 1992; 1998) and Lakonishok and Lee (2001) showed that aggregate insider trading significantly forecasts future US stock market movements in the long-run. This thesis mostly follows the methodology of a time series study and the evidence presented in this section uses regression analysis to examine the relationship between aggregate director trading and returns in the UK stock market.

4.3.1 Aggregate Director Trading Activity

In order to detect the relationship between corporate directors' (executive directors and non-executive directors) transactions and stock market returns, a measure of standardised aggregate director trading is constructed:

The net number of purchase transactions in firm *i* and month *t*, $NP_{i,t}$, is defined as follows:

$$NP_{i,t} = \sum_{j=1}^{N} H_{j,i,t} \text{ , (4)}$$

Where *N* denotes the number of purchases and sales by directors in firm *i* and month *t*, $H_{j,i,t}$ equals 1 if transaction *j* is a purchase and -1 if transaction *j* is a sale.

Defined as:

$$SANP_{k,t} = \sum_{i=1}^{I_k} (NP_{i,t} - \overline{NP_i}) / \sigma(NP_i), (5)$$

k = all firms or large firms or medium firms or small firms, where I_k is equal to the total number of firms in group *k* and $SANP_{k,t}$ refers to the standardized aggregate net number of purchases transactions by directors in firm-size group *k* and in month *t*.

In addition:

$$\overline{NP_i} = \sum_{t=1}^{276} NP_{i,t} / 276, (6)$$

and:

$$\sigma(NP_i) = \sqrt{\sum_{t=1}^{276} (NP_{i,t} - \overline{NP_i})^2 / 275}, (7)$$

Hence, $SANP_{k,t}$ is calculated by subtracting the mean and dividing by the sample standard deviation of net number of transactions over the 276 calendar months among January 1986 to December 2008, then totalled across firms for each firm-size group. Standardisation ensures that each firm receives approximately the same weight in the measure of aggregate director trading, thereby ensuring against the possibility that several firms receive an inadequate weight in the results.

The aggregate net number of transactions by directors in each month t and group k, ANP_t^k is computed by totalling the net number of transactions across firms:

$$ANP_t^k = \sum_{i=1}^{K} NP_{i,t}, (8)$$

Where K denotes the number of firms in group k - all firms, large firms, medium firms or small firms.

Calculation of the aggregate number of purchases transactions (AP), standardised aggregate number of purchases transactions (SAP), aggregate number of sales transactions (AS), and aggregate number of sales transactions (SAS) is similar to ANP and SANP.

ANP_t^{All}, AP_t^{All} and AS_t^{All} are plotted in Figure 4.1 and appear to be a slow-moving, mean-stationary series. The result also can be tested using the Unit Root test and the results of this are shown in Appendix A.

The net number of director purchase ratio (NPR) was introduced by John and Lang (1991) in an event study of US insider trading. It is defined as the ratio of net number purchases (the number of director purchases minus the number of director sales) / the total number of director transactions. Lakonishok and Lee (2001) employed this ratio to investigate aggregate insider trading activities in long-run US studies. The advantage of ratio methodology is it is 'not sensitive to changes in the number of firms or trading activity over time. Moreover, the ratio does not display heteroscedasticity or extreme outliers' (Seyhun, 1990). In addition, the purchase ratio (PR, denotes as ratio of the number of purchases to total director transactions) and sales ratio (SR, denotes as ratio of the number of sales to total director transactions) are also applied.

$$NPR = (AP - AS) / (AP + AS), (9)$$

$$PR = AP / (AP + AS), (10)$$

$$SR = AS / (AP + AS), (11)$$

Where A*P* is the aggregate number of director purchases transactions, *AS* is the aggregate number of director sales transactions, and A*P*+*AS* is total number of all director transactions.

In addition, a change of director transaction ratio is applied. The concept behind this method comes from the work of Knewtson et al. (2010), who applied the difference of aggregate net purchase ratio (ΔNPR) as an independent variable to examine the returns of value and growth markets. Similarly this thesis calculates the difference of aggregate purchase ratio (ΔPR), and difference of aggregate sale ratio (ΔSR) as independent variables to describe director trading activities.

$$\Delta NPR = NPR_t - NPR_{t-m}, (12)$$

$$\Delta PR = PR_t - PR_{t-m}, (13)$$

$$\Delta SR = SR_t - SR_{t-m}, (14)$$

Where *t* denotes director trading in month *t* and *t-m* denotes director trading in the previous *m*th month.

Next, the change of director transaction is applied to study director trading in order to avoid potential statistical problems when measuring aggregate director trading. It calculates the difference of aggregate net number of purchases (ΔANP), difference of aggregate number of purchases (ΔAP), and difference of aggregate number of sales (ΔAS).

$$\Delta ANP = ANP_t - ANP_{t-m}, (15)$$

$$\Delta AP = AP_t - AP_{t-m}, (16)$$

$$\Delta AS = AS_t - AS_{t-m}, (17)$$

Where ANP is the aggregate net number of director purchases transactions, A*P* is the aggregate number of director purchases transactions, *AS* is the aggregate number of director sales transactions, *t* denotes director trading in month *t*, and *t-m* denotes director trading in the previous *m*th month.

Finally, the change of director transaction is applied to study the director trading to avoid potential statistics problem when measuring aggregate director trading. The change of aggregate net number of purchase (NPGR), change of aggregate number of purchases (APGR) and change of aggregate number of sales (ASGR) are calculated:

$$NPGR = (ANP_t - ANP_{t-m}) / ANP_{t-m}, (18)$$

$$APGR = (AP_t - AP_{t-m}) / AP_{t-m}, (19)$$

$$ASGR = (AS_t - AS_{t-m}) / AS_{t-m}, (20)$$

Where ANP is the aggregate net number of director purchases transactions, A*P* is the aggregate number of director purchases transactions, *AS* is the aggregate number of director sales transactions, *t* denotes director trading in month *t*, and *t-m* denotes director trading in the previous *m*th month.

In addition to using the aggregate number of director trading, the aggregate number of director trading shares and aggregate sterling volume of director trading transactions are also applied. However, only the evidence regarding aggregate number of director trading is significant, as previous literature (Scholes, 1972; Jaffe, 1974; Seyhun, 1986; Lakonishok and Lee, 2001) has noted that insider trading based on dollar volume of trading contains less information, because it may be influenced by a few very large transactions.

Statistical properties of the aggregate number of director trading are shown in Appendix B. It can be seen that when the correlation coefficient is high and significant, many of them are significant even at 1%. Therefore, as Seyhun

(1988) noted, first-order and higher-order serial correlation tests need to be applied to detect autocorrelation. To check the first-order serial correlation, the Durbin-Watson d-statistic and Durbin's alternative test for serial correlation in the disturbance is employed. To detect the higher-order serial correlation, the Breusch-Godfrey test for higher-order serial correlation in the disturbance is applied.

4.3.2 Cumulative Excess Returns

Cumulative excess returns (CERs) for a time series regression of future excess stock returns is as follows:

$$CER = \sum_{k=t}^{t+m-1} (R_k^i - R_k^f), (21)$$

Where R_k^i is the returns on return of firm portfolio group *k* in month *t*, and R_k^f is 90-day Treasury Bills in month *t*.

4.3.3 Buy and Hold Excess Returns

Buy and hold excess returns (BHERs) are also applied to examine the relationship between aggregate director trading and the market returns:

$$BHER = \prod_{k=t}^{t+m-1} (1 + R_k^i) - \prod_{k=t}^{t+m-1} (1 + R_k^f), (22)$$

Similar to CER, R_k^i is the returns on return of firm portfolio group *k* in month *t*, and R_k^f is 90-day Treasury Bills in month *t*.

The main difference between these two measures of returns is that CERs ignores compounding, while raw returns and BHERs account for it.[9]

4.3.4 The Recursive Modelling Strategy

The methodology of Pesaran and Timmermann (1995, 2000) is utilised. In their papers, to simulate investors' search for a forecasting model a set of regressors needs to be established over which the search is to be conducted; in addition,

[9] Barber and Lyon (1997) provide a detailed description of the consequences of such differences during an event study.

the functional form of the estimated models and the criteria used to select a particular regression model also need to be specified.

Pesaran and Timmermann (1995, 2000) distinguished between three hierarchies of regressors: core, focal and potentially relevant. A_t is the highest level of regressors and are a set of 'core variables' believed to be important in forecasting stock returns on theoretical grounds and are always included in forecasting equations. The second set of regressors, referred to as 'focal' and denoted by B_t, are always considered in forecasting exercises as potentially important for capturing short-term variations in risk premia due to business cycle fluctuations, although some or all of these regressors may be left out of the preferred forecasting model according to the model selection criterion employed. The combined set of regressors in A_t and B_t will be referred to as the 'base set'. Finally, a third set of regressors, C_t, are considered as potentially relevant, but are utilised by investors only if they discover clear evidence of the failure of the forecasting models obtainable from the regressors in the base set. This last set of variables is only occasionally considered since agents have weak reasons to believe that they should be included in the forecasting equations. A search across variables in the C_t set is triggered at time t when the most recent residual from the excess return equation using variables in the base set exceeds three (recursive) standard errors.[10]

Based on Pesaran and Timmermann (1995, 2000), it was decided on the following three sets of regressors:

$$A_t = \{c, YALL_{t-1}, I3_{t-1}, PI_{t-2}\},$$

$$B_t = \{DI3_{t-1}, DGILT_{t-1}, JAN_t\},$$

$$C_t = \{DIP_{t-2}, DM0_{t-2}, DPSPOT_{t-1}\},$$

[10] For a broad class of distributions of stock returns, it seems reasonable to consider three standard errors from the mean as representing an extreme event. An alternative interpretation of this procedure can be found in the literature on Value at Risk and is provided by Duffie and Pan (1997).

Where *c* is the constant, *YALL* is the dividend yield on the FTSE All Share Index, *I3* is the 90-day T-bill rate, *DI3* = I3-I3(-1), *PI* is the rate of change of retail prices, *DGILT* is the change in the yield on a 2.5% government consol, *JAN* is a January dummy (which takes the value of unity in January of each year and zeros elsewhere), *DIP* is the rate of change in the index of industrial production, *DM0* is the rate of change of the money supply (the narrow definition), and *DPSPOT* is the rate of change in the spot price of oil.[11]

4.3.5 Serial Correlation Test

The Durbin–Watson statistic (Durbin and Watson, 1950) tests for first-order serial correlation in the disturbance when all the regressors are strictly exogenous. Durbin's alternative test is used to identify a serial correlation in the disturbance and does not require that all the regressors be strictly exogenous. The Breusch–Godfrey test is used for a higher-order serial correlation in the disturbance, and like Durbin's alternative test, it does not require that all the regressors be strictly exogenous.

The Durbin–Watson test is used to determine whether the error term in a linear regression model follows an AR(1) process. For a linear model:

$$y_t = x_t\beta + u_t, (23)$$

Where the AR(1) process can be written as:

$$u_{t=}\rho u_{t-1} + \varepsilon_t, (24)$$

In general, an AR(1) process requires only that ε_t be independent and identically distributed (i.i.d.). The Durbin–Watson test, however, requires ε_t to be distributed N (0, σ^2) for the statistic to have an exact distribution. In addition, the Durbin–Watson test can only be applied when the regressors are strictly exogenous. A regressor *x* is strictly exogenous if Corr(x_s; u_t) = 0 for all *s* and *t*, which precludes the use of the Durbin–Watson statistic with models where lagged values of the dependent variable are included as regressors.

[11] Definitions and descriptions of these variables are provided in Appendix C.

The null hypothesis of the test is that there is no first-order autocorrelation. The Durbin–Watson *d* statistic can take on values between 0 and 4 and under the null *d* is equal to 2. Values of less than 2 suggest positive autocorrelation ($\rho>0$), whereas values of *d* greater than 2 suggest a negative autocorrelation ($\rho<0$). Calculating the exact distribution of the *d* statistic is difficult, but empirical upper and lower bounds have been established based on the sample size and the number of regressors. Extended tables for the *d* statistic have been published by Savin and White (1977).

When lagged dependent variables are included among the regressors, the past values of the error term are correlated with those lagged variables at time *t*, implying that they are not strictly exogenous regressors. The inclusion of covariates that are not strictly exogenous causes the *d* statistic to be biased toward the acceptance of the null hypothesis. Durbin (1970) suggested an alternative test for models with lagged dependent variables and extended that test to the more general AR(*p*) serial correlation process:

$$u_t = \rho_1 u_{t-1} + \cdots + \rho_p u_{t-p} + \varepsilon_t, (25)$$

Where ε_t is i.i.d. with variance σ^2 but is not assumed or required to be normal for the test.

The null hypothesis of Durbin's alternative test is:

$$\mathrm{H}_0: \rho_1 = 0, \dots, \rho_p = 0$$

Where the alternative is that at least one of the ρ's is non-zero. Although the null hypothesis was originally derived for an AR(*p*) process, this test turns out to have power against MA(*p*) processes. Hence, the actual null of this test is that there is no serial correlation up to order *p* because the MA(*p*) and the AR(*p*) models are locally equivalent alternatives under the null (see Godfrey, 1988, pp.113–115, for a discussion of this result).

Durbin's alternative test is in fact a Lagrange Multiplier test (LM test), but it is most easily computed using a Wald test on the coefficients of the lagged residuals in an auxiliary ordinary least squares (OLS) regression of the residuals on their lags and all the covariates in the original regression. Consider the linear regression model:

$$y_t = \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + u_t, (26)$$

In which the covariates x_1 through x_k are not assumed to be strictly exogenous and u_t is assumed to be i.i.d. and to have finite variance. The process is also assumed to be stationary. Estimating the parameters in (26) by an OLS regression gives the residuals $\hat{u}_t$. Next, another OLS regression is performed of $\hat{u}_t$. on $\hat{u}_{t-1}$.,…, $\hat{u}_{t-p}$ and the other regressors:

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} + \cdots + \gamma_p \hat{u}_{t-p} + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \varepsilon_t, (27)$$

Where ε_t stands for the random-error term in this auxiliary OLS regression. Durbin's alternative test is then obtained by performing a Wald test where $\gamma_1, \cdots, \gamma_p$ are jointly zero. This test can be made robust to an unknown form of heteroscedasticity by using a robust variance-covariance matrix of the estimators (VCE) when estimating the regression in (27). When there are only strictly exogenous regressors and $p = 1$, this test is asymptotically equivalent to the Durbin–Watson test.

The Breusch–Godfrey test is also an LM test of the null hypothesis of no autocorrelation versus the alternative that u_t follows an AR(p) or MA(p) process. Like Durbin's alternative test, it is based on the auxiliary regression (27), and it is computed as $N R^2$, where N is the number of observations and R^2 is the simple R^2 from the regression. This test and Durbin's alternative test are asymptotically equivalent. The test statistic $N R^2$ has an asymptotic χ^2 distribution with p degrees of freedom. It is valid with or without the strict exogeneity assumption but is not robust to conditional heteroscedasticity, even if a robust VCE is used when fitting (27).

In fitting (27), the values of the lagged residuals will be missing in the initial periods. As noted by Davidson and MacKinnon (1993), the residuals will not be orthogonal to the other covariates in the model in this restricted sample, which implies that the R^2 from the auxiliary regression will not be zero when the lagged residuals are omitted. Hence, Breusch and Godfrey's $N R^2$ version of the test may over reject in small samples. To correct this problem, Davidson and MacKinnon (1993) recommended setting the missing values of the lagged residuals to zero and running the auxiliary regression in (27) over the full sample used in (26). This small-sample correction has become conventional for both the Breusch–Godfrey and Durbin's alternative test.

Consider the regression:

$$y_t = \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + u_t, \text{ (28)}$$

Where some of the covariates are not strictly exogenous; in particular, some of the x_{it} may be lags of the dependent variable. It is interested in whether there are serially correlated.

The Durbin–Watson *d* statistic is:

$$d = \frac{\sum_{t=1}^{n-1}(\hat{u}_{t+1} - \hat{u}_t)^2}{\sum_{t=1}^{n} \hat{u}_t^2}, (29)$$

Where $\hat{u}_t$ represents the residual of the the observation.

To compute Durbin's alternative test and the Breusch–Godfrey test against the null hypothesis that there is no *p*th order serial correlation, fit the regression in (28), compute the residuals, and then fit the following auxiliary regression of the residuals $\hat{u}_t$ on *p* lags of $\hat{u}_t$ and on all the covariates in the original regression in (28):

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} + \cdots + \gamma_p \hat{u}_{t-p} + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \varepsilon_t, \text{ (30)}$$

Durbin's alternative test is computed by performing a Wald test to determine whether the coefficients of $\hat{u}_{t-1}, \dots, \hat{u}_{t-p}$ are jointly different from zero. By default, STATA (it is one economics software) outputs the statistic and is assumed to be distributed $\chi^2(p)$. If a small sample is specified, the statics are assumed to follow an *F*(*p*, N-*p*-*k*) distribution (where *k* is number of parameters).

The Breusch–Godfrey test is computed as *N* R^2, where *N* is the number of observations in the auxiliary regression (30) and R^2 is the R^2 from the same regression (30). Like Durbin's alternative test, the Breusch–Godfrey test is asymptotically distributed $\chi^2(p)$, but specifying for small samples, causes the *p*-value to be computed using an *F* (*p*, *N*-*p*-*k*) by STATA.

4.3.6 Newey-West t-test and White Test

The Huber/White/sandwich robust variance estimator (White, 1980) produces consistent standard errors for OLS regression coefficient estimates in the presence of heteroscedasticity. The Newey–West (1987) variance estimator is an extension that produces consistent estimates when there is autocorrelation in addition to possible heteroscedasticity.

Calculating the estimates:

$$\widehat{\beta}_{\mathrm{OLS}} = (\mathrm{X'X})^{-1}\mathrm{X'y}, (31)$$

$$\widehat{\mathrm{Var}}(\widehat{\beta}_{\mathrm{OLS}}) = (\mathrm{X'X})^{-1}\mathrm{X'}\widehat{\Omega}\mathrm{X}(\mathrm{X'X})^{-1}, (32)$$

That is, the coefficient estimates are simply those of an OLS linear regression.

For no autocorrelation, the variance estimates are calculated using the White formulation:

$$\mathrm{X'}\widehat{\Omega}\mathrm{X} = \mathrm{X'}\widehat{\Omega}_0\mathrm{X} = \frac{n}{n-k}\sum_i \hat{e}_i^2 \mathrm{x}_i' \mathrm{x}_i, (33)$$

Here $\hat{e}_i = y_i - \mathrm{x}_i\hat{\beta}_{\mathrm{OLS}}$, where x_i is the *i*th row of the X matrix, n is the number of observations, and k is the number of predictors in the model, including a constant if there is one.

For the autocorrelated process, the variance estimates are calculated using the Newey-West (1987) formulation:

$$\mathrm{X'}\widehat{\Omega}\mathrm{X} = \mathrm{X'}\widehat{\Omega}_0\mathrm{X} + \frac{n}{n-k}\sum_{l=1}^{m}\left(1-\frac{l}{m+1}\right)\sum_{t=l+1}^{n} \hat{e}_t\,\hat{e}_{t-l}\left(\mathrm{x}_t'\mathrm{x}_{t-l} + \mathrm{x}_{t-l}'\mathrm{x}_t\right), (34)$$

Where x_t is the row of *X* matrix observed at time *t*, *l* stands for lag, *m* is number of lags, if lag(*m*), m>0.

4.4 Empirical Results

The evidence presented in this section uses regression analysis to examine the relationships between aggregate director transaction activities and future market excess returns.

The relationship between aggregate director trading and market excess returns was described by Seyhun (1988): if all director transactions occur due to firm-specific reasons, then no relationship between aggregate director trading and the market excess returns would be expected. If directors recognise the effects of changes in economy-wide factors in their own firms at the same time as other market investors do, and if they trade on the basis of their observations, then the relationship between aggregate director trading and excess market returns is expected to be positive and contemporaneous. If a director recognises the effects of changes in economy-wide activity before other market participants, and trades on these beliefs, then a positive relationship between current director trading and future excess market returns is expected.

4.4.1 Aggregate Director Trading and Market Returns

Table 4.1 indicates the results of regressing aggregate director trading on excess market returns. The results show the effect of applying different aggregate director trading variables of seasonality adjustments. The dependent variable in the regression is the difference between the monthly returns of FTSE All Share Index and the 90-day Treasury Bills returns. This difference presents the excess return to the market portfolio. The independent variables are the contemporaneous and lagged term of the aggregate director trading, as described in Section 4.3. As noted by Seyhun (1988), in order to avoid the potential issue of first-order and high order serial correlation, first-order and higher-order serial correlation tests are applied and there is no serial correlation in any of the models (serial correlation test are not shown in the table). The significance levels of the estimated coefficients are computed using the Newey and West (1987) covariance matrix to determine if there is a serial correlation, and the White (1980) covariance matrix is employed to test if the serial correlation is not significant. Two lag terms of the residuals are used to compute the Newey-West covariance matrix.

In models 1-3, the dependent variable is the excess return to market portfolio and the independent variable is the aggregate net number of director purchase transactions by all firms (ANP). In model 1, the independent variables are 1- and 2-month lagged terms of ANP (ANP_{t-1} and ANP_{t-2}). The estimated coefficient of ANP_{t-2} is insignificant and negative, while coefficient of ANP_{t-1} is positive and insignificant. The insignificant coefficients of ANP in model 1 is probably caused by positive correlations between ANP_{t-1} and ANP_{t-2} (see Appendix B), hence, ANP_{t-1} and ANP_{t-2} tend to proxy for each other.

In model 2, the independent variables include the contemporaneous term, ANP_t as well as the lagged terms, ANP_{t-1} and ANP_{t-2}. The estimated coefficient of ANP_{t-1} is positively significant at the 1% level. This regression suggests that an increase in current aggregate directors' purchases is associated with an increase in the future excess return of the market portfolio one month later. Given that the sample standard deviation is 78.48 (see Appendix C), the coefficient estimated is 0.000221, it indicates that one standard deviation change in ANP is associated with 1.7% change in the future excess market returns. Meanwhile, ANP_t is negative and significant at the 1% significance level, whilst the estimated coefficient of ANP_{t-2} is insignificantly positive.

Model 3 includes the one monthly leading term ANP_{t+1}. It shows that the estimated coefficient of ANP_{t-1} from model 2 is basically unchanged and is positively significant at the 1% significance level. Contemporaneous and leading terms of ANP are all negatively correlated to current market excess returns, while the leading term of ANP is negatively significant at the 1% significance level.

Models 4-9 apply the seasonal adjustment measurements. Models 4-6 use seasonally adjusted ANP for December and March fiscal year-ends by assumption (ANP_ADJ_1, also known as seasonality adjustment one[12]) as independent variable. All these three models indicate similar results to models

[12] Details of seasonality adjustment are fully described in Chapter 3.

1-3, but the estimated coefficient of $ANP\_ADJ\_1_{t-1}$ is significant at the 5% significance level, which is less significant than the ANP.

Models 7-9 use the seasonally adjusted ANP for December and March fiscal year-ends by observation (ANP_ADJ_2, also known as seasonality adjustment two[13]) as independent variable. The result of the estimated coefficient of $ANP\_ADJ\_2_{t-1}$ is significant at the 1% significance level which is similar to that of models 1-3, and the t-statics are better than those of $ANP\_ADJ\_1_{t-1}$ for models 4-6.

Models 1-9 duplicate Seyhun's (1998) work as they use the same measure of director trading-aggregate net number of director purchases (ANP). Models 10-18 apply the aggregate net number of director purchases ratio (NPR) to examine the performance of director trading. Models 10-12 present the performance of the real NPR, models 13-15 present the performance of the seasonally adjusted NPR for December and March fiscal year-ends by assumption (NPR_ADJ_1, seasonality adjustment one), and models 16-18 present the seasonally adjusted NPR for December and March fiscal year-ends by observation (NPR_ADJ_2, seasonality adjustment two).

In model 10, the independent variables are 1- and 2-month lagged terms of NPR (NPR_{t-1} and NPR_{t-2}). The estimated coefficient of NPR_{t-2} is insignificant and negative, while the coefficient of NPR_{t-1} is positive and significant at the 10% significance level. In model 11, the independent variables include the contemporaneous term, NPR_t as well as the lagged terms, NPR_{t-1} and NPR_{t-2}. The estimated coefficient of NPR_{t-1} is positively significant at the 5% level significance level. Consistent with model 2, this regression suggests that an increase in current aggregate directors' purchases is associated with increases in future excess returns of the market portfolio one month later. Given that the sample standard deviation is 0.24 (see Appendix C), the coefficient estimated at 0.057 indicates that one standard deviation change in NPR is associated with almost 1.4% change in future excess market returns. Meanwhile, NPR_t is negative and significant at the 1% significance level, while the estimated coefficient of NPR_{t-2} is insignificantly positive. Model 12 includes the one

[13] Details of seasonality adjustment are fully described in Chapter 3.

monthly leading term NPR_{t+1}. It shows that the estimated coefficient of NPR_{t-1} is positively significant at the 1% significance level. Contemporaneous and leading terms of NPR are all negatively correlated to current market excess returns, while the leading term of NPR is negatively significant at the 1% significance level.

Due to the mechanism of seasonality adjustment one, the performance of NPR_ADJ_1 in models 13-15 is exactly the same as in models 10-12. Models 16-18 use NPR_ADJ_2 as independent variable and the results of the estimated coefficient of $NPR\_ADJ\_2_{t-1}$ is similar to that of models 10-12, but the t-value of the 1-month lagged NPR is better than in models 10-12.

The results of the standardised aggregate net number of director purchase transactions are reported in Appendix E. Models 1-3 use standardised aggregate net number of transactions by all firms (SANP) as independent variable, while models 4-6 utilise the standardised seasonality adjustment one (SANP_ADJ_1) and models 7-9 utilise the standardised seasonality adjustment two (SANP_ADJ_2). The performance of all the standardised aggregate director trading is similar to that in models 1-9, Table 4.1.

In generally, the results presented in Table 4.1 suggest that aggregate director trading can forecast future market excess returns. An increase in current aggregate directors' purchases is associated with an increase in the future excess return of the stock market portfolio one month later. In contrast, the significantly negative contemporaneous or leading coefficients of series variables of aggregate director trading (real and seasonality adjustment measurements) indicate that directors reverse the direction of their transactions after the realisation of the stock price movements. These results show that directors are contrarian: they tend to purchase stock following market decreases and sell stock following market increases. Different measurements of aggregate director trading display similar results but the significant levels of t-values are slightly different.

Furthermore, to examine the forecasting power of aggregate director trading to market excess returns, a further regression was employed. Table 4.2 presents the results of the regression of market excess return on aggregate director trading and regressors, as applied by Pesaran and Timmermann (2000). Newey-West autocorrelation and heteroscedasticity-consistent covariance estimates are applied and two lag terms of the residuals are used to compute the Newey-West covariance matrix.

The dependent variable in the regression is the difference between the monthly returns of the FTSE All Share Index and the 90-day Treasury Bills returns. The independent regressors are: NPR, the aggregate net number of director purchases, JAN is a January dummy (which takes the value of unity in January of each year and zeros elsewhere), YALL is the dividend yield on the FTSE All Share Index, I3 is the 90-day T-bill rate, DI3 = $I3_t$-$I3_{t-1}$, PI is the rate of change of retail prices, DGILT is the change in the yield on a 2.5% government consol, DM0 is the rate of change of the money supply (the narrow definition), DIP is the rate of change in the index of industrial production, and DPSPOT is the rate of change in the spot price of oil.[14]

Models 1 and 2 duplicate the models of Pesaran and Timmermann (2000). Model 1 includes all the regressors with the January dummy, while model 2 includes all the regressors without the January dummy. Consistent with Pesaran and Timmermann (1995, 2000), the 1-month lagged dividend yield (YALL) is positively correlated to current excess returns. This may reflect the mean reversion in returns caused either by investor overreaction or persistent time-varying risk-premia. The rate of change in the index of industrial production (DIP) is positively correlated to the future market excess returns, and the rate of inflation (PI) and growth in the monetary supply (DM0) are all negative coefficients in the excess return regression. The interest rate (I3, DI3) and change in the gilt yield (DGILT) appear to be weakly correlated with future excess returns. All these regressors measure different aspects of the economy's inflation rate. The change in the log of oil prices is negatively correlated with stock returns. However, unlike Pesaran and Timmermann (2000), the significant levels are totally different: only dividend yield of FTSE All Share is significant at the 10% significance level, whilst all other independent variables are insignificant. The January dummy does not show any significance, which is

[14] Definitions and descriptions of these variables are presented in Appendix D.

consistent with the findings of Section 3.3.3, which showed that there is no significant January effect during the sample period from January 1986 to December 2008. Compared with Pesaran and Timmermann (2000), model 1 with the January dummy could only achieve 2.78% adjusted R-square, while the value of adjusted R-square for model 2 without the January dummy is 2.89% (adjusted R-square for the excess return regression without January dummy is 12% in Pesaran and Timmermann's paper).

Models 3 and 4 report the results of adding the aggregate director trading variable (aggregate net number of director purchases ratio, NPR) as independent variable into Pesaran and Timmermann's (2000) model; model 3 includes the January dummy, while model 4 excludes it. It can be seen that the coefficient of NPR in both models is positively significant at the 10% significance level for future excess returns. The performance of the remaining regressors matches those of models 1 and 2. The adjusted R-square is improved from 2.78% (model 1) to 3.43% (model 3), and from 2.89% (model 2) to 3.86% (model 4).

Overall, the results in Tables 4.1 and 4.2 indicate that consistent with previous insider/director studies, aggregate director trading is positively significantly correlated to future excess returns and has the ability to forecast to future market excess returns. Adding aggregate director trading into Pesaran and Timmermann's (2000) model improves the performance of the excess market return regression.

4.4.2 Aggregate Director Trading and Market Returns-Sensitivity Test

The evidence presented in this section uses the regression analysis method to examine the relationships between aggregate director transaction activities and returns to stock market in the long-run. It uses different length of time periods (3-, 6-, 9- and 12-month) to measure the performance of aggregate director transactions. Lakonishok and Lee (2001) explained that the reason for using longer time periods is that calculating director trading measures based on short periods (such as one month), probably results in many companies having no trading activity. Therefore, to obtain a better picture of aggregate director trading, applying a longer time period is rational and valuable.

Tables 4.3 and 4.4 employ regression analysis to examine the relationship between aggregate director trading measured by real data, seasonality adjustments one, two and three, and future market excess returns using buy-and-hold excess returns (BHERs):

$$\prod_{k=t}^{t+m-1}(1+R^{i}) - \prod_{k=t}^{t+m-1}(1+R^{f}) = a_0 + a_1 DT_{(t-n,t-1)}, (35)$$

Where *DT* represents the director trading variables. A summary of cumulative excess returns (CERs) and buy-and-hold excess returns (BHERs) is presented in Appendix F.

Tables 4.3 and 4.4 measure the extent to which different length multi-month aggregate director trading predicts future excess stock returns. The dependent variables are future 3-, 6-, 9- and 12-month excess stock returns, defined as the difference between monthly FTSE All share and the returns on monthly 90-day Treasury Bills using the methodology of BHERs. Seyhun (1992, 1998) calculated excess stock returns for all firms and groups of firms using non-overlapping periods. As discussed by Lakonishok and Lee (2001), the advantage of using this measurement is that it avoids possible problems when testing aggregate insider trading and market returns. However, this procedure introduces another issue: the extremely small number of observations. In this study there are only 276 calendar months from January 1986 to December 2008, therefore if Seyhun's methodology was utilised there would be too few observations in the regression and this would lead unreliable and spurious results. Therefore, this study uses longer time horizons of past director trading data and consequently has overlapping periods. Instead of calculating t-statistics, Newey-West autocorrelation and heteroscedasticity-consistent covariance estimates as suggested by Lakonishok and Lee (2001) will be applied. Two lag terms of the residuals are used to compute the Newey-West covariance matrix.

Tables 4.3 and 4.4 represent the performance of aggregate director trading for all firms after applying the different seasonality adjustment methods. Table 4.3 employs seasonality adjustments one and two to measure director trading, while seasonality adjustment three is utilised to examine director transactions in Table 4.4.[15]

The independent variables in the regression shown in Table 4.3 are the past 3-, 6-, 9- and 12-month aggregate net number of director purchases ratio (NPR) for all firms in Panels A to D, respectively. Panel A presents the regression of future m=3-, 6-, 9- and 12-month market excess returns for the past n=3-month NPR. It can be seen that the coefficients of NPR are all positively correlated to future market excess returns. To forecast the future 6-month excess returns, the coefficients of NPR after different seasonal adjustments are all significant, but others are not. In addition, no trend can be detected demonstrating that longer future excess returns have a better forecasting ability that aggregate director trading has.

Panel B presents the regression of future m=3-, 6-, 9-, and 12-month market excess returns on past n=6-month NPR. It is clear that the longer time periods of future excess returns, the better the explanatory ability of NPR. The coefficients of NPR are all positively correlated to future excess returns. NPR for different seasonality adjustments is all positively significant at the 1% significance level when using past 6-months NPR to forecast the future 12-month excess returns. Among the different seasonality adjustments, seasonality adjustment two results in the best adjusted R-square, while seasonality adjustment one gives the second best. Compared with Panel A, the performance of long-run forecasting ability is much improved in predicting long-run excess returns.

Seyhun (1992) stated: 'if aggregation over time smoothes out the variations in the aggregate insider trading that are not related to future stock returns, then the use of longer horizons to measure aggregate insider trading should lead to increased forecasting ability.' Consequently, coefficients of NPR and adjusted R-square in Panels C and D are expected to be more significant and better than those in Panels A and B.

[15] Details of the seasonality adjustments are fully described in Chapter 3.

Panel C presents the regressions for future m=3-, 6-, 9-, and 12-month market excess returns on past n=9-month NPR. The coefficients of NPR are all positively correlated to future excess returns and are all positively significant at the 1% significance level when using past 9-month NPR to forecast future 9-, and 12-month excess returns. There is a trend that the longer future excess returns, the better the forecasting power of the NPR. The best predicting ability is for the future 12-month excess return following the different seasonality adjustments of NPR; seasonality adjustment two always gives the best performance, while seasonality adjustment one results in the second best. The best adjusted R-square is 22.29% which is observed following seasonality adjustment two.

Panel D presents the regressions for future m=3-, 6-, 9-, and 12-month market excess returns on past n=12-month NPR. The coefficients of NPR are all positively correlated to future excess returns. Furthermore, except for forecasting future 3-month excess returns, the coefficients of NPR are all positively significant at the 1% significance level for the ability to forecast future 6-, 9- and 12-month excess returns. The longer the time horizons of future excess returns, the better the predicting ability of NPR. The best adjusted R-square is for future 12-month excess returns following different seasonal adjustments of the NPR. Consistent with Panels B and C, seasonality adjustment two always results in the best performance, while seasonality adjustment one results in the second best. The best adjusted R-square is achieved by seasonality adjustment two which gives 24.19%.

Consistent with Seyhun (1992), compared to Panels A and B, it can be seen that the long-run forecasting ability of aggregate director trading is dramatically improved in Panels C and D. Generally speaking, the overall results of Table 4.3 show that the coefficients of aggregate director trading are positively correlated to future market excess returns, and the coefficients are also positively significant when using longer time horizons of past aggregate director trading to forecast long-run future market excess returns. In addition, Panels C and D confirm the findings of previous insider/director studies: the longer the length of past aggregate director trading and future excess returns, the better the results, both in terms of significance and forecasting ability. By applying the seasonality measurements, it can be seen that seasonality adjustments one and two give a similar performance to the real director trading activities, but increase the adjusted R-square of the model. Between these two measurements, seasonality adjustment two always has a better forecasting ability than seasonality adjustment one.

Table 4.4 employs seasonality adjustment three [16] to measure aggregate director trading. The dependent variables are future m=3-, 6-, 9- and 12-month excess market returns, defined as the difference between monthly FTSE All share and the returns on monthly 90-day Treasury Bills by applying BHERs methodology. The independent variables are the past n=3-, 6-, 9- and 12-month aggregate net number of director purchases ratio (NPR) of all firms with month dummies[17] in Panels A to D, respectively. Panel A uses the past n=3-month NPR to forecast future excess returns. The coefficients of NPR are all positively correlated to future excess returns and only the NPR to future 6-month excess returns is significant at the 5% significance level (Newey-West t-value is 1.98). Panel B presents the results for the past n=6-month NPR to future excess returns. The coefficients of NPR are all positively correlated to future excess returns and the NPR to future 12-month excess returns is significant at the 1% significance level (Newey-West t-value is 2.63). The best adjusted R-square is 8.49% which can be observed for the future 12-month excess returns. Panel C presents the past n=9-month NPR to future excess returns. The coefficients of NPR are all positively correlated to future excess returns, and the NPR to future 9-month and 12-month excess returns are significant at the 1% significance level. Consistent with Panel B, the best forecasting ability is for future 12-month excess returns with an adjusted R-square of 19.62%. Panel D presents the past 12-month NPR to future excess returns. The coefficients of the past n=12-month NPR are all positively correlated to future excess returns, and the NPR to future 6-, 9- and 12-month market excess returns are significant at the 1% significance level. The best adjusted R-square is 21.48% which is for the future 12-month excess returns.

[16] Details of seasonality adjustment are fully described in Chapter 3.
[17] Details of the month dummy are fully described in Chapter 3.

In generally, the results in Table 4.4 are consistent with the findings in Table 4.3; aggregate director trading is positively correlated to future excess market returns, and there is a trend that the longer the length of both past director trading and future excess returns, the better the forecasting ability of aggregate director trading (the best adjusted R-square is 21.48% which is achieved when using the past 12-month NPR to forecast future 12-month market excess returns). None of the month dummy variables are significant at any level which indicates that the month dummies do not have a significant effect on future market excess returns.

The regression of CERs gives similar results. The robustness tests use different measurements of aggregate director trading as noted in Section 4.3 as independent variables are applied. These tests showed that some measurements of aggregate director trading (ANP, AS, ΔP, PR and SR) give similar results to the NPR while others did not (AP, ΔNPR, ΔPR, ΔSR, ΔNP, ΔS, NPGR, APGR and ASGR).

4.4.3 Aggregate Director Trading and Portfolio Returns by Firm Size

Previous studies in the US found that a small firm effect exists for aggregate insider trading. As mentioned in Section 3.1, firms were classified into 10 size groups by firm capitalisation for each year, and then further defined into large firms, medium-size firms, and small firms. Seyhun (1990) and Lakonishok and Lee (2001) employed this method to study aggregate insider trading activities in long-run studies in the US. The aggregate net number of director purchases ratio (NPR) is applied in this study which has the advantage of not being 'sensitive to changes in the number of firms or trading activity over time. Moreover, the ratio does not display heteroscedasticity or extreme outliers' (Seyhun, 1990). Table 4.5 displays the performance of NPR by different firm size.

The dependent variable in the regression is the difference between the monthly equal- or value-weighted returns of firm size portfolios and the 90-day Treasury Bills returns using the methodology of BHERs. Similar to Table 4.3, the independent variable is past n=3-, 6-, 9- and 12-month NPR for different firm sizes in Panels A to D, respectively. Equal- and value-weighted portfolio excess returns are compared in each panel.

Panel A presents the regression of future m=3-, 6-, 9-, and 12-month portfolio excess returns for the past n=3-month NPR. It can be seen that the coefficients of NPR for different firm sizes are all positively correlated to the future excess returns except for medium firms. The results of the equal-weighted excess returns shows that only the NPR of large firms demonstrates a positive significance at the 10% significance level when forecasting future 6- and 9-month excess returns. The results of the value-weighted excess returns show that except performance of medium firms, the NPR of all firm sizes is positively correlated to future portfolio excess returns, although none of the coefficients of NPR are significant when forecasting future 3-month excess returns. Similar to the equal-weighted excess returns, only the NPR of large firms is significant at the 5% significance level when predicting future 6-month excess returns. In forecasting the future 9-month excess portfolio returns, the NPR for all, large and small firms are positively significant, and the coefficients of large firms is significant at the 5% significance level while all firms and small firms are significant at the 10% significance level. For future 12-month excess returns, the NPRs of all firms and small firms are positively significant at the 5% and 10% significance levels, respectively, and the best predicting ability is 1.97% which is the result for all firms.

Panel B presents the regression of future m=3-, 6-, 9-, and 12-month portfolio excess returns for the past n=6-month NPR. The coefficients of most the NPRs of different sized firms are positively correlated to the future excess returns. The results of the equal-weighted excess returns show that none of the NPRs in firm size classifications are significant. The performance of the NPR on value-weighted excess returns tells another story: for future 3-month excess returns, the coefficients of NPR for all firms is positively significant at the 10% level; for future 6-month excess returns, the coefficients of NPR for all firms and large firms are positively significant at the 10% and 5% significance levels, respectively; for future 9-month excess returns, the coefficients of NPR for all firms and large firms are positively significant at the 5% significance level, while the coefficients of NPR for small firms is significant at the10% significance level;

and for future 12-month excess returns, the coefficients of NPR for all firms is positively significant at 1% with value of adjusted R-square 3.56%, while the NPRs of large firms and small firms are significant at the 10% significance level.

Consistent with the previously studies, the results in Panels A and B indicate that there is a trend that the longer the forecasting horizon, the better the predicting ability of all the firms. Aggregate director trading of large firms shows a strong significant ability to forecast future excess large firm portfolio returns, while past 3-month and 6-month aggregate director trading of small firms does not give more significant results than large firms or all firms.

Panel C presents the regression of future m=3-, 6-, 9-, and 12-month portfolio excess returns for the past n=9-month NPR. Except for medium sized firms, the coefficients of the NPR are positively correlated to the future excess returns. The results of the equal-weighted excess returns show that although the NPR coefficients of medium firms are negatively significant to future 3-, 6-, 9- and 12-month excess portfolio returns, the adjusted R-square demonstrates that the forecasting ability of medium sized firms is very poor. The coefficients of the NPR of all firms, large firms and small firms only result in a positive significant correlation when forecasting future 12-month excess returns: the coefficients of the NPR of large firms and small firms are significant at the 5% significance level, while the coefficients of the NPR of all firms is significant at the 1% significance level with adjusted R-square of 6.33%. The performance of the NPR for value-weighted excess portfolio returns is similar to that of the equal-weighted returns. The coefficients of the NPR of medium sized firms are negatively significant for future excess portfolio returns, whilst all other firm sizes are positively correlated to future excess returns. The NPRs of all firms, large firms and small firms are not significant for future 3- and 6-month excess returns. To predict the future 9-month excess returns, the NPR of all firms is significant at the 5% significance level, while for large firms and small firms it is significant at the 10% significance level. To forecast future 12-month excess returns, the NPR of all firms is significant at the 1% significance level with adjusted R-square of 4.56%, while that of large firms and small firms are significant at the 5% significance level.

Panel D presents the regression of future m=3-, 6-, 9-, and 12-month portfolio excess returns for the past n=12-month NPR. The coefficients of NPR for all firm sizes (except medium sized firms) are positively correlated to the future excess returns. The results of the equal-weighted excess returns show that there is no significance of the NPR in the different firm size groups for future 3- and 6-month excess returns. For future 9-month excess returns, the coefficients of the NPR for all firms, large firms, and small firms are significant at the 1%, 10% and 5% significance levels, respectively. For future 12-month excess returns, the coefficients of NPR for all firms is significant at the 1% significance level with adjusted R-square of 10.27%, while large firms and small firms are significant at the 5% significance level. The performance of the NPRs for value-weighted excess returns shows that for future 3-month excess returns none of the aggregate director trading are significant. Only the coefficients of the NPR for all firms demonstrate significance at the 10% significance level when forecasting future 6-month excess returns. For future 9-month excess returns, the coefficients of NPR for all firms and small firms are significant at the 1% significance level with adjusted R-square of 7.45% and 3.45%, respectively. The NPR of large firms is significant at the 5% significance level with 4.64% adjusted R-square. For future 12-month abnormal returns, the performance of NPR significance is the same as for future 9-month returns, but forecasting ability increases: the adjusted R-square of all firms, large firms and small firms are 7.76%, 4.73% and 4.78%, respectively.

The results of Panels C and D indicate that there is a significant trend that the longer the length of the forecasting time horizon and past director trading, the better the performance of directors. The performance of small firms demonstrates a higher significance and forecasting ability than large firms. Compared to Panels A and B, the performance of the NPR for all firms by equal-weighted excess returns results in a better forecasting ability than for the value-weighted excess returns in Panels C and D.

To conclude, the results in Table 4.5 are consistent with those of other studies, past director trading activities are positively significantly correlated to future portfolios movement: directors purchase (sell) stocks before a market goes up (down). The longer the forecasting horizon and past director trading, the better predicting ability of aggregate director trading achieved. In addition to the small firm effect, the performance of large firms maintains a positively significant correlation to future large firm stock changes. Equal-weighted excess returns have a better predicting ability than value-weighted when longer past director trading is included in forecasting longer time horizons of future excess returns. This is probably caused by the better performance of small firm effects in the long-run. Seasonality measurements of director trading with BHER method were also applied and the results are similar to those presented in Table 4.5.

4.4.4 Aggregate Director Trading in Ten Industries

Sections 4.4.1 and 4.4.2 examined the performance of future market excess returns on past aggregate director trading, while Section 4.4.3 analysed the performance of aggregate director trading for different firm size groups. This section tests the performance of aggregate director trading by industry segmentation using the sample data described in Section 3.1 (60,300 transactions with respect to 1,086 firms from 1994 to 2008). The sample firms are grouped using the ICB 10 classifications:[18] oil and gas (OS), basic materials (BM), industrials (I), consumer goods (CG), health care (HC), consumer services (CS), telecommunications (TC), utilities (U), financials (F), and technology (T). Using the ISIN code provided by HS, DataStream could provide the ICB classification for every single company. For the firms with ISIN codes not recognised by DataStream, the data was collected by hand using relevant information provided by HS, such as company name, director name, etc. For the industries portfolios data, value-weighted industry indices and UK 90-day Treasury Bills were applied as a risk-free rate provided by DataStream. The dependent variable in the regression is the difference between the monthly returns to industry indices and the 90-day Treasury Bills returns using the methodology of BHERs. The independent variables are past aggregate director trading of industries.

18 The Industry Classification Benchmark (ICB) is a definitive system categorizing more than 70,000 companies and 75,000 securities globally. It classifies company listed within a country by 10 industries. They are Oil & Gas, Basic Materials, Industrials, Consumer Goods, Health Care, Consumer Services, Telecommunications, Utilities, Financials, and Technology.

Table 4.6 presents the results, and it applies the aggregate net number of purchases ratio (NPR) among industries to measure aggregate director trading activities. Panel A presents the regression for future m=3-, 6-, 9-, and 12-month industry excess returns for the past n=3-month NPR. The results show that except for performance of consumer services, industrials and utilities, almost the NPR for the remaining industries are all positively correlated to future industries excess returns: for basic materials, the NPR is significant at the 10% significance level when forecasting future 9-month excess industry returns; for financials, the NPR is significant at the 10% and 1% significance levels when predicting future 9- and 12-month excess industry returns, respectively; for health care, the NPR is significant at the 5% significance level when forecasting future 6-month excess industry returns; for oil and gas, the NPR is all significant at least the 10% significance level for future 3-, 6-, 9- and 12-month excess industry returns; and for technology, the NPR is significant at the 1% significance level for future 12-month excess industry returns. The best forecasting ability among industries is obtained by financials, which has adjusted R-square of 6.05% when forecasting the future 12-month financial industry.

Panel B presents the regression for future m=3-, 6-, 9-, and 12-month industry excess returns for the past n=6-month NPR. The results show that except for the performance of consumer services and utilities, most NPRs for the other industries are positively correlated to future industries excess returns: for basic materials, the NPR is significant at the 5% significance level when forecasting future 6-month excess industry returns; for financials, the NPR is significant at the 5% and 1% significance levels when predicting future 9- and 12-month excess industry returns, respectively; for health care, the NPR is significant at the 10% significance level when forecasting future 3- and 6-month excess industry returns; for oil and gas, the NPR is significant at the 1% significance level for future 12-month excess industry returns; and for technology, the NPR is significant at the 1% significance level when predicting future 9- and 12-month industry excess returns. Among these industries, the best forecasting ability is by financials, which has adjusted R-square of 9.29% when forecasting the future 12-month financial industry.

Panel C presents the regression for future m=3-, 6-, 9-, and 12-month industry excess returns for the past n=9-month NPR. The results show that except for the performance of consumer services, health care and utilities, most of the NPR of the remaining industries is positively correlated to future industries excess returns: for basic materials, the NPR is significant at the 10% significance level when forecasting future 6-month excess industry returns; for financials, the NPR is significant at least the 10% significance level when predicting future 6-, 9- and 12-month excess industry returns; for oil and gas, the NPR is significant at least the 5% significance level for future 9- and 12-month excess industry returns; for technology, the NPR is significant at least the 5% significance level when forecasting future 6-, 9- and 12-month excess industry returns; and for telecommunications, the NPR is significant at the 5% significance level when predicting future 12-month industry excess returns. Among all the industries, the best predicting ability is still by financials, which has adjusted R-square of 14.39% when forecasting the future 12-month financial industry.

Panel D presents the regression for future m=3-, 6-, 9-, and 12-month industry excess returns for the past n=12-month NPR. The results show that except for the performance of consumer goods, consumer services, health care and utilities, the NPR of the remaining industries is positively correlated to future industries excess returns: for financials, the NPR is significant at least the 10% significance level when predicting future 6-, 9- and 12-month excess industry returns; and for oil and gas, technology and telecommunications, the NPR is significant at least the 5% significance level for future 6-, 9- and 12-month excess industry returns (NPR of telecommunications is significant at the 5% significance level for future 3-month excess industry returns as well). Among all the industries, the best predicting ability this time was achieved by oil and gas with adjusted R-square of 23.77% when forecasting the future 12-month oil and gas industry.

These findings show that the NPR of consumer goods, consumer services, industrials and utilities are not always positively significantly correlated to future industry excess returns, while that of the remaining industries are. The past 3-, 6-, 9-, and 12-month NPR of financials, oil and gas, and technology are positively significantly correlated to future 9-, and 12-month excess industry returns. The performance of basic materials shows that past 3-, 6- and 9-month aggregate director trading is positively significantly correlated to future 6- or 9-month excess industry returns and the performance of health care illustrates that the past 3- and 6-month NPR is positively significantly correlated to future 6-month excess industry returns. The past 9- and 12-month aggregate director trading of telecommunications is positively significantly correlated to future 12-month excess industry returns. In long-run forecasting, aggregate director trading transactions in financials, oil and gas, technology and telecommunications, are better indicators of future industry excess returns. Hence, other market participants could follow the trading activities among these industries.

Generally speaking, the performance of the NPR of industries to future industry excess returns is consistent with aggregate director trading to future market excess returns. The reason for this is the high correlation between market return and industry returns and the high correlation between the trading activity of directors of all firms and industry firms (Correlations are shown in Appendix G).

4.5 Conclusions

The evidence presented in this study documents a strong relationship between past aggregate director trading and future excess market returns. Considering the seasonality issue in UK director trading by following Seyhun's (1988) methodology, it confirms that aggregate director trading activity in a given month is significantly positively correlated to the return to the market portfolio in next month. The results also show directors are contrarian: they increase their stock purchases prior to an increase in the stock market and decrease their stock purchases following an increase in the stock market. Other models (Seyhun, 1992; Lakonishok and Lee, 2001) have also been applied and these indicate that aggregate director trading have a good ability to forecast future excess market returns in the long-run. Different measurements of director trading were employed but the results do not show large differences after the three seasonality methodologies of director trading were applied.

As mentioned in previous studies, this study includes models which analyse a robust check of the firm size effect of director trading. The results show that the performance of both large firms and small firms are positively significantly correlated to future excess firm size portfolio returns. In the long-run, small firms show a greater significance and better forecasting power than large firms. The results of the robust test of subsample industry are consistent with the findings of aggregate director trading. A plausible reason for this is the high correlation between return of market and industries, and trading activity between all firms and firms within different industries.

In short, aggregate director trading has sufficient power to forecast future market excess returns. The predictability of market excess returns increases with the length of forecasting horizon and the number of months of past director trading. A new finding is that aggregate director trading of large firms is also significant and has as a good a forecasting ability as all firms and small firms for future excess portfolio returns of firm size group.

Figure 4.1 **Monthly aggregate net number of transactions (ANP), aggregate purchases (AP) and aggregate sales (AS) in all firms from January 1986 to December 2008**

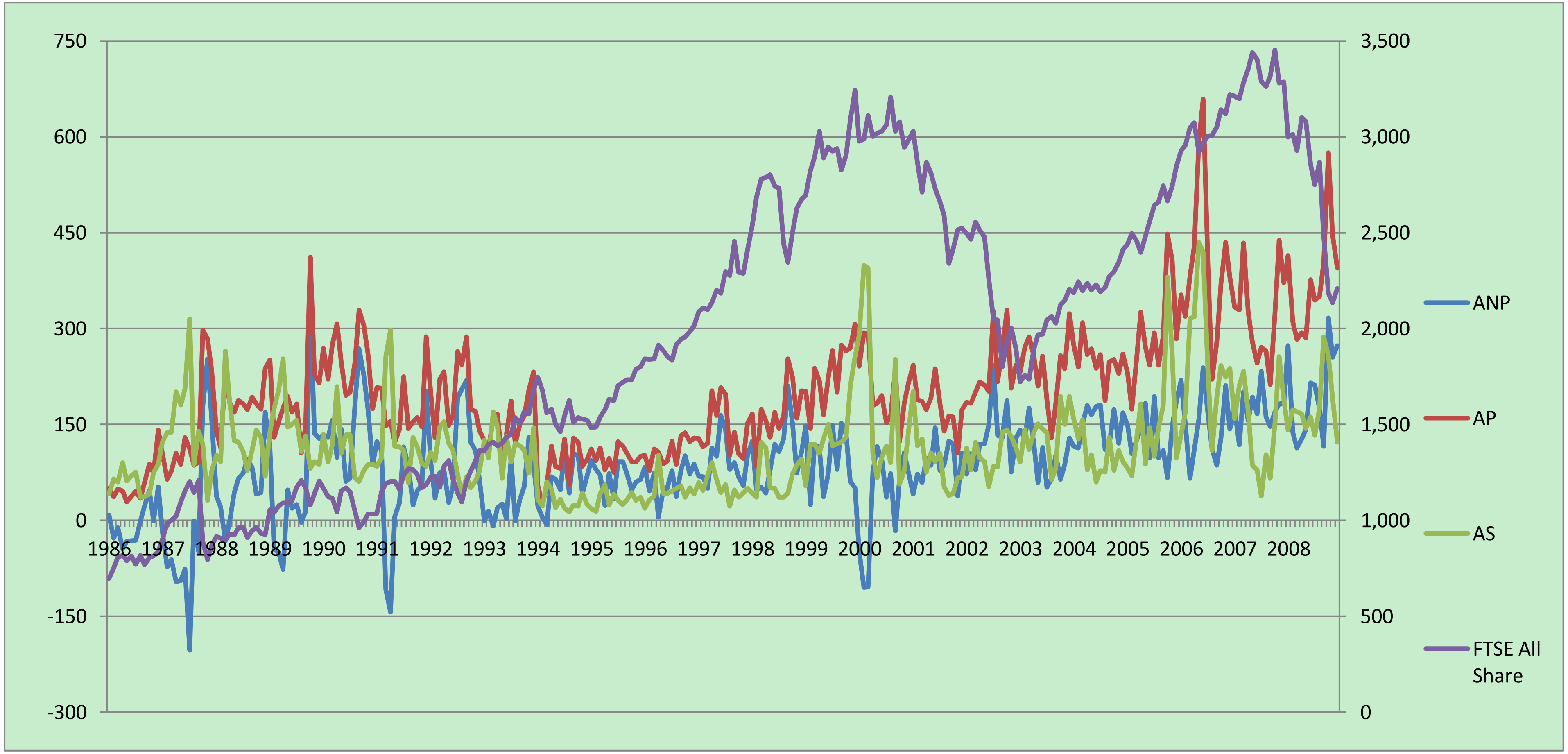

Table 4.1 Regression of the Excess Monthly Market Returns against the leading, Contemporaneous, and Lagged Values of Monthly Aggregate Net Number of Director Purchases (ANP) or Aggregate Net Number of Director Purchases Ratio (NPR) by All Firms

	Constant	ANP_{t+1}	ANP_t	ANP_{t-1}	ANP_{t-2}
1	-0.0045	…	…	0.000053	-0.000007
	(-0.91)			(1.01)	(-0.14)
2	0.003301	…	-0.000275	0.000221	0.000015
	(0.89)		(-4.04)***	(3.68)***	(0.35)
3	0.011935	-0.000289	-0.000102	0.000242	0.000015
	(3.12)***	(-5.55)***	(-1.49)	(4.05)***	(0.35)
	Constant	$ANP\_ADJ\_1_{t+1}$	$ANP\_ADJ\_1_t$	$ANP\_ADJ\_1_{t-1}$	$ANP\_ADJ\_1_{t-2}$
4	-0.00211	…	…	0.000013	-0.0000005
	(-0.44)			(0.50)	(-0.02)
5	0.00438	…	-0.000117	0.000071	0.000009
	(1.16)		(-3.26)***	(2.39)**	(0.30)
6	0.011497	-0.000148	-0.000046	0.000070	0.000033
	(2.89)***	(-4.75)***	(-1.26)	(2.26)**	(1.13)
	Constant	$ANP\_ADJ\_2_{t+1}$	$ANP\_ADJ\_2_t$	$ANP\_ADJ\_2_{t-1}$	$ANP\_ADJ\_2_{t-2}$
7	-0.00302	…	…	0.000044	-0.000019
	(-0.59)			(0.92)	(-0.38)
8	0.00357	…	-0.000226	0.000181	0.000009
	(0.91)		(-3.57)***	(3.24)***	(0.20)
9	0.011089	-0.000269	-0.000069	0.000198	0.000032
	(2.83)***	(-5.34)***	(-1.06)	(3.50)***	(0.72)

Sample periods are 276 months from 1986 to 2008. **ANP** is aggregate net number of director purchases transactions. **ANP_ADJ_1** denotes seasonal adjusted ANP based on December and March fiscal year end by assumption, **ANP_ADJ_2** denotes seasonal adjusted ANP based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. Excess market returns is defined as the actual return to the FTSE All Share index minus the return on the monthly 90-day Treasury Bills. The Newey-West t-statistics of estimated coefficients are shown in parentheses. The symbol *, **, *** presents significant level at the 10%, 5%, 1%, respectively.

Table 4.1 (Continued)

	Constant	NPR_{t+1}	NPR_t	NPR_{t-1}	NPR_{t-2}
10	-0.0078	…	…	0.054	-0.016
	(-0.85)			(1.77)*	(-0.52)
11	0.0002	…	-0.074	0.057	0.016
	(0.05)		(-3.81)***	(2.50)**	(1.12)
12	0.0084	-0.083	-0.024	0.066	0.012
	(1.84)	(-4.84)***	(-1.39)	(3.14)***	(0.85)
	Constant	$NPR\_ADJ\_1_{t+1}$	$NPR\_ADJ\_1_t$	$NPR\_ADJ\_1_{t-1}$	$NPR\_ADJ\_1_{t-2}$
13	-0.0078	…	…	0.054	-0.016
	(-0.85)			(1.77)*	(-0.52)
14	0.0002	…	-0.074	0.057	0.016
	(0.05)		(-3.81)***	(2.50)**	(1.12)
15	0.0084	-0.083	-0.024	0.066	0.012
	(1.84)	(-4.84)***	(-1.39)	(3.14)***	(0.85)
	Constant	$NPR\_ADJ\_2_{t+1}$	$NPR\_ADJ\_2_t$	$NPR\_ADJ\_2_{t-1}$	$NPR\_ADJ\_2_{t-2}$
16	-0.0066	…	…	0.047	-0.012
	(-0.70)			(1.39)	(-0.34)
17	0.0001	…	-0.085	0.069	0.014
	(0.03)		(-3.73)***	(2.60)**	(0.89)
18	0.0082	-0.093	-0.028	0.082	0.010
	(1.82)*	(-4.74)***	(-1.39)	(3.33)***	(0.62)

Sample periods are 276 months from 1986 to 2008. **NPR** denotes monthly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S). **NPR_ADJ_1** denotes seasonal adjusted NPR based on December and March fiscal year end by assumption, **NPR_ADJ_2** denotes seasonal adjusted NPR based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. Excess market returns is defined as the actual return to the FTSE All Share index minus the return on the monthly 90-day Treasury Bills. The Newey-West t-statistics of estimated coefficients are shown in parentheses. The symbol *, **, *** presents significant level at the 10%, 5%, 1%, respectively.

Table 4.2 Regression of the Excess Monthly Market Returns on all the Regressors: Jan 1986 to Dec 2008

Regressors	Model 1	Model 2	Model 3	Model 4
Constant	-0.0170	-0.0169	-0.0175	-0.0175
	(-0.70)	(-0.70)	(-0.79)	(-0.71)
Jan_t	0.0019	…	0.0004	…
	(0.17)		(0.03)	
$YALL_{t-1}$	1.0653	1.0658	0.8767	0.8762
	(1.89)*	(1.89)*	(1.69)*	(1.70)*
$I3_{t-1}$	-1.5223	-1.5181	-0.3019	-0.2976
	(-0.53)	(-0.53)	(-0.10)	(-0.10)
$PI12_{t-2}$	-0.1631	-0.1636	-0.2278	-0.2281
	(-0.57)	(-0.57)	(-0.78)	(-0.79)
$DI3_{t-1}$	5.1106	5.2400	2.8643	2.8829
	(0.48)	(0.49)	(0.26)	(0.27)
$DGILT_{t-1}$	-0.3346	-0.3485	-0.1504	-0.1526
	(-0.26)	(-0.28)	(-0.12)	(-0.12)
$DM012_{t-2}$	-0.0817	-0.0817	-0.1206	-0.1207
	(-0.37)	(-0.37)	(-0.54)	(-0.55)
$DIP12_{t-2}$	0.0841	0.0839	0.0907	0.0907
	(0.56)	(0.56)	(0.60)	(0.60)
$DPSPOT_{t-1}$	-0.0142	-0.0141	-0.0127	-0.0127
	(-0.59)	(-0.59)	(-0.54)	(-0.54)
NPR_{t-1}	…	…	0.0173	0.0173
			(1.71)*	(1.76)*
Adj R^2	0.0278	0.0289	0.0343	0.0386

Sample periods are 276 months from 1986 to 2008. **NPR** denotes monthly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S). Excess market returns is defined as the actual return to the FTSE All Share index minus the return on the monthly 90-day Treasury Bills. YALL is the dividend yield on the FTSE All Share Index, I3 is the 90-day T-bill rate, DI3 = $I3_t$-$I3_{t-1}$, PI is the rate of change of retail prices, DGILT is the change in the yield on a 2.5% government consol, JAN is a January dummy (which takes the value of unity in January of each year and zeros elsewhere), DIP is the rate of change in the index of industrial production, DM0 is the rate of change of the money supply (the narrow definition), and DPSPOT is the rate of change in the spot price of oil. The Newey-West t-statistics of estimated coefficients are shown in parentheses. The symbol *, **, *** presents significant level at the 10%, 5%, 1%, respectively.

Table 4.3 Time Series Regression of Future Excess Market Returns on Past, 3-, 6-, 9- and 12-Month Aggregate Net Number of Director Trading Ratio by All Firms

$$\prod_{k=t}^{t+m-1}(1+R)-\prod_{k=t}^{t+m-1}(1+R^{f})=\alpha_0+\alpha_1 NPR_{(t-n,t-1)}$$

Panel A	n=3 m=3			n=3 m=6			n=3 m=9			n=3 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	-0.0225	0.068	0.0211	-0.0374	0.123	0.0417	-0.0333	0.113	0.0246	-0.0440	0.149	0.0363
	(-1.21)	(1.38)		(-1.61)	(2.02)**		(-1.12)	(1.43)		(-1.28)	(1.57)	
Seasonal	-0.0223	0.067	0.0207	-0.0365	0.119	0.0397	-0.0328	0.110	0.0240	-0.0454	0.152	0.0392
Adj_1	(-1.18)	(1.33)		(-1.55)	(1.94)*		(-1.10)	(1.40)		(-1.33)	(1.63)	
Seasonal	-0.0229	0.064	0.0205	-0.0388	0.117	0.0423	-0.0379	0.118	0.0309	-0.0511	0.159	0.0474
Adj_2	(-1.22)	(1.38)		(-1.65)	(2.06)**		(-1.27)	(1.62)		(-1.48)	(1.81)*	
Panel B	n=6 m=3			n=6 m=6			n=6 m=9			n=6 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	-0.0254	0.081	0.0219	-0.0340	0.113	0.0249	-0.0433	0.144	0.0305	-0.0819	0.271	0.0975
	(-1.13)	(1.28)		(-1.11)	(1.33)		(-1.17)	(1.37)		(-2.32)**	(2.63)***	
Seasonal	-0.0240	0.075	0.0194	-0.0327	0.107	0.0232	-0.0447	0.146	0.0336	-0.0843	0.275	0.1062
Adj_1	(-1.05)	(1.18)		(-1.06)	(1.27)		(-1.22)	(1.44)		(-2.44)**	(2.82)***	
Seasonal	-0.0256	0.074	0.0218	-0.0364	0.112	0.0286	-0.0490	0.150	0.0397	-0.0888	0.271	0.1142
Adj_2	(-1.15)	(1.31)		(-1.21)	(1.46)		(-1.35)	(1.61)		(-2.58)**	(2.96)***	
Panel C	n=9 m=3			n=9 m=6			n=9 m=9			n=9 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	-0.0220	0.069	0.0110	-0.0451	0.145	0.0338	-0.0809	0.261	0.0895	-0.1318	0.428	0.2074
	(-0.82)	(0.88)		(-1.33)	(1.48)		(-2.39)**	(2.64)***		(-5.82)***	(6.39)***	
Seasonal	-0.0206	0.064	0.0097	-0.0441	0.140	0.0340	-0.0807	0.257	0.0941	-0.1312	0.421	0.2168
Adj_1	(-0.77)	(0.83)		(-1.31)	(1.48)		(-2.45)**	(2.74)***		(-5.80)***	(6.63)***	
Seasonal	-0.0228	0.066	0.0125	-0.0473	0.140	0.0387	-0.0844	0.251	0.1006	-0.1349	0.403	0.2229
Adj_2	(-0.88)	(0.97)		(-1.45)	(1.65)		(-2.61)***	(2.92)***		(-5.98)***	(6.66)***	

Table 4.3 (Continued)

Panel D	n=12 m=3			n=12 m=6			n=12 m=9			n=12 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	-0.0362	0.111	0.0301	-0.0811	0.257	0.1046	-0.1282	0.408	0.2123	-0.1473	0.483	0.2265
	(-1.38)	(1.42)		(-2.98)***	(3.12)***		(-6.23)***	(6.47)***		(-5.59)***	(6.51)***	
Seasonal	-0.0351	0.106	0.0303	-0.0787	0.245	0.1055	-0.1256	0.394	0.2192	-0.1445	0.467	0.2346
Adj_1	(-1.37)	(1.41)		(-2.93)***	(3.10)***		(-6.13)***	(6.58)***		(-5.46)***	(6.52)***	
Seasonal	-0.0361	0.101	0.0312	-0.0804	0.233	0.1070	-0.1274	0.372	0.2188	-0.1489	0.449	0.2419
Adj_2	(-1.46)	(1.51)		(-3.08)***	(3.26)***		(-6.23)***	(6.54)***		(-5.71)***	(6.73)***	

Sample periods are 276 months from 1986 to 2008. **NPR** denotes monthly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), **Seasonal Adj_1** denotes seasonal adjusted director trading transactions based on December and March fiscal year end by assumption, **Seasonal Adj_2** denotes seasonal adjusted director trading transactions based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. Excess market returns is defined as buy-and-hold excess returns between the actual return to the FTSE All Share index and the return on the monthly 90-day Treasury Bills. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Table 4.4 Time Series Regression of Future Excess Market Returns on Past 3-Month, 6-Month, 9-Month and 12-Month Aggregate Director Trading by All Firms

$$\prod_{k=t}^{t+m-1}(1+R)-\prod_{k=t}^{t+m-1}(1+R^{f})=\alpha_0+\alpha_1 NPR_{(t-n,t-1)}+D_{1,7}+D_{2,8}+D_{4,10}+D_{5,11}$$

Panel A	n=3		n=3		n=3		n=3	
	m=3		m=6		m=9		m=12	
α_0	-0.027	(-1.45)	-0.041	(-1.70)*	-0.038	(-1.22)	-0.048	(-1.33)
α_1	0.071	(1.42)	0.123	(1.98)**	0.117	(1.45)	0.150	(1.54)
$D_{1,7}$	-0.0029	(-0.23)	0.0081	(0.49)	-0.0061	(-0.36)	0.0099	(0.49)
$D_{2,8}$	-0.0040	(-0.29)	0.0024	(0.15)	-0.0098	(-0.55)	0.0007	(0.03)
$D_{4,10}$	0.0171	(1.41)	0.0066	(0.44)	0.0202	(1.07)	0.0080	(0.42)
$D_{5,11}$	0.0137	(1.19)	0.0033	(0.24)	0.0154	(0.92)	0.0047	(0.25)
Adj R^2	0.0144		0.0276		0.0154		0.0218	
Panel B	n=6		n=6		n=6		n=6	
	m=3		m=6		m=9		m=12	
α_0	-0.029	(-1.30)	-0.038	(-1.21)	-0.047	(-1.26)	-0.087	(-2.42)**
α_1	0.080	(1.27)	0.114	(1.32)	0.143	(1.36)	0.271	(2.63)***
$D_{1,7}$	-0.0030	(-0.23)	0.0090	(0.55)	-0.0030	(-0.17)	0.0164	(0.78)
$D_{2,8}$	-0.0023	(-0.18)	0.0063	(0.40)	-0.0040	(-0.23)	0.0100	(0.50)
$D_{4,10}$	0.0178	(1.42)	0.0067	(0.41)	0.0206	(1.06)	0.0069	(0.39)
$D_{5,11}$	0.0117	(1.00)	0.0008	(0.05)	0.0112	(0.67)	-0.0018	(-0.11)
Adj R^2	0.0142		0.0106		0.0191		0.0849	
Panel C	n=9		n=9		n=9		n=9	
	m=3		m=6		m=9		m=12	
α_0	-0.027	(-0.98)	-0.049	(-1.42)	-0.087	(-2.56)**	-0.138	(-5.70)***
α_1	0.071	(0.90)	0.146	(1.47)	0.265	(2.71)***	0.430	(6.33)***
$D_{1,7}$	-0.0028	(-0.22)	0.0090	(0.54)	-0.0047	(-0.29)	0.0100	(0.54)
$D_{2,8}$	-0.0042	(-0.31)	0.0012	(0.08)	-0.0120	(-0.77)	-0.0003	(-0.01)
$D_{4,10}$	0.0181	(1.44)	0.0095	(0.57)	0.0267	(1.27)	0.0145	(0.83)
$D_{5,11}$	0.0128	(1.07)	0.0050	(0.33)	0.0193	(1.15)	0.0091	(0.59)
Adj R^2	0.0039		0.0197		0.0844		0.1962	
Panel D	n=12		n=12		n=12		n=12	
	m=3		m=6		m=9		m=12	
α_0	-0.040	(-1.55)	-0.086	(-3.11)***	-0.133	(-6.05)***	-0.153	(-5.53)***
α_1	0.111	(1.41)	0.257	(3.12)***	0.408	(6.45)***	0.484	(6.48)***
$D_{1,7}$	0.00001	(0.00)	0.0148	(0.82)	0.0024	(0.16)	0.0124	(0.69)
$D_{2,8}$	-0.0008	(-0.06)	0.0078	(0.53)	-0.0032	(-0.23)	0.0054	(0.32)
$D_{4,10}$	0.0169	(1.37)	0.0063	(0.43)	0.0184	(1.09)	0.0096	(0.56)
$D_{5,11}$	0.0099	(0.86)	-0.0001	(-0.01)	0.0125	(0.82)	0.0054	(0.34)
Adj R^2	0.0203		0.0925		0.2029		0.2148	

Sample periods are 276 months from 1986 to 2008. **NPR** denotes monthly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), Table 4.4 presents performance of aggregate director trading with **Seasonality Adjustment three** which applies method of monthly dummy variables. Method of seasonality adjustment three is fully described in Chapter 3. **$D_{1,7}$** is January and July dummy, which is takes the value of unity in January and July of each year and zeros elsewhere. **$D_{2,8}$** is February and

Table 4.4 (Continued)

August dummy, which is takes the value of unity in February and August of each year and zeros elsewhere. $\mathbf{D_{4,10}}$ is April and October of unity in February and August of each year and zeros elsewhere. $\mathbf{D_{4,10}}$ is April and October dummy, which is takes the value of unity in April and October of each year and zeros elsewhere. $\mathbf{D_{5,11}}$ is May and November dummy, which is takes the value of unity in May and November of each year and zeros elsewhere. Excess market returns is defined as buy-and-hold excess returns between the actual return to the FTSE All Share index and the return on the monthly 90-day Treasury Bills. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Table 4.5 **Time Series Regression of Future Excess Portfolio Returns on Past 3-Month, 6-Month, 9-Month and 12-Month Aggregate Net Director Purchase Ratio**

$$\prod_{k=t}^{t+m-1}(1+R^{i})-\prod_{k=t}^{t+m-1}(1+R^{f})=\alpha_0+\alpha_1 NPR^{j}_{(t-n,t-1)}$$

Panel A		n=3 m=3			n=3 m=6			n=3 m=9			n=3 m=12		
(i,j)		α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
EW	A,A	-0.015	0.040	0.0022	-0.037	0.116	0.0180	-0.042	0.117	0.0112	-0.033	0.087	0.0030
		(-0.64)	(0.64)		(-1.25)	(1.51)		(-1.20)	(1.26)		(-0.76)	(0.73)	
	L,L	-0.007	0.022	-0.0029	-0.028	0.123	0.0079	-0.044	0.172	0.0131	-0.036	0.194	0.0111
		(-0.37)	(0.58)		(-0.95)	(1.95)*		(-1.30)	(1.92)*		(-0.90)	(1.37)	
	M,M	-0.017	0.005	-0.0034	-0.026	0.018	-0.0023	-0.045	0.016	-0.0031	-0.045	0.002	-0.0037
		(-1.19)	(0.37)		(-1.08)	(0.83)		(-1.41)	(0.50)		(-1.25)	(0.05)	
	S,S	-0.044	0.054	-0.0009	-0.087	0.104	0.0011	-0.119	0.196	0.0056	-0.136	0.244	0.0065
		(-1.12)	(0.56)		(-1.58)	(0.77)		(-1.88)*	(1.31)		(-1.77)*	(1.38)	
VW	A,A	-0.024	0.092	0.0060	-0.026	0.130	0.0048	-0.055	0.221	0.0113	-0.061	0.317	0.0197
		(-0.98)	(1.50)		(-0.82)	(1.59)		(-1.44)	(1.97)*		(-1.33)	(2.19)**	
	L,L	-0.004	0.055	0.0015	-0.021	0.159	0.0152	-0.033	0.224	0.0217	-0.020	0.226	0.0155
		(-0.23)	(1.51)		(-0.73)	(2.53)**		(-0.93)	(2.32)**		(-0.50)	(1.62)	
	M,M	-0.016	0.004	-0.0035	-0.021	0.017	-0.0025	-0.040	0.007	-0.0036	-0.042	-0.004	-0.0037
		(-1.09)	(0.31)		(-0.86)	(0.81)		(-1.28)	(0.25)		(-1.22)	(-0.10)	
	S,S	-0.045	0.060	0.0000	-0.085	0.109	0.0017	-0.129	0.247	0.0098	-0.145	0.292	0.0103
		(-1.24)	(0.68)		(-1.67)	(0.86)		(-2.23)**	(1.69)*		(-1.98)**	(1.68)*	

Table 4.5 (Continued)

Panel B (i,j)		n=6 m=3 α_0	α_1	Adj R^2	n=6 m=6 α_0	α_1	Adj R^2	n=6 m=9 α_0	α_1	Adj R^2	n=6 m=12 α_0	α_1	Adj R^2
EW	A,A	-0.024	0.069	0.0091	-0.036	0.111	0.0112	-0.042	0.112	0.0066	-0.063	0.182	0.0182
		(-0.86)	(0.90)		(-0.98)	(1.09)		(-0.95)	(0.89)		(-1.31)	(1.25)	
	L,L	-0.011	0.039	-0.0018	-0.024	0.113	0.0034	-0.045	0.177	0.0092	-0.042	0.216	0.0096
		(-0.51)	(0.75)		(-0.74)	(1.51)		(-1.17)	(1.51)		(-0.99)	(1.41)	
	M,M	-0.017	0.005	-0.0033	-0.024	0.012	-0.0028	-0.044	0.008	-0.0035	-0.046	-0.004	-0.0037
		(-1.24)	(0.50)		(-1.01)	(0.64)		(-1.37)	(0.25)		(-1.25)	(-0.11)	
	S,S	-0.055	0.080	0.0011	-0.095	0.121	0.0013	-0.139	0.239	0.0070	-0.170	0.315	0.0096
		(-1.25)	(0.71)		(-1.51)	(0.77)		(-1.80)*	(1.26)		(-2.00)**	(1.50)	
VW	A,A	-0.039	0.144	0.0138	-0.041	0.184	0.0088	-0.076	0.292	0.0158	-0.109	0.477	0.0356
		(-1.48)	(1.94)*		(-1.17)	(1.84)*		(-1.76)*	(2.13)**		(-2.22)**	(2.77)***	
	L,L	-0.007	0.067	0.0020	-0.019	0.153	0.0089	-0.034	0.233	0.0161	-0.036	0.287	0.0188
		(-0.33)	(1.34)		(-0.58)	(2.05)**		(-0.90)	(1.98)**		(-0.84)	(1.90)*	
	M,M	-0.016	0.005	-0.0033	-0.019	0.012	-0.0028	-0.041	0.005	-0.0037	-0.044	-0.006	-0.0036
		(-1.16)	(0.51)		(-0.81)	(0.69)		(-1.31)	(0.16)		(-1.25)	(-0.18)	
	S,S	-0.054	0.079	0.0013	-0.097	0.135	0.0027	-0.158	0.314	0.0134	-0.190	0.391	0.0455
		(-1.31)	(0.75)		(-1.66)*	(0.91)		(-2.18)**	(1.67)*		(-2.33)**	(1.86)*	

Table 4.5 (Continued)

Panel C		n=9 m=3			n=9 m=6			n=9 m=9			n=9 m=12		
(i,j)		α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
EW	A,A	-0.019	0.052	0.0019	-0.031	0.089	0.0038	-0.065	0.182	0.0179	-0.118	0.349	0.0633
		(-0.60)	(0.56)		(-0.73)	(0.72)		(-1.46)	(1.36)		(-3.15)***	(3.00)***	
	L,L	-0.002	0.008	-0.0037	-0.012	0.060	-0.0021	-0.037	0.141	0.0028	-0.053	0.250	0.0208
		(-0.11)	(0.13)		(-0.36)	(0.73)		(-1.01)	(1.33)		(-1.35)	(2.00)**	
	M,M	-0.013	-0.010	-0.0010	-0.015	-0.024	0.0012	-0.035	-0.038	0.0029	-0.047	-0.024	-0.0015
		(-1.00)	(-2.26)**		(-0.66)	(-3.22)***		(-1.15)	(-3.04)***		(-1.39)	(-1.71)*	
	S,S	-0.076	0.130	0.0067	-0.121	0.180	0.0055	-0.167	0.297	0.0101	-0.232	0.451	0.0391
		(-1.64)	(1.12)		(-1.79)*	(1.08)		(-2.13)**	(1.53)		(-2.94)***	(2.18)**	
VW	A,A	-0.035	0.134	0.0080	-0.034	0.156	0.0033	-0.094	0.345	0.0276	-0.149	0.603	0.0456
		(-1.12)	(1.42)		(-0.84)	(1.27)		(-2.08)**	(2.37)**		(-3.24)***	(3.63)***	
	L,L	0.001	0.041	-0.0021	-0.007	0.107	0.0012	-0.024	0.188	0.0067	-0.042	0.304	0.0267
		(0.04)	(0.70)		(-0.22)	(1.30)		(-0.65)	(1.76)*		(-1.03)	(2.44)**	
	M,M	-0.012	-0.010	-0.0012	-0.010	-0.024	0.0011	-0.032	-0.040	0.0036	-0.045	-0.025	-0.0013
		(-0.92)	(-2.20)**		(-0.44)	(-3.26)***		(-1.07)	(-3.29)***		(-1.38)	(-1.80)*	
	S,S	-0.071	0.121	0.0059	-0.118	0.182	0.0059	-0.174	0.344	0.0132	-0.237	0.492	0.0322
		(-1.63)	(1.11)		(-1.82)*	(1.13)		(-2.34)**	(1.82)*		(-3.15)***	(2.44)**	

Table 4.5 (Continued)

Panel D (i,j)		n=12 m=3 α_0	α_1	Adj R^2	n=12 m=6 α_0	α_1	Adj R^2	n=12 m=9 α_0	α_1	Adj R^2	n=12 m=12 α_0	α_1	Adj R^2
EW	A,A	-0.022	0.057	0.0022	-0.059	0.172	0.0215	-0.122	0.355	0.0721	-0.156	0.470	0.1027
		(-0.66)	(0.57)		(-1.46)	(1.41)		(-3.83)***	(3.54)***		(-4.56)***	(4.55)***	
	L,L	-0.005	0.011	-0.0037	-0.018	0.075	-0.0016	-0.056	0.201	0.0281	-0.064	0.294	0.0437
		(-0.21)	(0.17)		(-0.60)	(0.81)		(-1.73)	(1.90)*		(-1.57)	(2.15)**	
	M,M	0.011	-0.085	0.0064	0.002	-0.081	-0.0008	-0.055	0.010	-0.0038	-0.062	0.017	-0.0038
		(0.31)	(-0.94)		(0.04)	(-0.61)		(-1.05)	(0.06)		(-1.11)	(0.09)	
	S,S	-0.091	0.160	0.0100	-0.161	0.266	0.0141	-0.240	0.460	0.0455	-0.286	0.572	0.0582
		(-1.85)*	(1.30)		(-2.49)**	(1.60)		(-3.46)***	(2.47)**		(-3.53)***	(2.60)**	
VW	A,A	-0.041	0.149	0.0089	-0.060	0.239	0.0103	-0.136	0.477	0.0745	-0.170	0.672	0.0776
		(-1.31)	(1.49)		(-1.55)	(1.79)*		(-3.26)***	(3.31)***		(-3.28)***	(3.72)***	
	L,L	-0.004	0.055	-0.0011	-0.013	0.125	0.0021	-0.041	0.247	0.0464	-0.053	0.350	0.0473
		(-0.18)	(0.87)		(-0.46)	(1.36)		(-1.24)	(2.23)**		(-1.24)	(2.61)**	
	M,M	0.011	-0.083	0.0053	0.010	-0.089	-0.0003	-0.043	-0.016	-0.0038	-0.051	-0.012	-0.0038
		(0.31)	(-0.92)		(0.20)	(-0.68)		(-0.86)	(-0.10)		(-0.93)	(-0.07)	
	S,S	-0.086	0.153	0.0097	-0.154	0.260	0.0135	-0.233	0.474	0.0345	-0.278	0.583	0.0478
		(-1.90)*	(1.34)		(-2.50)**	(1.61)		(-3.60)***	(2.62)***		(-3.69)***	(2.76)***	

Table 4.5 (Continued)

Sample periods are 276 months from 1986 to 2008. **NPR** denotes monthly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), Excess portfolio returns is defined as buy-and-hold excess returns between the actual return to the sample firm portfolios and the return on the monthly 90-day Treasury Bills. **EW** is equal-weighted buy-and-hold excess returns. **VW** is value-weighted buy-and-hold excess returns. **A,A** presents buy-and-hold excess returns of all sample firms with NPR of all sample firms. **L,L** presents buy-and-hold excess returns of large sample firms with NPR of large sample firms. **M,M** presents buy-and-hold excess returns of medium sample firms with NPR of medium sample firms. **S,S** presents buy-and-hold excess returns of small sample firms with NPR of small sample firms. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Table 4.6 Time Series Regression of Future Excess Market Returns on Past 3-Month, 6-Month, 9-Month and 12-Month Aggregate Net Director Purchases Ratio by ICB 10 industry classifications

$$\prod_{k=t}^{t+m-1}(1+R^{i})-\prod_{k=t}^{t+m-1}(1+R^{f})=\alpha_0+\alpha_1 NPR^{j}_{(t-n,t-1)}$$

Panel A	n=3 m=3			n=3 m=6			n=3 m=9			n=3 m=12		
I,j	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
BM	-0.0089	0.02621	-0.0010	-0.0225	0.09417	0.0275	-0.0168	0.12141	0.0309	0.0210	0.07183	0.0038
	(-0.33)	(0.66)		(-0.60)	(1.61)		(-0.38)	(1.82)*		(0.39)	(0.85)	
CG	-0.0135	0.03044	-0.0023	-0.0371	0.09030	0.0093	-0.0520	0.13503	0.0173	-0.0268	0.09175	0.0038
	(-0.46)	(0.56)		(-0.88)	(1.16)		(-0.96)	(1.37)		(-0.52)	(0.95)	
CS	-0.0037	-0.02239	-0.0024	-0.01202	-0.00888	-0.0056	-0.0236	0.03024	-0.0042	-0.0152	0.00615	-0.0060
	(-0.22)	(-0.43)		(-0.47)	(-0.13)		(-0.64)	(0.41)		(-0.33)	(0.07)	
F	0.0047	-0.01015	-0.0055	-0.0045	0.02854	-0.0046	-0.0530	0.15790	0.0196	-0.1019	0.29589	0.0605
	(0.18)	(-0.17)		(-0.12)	(0.33)		(-1.29)	(1.67)*		(-2.04)**	(2.62)***	
HC	-0.0047	0.01789	0.0008	-0.0230	0.06858	0.0490	0.0035	0.02941	0.0002	0.0114	0.03031	-0.0017
	(-0.36)	(0.86)		(-1.21)	(2.33)**		(0.13)	(0.76)		(0.30)	(0.54)	
I	0.0213	-0.07109	0.0092	-0.0019	-0.02015	-0.0053	-0.0143	0.01398	-0.0058	0.0101	-0.04003	-0.0050
	(0.94)	(-1.16)		(-0.04)	(-0.21)		(-0.26)	(0.12)		(0.16)	(-0.28)	
OS	-0.0203	0.05310	0.0373	-0.0133	0.06453	0.0325	0.0069	0.06107	0.0174	-0.0080	0.11495	0.0538
	(-1.10)	(2.36)**		(-0.49)	(1.97)*		(0.24)	(1.66)*		(-0.22)	(2.47)**	
T	-0.0139	-0.02640	-0.0036	-0.0349	0.00719	-0.0058	-0.0925	0.15017	0.0159	-0.1410	0.27396	0.0516
	(-0.41)	(-0.53)		(-0.60)	(0.08)		(-1.41)	(1.51)		(-2.11)**	(2.72)***	
TC	-0.0165	0.02701	0.0026	0.0053	0.00361	-0.0058	0.0219	-0.00020	-0.0060	0.0022	0.06033	0.0008
	(-0.66)	(0.85)		(0.13)	(0.07)		(0.38)	(-0.00)		(0.03)	(0.63)	
U	0.0100	-0.00267	-0.0054	0.0297	-0.01526	0.0002	0.0552	-0.03530	0.0130	0.0809	-0.04679	0.0141
	(0.73)	(-0.18)		(1.39)	(-0.66)		(2.06)**	(-1.16)		(2.24)**	(-1.13)	

Table 4.6 (Continued)

Panel B	n=6 m=3			n=6 m=6			n=6 m=9			n=6 m=12		
i,j	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
BM	-0.0265	0.07312	0.0202	-0.0438	0.15315	0.0553	-0.0205	0.14076	0.0290	0.0182	0.08594	0.0037
	(-0.85)	(1.36)		(-1.08)	(2.12)**		(-0.39)	(1.52)		(0.29)	(0.76)	
CG	-0.0155	0.03614	-0.0028	-0.0494	0.11987	0.0111	-0.0331	0.10305	0.0026	-0.0122	0.06393	-0.0032
	(-0.50)	(0.57)		(-1.10)	(1.34)		(-0.58)	(0.93)		(-0.22)	(0.54)	
CS	0.0037	-0.05170	0.0067	-0.00697	-0.02887	-0.0042	-0.0090	-0.01988	-0.0056	-0.0054	-0.03175	-0.0052
	(0.20)	(-0.80)		(-0.24)	(-0.36)		(-0.22)	(-0.20)		(-0.11)	(-0.25)	
F	0.0001	-0.00119	-0.0059	-0.0389	0.10148	0.0052	-0.1160	0.29790	0.0557	-0.1657	0.43787	0.0929
	(0.00)	(-0.02)		(-0.99)	(1.04)		(-2.40)**	(2.51)**		(-2.84)***	(2.98)***	
HC	-0.0230	0.05554	0.0321	-0.0214	0.06514	0.0233	-0.0005	0.03644	-0.0004	0.0209	0.00617	-0.0061
	(-1.31)	(1.89)*		(-0.94)	(1.82)*		(-0.01)	(0.69)		(0.50)	(0.09)	
I	0.0077	-0.03890	-0.0031	-0.0128	0.01096	-0.0059	-0.0084	0.00576	-0.0061	-0.0101	0.01232	-0.0061
	(0.24)	(-0.44)		(-0.23)	(0.08)		(-0.12)	(0.03)		(-0.12)	(0.06)	
OS	-0.0183	0.04863	0.0158	-0.0111	0.05919	0.0129	-0.0155	0.09737	0.0283	-0.0595	0.19484	0.0884
	(-0.64)	(1.29)		(-0.29)	(1.10)		(-0.35)	(1.51)		(-1.23)	(2.74)***	
T	-0.0205	-0.00659	-0.0058	-0.0767	0.12503	0.0093	-0.1489	0.30865	0.0571	-0.1867	0.38565	0.0730
	(-0.55)	(-0.10)		(-1.42)	(1.44)		(-2.40)**	(2.85)***		(-2.45)**	(2.95)***	
TC	-0.0134	0.02100	-0.0020	0.0004	0.00990	-0.0056	-0.0079	0.04683	-0.0013	-0.0482	0.14060	0.0227
	(-0.45)	(0.53)		(0.01)	(0.14)		(-0.12)	(0.48)		(-0.61)	(1.22)	
U	0.0110	-0.00692	-0.0038	0.0308	-0.02143	0.0031	0.0613	-0.04973	0.0218	0.0795	-0.04327	0.0066
	(0.74)	(-0.38)		(1.38)	(-0.77)		(2.11)**	(-1.29)		(2.01)**	(-0.84)	

Table 4.6 (Continued)

Panel C	n=9 m=3			n=9 m=6			n=9 m=9			n=9 m=12		
i,j	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
BM	-0.0316	0.09098	0.0278	-0.0369	0.14678	0.0415	-0.0089	0.12010	0.0152	0.0168	0.09812	0.0045
	(-0.99)	(1.56)		(-0.83)	(1.77)*		(-0.16)	(1.16)		(0.26)	(0.79)	
CG	-0.0280	0.06377	0.0012	-0.0301	0.08391	0.0001	-0.0068	0.04767	-0.0049	0.0172	-0.00045	-0.0063
	(-0.85)	(0.89)		(-0.66)	(0.87)		(-0.11)	(0.37)		(0.28)	(-0.00)	
CS	0.0045	-0.05944	0.0062	0.00024	-0.05705	-0.0008	-0.0035	-0.04512	-0.0041	-0.0095	-0.01979	-0.0060
	(0.24)	(-0.90)		(0.01)	(-0.64)		(-0.08)	(-0.38)		(-0.18)	(-0.14)	
F	-0.0143	0.02881	-0.0046	-0.0819	0.19759	0.0270	-0.1604	0.39710	0.0800	-0.2429	0.61124	0.1439
	(-0.43)	(0.34)		(-1.98)**	(1.85)*		(-2.90)***	(2.78)***		(-3.95)***	(3.91)***	
HC	-0.0098	0.02761	0.0010	-0.0094	0.04019	0.0021	0.0236	-0.01778	-0.0052	0.0461	-0.05201	-0.0006
	(-0.60)	(1.01)		(-0.40)	(1.01)		(0.77)	(-0.35)		(1.22)	(-0.77)	
I	0.0001	-0.01705	-0.0056	-0.0071	0.00101	-0.0061	-0.0207	0.03964	-0.0055	-0.0800	0.19687	0.0068
	(0.00)	(-0.16)		(-0.11)	(0.01)		(-0.27)	(0.19)		(-0.77)	(0.74)	
OS	-0.0196	0.05086	0.0131	-0.0307	0.09331	0.0315	-0.0553	0.16270	0.0684	-0.1075	0.27390	0.1377
	(-0.62)	(1.14)		(-0.70)	(1.45)		(-1.20)	(2.30)**		(-2.18)**	(3.58)***	
T	-0.0515	0.07987	0.0043	-0.1177	0.24082	0.0358	-0.1861	0.39748	0.0726	-0.2408	0.50267	0.0988
	(-1.30)	(1.12)		(-2.02)**	(2.36)**		(-2.54)**	(3.00)***		(-2.82)***	(3.25)***	
TC	-0.0232	0.03744	0.0051	-0.0359	0.07022	0.0107	-0.0690	0.14817	0.0369	-0.1164	0.25717	0.0802
	(-0.81)	(0.92)		(-0.73)	(0.97)		(-1.06)	(1.49)		(-1.57)	(2.28)**	
U	0.0092	-0.00521	-0.0050	0.0301	-0.02057	0.0007	0.0561	-0.03826	0.0072	0.0752	-0.03292	-0.0003
	(0.61)	(-0.26)		(1.35)	(-0.68)		(1.89)*	(-0.89)		(1.91)*	(-0.59)	

Table 4.6 (Continued)

Panel D	n=12 m=3			n=12 m=6			n=12 m=9			n=12 m=12		
i,j	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
BM	-0.0255	0.08092	0.0173	-0.0255	0.12202	0.0225	-0.0015	0.10702	0.0085	0.0215	0.09556	0.0026
	(-0.77)	(1.31)		(-0.56)	(1.39)		(-0.03)	(0.97)		(0.32)	(0.73)	
CG	0.0066	-0.00770	-0.0060	0.0195	-0.02459	-0.0058	0.0423	-0.06183	-0.0046	0.0893	-0.16312	0.0049
	(0.19)	(-0.10)		(0.38)	(-0.21)		(0.68)	(-0.45)		(1.31)	(-1.06)	
CS	0.0058	-0.06357	0.0056	-0.00005	-0.05916	-0.0013	-0.0095	-0.02406	-0.0058	-0.0182	0.01387	-0.0063
	(0.30)	(-0.94)		(-0.00)	(-0.58)		(-0.21)	(-0.19)		(-0.33)	(0.09)	
F	-0.0370	0.08052	0.0027	-0.1047	0.24834	0.0371	-0.2099	0.50903	0.1098	-0.3311	0.80926	0.2092
	(-1.02)	(0.87)		(-2.07)**	(1.89)*		(-3.49)***	(3.37)***		(-5.88)***	(6.13)***	
HC	-0.0097	0.02751	-0.0003	0.0036	0.00945	-0.0058	0.0366	-0.05063	0.0005	0.0710	-0.11177	0.0159
	(-0.53)	(0.86)		(0.15)	(0.23)		(1.29)	(-0.96)		(2.03)**	(-1.70)*	
I	0.0059	-0.03075	-0.0049	-0.0130	0.01509	-0.0061	-0.0662	0.15891	0.0042	-0.1194	0.30184	0.0208
	(0.16)	(-0.29)		(-0.22)	(0.09)		(-0.80)	(0.74)		(-1.12)	(1.12)	
OS	-0.0350	0.07861	0.0338	-0.0693	0.15770	0.0850	-0.1010	0.23838	0.1287	-0.1771	0.38833	0.2377
	(-1.05)	(1.61)		(-1.61)	(2.45)**		(-2.25)**	(3.46)***		(-3.54)***	(5.00)***	
T	-0.0670	0.12142	0.0144	-0.1392	0.27978	0.0443	-0.2224	0.45805	0.0922	-0.2685	0.53806	0.1058
	(-1.56)	(1.54)		(-2.04)**	(2.21)**		(-2.80)***	(2.96)***		(-2.99)***	(3.08)***	
TC	-0.0468	0.07928	0.0409	-0.0840	0.15275	0.0695	-0.1224	0.24127	0.1024	-0.1696	0.35619	0.1515
	(-1.73)*	(2.00)**		(-1.92)*	(2.25)**		(-2.14)**	(2.66)***		(-2.45)**	(3.44)***	
U	0.0084	-0.00088	-0.0061	0.0245	-0.00315	-0.0061	0.0489	-0.01867	-0.0034	0.0632	0.00262	-0.0064
	(0.57)	(-0.04)		(1.12)	(-0.10)		(1.71)*	(-0.41)		(1.66)*	(0.05)	

Table 4.6 (Continued)

Sample periods are 276 months from 1986 to 2008. **NPR** denotes monthly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), Excess market returns is defined as buy-and-hold excess returns between the actual return to the FTSE ICB 10 industry indices and the return on the monthly 90-day Treasury Bills. **BM** denotes buy-and-hold excess returns of index of Basic Material with NPR of Basic Material firms. **CG** denotes buy-and-hold excess returns of index of Consumer Goods with NPR of Consumer Goods firms. **CS** denotes buy-and-hold excess returns of index of Consumer Services with NPR of Consumer Services firms. **F** denotes buy-and-hold excess returns of index of Financials with NPR of Financials firms. **HC** denotes buy-and-hold excess returns of index of Health Care with NPR of Health Care firms. **I** denotes buy-and-hold excess returns of index of Industrials with NPR of Industrials firms. **OS** denotes buy-and-hold excess returns of index of Oil & Gas with NPR of Oil & Gas firms. **T** denotes buy-and-hold excess returns of index of Technology with NPR of Technology firms. **TC** denotes buy-and-hold excess returns of index of Telecommunications with NPR of Telecommunications firms. **U** denotes buy-and-hold excess returns of index of Utilities with NPR of Utilities firms. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Chapter 5: Aggregate Director Trading and Macroeconomy

5.1 Introduction

As discussed and analysed in Chapter 4, director trading could forecast future market excess returns. Furthermore, economic theory and empirical evidence suggest that stock prices reflect expectations about future corporate earnings and that stock prices are valuable indicators of economic activity. This chapter will therefore investigate the relationship between director trading and a series of macroeconomic variables related to the state of the UK macroeconomy.

Aggregate director trading can be used as a measurement of 'business confidence' due to the cash flow hypothesis established by Seyhun (1992). This postulates that directors can predict future cash flows in their own firms earlier than other market participants. If changes in a firm's cash flows are due to future economy-wide activity, directors in all firms will observe similar signals in their own firms, and will trade their own firms in the same direction. After a while, as changes in economy-wide cash flows are recognised by other market participants, the stock prices of all firms will tend to adjust. Hence, aggregate insider trading will predict the future stock returns and future real activity. Figure 5.1 illustrates this logic, showing that aggregated director trading has the ability to predict future excess market returns, as discussed in Chapter 4. And previous literature indicates that the market index is a leading indicator of changes to macroeconomy. In this chapter, it will therefore investigate whether aggregate director trading can contribute to the forecasting of variables such as market returns, which in turn allow us to predict changes in GDP. Another indicator examined in this chapter is the industrial trends survey data provided by Confederation of British Industry (CBI business confidence), which is treated as a measurement of 'business confidence' in the UK economy. This chapter also analyses this CBI business confidence variable to investigate whether it forms a key predictor of the performance of the economy.

Section 5.2 presents the data sources. These sources relate to the aggregate economy activities and business cycle. It includes data such as nominal and real GDP, industrial trends survey data provided by Confederation of British Industry (CBI business confidence), index of industrial production, dividend yield of FTSE All Share and TERM spread, etc.

Section 5.3 describes the methodology, and introduces the Fama-French 3 factors and multicollinearity test.

Section 5.4 presents the empirical results. Sensitivity test is applied. It then employs models with aggregate director trading, Fama-French 3-factor and business cycle variables to predict future aggregate economic change.

Finally, Section 5.5 summarises the results and concludes the chapter.

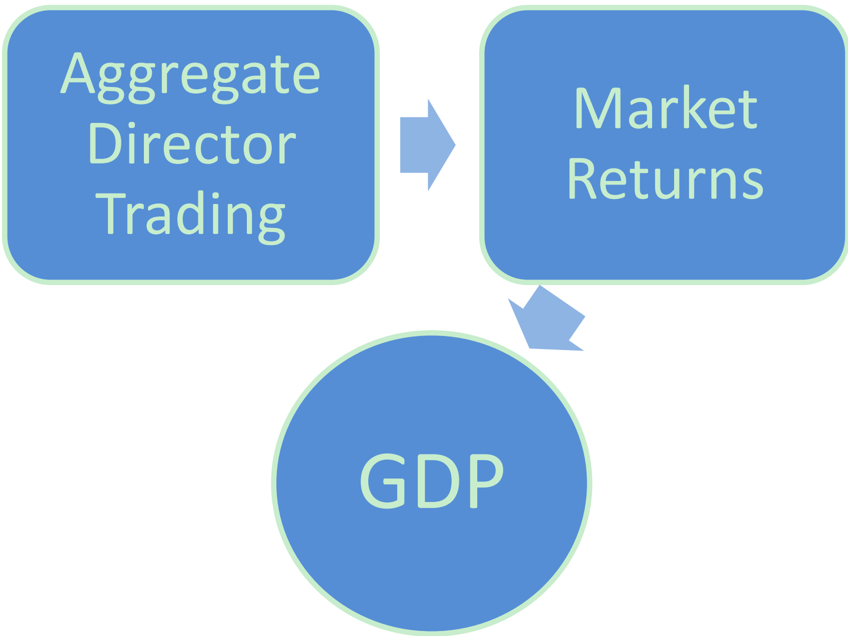

Figure 5.1 Links between aggregate director trading, future market returns and future GDP growth

5.2 Data

The sources for aggregate director trading data are fully described in Chapter 3. Data on Monthly/Quarterly FTSE All Share returns, the 90-day UK Treasury Bill rate (as risk-free interest rate), the yield to maturity of UK 10-year government bond (as long-run rate) and dividend yield of FTSE All Share are obtained from the files of LSPD and dataset DataStream. Furthermore, the firm capitalisation and book-to-market value are collected via both LSPD and DataStream.

For macroeconomic variables, the majority of UK data can be accessed from Office for National Statistics (ONS, http://www.ons.gov.uk/ons/index.html). From the official website of ONS, I can obtain quarterly nominal UK GDP from 1955 Q1 to 2010 Q3 (annual GDP is available from 1948 to 2009). Ticker YBHA offers data on seasonal adjusted GDP at current market prices (Unit: £Million). Real GDP is normally calculated by applying Consumer Price Inflation (CPI); however, CPI data is available only from January 1988 onwards. Therefore, I use Retail Prices Index (RPI) rather than CPI to calculate inflation. There are two tickers used for verification purposes: ticker CHAW denotes RPI of all items index (13 January 1987=100), while CZBH represents RPI of all items percentage change over 12 months. Monthly, quarterly and annual indices of production are available from 1980 to the present day (2006=100), ticker CKYW presents a seasonally adjusted index of total production industries. Term spread is calculated according to the methodology used by Hardouvelis (1994), subtracting the 90-day UK Treasury Bill rate on last business day of the quarter from the yield to maturity of UK 10-year government bond.

In addition to aggregate director trading, it will also use industrial trends survey data provided by Confederation of British Industry (CBI business confidence) as another measurement of business confidence. The time range of CBI business confidence data is from 1986 Q1 to 2009 Q4. To compile this survey data, respondents are asked the question: ‘Are you more or less optimistic than you were three months ago about the general business situation in your industry?’, to which they can answer ‘more’, ‘the same’ or ‘less’. Finally, the balanced result is calculated by subtracting the weighted percentage of firms saying that they are less optimistic from those who are more optimistic.[19]

To check the macro effect, 3 macro-environment variables are also used: business cycle, growth rate cycle, and depression periods. The first two

19 Many thanks to Confederation of British Industry provided data of CBI business confidence.

variables are provided by the Economic Cycle Research Institute (ECRI), and the last one is obtained from Mitchell et al.'s 2009 report.

ECRI co-founder Geoffrey H. Moore establishes dates using the same approach as that employed by The National Bureau of Economic Research (NBER) to measure the US business cycle. ECRI has determined recession start and end dates for 20 other countries (data available from ECRI: http://www.businesscycle.com/). Dates of the UK business cycle from trough to peak are May 1981 to May 1990 and March 1992 to May 2008; dates from peak to trough are May 1990 to March 1992 and May 2008 to January 2010. Dates of the UK growth rate cycle from trough to peak are: December 1985 to January 1988; April 1991 to July 1994; August 1995 to July 1997; February 1999 to January 2000; February 2003 to March 2004; May 2005 to September 2007; and February 2009 to June 2010. Meanwhile, dates from peak to trough are: January 1988 to April 1991; July 1994 to August 1995; July 1997 to February 1999; January 2000 to February 2003; March 2004 to May 2005; and September 2007 to February 2009. The UK depressions of recent decades occurred between March 1990 to March 1993, and from April 2008 to the present day (for the purposes of this sample, it will examine the current depression up until December 2008). If it applies a time dummy to the business cycle and the growth rate cycle, it treats peak to trough as -1 and trough to peak as 0 (for business cycle: 81 quarters as 0 and 15 quarters as -1; and for growth rate cycle: 47 quarters as 0 and 49 quarters as -1). For periods of depression time, it treats depressions as -1, and the rest as 0 (77 quarters as 0 and 19 quarters as -1).

5.3 Methodology

5.3.1 Fama-French 3 factors

The main methodology builds upon and improves the methods of Liew and Vassalou (2000) and Gregory et al. (2003), applying Fama-French 3-factor model to detect the explanatory power of the model and adding in aggregate director trading as an independent variable. This chapter will start by introducing the Fama-French 3-factor model.

Fama and French (1993) presented size and book-to-market control as essential to carrying out time-series regressions with returns. Therefore, they constructed SMB (small minus big) and HML (high minus low). In June of each year from 1963 to 1991, all NYSE stocks were ranked on firm value via the Center for Research in Security Prices (CRSP). Fama and French took this data, and used median NYSE size to split NYSE, Amex, and NASDAQ stocks into two groups: small (S) and big (B). They then divided NYSE, Amex and NASDAQ stocks into three book-to-market equity groups, based on the breakpoints for the bottom 30% (Low, L), medium 40% (Medium, M), and top 30% (High, H) of the ranked values of B/M for NYSE stocks. After that, they constructed six portfolios (S/L, S/M, S/H, B/L, B/M, B/H) from the intersections of the two market values and the three B/M groups.

The portfolio SMB (small minus big), meant to mimic the risk factor in returns related to size, is the monthly difference between the simple average of the returns on the three small-stock portfolios (S/L,S/M, and S/H) and the simple average of the returns on the three big-stock portfolios (B/L, B/M, and B/H). Thus, SMB is the difference between the returns on small- and big-stock portfolios with about the same weighted-average B/M equity. This difference should be largely free of the influence of B/M, focusing instead on the differences between the return behaviours of small and big stocks.

The portfolio HML (high minus low), meant to mimic the risk factor in returns related to B/M equity, is similarly defined. HML is the monthly difference between the simple average of the returns on the two high-B/M portfolios (S/H and B/H) and the average of the returns on the two low-B/M portfolios (S/L and B/L). The two components of HML are returns on high- and low-B/M portfolios with about the same weighted-average size. Thus, the difference between the two returns should be largely free of the influence of size, focusing instead on the difference between the return behaviours of high- and low-B/M firms.

This method is the basis for analysing US data. However, there is a big problem in trying to build Fama-French factors for the UK: it is difficult to find a UK proxy for the NYSE break points which are used to form the factors and portfolios on Ken French's website. 'There is an important issue as the London Stock

Exchange exhibits a large ‘tail’ of small and illiquid stocks, which are almost certainly not part of the tradable universe of the major institutional investors that make up a large part of the UK market’ (Gregory et al., 2011).

SMB and HML of UK come from the Xfi Centre for Finance and Investment, University of Exeter.[20] It follows the largest firms method, explained in Gregory et al. (2001, 2003) and Gregory and Michou (2009). All these papers recognise the importance of this effect by using the median of the 350 largest firms (by market capitalisation) and of the 70th percentile of firms in forming the size breakpoints for market value, in both cases excluding financial stocks (banks, insurance companies, investment funds and property companies). Gregory et al. (2001) base their book-to-market breakpoints on the 30th and 70th percentiles of the 350 largest firms. More typically, other UK studies use the median of all firms (Al-Horani et al., 2003; Fletcher, 2001; Fletcher and Forbes, 2002; Hussain et al., 2002; Liu et al., 1999; Miles and Timmerman, 1996).

In detail, the portfolios are formed as follows. Using the proxy for the Fama-French NYSE cut-off, paper (Gregory et al., 2011) uses the median firm in the 350 largest companies by market capitalisation (excluding financials) for the size breakpoint, and uses the top 350 firms to set the cut-offs for the book-to-market portfolios. For the Fama-French factors, the following six intersecting portfolios are formed: S/H; S/M; S/L; B/H; B/M; B/L (where ’S’ denotes small firms, ‘B’ denotes big firms, and ‘H’, ‘M’ and ‘L’ denotes high, medium, and low book-to-market firms, respectively). The SMB and HML factor portfolios are then formed using the universe of UK main-market stocks, for which market capitalisation, returns, and book-to-market ratios can be constructed from any of DataStream and LSPD. Following the logic of Agarwal and Taffler (2008), who note that 22% of UK firms have March year end, with only 37% of firms have December year end, it applies March year *t* accounting data and end of September year *t* market capitalization data. The portfolios are formed at the beginning of October in year *t*, and financial firms, negative book-to-market stocks and alternative Investment Market (AIM) stocks are all excluded. Exactly

20 Many thanks to Prof. Alan Gregory, Dr. Rajesh Tharyan and Dr. Angela Huang for constructing the Fama-French 3-factor and momentum factors in the UK. Available at: http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/

as described on Ken French's website, the factors are constructed using the six value-weighted portfolios, so that SMB is the average return on the three small portfolios minus the average return on the three big portfolios, whilst HML is the average return on the two value portfolios minus the average return on the two growth portfolios.

The other issue when applying the model used by Liew and Vassalou (2000) and Gregory et al. (2003) is that mentioned in Section 4.3: the models end up with overlapping periods. Therefore, in calculating t-statistics, it is necessary to employ Newey-West autocorrelation and heteroskedasticity-consistent covariance estimates (Newey and West, 1987).

5.3.2 Multicollinearity Test

It will probably meet regression problem of multicollinearity when applying the models of Liew and Vassalou (2000) and Gregory et al. (2003) (these will be discussed in the following pages). Therefore, it is necessary to test for variance inflation factor.

Assume that it already fits the regression model

$$y = Xb + \varepsilon, (36)$$

where X is $n \times k$.

The predicted value is defined as $\hat{y}_j = X_j b$

It can calculate the centred variance inflation factor (VIF_C) (Chatterjee and Hadi, 2006, 235-239) for X_j using the formula

$$VIF_c(X_j) = \frac{1}{1 - \hat{R}_j^2}, (37)$$

where $\hat{R}_j^2$ is the square of the centred multiple correlation coefficient that results when X_j is regressed with intercept against all the other explanatory variables.

The uncentered variance inflation factor (VIF_{uc}) (Belsley, 1991, 28-29) for X_j is given by the formula

$$VIF_{uc}(X_j) = \frac{1}{1 - \tilde{R}_j^2}, (38)$$

where $\tilde{R}_j^2$ is the square of the uncentred multiple correlation coefficients that results when X_j is regressed without intercept against all the other explanatory variables, including the constant term.

5.4 Empirical Evidence

As discussed in Chapter 2 and Section 5.1, there should logically be a connection between aggregate director trading or CBI business confidence and future macroeconomic changes. It will use empirical methods in an attempt to find solid evidence for a link between aggregate director trading or CBI business confidence and future changes in aggregate economic activities.

5.4.1 Sensitivity test

Tables 5.1 and 5.2 display the results of the sensitivity test between future nominal GDP change and the two business confidence variables of aggregate director trading and CBI Industrial Survey Data (CBI business confidence). The test uses longer horizons of director trading or CBI and GDP data, and ends up with overlapping periods. Instead of calculating t-statistics, the Newey-West autocorrelation and heteroscedasticity-consistent covariance estimation is applied.

The independent variables are the past j=1-, 2-, 3-, and 4-quarter aggregate director trading (Table 5.1) or CBI business confidence (Table 5.2). The dependent variables are future i=1-, 2-, 3-, and 4-quarter GDP growth in Panel A to D, respectively. Using the aggregate net number of director trading ratio (NPR) to measure aggregate director trading, the results in Table 5.1 indicate that forecasting power increases with a longer horizon to measure both past director trading and future nominal GDP growth rate. For real NPR, adjusted R-square changes from 0.97% (past 2-quarter NPR and future 1-quarter nominal GDP growth rate) to 24.22% (past 4-quarter NPR and future 4-quarter nominal GDP change). For seasonality adjustment one,[21] adjusted R-square changes from -0.54% (past 1-quarter and future 1-quarter) to 24.59% (past 4-quarter and

[21] Details of seasonality adjustment are fully described in Chapter 3.

future 4-quarter). For seasonality adjustment two,[22] adjusted R-square changes from 1.74% (past 2-quarter and future 1-quarter) to 27.17% (past 4-quarter and future 4-quarter). Among these different measurements of NPR, seasonality adjustment two consistently offers the best performance of explanation. Most of the Newey-West t-values are significant at least 10% significance level. Coefficients of NPR are all positively correlated with future nominal GDP growth, which means directors tend to buy more of their own company's stocks when economic performance is about to improve, and sell the stocks when it is about to deteriorate. The overall results indicate that different seasonality measurements of NPR have similar significant level, but the magnitude of explanatory power varies.

For real GDP growth (Appendix H), results show a similar trend, where forecasting ability increases with a longer horizon on both past NPR and future growth of real GDP. Similarly to the results shown in Table 5.1, coefficients of director trading are all positively correlated with future real GDP growth. The longer the past director trading, the better forecasting power it achieves. However, compared with Table 5.1, the significance and forecasting power are much weaker than they are for nominal GDP growth. This probably implies that directors pay more attention to the growth rate of nominal GDP than to that of real GDP. This is parallel to the observed phenomenon that people who put money into banks are more concerned about the bank's nominal interest rate than about real interest rate, which inflation of the entire economy is considered.

Table 5.2 presents the growth rate of nominal GDP and CBI business confidence. The results show that the coefficients of CBI business confidence are all positively significant at least 5% significance level. However, contrastingly with the results of aggregate director trading trends shown in Table 5.1, a longer period of CBI business confidence does not result in better forecasts of future GDP, but short-term CBI business confidence does. The best adjusted R-square is 18.99%, with past j=2-quarter CBI business confidence forecasting future i=2-quarter GDP growth. Furthermore, when the fixed growth rate of nominal GDP is unchanged (i unchanged), the CBI business confidence

[22] Details of seasonality adjustment are fully described in Chapter 3.

of the past two quarters always obtains the best explanatory power (except in forecasting future 3-quarter GDP, where the best adjusted R-square occurs on past j=1-quarter CBI business confidence). Table 5.2 shows that CBI business confidence data has better predictive power in forecasting GDP change 2 quarters ahead; but beyond that time span, CBI business confidence retains its explanatory power but its accuracy decreases a little. Appendix I presents the results of growth rate of real GDP and CBI business confidence; this indicates a similar performance to that seen in Table 5.2, but the significance level and explanatory power decreases.

Thus far, the empirical results confirm that the measures of business confidence, aggregate director trading and CBI business confidence, are significantly positively correlated with future aggregate economy activities when using full sample size. It will now break down the sample into different periods of macroeconomic conditions, as measured by business cycles, growth rate cycles and depression.

Tables 5.3 and 5.4 show the results of nominal GDP growth with aggregate director trading (aggregate net number of director purchases ratio, NPR) and CBI business confidence respectively, under different macro-conditions. Panels A, C, E and G present performance during periods of macroeconomic success, as measured by business cycle, growth rate cycle and depression. The rest of the grey-shaded panels (Panels B, D, F and H) display sensitivity tests for periods of macroeconomic difficulty. Results of real GDP change on past NPR and CBI business confidence are shown in Appendices J and K respectively.

For successful periods: Panel A of Table 5.3 displays future i=1-quarter growth rate of nominal GDP, with past j=1-, 2-, 3-, and 4-quarter NPR. It shows that coefficients of NPR are all positively significant to future GDP change. The best adjusted R-squares of growth rate cycle and depression, which happened on past 4-quarter NPR, are 6.17% and 8.24% respectively. For business cycle, the best performance is 6.03% when using past 1-quarter NPR to forecast.

Panel C indicates the results of future i=2-quarter growth rate of nominal GDP. The coefficients of all NPR are positively significant at least 10% significance level (except past j=1-quarter NPR by growth rate cycle measurement, which is positive but does not show any significance) in periods of economic success. Here, the best adjusted R-squares appear on past 4-quarter NPR of business cycle, growth rate cycle and depression measurements (16.56%, 15.67% and 22.30%, respectively). Compared with Panel A, the significance of longer time length of past NPR is much improved and the explanatory power of NPR increases.

Panel E shows the performance of future i=3-quarter growth rate of nominal GDP. Results of aggregate director trading in periods of economic success by all measurements show that the longer the horizon of past NPR, the better adjusted the R-square. The best forecasting powers of business cycle, growth rate cycle and depression are 20.91%, 14.56% and 25.73% respectively, all of which occurred on past j=4-quarter NPR. However, the best explanatory power of economic success in growth rate cycle decreases from 15.67% in Panel C to 14.56%.

Panel G presents the results of future i=4-quarter growth rate of nominal GDP. For business cycle and depression, the best explanatory power appears on past j=4-quarter NPR, while the best adjusted R-square is on past j=3-quarter NPR for growth rate cycle. The best adjusted R-squares of business cycle, growth rate cycle and depression are 23.55%, 15.79% and 29.72%, respectively.

Results of macroeconomic success periods indicate: for business cycle, to forecast future 1-quarter growth of nominal GDP, the best adjusted R-square happens on past 1-quarter NPR, while the best explanatory power appears on past 4-quarter when predicting future 2-, 3- and 4-quarter GDP change. From this, it follows that, as shown in Table 5.1, the longer the time length of both future GDP growth and past director trading, the better the explanatory power. For growth rate cycle, to predict future 1-, 2- and 3-quarter GDP, the best adjusted R-square is on past 4-quarter NPR; however, the best explanatory power of future 3-quarter decreases from 15.67% (future 2-quarter GDP) to 14.56%. To forecast future 4-quarter GDP growth, the best performance is on past 3-quarter with adjusted R-square 15.79% (which is the overall best adjusted R-square on growth rate cycle measurement). For periods of depression, it shows that (as seen from Table 5.1) the longer the horizon of future GDP growth and past director trading activities, the better the forecasting power achieved. The adjusted R-square could reach to 29.72% (future 4-quarter and past 4-quarter), which is better than the best performance of NPR in Table 5.1. If it compares this with the full sample in Table 5.1, it can see that the best explanatory result of business cycle and growth rate cycle time measurements is not as good as that shown in Table 5.1. However, the results of aggregate director trading in periods of depression are generally better than the full sample performance, and the best adjusted R-square could reach to 29.72% compared with 24.22% of real NPR in Table 5.1.

For periods of macroeconomic difficulty, Panel B shows future i=1-quarter growth rate of nominal GDP with past j=1-, 2-, 3-, and 4-quarter NPR. Coefficients of NPR of business cycle and depression are all negatively significant, and the best adjusted R-square appears on past 4-quarter NPR (71.02% and 60.51% respectively). For growth rate cycle, NPR is not significant, and all adjusted R-squares have negative value, signifying that there is no explanatory power whatsoever.

Panel D gives the results of future i=2-quarter growth rate of nominal GDP. Coefficients of NPR of all business cycle and depression are negative, as is most of the growth rate cycle. NPR of all business cycle and depression is significant at least 5% significance level, while growth rate cycle does not show any significance, with negative adjusted R-square.

Panel F shows performance of future i=3-quarter growth rate of nominal GDP. Coefficients of NPR of business cycle and depression are all negatively significant at 1% significance level, while growth rate cycle does not show any significance. However, in this case, adjusted R-square of growth rate cycle on past 4-quarter NPR shows a none-zero positive value (0.24%).

Panel H presents the results of future i=4-quarter growth rate of nominal GDP. Coefficients of NPR on periods of macro-economic difficulty are all negative. NPR of business cycle and depression is significant at least 5% significance level, while NPR of growth rate cycle does not show any significance.

The results for difficult macro-economic periods indicate: first, unlike in periods of economic success (Panels A, C, E and G), most of coefficients of NPR are negative. Even worse, NPR of business cycle and depression is all negatively significant to future GDP change. Meanwhile, adjusted R-square of growth rate shows neither negative nor very small positive value, which does not have sufficient explanatory power. Second, there is no relationship whereby a longer horizon of both past aggregate director trading and future GDP growth leads to better forecasting power. Third, there is very big adjusted R-square on business cycle and depression time, the largest adjusted R-square can reach to 89.96% (past 3-quarter with future 3-quarter) and 77.63% (past 4-quarter with future 2-quarter).

Table 5.4 presents the CBI business confidence variable for periods of both good and bad economic performance. As in Table 5.3, Panels A, C, E and G show the results for successful periods, while the other panels (B, D, F and H) show periods of macroeconomic difficulty.

In Panel A, for future i=1-quarter nominal GDP growth, the coefficients of NPR of all three time measurements are positive. Most NPR of business cycle and depression are positively significant. The best explanatory result of all time measurements occurs when past j=4-quarter NPR is used to forecast.

In Panel C is similar to Panel A, in that for future i=2-quarter nominal GDP growth coefficients of NPR of all time are positive. All NPR of business cycle and depression are positively significant at least 10% significance level, while the growth rate cycle does not show any significance. The best explanatory result of all time measurements appears on past j=4-quarter NPR.

In Panel E, for future i=3-quarter nominal GDP growth, coefficients of all NPR are positive. All NPR of business cycle and depression are positively significant at least 5% significance level. For growth rate cycle, coefficients of NPR on past j=3- and 4-quarter are positively significant at 10% significance level. The best explanatory power of business cycle and depression appears on past 4-quarter, while growth rate cycle occurs on past 3-quarter.

In Panel G, for future i=4-quarter nominal GDP growth, the coefficients of all NPR are positive. All NPR of business cycle and depression are positively significant at least 10% significance level. For growth rate cycle, coefficients of NPR on past j=2- and 3-quarter are positively significant at 10% significance level. The best explanatory power of business cycle and depression is on past 4-quarter, while growth rate cycle is on past 2-quarter.

The results relating to periods of macroeconomic success indicate that by looking at these periods rather than the full sample, the CBI business confidence shows the trend where the longer the horizon of past aggregate director trading and future GDP growth, the better the performance. However, among these time measurements, the best adjusted R-square is 16.87% (on past 4-qaurter and future 4-quarter on business cycle) with Newey t-statics significant at 5%; in the full sample (Table 5.2), the best explanatory ability could reach to 18.99%, with Newey t-statics significant at 1% (on past 2-quarter and future 2-quarter).

For periods of weaker macroeconomic performance, the results are similar to those of Table 5.3: most NPR are neither negatively significant nor positive, but do not show any significance. Compared with the full sample (Table 5.2) or periods of good performance (Panels A, C, E and G), adjusted R-square of bad time is neither too big nor too small.

Results of real GDP change with aggregate director trading and CBI business confidence shown in Appendices J and K are all not good, and none of them show valuable information.

The robustness check in Tables 5.3 and 5.4 shows that results for periods of good macroeconomic performance, as measured by a variety of standards, present similar findings to those of the full sample: the longer the horizon of future aggregate economic activities, past aggregate director trading and CBI business confidence, the better its forecasting power. However, for periods of poor macroeconomic performance, it does not show any valuable information: the coefficients of NPR/CBI business confidence are neither negatively significant nor positive, but do not show any significance. Generally speaking, when controlling for macroeconomic performance, it finds that aggregate director trading and CBI business confidence have more success in a good macro-environment. However, another possible explanation is that the totally different performance between good and bad economic periods is caused by sample size: there are only 15 quarters of bad economic performance measured by business cycle, and 19 quarters measured by depression. By contrast, there are 81 quarters and 77 quarters of good economic performance measured by business cycle and depression, respectively. Compared with Tables 5.3 and 5.4, it can be seen that the longer the forecasting period in good economic conditions, the better the significance level and adjusted R-square NPR and CBI business confidence. However, a longer past horizon of NPR results in better performance than that of CBI business confidence.

To sum up Tables 5.1-5.4, the results of the sensitivity test indicate that aggregate director trading and CBI business confidence are well able to forecast future economic movements. The longer the horizon of both future macroeconomic change and past director trading, the better the explanatory power of director trading. For the CBI business confidence variable, the overall predictive power is good, but the best adjusted R-square occurs within past 2 quarters. Furthermore, aggregate director trading and CBI business confidence is much better at forecasting future nominal GDP than real GDP. They also have better explanatory power in periods of macroeconomic success than in periods of difficulty. This implies two things. First, that directors pay more attention to nominal than real economic indicators when comparing their own company's situation to the future economy. Second, that directors have a better view of their own companies and industries when they are operating in a successful macro-environment.

5.4.2 Aggregate Director Trading and Market Factors

As explained and proved in Chapter 4, aggregate director trading is one significant forecasting variable used to predict future market movements (excess returns). This section will therefore compare the explanatory power of aggregate director trading with other measurements of market movement. As mentioned in Section 5.3, it will apply Fama-French 2 factors (SMB and HML) as dependent variables to evaluate their relationship to aggregate director trading.[23]

The results are shown in Appendices L and M, which present the interactions of aggregate director trading with SMB and HML, respectively. Appendix L illustrates future m=1-, 3-, 6-, 9- and 12-month SMB on the past n=1-, 3-, 6-, 9-, 12-month aggregate net number of director purchases trading ratio (NPR). The results of past n=1-, 3-, 6-, 9-, 12-month NPR are presented in Panels A-E, respectively. The results show that no matter how NPR is measured (through real data or seasonality methods), there is no significance between future SMB and past NPR (only past 1-month with future 1-month shows significance). The adjusted R-square is neither negative nor positive, as its value is very small. The overall results indicate that aggregate director trading does not have sufficient ability to explain future SMB.

The sensitivity test in Appendix M illustrates the performance of future HML on past NPR. It illustrates future m=1-, 3-, 6-, 9- and 12-month HML on past n=1-, 3-, 6-, 9-, 12-month NPR. Results of past n=1-, 3-, 6-, 9-, 12-month NPR are presented in Panels A-E, respectively. All coefficients of NPR are negatively correlated with future HML, and all NPRs except past 1-month with future 1-month are negatively significant at least 5% significance level (Newey-West t-statistics). Adjusted R-square increases from minimum 0.17% (future 1-month HML on past 1-month real NPR) to maximum 18.76% (future 12-month HML on past 12-month NPR of seasonality adjustment two). Seasonality adjustment two usually achieves the best results. The overall results show that the longer the horizon of past aggregate director trading and future HML, the better its explanatory power.

As an extra robustness check to test the relationship between HML and aggregate director trading, it applies change in the net director purchase ratio (ΔNPR), which was introduced by Knewtson et al. (2010). Here, it applies their sensitivity test (Table 7, Knewtson et al., 2010, p. 12) to UK data. The result is

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[23] The relationship between the Fama-French factor of aggregate market excess returns and aggregate director trading has already been examined in detail by previous US/UK studies and in Chapter 4.

shown in Appendix N. Knewtson et al. (2010) called HML as Value Premium, and referred to ∆NPR as ∆Insider Demand. Results of past n=1-, 3-, 6-, 9- and 12-month ∆NPR are presented in Panels A-E, respectively. Like those of Knewtson et al. (2010), results show past 1-month ∆NPR (∆Insider Demand) is positively significant. However, results regarding explanatory power are totally different to those of Knewtson et al. (2010): the significance and adjusted R-square in Appendix N is just 10% significant and 0.70%, respectively, while in Knewtson et al. (2010) it is 1% significant and 10.57%, respectively. It also finds that the coefficients of past 12-month ∆NPR to future 1-, 3-, and 6-month HML (Panel E) are significant, but that this significance decreases with as the length of future HML increases. Also, the best adjusted R-square appears among them, but it is much weaker than the NPR shown in Appendix M. Furthermore, there is no relationship between the length of aggregate director trading and the accuracy in forecasting HML.

In summary, results show that aggregate director trading is significantly correlated with future HML, but there is no evidence for such a relationship between aggregate director trading and SMB. These findings imply that aggregate director trading probably is more sensitive to the firms under B/M classification than capitalisation. Further evidence shows aggregate director trading (NPR) is negatively significant correlated with future HML. The longer the horizon of past NPR and future HML, the better explanatory ability aggregate director trading it has.

5.4.3 Aggregate Director Trading, Market Factors and Macroeconomy

Liew and Vassalou (2000), Vassalou (2003) and Gregory et al. (2003) all argue that Fama-French 3 factors contain information about future macroeconomic changes. This section examines the relation between MKT (excess returns between return of FTSE All Share and 90-day T-bill rate), SMB (small minus big, the difference in the returns of a value-weighted portfolio of small stocks and big stocks), HML (high minus low, the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks) and aggregate director trading together with future GDP growth using univariate and multivariate regression analysis. First, it tests the effect of Fama-French 3 factors on future GDP growth.

5.4.3.1 Regressions with Fama-French 3 factors

Regressions applying quarterly data on future GDP growth to past holding period returns in MKT, SMB and HML take the form:

$$GDPGrowth_{(t,t+4)} = a + b * Factor\,\mathrm{Re}\,t_{(t-4,t)} + \varepsilon_{(t,t+4)} \text{ , (39)}$$

where GDPGrowth represents nominal and real growth rates of the UK; FactorRet denotes MKT (excess returns between return of FTSE All Share and 90-day T-bill rate), SMB (small minus big, the difference in the returns of a value-weighted portfolio of small stocks and big stocks), HML (high minus low, the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks); and $\varepsilon_{(t,t+4)}$ is the residual term of the regression.

GDP growth rates are observed at quarterly frequencies; consecutive annual growth rates therefore have three overlapping quarters. This induces serial correlation in the residuals of the regressions. To correct for this, it uses the Newey and West (1987) estimator and set the lag parameter to three.

Fama (1981) documents the presence of a positive and statistically significant relationship between the market factor and future economic growth in the US. Aylward and Glen (2000) build upon this analysis using international data. Liew and Vassalou (2000) also provide evidence for this relationship, and Gregory et al. (2003) offer UK evidence supporting this existence. More importantly, these studies show that a positive and equally strong relation also exists between future economic growth and the performance of HML and SMB.

A positive relationship would exist if high returns in SMB and HML were associated with good future economic performance. That would mean that high B/M and small capitalisation stocks are better able to prosper than low B/M and big capitalisation stocks when periods of high economic growth are expected. The observed positive relation between HML and future GDP growth makes sense. Presumably, investors would rather hold stocks whose returns are relatively high when they discover that the economy is struggling. They therefore hold onto low B/M stocks with good potential for growth.

Table 5.5 shows the regression of future change of GDP on past MKT, SMB and HML. Panels A and B display the results of growth rate of nominal and real GDP respectively. Performance of univariate regression (model 1-3 and 8-10) illustrates that Fama-French 3 factors are all positively correlated to future nominal and real GDP growth. However, only MKT shows significance at 10% significance level in Panel A and 5% significance level in Panel B; SMB and HML do not show any significance. Models 4 and 11 present the results of future GDP change with SMB and HML. The coefficients of SMB and HML in these two models are insignificant. Models 5-6 and 12-13 indicate the results of MKT with SMB/HML. It can be seen that coefficient of SMB does not have sufficient significance to future GDP change. However, Models 6 and 13 show that MKT and HML are positively significant, and Newey-West t-statistic of real GDP (1% significance for MKT and 5% significance for HML, Panel B) is more significant than nominal GDP (5% significance for MKT and 10% significance for HML, Panel A). Meanwhile, the adjusted R-square increases from 11.94% (Model 5) to 18.89% (Model 6) in Panel A, and from 11.92% (Model 12) to 18.53% (Model 13) in Panel B. This shows that HML has more explanatory ability than SMB by introducing MKT into the model. Models 7 and 14 show future GDP growth together with Fama-French 3 factors. As in Models 5-6 and 12-13, the coefficients of MKT and HML are positively significant at least 10% significance level, while SMB is positive but does not show significance. Compared with model of MKT and HML (Models 6 and 13), model of the Fama-French 3 factors together decrease explanatory power, implying that SMB does not contain sufficient information on future GDP growth.

Generally, it can be seen from Table 5.5 that the Fama-French 3 factors are all positively correlated with future change in GDP. Performance of past MKT and HML contains more valuable information on future aggregate economic activities. The coefficients of MKT and HML on future growth rate of real GDP are more significant than those on nominal GDP, but the adjusted R-square does not: the forecasting power of nominal GDP growth is better than real GDP. The performance of the model with Fama-French 3 factors, does not achieve best explanatory result, but the model without SMB does. This implies that SMB does not include valuable information about future aggregate economic change. This is reflected in Models 5-7 and 12-14.

Furthermore, the information about economic growth contained in the returns of HML and SMB is largely independent of the information contained in the market factor. Appendices O and P show the results of regressions of SMB and HML respectively on the market factor. They show that the coefficients are generally small and often statistically insignificant. Therefore, the positive relation between SMB, HML and future economic growth is unlikely to be due to the known positive relation between the market factor and future economic growth. This hypothesis is also supported by the results of the following section.

5.4.3.2 Multiple regressions with Fama-French 3 factors and aggregate director trading

This section compares the information content aggregate director trading and CBI business confidence with that of MKT, SMB and HML.

The estimated regressions include the market factor and the return on a trading strategy:

$$GDPGrowth_{(t,t+4)} = a + c * Factor\mathrm{Re}\,t_{(t-4,t)} + d * DT / CBI_{(t-4,t)} + k_{(t,t+4)}, \quad (40)$$

$$GDPGrowth_{(t,t+4)} = a + b * MKT_{(t-4,t)} + c * Factor\mathrm{Re}\,t_{(t-4,t)} + d * DT / CBI_{(t-4,t)} + k_{(t,t+4)}, \quad (41)$$

where MKT is the quarterly excess market return over the risk-free rate; FactorRet stands for the quarterly returns on SMB and HML; DT/CBI business confidence denotes aggregate director trading or CBI business confidence; and $k_{(t,t+4)}$ are the residuals of the regression. GDP growth rates are observed at quarterly frequencies; and consecutive annual growth rates therefore have three overlapping quarters. This induces serial correlation in the residuals of the regressions. To correct for this, it uses the Newey and West (1987) estimator and set the lag parameter to three.

Tables 5.6 and 5.7 show evidence of aggregate director trading: Table 5.6 displays models without MKT, while Table 5.7 presents models with MKT. Both tables indicate the results using aggregate net number of director purchases ratio (NPR). In both tables, Panels A and B display the real data of NPR to future nominal and real GDP growth, respectively; Panels C and D present seasonality adjustment one of NPR to future change in nominal and real GDP, respectively; and Panels E and F show seasonality adjustment two of NPR to future growth rate of nominal and real GDP, respectively.

Both tables indicate that the coefficients of NPR are all positively correlated with future GDP growth, and are positively significant at a level of 1% under Newey-West t-test to future growth rate of nominal GDP. NPR has better power to explain future nominal than real GDP growth, which is consistent with the results of the sensitivity tests. Different seasonality measurements of aggregate director trading do not affect the significance of NPR. Among these measurements, Seasonality Adjustment Two shows the best forecasting ability, while Seasonality Adjustment One has a better result than real NPR.

In both tables, coefficients of SMB are shown to be positively correlated with future GDP, but do not show any significance. Meanwhile, the coefficients of HML are all positively correlated to future GDP growth and significant at least 10% significance level in all panels. In Table 5.7, most coefficients of MKT are positively correlated with future changes in nominal and real GDP, but do not show any significance. Furthermore, in Table 5.7, the best adjusted R-squares to future nominal GDP change all appear in models with MKT, HML and NPR, but not those with Fama-French 3 factors and NPR. This finding is consistent with the results shown in Table 5.5: by introducing MKT into the model to forecast future GDP, the best results occur in models with MKT and HML, but not the model with all Fama-French 3 factors together.

Compared with performance of Fama-French 3 factors in Table 5.5, MKT loses its significance dramatically when forecasting future growth rate of nominal and real GDP in Table 5.7. This is probably due to multicollinearity among MKT and aggregate director trading. However, as discussed in Section 5.3.2, variance inflation factors (VIF) test for the independent variables of multicollinearity does not show marginal significance between them.[24]

The performance of CBI business confidence is presented in Table 5.8. Panels A and B indicate the results of models without MKT to forecast future change of nominal and real GDP, respectively; Panels C and D illustrate the results of models with MKT to forecast future growth rate of nominal and real GDP, respectively. Similarly, as shown in Tables 5.6 and 5.7, the coefficients of CBI business confidence, MKT, SMB and HML are all positively correlated with future GDP change. Explanatory ability is better for future nominal GDP than for real GDP. The coefficients of HML are all positively significant at 5% significance level. The coefficients of SMB to future nominal GDP do not show any significance; however, SMB's coefficients to future real GDP do. Except in models with MKT and SMB, the coefficients of MKT are all positively significant to future nominal GDP in Panel C, but do not show any significance in Panel D. The coefficients of CBI business confidence to future nominal GDP are all positively significant. However, the significance is different: in Panel A, it is significant at 5% significance level, while in Panel C, it is significant at 10% significance level. The decreasing significance is probably caused by the introduction of MKT into the model.

Generally speaking, Tables 5.6, 5.7 and 5.8 indicate that aggregate director trading (measured by NPR) and CBI business confidence are leading indicators of future economic change, and they significantly improve the explanatory performance of Fama-French 3 factors model in forecasting future GDP growth.

[24] The results of multicollinearity are not shown. It tests multicollinearity with and without constant. In STATA, the output shows the variance inflation factors together with their reciprocals. Some analysts compare the reciprocals with a predetermined tolerance;. If the reciprocal of the VIF is smaller than the tolerance, the associated predictor variable is removed from the regression model. However, most analysts rely on informal rules of thumb applied to the VIF (Chatterjee and Hadi, 2006). According to these rules, there is evidence of multicollinearity if the largest VIF is greater than 10 (some choose a more conservative threshold value of 30), and the mean of all the VIFs is considerably larger than 1.

5.4.3.3 Multiple regressions that include business cycle variables, Fama-French 3 factors and aggregate director trading/CBI business confidence

It will now examine how much of the information on future economic growth contained in MKT, HML, SMB and aggregate director trading is also presents in popular business cycle variables (dividend yield of FTSE All Share, growth of industrial production and Term spread[25]). The reason these business cycle variables applied into model is what paper of Seyhun (1992) and Liew and Vassalou (2000) recommended.

The multiple regressions estimated are of the form:

$$GDPGrowth_{(t,t+4)} = a + b*FF_{(t-4,t)} + c*DT/CBI_{(t-4,t)} + d*DY_{(t)} + e*IPGrwoth_{(t-4,t)} + f*TERM_{(t)} + \varepsilon_{(t,t+4)} \quad (42)$$

where $\mathrm{FF}_{(t-4,t)}$ stands for the past 1-year Fama-French 3 factors (MKT, SMB and HML); $\mathrm{DT/CBI\ business\ confidence}_{(t-4,t)}$ represents aggregate director trading (NPR) or CBI business confidence Industrial Trends Survey data (CBI business confidence); $\mathrm{DY}_{(t)}$ is the dividend yield of FTSE All Share; $\mathrm{IPGrowth}_{(t-4,t)}$ is the past 1-year growth of UK industrial production; $\mathrm{TERM}_{(\mathrm{t})}$ is the 10-year UK government bond yield minus the 90-day UK Treasury Bill yield; and $\varepsilon_{(t,t+4)}$ is the residual of the regression. GDP growth rates are observed at quarterly frequencies, meaning that consecutive annual growth rates have three overlapping quarters. This induces serial correlation in the residuals of the regressions. To correct for this, it uses the Newey and West (1987) estimator and set the lag parameter to three. Tables 5.9 and 5.10 present the performance of aggregate director trading and of CBI business confidence.

In Table 5.9, Panels A and B indicate the future growth of nominal and real GDP. Models 1, 4, 7and 10 present results of real NPR, while Models 2, 5, 8 and 11 (shadowed light grey) present results of NPR with seasonality adjustment one. Models 3, 6, 9 and 12 (shadowed dark grey) present results of NPR with seasonality adjustment two.

[25] Term Spread in the UK is calculated by long-run rate (the yield to maturity of a 10-year government bond) minus short term rate (90-day UK Treasury Bill rate) (Hardouvelis, 1994).

Even when business cycle variables are introduced into the model, NPR maintains positive correlation with future economic growth. The coefficients of NPR under different seasonality adjustment measurements are all positive correlated with future GDP growth. NPR is significant at 1% significance level (5% significance level in Model 1) to future nominal GDP in Panel A, and at 10% significance level (except in Models 7, 8 and 10, where NPR does not show significance) to future real GDP in Panel B.

Compared with the results in Tables 5.6 and 5.7, the significance of NPR decreases very little, by introduced business cycle variables. By different NPR measurements for nominal GDP growth (Panel A), seasonality adjustment two has the best explanatory power in models without MKT (Models 1-3), while Seasonality Adjustment One has the best explanatory ability in models with MKT (Models 4-6). For real GDP growth (Panel B), the best results are achieved by seasonality adjustment two in models with or without MKT. Adjusted R-square differs only slightly between Panels where the same model is applied, which suggests different aggregate director trading measurements do not cause a big difference in performance in forecasting future economic activities.

HML is all positively correlated to future nominal and real GDP growth. The coefficients of HML are positively significant at 1% significance level to future nominal GDP, and are positively significant at 5% significance level to future real GDP. SMB is positively correlated to future economic change, but does not show any significance; this is consistent with Tables 5.5-5.7. MKTs are also positively correlated with future GDP change. The coefficients of MKT are significant at 5%significance level to future growth of nominal GDP (Panel A). Meanwhile, MKT is all positively significant at 10% significance level to future growth of real GDP, except in Model 12 (Panel B).

For business cycle variables, the coefficients of IPGrowth are all positively significant at 1% significance level, while coefficients of TERM are all negative but insignificant. Coefficients of DY are positively significant at 5% significance level (except Models 1 and 3, where it is significant at 10% significance level).

Compared the results in Tables 5.6 and 5.7, the coefficients of NPR are still positively significant to future aggregate economic growth, even when business cycle variables are introduced into the model. The explanatory power presented in Table 5.9 is much better than that in Tables 5.6 and 5.7. This implies that future economic activities are indeed dependent on business cycle change.

Table 5.10 shows the performance of CBI business confidence variable. Models 1 and 2 display the results of future growth of nominal GDP, while Models 3 and 4 show the results of real GDP. The introduction of business cycle variables into the model leads CBI business confidence to lose its power predict to future economic growth. None of models present significance. Meanwhile, HML is positively significant at 1% significance level to future nominal GDP, and at 5% significance level to future real GDP. SMB and MKT are positively correlated to future economic change, but only significant at 10% significance level to future nominal GDP. For business cycle variables, the coefficients of IPGrowth and DY are all positively significant at 5% significance level (DY is significant at 1% significance level in Model 4), while the coefficients of TERM are all negative and most of them are insignificant. Overall, the results of Table 5.10 show that performance of CBI business confidence to predict future GDP change is replaced by MKT (shown in Table 5.8) and business cycle variables.

Generally speaking, aggregate director trading and CBI Industrial Trends Survey (CBI business confidence) could be used to make economic forecasts for the future. Sensitivity tests present a significant positive relationship between aggregate director trading/CBI business confidence and future economic change. The results of Tables 5.5-5.10 show that aggregate net number of director trading ratio (NPR) and CBI business confidence are strongly and significantly correlated with future economic change; they also confirm the earlier results that Fama-French 3 factors (MKT, SMB and HML) are positively correlated with future GDP change. By introducing Fama-French 3 factors and business cycle variables (dividend yield of FTSE All Share, growth of industrial production and term spread) into the model, NPR maintains its significant level and explanatory ability. This implies that other time series variations predicting future economic change, such as Fama-French 3 factors and business cycle variables, do not attenuate the predictive power of aggregate director trading.

However, on the same is not true of CBI business confidence. CBI business confidence does good job at forecasting future GDP change in models with Fama-French 3 factors, but when business cycle variables are introduced into the model, the significant and explanatory ability disappears. This means that CBI business confidence does not as robust as NPR, but is still a leading indicator of future aggregate economic activities.

5.5 Conclusion

The empirical work of this chapter documents a strong relationship between past aggregate director trading, CBI Industrial Trends Survey data (CBI business confidence) and future economic activity. Different methods, such as sensitivity tests, models of Fama-French 2-factor or 3-factor and with business cycle variables, are applied. The findings show that aggregate director trading activities and CBI business confidence are positively significant and have good explanatory power in forecasting future movements in the economy. The predictability of future real activities increases with the length of forecasting horizon, the number of quarters of past director trading.

Evidence also indicates that director trading retains marginal explanatory power when Fama-French factors and other business cycle variables are included as additional explanatory variables. CBI business confidence maintains good forecasting power in models with Fama-French factors, but not with other business cycle variables. This suggests that aggregate director trading and CBI business confidence capture a component of market factors (SMB, HML and MKT) and business cycle variables (DY, IPGrowth and TERM) not related to movements in future real activity. Aggregate director trading is therefore more robust than CBI business confidence. Moreover, by applied different measures of forecasting accuracy (mean square error, mean absolute error, mean absolute percentage error) proposed by Diebold and Mariano (1995), the summary statistics of models within Table 5.6 to 5.10 indicate predictive accuracy of aggregate director trading is better than CBI business confidence.[26]

[26] Summary statistics of forecasting accuracy is presented in Appendix Q.

Overall, the evidence suggests that aggregate director trading and CBI business confidence are leading indicators with good ability to forecast the UK's macroeconomy.

Table 5.1 **Time Series Regression of Future 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Nominal GDP Growth on Past 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Aggregate Net Number of Director Purchases Trading Ratio**

$$\sum_{k=t+1}^{t+i} GDPGrowth\_N = \alpha_0 + \alpha_1 NPR_{(t-j,t)}$$

Panel A	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0144	0.004885	0.0392	0.0144	0.002834	0.0097	0.0141	0.003836	0.0434	0.0140	0.003536	0.0359
	(17.87)***	(2.60)**		(15.87)***	(1.74)*		(13.98)***	(2.95)***		(15.23)***	(1.53)	
Seasonal Adj_1	0.0146	0.001535	-0.0054	0.0144	0.002799	0.0092	0.0141	0.003631	0.0440	0.0140	0.0036347	0.0396
	(17.74)***	(0.73)		(15.90)***	(1.72)*		(14.59)***	(2.71)***		(15.01)***	(1.63)	
Seasonal Adj_2	0.0144	0.005310	0.0350	0.0144	0.003635	0.0174	0.0141	0.004478	0.0498	0.0139	0.004282	0.0494
	(17.90)***	(2.34)**		(15.78)***	(2.18)**		(14.06)***	(3.36)***		(15.25)***	(1.93)*	
Panel B	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0291	0.008815	0.0501	0.0287	0.009593	0.0781	0.0281	0.009457	0.1141	0.0277	0.009439	0.1163
	(21.00)***	(3.00)***		(17.11)***	(4.06)***		(15.99)***	(3.62)***		(16.97)***	(2.12)**	
Seasonal Adj_1	0.0292	0.005755	0.0196	0.0286	0.009833	0.0825	0.0285	0.006507	0.0556	0.0277	0.009592	0.1233
	(21.29)***	(1.84)*		(17.13)***	(4.18)***		(16.44)***	(2.30)**		(16.72)***	(2.23)**	
Seasonal Adj_2	0.0291	0.010216	0.0524	0.0286	0.011120	0.0886	0.0281	0.010415	0.1135	0.0275	0.010816	0.1356
	(21.05)***	(2.98)***		(17.09)***	(4.57)***		(16.21)***	(3.56)***		(17.20)***	(2.50)**	

Table 5.1 (Continued)

Panel C	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0440	0.010725	0.0407	0.0434	0.012746	0.0792	0.0426	0.012699	0.1189	0.0415	0.015891	0.1994
	(24.43)***	(1.83)*		(19.30)***	(3.05)***		(17.95)***	(3.22)***		(17.96)***	(2.89)***	
Seasonal	0.0445	0.003826	-0.0038	0.0434	0.012968	0.0822	0.0427	0.010761	0.0944	0.0415	0.015924	0.2052
Adj_1	(25.11)***	(0.83)		(19.31)***	(3.10)***		(18.35)***	(2.49)**		(17.92)***	(2.98)***	
Seasonal	0.0441	0.011673	0.0359	0.0433	0.015126	0.0947	0.0424	0.014916	0.1366	0.0412	0.018121	0.2284
Adj_2	(24.63)***	(1.77)*		(19.34)***	(3.60)***		(18.18)***	(3.42)***		(18.14)***	(3.59)***	
Panel D	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0591	0.011963	0.0314	0.0582	0.015195	0.0736	0.0567	0.018655	0.1773	0.0554	0.020811	0.2422
	(26.86)***	(1.51)		(21.65)***	(2.25)**		(19.59)***	(3.43)***		(19.06)***	(2.75)***	
Seasonal	0.0593	0.0072713	0.0069	0.0582	0.0152449	0.0740	0.0573	0.012943	0.0909	0.0553	0.020728	0.2459
Adj_1	(27.21)***	(1.21)		(21.62)***	(2.29)**		(20.22)***	(2.20)**		(19.11)***	(2.84)***	
Seasonal	0.0590	0.014614	0.0378	0.0581	0.018048	0.0883	0.0565	0.020874	0.1831	0.0550	0.023513	0.2717
Adj_2	(26.88)***	(1.69)*		(21.77)***	(2.54)**		(20.01)***	(3.52)***		(19.34)***	(3.31)***	

Sample periods are 92 quarters from 1986 to 2008, **GDPGrowth_N** denotes quarterly growth rate of nominal GDP which is seasonally adjusted. **NPR** denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), **Seasonal Adj_1** denotes seasonal adjusted director trading transactions based on December and March fiscal year end by assumption, **Seasonal Adj_2** denotes seasonal adjusted director trading transactions based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Table 5.2 **Time Series Regression of Future 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Nominal GDP Growth on Past 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter CBI Industrial Trends Survey Data**

$$\sum_{k=t+1}^{t+i} GDPGrowth\_N = \alpha_0 + \alpha_1 \sum_{k=t-j}^{t} CBI$$

Panel A		i=1			i=1			i=1			i=1	
		j=1			j=2			j=3			j=4	
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.015	0.00017	0.1492	0.016	0.00010	0.1636	0.016	0.00007	0.1615	0.015	0.00005	0.1456
	(18.45)***	(2.77)***		(16.49)***	(2.57)**		(14.38)***	(2.56)**		(12.82)***	(2.47)**	
Panel B		i=2			i=2			i=2			i=2	
		j=1			j=2			j=3			j=4	
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.031	0.00034	0.1838	0.031	0.00019	0.1899	0.031	0.00013	0.1769	0.031	0.00010	0.1710
	(21.91)***	(3.30)***		(16.79)***	(2.87)***		(14.05)***	(2.68)***		(12.39)***	(2.61)**	
Panel C		i=3			i=3			i=3			i=3	
		j=1			j=2			j=3			j=4	
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.046	0.00048	0.1852	0.046	0.00026	0.1832	0.045	0.00019	0.1792	0.045	0.00015	0.1748
	(22.75)***	(3.78)***		(16.52)***	(3.05)***		(13.56)***	(2.75)***		(11.94)***	(2.63)**	
Panel D		i=4			i=4			i=4			i=4	
		j=1			j=2			j=3			j=4	
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.060	0.00056	0.1477	0.060	0.00032	0.1536	0.060	0.00023	0.1505	0.059	0.00018	0.1514
	(22.29)***	(3.62)***		(16.06)***	(2.90)***		(13.12)***	(2.62)**		(11.52)***	(2.56)**	

Table 5.2 (Continued)

Sample periods are 92 quarters from 1986 to 2008, **GDPGrowth_N** denotes quarterly growth rate of nominal GDP which is seasonally adjusted. **CBI** denotes quarterly industrial trends survey data provided by Confederation of British Industry (CBI business confidence). The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Table 5.3 **Time Series Regression of Future 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Growth Rate of Nominal GDP on Past 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Aggregate Net Number of Director Purchases Trading Ratio Decomposed by Different Macro-Effect Variables**

$$\sum_{k=t+1}^{t+i} GDPGrowth\_N = \alpha_0 + \alpha_1 NPR_{(t-j,t)}$$

Panel A	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0151	0.00502	0.0603	0.0151	0.00397	0.0417	0.0149	0.00371	0.0549	0.0148	0.00323	0.0401
	(19.67)***	(2.76)***		(17.26)***	(2.84)***		(15.37)***	(2.97)***		(18.42)***	(1.40)	
Growth Rate Cycle	0.0139	0.00304	0.0050	0.0144	0.00277	0.0153	0.0144	0.00211	0.0093	0.0136	0.00313	0.0617
	(10.59)***	(1.38)		(12.18)***	(1.68)		(12.84)***	(1.45)		(15.06)***	(1.65)	
Depression	0.0154	0.00447	0.0499	0.0153	0.00388	0.0444	0.0152	0.00352	0.0524	0.0149	0.00422	0.0824
	(20.52)***	(2.45)**		(17.81)***	(2.86)***		(15.35)***	(2.71)***		(17.56)***	(2.00)*	

Panel B	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0052	-0.02022	0.1052	0.0088	-0.01259	0.3222	0.0109	-0.01120	0.6736	0.0093	-0.00942	0.7102
	(1.50)	(-2.16)*		(4.03)***	(-4.03)***		(6.54)***	(-6.20)***		(7.04)***	(-6.13)***	
Growth Rate Cycle	0.0134	-0.00335	-0.0160	0.0139	0.00148	-0.0198	0.0134	0.00262	-0.0106	0.0133	-0.00048	-0.0232
	(9.65)***	(-0.48)		(9.98)***	(0.38)		(9.46)***	(0.72)		(10.51)***	(-0.20)	
Depression	0.0063	-0.01035	0.0641	0.0095	-0.00982	0.4038	0.0106	-0.00848	0.5804	0.0096	-0.01049	0.6051
	(2.06)*	(-2.36)**		(4.99)***	(-5.19)***		(9.24)***	(-6.21)***		(8.01)***	(-5.54)***	

Table 5.3 (Continued)

Panel C	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0306	0.00688	0.0387	0.0300	0.00900	0.0938	0.0296	0.00829	0.1177	0.0289	0.00952	0.1656
	(22.99)***	(2.34)**		(18.56)***	(4.06)***		(18.10)***	(3.14)***		(19.78)***	(2.18)**	
Growth Rate Cycle	0.0279	0.00406	-0.0048	0.0280	0.00658	0.0441	0.0269	0.00730	0.1050	0.0256	0.00810	0.1567
	(12.90)***	(0.90)		(11.66)***	(2.03)*		(12.03)***	(1.99)*		(11.18)***	(2.04)**	
Depression	0.0313	0.00555	0.0230	0.0307	0.00795	0.0790	0.0301	0.00838	0.1315	0.0292	0.01067	0.2230
	(23.58)***	(1.79)*		(19.02)***	(3.55)***		(18.04)***	(3.19)***		(18.88)***	(2.57)**	
Panel D	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0090	-0.04171	0.1384	0.0160	-0.03085	0.3846	0.0186	-0.02939	0.8584	0.0156	-0.02461	0.7943
	(1.35)	(-2.54)**		(3.63)***	(-4.29)***		(5.85)***	(-8.04)***		(6.78)***	(-6.73)***	
Growth Rate Cycle	0.0267	0.00252	-0.0213	0.0269	-0.00057	-0.0226	0.0261	-0.00090	-0.0228	0.0261	-0.00491	-0.0070
	(11.51)***	(0.24)		(9.94)***	(-0.06)		(9.07)***	(-0.14)		(9.17)***	(-1.16)	
Depression	0.0112	-0.01710	0.0306	0.0171	-0.01933	0.3444	0.0186	-0.02078	0.7647	0.0169	-0.02603	0.7763
	(1.95)*	(-2.45)**		(4.34)***	(-6.64)***		(9.09)***	(-20.04)***		(5.94)***	(-15.04)***	
Panel E	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0459	0.00844	0.0295	0.0454	0.01045	0.0659	0.0444	0.01178	0.1332	0.0432	0.01416	0.2091
	(26.58)***	(1.35)		(20.65)***	(2.39)**		(19.38)***	(2.89)***		(20.81)***	(2.47)**	
Growth Rate Cycle	0.0413	0.00833	0.0252	0.0410	0.01118	0.0878	0.0396	0.01061	0.1326	0.0382	0.01018	0.1456
	(15.45)***	(1.20)		(12.72)***	(1.96)*		(12.15)***	(1.68)		(10.45)***	(1.86)*	
Depression	0.0467	0.00946	0.0426	0.0462	0.01045	0.0710	0.0451	0.01229	0.1527	0.0437	0.01554	0.2573
	(26.32)***	(1.67)*		(20.57)***	(2.53)**		(19.04)***	(3.10)***		(19.87)***	(2.81)***	

Table 5.3 (Continued)

Panel F	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0131	-0.07377	0.3403	0.0211	-0.05729	0.5823	0.0226	-0.04671	0.8996	0.0186	-0.03978	0.8438
	(1.55)	(-5.10)***		(3.66)***	(-5.72)***		(8.07)***	(-17.94)***		(9.56)***	(-8.19)***	
Growth Rate Cycle	0.0405	0.00187	-0.0227	0.0403	0.00373	-0.0201	0.0396	-0.00077	-0.0236	0.0400	-0.00774	0.0024
	(13.33)***	(0.16)		(10.60)***	(0.42)		(9.76)***	(-0.12)		(10.79)***	(-1.24)	
Depression	0.0166	-0.03378	0.1727	0.0229	-0.03300	0.4519	0.0239	-0.03140	0.7571	0.0207	-0.03548	0.5897
	(2.28)**	(-3.66)***		(4.11)***	(-6.20)***		(5.01)***	(-15.47)***		(3.41)***	(-12.91)***	
Panel G	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0610	0.01254	0.0470	0.0602	0.01523	0.0937	0.0587	0.01720	0.1875	0.0574	0.01810	0.2355
	(27.90)***	(1.61)		(22.68)***	(2.23)**		(21.39)***	(3.02)***		(22.20)***	(2.25)**	
Growth Rate Cycle	0.0557	0.00817	0.0111	0.0538	0.01561	0.1263	0.0521	0.01355	0.1579	0.0509	0.01029	0.1177
	(17.92)***	(1.06)		(14.61)***	(1.88)*		(12.78)***	(1.66)		(11.30)***	(1.69)	
Depression	0.0621	0.01290	0.0517	0.0611	0.01628	0.1142	0.0595	0.01832	0.2192	0.0579	0.02032	0.2972
	(27.38)***	(1.76)*		(22.20)***	(2.59)**		(20.67)***	(3.40)***		(20.63)***	(2.66)**	
Panel H	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0156	-0.08868	0.3709	0.0251	-0.07919	0.7792	0.0238	-0.05433	0.8110	0.0179	-0.04728	0.8937
	(1.43)	(-4.74)***		(4.64)***	(-9.86)***		(4.99)***	(-6.19)***		(4.16)***	(-11.77)***	
Growth Rate Cycle	0.0547	-0.00528	-0.0205	0.0546	-0.00119	-0.0235	0.0543	-0.00818	-0.0068	0.0543	-0.01328	0.0395
	(15.87)***	(-0.44)		(12.31)***	(-0.12)		(12.47)***	(-0.93)		(12.42)***	(-1.64)	
Depression	0.0211	-0.04225	0.2094	0.0284	-0.04586	0.6006	0.0267	-0.03248	0.5081	0.0223	-0.03655	0.3999
	(2.34)**	(-3.01)**		(3.92)***	(-6.85)***		(2.70)**	(-6.70)***		(2.09)*	(-7.22)***	

Table 5.3 (Continued)

Sample periods are 92 quarters from 1986 to 2008. **GDPGrowth_N** denotes quarterly growth rate of nominal GDP which is seasonally adjusted. **NPR** denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), **Business cycle** denotes business cycle peak and trough provided by Economic Cycle Research Institute (ECRI), there are 81 quarters are good time, 15 quarters are bad time. **Growth rate cycle** denotes growth rate cycle peak and trough provided by Economic Cycle Research Institute (ECRI), there are 47 quarters are good time, 49 quarters are bad time. **Depression** denotes UK depression time periods got from report Mitchell et al (2009), there are 77 quarters are good time, 19 quarters are bad time. **Panel A, C, E** and **G** presents NPR performance on good time by different measurements of macroeconomic conditions. **Panel B, D, F** and **H** (the shadow panels) present NPR performance on bad time by different measurements of macroeconomic conditions. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Table 5.4 **Time Series Regression of Future 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Growth Rate of Nominal GDP on Past 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter CBI Industrial Trends Survey Data Decomposed by Different Macro-Effect Variables**

$$\sum_{k=t+1}^{t+i} GDPGrowth\_N = \alpha_0 + \alpha_1 \sum_{k=t-j}^{t} CBI$$

Panel A	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0158	0.00007	0.0200	0.0159	0.00005	0.0467	0.0160	0.00005	0.0729	0.0159	0.00004	0.0731
	(18.86)***	(1.50)		(16.95)***	(1.99)*		(15.27)***	(2.11)**		(14.00)***	(1.91)*	
Growth Rate Cycle	0.0142	0.00004	-0.0144	0.0142	0.00004	-0.0087	0.0142	0.00005	0.0088	0.0139	0.00004	0.0181
	(11.79)***	(0.59)		(10.18)***	(0.80)		(9.90)***	(1.53)		(10.27)***	(1.62)	
Depression	0.0162	0.00009	0.0437	0.0162	0.00005	0.0472	0.0163	0.00004	0.0662	0.0162	0.00003	0.0708
	(19.76)***	(1.91)*		(16.98)***	(1.93)*		(14.93)***	(2.00)**		(13.63)***	(1.83)*	
Panel B	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0160	0.00037	0.2275	0.0135	0.00016	0.0647	0.0087	0.00005	-0.0711	-0.0004	-0.00002	-0.1062
	(3.66)***	(2.11)*		(2.09)*	(1.32)		(1.17)	(0.73)		(-0.07)	(-0.50)	
Growth Rate Cycle	0.0156	0.00016	0.1003	0.0154	0.00008	0.0717	0.0151	0.00006	0.0589	0.0151	0.00005	0.0673
	(11.52)***	(1.80)*		(9.24)***	(1.43)		(10.21)***	(1.36)		(12.01)***	(1.51)	
Depression	0.0110	0.00022	0.0939	0.0106	0.00011	0.0537	0.0088	0.00005	-0.0312	0.0048	0.00001	-0.0758
	(2.78)**	(1.35)		(2.33)**	(1.12)		(2.20)**	(0.82)		(1.03)	(0.19)	

Table 5.4 (Continued)

Panel C	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0317	0.00017	0.0616	0.0319	0.00011	0.1001	0.0320	0.00009	0.1143	0.0318	0.00007	0.1255
	(23.65)***	(2.39)**		(18.33)***	(2.40)**		(15.77)***	(2.18)**		(14.34)***	(2.01)**	
Growth Rate Cycle	0.0284	0.00009	-0.0094	0.0283	0.00009	0.0075	0.0280	0.00010	0.0257	0.0275	0.00009	0.0323
	(14.31)***	(0.81)		(11.21)***	(1.35)		(10.33)***	(1.66)		(10.54)***	(1.69)	
Depression	0.0323	0.00016	0.0616	0.0324	0.00010	0.0814	0.0324	0.00008	0.0966	0.0324	0.00007	0.1154
	(23.85)***	(2.42)**		(17.96)***	(2.22)**		(15.30)***	(2.03)**		(13.86)***	(1.90)*	
Panel D	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0211	0.00044	0.0485	0.0125	0.00010	-0.0786	-0.0008	-0.00005	-0.1013	-0.0190	-0.00016	-0.0085
	(2.50)**	(1.44)		(0.98)	(0.55)		(-0.06)	(-0.57)		(-1.62)	(-3.06)**	
Growth Rate Cycle	0.0297	0.00018	0.0338	0.0293	0.00010	0.0261	0.0289	0.00008	0.0341	0.0288	0.00007	0.0379
	(12.51)***	(1.49)		(9.76)***	(1.27)		(10.54)***	(1.50)		(10.11)***	(1.62)	
Depression	0.0180	0.00032	0.0455	0.0158	0.00012	-0.0215	0.0100	0.00002	-0.0753	0.0042	-0.00003	-0.0759
	(2.76)**	(1.23)		(1.78)*	(0.77)		(0.99)	(0.18)		(0.33)	(-0.39)	
Panel E	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0477	0.00028	0.0971	0.0478	0.00017	0.1210	0.0478	0.00013	0.1399	0.0476	0.00011	0.1519
	(26.16)***	(2.99)***		(19.19)***	(2.53)**		(16.08)***	(2.25)**		(14.62)***	(2.06)**	
Growth Rate Cycle	0.0426	0.00018	0.0014	0.0421	0.00015	0.0198	0.0416	0.00013	0.0345	0.0408	0.00010	0.0237
	(16.43)***	(1.28)		(12.22)***	(1.65)		(10.88)***	(1.76)*		(11.10)***	(1.76)*	
Depression	0.0485	0.00026	0.0839	0.0486	0.00015	0.0986	0.0486	0.00012	0.1199	0.0484	0.00010	0.1393
	(25.77)***	(2.85)***		(18.66)***	(2.34)**		(15.57)***	(2.11)**		(14.13)***	(1.97)*	

Table 5.4 (Continued)

Panel F	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0165	0.00025	-0.0748	0.0026	-0.00005	-0.1078	-0.0195	-0.00025	-0.0220	-0.0486	-0.00040	0.1787
	(1.19)	(0.66)		(0.13)	(-0.24)		(-0.96)	(-1.32)		(-3.19)**	(-2.57)**	
Growth Rate Cycle	0.0439	0.00020	0.0170	0.0436	0.00012	0.0294	0.0431	0.00010	0.0346	0.0429	0.00008	0.0327
	(13.26)***	(1.61)		(10.97)***	(1.66)		(10.27)***	(1.80)*		(9.12)***	(1.65)	
Depression	0.0208	0.00027	-0.0234	0.0153	0.00006	-0.0716	0.0077	-0.00005	-0.0757	0.0007	-0.00010	-0.0564
	(2.26)**	(0.88)		(1.03)	(0.24)		(0.41)	(-0.29)		(0.03)	(-0.64)	
Panel G	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0636	0.00035	0.1007	0.0637	0.00022	0.1295	0.0635	0.00016	0.1455	0.0630	0.00014	0.1687
	(27.02)***	(3.10)***		(19.66)***	(2.56)**		(16.47)***	(2.25)**		(15.14)***	(2.08)**	
Growth Rate Cycle	0.0572	0.00022	0.0046	0.0566	0.00020	0.0341	0.0558	0.00014	0.0228	0.0543	0.00011	0.0286
	(18.58)***	(1.39)		(13.95)***	(1.93)*		(12.58)***	(1.70)*		(13.64)***	(1.65)	
Depression	0.0648	0.00034	0.0904	0.0648	0.00020	0.1113	0.0646	0.00016	0.1293	0.0641	0.00013	0.1565
	(26.59)***	(2.96)***		(19.10)***	(2.41)**		(15.94)***	(2.14)**		(14.61)***	(2.00)*	
Panel H	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0070	-0.00011	-0.1085	-0.0210	-0.00047	-0.0057	-0.0569	-0.00070	0.2513	-0.0957	-0.00083	0.5751
	(0.36)	(-0.19)		(-0.76)	(-1.05)		(-2.46)**	(-2.45)**		(-6.57)***	(-4.15)***	
Growth Rate Cycle	0.0590	0.00028	0.0406	0.0583	0.00016	0.0447	0.0577	0.00011	0.0427	0.0569	0.00009	0.0302
	(15.39)***	(2.35)**		(11.95)***	(1.98)*		(10.53)***	(1.78)*		(9.16)***	(1.44)	
Depression	0.0184	0.000003	-0.0769	0.0092	-0.00017	-0.0591	-0.0010	-0.00025	-0.0002	-0.0125	-0.00031	0.0785
	(1.30)	(0.01)		(0.41)	(-0.42)		(-0.04)	(-0.93)		(-0.45)	(-1.61)	

Table 5.4 (Continued)

Sample periods are 92 quarters from 1986 to 2008. **GDPGrowth_N** denotes quarterly growth rate of nominal GDP which is seasonally adjusted. **CBI** denotes quarterly industrial trends survey data provided by Confederation of British Industry (CBI business confidence). **Business cycle** denotes business cycle peak and trough provided by Economic Cycle Research Institute (ECRI), there are 81 quarters are good time, 15 quarters are bad time. **Growth rate cycle** denotes growth rate cycle peak and trough provided by Economic Cycle Research Institute (ECRI), there are 47 quarters are good time, 49 quarters are bad time. **Depression** denotes UK depression time periods got from report Mitchell et al (2009), there are 77 quarters are good time, 19 quarters are bad time. **Panel A, C, E** and **G** presents NPR performance on good time by different measurements of macroeconomic conditions. **Panel B, D, F** and **H** (the shadow panels) present NPR performance on bad time by different measurements of macroeconomic conditions. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Table 5.5 Regressions of 1-Year Lead of Quarterly Nominal and Real GDP Growth Rates on 1-Year lag of Market Excess Returns, SMB and HML on: 1986-2008

$$GDPGrowth_{(t,t+4)} = a + b * Factor\,\mathrm{Re}\,t_{(t-4,t)} + \varepsilon_{(t,t+4)}$$

Panel A		Constant	MKT	SMB	HML	R^2	Adj R^2
	1	0.058	0.055	…	…	0.1149	0.1048
		(11.56)***	(1.73)*				
	2	0.061	…	0.046	…	0.0556	0.0448
		(13.49)***		(1.13)			
	3	0.059	…	…	0.036	0.0691	0.0584
		(13.85)***			(1.30)		
	4	0.059	…	0.036	0.030	0.1023	0.0814
		(14.44)***		(1.04)	(1.28)		
	5	0.059	0.049	0.031	…	0.1394	0.1194
		(11.86)***	(1.63)	(0.87)			
	6	0.055	0.061	…	0.042	0.2074	0.1889
		(12.41)***	(2.12)**		(1.91)*		
	7	0.056	0.057	0.017	0.039	0.2138	0.1860
		(12.59)***	(1.99)*	(0.53)	(2.00)**		
Panel B		Constant	MKT	SMB	HML	R^2	Adj R^2
	8	0.059	0.055	…	…	0.1159	0.1058
		(13.98)***	(2.24)**				
	9	0.061	…	0.045	…	0.0541	0.0432
		(14.66)***		(1.19)			
	10	0.059	…	…	0.034	0.0651	0.0543
		(15.84)***			(1.43)		
	11	0.060	…	0.036	0.029	0.0977	0.0767
		(15.73)***		(1.09)	(1.36)		
	12	0.059	0.049	0.030	…	0.1392	0.1192
		(13.98)***	(2.16)**	(0.88)			
	13	0.056	0.061	…	0.040	0.2038	0.1853
		(15.90)***	(2.77)***		(2.22)**		
	14	0.057	0.057	0.016	0.037	0.2100	0.1821
		(15.53)***	(2.64)**	(0.55)	(2.33)**		

Sample periods are 92 quarters from 1986 to 2008, quarterly Gross Domestic Product (GDP) is seasonally adjusted. **GDPGrowth** denotes nominal and real GDP growth in Panel A and Panel B, respectively. **'FactorRet'** stands for MKT, SMB and HML. **MKT** denotes excess returns between return on index of FTSE All Share and return on the 90-day Treasury Bills, **SMB** is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, **HML** is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics with 3 lags present in parentheses.

Table 5.6 Regressions of 1-Year Leads of Quarterly Nominal and Real GDP Growth Rates on 1-Year Lag of SMB, HML and Aggregate Net Number of Director Purchases Trading Ratio on: 1986-2008

$$GDPGrowth_{(t,t+4)} = a + b * Factor\mathrm{Re}\,t_{(t-4,t)} + c * NPR_{(t-4,t)} + \varepsilon_{(t,t+4)}$$

Panel A	Constant	SMB	HML	NPR	R^2	Adjust R^2
	0.055	0.024	…	0.020	0.2719	0.2542
	(18.88)***	(1.11)		(2.90)***		
	0.054	…	0.029	0.021	0.3138	0.2970
	(19.72)***		(2.02)**	(3.05)***		
	0.054	0.018	0.027	0.020	0.3252	0.3002
	(19.82)***	(1.01)	(2.04)**	(3.21)***		
Panel B	Constant	SMB	HML	NPR	R^2	Adjust R^2
	0.021	0.051	…	0.010	0.1759	0.1558
	(6.65)***	(1.44)		(1.40)		
	0.019	…	0.026	0.012	0.1378	0.1167
	(4.88)***		(1.96)*	(1.66)		
	0.020	0.046	0.021	0.010	0.2097	0.1804
	(5.62)***	(1.37)	(2.10)**	(1.49)		
Panel C	Constant	SMB	HML	NPR _ADJ_1	R^2	Adjust R^2
	0.055	0.024	…	0.020	0.2754	0.2577
	(18.95)***	(1.10)		(3.00)***		
	0.053	…	0.028	0.020	0.3160	0.2993
	(19.84)***		(2.01)**	(3.15)***		
	0.054	0.0183	0.026	0.020	0.3273	0.3024
	(19.94)***	(0.99)	(2.03)**	(3.31)***		
Panel D	Constant	SMB	HML	NPR _ADJ_1	R^2	Adjust R^2
	0.021	0.050	…	0.010	0.1774	0.1573
	(6.63)***	(1.45)		(1.45)		
	0.019	…	0.026	0.012	0.1389	0.1179
	(4.86)***		(1.96)*	(1.70)*		
	0.020	0.046	0.021	0.010	0.2107	0.1814
	(5.61)***	(1.38)	(2.09)**	(1.53)		
Panel E	Constant	SMB	HML	NPR _ADJ_2	R^2	Adjust R^2
	0.055	0.022	…	0.022	0.2967	0.2796
	(19.16)***	(1.01)		(3.52)***		
	0.053	…	0.029	0.023	0.3421	0.3260
	(19.80)***		(2.10)**	(3.75)***		
	0.053	0.016	0.027	0.022	0.3503	0.3263
	(20.02)***	(0.87)	(2.14)**	(3.98)***		
Panel F	Constant	SMB	HML	NPR _ ADJ_2	R^2	Adjust R^2
	0.021	0.049	…	0.011	0.1816	0.1616
	(6.62)***	(1.38)		(1.47)		
	0.019	…	0.026	0.013	0.1482	0.1274
	(4.81)***		(1.96)*	(1.82)*		
	0.020	0.044	0.021	0.011	0.2155	0.1865
	(5.59)***	(1.31)	(2.10)**	(1.57)		

Table 5.6 (Continued)

Sample periods are 92 quarters from 1986 to 2008, quarterly Gross Domestic Product (GDP) is seasonally adjusted. **GDPGrowth** denotes nominal and real GDP growth rate. It stands for nominal GDP growth in **Panel A, C** and **E**, while in **Panel B, D** and **F** (Panels covered by grey shadow) for real GDP growth. **'FactorRet'** stands for SMB and HML. **SMB** is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, **HML** is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. **NPR** denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), **NPR_ ADJ_1** denotes seasonal adjusted NPR based on December and March fiscal year end by assumption, **NPR_ ADJ_2** denotes seasonal adjusted NPR based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics with 3 lags present in parentheses.

Table 5.7 **Regressions of 1-Year Leads of Quarterly Nominal and Real GDP Growth Rate on 1-Year Lag of MKT, SMB, HML and Aggregate Net Number of Director Purchases Trading Ratios on: 1986-2008**

$$GDPGrowth_{(t,t+4)} = a + b * MKT_{(t-4,t)} + c * Factor\mathrm{Re}\,t_{(t-4,t)} + d * NPR_{(t-4,t)} + \varepsilon_{(t,t+4)}$$

Panel A	Constant	MKT	SMB	HML	NPR	R^2	Adjust R^2
	0.055	0.007	0.024	…	0.019	0.2742	0.2473
	(18.34)***	(0.43)	(1.04)		(2.84)***		
	0.052	0.020	…	0.033	0.019	0.3312	0.3064
	(18.14)***	(1.27)		(2.47)**	(3.11)***		
	0.053	0.018	0.015	0.031	0.019	0.3388	0.3057
	(18.53)***	(1.08)	(0.81)	(2.52)**	(3.25)***		
Panel B	Constant	MKT	SMB	HML	NPR	R^2	Adjust R^2
	0.021	-0.004	0.051	…	0.010	0.1767	0.1462
	(7.17)***	(-0.26)	(1.43)		(1.46)		
	0.019	0.010	…	0.028	0.011	0.1422	0.1104
	(4.49)***	(0.61)		(1.87)*	(1.70)*		
	0.020	0.004	0.045	0.022	0.010	0.2103	0.1708
	(5.73)***	(0.24)	(1.32)	(1.93)*	(1.54)		
Panel C	Constant	MKT	SMB	HML	NPR _ADJ_1	R^2	Adjust R^2
	0.055	0.007	0.023	…	0.019	0.2775	0.2507
	(18.28)***	(0.42)	(1.03)		(2.94)***		
	0.052	0.020	…	0.032	0.019	0.3328	0.3081
	(18.15)***	(1.27)		(2.47)**	(3.23)***		
	0.053	0.018	0.015	0.030	0.019	0.3404	0.3075
	(18.50)***	(1.07)	(0.80)	(2.52)**	(3.37)***		
Panel D	Constant	MKT	SMB	HML	NPR _ADJ_1	R^2	Adjust R^2
	0.021	-0.004	0.051	…	0.010	0.1782	0.1478
	(7.17)***	(-0.27)	(1.43)		(1.50)		
	0.019	0.010	…	0.028	0.011	0.1431	0.1113
	(4.50)***	(0.61)		(1.87)*	(1.75)*		
	0.020	0.0036	0.045	0.022	0.010	0.2112	0.1718
	(5.75)***	(0.23)	(1.33)	(1.93)*	(1.59)		
Panel E	Constant	MKT	SMB	HML	NPR _ ADJ_2	R^2	Adjust R^2
	0.055	0.004	0.021	…	0.022	0.2974	0.2714
	(18.47)***	(0.23)	(0.96)		(3.37)***		
	0.052	0.017	…	0.032	0.022	0.3534	0.3295
	(18.16)***	(1.05)		(2.50)**	(3.71)***		
	0.052	0.015	0.013	0.030	0.021	0.3592	0.3272
	(18.53)***	(0.88)	(0.71)	(2.57)**	(3.91)***		
Panel F	Constant	MKT	SMB	HML	NPR _ ADJ_2	R^2	Adjust R^2
	0.021	-0.006	0.050	…	0.012	0.1831	0.1529
	(7.12)***	(-0.37)	(1.37)		(1.54)		
	0.019	0.008	…	0.027	0.013	0.1508	0.1193
	(4.48)***	(0.49)		(1.85)*	(1.84)*		
	0.019	0.002	0.044	0.022	0.011	0.2157	0.1765
	(5.71)***	(0.13)	(1.27)	(1.93)*	(1.62)		

Table 5.7 (Continued)

Sample periods are 92 quarters from 1986 to 2008, quarterly Gross Domestic Product (GDP) is seasonally adjusted. **GDPGrowth** denotes nominal and real GDP growth rate. It stands for nominal GDP growth in **Panel A, C** and **E**, while in **Panel B, D** and **F** (Panels covered by grey shadow) for real GDP growth. **MKT** denotes excess returns between return on index of FTSE All Share and return on the 90-day Treasury Bills. **'FactorRet'** stands for SMB and HML. **SMB** is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, **HML** is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. **NPR** denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), **NPR_ ADJ_1** denotes seasonal adjusted NPR based on December and March fiscal year end by assumption, **NPR_ ADJ_2** denotes seasonal adjusted NPR based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics with 3 lags present in parentheses.

Table 5.8 Regressions of 1-Year Leads of Quarterly Nominal and Real GDP Growth Rates on 1-Year Lag of MKT, SMB, HML and CBI Industrial Trends Survey Data on: 1986-2008

$$GDPGrowth_{(t,t+4)} = a + b * MKT_{(t-4,t)} + c * FactorRet_{(t-4,t)} + d * CBI_{(t-4,t)} + \varepsilon_{(t,t+4)}$$

Panel A	Constant	MKT	SMB	HML	CBI	R^2	Adjust R^2
	0.059	…	0.061	…	0.00014	0.2276	0.2096
	(11.18)***		(1.33)		(2.52)**		
	0.056	…	…	0.048	0.00016	0.2520	0.2347
	(10.69)***			(1.99)**	(2.69)***		
	0.056	…	0.049	0.042	0.00013	0.2937	0.2688
	(10.90)***		(1.27)	(2.08)**	(2.46)***		
Panel B	Constant	MKT	SMB	HML	CBI	R^2	Adjust R^2
	0.023	…	0.070	…	0.00006	0.2217	0.2036
	(5.85)***		(2.02)**		(1.44)		
	0.021	…	…	0.036	0.00009	0.1661	0.1467
	(4.77)***			(2.26)**	(1.96)*		
	0.021	…	0.062	0.028	0.00006	0.2679	0.2421
	(5.03)***		(2.02)**	(2.44)**	(1.28)		
Panel C	Constant	MKT	SMB	HML	CBI	R^2	Adjust R^2
	0.056	0.043	0.052	…	0.00012	0.2748	0.2492
	(9.39)***	(1.45)	(1.23)		(1.94)*		
	0.052	0.062	…	0.056	0.00012	0.3488	0.3258
	(8.03)***	(1.93)*		(2.44)**	(1.98)*		
	0.052	0.056	0.035	0.051	0.00010	0.3687	0.3386
	(8.65)***	(1.93)*	(1.05)	(2.65)**	(1.72)*		
Panel D	Constant	MKT	SMB	HML	CBI	R^2	Adjust R^2
	0.022	0.015	0.067	…	0.00005	0.2305	0.2034
	(5.66)***	(0.66)	(1.91)*		(1.22)		
	0.019	0.033	…	0.040	0.00007	0.2077	0.1798
	(3.95)***	(1.42)		(2.33)**	(1.54)		
	0.019	0.0228	0.056	0.032	0.00004	0.2873	0.2534
	(4.63)***	(1.06)	(1.81)*	(2.43)**	(0.94)		

Sample periods are 92 quarters from 1986 to 2008, quarterly Gross Domestic Product (GDP) is seasonally adjusted. **GDPGrowth** denotes nominal and real GDP growth rate. It stands for nominal GDP growth in **Panel A** and **C**, while in **Panel B** and **D** (Panels covered by grey shadow) for real GDP growth. **MKT** denotes excess returns between return on index of FTSE All Share and return on the 90-day Treasury Bills. **'FactorRet'** stands for SMB and HML. **SMB** is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, **HML** is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. **CBI** denotes quarterly industrial trends survey data provided by Confederation of British Industry (CBI business confidence). The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics with 3 lags present in parentheses.

Table 5.9 **Regressions of 1-Year Leads of Quarterly Nominal and Real GDP Growth Rates on 1-Year Lag of Fama-French 3 Factors and Aggregate Net Number of Director Purchases Trading Ratio in the Presence of Business Cycle Variables**

$$GDPGrowth_{(t,t+4)} = a + b*MKT_{(t-4,t)} + c*FactorRet_{(t-4,t)} + d*NPR_{(t-4,t)} + e*DY_{(t)} + f*IPGrowth_{(t-4,t)} + g*TERM_{(t)} + \varepsilon_{(t,t+4)}$$

Panel A	Constant	MKT	SMB	HML	NPR	DY	IPGrowth	TERM	R^2	Adj R^2
1	0.022	…	0.077	0.047	0.0132974	0.722	0.428	-2.810	0.4751	0.4362
	(1.43)		(1.61)	(3.11)***	(2.57)**	(1.97)*	(4.04)***	(-1.09)		
2	0.021	…	0.077	0.047	0.0135398	0.729	0.424	-2.796	0.4777	0.4390
	(1.42)		(1.62)	(3.09)***	(2.74)***	(2.00)**	(4.04)***	(-1.10)		
3	0.022	…	0.075	0.047	0.0150378	0.717	0.430	-2.746	0.4805	0.4420
	(1.44)		(1.55)	(3.14)***	(2.77)***	(1.95)*	(4.07)***	(-1.06)		
4	0.019	0.055	0.071	0.053	0.0142586	0.781	0.311	-1.245	0.4979	0.4540
	(1.28)	(2.35)**	(1.52)	(3.39)***	(2.97)***	(2.11)**	(3.25)***	(-0.49)		
5	0.019	0.058	0.071	0.053	0.0147566	0.790	0.301	-1.151	0.5024	0.4588
	(1.26)	(2.44)**	(1.52)	(3.39)***	(3.26)***	(2.15)**	(3.22)***	(-0.45)		
6	0.019	0.051	0.070	0.052	0.0155446	0.775	0.323	-1.313	0.5004	0.4567
	(1.28)	(2.21)**	(1.46)	(3.37)***	(2.97)***	(2.09)**	(3.44)***	(-0.51)		
Panel B	**Constant**	**MKT**	**SMB**	**HML**	**NPR**	**DY**	**IPGrowth**	**TERM**	R^2	**Adj** R^2
7	0.027	…	0.052	0.039	0.0095577	0.607	0.454	-3.876	0.3446	0.2961
	(2.21)**		(1.23)	(2.48)**	(1.42)	(2.05)**	(4.00)***	(-1.55)		
8	0.027	…	0.052	0.039	0.0097808	0.612	0.451	-3.863	0.3462	0.2978
	(2.21)**		(1.24)	(2.46)**	(1.56)	(2.09)**	(4.00)***	(-1.56)		
9	0.027	…	0.050	0.039	0.0117091	0.596	0.452	-3.780	0.3519	0.3039
	(2.24)**		(1.16)	(2.48)**	(1.68)*	(2.01)**	(3.97)***	(-1.51)		
10	0.025	0.047	0.047	0.044	0.0103833	0.658	0.353	-2.531	0.3613	0.3054
	(2.05)**	(1.69)*	(1.14)	(2.61)**	(1.62)	(2.22)**	(3.69)***	(-1.11)		
11	0.025	0.049	0.047	0.044	0.0108207	0.664	0.346	-2.457	0.3640	0.3084
	(2.04)**	(1.75)*	(1.14)	(2.60)**	(1.83)*	(2.27)**	(3.69)***	(-1.09)		
12	0.026	0.045	0.046	0.044	0.0121518	0.647	0.359	-2.528	0.3669	0.3115
	(2.06)**	(1.60)	(1.08)	(2.58)**	(1.77)*	(2.17)**	(3.79)***	(-1.10)		

Table 5.9 (Continued)

Sample periods are 92 quarters from 1986 to 2008, quarterly Gross Domestic Product (GDP) is seasonally adjusted. **GDPGrowth** denotes nominal and real GDP growth rate in Panel A and B, respectively. **MKT** denotes excess returns between return on index of FTSE All Share and return on the 90-day Treasury Bills. **'FactorRet'** stands for SMB and HML. **SMB** is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, **HML** is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks.

NPR denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), results of real NPR present in model 1, 4, 7 and 10; model 2, 5, 8 and 11 present results of NPR with **Seasonality Adjustment One** which is seasonal adjusted NPR based on December and March fiscal year end by assumption; model 3, 6, 9 and 12 present results of NPR with **Seasonality Adjustment Two** which is seasonal adjusted NPR based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3.

DY denotes the dividend yield of FTSE All Share. **IPGrowth** denotes industrial production growth. **TERM** denotes long-run rate minus short term rate in UK, calculated by long-run rate (the yield to maturity of a 10-year government bond) minus short term rate (90-day UK Treasury Bill rate).

The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics with 3 lags present in parentheses.

Table 5.10 Regressions of 1-Year Leads of Quarterly Nominal and Real GDP Growth Rates on 1-Year Lag of Fama-French 3 Factors and CBI Industrial Trends Survey Data in the Presence of Business Cycle Variables

$$GDPGrowth_{(t,t+4)} = a + b*MKT_{(t-4,t)} + c*FactorRet_{(t-4,t)} + d*CBI_{(t-4,t)} + e*DY_{(t)} + f*IPGrowth_{(t-4,t)} + g*TERM_{(t)} + \varepsilon_{(t,t+4)}$$

	Constant	MKT	SMB	HML	CBI	DY	IPGrowth	TERM	R^2	Adj R^2
1	0.016	…	0.090	0.048	-0.0000738	0.859	0.628	-3.207	0.4394	0.3979
	(0.90)		(1.83)*	(2.95)***	(-0.80)	(2.33)**	(2.63)**	(-1.32)		
2	0.012	0.054	0.086	0.054	-0.0000926	0.930	0.554	-1.630	0.4611	0.4140
	(0.71)	(1.68)*	(1.80)*	(3.20)***	(-0.98)	(2.62)**	(2.46)**	(-0.65)		
3	0.023	…	0.061	0.040	-0.0000456	0.703	0.583	-4.198	0.3251	0.2751
	(1.57)		(1.39)	(2.40)**	(-0.51)	(2.36)**	(2.41)**	(-1.80)*		
4	0.021	0.046	0.058	0.045	-0.0000616	0.764	0.520	-2.854	0.3407	0.2830
	(1.37)	(1.31)	(1.35)	(2.51)**	(-0.67)	(2.67)***	(2.29)**	(-1.30)		

Sample periods are 92 quarters from 1986 to 2008, quarterly Gross Domestic Product (GDP) is seasonally adjusted. **GDPGrowth** denotes nominal and real GDP growth rate. Model 1 and 2 presents results of Nominal GDP growth, while model 3 and 4 present real GDP. **MKT** denotes excess returns between return on index of FTSE All Share and return on the 90-day Treasury Bills. **'FactorRet'** stands for SMB and HML. **SMB** is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, **HML** is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. **CBI** denotes quarterly industrial trends survey data provided by Confederation of British Industry (CBI business confidence).

DY denotes the dividend yield of FTSE All Share. **IPGrowth** denotes industrial production growth. **TERM** denotes long-run rate minus short term rate in UK, calculated by long-run rate (the yield to maturity of a 10-year government bond) minus short term rate (90-day UK Treasury Bill rate).

The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics with 3 lags present in parentheses.

Chapter 6: Firm Characteristics, Director Role and Market Reaction

6.1 Introduction

Chapter 4 concludes that aggregate director trading is positively significant and can be used to forecast future UK market excess returns. This is consistent with previous studies from both the USA and the UK. Chapter 5 investigates the relationship between aggregate director trading and future aggregate economic activities in the UK. Having examined the macro-picture of aggregate director trading, it is going to examine a more micro-picture. Therefore, Chapter 6 is about long-run director trading study concentrated the micro-aspects. This Chapter will investigate the performance of market reaction to director trading by firm characteristics and type of directors.

Section 6.2 is a literature review. It discusses and summarises the existing evidence for a relationship of abnormal returns and firm characteristics with aggregate director trading and information hierarchy hypothesis, taking evidence from both the USA and the UK.

Section 6.3 presents data and sample characteristics. It mainly describes the classification of director roles (CEOs, CFOs, Executive Chairmen, Nonexecutive Chairmen, Other Executives and Other Nonexecutives).

Section 6.4 discusses methodology, introducing mean monthly calendar-time abnormal returns and Calendar-Time portfolio regression with Fama-French 3-factor and Carhart 4-factor models.

Section 6.5 contains empirical results. It first presents results of firm characteristics and director trading, and then documents the performance of market reaction to director roles.

Finally, Section 6.6 summarises the results and concludes Chapter 6.

6.2 Literature Review

6.2.1 Abnormal Returns, Firm Characteristics and Director Trading

Previous studies provide evidence indicating that abnormal returns depend on company characteristics (firm size and low- or high-B/M ratio).

In the US, Chopra et al. (1992) documented an economically-important overreaction effect in the stock market, concentrated among small firms. Fama and French argue that size and B/M ratio 'provide a simple and powerful characterisation of the cross-section of average returns for the 1963-1990 period' (1992). In their later paper (1993), they introduce the Fama-French 3 factors (MKT, SMB and HML)[27] and show that the slopes on SMB for stocks are related to size. 'In every book-to-market quintile, the slopes on SMB decrease monotonically from smaller- to bigger-size quintiles.' Similarly, the slopes on HML are systematically related to B/M. 'In every size quintile of stocks, the HML slopes increase monotonically from strong negative values for the lowest-B/M quintile to strong positive value for the highest-B/M quintile.' The results of Lakonishok et al. (1994) show lower average returns and cumulative returns over the past 5 years in their sample; they therefore conclude that a low B/M implies an overvalued glamour stock. Loughran (1997) examined average equally weighted annual returns for size and B/M quintiles from July 1963 to December 1995, and found that the smallest sized group achieved better annual returns than the largest size quintile within NYSE, Amex and NASDAQ firms. Lakonishok et al. (1994) reported a similar book-to-market effect after controlling for firm size in a sample of NYSE and Amex firms.

[27] Details are fully described in Chapter 5.

Lakonishok and Lee (2001) investigated insider trading from 1975 to 1995; their findings, consistently with previous US studies, suggested that there is a more efficient market for larger stocks, as they are under much greater scrutiny than smaller stocks. The performance of aggregate insider activities is related to firm size. Insiders have a greater advantage in timing an index of small stocks than an index of large stocks. Consistent with the results of other similar studies, the usefulness of insider activities is not uniform across all market-cap groups. Insider trading is a stronger indicator in small-cap stocks, which are often perceived to be less efficient. They observe that the largest spread in returns between stocks bought and sold by insiders occurs in small-growth stocks. Insiders in general are heavy sellers of such stocks; indeed, those stocks are associated with relatively low returns. However, when they buy such stocks, insiders know what they are doing. In addition, insiders generally invest in small-value stock, which is associated with high returns.

In the UK, Gregory et al. (1994) examined director trading activities for 150 listed non-financial companies for the period January 1984 to December 1986 in LSE. They found that a large proportion of abnormal returns following director trades occurred in small and medium sized firms: these abnormal returns could be explained by the size effect. In another study, Gregory et al. (1997) examined director trading from January 1986 to December 1990; they found that controlling for the size effect can be of fundamental importance when studying CARs over long post-event windows, particularly where the sample includes a large number of smaller companies. Later, Gregory et al. (2013) examined the patterns of, and long-run returns to, director trading along the value-glamour continuum in all stocks listed on the main LSE. They found that abnormal returns are particularly concentrated in smaller value stocks; when size and B/M are controlled for, the abnormal returns to small-value stocks are similar and always significant for small firms.

6.2.2 Information Hierarchy and Director Trading

The information hierarchy hypothesis and relative empirical works are fully discussed in Section 2.1.3.

6.3 Data and Sample Characteristics

This Chapter uses the same dataset as in Chapter 3: the Hemscott Company Guru Academic, which covers the period 1994-2008.It includes 488,671 original transaction records, listing company names, director's names, director's shareholdings, director's positions on the board, transaction and announcement dates, number of shares traded, price, transaction types (13 different types)[28] and transaction descriptions (27 different types).[29] The reason that it has not used Directus (which covers the period 1986-1993) is that this dataset does not classify director roles or job title among director transactions.

From previous research (Seyhun, 1988; 1990; 1992; 1998), it seems that directors' open market sales and purchases are more likely to represent actions taken as a result of special director information. Other empirical works (Seyhun, 1990; Gregory, Matatko et al., 1994; Fidrmuc, Goergen et al., 2006) indicate that option-related trade by directors shows lower information and is insignificantly related to post-signal abnormal returns. Therefore, following these papers, this study will only analyse open market sales and purchases by directors for the period 1986-2008. This means that the sample data relates only to ordinary shares or common shares. All other types of directors'

[28] Transaction types include: purchase, sale, exercise of option, sale of option shares, in lieu of dividend, rights taken up, Sale of rights, received on conversion, transfer in between holdings, transfer out, n/a, and B&B purchase and sale.

[29] Transaction descriptions include any relevant additional information relating to the transaction, such as ADRs, ISA, trust, warrants, etc.

transactions are excluded (e.g. rights taken up, exercises of options, shares acquired through a plan, etc.).[30]

Following the above adjustments, the sample contains 60,300 directors' transaction records relating to 1,086 firms, from 1994 to 2008.

It classifies the firms in the sample into the 3 groups (small, medium and big) described in Chapter 3. It then splits each firm capitalisation group into 3 book-to-market groups (low, medium and high). After adding in these size and book-to-market factors, it is left with 55,848 transactions out of the original 60,300.

Meanwhile, it obtains the benchmark portfolio from website of University of Exeter,[31] which was constructed and applied by Gregory et al. (2013). It will form the portfolios by independently sorts the sample firms by market capitalisation and B/M. Sorting by market capitalisation first, it forms two size groups – 'S'-small and 'B'-big – using the median market capitalisation of the largest 350 companies in UK (proxy for the Fama–French NYSE break point) in year *t* as the size break point. Then it sorts the data into three B/M groups – 'H'-High, 'M'-medium and 'L'-Low, using the 30th and 70th percentiles of B/M of the largest 350 firms as break points for the B/M. This process ultimately results in the following six intersecting portfolios: SH, SM, SL, BH, BM, and BL where 'S' and 'B' represent small and big firm sizes respectively, and 'H', 'M' and 'L' represent high, medium and low B/M.

These six portfolios are then used to form the *SMB* and *HML* factors. The SMB factor is

$$(SL+SM+SH)/3-(BL+BM+BH)/3, \quad (43)$$

and the HML factor is

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[30] Numerous consistency checks on dates, prices, and shares were performed to eliminate approximately 10,400 transaction records containing apparent data errors.

[31] http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/

$$(SH + BH)/2 - (SL + BL)/2, \quad (44)$$

Note that in this model, all the information of individual firm from which *SMB* and *HML* are formed receives equal weighting. However, as Cremers et al. (2012) and Gregory et al. (2013) point out, it may be preferable to construct the Fama-French factors by value-weighting (rather than equally weighting) the individual component portfolios. Therefore, the factors are value-weighted in the data available. The UK Fama-French factors are available from Xfi Centre for Finance and Investment, University of Exeter Business School.

The next step is to classify the director roles. In the dataset, there are 3 columns giving information on the director's role: these are Role, Director and Job title.[32]. In order to test the information hierarchy hypothesis, directors must be split into six categories: CEO (Executive), CFO (Executive), Chairman (Executive), Chairman (Non-executive), all other executives, and all other non-executives.

The general categories of role are:

1. Any job with the title Chief Executive, CEO, or similar; managing directors with executive positions. (Managing director is often another name for CEO. For chief operation/retail/commercial officer, etc., these roles do not fall into this category, but are treated as 'Other executives'). Any individual combining the role of chief executive with any other role or title is also included here

2. Any executive role containing the word 'finance': the finance officer or 'CFO' with an executive position.

[32] '**Role'** is short for 'job role', and includes such position as CEO (Chief Executive Officer), COO (Chief Operating Officer) and CFO (Chief Financial Officer). **Director** is director type where **D**=Executive, **N**=Non-Executive, **E**=Company Secretary. The Executive or Non-Executive status is as reported by the companies themselves via the regulatory news service and also in their Annual Reports and Accounts. **The job title** is a detailed description of a director's current abbreviated job role, where applicable.

3. Any role like Chairman, President, etc. is classed as ‘Chairman’. If they hold an executive position, as recorded in the ‘Director’ column (where ’D’ denotes an executive and ‘N’ a non-executive), then they are placed in this class
4. Other executives
5. Other non-executives.

If an individual holds a combination of roles, they are categorised by the higher-hierarchy position (e.g. a Chairman & CEO is treated as a CEO; a CFO & Company Secretary as a CFO, etc.). A title including vice-, deputy and joint- is treated as it would be without this prefix (e.g. a vice-president/chairman is treated as a president/chairman). If there is no description in the columns Role and Job Title, these positions are classed as ‘Other executives’ or ‘Other non-executives’ depending on the record in the Director column (’D’ or ’N’).

Furthermore, it deletes 27,603 transactions which had no description for ‘Role’, ‘Director’ or ‘Job Title’. A further 49 traders with only E (described as company secretary) in the Director column are also deleted. This left with a sample of 32,648 transactions from 1,037 companies.

Table 6.1 summarises the statistics of the relationship between director trading, firm characteristics and director roles. Panels A and B describe the sample characteristics based on firm size and book-to-market ratio. Panel A presents director purchases, and Panel B shows director sales. It can be seen that, regardless of director purchases or sales, small firms always have a much lower number of total transactions than big firms (3,472 vs. 25,889 purchases; 821 vs. 14,360 sales). But average shares per transaction in director purchases and sales in small firms are twice as high as those in big firms (508,669 vs. 156,023 in purchases; 453,495 vs. 215,413 in sales).

For B/M ratio, there are a similar number of purchases transactions in low and high B/M firms, while the number of purchases transactions in medium B/M firms is more than those in low and high B/M firms combined: the frequency of purchases trading in medium B/Ms is more double that in the others. Medium B/M firms also trade the largest total number of shares. Meanwhile, high B/M firms achieve the lowest number of shares traded on a monthly basis and low B/M firms obtain the biggest number of shares per transaction, on average. For director sales, the total number of transactions in medium B/M firms is again more than that of low and high B/M firms combined. Low B/M firms trade the largest total number of shares, and have the highest average of shares per trade. Meanwhile, high B/M firms have the smallest total number of shares and transactions.

Panels C and D describe the sample characteristics of director trading by director roles, with Panel C showing purchases and Panel D showing sales. From Panel C, it can be seen that CEOs trade very frequently. They record much higher figures than CFOs in their number of shares traded on monthly basis (3,098,464 vs. 913,550), total number of shares (557,723,573 vs. 164,438,960), total number of transactions (6,728 vs. 3,612) and average shares per transaction (82,896 vs. 45,526).

The sales activities in Panel D are more obvious. CEOs record the highest figures among all director roles for number of shares traded on monthly basis (2,612,037), total number of shares (470,166,684) and total number of transactions (1,454). The Higgs (2003) report shows that the average board size of all UK-listed firms is 6.7 consisting of 1 chairman, 3 executive directors, and 2.7 non-executive directors on average (p. 18). It is therefore logical that CEOs trade most frequently. CEOs may achieve valuable information to stimulate them to trade.

6.4 Methodology

This Chapter uses the buy-and-hold abnormal returns and the calendar-time approach. Buy-and-hold abnormal returns measure the average multimonth or multiyear return from the investment strategy of all firms that complete an event and sell at the end of a pre-specified holding period; this is compared to an equivalent strategy using otherwise similar non-event firms. In the calendar-time approach, an event portfolio is formed for each calendar month: this includes all the firms that experienced the event over the months prior to the given month, where τ refers to the specific investment holding period of event firms. So, if one is looking at a 24-month return, one would include all the firms which experienced an event in that particular month, y, of the past 24 months. The portfolio can be equally-weighted or value-weighted, and the abnormal returns can be specified by running a regression of the excess returns on a factor model (the calendar-time portfolio regression method, CTPR).

6.4.1 Buy and Hold Abnormal Returns (BHAR)

Buy-and-hold abnormal returns have become the standard method of measuring long-run abnormal returns (Barber and Lyon, 1997; Lyon et al., 1999).

Barber and Lyon (1997) and Lyon et al. (1999) argue that BHARs are important because they 'precisely measure investor experience.' While it is true that BHARs capture the investor's experience from buying and holding securities for 3–5 years, this is not a particularly compelling reason to restrict attention to this methodology, if the objective is a reliable assessment of long-run stock price performance. First, the buy-and-hold experience is only one type of investor experience. Second, because of compounding, the buy-and-hold abnormal performance measure increases over the holding period, giving abnormal performance during any portion of the return series. For instance, if abnormal performance exists for only the first 6 months following an event and if one calculates 3- and 5-year BHARs, both can be significant, and the 5-year BHAR will be larger in magnitude than the 3-year BHAR. This is important to consider, since the length of the holding period is arbitrary and various holding period intervals are often analysed to determine how long the abnormal performance continues after the event. Finally, and most important, this shows that there is serious statistical problem with BHARs that cannot be easily corrected. Since the objective is to reliably measure abnormal returns, it is imperative that the methodology allow for reliable statistical inference.

It calculates 6-, 12-, 18- and 24-month BHARs for each sample firm's purchasing activities by size-B/M portfolio, using 6 value-weighted, non-rebalanced, size-B/M portfolios as expected return benchmarks:[33]

$$BHAR_i = \prod_{t=1}^{T}(1+R_{i,t}^{k}) - \prod_{t=1}^{T}(1+R_{benchmark,t}^{k}) \quad , (45)$$

where $R_{i,t}^{k}$ is return of firm i in size-B/M portfolio group k on month t. The main difference between returns of cumulative abnormal returns (CARs) and BHARs is that CARs ignore compounding, while raw returns and BHARs account for it.[34]

The mean buy-and-hold abnormal returns is the equal-weighted average of the individual BHARs:

$$\overline{BHAR} = \frac{1}{N}\sum_{i=1}^{N} BHAR_i^{k} \quad , (46)$$

[33] Returns of 6 equal-weighted benchmark UK portfolios were obtained from the University of Exeter Business School website: http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/.

[34] Barber & Lyon (1997) provide a detailed description of the consequences of such differences in event study.

The size-B/M portfolio benchmarks are designed to control for the empirical relation between expected returns and these two firm characteristics (see Fama and French, 1992, 1993 for discussion and evidence).

6.4.2 The statistical tests

Since the BHAR is the difference between a sample firm's 6, 12, 18-, and 24-month returns and the 6, 12, 18-, and 24-month return on a benchmark portfolio, the distribution of individual firm BHARs is strongly positively skewed (Barber and Lyon, 1997) and generally does not have a zero mean. Therefore, the skewness-adjusted t-statistic is introduced.

For each portfolio holding time *t*, it calculates the conventional t-statistic as:

$$t_t = \frac{\overline{BHAR_t}}{\sigma(BHAR_{i,t})/\sqrt{N}} \text{, (47)}$$

where $\overline{BHAR_t}$ is the cross sectional sample mean, $\sigma(BHAR_t)$ is the cross sectional standard deviation, and n is the number of firms that have director purchase activities. Because the data is likely to be skewed, it then corrects using Johnson's (1978) correction:

$$Skewness\text{–}adj\_t = \sqrt{n}(S + \frac{1}{3}\hat{\gamma}S^2 + \frac{1}{6n}\hat{\gamma}) \text{, (48)}$$

where $\hat{\gamma}$ is the coefficient of skewness, and $S = \overline{BHAR_t}/\sigma(BHAR_t)$. This adjustment was advocated by Barber and Lyon (1997), Lyon et al. (1999) and Gregory et al. (2010) because of the suspected skewness of BHAR returns.

As recommended by Sutton (1993) and Lyon et al. (1999), it finds well-specified test statistics through a bootstrapped application of this skewness-adjusted test statistic. Bootstrapping the test statistic involves drawing b resamples of size n_b from the original sample. In general, the skewness-adjusted test statistic is calculated in each of these b bootstrapped resamples, and the critical values for the transformed test statistics are calculated from the b values of the transformed statistics.

The bootstrapping is carried out as follows: draw 1,000 bootstrapped resamples from the original sample of size $n_b = n/4$.[35] In each resample, calculate the statistic:

$$Skewness\text{–}adj\_t^b = \sqrt{n_b}\,(S^b + \frac{1}{3}\hat{\gamma}^b S^{b\,2} + \frac{1}{6n_b}\hat{\gamma}^b) \text{, (49)}$$

where $\hat{\gamma}^b$ is the coefficient of skewness, and $S^b = \overline{BHAR_t^b} / \sigma^b(BHAR_t)$. Thus, $Skewness\text{–}adj\_t^b$, S^b, and $\hat{\gamma}^b$ are the bootstrapped resample analogues of $Skewness\text{–}adj\_t$, S, and $\hat{\gamma}$ from the original sample for the $b = 1, \ldots, 1{,}000$ resamples. The null hypothesis that the mean long-run abnormal return is zero is rejected if: $Skewness\text{–}adj\_t < x_l^*$ or $Skewness\text{–}adj\_t > x_u^*$. From the 1,000 resamples, it calculates the two critical values (x^*s) for the transformed test statistic ($Skewness\text{–}adj\_t$). It can then reject the null hypothesis that the mean long-run abnormal returns is zero at the α significance level by solving:

$$\Pr[Skewness\text{–}adj\_t^b \le x_l^*] = \Pr[Skewness\text{–}adj\_t^b \ge x_u^*] = \frac{\alpha}{2}$$

6.4.3 Calendar-Time Portfolio Regressions (CTPR)

An alternative approach to measuring long-run stock price performance is to track the performance of an event portfolio in calendar time, relative either to an explicit asset-pricing model or to some other benchmark. The calendar-time

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[35] The choice of $n_b = n/4$ is based on empirical analysis. It is suggested by Lyon et al. (1999). An analysis of resampling fewer than *n* observations can be found in Shao (1996) and Bickel et al. (2012).

portfolio approach was first used by Jaffe (1974) and Mandelker (1974), and is strongly advocated by Fama (1998). Mitchell and Stafford (2000) have a strong preference for calendar time methods to allow for cross-sectional correlation. The event portfolio is formed each period and includes all companies that have completed the event within the prior n period. By forming event portfolios, the cross-sectional correlations of the individual event firm returns are automatically accounted for in the portfolio variance at each point in calendar time. Calendar-time portfolios represent an important improvement over the traditional BHAR methodology, which assumes independence of the abnormal returns of each individual firm.

In calendar-time approach methodology an event portfolio is formed for each calendar month, and includes all the firms that experienced the event within the past n months prior to the given month, where the n refers to the specific investment holding period of event firms. So, if one is looking at a 24-month return, one would include all the firms which experienced an event in that particular month or in y of the past 24 months. The abnormal returns can be specified by running a regression of the excess returns on a factor model (e.g. the calendar-time portfolio regression method, CTPR). In the CTPR method, the excess monthly return of the event portfolio is calculated and regressed against the excess market returns, the monthly return on the zero investment portfolio for the common size factor in stock returns, and the monthly return on the zero investment portfolio for the common book-to-market equity factor in stock returns. Fama (1993) shows that size and book-to-market characteristics appear to capture a large proportion of the variation in stock returns.

Loughran and Ritter (1995) and Brav and Gompers (1997) employ the Fama-French 3-factor model to analyse returns on calendar-time portfolios of firms that issue equity. Jaffe (1974) and Mandelker (1974) also use variations of this calendar-time portfolio method, and the approach is strongly advocated by

Fama (1998). The event portfolio is formed each period to include all companies that have completed the event within the prior *n* periods. By forming event portfolios, the cross-sectional correlations of the individual event firm returns are automatically accounted for in the portfolio variance at each point in calendar time. In light of our strong evidence that the individual event firm abnormal returns are cross-sectionally correlated, calendar-time portfolios represent an important improvement over the traditional BHAR methodology, which assumes independence the abnormal returns of individual firms.

Many studies have used calendar-time portfolio methods to detect the performance of aggregate insider trading and abnormal market returns in the US market (Jaffe, 1974; Finnerty, 1976; Seyhun, 1988; Seyhun, 1990; Seyhun, 1992; Lakonishok and Lee, 2001). For the UK, Gregory et al. (2012; 2013) have used calendar-time portfolio methods to examine the long-run returns from director trading in the UK market, and the effect of gender on both short-run and long-run returns.

The calendar-time portfolio methods offer some advantages over tests using either cumulative or buy-and-hold abnormal returns. First, this approach eliminates the problem of cross-sectional dependence between sample firms, because the returns of sample firms are aggregated into a single portfolio. Second, the calendar-time portfolio methods yield more robust test statistics in non-random samples. Nonetheless, in non-random samples, calendar-time portfolio methods can yield mis-specified test statistics.

6.4.4 The Fama-French 3-factor Model and Calculating Calendar-Time Abnormal Returns (CTARs)

The excess returns are then regressed against the Fama-French three factors (FF3F) as shown below:

$$\mathrm{R}_{pt} - \mathrm{R}_{ft} = \alpha_i + \beta_i\left(\mathrm{R}_{mt} - \mathrm{R}_{ft}\right) + \mathrm{s}_i\mathrm{SMB}_t + \mathrm{h}_i\mathrm{HML}_t + \varepsilon_{it}, (50)$$

where R_{pt} represents event portfolios return in month t, R_{ft} is the risk free rate (the 90 day T bill rate), and R_{mt} is the monthly market return (these three factors are zero-investment portfolios representing the excess return of the market). The size factor SMB is the difference in returns between a portfolio of small-capitalisation firms and a portfolio of big-capitalisation firms, and SMB is the monthly return on the zero investment portfolio for size factor in stock returns. The HML factor is the difference in returns between a portfolio of firms with high B/M ratios and a portfolio of firms with low B/M ratios, and HML is the monthly return on the zero investment portfolio for common book-to-market equity factor in stock returns. α_t shows the average monthly abnormal return on the portfolio of event firms, which is zero under the null of no abnormal performance, given the model.

6.4.5 The Carhart 4-factor Model and Calculating Calendar-Time Abnormal Returns (CTARs)

Jegadeesh and Titman (1993; 2001) show that returns on portfolios formed on past returns cannot be explained by differences in size and book-to-market characteristics alone. The past returns or momentum is an important factor, and is explored by Carhart (1997). Therefore, to account for the momentum effect, it will employ the Fama-French 3 factors plus Carhart's momentum factor, as shown below.

$$\mathrm{R}_{pt} - \mathrm{R}_{ft} = \alpha_i + \beta_i\left(\mathrm{R}_{mt} - \mathrm{R}_{ft}\right) + \mathrm{s}_i\mathrm{SMB}_t + \mathrm{h}_i\mathrm{HML}_t + \mathrm{m}_i\mathrm{MOM}_t + \varepsilon_{it}, (51)$$

where MOM_t (the momentum factor) is the difference in the returns of equal-weighted portfolios of best stocks and worst stocks. The rest of the symbols are the same as those used in the Fama-French 3-factor model. The regression yields parameter estimates of α_i, β_i, s_i, h_i and m_i. The error term in the regression is denoted by $\varepsilon_{\mathrm{it}}$. If the Carhart 4-factor model provides a complete description of expected returns, then the estimate of the intercept term (α_i), which measures mispricing, provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero.

One problem is that the error term (ε_{it}) in both of the above regressions may be heteroscedastic, since the number of securities in the calendar-time portfolio varies from one month to the next. However, this heteroscedasticity does not significantly affect the specification of the intercept test in random samples. However, a correction for heteroscedasticity can be performed using weighted least squares (WLS) estimation, where the weighting factor is based on the number of securities in the portfolio in each calendar month.

Another issue is that, if the model provides only an imperfect description of expected returns, the intercept represents the combined effects of mispricing and model misspecification. This is what Fama (1970) refers to as the 'joint-test problem': tests of market efficiency are necessarily joint tests of market efficiency and the assumed model of expected returns.

In the next section, it will present the results of the BHAR and CTPR methods, examining the relationship of aggregate director trading with firm characteristics and director role.

6.5 Empirical Results

6.5.1 Buy-and-Hold Abnormal Returns

6.5.1.1 Monthly Buy-and-Hold Abnormal Returns with Firm Characteristics

As discussed in Section 6.4.1, it applies the BHAR methodology to analyse the performance of firm characteristics (size and B/M). Table 6.2 presents the results. It shows the performance of 6-, 12-, 18- and 24-month holding periods of director trading, in Panels A-D respectively.

Generally, the results of Table 6.2 show that firm characteristics (size and B/M) have significant effects on the performance of abnormal returns. For a 6-month holding time (Panel A), all portfolios except small/low and small/high achieve significant positive none-zero abnormal returns. The abnormal returns of small/medium are 2.19% which is significant at 5% significance level. The abnormal returns of big/low, big/medium and big/high are 4.04%, 1.26% and 2.22%, respectively: they are therefore all significant at 1% significance level. Contrastingly, small/low and small/high receive negative insignificant abnormal returns (-10.56% and -1.49%).

In Panel B, the abnormal returns of small/low and small/high are negative but insignificant, while small/medium, big/low, big/medium and big/high are positively significant. Among these positives, small/medium is 10% significance with 1.70% abnormal returns; big/high has 1.80% abnormal returns which are significant at 5% significance level; and both big/low and big/medium are significant at 1% significance level, with abnormal returns of 7.15% and 1.00%, respectively.

In Panel C, the results once again show that the abnormal returns of small/low and small/high are negative, and those of small/medium, big/low, big/medium and big/high are positive. However, this time, small/high is negatively significant at 10% with -7.62% abnormal returns. Only small/medium and big/low show significantly positive abnormal returns at 1% significance level, with 2.84% and 9.56% each. The abnormal returns of big/medium and big/high do not show significance.

Panel D is consistent with previous panels in that the abnormal returns of small/low and small/high are negative, and those of small/medium, big/low, big/medium and big/high are positive. Small/high is negatively significant at 1% significance level, with -9.15% abnormal returns. Small/medium is positively significant at 10% significance level, with 1.69% abnormal returns, and big/low receives 9.94% abnormal returns, which is significant at a 1% significance level.

A vertical comparison across every portfolio shows that the performance of portfolios with different size-B/M is totally different. The BHAR of small/low is always negatively insignificant. The abnormal returns of small/medium are always positively significant, with a maximum abnormal return of 2.84% in 18-month holding time. Small/high always receives negative abnormal returns: the longer the holding time, the more negative the abnormal returns. The negative abnormal returns become significant after 12-month holding time. By contrast, big/low always shows positively significant abnormal returns. The longer the holding time, the better the abnormal returns and the more significant the t-value gets. The abnormal returns could reach a maximum of 9.94% in 24-month holding time. The performance of big/medium and big/high is similar. Both of them get positive abnormal returns in different holding times, and their abnormal returns are only significant at 6- and 12-month holding time. Beyond that, abnormal returns drop sharply.

The results of Table 6.2 indicate that the performance of stock movements is strongly affected by firm characteristics after director purchasing. Compared to the benchmark portfolio, big firms always receive positive abnormal returns. Among small firms, only small/medium beats the performance of the benchmark.

6.5.1.2 Monthly Buy-and-Hold Abnormal Returns with Firm Characteristics and Director Role

As shown in Table 6.2, firm characteristics affect the performance of portfolios' abnormal returns. Next it splits every size-B/M portfolio into two groups according to whether the director trading was executives or non-executives. Executives include directors such as CEOs, CFOs, executive chairmen and other executives. Non-Executives include non-executive chairmen and other non-executives. [36] The results of firm characteristics and director role are

[36] Details of director classification are described in Section 6.3. They can also be seen from Table 6.1.

presented in Table 6.3. Panels A-D show the performance of 6-, 12-, 18- and 24-month holding periods, respectively.

Generally, the abnormal returns of directors are totally different in different size-B/M firms in post-purchasing time. For a 6-month holding time, the abnormal returns of Executives and Non-Executives are all negative in small/low firms, while small/medium, big/low, big/medium and big/high are all positive (Panel A). This is consistent with the results presented in Panel A, Table 6.2. Moreover, most of these positives are significant at least 5% significance level. In small/high firms, Executives received positive insignificant abnormal returns of 1.75%, while the abnormal returns of Non-Executives are -4.92%, which are negatively significant at 1% significance level.

The results of Panel B are also similar to those of Panel B, Table 6.2. For 12-month holding periods, the abnormal returns of Executives and Non-Executives in big/low, big/medium and big/high are all positive, and most of them are positively significant at 1% significance level. The abnormal returns of Executives and Non-Executives in small/low and small/high are all negative: of these, the results for Executives of small/low and Non-Executives of small/high are negatively significant (abnormal returns of -9.25% and -5.30%). In small/medium firms, abnormal returns of Executives are negatively insignificant, while Non-Executives are 5.84%, which is positively significant at 5% significance level.

Panels C and D show the results for 18- and 24-month holding times. The abnormal returns of Executives and Non-Executives in big/low and big/high are all positively significant at least 5% significance level, while the abnormal returns of Executives and Non-Executives in small/low and small/high are all negative. The abnormal returns of Executives in small/medium and big/medium are negative. Meanwhile, Non-Executives of small/medium and big/medium all have positive abnormal returns. However, there are some differences between

Panels C and D: the abnormal returns of both Executives and Non-Executives in big/low are better in Panel D than in Panel C. The rest of the positive abnormal returns decrease. and most of the negative abnormal returns become more negative.

By vertically comparing every portfolio, it can be seen that the abnormal returns of both Executives and Non-Executives in small/low firms are all negative. The longer the holding time, the more negative the value and the more significant the t-value of the abnormal returns. This implies that compared to the benchmark, both Executives and Non-Executives in small/low firms do not achieve positive abnormal returns after their purchasing trading.

For small/medium, except for a 6-month holding time, the abnormal returns of Executives are all negative: the longer the holding time, the more negative the returns. Non-Executives always obtain positively significant abnormal returns. Abnormal returns reach peak in 18-month holding time (18.22%) and maintain a high level (14.30%) in 24-month holding time.

For small/high, except for 6-month holding time, abnormal returns of Executives are all negative. The abnormal returns of Non-Executives are also negative, and reach a trough (-5.30%) at 12-month holding time. The performance of directors in small/high firms shows that neither Executives nor Non-Executives could make positively significant abnormal returns in different holding time after their purchases.

For big/low, the abnormal returns of both Executives and Non-Executives are positively significant at least 5% significance level; and the longer the holding time, the better the abnormal returns.

For big/medium firms, abnormal returns of Executives are positive in 6- and 12-month holding times, although it is only significant in 6-month (1.37%). In 18-, and 24-month holding, Executives' returns are negatively insignificant; abnormal returns of Non-Executives are all positively significant at 1% significance level, but the value decreases with increasing the holding time. The best abnormal returns are 3.43% on 6-month holding time.

For big/high firms, the abnormal returns of Executives and Non-Executives are all positively significant at least 5% significance level. The abnormal returns reach a peak in the 18-month holding time (4.21% for Executives and 13.00% for Non-Executives) and then drop.

The results of Table 6.3 indicate similar findings to those of Table 6.2: compared with the benchmark, the performance of directors in big firms is better than that of directors in small firms. Furthermore, among portfolios with positive abnormal returns, the performance of Non-Executives seems better than that of Executives. There is just one exception: in big/low firms, Executives are much better than Non-Executives in different holding times. Where there are points of inconsistency between the findings of Tables 6.2 and 6.3, these are probably caused by the sample data described in Section 6.3: there are some transactions which for which it has information on firm characteristics but not on director trading (some director trading data have no executives/non-executives information). In other words, the sample of Table 6.3 is not exactly the same as that of Table 6.2.

6.5.2 Calendar-Time Abnormal Returns

As discussed in Section 6.4, the methodology of calendar-time abnormal returns is better for presenting cross-sectional data. Therefore, it applies Fama-French 3-factor models, to examine the relationship between abnormal returns, firm characteristics and director role.[37]

[37] It uses the same UK Fama-French 3 factors data as Gregory et al. (2013). Data taken from: http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/

6.5.2.1 Calendar-Time Abnormal Returns with Firm Characteristics

Table 6.4 presents the results of Fama-French 3-factor calendar time portfolio regressions of firm characteristics (size and B/M). Panels A-D display the performance of director purchasing trading in 6-, 12-, 18- and 24-month holding periods respectively.

For 6-month holding time, all firms except small/low achieve positively significant abnormal returns (Panel A). Among these positive returns, those of small/medium, small/high, big/low and big/high are all significant at 1% significance level, while big/medium is significant at 10% significance level. Small/high firms get the best abnormal returns (2.76% per month).

The results for 12-month holding periods (Panel B) are similar. The abnormal returns of small/low are negatively insignificant, and the rest are all positive. However, the monthly abnormal returns and the magnitude of significant levels are lower than those shown in Panel A. The abnormal returns of small/medium are 2.57% with 1% significance on 6-month holding, but falls to 1.04% with 10% significance on 12-month holding time. On 6-month holding, small/high firms receive 2.76% abnormal returns per month with significance at 1% significance level, but on 12-month holding periods, the firms get 1.56% abnormal returns with 5% significance. The abnormal returns of big/low firms drop sharply from 1.90% with 1% significance in Panel A, to only 0.03% in Panel B. Big/medium firms maintain their abnormal returns and significance: the firms obtain 1.56% abnormal returns per month on 6-month holding, and 1.53% on 12-month holding. Both of these returns are significant at a 10% significance level. The abnormal returns of big/high decrease from 2.10% per month with 1% significance in Panel A, to 1.22% with 10% significance in Panel B.

Panels C and D show the results for 18- and 24-month holding periods. Consistently with Panels A and B, the abnormal returns of small/low firms are negative, while the rest are positive. However, none of firms shows any significance. This means that after a 12-month holding time, by controlled excess returns of market index, size and B/M effects (Fama-French 3 factors), no firm group could not make any significant none-zero abnormal returns.

The findings of Table 6.4 are that small/low firms make negative abnormal returns, none of which were significant. The rest of the firm groups achieved positive abnormal returns, but none of them made any significant, none-zero abnormal returns beyond 12-month holding time. The firm groups small/medium, small/high, big/medium and big/high could achieve positively significant abnormal returns on 6- and 12-month holding times; however, the value of these abnormal returns decreases. Big/low firms could only make positively significant abnormal returns on 6-month holding time. After that, the value and significance magnitude of the abnormal returns dropped sharply to almost zero.

Generally, these results indicate that both small and big firms could make positive significant abnormal returns, as could medium and high B/M firms.

6.5.2.2 Calendar-Time Abnormal Returns with Firm Characteristics and Director Role

Like Table 6.3, Table 6.5 splits every size-B/M portfolio into two director groups: Executives and Non-Executives. Panels A-D present the performance of directors' abnormal returns on 6-, 12-, 18- and 24-month holding periods respectively.

For 6-month holding time (Panel A), both Executives and Non-Executives of big/medium and big/high firms make positively significant abnormal returns. Meanwhile, Executives of small/medium and small/high and Non-Executives of big/low firms also obtain positively significant abnormal returns. Directors in small/low firms do not achieve significant abnormal returns.

Panel B shows the results for 12-month holding periods, where only Executives of small/high and big/high and Non-Executives of big/medium had positive significant abnormal returns. Of these, only Executives of small/high make 1% significant abnormal returns (1.87% per month).

For 18-month holding time (Panel C), only Executives of small/high firms achieved positively significant abnormal returns of 1.76% per month, which are significant at 1% significance level. The abnormal returns of directors in the rest of the firm groups are insignificant.

In Panel D (24-month holding periods), no Executives or Non-Executives in any firm groups show significant abnormal returns. Only Executives of small/high firms come close to the 10% significant level (1.36% abnormal returns per month with WLS t-value 1.57).

The findings of Table 6.5 are consistent with those of Table 6.4 that almost abnormal returns occur on 6- and 12-month holding times. Both Executives and Non-Executives in big firms obtain positively significant abnormal returns; meanwhile, in small firms (small/medium and small/high), only Executives could receive positively significant abnormal returns. However, the results here differ from those of Table 6.4, as on 18-month holding time, Executives of small/high firms could still get 1% significant abnormal returns (1.76% per month).

All these findings indicate that, regardless of the firm's B/M, directors in all big firms (except Executives of big/low firms) could get significant abnormal returns on 6-month holding time. Some of them even continued to receive abnormal returns until 12-month holding time. Furthermore, Executives of small/high firms could make very positively significant none-zero abnormal returns up until the 18-month holding time: this implies that they have access to some superior information about the companies, which helps them to make a better profit than other investors, including Non-Executives in their companies. Another interesting result is that, in big/low and big/medium firms, the performance of Non-Executives is better than that of Executives. This is probably because Non-

Executives in these firm groups are more independent to make sensitive judgements, based not only on company information but also on competitors of the company, movements in the industry, market and macroeconomy.

6.5.3 Calendar-Time Abnormal Returns with Director Roles

Sections 6.5.1 and 6.5.2 discussed firm characteristics and director roles; this Section, however, will focus only on directors' trading activities by role, using the methodology of calendar-time abnormal returns.

6.5.3.1 Calendar-Time Abnormal Returns (Fama-French 3-factor model)

Table 6.6 presents the results of the calendar-time abnormal returns using Fama-French 3-factor model. It applies 1-, 3-, 6-, 12-, 18- and 24-month holding periods of director purchase transactions. As described in Section 6.3, directors are classified into 6 groups: CEOs, CFOs, Executive Chairmen, Non-Executive Chairmen, other Executives and other Non-Executives.

For 1-month holding time, the abnormal returns of all groups of director are positively significant at 1% significant level. CFOs obtain 3.62% abnormal returns per month, which is the best performance among all directors. Executive Chairmen and Non-Executive Chairmen achieve the second- and third-best abnormal returns respectively (2.97% and 2.96%). Other Non-Executives receive 2.66% monthly abnormal returns; CEOs obtain 2.24% per month, which is just higher than the Other Executives (2.21%).

For 3-month holding period, the abnormal returns of all director groups are positive. All of them are significant at least 10% significance level, except Executive and Non-Executive Chairmen. As with 1-month holdings, CFOs received the best abnormal returns (2.04% per month). Other Non-Executives get the second-best result with 1.83% abnormal returns per month. Executive Chairmen come third (but the value is not significant), followed by Other Executives and Non-Executive Chairmen. Surprisingly, although the abnormal returns of CEOs are significant at 10% significance level, the value is the lowest among director groups: CEOs achieved only 0.79% monthly abnormal returns.

For 6-month holding periods, the abnormal returns of CFOs, Other Executives and Other Non-Executives are all positively significant at 5%. The other results do not show any significance. Executive Chairmen get the best abnormal returns, followed by CFOs. Other Non-Executives and Other Executives obtain 1.14% and 0.85% abnormal returns per month respectively. CEOs receive only 0.35% monthly abnormal returns. The abnormal returns of Non-Executive Chairmen are just 0.11% per month, which is insignificant and close to zero.

Beyond the 6-month holding time, none of the director groups makes positively significant abnormal returns. Moreover, Executive Chairmen and Other Non-Executives obtain negative insignificant abnormal returns for the 24-month holding period.

Table 6.6 finds that directors could make positively significant abnormal returns within 6-month holding time. All kinds of directors could achieve positively significant abnormal returns at 1% significance level one month after purchasing activities. The abnormal returns of CFOs get the highest value on 1- and 3-month holding time; this partially support the information hypothesis, that directors like CEOs and CFOs who are familiar with the day-to-day operations of the company trade on more valuable information. However, CEOs, who should also have more valuable information than other directors, do not perform well.

One interesting phenomenon is the performance of Executive Chairmen. During 1-, 3- and 6-month holding time, Executive Chairmen get very high abnormal returns; however, the magnitude of t-statistics is much smaller than for other director groups. This is probably due to the fact that there are fewer observations. As it can see from Table 6.1, it only has records of 1,351 purchase transactions by Executive Chairmen over 180 calendar months, which means that there are less than 10 transactions per month on average. Insufficient trading frequency could damage the reliability or credibility of the results of calendar-time abnormal returns. If it does not consider the performance of Executive Chairmen, the abnormal returns of CFOs are the best in 6-month holding time, which better fits with the information hypothesis.

6.5.3.2 Calendar-Time Abnormal Returns (Carhart 4-factor model)

It also applies calendar-time abnormal returns using Carhart 4-factor model (Appendix R). The Carhart 4-factor model leads to similar results to those of the Fama-French 3-factor model. Most differences are in the magnitude of the abnormal returns. Furthermore, the WLS t-value of the Carhart 4-factor model is smaller and weaker than that of Fama-French 3-factor model, which implies that the momentum factor somehow replaces and smoothes abnormal returns of directors.

6.6 Conclusion

This chapter examines the market reaction to director trading, and its relationship with firm characteristics, director role and the information hierarchy hypothesis. The performance of both firm characteristics and director roles shows that directors do successfully make significant abnormal return after their purchases. It has also found some evidence for the information hypothesis, in the form of CFOs' performance on 1-, 3-, and 6-month holding periods as shown through calendar-time abnormal returns (CTAR) methodology with Fama-French 3 factor and Carhart 4 factor models. However, results on the abnormal returns of CEOs do not have sufficient evidence to support the hypothesis.

To examine the performance of firm characteristics and director roles, it used the methodology of BHAR and CTAR. Empirical evidence indicates that the performance of stock movements is affected by firm characteristics and director roles. Generally, the results show that both small and big firms can make positive significant abnormal returns, as can medium and high B/M firms. Executives and Non-Executives in big firms always get positively significant abnormal returns.

The results of the information hypothesis test indicate that all directors make positively significant abnormal returns one month after their purchases. The performance of CFOs supports the hypothesis within 6-month holding time. Although CEOs are assumed to have the same superior knowledge about their company's prospects as CFOs, the results of CEO trading do not support the hypothesis. One possible explanation is that CFOs' purchases may be pursuing longer-term post-trade return, while other directors try to make a quick profit when they trade. Another plausible explanation for this result is proposed by Fidrmuc et al. (2006), who state that the FSA, the regulators and market may follow the transactions of CEOs more closely, which causes these directors to trade more cautiously and at less informed moments. Also, trades of CFOs are more informative than other directors. This might suggest that aggregate director trading of CFOs might be more informative of market Movements and future changes in GDP. Therefore, future work would investigate this.

Table 6.1 Sample Characteristics of Directors' Trading From January 1994 to December 2008

Panel A: Purchases	Small Firms	Big Firms	Low B/M	Medium B/M	High B/M
No. of Shares Traded on Monthly Basis	9,810,433	22,440,895	13,474,002	18,157,419	7,004,301
Total No. of Shares	1,765,877,850	4,039,361,120	2,425,320,308	3,268,335,347	1,260,774,165
Total No. of Transactions	3,472	25,889	8,476	20,553	8,673
Average shares*	508,669	156,023	286,155	159,021	145,373
Total No. of Month	180	180	180	180	180
Panel B: Sales	**Small Firms**	**Big Firms**	**Low B/M**	**Medium B/M**	**High B/M**
No. of Shares Traded on Monthly Basis	2,067,313	17,184,781	10,980,959	9,188,858	2,673,448
Total No. of Shares	372,116,316	3,093,260,625	1,976,572,658	1,653,994,509	481,220,717
Total No. of Transactions	821	14,360	5,789	9,716	2,642
Average shares*	453,495	215,413	341,428	170,231	182,212
Total No. of Month	180	180	180	180	180

Table 6.1 (Continued)

Panel C: Purchases	CEO	CFO	Chairman (Exe)	Chairman(Non)	Other Exe	Other Non
No. of Shares Traded on Monthly Basis	3,098,464	913,550	3,352,591	2,269,536	1,094,222	5,225,615
Total No. of Shares	557,723,573	164,438,960	603,466,436	408,516,440	196,959,940	940,610,760
Total No. of Transactions	6,728	3,612	1,351	3,737	4,628	6,787
Average shares*	82,896	45,526	446,681	109,317	42,558	138,590
Total No. of Month	180	180	180	180	180	180
Panel D: Sales	**CEO**	**CFO**	**Chairman (Exe)**	**Chairman(Non)**	**Other Exe**	**Other Non**
No. of Shares Traded on Monthly Basis	2,612,037	196,146	1,645,712	1,055,475	977,053	2,370,610
Total No. of Shares	470,166,684	35,306,279	296,228,163	189,985,555	175,869,594	426,709,771
Total No. of Transactions	1,454	783	524	511	1,333	1,200
Average shares*	323,361	45,091	565,321	371,792	131,935	355,591
Total No. of Month	180	180	180	180	180	180

* The average shares in Panels A to D are per transaction.

Table 6.2 Monthly Buy and Hold Abnormal Returns (BHAR) of Director Purchases for Firm Characteristics defined by size and B/M from January 1994 to December 2008

$BHAR_i = \prod_{t=1}^{T}(1+R_{i,t}^{k}) - \prod_{t=1}^{T}(1+R_{benchmark,t}^{k})$ Where $R_{i,t}^{k}$ presents return of firm i in size-B/M portfolio group k on month t. $R_{benchmark}^{k}$ presents return of control portfolio k based on size-B/M, it is from http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/ . Small low denotes small firms with low B/M, small medium denotes small firms with medium B/M, small high denotes small firms with high B/M, big low denotes big firms with low B/M, big medium denotes big firms with medium B/M, and big high denotes big firms with high B/M formed on the basis of their size and the B/M ratios. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, for the two-tailed hypothesis test that the null hypothesis of no monthly excess return when post trading period is 6, 12, 18 and 24 months. Skewness-adjusted t-value presents in the table.

	Purchases				Purchases		
Panel A	6-month	t-value		**Panel C**	18-month	t-value	
Small Low	-10.56%	-1.02		Small Low	-16.39%	-1.44	
Small Medium	2.19%	2.24	**	Small Medium	2.84%	2.71	***
Small High	-1.49%	-0.70		Small High	-7.62%	-1.66	*
Big Low	4.04%	5.16	***	Big Low	9.56%	11.54	***
Big Medium	1.26%	4.79	***	Big Medium	0.32%	0.79	
Big High	2.22%	3.61	***	Big High	0.67%	0.75	
Panel B	12-month	t-value		**Panel D**	24-month	t-value	
Small Low	-14.09%	-1.18		Small Low	-16.93%	-1.37	
Small Medium	1.70%	1.90	*	Small Medium	1.69%	1.90	*
Small High	-6.32%	-0.68		Small High	-9.15%	-7.00	***
Big Low	7.15%	8.14	***	Big Low	9.94%	16.17	***
Big Medium	1.00%	3.26	***	Big Medium	0.09%	0.33	
Big High	1.80%	2.33	**	Big High	0.13%	0.46	

Table 6.3 Monthly Buy and Hold Abnormal Returns (BHAR) of Director Purchases with Firm Characteristics and Director Role from January 1994 to December 2008

$BHAR_i = \prod_{t=1}^{T}(1+R_{i,t}) - \prod_{t=1}^{T}(1+R_{benchmark,t})$ where $R_{i,t}$ presents portfolio returns of sample based on size-B/M. $R_{benchmark}$ presents return of control portfolios based on size-B/M, it is from http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/ (University of Exeter). Small low denotes small firms with low B/M, small medium denotes small firms with medium B/M, small high denotes small firms with high B/M, big low denotes big firms with low B/M, big medium denotes big firms with medium B/M, and big high denotes big firms with high B/M formed on the basis of their size and the B/M ratios. **Exe** denotes Executives which include Chief Executive Officer (CEO), Chief Financial Officer (CFO), Executive Chairman, and other Executives exclude CEO, CFO and Executive Chairman. **Non** denotes Non-Executives which include Non-Executive Chairman and other Non-Executives exclude Non-Executive Chairman. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, for the two-tailed hypothesis test that the null hypothesis of no monthly excess return when post trading period is 6, 12, 18 and 24 months. Skewness-adjusted t-value presents in the table.

		Purchases					Purchases		
Panel A		6-month	t-value		**Panel C**		18-month	t-value	
Small Low	Exe	-7.53%	-1.23		**Small Low**	Exe	-12.96%	-6.32	***
	Non	-5.17%	-0.90			Non	-6.55%	-1.49	
Small Medium	Exe	1.71%	1.24		**Small Medium**	Exe	-3.92%	-1.43	
	Non	4.99%	3.59	***		Non	18.22%	3.31	***
Small High	Exe	1.75%	1.47		**Small High**	Exe	-3.29%	-0.79	
	Non	-4.92%	-5.72	***		Non	-3.92%	-1.88	*
Big Low	Exe	4.21%	4.03	***	**Big Low**	Exe	11.06%	9.49	***
	Non	3.10%	2.26	**		Non	5.65%	4.02	***
Big Medium	Exe	1.37%	2.69	***	**Big Medium**	Exe	-1.25%	-0.66	
	Non	3.43%	5.14	***		Non	3.16%	3.36	***
Big High	Exe	1.22%	3.12	***	**Big High**	Exe	4.21%	2.43	**
	Non	1.88%	2.81	***		Non	13.00%	6.91	***
Panel B		12-month	t-value		**Panel D**		24-month	t-value	
Small Low	Exe	-9.25%	-3.68	***	**Small Low**	Exe	-12.48%	-9.05	***
	Non	-6.00%	-1.48			Non	-15.90%	-3.04	***
Small Medium	Exe	-2.21%	-1.07		**Small Medium**	Exe	-4.96%	-0.67	
	Non	5.84%	2.16	**		Non	14.30%	5.66	***
Small High	Exe	-0.93%	-0.19		**Small High**	Exe	-14.43%	-1.25	
	Non	-5.30%	-1.99	**		Non	-3.24%	-1.53	
Big Low	Exe	8.07%	6.94	***	**Big Low**	Exe	11.46%	12.74	***
	Non	4.80%	3.37	***		Non	6.08%	5.27	***
Big Medium	Exe	0.42%	0.87		**Big Medium**	Exe	-1.52%	-0.12	
	Non	3.22%	3.86	***		Non	2.26%	2.72	***
Big High	Exe	3.72%	2.67	***	**Big High**	Exe	1.95%	1.99	**
	Non	8.24%	4.82	***		Non	6.92%	4.62	***

Table 6.4 Alphas from the Fama-French 3 Factor Calendar Time Portfolio Regressions for Firm Characteristics defined by Size and B/M from January 1994 to December 2008

This table reports the calendar-time abnormal returns using WLS regression for 6 months, 12 months, 18 months and 24 months holding periods. AR is monthly abnormal returns. The abnormal returns are the α_s from the regression $R_{pt} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it}$. R_{pt} is the simple return on the calendar-time portfolio. R_{ft} is the return on the 90-day Treasury Bills. R_{mt} is the return on index of FTSE All Share. SMB is the return to a small minus big factor mimicking portfolio, and HML is the return to high B/M minus low B/M factor mimicking portfolio. Small low denotes small firms with low B/M, small medium denotes small firms with medium B/M, small high denotes small firms with high B/M, big low denotes big firms with low B/M, big medium denotes big firms with medium B/M, and big high denotes big firms with high B/M formed on the basis of their size and the B/M ratios. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, for the two-tailed hypothesis test that the coefficient equals zero. T-value presents in the table.

	Purchases				Purchases	
Panel A	**6-month AR**	**WLS-t**		**Panel C**	**18-month AR**	**WLS-t**
Small Low	-0.74%	-1.62		Small Low	-0.31%	-0.82
Small Medium	2.57%	3.13	***	Small Medium	0.71%	1.56
Small High	2.76%	3.29	***	Small High	0.97%	1.52
Big Low	1.90%	2.99	***	Big Low	0.01%	0.06
Big Medium	1.56%	1.94	*	Big Medium	0.62%	1.28
Big High	2.10%	3.76	***	Big High	0.90%	1.54
	Purchases				**Purchases**	
Panel B	**12-month AR**	**WLS-t**		**Panel D**	**24-month AR**	**WLS-t**
Small Low	-0.33%	-0.92		Small Low	-0.30%	-0.71
Small Medium	1.04%	1.68	*	Small Medium	0.19%	0.49
Small High	1.56%	2.14	**	Small High	0.81%	1.27
Big Low	0.03%	0.25		Big Low	0.03%	0.05
Big Medium	1.53%	1.85	*	Big Medium	0.57%	0.87
Big High	1.22%	1.73	*	Big High	0.30%	0.83

Table 6.5 Post-trade long-run CTAR of Director Purchases by Firm Characteristics and Director Role Using the Fama-French 3 Factor Model for Holding Periods of 6-, 12-, 18- and 24-Month from January 1994 to December 2008

$$R_{pt} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it}$$

Panel A		Purchase			Panel C		Purchase		
		6-month AR	WLS-t				18-month AR	WLS-t	
Small Low	Exe	0.52%	1.02		Small Low	Exe	-0.59%	-1.36	
	Non	-0.10%	-0.35			Non	-0.86%	-1.54	
Small Medium	Exe	1.78%	2.85	***	Small Medium	Exe	0.42%	1.20	
	Non	1.03%	1.56			Non	0.57%	1.04	
Small High	Exe	2.53%	3.11	***	Small High	Exe	1.76%	2.73	***
	Non	-0.86%	-1.43			Non	-0.76%	-1.04	
Big Low	Exe	-0.68%	-1.54		Big Low	Exe	-0.55%	-1.23	
	Non	1.90%	3.16	***		Non	0.12%	0.37	
Big Medium	Exe	1.08%	2.25	**	Big Medium	Exe	0.36%	0.94	
	Non	1.65%	2.67	***		Non	0.77%	1.01	
Big High	Exe	3.99%	4.45	***	Big High	Exe	0.87%	1.52	
	Non	0.77%	1.66	*		Non	0.61%	1.40	

		Purchase					Purchase		
Panel B		12-month AR	WLS-t		Panel D		24-month AR	WLS-t	
Small Low	Exe	0.06%	0.27		Small Low	Exe	-0.44%	-0.90	
	Non	-0.72%	-1.62			Non	-0.82%	-1.44	
Small Medium	Exe	0.97%	1.51		Small Medium	Exe	0.63%	1.29	
	Non	0.67%	1.55			Non	0.14%	0.26	
Small High	Exe	1.87%	3.09	***	Small High	Exe	1.36%	1.57	
	Non	-0.67%	-1.41			Non	-0.11%	-0.24	
Big Low	Exe	-0.98%	-1.37		Big Low	Exe	-0.45%	-0.94	
	Non	0.67%	1.49			Non	0.11%	0.21	
Big Medium	Exe	0.51%	1.05		Big Medium	Exe	0.14%	0.30	
	Non	1.45%	1.82	*		Non	0.79%	1.05	
Big High	Exe	0.76%	1.66	*	Big High	Exe	0.82%	1.25	
	Non	0.76%	1.03			Non	0.07%	0.18	

ARs are intercepts from Fama-French regression of the calendar time portfolio on a market factor, a size factor and a book-to-market factor. Weighted Least Squares estimation, where the weighting factor is based o the number of securities in the portfolio in each calendar month, is applied.

Small low denotes small firms with low B/M, small medium denotes small firms with medium B/M, small high denotes small firms with high B/M, big low denotes big firms with low B/M, big medium denotes big firms with medium B/M, and big high denotes big firms with high B/M formed on the basis of their size and the B/M ratios. **Exe** denotes Executives which include Chief Executive Officer (CEO), Chief Financial Officer (CFO), Executive Chairman, and other Executives exclude CEO, CFO and Executive Chairman. **Non** denotes Non-Executives which include Non-Executive Chairman and other Non-Executives exclude Non-Executive Chairman.

Table 6.5 (Continued)

R_{pt} is the simple return on the calendar-time portfolio, R_{ft} is the return on the 90-day Treasury Bills, R_{mt} is the return on index of FTSE All Share, SMB_t is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, HML_t is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. The estimate of the intercept term (α_i), provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero.

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, with t-statistics in parentheses.

Table 6.6 Post-trade long-run CTAR of Director Purchases by Director Role Using the Fama-French 3 Factor Model for Holding Periods of 1-, 3-, 6-, 12-, 18- and 24-Month from January 1994 to December 2008

$$R_{pt} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it}$$

Director Group	1-month AR	3-month AR	6-month AR	12-month AR	18-month AR	24-month AR
CEO	2.24% (4.31)***	0.79% (1.81)*	0.35% (0.83)	0.46% (1.20)	0.34% (0.91)	0.18% (0.48)
CFO	3.62% (4.40)***	2.04% (3.65)***	1.31% (2.58)**	0.41% (0.87)	0.27% (0.62)	0.40% (0.92)
Chair Exe	2.97% (2.74)***	1.39% (1.59)	1.51% (1.64)	0.80% (1.25)	0.39% (0.68)	-0.08% (-0.18)
Chair Non	2.96% (3.47)***	0.93% (1.52)	0.11% (0.21)	0.60% (1.30)	0.63% (1.29)	0.55% (1.21)
Other Exe	2.21% (3.84)***	1.31% (3.04)***	0.85% (2.05)**	0.42% (1.15)	0.26% (0.70)	0.08% (0.21)
Other Non	2.66% (3.37)***	1.83% (3.09)***	1.14% (2.39)**	0.35% (0.80)	0.25% (0.60)	-0.16% (-0.39)

ARs are intercepts from Fama-French regression of the calendar time portfolio on a market factor, a size factor and a book-to-market factor. Weighted Least Squares estimation, where the weighting factor is based o the number of securities in the portfolio in each calendar month, is applied.

CEO: Chief Executive Officer; **CFO**: Chief Financial Officer; **Chair Exe**: Executive Chairman; **Chair Non**: Non-Executive Chairman; **Other Exe**: Other Executives exclude CEO, CFO and Executive Chairman; **Other Non**: Other Non-Executives exclude Non-Executive Chairman.

R_{pt} is the simple return on the calendar-time portfolio, R_{ft} is the return on the 90-day Treasury Bills, R_{mt} is the return on index of FTSE All Share, SMB_t is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, HML_t is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. The estimate of the intercept term (α_i), provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero.

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, with t-value in parentheses.

Chapter 7: Conclusion

7.1 Conclusion

The majority of the work in this thesis focuses on long-run director trading (director trading accumulated over long periods) in the UK market. Chapter 4 tests the relationship between aggregate director trading and future market excess returns, and Chapter 5 goes further to investigate the link between aggregate director trading and future UK economic change. Chapter 4 and 5 are long-run director trading studies focused on macro-aspects. In Chapter 6, it investigates long-run director trading focused on more micro-aspects. It checks whether director trading with firm characteristics affects the performance of abnormal returns and whether the information hierarchy hypothesis is supported by UK data.

The main aim of the thesis is to examine long-run trading patterns and returns based on characteristics of the trades and trader themselves, rather than those of the firms in which they trade. Chapter 4 researches aggregate director trading to discover whether directors are contrarian and whether aggregate director trading could forecast future market excess returns. The advanced study in Chapter 5 aims to detect whether aggregate director trading is a leading indicator of future economic activities. Chapter 6 concentrates on the long-run relationship between director trading, firm characteristics and director role (CEO, CFO, executive chairman, non-executive chairman, other executives and other non-executives). It aims to discover whether director trading with firm characteristics affect the performance of stock abnormal returns, and whether the performance of director trading by different types of director supports the information hierarchy hypothesis in long-run study.

Chapter 4 documents a strong, significant positive relationship between past aggregate director trading and future market excess returns, by following methodology of Seyhun (1988; 1992) and Lakonishok and Lee (2001). The results find evidence that directors are contrarian. They increase their stock purchases prior to an increase in the stock market, and decrease their stock purchases following increases in the stock market. By applying long-run CER and BHER time series models (Seyhun, 1992; Lakonishok and Lee, 2001), it finds that aggregate director trading has a ability to forecast future excess market returns. Evidence here shows that aggregate director trading of both large and small firms is positively significant, with predictive power of future excess returns of large and small firm portfolios.

Due to various the fiscal year-ends of companies listed on LSE and to UK regulation requirements, this thesis introduced several seasonal adjustment measurements, to more accurately describe director trading. Furthermore, it employs a variety of measurements of director trading (net number of purchase transactions, the net purchase ratio, the difference of net purchase ratio, the difference of net purchase transaction, and the growth rate of net purchases). Evidence in Chapter 4 suggests that director trading has the power to forecast future market excess returns: the predictability of market excess returns increases with the length of forecasting horizon and the number of months of past director trading.

One major contribution of this study to the UK literature is that it finds evidence linking aggregate director trading to future economic growth. After confirming the relationship between aggregate director trading and future market excess return in Chapter 4, Chapter 5 finds that aggregate director trading is positively significant and has good explanatory power to forecast future movements of the economy. In other words, aggregate director trading is one reliable leading indicator of the UK economy. Aggregate director trading retains marginal explanatory power when business cycle variables are introduced as independent variables. This suggests that aggregate director trading captures some element of market factors (SMB, HML and MKT) and business cycle variables (dividend yield of FTSE All share, growth rate of industrial production and term spread) which is unrelated to movement in future real activity.

Finally, this thesis introduces into the UK literature the theme of the market's reaction to director trading, based on firm characteristics and the information hierarchy hypothesis. In Chapter 6, it considers the effects of long-run director trading with firm characteristics and director trading patterns on the market timing and the subsequent market reaction to director's trades. Using long-run

BHAR and calendar time portfolio regression with Fama-French 3-factor and Carhart 4-factor models, it finds that directors can make significant abnormal returns after they purchase the stocks of their own companies. Empirical work shows that firm characteristics (size and B/M ratio) of director trading do have significant impact on the performance of abnormal returns. Firms with small capitalisation and high B/M ratio achieve significant abnormal returns. It also finds some evidence to support the information hierarchy hypothesis, as CFOs do better than other members of the board of directors in the short-run after their purchase activities. However, CEOs, who also have the best knowledge about their company's prospects and are able to achieve more valuable information, do not perform better than other directors.

7.2 Limitations of the Research

There are some specific limitations on the work of Chapters 4 to 6, which will be discussed below.

Chapter 4 only applies the director trading with firm size control as robustness test. It does not use B/M ratio data because the Dataset LSPD does not have B/M information, and Datastream could output very little B/M information of sample companies for the period 1986-1993. The time period of director trading covers in this thesis is 1986-2008: if it deletes the data from 1986 to 1993, it sacrifices more than one third of data time. This may lead to biased results, as it would not have director trading data from a long enough period to run a long-run time series model. Furthermore, as mentioned by Gregory et al. (2011), for UK-list companies, it has an issue that there are small illiquid firms in the sample. This may lead to potential problem that it fails to output sufficient data about these small illiquid firms when forming the portfolios.

Chapter 5 uses nominal and real GDP to denote economic activity, and applies dividend yield of FTSE All Share, growth rate of industrial production and term spread to proxy business cycle movement. However, it is also valuable to check other business cycle macroeconomic variables (unemployment claims, real value of manufacture's new orders for consumer goods and materials, monetary growth rate, etc) to check the performance of aggregate director trading. Another potential problem is that GDP is measured quarterly, so in sample period of 23 years (1986-2008) there are only 92 observations. Even using overlapping measurement with Newey-West t-test methodology, it still does not have sufficient data on GDP, which may lead to biased results.

In Chapter 6, it forms 6 groups of firms (small/low, small/medium, small/high, big/low, big/medium and big/high) to compare director trading with firm characteristics. It may therefore be valuable to check the results using with other firm classifications: for example, by looking at small and big firms or low B/M and high B/M firms separately. Another limitation related to the finding is that abnormal returns of 1-month to 6-month post-purchase are significantly higher for CFOs than for other director: it only runs a long-run calendar time portfolio regression model, and does not apply short-run event study methodology to further test this finding. One limitation is that, while the long-run calendar time methodology has the statistical power to detect abnormal returns, these estimates do not allow for analysis of long-run abnormal returns within a fixed-effects regression framework. Another limitation is that, if the model provides only an imperfect description of expected returns, then the intercept represents the combined effects of mispricing and model misspecification. This is what Fama (1970) refers to as the 'joint-test problem'.

7.3 Suggestions for Future Research

There are several ways in which the work of these chapters could be extended. Chapter 4 examines director trading within a time series framework. The findings show that aggregate director trading indicate future market excess returns, and that the longer the future market excess returns and past director trading, the better explanatory power aggregate director trading gets. If the time length of data is long enough, it could build on this result by splitting the sample into different time periods based on economic change or regulation of director trading changes, to examine the performance of aggregate director trading. If data on recent director trading is available, it could examine the performance of director trading during the financial crisis of 2008. Finally, it could test the performance of director trading based on firm characteristics, by testing aggregate director trading on value stock (high B/M ratio) and growth stock (low B/M ratio), if the B/M data is available.

Chapter 5 could be extended by using different macroeconomic indicators as the dependent variables, and other business cycle variables (unemployment claims, real value of manufacture's new orders for consumer goods and materials, monetary growth rate, etc.) to test robustness of aggregate director trading. Also, it can apply dummy variable to evaluate macro-conditions.

Chapter 6 finds that the abnormal returns of 1- to 6-month post-purchase are significantly higher for CFOs than for other directors. However, it only uses long-run calendar time portfolio regression model. Gregory et al. (2012) find that the returns of female executive trades are significantly greater than returns of male executive trades when returns of 10 days or more post-trade are considered. This hints that it may be valuable to apply short-run event study methodology to further test the performance of director trading patterns. Also, as documented in Chapter 6, trades of CFOs are more informative than other directors. This might suggest that aggregate director trading of CFOs might be more informative of market movements and future changes in GDP. Therefore, further work could investigate this.

Appendices

Appendix A

Unit root test of Aggregate net Number of Purchases (ANT), aggregate ANP and ANS

Unit Root Test of ANT

Dickey-Fuller test for unit root Number of obs = 275

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-7.253	-3.458	-2.879	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

D.NT	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
NT L1.	-.3311309	.0456535	-7.25	0.000	-.4210085	-.2412533
_cons	30.33916	5.383533	5.64	0.000	19.74065	40.93768

Unit Root Test of ANP

Dickey-Fuller test for unit root Number of obs = 275

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.317	-3.458	-2.879	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

D.ANP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ANP L1.	-.190062	.0357433	-5.32	0.000	-.2604294	-.1196945
_cons	39.79773	8.0832	4.92	0.000	23.8844	55.71106

Unit Root Test of ANS

Dickey-Fuller test for unit root Number of obs = 275

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-6.872	-3.458	-2.879	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

D.ANS	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ANS L1.	-.293224	.0426714	-6.87	0.000	-.3772308	-.2092172
_cons	33.7419	5.814523	5.80	0.000	22.2949	45.1889

Appendix B

Correlation of Aggregate Director Trading Variables

	ANP_{t+1}	ANP_{t}	ANP_{t-1}		AP_{t+1}	AP_{t}	AP_{t-1}		AS_{t+1}	AS_{t}	AS_{t-1}
ANP_{t}	0.66***			AP_{t}	0.81***			AS_{t}	0.71***		
ANP_{t-1}	0.48***	0.66***		AP_{t-1}	0.68***	0.81***		AS_{t-1}	0.51***	0.71***	
ANP_{t-2}	0.35***	0.48***	0.66***	AP_{t-2}	0.67***	0.68***	0.81***	AS_{t-2}	0.41***	0.51***	0.71***
	$SANP_{t+1}$	$SANP_{t}$	$SANP_{t-1}$		SAP_{t+1}	SAP_{t}	SAP_{t-1}		SAS_{t+1}	SAS_{t}	SAS_{t-1}
$SANP_{t}$	0.66***			SAP_{t}	0.81***			SAS_{t}	0.71***		
$SANP_{t-1}$	0.48***	0.66***		SAP_{t-1}	0.68***	0.81***		SAS_{t-1}	0.51***	0.71***	
$SANP_{t-2}$	0.35***	0.48***	0.66***	SAP_{t-2}	0.67***	0.68***	0.81***	SAS_{t-2}	0.41***	0.51***	0.71***
	NPR_{t+1}	NPR_{t}	NPR_{t-1}		PR_{t+1}	PR_{t}	PR_{t-1}		SR_{t+1}	SR_{t}	SR_{t-1}
NPR_{t+1}	0.67***			PR_{t+1}	0.67***			SR_{t+1}	0.67***		
NPR_{t}	0.50***	0.67***		PR_{t}	0.50***	0.67***		SR_{t}	0.50***	0.67***	
NPR_{t-1}	0.34***	0.50***	0.67***	PR_{t-1}	0.34***	0.50***	0.67***	SR_{t-1}	0.34***	0.50***	0.67***
	ΔNPR_{t+1}	ΔNPR_{t}	ΔNPR_{t-1}		ΔPR_{t+1}	ΔPR_{t}	ΔPR_{t-1}		ΔSR_{t+1}	ΔSR_{t}	ΔSR_{t-1}
ΔNPR_{t+1}	-0.24***			ΔPR_{t+1}	-0.24***			ΔSR_{t+1}	-0.24***		
ΔNPR_{t}	-0.03	-0.24***		ΔPR_{t}	-0.03	-0.24***		ΔSR_{t}	-0.03	-0.24***	
ΔNPR_{t-1}	-0.13*	-0.03	-0.24***	ΔPR_{t-1}	-0.13*	-0.03	-0.24	ΔSR_{t-1}	-0.13*	-0.03	-0.24

Appendix B (Continued)

	ΔANP_{t+1}	ΔANP_{t}	ΔANP_{t-1}		ΔAP_{t+1}	ΔAP_{t}	ΔAP_{t-1}		ΔAS_{t+1}	ΔAS_{t}	ΔAS_{t-1}
ΔANP_{t+1}	-0.24***			ΔAP_{t+1}	-0.18***			ΔAS_{t+1}	-0.16***		
ΔANP_{t}	-0.08	-0.24***		ΔAP_{t}	-0.31***	-0.18***		ΔAS_{t}	-0.16***	-0.16***	
ΔANP_{t-1}	-0.10	-0.08	-0.24***	ΔAP_{t-1}	0.06	-0.31***	-0.19***	ΔAS_{t-1}	-0.03	-0.16***	-0.17***
	$NPGR_{t+1}$	$NPGR_{t}$	$NPGR_{t-1}$		$APGR_{t+1}$	$APGR_{t}$	$APGR_{t-1}$		$ASGR_{t+1}$	$ASGR_{t}$	$ASGR_{t-1}$
$NPGR_{t+1}$	-0.03			$APGR_{t+1}$	-0.20***			$ASGR_{t+1}$	-0.27***		
$NPGR_{t}$	-0.12*	-0.03		$APGR_{t}$	-0.27***	-0.20***		$ASGR_{t}$	-0.07	-0.27***	
$NPGR_{t-1}$	0.13**	-0.12*	-0.03	$APGR_{t-1}$	0.13**	-0.27***	-0.21***	$ASGR_{t-1}$	0.04	-0.07	-0.27***

ANP denotes aggregate net number of purchases. **AP** denotes aggregate number of purchases transactions. **AS** denotes aggregate number of sales transactions. **SANP** denotes standardized aggregate net number of purchase. **SAP** denotes standardized aggregate number purchases transactions. **SAS** denotes aggregate number of sales transactions. **NPR** denotes Net number of director purchase ratio. **PR** denotes purchase ratio. **SR** denotes sales ratio. ∆**NPR** denotes differences of aggregate net purchase ratio. ∆**PR** denotes differences of aggregate purchase ratio. ∆**SR** denotes differences of aggregate sale ratio. ∆**ANP** denotes differences of aggregate net number of purchase. ∆**AP** denotes differences of aggregate number of purchases. ∆**AS** denotes differences of aggregate number of sales. **NPGR** denotes change of aggregate net number of purchase. **APGR** denotes change of aggregate number of purchases. **ASGR** denotes change of aggregate number of sales.

Symbol *, ** and *** denote significant level of 10%, 5% and 1%, respectively

Appendix C

Summary Statistics of Aggregate Director Trading Variables

Variable	Mean	Std. Dev	Min	Max
ANP	89.38	78.48	-203	331
AP	203.49	100.75	26	659
AS	114.11	74.52	13	435
NPR	0.30	0.24	-0.48	0.80
PR	0.65	0.12	0.26	0.90
SR	0.35	0.12	0.10	0.74
ΔNPR	0.0016	0.19	-0.62	0.64
ΔPR	0.0008	0.10	-0.31	0.32
ΔSR	-0.0008	0.10	-0.32	0.31
ΔANP	0.96	64.12	-217	317
ΔAP	1.25	62.21	-255	266
ΔAS	0.29	57.01	-291	201
NPGR	-0.20	5.97	-54	48
APGR	0.06	0.36	-0.77	2.27
ASGR	0.11	0.52	-0.78	2.39

Appendix D

Data Description by applied methodology of Pesaran and Timmermann (2000)

YALL: Dividend yield on the FTSE All Share Index.

I3: 90-day T-bill rate.

PI: Rate of change of retail prices, computed as ln[RPI12/RPI12(-12)] where RPI12 is a twelve-month moving average of the Retail Price Index.

GILT: Yield on a 2.5% government consol measured at the end of the month.

DM0: Year-on-year rate of change in the narrow money stock M0.

DIP: Year-on-year rate of change in industrial production of the manufacturing sector.

DPSPOT: Year-on-year change in the spot price of oil (in logs). Both spot oil price of WTI and Brent are applied.

Appendix E

Regression of the Excess Monthly Stock Returns against the leading, Contemporaneous, and Lagged Values of the Monthly Standardized Aggregate Net Number of Director Purchases Transactions (SANP) by All Firms

	Constant	$SANP_{t+1}$	$SANP_{t}$	$SANP_{t-1}$	$SANP_{t-2}$
1	-0.00045	…	…	0.004127	-0.000567
	(-0.16)			(1.01)	(-0.14)
2	-0.00016	…	-0.021566	0.017335	0.001193
	(-0.06)		(-4.04)***	(3.68)***	(0.35)
3	0.000004	-0.022706	-0.007975	0.019001	0.001205
	(0.00)	(-5.55)***	(-1.49)	(4.05)***	(0.35)
	Constant	$SANP\_ADJ\_1_{t+1}$	$SANP\_ADJ\_1_{t}$	$SANP\_ADJ\_1_{t-1}$	$SANP\_ADJ\_1_{t-2}$
4	-0.00046	…	…	0.001628	-0.000055
	(-0.16)			(0.50)	(-0.02)
5	-0.00032	…	-0.014253	0.008698	0.001075
	(-0.12)		(-3.26)***	(2.39)**	(0.30)
6	-0.000187	-0.018069	-0.005591	0.008518	0.003992
	(-0.08)	(-4.75)***	(-1.26)	(2.26)**	(1.13)
	Constant	$SANP\_ADJ\_2_{t+1}$	$SANP\_ADJ\_2_{t}$	$SANP\_ADJ\_2_{t-1}$	$SANP\_ADJ\_2_{t-2}$
7	-0.00047	…	…	0.003791	-0.001642
	(-0.17)			(0.92)	(-0.38)
8	-0.00022	…	-0.019709	0.015734	0.000785
	(-0.09)		(-3.57)***	(3.24)***	(0.20)
9	-0.000003	-0.023405	-0.005969	0.017263	0.002770
	(-0.00)	(-5.34)***	(-1.06)	(3.50)***	(0.72)

Sample periods are 276 months from 1986 to 2008. **SANP** is standardized aggregate net number of director purchases transactions. **SANP_ADJ_1** denotes seasonal adjusted ANP based on December and March fiscal year end by assumption, **SANP_ADJ_2** denotes seasonal adjusted ANP based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. Excess market returns is defined as the actual return to the FTSE All Share index minus the return on the monthly 90-day Treasury Bills. The Newey-West t-statistics of estimated coefficients are shown in parentheses. The symbol *, **, *** presents significant level at the 10%, 5%, 1%, respectively.

Appendix F

Summary Statistics of Excess Monthly Stock Returns

$$\prod_{k=t}^{t+m-1}(1+R_k)-\prod_{k=t}^{t+m-1}(1+R_k^f)=\alpha_0$$

m=3	m=6	m=9	m=12
α_0	α_0	α_0	α_0
−0.00133	−0.00090	0.00048	0.00216

Excess market returns is defined as buy-and-hold excess returns between the actual return to the FTSE All Share index and the return on the monthly 90-day Treasury Bills.

$$\sum_{k=t}^{t+m-1}(R_k-R_k^f)=\alpha_0$$

m=3	m=6	m=9	m=12
α_0	α_0	α_0	α_0
−0.0010063	0.0064833	0.0007564	0.002736

Excess market returns is defined as cumulative excess returns between the actual return to the FTSE All Share index and the return on the monthly 90-day Treasury Bills.

Appendix G

Correlation Between Monthly Return of FTSE All Share/Excess Market Return/Aggregate Net Number of Director Purchases/Aggregate Number of Director Purchases/Aggregate Number of Director Sales and Performance of Industries

Panel A			Panel B	
	R_FTSE All			**NPR_All**
R_BM	0.6498***		NPR_BM	0.3747***
R_CG	0.5327***		NPR _CG	0.2532***
R_CS	0.7515***		NPR _CS	0.4604***
R_F	0.7821***		NPR _F	0.5694***
R_HC	0.3877***		NPR _HC	0.1479**
R_I	0.7135***		NPR _I	0.4258***
R_OS	0.5618***		NPR _OG	0.2693***
R_T	0.5511***		NPR _T	0.1394*
R_TC	0.5569***		NPR _TC	0.2384***
R_U	0.3572***		NPR _U	-0.0639

Panel A represents Correlation between monthly returns of FTSE All Share and return of industries. Panel B represents correlation between aggregate net number of director purchases of all firms and aggregate net number of director purchases of industries. BM- Basic Material, CG-Consumer Goods, CS-Consumer Services, F-Financials, HC-Health Care, I-Industrial, OS-Oil & Gas, T-Technology, TC-Telecommunication, U-Utilities. Symbol *, **,*** denote significant at 10%, 5% and 1%, respectively.

Appendix H

Time Series Regression of Future 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Real GDP Growth on Past 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Aggregate Net Number of Director Purchases Trading Ratio

$$\sum_{k=t+1}^{t+i} GDPGrowth\_R = \alpha_0 + \alpha_1 NPR_{(t-j,t)}$$

Panel A	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0053	0.008036	0.0710	0.0054	0.004387	0.0190	0.0056	0.001000	-0.0092	0.0055	0.001419	-0.0071
	(4.93)***	(3.61)***		(4.91)***	(2.31)**		(5.00)***	(0.61)		(5.42)***	(0.53)	
Seasonal Adj_1	0.0062	-0.003068	0.0031	0.0054	0.004324	0.0182	0.0047	0.006571	0.0987	0.0054	0.001564	-0.0060
	(5.73)***	(-1.06)		(4.90)***	(2.29)**		(4.21)***	(4.84)***		(5.32)***	(0.60)	
Seasonal Adj_2	0.0055	0.005416	0.0177	0.0054	0.005025	0.0218	0.0053	0.003055	0.0058	0.0054	0.001953	-0.0041
	(5.05)***	(1.64)		(4.88)***	(2.35)**		(4.82)***	(1.93)*		(5.39)***	(0.73)	
Panel B	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0114	0.004675	0.0031	0.0108	0.008292	0.0449	0.0107	0.005370	0.0227	0.0105	0.005179	0.0203
	(7.65)***	(1.24)		(5.84)***	(2.78)***		(5.81)***	(1.62)		(5.57)***	(0.92)	
Seasonal Adj_1	0.0114	0.004372	0.0036	0.0108	0.008619	0.0494	0.0109	0.003771	0.0075	0.0104	0.005485	0.0250
	(7.74)***	(1.36)		(5.81)***	(2.90)***		(5.82)***	(1.31)		(5.45)***	(0.99)	
Seasonal Adj_2	0.0115	0.004665	-0.0003	0.0108	0.008918	0.0428	0.0107	0.005777	0.0210	0.0103	0.006464	0.0320
	(7.72)***	(1.16)		(5.86)***	(2.68)***		(5.85)***	(1.57)		(5.52)***	(1.14)	

Appendix H (Continued)

Panel C	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0172	0.006929	0.0076	0.0170	0.006328	0.0080	0.0169	0.003707	-0.0020	0.0157	0.009504	0.0527
	(9.03)***	(1.14)		(7.19)***	(1.45)		(0.72)	(0.74)		(5.66)***	(1.51)	
Seasonal	0.0182	-0.004626	-0.0016	0.0170	0.006814	0.0111	0.0158	0.009883	0.0670	0.0156	0.009629	0.0559
Adj_1	(9.64)***	(-1.03)		(7.15)***	(1.54)		(6.26)***	(2.47)**		(5.61)***	(1.54)	
Seasonal	0.0175	0.003701	-0.0074	0.0170	0.006912	0.0079	0.0165	0.007070	0.0175	0.0155	0.010956	0.0631
Adj_2	(9.16)***	(0.52)		(7.26)***	(1.38)		(6.64)***	(1.32)		(5.63)***	(1.72)*	

Panel D	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0235	0.005374	-0.0027	0.0231	0.007703	0.0111	0.0219	0.011080	0.0573	0.0210	0.012060	0.0748
	(11.03)***	(0.68)		(8.50)***	(1.05)		(7.12)***	(1.74)*		(6.11)***	(1.54)	
Seasonal	0.0234	0.005679	0.0001	0.0230	0.007955	0.0126	0.0221	0.008828	0.0376	0.0210	0.012055	0.0767
Adj_1	(10.90)***	(1.08)		(8.46)***	(1.09)		(7.19)***	(1.56)		(6.07)***	(1.58)	
Seasonal	0.0235	0.007620	0.0023	0.0230	0.009204	0.0154	0.0218	0.012687	0.0627	0.0208	0.013690	0.0858
Adj_2	(11.01)***	(0.87)		(8.54)***	(1.11)		(7.15)***	(1.80)*		(6.06)***	(1.68)*	

Sample periods are 92 quarters from 1986 to 2008, GDPGrowth_R denotes quarterly growth rate of real GDP which is seasonally adjusted. NPR denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), Seasonal Adj_1 denotes seasonal adjusted director trading transactions based on December and March fiscal year end by assumption, Seasonal Adj_2 denotes seasonal adjusted director trading transactions based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Appendix I

Time Series Regression of Future 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Real GDP Growth on Past 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter CBI Industrial Trends Survey Data

$$\sum_{k=t+1}^{t+i} GDPGrowth\_R = \alpha_0 + \alpha_1 \sum_{k=t-j}^{t} CBI$$

	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
Panel A	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.006	0.00013	0.0549	0.007	0.00007	0.0669	0.007	0.00005	0.0685	0.006	0.00004	0.0423
	(6.07)***	(2.01)**		(6.78)***	(2.40)**		(6.45)***	(2.42)**		(6.15)***	(2.06)**	
	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
Panel B	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.013	0.00025	0.1206	0.013	0.00014	0.1317	0.013	0.00009	0.1002	0.012	0.00007	0.0847
	(9.15)***	(3.15)***		(7.53)***	(2.75)***		(6.72)***	(2.33)**		(6.09)***	(2.18)**	
	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
Panel C	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.019	0.00036	0.1409	0.019	0.00018	0.1148	0.018	0.00013	0.1032	0.018	0.00010	0.0930
	(10.58)***	(3.37)***		(8.03)***	(2.56)**		(6.67)***	(2.25)**		(5.99)***	(2.18)**	
	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
Panel D	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.024	0.00035	0.0820	0.024	0.00020	0.0866	0.024	0.00014	0.0829	0.023	0.00011	0.0766
	(11.16)***	(2.77)***		(8.06)***	(2.25)**		(6.64)***	(2.10)**		(5.87)***	(2.08)**	

Appendix I (Continued)

Sample periods are 92 quarters from 1986 to 2008, GDPGrowth_R denotes quarterly growth rate of real GDP which is seasonally adjusted. CBI denotes quarterly industrial trends survey data provided by Confederation of British Industry (CBI business confidence). The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Appendix J

Time Series Regression of Future 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Growth Rate of Real GDP on Past One-Quarter, Two-Quarter, Three-Quarter and Four-Quarter Aggregate Net Number of Director Purchases Trading Ratio Decomposed by Different Macro-Effect Variables

$$\sum_{k=t+1}^{t+i} GDPGrowth\_R = \alpha_0 + \alpha_1 NPR_{(t-j,t)}$$

Panel A	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0067	0.00677	0.0671	0.0068	0.00372	0.0158	0.0071	0.00084	-0.0110	0.0069	0.00141	-0.0074
	(6.52)***	(2.99)***		(6.92)***	(1.92)*		(7.12)***	(0.57)		(8.80)***	(0.58)	
Growth Rate Cycle	0.0064	0.00174	-0.0185	0.0071	0.00126	-0.0206	0.0071	0.00029	-0.0253	0.0068	0.00042	-0.0255
	(3.71)***	(0.40)		(4.47)***	(0.60)		(4.84)***	(0.18)		(6.09)***	(0.21)	
Depression	0.0068	0.00657	0.0740	0.0069	0.00397	0.0251	0.0072	0.00073	-0.0120	0.0067	0.00247	0.0067
	(7.04)***	(3.08)***		(7.73)***	(2.52)**		(7.32)***	(0.49)		(9.26)***	(1.10)	

Panel B	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	-0.0024	-0.00666	-0.0861	-0.0011	-0.00941	0.0302	0.0005	-0.00524	-0.0255	-0.0007	-0.00626	0.1238
	(-0.61)	(-0.69)		(-0.34)	(-1.65)		(0.19)	(-1.27)		(-0.26)	(-1.45)	
Growth Rate Cycle	0.0044	-0.00582	-0.0034	0.0043	0.00006	-0.0227	0.0043	-0.00243	-0.0163	0.0044	-0.00385	-0.0016
	(2.86)***	(-1.15)		(2.55)**	(0.01)		(2.80)***	(-0.55)		(3.39)***	(-1.02)	
Depression	0.0003	-0.00791	-0.0063	0.0019	-0.01099	0.1872	0.0021	-0.00371	-0.0379	0.0013	-0.00609	-0.0026
	(0.08)	(-1.16)		(0.52)	(-2.19)*		(0.67)	(-1.10)		(0.44)	(-1.05)	

Appendix J (Continued)

Panel C	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0143	0.00351	-0.0001	0.0137	0.00677	0.0452	0.0136	0.00481	0.0294	0.0132	0.00535	0.0400
	(10.87)***	(1.03)		(8.87)***	(2.43)**		(9.29)***	(1.63)		(9.29)***	(1.06)	
Growth Rate Cycle	0.0126	0.00256	-0.0178	0.0131	0.00351	-0.0085	0.0126	0.00284	-0.0091	0.0113	0.00537	0.0375
	(5.43)***	(0.47)		(4.81)***	(0.85)		(4.90)***	(0.71)		(4.08)***	(1.35)	
Depression	0.0145	0.00210	-0.0084	0.0139	0.00622	0.0455	0.0137	0.00505	0.0415	0.0131	0.00670	0.0817
	(11.29)***	(0.66)		(9.53)***	(2.35)**		(9.84)***	(1.76)*		(10.10)***	(1.37)	

Panel D	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	-0.0056	-0.01090	-0.0668	-0.0021	-0.01186	0.0624	-0.0015	-0.00930	0.0985	-0.0012	-0.01130	0.2868
	(-1.14)	(-0.96)		(-0.61)	(-1.81)		(-0.44)	(-1.55)		(-0.57)	(-2.18)*	
Growth Rate Cycle	0.0087	-0.01281	0.0211	0.0088	-0.00736	0.0010	0.0088	-0.01009	0.0346	0.0093	-0.01199	0.0803
	(3.95)***	(-1.71)*		(3.11)***	(-1.07)		(3.43)***	(-1.55)		(4.07)***	(-1.72)	
Depression	-0.0014	-0.00154	-0.0818	0.0027	-0.01167	0.1086	0.0022	-0.00512	-0.0339	0.0027	-0.01009	0.0436
	(-0.29)	(-0.16)		(0.55)	(-2.19)*		(0.45)	(-1.67)		(0.64)	(-1.48)	

Panel E	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0213	0.00581	0.0098	0.0212	0.00480	0.0057	0.0210	0.00350	0.0013	0.0197	0.00846	0.0737
	(13.20)***	(1.08)		(11.22)***	(1.25)		(10.61)	(0.83)		(9.75)***	(1.55)	
Growth Rate Cycle	0.0183	0.00509	-0.0063	0.0188	0.00575	0.0049	0.0176	0.00640	0.0316	0.0173	0.00495	0.0109
	(6.62)***	(0.67)		(5.60)***	(1.00)		(4.84)***	(1.04)		(4.06)***	(0.86)	
Depression	0.0214	0.00718	0.0268	0.0214	0.00525	0.0128	0.0210	0.00452	0.0142	0.0196	0.00981	0.1170
	(13.41)***	(1.62)		(11.41)***	(1.61)		(10.99)***	(1.13)		(10.83)***	(1.85)*	

Appendix J (Continued)

Panel F	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	-0.0090	-0.02483	0.1206	-0.0058	-0.02105	0.2902	-0.0031	-0.01960	0.6246	-0.0057	-0.01585	0.5228
	(-1.68)	(-1.61)		(-1.27)	(-4.53)***		(-1.01)	(-4.67)***		(-1.50)	(-4.72)***	
Growth Rate Cycle	0.0128	-0.01736	0.0276	0.0131	-0.01354	0.0255	0.0135	-0.01766	0.0850	0.0140	-0.01552	0.0846
	(4.60)***	(-1.72)*		(3.87)***	(-1.41)		(4.29)***	(-1.67)		(4.48)***	(-1.70)*	
Depression	-0.0025	-0.00801	-0.0471	0.0007	-0.01185	0.0736	0.0024	-0.01133	0.1645	0.0015	-0.01370	0.1255
	(-0.46)	(-1.14)		(0.14)	(-3.47)***		(0.46)	(-13.95)***		(0.32)	(-3.38)***	

Panel G	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0285	0.00586	0.0064	0.0280	0.00787	0.0296	0.0270	0.00984	0.0848	0.0262	0.00964	0.0917
	(15.95)***	(1.03)		(13.02)***	(1.28)		(11.69)***	(1.78)*		(10.51)***	(1.37)	
Growth Rate Cycle	0.0249	0.00722	0.0063	0.0236	0.01151	0.0663	0.0233	0.00683	0.0245	0.0229	0.00343	-0.0106
	(8.50)***	(0.87)		(6.05)***	(1.36)		(4.91)***	(0.86)		(4.21)***	(0.56)	
Depression	0.0287	0.00712	0.0194	0.0280	0.01025	0.0711	0.0270	0.01150	0.1390	0.0260	0.01182	0.1640
	(16.40)***	(1.50)		(13.31)***	(1.99)*		(12.51)***	(2.18)**		(11.54)***	(1.76)*	

Panel H	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	-0.0110	-0.04232	0.4542	-0.0070	-0.03654	0.8482	-0.0078	-0.02138	0.5535	-0.0121	-0.01685	0.5774
	(-2.25)*	(-4.58)***		(-2.69)**	(-11.29)***		(-1.48)	(-2.98)**		(-2.59)**	(-4.27)***	
Growth Rate Cycle	0.0175	-0.02327	0.0547	0.0180	-0.02044	0.0723	0.0187	-0.02132	0.1080	0.0189	-0.01837	0.1015
	(5.95)***	(-1.60)		(5.07)***	(-1.76)*		(5.21)***	(-1.85)*		(4.54)***	(-1.99)*	
Depression	-0.0020	-0.02185	0.1801	0.0017	-0.02299	0.4987	0.0014	-0.01378	0.2655	-0.0008	-0.01346	0.1104
	(-0.40)	(-2.91)**		(0.39)	(-6.85)***		(0.23)	(-5.48)***		(-0.12)	(-3.63)***	

Appendix J (Continued)

Sample periods are 92 quarters from 1986 to 2008. **GDPGrowth_R** denotes quarterly growth rate of real GDP which is seasonally adjusted. **NPR** denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), **Business cycle** denotes business cycle peak and trough provided by Economic Cycle Research Institute (ECRI), there are 81 quarters are good time, 15 quarters are bad time. **Growth rate cycle** denotes growth rate cycle peak and trough provided by Economic Cycle Research Institute (ECRI), there are 47 quarters are good time, 49 quarters are bad time. **Depression** denotes UK depression time periods got from report Mitchell et al. (2009), there are 77 quarters are good time, 19 quarters are bad time. **Panel A, C, E** and **G** presents NPR performance on good time by different measurements of macroeconomic conditions. **Panel B, D, F** and **H** (the shadow panels) present NPR performance on bad time by different measurements of macroeconomic conditions. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Appendix K

Time Series Regression of Future 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter Growth Rate of Real GDP on Past 1-Quarter, 2-Quarter, 3-Quarter and 4-Quarter CBI Industrial Trends Survey Data Decomposed by Different Macro-Effect Variables

$$\sum_{k=t+1}^{t+i} GDPGrowth\_R = \alpha_0 + \alpha_1 \sum_{k=t-j}^{t} CBI$$

Panel A	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0073	0.00001	-0.0124	0.0074	0.00002	-0.0086	0.0074	0.00002	-0.0064	0.0072	0.000005	-0.0125
	(6.84)***	(0.16)		(7.75)***	(0.54)		(7.46)***	(0.66)		(7.47)***	(0.27)	
Growth Rate Cycle	0.0063	0.00002	-0.0216	0.0064	0.00004	-0.0135	0.0063	0.00005	0.0024	0.0061	0.00003	-0.0151
	(4.15)***	(0.17)		(4.22)***	(0.59)		(4.32)***	(1.08)		(4.33)***	(0.68)	
Depression	0.0075	0.00003	-0.0078	0.0075	0.000015	-0.0103	0.0074	0.000010	-0.0108	0.0073	0.000002	-0.0139
	(7.16)***	(0.52)		(7.81)***	(0.46)		(7.35)***	(0.44)		(7.32)***	(0.12)	

Panel B	i=1 j=1			i=1 j=2			i=1 j=3			i=1 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0019	0.00017	0.0164	0.0000	0.00006	-0.0612	-0.0007	0.00002	-0.0929	-0.0071	-0.00002	-0.0990
	(0.40)	(1.19)		(-0.00)	(0.54)		(-0.07)	(0.24)		(-1.05)	(-0.41)	
Growth Rate Cycle	0.0039	-0.00001	-0.0216	0.0041	-0.000002	-0.0222	0.0037	-0.000003	-0.0225	0.0040	0.000005	-0.0226
	(2.51)**	(-0.08)		(2.70)**	(-0.04)		(2.78)***	(-0.10)		(2.57)**	(0.17)	
Depression	0.0009	0.00010	-0.0341	0.0016	0.00006	-0.0346	0.0036	0.00005	-0.0195	0.0008	0.00002	-0.0625
	(0.18)	(0.67)		(0.25)	(0.71)		(0.63)	(1.03)		(0.17)	(0.62)	

Appendix K (Continued)

Panel C	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0148	0.00006	-0.0042	0.0148	0.00005	0.0045	0.0146	0.00002	-0.0058	0.0144	0.00001	-0.0101
	(10.89)***	(0.73)		(8.98)***	(0.85)		(8.37)***	(0.58)		(7.92)***	(0.42)	
Growth Rate Cycle	0.0129	0.00009	-0.0117	0.0127	0.00011	0.0130	0.0123	0.00008	0.0067	0.0121	0.00006	-0.0053
	(5.95)***	(0.66)		(4.90)***	(1.18)		(4.63)***	(1.00)		(4.50)***	(0.91)	
Depression	0.0149	0.00005	-0.0068	0.0149	0.00002	-0.0082	0.0146	0.000008	-0.0129	0.0145	0.000006	-0.0133
	(11.06)***	(0.64)		(8.89)***	(0.49)		(8.18)***	(0.23)		(7.79)***	(0.22)	

Panel D	i=2 j=1			i=2 j=2			i=2 j=3			i=2 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	-0.0029	0.00015	-0.0460	-0.0060	0.00002	-0.0984	-0.0130	-0.00006	-0.0785	-0.0199	-0.00009	-0.0295
	(-0.38)	(0.81)		(-0.47)	(0.10)		(-1.38)	(-0.59)		(-2.16)*	(-0.97)	
Growth Rate Cycle	0.0079	-0.00003	-0.0198	0.0079	-0.00001	-0.0220	0.0078	0.000002	-0.0232	0.0077	0.000002	-0.0237
	(3.82)***	(-0.34)		(3.20)***	(-0.15)		(3.18)***	(0.04)		(2.63)**	(0.05)	
Depression	0.0011	0.00017	-0.0166	0.0041	0.00013	0.0126	0.0026	0.00007	-0.0368	-0.0001	0.00003	-0.0739
	(0.12)	(0.73)		(0.37)	(0.87)		(0.27)	(0.72)		(-0.01)	(0.36)	

Panel E	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0222	0.00010	0.0045	0.0221	0.00005	-0.0024	0.0218	0.00003	-0.0064	0.0216	0.00002	-0.0085
	(13.10)***	(0.98)		(10.39)***	(0.71)		(8.90)***	(0.57)		(8.37)***	(0.53)	
Growth Rate Cycle	0.0192	0.00019	0.0034	0.0188	0.00012	0.0034	0.0184	0.00010	0.0050	0.0180	0.00005	-0.0138
	(7.33)***	(1.16)		(5.63)***	(1.03)		(4.90)***	(1.00)		(4.65)***	(0.72)	
Depression	0.0224	0.00007	-0.0055	0.0222	0.00002	-0.0119	0.0220	0.000013	-0.0123	0.0218	0.000012	-0.0118
	(13.05)***	(0.68)		(10.25)***	(0.33)		(8.81)***	(0.30)		(8.34)***	(0.36)	

Appendix K (Continued)

Panel F	i=3 j=1			i=3 j=2			i=3 j=3			i=3 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	-0.0103	0.00004	-0.0971	-0.0179	-0.00009	-0.0705	-0.0242	-0.00013	-0.0048	-0.0335	-0.00016	0.0841
	(-1.09)	(0.17)		(-1.83)	(-0.58)		(-2.44)**	(-0.91)		(-2.85)**	(-1.14)	
Growth Rate Cycle	0.0122	-0.000019	-0.0223	0.0125	0.000015	-0.0223	0.0120	0.000009	-0.0233	0.0122	0.000005	-0.0241
	(5.08)***	(-0.16)		(4.31)***	(0.19)		(3.44)***	(0.15)		(2.98)***	(0.11)	
Depression	0.0030	0.00029	0.0644	0.0024	0.00014	0.0038	0.0017	0.00008	-0.0422	-0.0009	0.00004	-0.0750
	(0.29)	(1.08)		(0.21)	(0.90)		(0.12)	(0.57)		(-0.06)	(0.37)	
Panel G	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	0.0294	0.00006	-0.0088	0.0293	0.00004	-0.0060	0.0290	0.00003	-0.0064	0.0285	0.00002	-0.0079
	(15.52)***	(0.59)		(11.33)***	(0.64)		(9.61)***	(0.61)		(9.05)***	(0.54)	
Growth Rate Cycle	0.0261	0.00010	-0.0174	0.0257	0.00013	0.0019	0.0252	0.00007	-0.0105	0.0241	0.00004	-0.0181
	(8.90)***	(0.60)		(6.62)***	(1.03)		(5.75)***	(0.70)		(5.54)***	(0.43)	
Depression	0.0297	0.00003	-0.0124	0.0295	0.000024	-0.0113	0.0293	0.000020	-0.0106	0.0287	0.000017	-0.0101
	(15.53)***	(0.36)		(11.33)***	(0.39)		(9.66)***	(0.43)		(9.24)***	(0.44)	
Panel H	i=4 j=1			i=4 j=2			i=4 j=3			i=4 j=4		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
Business Cycle	-0.0241	-0.00030	-0.0008	-0.0354	-0.00034	0.1994	-0.0472	-0.00037	0.3721	-0.0570	-0.00034	0.5230
	(-2.84)**	(-1.03)		(-3.51)***	(-1.69)		(-5.78)***	(-2.85)**		(-7.11)***	(-3.32)**	
Growth Rate Cycle	0.0173	0.00004	-0.0214	0.0170	0.000018	-0.0227	0.0166	0.000004	-0.0243	0.0154	-0.00002	-0.0217
	(6.94)***	(0.36)		(4.93)***	(0.25)		(3.67)***	(0.07)		(2.59)**	(-0.45)	
Depression	-0.0034	0.00007	-0.0699	-0.0041	0.00001	-0.0832	-0.0056	-0.00002	-0.0880	-0.0110	-0.00007	-0.0702
	(-0.37)	(0.26)		(-0.29)	(0.03)		(-0.34)	(-0.15)		(-0.61)	(-0.58)	

Appendix K (Continued)

Sample periods are 92 quarters from 1986 to 2008. **GDPGrowth_R** denotes quarterly growth rate of real GDP which is seasonally adjusted. **CBI** denotes quarterly industrial trends survey data provided by Confederation of British Industry (CBI business confidence). **Business cycle** denotes business cycle peak and trough provided by Economic Cycle Research Institute (ECRI), there are 81 quarters are good time, 15 quarters are bad time. **Growth rate cycle** denotes growth rate cycle peak and trough provided by Economic Cycle Research Institute (ECRI), there are 47 quarters are good time, 49 quarters are bad time. **Depression** denotes UK depression time periods got from report Mitchell et al. (2009), there are 77 quarters are good time, 19 quarters are bad time. **Panel A, C, E** and **G** presents NPR performance on good time by different measurements of macroeconomic conditions. **Panel B, D, F** and **H** (the shadow panels) present NPR performance on bad time by different measurements of macroeconomic conditions. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Appendix L

Time Series Regression of Future 1-, 3-, 6-, 9- and 12-Month SMB on Past 1-, 3-, 6-, 9- and 12-month Aggregate Net Number of Director Purchases Ratio by All Firms

$$\sum_{k=t}^{t+m-1} SMB = \alpha_0 + \alpha_1 NPR_{(t-n,t-1)}$$

Panel A	n=1 m=1			n=1 m=3			n=1 m=6			n=1 m=9			n=1 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0038	-0.016	0.0103	0.0042	-0.021	0.0033	0.0039	-0.024	0.0006	0.00083	-0.016	-0.0025	0.0071	-0.038	0.0016
	(1.22)	(-2.07)**		(0.71)	(-1.38)		(0.51)	(-1.16)		(0.08)	(-0.63)		(0.62)	(-1.28)	
Seasonal	0.0038	-0.016	0.0103	0.0042	-0.021	0.0033	0.0039	-0.024	0.0006	0.00083	-0.016	-0.0025	0.0071	-0.038	0.0016
Adj_1	(1.22)	(-2.07)**		(0.71)	(-1.38)		(0.51)	(-1.16)		(0.08)	(-0.63)		(0.62)	(-1.28)	
Seasonal	0.0039	-0.017	0.0101	0.0054	-0.026	0.0056	0.0049	-0.028	0.0015	0.00350	-0.026	-0.0009	0.0101	-0.050	0.0044
Adj_2	(1.24)	(-2.07)**		(0.89)	(-1.60)		(0.63)	(-1.28)		(0.36)	(-0.96)		(0.89)	(-1.59)	
Panel B	n=3 m=1			n=3 m=3			n=3 m=6			n=3 m=9			n=3 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0023	-0.011	0.0013	0.0023	-0.016	-0.0006	-0.00105	-0.0082	-0.0033	0.0018	-0.021	-0.0022	0.0077	-0.043	0.0014
	(0.64)	(-1.09)		(0.26)	(-0.65)		(-0.09)	(-0.25)		(0.12)	(-0.50)		(0.40)	(-0.80)	
Seasonal	0.0025	-0.011	0.0020	0.0032	-0.019	0.0007	-0.00024	-0.0109	-0.0030	0.0027	-0.024	-0.0016	0.0088	-0.046	0.0024
Adj_1	(0.70)	(-1.17)		(0.36)	(-0.79)		(-0.02)	(-0.33)		(0.18)	(-0.58)		(0.46)	(-0.87)	
Seasonal	0.0028	-0.013	0.0025	0.0034	-0.021	0.0008	0.00041	-0.0136	-0.0027	0.0046	-0.031	-0.0005	0.0116	-0.058	0.0048
Adj_2	(0.75)	(-1.22)		(0.38)	(-0.79)		(0.03)	(-0.38)		(0.31)	(-0.71)		(0.61)	(-1.04)	
Panel C	n=6 m=1			n=6 m=3			n=6 m=6			n=6 m=9			n=6 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.00052	-0.0056	-0.0027	-0.00176	-0.0038	-0.0036	-0.00139	-0.0083	-0.0035	0.0044	-0.032	-0.0010	0.0059	-0.040	-0.0004
	(0.13)	(-0.50)		(-0.19)	(-0.14)		(-0.11)	(-0.22)		(0.26)	(-0.62)		(0.26)	(-0.59)	
Seasonal	0.00112	-0.0076	-0.0018	-0.00031	-0.0086	-0.0031	-0.00020	-0.0122	-0.0031	0.0049	-0.033	-0.0006	0.0074	-0.045	0.0006
Adj_1	(0.29)	(-0.69)		(-0.03)	(-0.32)		(-0.02)	(-0.33)		(0.29)	(-0.65)		(0.33)	(-0.67)	
Seasonal	0.00087	-0.0070	-0.0023	0.00039	-0.0087	-0.0031	0.00083	-0.0162	-0.0027	0.0075	-0.043	0.0011	0.0097	-0.054	0.0020
Adj_2	(0.22)	(-0.59)		(-0.04)	(-0.30)		(0.07)	(-0.42)		(0.46)	(-0.84)		(0.44)	(-0.79)	

Appendix L (Continued)

Panel D	n=9 m=1			n=9 m=3			n=9 m=6			n=9 m=9			n=9 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.00008	-0.0041	-0.0033	0.00068	-0.012	-0.0028	0.0037	-0.026	-0.0014	0.0050	-0.036	-0.0010	-0.0110	0.0117	-0.0037
	(0.02)	(-0.33)		(0.07)	(-0.40)		(0.26)	(-0.59)		(0.25)	(-0.58)		(-0.42)	(0.15)	
Seasonal Adj_1	0.00037	-0.0050	-0.0031	0.00136	-0.014	-0.0023	0.0039	-0.027	-0.0011	0.0054	-0.037	-0.0006	-0.0091	0.0050	-0.0039
	(0.09)	(-0.43)		(0.14)	(-0.49)		(0.27)	(-0.62)		(0.28)	(-0.62)		(-0.36)	(0.07)	
Seasonal Adj_2	0.00073	-0.0064	-0.0028	0.00235	-0.018	-0.0017	0.0063	-0.036	0.0005	0.0087	-0.049	0.0012	-0.0051	-0.0088	-0.0038
	(0.18)	(-0.51)		(0.24)	(-0.58)		(0.45)	(-0.80)		(0.44)	(-0.79)		(-0.20)	(-0.11)	

Panel E	n=12 m=1			n=12 m=3			n=12 m=6			n=12 m=9			n=12 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0013	-0.0085	-0.0022	0.0029	-0.020	-0.0014	0.0019	-0.023	-0.0023	-0.0126	0.0180	-0.0033	-0.026	0.057	0.0009
	(0.30)	(-0.64)		(0.26)	(-0.60)		(0.12)	(-0.43)		(-0.57)	(0.26)		(-0.94)	(0.66)	
Seasonal Adj_1	0.0016	-0.0095	-0.0016	0.0033	-0.022	-0.0008	0.0031	-0.026	-0.0016	-0.0107	0.0114	-0.0037	-0.024	0.048	-0.0002
	(0.39)	(-0.76)		(0.32)	(-0.67)		(0.19)	(-0.53)		(-0.51)	(0.18)		(-0.89)	(0.59)	
Seasonal Adj_2	0.0019	-0.0108	-0.0014	0.0046	-0.027	0.0002	0.0048	-0.033	-0.0007	-0.0072	-0.0007	-0.0039	-0.019	0.032	-0.0026
	(0.45)	(-0.80)		(0.43)	(-0.78)		(0.30)	(-0.63)		(-0.34)	(-0.01)		(-0.70)	(0.37)	

Sample periods are 92 quarters from 1986 to 2008. SMB denotes small minus big, is the difference in the returns of a value-weighted portfolio of small stocks and big stocks. NPR denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), Seasonal Adj_1 denotes seasonal adjusted director trading transactions based on December and March fiscal year end by assumption, Seasonal Adj_2 denotes seasonal adjusted director trading transactions based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Appendix M

Time Series Regression of Future 1-, 3-, 6-, 9- and 12-Month HML on Past 1-, 3-, 6-, 9- and 12-month Aggregate Net Number of Director Purchases Ratio by All Firms

$$\sum_{k=t}^{t+m-1} HML = \alpha_0 + \alpha_1 NPR_{(t-n,t-1)}$$

Panel A	n=1 m=1			n=1 m=3			n=1 m=6			n=1 m=9			n=1 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0073	-0.0098	0.0017	0.026	-0.043	0.0187	0.051	-0.080	0.0265	0.074	-0.106	0.0280	0.104	-0.160	0.0477
	(2.24)**	(-1.29)		(4.11)***	(-3.09)***		(5.35)***	(-3.80)***		(5.24)***	(-3.33)***		(6.35)***	(-4.10)***	
Seasonal	0.0073	-0.0098	0.0017	0.026	-0.043	0.0187	0.051	-0.080	0.0265	0.074	-0.106	0.0280	0.104	-0.160	0.0477
Adj_1	(2.24)**	(-1.29)		(4.11)***	(-3.09)***		(5.35)***	(-3.80)***		(5.24)***	(-3.33)***		(6.35)***	(-4.10)***	
Seasonal	0.0087	-0.0150	0.0073	0.028	-0.050	0.0227	0.055	-0.097	0.0350	0.081	-0.135	0.0415	0.114	-0.200	0.0666
Adj_2	(2.56)**	(-1.84)*		(4.27)***	(-3.34)***		(5.59)***	(-4.23)***		(5.49)***	(-3.88)***		(6.52)***	(-4.63)***	

Panel B	n=3 m=1			n=3 m=3			n=3 m=6			n=3 m=9			n=3 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.011	-0.020	0.0141	0.032	-0.062	0.0321	0.057	-0.103	0.0349	0.083	-0.143	0.0411	0.124	-0.233	0.0809
	(2.71)***	(-2.39)**		(3.56)***	(-3.30)***		(3.59)***	(-3.01)***		(3.66)***	(-2.78)***		(4.66)***	(-3.67)***	
Seasonal	0.011	-0.020	0.0142	0.033	-0.065	0.0366	0.059	-0.107	0.0385	0.086	-0.149	0.0461	0.127	-0.240	0.0877
Adj_1	(2.74)***	(-2.46)**		(3.76)***	(-3.61)***		(3.79)***	(-3.25)***		(3.86)***	(-3.03)***		(4.92)***	(-3.93)***	
Seasonal	0.011	-0.022	0.0144	0.033	-0.068	0.0350	0.061	-0.119	0.0429	0.091	-0.175	0.0564	0.133	-0.272	0.0998
Adj_2	(2.71)***	(-2.38)**		(3.57)***	(-3.30)***		(3.66)***	(-3.09)***		(3.71)***	(-2.98)***		(4.62)***	(-3.75)***	

Panel C	n=6 m=1			n=6 m=3			n=6 m=6			n=6 m=9			n=6 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.011	-0.023	0.0124	0.033	-0.068	0.0282	0.061	-0.120	0.0355	0.101	-0.210	0.0686	0.149	-0.327	0.1207
	(2.70)***	(-2.40)**		(3.19)***	(-2.82)***		(3.45)***	(-2.88)***		(4.19)***	(-3.58)***		(4.95)***	(-4.21)***	
Seasonal	0.011	-0.024	0.0156	0.035	-0.073	0.0355	0.065	-0.130	0.0449	0.106	-0.222	0.0814	0.154	-0.339	0.1365
Adj_1	(2.89)***	(-2.68)***		(3.52)***	(-3.27)***		(3.90)***	(-3.44)***		(4.63)***	(-4.07)***		(5.38)***	(-4.68)***	
Seasonal	0.012	-0.025	0.0154	0.035	-0.077	0.0350	0.067	-0.143	0.0484	0.109	-0.243	0.0867	0.158	-0.365	0.1401
Adj_2	(2.76)***	(-2.52)**		(3.26)***	(-2.95)***		(3.54)***	(-3.08)***		(4.20)***	(-3.69)***		(4.88)***	(-4.24)***	

Appendix M (Continued)

Panel D	n=9 m=1			n=9 m=3			n=9 m=6			n=9 m=9			n=9 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.012	-0.026	0.0138	0.035	-0.077	0.0284	0.075	-0.171	0.0589	0.124	-0.293	0.1071	0.173	-0.417	0.1554
	(2.50)**	(-2.20)**		(2.97)***	(-2.58)**		(3.96)***	(-3.53)***		(4.72)***	(-4.22)***		(5.05)***	(-4.47)***	
Seasonal Adj_1	0.012	-0.028	0.0172	0.036	-0.082	0.0355	0.077	-0.177	0.0686	0.126	-0.297	0.1195	0.176	-0.420	0.1704
	(2.71)***	(-2.50)**		(3.30)***	(-3.01)***		(4.34)***	(-3.99)***		(5.07)***	(-4.61)***		(5.38)***	(-4.83)***	
Seasonal Adj_2	0.013	-0.030	0.0180	0.038	-0.091	0.0382	0.081	-0.197	0.0741	0.132	-0.328	0.1264	0.182	-0.457	0.1745
	(2.64)***	(-2.40)**		(3.13)***	(-2.85)***		(4.05)***	(-3.70)***		(4.72)***	(-4.30)***		(5.09)***	(-4.57)***	

Panel E	n=12 m=1			n=12 m=3			n=12 m=6			n=12 m=9			n=12 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.013	-0.032	0.0189	0.044	-0.110	0.0533	0.092	-0.232	0.0949	0.142	-0.360	0.1395	0.187	-0.471	0.1709
	(2.75)***	(-2.56)**		(3.88)***	(-3.64)***		(4.89)***	(-4.34)***		(5.07)***	(-4.50)***		(5.39)***	(-4.84)***	
Seasonal Adj_1	0.014	-0.033	0.0217	0.045	-0.111	0.0606	0.092	-0.230	0.1042	0.143	-0.356	0.1521	0.187	-0.464	0.1837
	(2.94)***	(-2.81)***		(4.10)***	(-3.95)***		(5.10)***	(-4.63)***		(5.27)***	(-4.75)***		(5.53)***	(-5.02)***	
Seasonal Adj_2	0.014	-0.036	0.0233	0.047	-0.122	0.0626	0.097	-0.255	0.1089	0.149	-0.390	0.1553	0.195	-0.508	0.1876
	(2.87)***	(-2.73)***		(3.96)***	(-3.77)***		(4.89)***	(-4.44)***		(5.12)***	(-4.63)***		(5.49)***	(-4.98)***	

Sample periods are 92 quarters from 1986 to 2008. HML denotes high minus low, is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. NPR denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), Seasonal Adj_1 denotes seasonal adjusted director trading transactions based on December and March fiscal year end by assumption, Seasonal Adj_2 denotes seasonal adjusted director trading transactions based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Appendix N

Time Series Regression of Future 1-, 3-, 6-, 9- and 12-Month HML on Past 1-, 3-, 6-, 9- and 12- Change of Aggregate Net Director Purchases Ratio by All Firms

$$\sum_{k=t}^{t+m-1} HML = \alpha_0 + \alpha_1 \Delta NPR_{(t-n,t-1)}$$

Panel A	n=1 m=1			n=1 m=3			n=1 m=6			n=1 m=9			n=1 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0044	0.017	0.0070	0.013	0.023	0.0005	0.027	0.013	-0.0032	0.042	0.017	-0.0032	0.057	0.044	-0.0013
	(2.26)**	(1.86)*		(3.18)***	(1.05)		(4.03)***	(0.38)		(4.77)***	(0.39)		(5.35)***	(0.73)	
Seasonal	0.0044	0.017	0.0070	0.013	0.023	0.0005	0.027	0.013	-0.0032	0.042	0.017	-0.0032	0.057	0.044	-0.0013
Adj_1	(2.26)**	(1.86)*		(3.18)***	(1.05)		(4.03)***	(0.38)		(4.77)***	(0.39)		(5.35)***	(0.73)	
Seasonal	0.0044	0.018	0.0056	0.013	0.017	-0.0018	0.027	0.010	-0.0035	0.042	0.017	-0.0033	0.057	0.040	-0.0021
Adj_2	(2.26)**	(1.81)*		(3.18)***	(0.80)		(4.03)***	(0.32)		(4.77)***	(0.38)		(5.34)***	(0.72)	
Panel B	n=3 m=1			n=3 m=3			n=3 m=6			n=3 m=9			n=3 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.004	0.011	0.0052	0.013	0.012	-0.0014	0.027	-0.0006	-0.0038	0.042	0.014	-0.0031	0.056	0.046	0.0017
	(1.85)*	(1.48)		(2.01)**	(0.74)		(2.39)**	(-0.02)		(2.76)***	(0.37)		(3.08)***	(0.98)	
Seasonal	0.004	0.011	0.0052	0.013	0.012	-0.0014	0.027	-0.0006	-0.0038	0.042	0.014	-0.0031	0.056	0.046	0.0017
Adj_1	(1.85)*	(1.48)		(2.01)**	(0.74)		(2.39)**	(-0.02)		(2.76)***	(0.37)		(3.08)***	(0.98)	
Seasonal	0.005	0.008	0.0003	0.013	0.010	-0.0025	0.027	-0.0002	-0.0038	0.042	0.017	-0.0030	0.056	0.046	0.0007
Adj_2	(1.85)*	(1.04)		(2.01)**	(0.51)		(2.39)**	(-0.01)		(2.76)***	(0.40)		(3.08)***	(0.88)	
Panel C	n=6 m=1			n=6 m=3			n=6 m=6			n=6 m=9			n=6 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.004	0.007	0.0002	0.013	0.002	-0.0037	0.026	0.004	-0.0037	0.040	0.047	0.0054	0.054	0.061	0.0073
	(1.73)*	(0.92)		(1.91)*	(0.13)		(2.27)**	(0.14)		(2.61)**	(1.19)		(2.92)***	(1.20)	
Seasonal	0.004	0.007	0.0002	0.013	0.002	-0.0037	0.026	0.004	-0.0037	0.040	0.047	0.0054	0.054	0.061	0.0073
Adj_1	(1.73)*	(0.92)		(1.91)*	(0.13)		(2.27)**	(0.14)		(2.61)**	(1.19)		(2.92)***	(1.20)	
Seasonal	0.004	0.006	-0.0012	0.013	0.003	-0.0036	0.026	0.009	-0.0033	0.040	0.048	0.0050	0.054	0.058	0.0051
Adj_2	(1.73)*	(0.72)		(1.91)*	(0.15)		(2.27)**	(0.32)		(2.61)**	(1.13)		(2.92)***	(1.06)	

Appendix N (Continued)

Panel D	n=9 m=1			n=9 m=3			n=9 m=6			n=9 m=9			n=9 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.004	0.008	0.0010	0.012	0.011	-0.0016	0.024	0.043	0.0095	0.038	0.071	0.0176	0.051	0.065	0.0086
	(1.64)	(1.00)		(1.78)*	(0.72)		(2.11)**	(1.61)		(2.46)**	(1.67)*		(2.77)***	(1.32)	
Seasonal	0.004	0.008	0.0010	0.012	0.011	-0.0016	0.024	0.043	0.0095	0.038	0.071	0.0176	0.051	0.065	0.0086
Adj_1	(1.64)	(1.00)		(1.78)*	(0.72)		(2.11)**	(1.61)		(2.46)**	(1.67)*		(2.77)***	(1.32)	
Seasonal	0.004	0.007	-0.0004	0.012	0.013	-0.0010	0.024	0.047	0.0097	0.038	0.072	0.0152	0.051	0.059	0.0051
Adj_2	(1.65)	(0.88)		(1.78)*	(0.78)		(2.10)**	(1.67)*		(2.45)**	(1.61)		(2.76)***	(1.18)	
Panel E	n=12 m=1			n=12 m=3			n=12 m=6			n=12 m=9			n=12 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.003	0.024	0.0391	0.011	0.047	0.0311	0.023	0.069	0.0251	0.036	0.077	0.0175	0.049	0.061	0.0057
	(1.42)	(2.85)***		(1.62)	(2.31)**		(1.96)*	(1.96)*		(2.31)**	(1.65)		(2.64)***	(1.17)	
Seasonal	0.003	0.024	0.0391	0.011	0.047	0.0311	0.023	0.069	0.0251	0.036	0.077	0.0175	0.049	0.061	0.0057
Adj_1	(1.42)	(2.85)***		(1.62)	(2.31)**		(1.96)*	(1.96)*		(2.31)**	(1.65)		(2.64)***	(1.17)	
Seasonal	0.004	0.022	0.0255	0.011	0.044	0.0235	0.023	0.067	0.0199	0.036	0.068	0.0111	0.050	0.044	0.0005
Adj_2	(1.43)	(2.32)**		(1.62)	(1.89)*		(1.96)*	(1.73)*		(2.31)**	(1.37)		(2.62)***	(0.75)	

Sample periods are 92 quarters from 1986 to 2008. HML denotes high minus low, is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. ∆NPR denotes NPR in month t minus NPR in month t-1, where NPR denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S), Seasonal Adj_1 denotes seasonal adjusted director trading transactions based on December and March fiscal year end by assumption, Seasonal Adj_2 denotes seasonal adjusted director trading transactions based on December and March fiscal year end by Observations. Both methods of seasonal adjustment are fully described in Chapter 3. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Appendix O

Regressions of Future 3-, 6-, 9-, 12-Month SMB on Past 3-, 6-, 9-, 12-Month Market Excess Returns on: 1986-2008

$$\sum_{k=t}^{t+m-1} SMB = \alpha_0 + \alpha_1 \sum_{k=t-n}^{t-1} MKT$$

Panel	n=3 m=3			n=3 m=6			n=3 m=9			n=3 m=12		
A	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	-0.0006	0.175	0.0476	0.0022	0.017	-0.0034	0.0031	-0.005	-0.0036	0.0022	-0.055	-0.0024
	(-0.12)	(1.73)*		(0.20)	(0.16)		(0.19)	(-0.03)		(0.10)	(-0.39)	
Panel B	n=6 m=3			n=6 m=6			n=6 m=9			n=6 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0008	-0.004	-0.0036	0.0034	-0.096	0.0105	0.0048	-0.148	0.0187	0.0033	-0.144	0.0119
	(0.13)	(-0.06)		(0.30)	(-0.93)		(0.29)	(-1.18)		(0.15)	(-1.10)	
Panel C	n=9 m=3			n=9 m=6			n=9 m=9			n=9 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0010	-0.011	-0.0031	0.0042	-0.104	0.0205	0.0053	-0.136	0.0232	0.0040	-0.175	0.0290
	(0.16)	(-0.20)		(0.36)	(-1.18)		(0.32)	(-1.28)		(0.18)	(-1.52)	
Panel D	n=12 m=3			n=12 m=6			n=12 m=9			n=12 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0015	-0.029	0.0011	0.0045	-0.100	0.0251	0.0060	-0.162	0.0459	0.0046	-0.193	0.0497
	(0.24)	(-0.63)		(0.38)	(-1.30)		(0.36)	(-1.63)		(0.22)	(-1.68)*	

Sample periods are 276 months from 1986 to 2008. **SMB** denotes the difference in the returns of a value-weighted portfolio of small stocks and big stocks. **MKT** denotes excess returns between return on index of FTSE All Share and return on the 90-day Treasury Bills. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Appendix P

Regressions of Future 3-, 6-, 9-, 12-Month HML on Past 3-, 6-, 9-, 12-Month Market Excess Returns on: 1986-2008

$$\sum_{k=t}^{t+m-1} HML = \alpha_0 + \alpha_1 \sum_{k=t-n}^{t-1} MKT$$

Panel B	n=3 m=3			n=3 m=6			n=3 m=9			n=3 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0114	-0.013	-0.0033	0.0225	-0.009	-0.0036	0.0333	-0.130	0.0012	0.0428	-0.213	0.0053
	(1.62)	(-0.23)		(1.45)	(-0.09)		(1.39)	(-0.91)		(1.31)	(-1.18)	
Panel C	n=6 m=3			n=6 m=6			n=6 m=9			n=6 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0112	-0.011	-0.0033	0.0226	-0.069	0.0008	0.0336	-0.185	0.0151	0.0422	-0.158	0.0053
	(1.56)	(-0.25)		(1.46)	(-0.75)		(1.41)	(-1.31)		(1.27)	(-0.95)	
Panel D	n=9 m=3			n=9 m=6			n=9 m=9			n=9 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0116	-0.050	0.0047	0.0234	-0.129	0.0186	0.0337	-0.166	0.0178	0.0412	-0.127	0.0044
	(1.64)	(-1.25)		(1.54)	(-1.41)		(1.39)	(-1.33)		(1.20)	(-0.83)	
Panel E	n=12 m=3			n=12 m=6			n=12 m=9			n=12 m=12		
	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2	α_0	α_1	Adj R^2
	0.0120	-0.067	0.0154	0.0229	-0.096	0.0126	0.0324	-0.112	0.0088	0.0399	-0.106	0.0036
	(1.73)*	(-1.68)*		(1.47)	(-1.37)		(1.28)	(-1.17)		(1.14)	(-0.81)	

Sample periods are 276 months from 1986 to 2008. **HML** is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. **MKT** denotes excess returns between return on index of FTSE All Share and return on the 90-day Treasury Bills. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics present in parentheses.

Appendix Q

Summary of Forecasting Accuracy to Regressions of 1-Year Leads of Quarterly Nominal GDP Growth Rates on 1-Year Lags of MKT, SMB, HML and NPR/CBI on 1986-2008

$$GDPGrowth_{(t,t+4)} = a + b*MKT_{(t-4,t)} + c*Factor\mathrm{Re}\,t_{(t-4,t)} + d*NPR/CBI_{(t-4,t)} + \varepsilon_{(t,t+4)}$$

$$GDPGrowth_{(t,t+4)} = a + b*MKT_{(t-4,t)} + c*Factor\mathrm{Re}\,t_{(t-4,t)} + d*NPR/CBI_{(t-4,t)} + e*DY_{(t)} + f*IPGrowth_{(t-4,t)} + g*TERM_{(t)} + \varepsilon_{(t,t+4)}$$

Con	…	SMB		NPR/CBI	…	…	…	**NPR is Better than CBI**
Con	…	…	HML	NPR/CBI	…	…	…	**NPR is Better than CBI**
Con	…	SMB	HML	NPR/CBI	…	…	…	**NPR is Better than CBI**
Con	MKT	SMB	…	NPR/CBI	…	…	…	**NPR is Better than CBI**
Con	MKT	…	HML	NPR/CBI	…	…	…	**NPR is Better than CBI**
Con	MKT	SMB	HML	NPR/CBI	…	…	…	**NPR is Better than CBI**
Con	…	SMB	HML	NPR/CBI	DY	IPGrowth	Term	**NPR is Better than CBI**
Con	MKT	SMB	HML	NPR/CBI	DY	IPGrowth	Term	**NPR is Better than CBI**

Sample periods are 92 quarters from 1986 to 2008, quarterly Gross Domestic Product (GDP) is seasonally adjusted. **GDPGrowth** denotes nominal GDP growth rate. **MKT** denotes excess returns between return on index of FTSE All Share and return on the 90-day Treasury Bills. **'FactorRet'** stands for SMB and HML. **SMB** is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, **HML** is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. **NPR** denotes quarterly aggregate net number of purchases trading ratio, calculated by dividing the net number of purchases (number of purchases minus number of sales) by the total number of director transaction of all firms (P-S)/(P+S). **CBI** denotes quarterly industrial trends survey data provided by Confederation of British Industry (CBI business confidence). **DY** denotes the dividend yield of FTSE All Share. **IPGrowth** denotes industrial production growth. **TERM** denotes long-run rate minus short term rate in UK, calculated by long-run rate (the yield to maturity of a 10-year government bond) minus short term rate (90-day UK Treasury Bill rate). The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Newey-West t-statistics with 3 lags present in parentheses.

Appendix R

Post-trade long-run CTAR of Director Purchases by Director Role Using the Carhart 4 Factor Model for Holding Periods of 1-, 3-, 6-, 12-, 18- and 24-Month from January 1994 to December 2008

$$R_{pt} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + m_i MOM_t + \varepsilon_{it}$$

Director Group	1-month AR	3-month AR	6-month AR	12-month AR	18-month AR	24-month AR
CEO	2.28% (4.21)***	0.76% (1.66)*	0.26% (0.61)	0.36% (0.92)	0.27% (0.71)	0.10% (0.27)
CFO	3.35% (3.78)***	1.70% (2.70)***	1.30% (2.45)**	0.43% (0.89)	0.23% (0.51)	0.32% (0.71)
Chair Exe	2.49% (2.25)**	1.02% (1.13)	1.27% (1.34)	0.54% (0.81)	0.21% (0.35)	-0.14% (-0.28)
Chair Non	2.82% (2.92)***	0.58% (0.88)	0.46% (0.79)	0.47% (0.99)	0.53% (1.04)	0.45% (0.95)
Other Exe	1.91% (3.17)***	1.23% (2.70)***	0.66% (1.54)	0.31% (0.82)	0.19% (0.49)	-0.02% (-0.05)
Other Non	2.54% (3.11)***	1.86% (3.09)***	1.07% (2.22)**	0.25% (0.58)	0.17% (0.38)	-0.21% (-0.50)

ARs are intercepts from Fama-French regression of the calendar time portfolio on a market factor, a size factor and a book-to-market factor. Weighted Least Squares estimation, where the weighting factor is based o the number of securities in the portfolio in each calendar month, is applied.

CEO: Chief Executive Officer; **CFO**: Chief Financial Officer; **Chair Exe**: Executive Chairman; **Chair Non**: Non-Executive Chairman; **Other Exe**: Other Executives exclude CEO, CFO and Executive Chairman; **Other Non**: Other Non-Executives exclude Non-Executive Chairman.

R_{pt} is the simple return on the calendar-time portfolio, R_{ft} is the return on the 90-day Treasury Bills, R_{mt} is the return on index of FTSE All Share, SMB_t is the difference in the returns of a value-weighted portfolio of small stocks and big stocks, HML_t is the difference in the returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks. MOM_t is difference in average return on high prior return portfolios and low prior return portfolios. The estimate of the intercept term (α_i), provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero.

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, with t-value in parentheses.

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