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A study on the correlation between future economic conditions and stock returns under China's A-share market

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Declaration

"This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism and intellectual property".

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Abstract

Our study aims to investigate the explanatory power of future economic conditions on the returns of individual stocks in the Chinese A-share market. We use an integrated research methodology to study this topic scientifically and systematically. All A-share stocks in the Shanghai Stock Exchange and Shenzhen Stock Exchange are selected as the primary research objects, and data representing China's real economic activity are widely collected. With these data, we analyze a new trading strategy based on a reasonable prediction of future real activities using the capital asset pricing model and the Fama-French three-factor model. In addition, we have specifically examined the performance of this trading strategy on two different types of stocks (pro-cyclical and counter-cyclical stocks). Particularly noteworthy is that, unlike previous studies, we innovatively adopt the producer price index (PPI) as a measure of China's real economic activity based on the largest possible selection of sample intervals. This innovative approach provides a new perspective for us to deeply understand the operating mechanism of China's A-share market and the impact of economic conditions on the performance of individual stocks. The study results show no significant relationship between future economic conditions and individual stock returns in China's A-share market. Besides, those investors who want to get excess returns can short the pro-cyclical stocks and/or long the counter-cyclical stocks if production growth in the following month is anticipated to be above the steady state and vice versa. Our new trading strategy demonstrates potential advantages and gives investors a unique decision-making perspective. This finding not only provides investors with a more reliable basis for decision-making but also helps us to gain a deeper understanding of the operating rules of the Chinese stock market. This new perspective sheds light on the potential impact mechanism of economic activities on the Chinese stock market, which sheds important light on the optimization of investment strategies and risk management. Meanwhile, our trading strategy research provides an innovative way for investors to seek better returns among different classes of stocks. However, some things could be improved in this study. Future research can be further deepened and expanded to understand the relationship between China's A-share market and economic conditions

more comprehensively and continuously optimize trading strategies' practicality and robustness. Overall, the findings of this thesis fill a research gap in the academic field and provide new perspectives and methods for investment decision-making and risk management. These findings will provide valuable references for relevant scholars and practitioners and contribute to a deeper understanding of China's macroeconomic conditions and their relationship with the A-share market.
Keywords: Producer Price Index (PPI), Pro-cyclical, Counter-cyclical, Chinese A-share Markets

1. Introduction

The relationship between stock returns and real economic activity has received much attention from researchers in recent years, and there is a growing body of academic research evidence suggesting that these two are inextricably linked. (Fama, 1990; Schwert, 1990; Zhu, Gao and Sherman, 2020) Specifically, there is an interdependent relationship between stock returns and the development and changes in the real economic activity, i.e., the development status of the real economy affects the performance of the stock market; and the performance of the stock market, in turn, affects the development of the real economy. The existence of this relationship can help investors better understand and analyze changes in the stock market and make more informed investment decisions.

However, to obtain greater investment returns, in addition to having professional investment knowledge, investors should also pay attention to fluctuations as well as changes in real economic activity and adjust their investment strategies in a timely manner according to the changes in the market. This is because changes in the macroeconomy can have an impact on the performance of various industries and companies, which further affects the performance of the stock market. Therefore, investors need to have certain macroeconomic analysis skills and pay close attention to domestic and international economic policies, market environment, industry dynamics, and other factors. Through timely analysis and grasp of changes in the real economy, investors can more accurately judge the development trend of the stock market, make more reasonable investment plans, and ultimately achieve higher investment returns.

Inspired by the above two reasons, we conduct this study. We focus on all A-shares in the Chinese stock market, and the main objective of this paper is to investigate the relationship between stock returns and macroeconomic changes in the Chinese stock market, i.e., whether changes in real economic activity can reflect changes in stock returns. With the aim of making this study more adequate, we also distinguish stocks into pro-cyclical stocks and counter-cyclical stocks based on the changes in business cycles. Besides, this study explores the interaction between the stock markets and the macroeconomy through regression analysis in order to provide new research perspectives and theoretical support for academics, as well as scientific investment advice and practical guidelines for investors.

Through an in-depth exploration of the relationship between the two, we mainly expect to provide new evidence and theoretical support for this academic research area while providing investors with more scientific and reasonable investment advice from a relatively more novel perspective. Specifically, we aim to provide investors with targeted recommendations through our research findings on how to better use macroeconomic indicators to forecast stock market trends and adjust investment strategies to achieve higher abnormal returns. These recommendations will help investors better grasp market changes and improve the accuracy and success rate of investment decisions.

After clarifying the reasons for conducting the study and the related research objectives, we will elaborate on this aspect in more detail with the purpose of providing a clearer and more explicit description of the contributions and related innovations of this study. Thus, our paper has several contributions below:

First, we adopt an integrated research approach, abandoning the constraint of a single research approach. To study the issue more comprehensively and deeply, we combine both literature review and empirical research methods. The literature review approach plays an important role in our study. By systematically sorting, integrating, and analyzing the existing relevant research results and theoretical knowledge, we gain a comprehensive understanding and research direction of the existing literature studying this issue. The literature review helps us to gain an in-depth understanding of the results, methods, and limitations of the existing research so that we can be clearer and more focused in determining the research objectives and research questions. In addition, the literature review provides a theoretical framework and research basis for our study, which guides our research design and methodological choices. On the other hand, we also adopt an empirical research approach to support our research objectives. Empirical research draws more reliable and convincing conclusions by collecting, gathering, and analyzing relevant actual data and by verifying or refuting our research hypotheses. By using a combination of literature review and empirical research methods, we are able to fully utilize the advantages of both methods to achieve the comprehensiveness and reliability of our research objectives. Based on the systematic acquisition of relevant theoretical support and the construction of a research framework, we also obtain more practical as well as more convincing research results through the analysis and verification of actual data.

Second, we also innovate in the selection of macro factors to be able to analyze the Chinese stock market from a new perspective. The producer price index (PPI), which has never been used before in the analysis of China's macroeconomic issues, is chosen to represent the changes in China's macroeconomic conditions during the sample period. After a systematic review of the existing research literature, we also notice that no scholar has yet studied the relationship between stock returns and real economic activity in China using asset pricing models. Research in this area is important because real economic activity is one of the critical factors affecting stock market performance. Meanwhile, as far as the extant literature is concerned, most scholars use the business index of macroeconomics and GDP to study as well as represent the level of macroeconomic development in China, and less often use other economic indices to represent the macroeconomic activity in China in their studies. After our analysis, we find that PPI is closer to the change in actual economic activity. Therefore, we use the producer price index (PPI) to represent the actual level of economic activity in China in this study. It is expected to provide new perspectives and ideas for studying stock returns as well as macroeconomic changes in Chinese stock markets.

Third, in this study, we are open to analyzing the impact of a single macroeconomic factor on the Chinese stock markets in contrast to domestic studies. In addition to PPI, we also select some very common indices that are used to represent macroeconomic changes in China. The macroeconomic indicators we explore include but are not limited to gross domestic product (GDP), consumer price index (CPI), industrial production index (IPI), business index of macro-economic, etc. The differences between these macroeconomic factors are discussed specifically in Section 3. In our study, we aim to ensure the reliability and robustness of our results by selecting a longer sample period and including as many sample intervals as possible. In selecting the upper limit of the sample period, our selection is based on the earliest available CSI 300 Index as the market index (Rm). By analyzing a large amount of historical data, we systematically examine the correlation between macroeconomic indicators and stock returns, and we also classify all A-share stocks into pro-cyclical and counter-cyclical based on the changing in the business cycle.

Fourth, the paper also has outstanding contributions in terms of sample interval span and the number of stocks covered. In addition, for the selection of stocks, we select all A-shares in the Shanghai Stock Exchange and Shenzhen Stock Exchange, only excluding the ST-shares in the sample period. Compared to other studies, our sample is more comprehensive, covering all stock types in the Chinese A-share market, and is a more comprehensive representation of the changing conditions in the Chinese stock market by sector. This sample selection can make our findings more credible and useful. Also, and more notably, our sample period is long enough. It runs from December 2004 to September 2022. The scope of the study covers the start-up and improvement phases of the Chinese stock market. At the same time, it also covers the Global Economic Crisis (2007 to 2008) and the volatile phase of the economy caused by the Covid-19 epidemic. Therefore, the selection of the sample and the determination of the sample period before the formal start of the study ensured the comprehensiveness and extensiveness of the study to a certain extent and minimized the research error.

Fifth, our research innovatively classifies stocks in the Chinese stock market into pro-cyclical and counter-cyclical stocks based on the business cycle. We also give specific trading recommendations for investors based on the difference in stock cyclicality. In our study, expect to explore the relationship between stock returns and real economic activity in the Chinese stock market through regression analysis, and in particular, we also hope to verify whether the findings of Zhu, Gao and Sherman (2020) can be applied in the Chinese stock market as well. In addition, we will classify the A-share stocks according to the business cycle and further analyze the relationship between pro-cyclical stock returns (or counter-cyclical stock returns) and real economic activity under different business cycles. Besides, based on the regression results, corresponding trading suggestions are given for different types of stocks, thus allowing investors to gain more investment returns.

In summary, our study fills the research gap in the academic field, provides new ideas for studying the relationship between stock returns and real economic activity, and uses a comprehensive sample that aims to reflect the situation in the Chinese stock market more accurately.

Although various factors have been considered in this paper to ensure the accuracy and credibility of the study results, there is still some room for improvement. For example, in selecting the sample, we have chosen long time periods whenever possible, but as mentioned in Section 3.5, there are missing data for some indices representing real economic activities. Although we used interpolation to fill in these missing data, this may also lead to some degree of bias. We need to deal with missing data more precisely for the purpose of obtaining more accurate findings.

In addition, the model used in this paper is relatively basic and needs to be explored in further depth. Future research could consider using some more sophisticated asset pricing models, such as the conditional beta model or the conditional alpha-beta model, to further analyze the relationship between stock returns and real economic activity in China. Such a research approach may lead to more refined analytical results and more accurate forecasting capabilities. We expect future research to explore these issues in depth and contribute more deeply to further understanding the relationship between the Chinese stock markets and real economic activity.

Through the above analysis, we can clearly see that this study provides an important reference for exploring the relationship between stock returns and real economic changes in China. Meanwhile, through the classification study of Shanghai A-shares and Shenzhen A-shares, the method of categorizing stocks in China's stock market is further improved, and the changes in China's stock market are deeply explored and explained from a completely new perspective. This study expands and broadens the base of the original research and bridges the gap in the field of academic research. More importantly, the contribution of this study is not only limited to academia but also has practical application value. Through an in-depth study, we provide new perspectives and methods for further exploration in this area and for investors' decision-making. We hope this study will contribute positively to promoting the healthy development of China's stock market and investors' rational decision-making.

It is, therefore, evident that our paper is not only aimed at professionals in the field of economics but also at investors who are interested in or have already invested in the Chinese stock market. We realize that readers may have different backgrounds and levels of knowledge, so in the paper, we try to explain and elaborate on the fundamental concepts as much as possible to ensure that readers who are not familiar with the field will also be able to understand our research.

By using clear and unambiguous language in our papers, we hope to be able to translate complex economics and finance concepts into an easy-to-understand form, writing papers in a balanced way that makes it possible to satisfy the academic requirements of professionals while allowing the average investor to understand and benefit from them. We hope that such a presentation of the paper will provide readers with comprehensive, accurate, and easy-to-understand research content and provide practical references for their investment decisions in the Chinese stock market.

To have a clearer understanding of the structure of the paper, the remaining chapters are organized as follows. In the second section, to provide a more comprehensive understanding of the research theory in this area and the current state of research in the Chinese stock market, we conduct a thorough literature review of the classical literature in this research area as well as the literature that especially has studied the relationship between stock returns and real economic activity in China in recent years. Then, in Section 3, we explain the reasons for the choice of stock types and model risk factors, respectively. The data that are representative of China's real economic activity are also screened, and missing data are treated.

In Section 4 of this paper, we focus on the analytical idea of this paper and the reasons for setting the backward-looking evaluation periods. Besides we also describe how stocks are classified according to the business cycle. After obtaining the analysis methodology, we systematically analyze the relationship between the monthly stock returns and real economic activities of Shanghai and Shenzhen A-shares and present the regression results in a centralized table in Section 5. We also provide stock trading suggestions for the performance of pro-cyclical stocks and counter-cyclical stocks in different markets. Finally, the sixth section of the paper concludes.

2. A review of classic literature

The relationship between stock returns and real economic activity has been an important issue that has received much attention in economics. Scholars in various countries have been actively studying it in depth by constructing various models to analyze the realization mechanism between the two and trying to develop corresponding trading strategies to obtain excess returns (Fama, 1990; Schwert, 1990). The relationship between stock returns and real economic activity is complex and affected by a variety of factors, including political, financial and market expectations, etc. On this basis, scholars have conducted a large number of empirical studies, trying to explore the interrelationship between the two in depth from the macroeconomic and microeconomic perspectives, intending to draw more accurate conclusions and effective investment strategies.

In order to better explore the relationship between Chinese stock returns and real economic activity, we have conducted an extensive literature review and meticulously studied some literature on the Chinese stock markets. We aim to comprehensively sort out and analyze the progress of related studies through this literature review and provide references for further research on the relationship between China's stock markets and real economic activity.

In the process of the literature review, we use the classical literature approach. While reviewing the past research results, we also focus on the research trends in recent years. We identify the close link between stock returns and real economic activity through an in-depth analysis of the relevant literature. We explore the stock market's mechanisms and modes of influence on the real economy.

In addition, we have reviewed several studies focused on the Chinese stock markets, as well as carefully analyzed and synthesized their sample period, research methods, conclusions, and potential limitations. In those pieces of literature, we find new perspectives and research methods and some relevant indices that can be used to represent real economic activity in China, which provide new methodological as well as analytical insights for our study. To ensure the reliability of the references, all references to Chinese literature are from the China National Knowledge Infrastructure (CNKI)[1].

2.1 Classic Literature focuses on stock returns and real economic activity

Fama's (1990) study aims to explore the relationship between stock market prices and real economic activity. He collected monthly, quarterly, and annual data on New York Stock Exchange (NYSE) stocks from 1953 to 1987 and constructed simple and multiple regression models to analyze the link between stock market price changes and real economic activity. The findings suggest that stock market price changes can be interpreted as adjustments for future returns and risks, implying that expected stock returns are related to future economic activity. Changes in stock returns are caused by two main factors: changes in expected returns over time, and forecasts of actual events. In addition, this study finds that regressing long-term returns on future production growth rates more accurately reflects the proportional change in returns due to production information. This suggests that the link between stock market prices and real economic activity exists over time.

Schwert (1990) conducts an analysis of the correlation between real stock returns and real economic activity from 1889 to 1988 and confirmed Fama's (1990) findings. Additionally, Schwert compares two different measures of industrial production and concludes that the new Miron-Romer measure of industrial production was not the same as the one used by Fama (1990). He also finds that the new Miron-Romer measure of

[1] China National Knowledge Infrastructure (CNKI) is one of the largest digital libraries and knowledge resource repositories in China, providing comprehensive, efficient, timely and accurate academic information services, including academic papers, journals, doctoral and master's theses, conference papers, newspapers, yearbooks, books and many other literature resources. The Chinese literature cited in this paper are labeled with DOIs and original links in the reference list.

industrial production is not as strongly correlated with stock price movements as the old Babson and Federal Reserve Board measures.

In addition to the scholars mentioned above, many other scholars have also conducted relevant studies and found a significant positive correlation between the stock market and real economic activity.

Chen, Roll and Ross (1986) study the impact of macroeconomic variables on stock market returns and their effect on asset pricing. The study examines the systematic impact of a range of economic state variables on stock market returns, explores the impact of macroeconomic variables on stock market returns, and tests whether they yielded risky returns. The study shows that macroeconomic variables such as the spread between long and short-term interest rates, expected and unexpected inflation, the index of industrial production, and the spread between high-grade and low-grade bonds should have a systematic effect on stock market returns. It is worth noting that Chen, Roll and Ross (1986) focus on the relationship between monthly growth rates, annual growth rates and the US industrial production index (IPI) in their study, which provides an important reference idea for our paper in terms of the selection of macroeconomic variables.

Meanwhile, Zhu and Zhu (2014) study the relationship between European leading economic indicator and European stock returns by using monthly stock data from January 1980 to July 2013, for 12 European countries (which are Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Swiss, and the United Kingdom). They employ the model proposed by Campbell and Thompson (2008) to measure forecast performance and conclude that this indicator can effectively predict European stock returns and bring practical value. Notably, the forecasting power of the European leading economic indicator exceeds that contained in the country-specific leading indicator. Moreover, the study finds that the forecasting power of the leading European economic indicator is stable.

However, some scholars have come to the opposite opinions when examining the relationship between the two.

2.2 Some literature holding the opposite view

Fama (1981) study the impact of real economic activity, inflation, and monetary factors on stock returns. The study finds a negative relationship between monthly and quarterly stock returns and unexpected inflation rates. Also, financial factors, such as changes in money supply and interest rates, which are essential measures of real economic activity, will affect stock returns. Similarly, a similar conclusion is reached by Kaul (1987), whose study uses monthly, quarterly, and annual data on stock returns for the US, Canada, the UK, and Germany, with inflation as a proxy for changes in real economic activity. Research has shown a negative relationship between equity returns and the inflation rate. The reasons for such findings are the demand for money supply and counter-cyclical money supply effects. Specifically, changes in the inflation rate affect investment decisions and corporate profits through their impact on the real interest rate, which in turn affects equity returns. It is argued that, in the long run, real economic activity explains more of the variation in equity returns.

The above studies mainly focus on the stock markets of the United States and the United Kingdom. Compared to the stock markets in China, the stock markets in these countries and regions are more developed and have more sophisticated trading systems. This difference may have an impact on the results of the study. Therefore, in order to reduce the effect of the difference in the selection of research subjects on the results, in addition to reviewing the previous literature, in the below sections we also examine a large body of literature that explores the relationship between stock prices volatility and real economic activities in China and provides a comprehensive summary.

2.3 Literature focuses on Chinese stock returns and real economic activity

Gao and Hu (2010) collect relevant data on China's stock prices, the real gross domestic product (real GDP), and the consumer price index (CPI) from January 1996 to December 2006 and start from the perspective of the information connotation of stock prices. Gao and Hu (2010) analyze whether the stock price should be included in the monetary policy target system and whether the central bank should react to the change in the stock price. They systematically investigate the possibility that stock prices may contain information about future real GDP and CPI. In their study, the authors also use real industrial value added instead of real GDP. The researchers start from the present value solution formula for stock prices and find an important feature that asset prices are forward-looking. Expected future returns on assets strongly influence asset prices and are closely related to expectations of future economic prospects, price trends and monetary policy. Therefore, the paper hypothesizes that asset prices may imply information about future economic activity and price inflation. Gao and Hu (2010) use a vector autoregressive model (VAR model) to systematically analyze the relationship between stock price changes and real GDP and CPI in the Shanghai Stock Exchange to test this hypothesis. To improve the accuracy of the model analysis, the researchers made minor differences in the selection of the sample intervals of real GDP and CPI. Ultimately, the results of the empirical analysis by Gao and Hu (2010) indicate that the explanatory power of real stock price changes on GDP and CPI changes is insignificant. Moreover, the out-of-sample predictions of stock prices on GDP and CPI changes also perform poorly. In other words, the information content of stock price movements does not provide useful information about future economic activity and price changes. Therefore, the central bank's attitude toward the stock market can only be one of concern rather than fixation, and stock price movements should not be included in the central bank's reaction function.

Besides, Yang and Yang (2015) conduct a study on the relationship between stock price volatility and real economic activity in China. The authors collect monthly data for China from 2007 to 2014 for a total sample of 85 groups. The study uses the growth rate of industrial value added to measure the performance of real economic activity and the Shanghai Stock Exchange Composite Index[2] to measure the degree of stock price volatility. After a simple integration of the sample data, the authors empirically analyze the relationship between real economic activity and stock price volatility in China using the unit root test, cointegration test, and Granger causality test, respectively. And the study concludes that the development of the Chinese stock market deviates from the real economy to a certain extent, i.e., there is no significant long-term stable cointegration relationship between the real economy and the stock market. Moreover, the real economy is not a Granger causality for stock market development. Based on the study, the authors specifically discuss the reasons for the divergence between the real economy and stock price fluctuations from four aspects, including monetary policy, market trading system, corporate system, and related policies. Based on the characteristics of China's macroeconomic development, the authors propose corresponding policy recommendations to promote the coordinated development of the real economy and the stock market. The results of this study suggest that there is a certain divergence between the real economy and stock price volatility in China. The stock market is somewhat detached from the real economy and there is a lack of a stable long-term cointegration relationship between the two. Yang and Yang (2015) also explore the causes of this divergence and propose corresponding policy recommendations to promote the coordinated development of the real economy and the stock market.

Meanwhile, Zhang, Yang, and He (2016) also conduct a systematic study on the relationship between the Chinese stock market and macroeconomic

[2] The Shanghai Stock Exchange Composite Index (Shanghai Composite Index or SSE Composite Index) is a composite index of the Shanghai Stock Exchange, which is one of the most representative indices in China's A-share market and includes all stocks listed on the Shanghai Stock Exchange. It covers companies of different industries, sizes and market capitalizations, and reflects the overall trend of the entire A-share market. The SSE Index covers stocks in the entire market of the Shanghai Stock Exchange, while the SSE 50 Index (mentioned in Section 4) is a selection of 50 stocks with high market capitalization and liquidity from among them. The SSE Index reflects the performance of the entire A-share market more broadly, while the SSE 50 Index focuses more on blue-chip stocks with larger market capitalization and higher market influence.

development. They explore the correlation between macroeconomic growth and the stock market based on VAR models and use ADF tests and cointegration tests and establish impulse response functions to reveal the possible interrelationship between the two. The research results show that GDP plays an important role in influencing the fluctuation of the SSE Composite Index, i.e., macroeconomic factors have a more noticeable impact on the stock market. The fluctuations of the stock market can fully reflect the operation of the macroeconomy. However, the study also confirms that there may be deviations between the stock market and macroeconomic developments, i.e., the relationship between them is only sometimes consistent. Ultimately, based on the conclusions drawn, the researchers propose some feasible recommendations to improve the stability of the stock market and promote healthy macroeconomic development. Not surprisingly, the study by Zhang, Yang, and He (2016) demonstrates the close relationship between the Chinese stock market and macroeconomic developments. The fluctuations of the stock market can fully reflect the operation of the macroeconomy, and the macroeconomic factors have a more significant impact on the stock market. However, the relationship between the two may sometimes diverge. Based on the results of the study, feasible recommendations are proposed to help improve the stability of the stock market and promote healthy macroeconomic development.

In their 2003 study, Zhao and Zhang (2003) explored the link between stock market development and macroeconomic development. To estimate stock market volatility, the authors use two methods, which are multiple regression and VAR models, to investigate this relationship. The first one is the simplest variance method, which calculates the variance value for each month based on the daily returns for that month. The second one is the generalized conditional heteroskedasticity autoregressive model (GARCH). Therefore, based on these two methods of analysis of stock passages, Zhao and Zhang (2003) collect relevant daily data and monthly data to accommodate the different needs of these two methods of analysis, respectively. The empirical results show that there is a relationship between stock market volatility and macroeconomic volatility, but this interrelationship is still relatively weak. The explanatory power of macroeconomic volatility on stock market volatility is also weaker, while the predictive power of macroeconomic volatility on stock market volatility is stronger than that of stock market volatility on macroeconomic volatility. Therefore, the researcher believes that the possible reason for this result is that there are too many factors affecting the stock market. In China, the stock market is more vulnerable to policies or major events. This may explain why macroeconomic fluctuations have less explanatory power for stock market volatility. In conclusion, the study concludes that there are various links between stock market development and macroeconomic development, but these links are weaker. Stock markets are influenced by a variety of factors, especially policies and major events. This has important implications for understanding the relationship between the stock market and the macroeconomy and for making forecasts.

It is easy to see from the above analysis that Gao and Hu (2010), Yang and Yang (2015), Zhang, Yang, and He (2016), and Zhao and Zhang (2003) all use the vector autoregressive model (VAR model) when studying the relationship between stock returns and the real economic activity in China. The model is used as a multivariate time series analysis method to predict the future trend of multiple variables based on the ability to analyze their interrelationships simultaneously. These studies all come to a similar conclusion that there is no significant “barometer” function in the Chinese stock market (Yang and Yang, 2015; Zhang, Yang and He, 2016), which means there is no significant correlation between the stock returns and real economic activity in China. Alternatively, even if there is some relationship between stock market volatility and macroeconomic volatility, this relationship is weak and macroeconomic volatility has weak explanatory power for stock market volatility (Zhao and Zhang, 2003).

Yu and Zhu (2014) conduct a study in China and construct a regression model using market returns as the independent variable and industry returns as the dependent variable. They collect quarterly and monthly data from 1999 to 2010 to measure the correlation between stock prices and macroeconomic information at different time frequencies. The study proposes three hypotheses to explore the relationship between the two more precisely. First, macroeconomic information has significant explanatory power on stock prices. Second, there are differences in the effects of macroeconomic information on stock price correlations in different industries. Finally, there are also differences in the effects of macroeconomic information on stock price correlations in the same industry under different market environments, i.e., the effects are more potent in bear markets. This study is the first to quantitatively explore the impact of macroeconomic information on stock price correlation in the Chinese A-share market at the industry level and to measure it by constructing stock price correlation indicators. The research results show that macroeconomic indicators (e.g., gross domestic product, etc.) significantly affect the stock price correlation of all industries in the A-share market except finance and insurance. Still, the extent of the effect varies among industries. In addition, the impact of macroeconomic information on stock price correlations in the same industry differs significantly across market environments, i.e., the impact of macroeconomic information on stock price correlations is more significant in bear markets relative to bull markets. This suggests that the effects of macroeconomic information on stock price correlation in the Chinese securities market are related to both industry characteristics and market environment characteristics.

Table 1: Common models used in the analysis of the Chinese stock markets

Study	Sample Period	Market	Models	Conclusion
Chen and Kawaguchi (2018)	1995-07 to 2015-03	SSE and SZSE	CAPM and FF3	Investment strategies based on a three-factor model may be helpful.
Zhao, Yan and Zhang (2016)	1993-01 to 2014-12	All A-share stocks in SSE and SZSE	FF3 and FF5	For the Chinese security market, FF3 is better than FF5.
Wu and Xu (2004)	1995-02 to 2002-06	A-share listed companies in SSE and SZSE as a sample	CAPM, FF3 and Characteristic model	The cross-sectional returns of Chinese stocks depend on the book value ratio and the size of the firm.
Feng and Liu (2018)	2011-06 to 2015-06	Chinese stock markets	FF3	The three-factor model is able to explain the cross-sectional returns of small-cap stocks more comprehensively, while the ability to explain the returns of large-cap stocks needs to be improved.
Ouyang and Li (2016)	1997-01 to 2015-06	Shanghai A-share stocks and Shenzhen A-share stocks	Carhart 4-factor model and FF3	A four-factor asset pricing model with a six-month lagged momentum factor is applied to the Chinese stock market, which has higher explanatory power than the Fama-French three-factor model and the CAPM.
Hu and Xie (2019)	2015-04 to 2017-04	24 stocks in the Shanghai A-share	CAPM	In the construction and decoration industry market, the CAPM model did not yield significant results.

2.4 Common models used in the analysis of the Chinese stock market

After understanding the broad relationship between stock returns and real economic activity, it becomes particularly important to further explore the current state of research and commonly used models in the Chinese stock market. As an emerging financial market, the Chinese stock market is in the process of rapid development and continuous improvement, attracting a high level of attention from economists and investors. As a result, the study of the Chinese stock markets has become an area of great interest.

Table 1 summarizes some of the classic literature on the Chinese stock markets that have been studied in recent years, with a detailed list of the stock markets studied and the models used in each paper. It is easy to see from Table 1 that the models used are basically focused on single-factor models as well as multi-factor models, regardless of whether the study is on stocks in the Shanghai Stock Exchange or in the Shenzhen Stock Exchange.

Ouyang and Li (2016) used the Carhart four-factor model in their analysis of Shanghai A-shares and Shenzhen A-shares and made some improvements to it. They added the momentum factor with a six-month lag to the four-factor asset pricing model, which gives the model higher explanatory power in the Chinese stock markets than both the Fama-French three-factor model and the CAPM. And this explanatory power is enhanced with the completion of China's equity share reform. It is also found that the momentum factor is negatively correlated with the average stock return in the Chinese stock markets for portfolios that have performed poorly in the past and positively correlated with the average stock return for portfolios that have performed well in the past. In addition, some scholars have also compared the performance of the Fama-French three-factor model and the Fama-French five-factor model in the Chinese market (e.g., Zhao, Yan and Zhang, 2016; Feng and Liu, 2018). These studies all reach similar conclusions that the three-factor model outperforms the five-factor model in the Chinese stock markets, and the three-factor model is able to explain the cross-sectional returns of small-cap stocks more comprehensively, while its ability to explain the returns of large-cap stocks needs to be improved.

Although CAPM occupies an important position in capital market theory, in practical application, its assumptions have certain limitations due to factors such as volatility and complexity of the stock market, for example, the assumption of stable risk-free returns is difficult to maintain in the real market. Therefore, when studying the Chinese stock markets, scholars also often improve the CAPM or conduct comparative studies with other models.

Specifically, in their studies on the Chinese stock market, Chen and Kawaguchi (2018) and Wu and Xu (2004) compare the performance of CAPM and the Fama-French three-factor model. They conclude that the three-factor model has better explanatory power than the CAPM and is more suitable for developing relevant investment policy approaches. This highlights the importance of considering alternative models in addition to the traditional CAPM when examining the Chinese stock markets and demonstrates the need for continued research into developing and refining models that can better capture the unique characteristics and dynamics of this rapidly evolving market. This is because the three-factor model explains the asset pricing problem more comprehensively than the single-factor model by considering the effects of several factors on stock returns, such as market risk, size risk and value risk. In addition, their studies also show that the three-factor model performs better in explaining the cross-sectional returns of small-cap stocks, but its ability to explain the returns of large-cap stocks still needs to be improved.

In the study by Hu and Xie (2019), they select twenty-four stocks in the Chinese construction and decoration industry market as the main subjects and analyze the performance of these stocks by using CAPM. However, the analysis results showed that the test for the relationship between the beta coefficient and the daily average stock returns is not significant. This suggests that the CAPM does not explain the degree of expected stock returns from a systematic risk perspective nearly enough. The degree of systematic risk is not deep enough in the total risk, and for systematic risk, the stock returns are not compensated enough. It also indicates that in the pricing of stocks, there are other factors besides systematic risk that are important in influencing stock returns.

Therefore, a combination of the above analyses leads to the conclusion that multi-factor models are more popular and widely used for the study of the Chinese stock markets than single-factor models. Among them, the Fama-French three-factor model is widely considered to be the most commonly used and best-performing multi-factor model. Therefore, one of the reasons for choosing the three-factor model as the research framework and using it first for the analysis in our paper. We also further elaborate on the model selection in more detail in the fourth section of this paper.

2.5 Business cycle, pro-cyclical stocks and counter-cyclical stocks

In addition to studying the relationship between stock prices and real economic activity, another important focus of our paper is to categorize each individual stock as pro-cyclical or counter-cyclical based on its sensitivity to the business cycle. To this end, we review and summarize the relevant literature with the aim of exploring in depth the characteristics and performance of pro-cyclical and counter-cyclical stocks in the stock market, as well as providing ideas for our research.

Pro-cyclical stocks are those of companies that perform well during economic boom periods and usually rise in tandem with the economic cycle. Stocks of companies that perform better during economic downturns are known as counter-cyclical equities, which typically move in the opposite direction of the economic cycle. Compared to counter-cyclical stocks, pro-cyclical stocks are more likely to receive more attention from investors but also carry a higher level of investment risk. Counter-cyclical stocks, on the other hand, are not affected by the degree of economic boom, and therefore counter-cyclical stocks are less volatile and carry less investment risk.

Beaudry and Portier (2006) propose a new theory of the economic cycle while examining the relationship that exists between the US stock market and real economic activity. The study finds that changes in technological opportunities may be at the heart of business cycle fluctuations, even if unexpected changes in productivity are not the main factor contributing to business cycle fluctuations. This suggests that the impact of technological opportunities on economic activity is significant and may be one of the critical factors contributing to business cycle fluctuations. Also, stocks can be divided into pro-cyclical stocks and counter-cyclical stocks based on changes in the volatility of the business cycle.

Goetzmann, Watanabe and Watanabe (2012) use half a century of survey data to investigate whether pro-cyclical stocks, i.e., those that are aligned with the business cycle, can earn higher returns. The study tests the predictive power of expected real gross domestic product (real GDP) for future excess market returns by systematically testing regressions using the conditional asset pricing model and the Fama-French MacBeth model. By ranking the return sensitivity of individual stocks to expected real GDP growth rates from the Livingston survey and forming portfolios, the study concludes that pro-cyclical stocks return in tandem with the business cycle and earn higher average returns than counter-cyclical stocks. In addition, the study finds that the pro-cyclical stocks spread are the largest among value companies, especially among large value companies. Meanwhile, counter-cyclical stocks tend to have lower past returns. Therefore, these findings suggest that investors can add pro-cyclical stocks to their stock portfolios to achieve better returns.

Zhu, Gao and Sherman (2020) pioneer a novel approach by integrating the relationship between future economic conditions and stock returns. The study collects monthly and annual data on UK and US stocks and focused on the following three aspects: the relationship between future economic conditions and stock returns; the classification of pro-cyclical and counter-cyclical stocks by analyzing the sensitivity of each stock to the business cycle; and the relationship between stock returns and the business cycle. The results of the study indicate that there is a highly persistent relationship between the returns of pro-cyclical stocks and the business cycle. Based on this, the study gives relevant stock trading recommendations, i.e., investors with accurate forecasts of actual future economic activity can hold pro-cyclical stocks when they expect future economic conditions to be higher than the long-term trend, and conversely, they can trade short counter-cyclical stocks to increase the profitability of their investments.

Chen (2021) conducts a study on open-end funds in the Chinese market and uses theories related to the cyclical investment behavior of open-end funds as the basis of the study. In the study, the authors use semi-annual and annual reports to detail data on open-end fund stock portfolios from June 2005 to June 2020 and construct the critical variable of incremental fund holdings as the basis for the empirical study. In the study, the author further analyzes the investment behavior of open-end funds by incorporating the unique phenomenon of the long duration of the bull market and the short duration of the bear market in the Chinese stock markets. The results show that open-end funds exhibit significant counter-cyclical rather than pro-cyclical investment behavior in the Chinese markets, a finding that has important implications for understanding fund investment behavior in the Chinese stock markets. Overall, Chen's (2021) study has some reference value in revealing the patterns of fund investment behavior in the Chinese market and provides some valuable insights for investors and policymakers. Also, this finding serves as an inspiration for the research in this paper.

After reviewing the literature as mentioned above, it is easy to see that the most commonly used models in studying such problems are CAPM and Fama-French three-factor models (e.g., Goetzmann, Watanabe and Watanabe, 2012), in addition to VAR models, which are often used in studying the Chinese stock market (e.g., Gao and Hu, 2010; Yang and Yang, 2015).

Although compared with the CAPM and Fama-French three-factor models, the VAR model has apparent advantages, such as the VAR model does not require any a priori assumptions and can obtain the relationship between economic variables simply by analyzing economic data without considering the market equilibrium conditions. However, the drawbacks of the model are apparent. The VAR model does not provide information on market risk premiums and excess returns, which makes it of limited use in capital asset pricing. The VAR model is also prone to "spurious regressions", where two variables that have no real relationship are correlated, which may lead to incorrect inferences about economic relationships.

Based on existing research, there is currently a gap in knowledge regarding the relationship between Chinese A-share returns and real economic activity when stocks are classified according to the business cycle. Additionally, further research is necessary to explore the relationship between China's A-share market and real economic activities using the CAPM and Fama-French three-factor model. Therefore, the CAPM and Fama-French three-factor models are selected in this paper, which will fill this research gap. Also, the study by Zhu, Gao and Sherman (2020) provides the necessary guidance for our study. Our study will continue to explore this theme by classifying Shanghai A-share and Shenzhen A-share stocks into pro-cyclical and counter-cyclical stocks and exploring their relationship with the business cycle and the real economic activity, expecting to gain a deeper understanding of the cyclical behavior of the Chinese stock markets.

The specific reasons for the model selection and how to classify pro-cyclical and counter-cyclical stocks are also discussed in Section 4.

3. Data

The central question of this research paper is to explore the relationship between Chinese stock returns and real economic activity to determine whether future economic conditions and business cycle changes can be used to predict stock price movements. Therefore, the focus is on obtaining the monthly returns of Chinese stocks and finding an indicator that is representative of the level of real economic activity in China. This section will focus on this issue.

This research presents an analysis of the Shanghai A-share market and the Shenzhen A-share market. To ensure the accuracy of the analysis and avoid errors caused by incomplete data collection, eleven groups of macroeconomic variables were carefully selected based on their classification as nominal or real indicators, effectively representing China's macroeconomic conditions. The study ultimately uses regression analysis, with the producer price index (PPI) serving as the chosen indicator to reflect real economic activity in China.

For a thorough view of the Chinese stock markets, we select a sample period of December 2004 to September 2022, a total of 214 months of data. In collecting the data, we collect stock prices and real economic indices at monthly frequencies, except for GDP data, which we explain in detail later in this section due to its quarterly frequency.

To ensure the accuracy and reliability of the data, the data use in the study are sourced from the RESSET database[3], the National Bureau of Statistics of China[4], the General Administration of Customs of China[5], and some data from EIKON. In the study, the paper analyses historical stock data to quantitatively analyze the database on the construction of panel data. Throughout the research process, we rigorously follow a predefine sampling period for data collection and analysis to ensure comparability and consistency in the study. This helps us to accurately assess the relationship between macroeconomic variables and stock market returns and provides investors with more reliable benchmarks for decision-making.

3.1 The reasons for selecting A-share stocks in the SSE and SZSE

As shown in Table 2, there are three primary stock markets in China, which are the Shanghai Stock Exchange (SSE), the Shenzhen Stock Exchange (SZSE), and the Beijing Stock Exchange (BSE). The Shanghai Stock Exchange is one of the first stock exchanges in China and one of the country's largest stock exchanges. The Shenzhen Stock Exchange (SZSE) is China's second-largest stock exchange and the first securities

[3] RESSET (Resource Evaluation and Selection System for Equity and bond Trading) database is one of the largest financial information service providers in China, providing comprehensive financial data and information services. Including macroeconomic data, enterprise financial data, securities market data, and macro analysis reports. It can provide investors and financial institutions with comprehensive, accurate and timely financial data and information services to help them make more accurate investment decisions.

[4] The National Bureau of Statistics of China (NBSC) is the official statistical agency of the Chinese government, responsible for collecting, compiling and publishing national statistics. Its mission is to collect data on demographic, economic, social, resource and environmental aspects through various channels, and to process, analyze and publish them.

[5] The General Administration of Customs of the People's Republic of China (GAC) is the Chinese government's agency responsible for managing and supervising the import and export of goods, technologies and services. Its main responsibilities are to formulate import and export policies, plans, standards and regulations, perform customs supervision, inspection, quarantine and inspection functions, maintain national security and social stability, and promote economic development and foreign trade. The agency also regularly publishes data on China's imports and exports.

exchange to create a Growth Enterprise Market (GEM) in 2004. This market is often compared to the NASDAQ stock market in the United States, as both provide a platform for early-stage and high-growth companies to access capital and gain public listings.

Table 2

Three Main Stock Exchanges in China

Stock Market	Established Year	Stock Categories	Trading Currency	Trading Objects
Shanghai Stock Exchange (SSE)	1990-11	A-Share Stocks	RMB	Individuals or companies in China
		Shanghai B-Share Stocks	USD	Individuals or enterprises abroad; individuals or institutions with foreign currency in cash or cash remittances
Shenzhen Stock Exchange (SZSE)	1990-12	A-Share Stocks	RMB	Individuals or companies in China
		Shenzhen B-Share Stocks	HKD	Individuals or enterprises abroad; individuals or institutions with foreign currency in cash or cash remittances
Beijing Stock Exchange (BSE)	2021-09	Issued by innovative companies and those listed on the New Third Board		

The Beijing Stock Exchange is founded relatively late and was officially established in September 2021. Its stocks are mainly transferred from the New Third Board stocks[6]. The stocks circulating in this market are usually issued by small and medium-sized enterprises. Although the stocks in the Beijing Stock Exchange are more profitable at present, there are more significant risks because the returns of stocks are inversely proportional to the risks, which leads to the poor stability of this stock market. In

[6] Founded in 2013, China New Exchange and Quotations (NEEQ) is a domestic stock exchange in China, also known as the "New Third Board Market "or "Sanban Market". It is an unlisted trading venue regulated by the China Securities Regulatory Commission (CSRC) and is designed to provide a channel for financing and equity transfer for small, medium and micro enterprises. The NSSM has a lower threshold and is relatively easier to enter. It provides a financing and trading option for companies that do not qualify for listing on the Main Board.

addition, some economic policies issued by the government also favor small and medium-sized enterprises, which cannot fully reflect the changes in the capital market. Some trading mechanisms of the Beijing Stock Exchange, such as the information disclosure system, also need further improvement.

Besides, BSE is one of the newer stock exchanges in China, with a smaller market capitalization compared to the larger and more established exchanges such as the Shanghai Stock Exchange and the Shenzhen Stock Exchange. At the same time, some of the economic policies formulate and promulgate by the government are somewhat biased towards small and medium-sized enterprises and do not reflect the changes in the capital market. Besides, some of the trading mechanisms of the BSE, such as the information disclosure system, also need further improvement.

To sum up, compared with the Beijing Stock Exchange, the Shanghai Stock Exchange and the Shenzhen Stock Exchange are established earlier, with a larger capital market scale, a more significant number of listed companies, and a larger transaction scale. And also have greater advantages in terms of financial product innovation, which can better reflect the changes in the capital market.

It is also clear from Table 2 that in the Shanghai Stock Exchange and Shenzhen Stock Exchange, in addition to A-share stocks, there are also B-share stocks. However, A-share stocks have some irreplaceable advantages over B-share stocks. Firstly, the settlement currency for A-share stocks transaction is RMB, whereas the settlement currencies for B-shares are USD and HKD, respectively. In addition, the risk-free assets used in this article are also denominated in RMB as the settlement currency. Therefore, A-share stock trading can avoid errors due to exchange rate fluctuations and make the calculated stock returns more accurate. Secondly, compared to B-share stocks, A-share stocks are traded mainly for individuals and companies in China.

On the other hand, B-share stocks are primarily available to individuals and institutions outside of China, as well as those with offshore trading accounts within China. Therefore, A-share stocks have a broader audience and lower threshold for stock trading and are more reflective of the overall level of the Chinese stock markets and capital changes. In short, A-share stocks have a broader audience and more accurate return calculations than B-share stocks and better reflect the actual situation of the Chinese stock markets.

Based on the characteristics of A-share stocks and the differences between the three stock exchanges, this paper selects all the A-share stocks of the SSE and SZSE as the main research subjects to ensure that the research sample is sufficient. At the same time, to avoid the problem of survivorship bias, only the ST stocks in Shanghai A-share and Shenzhen A-share are excluded from this paper. Thus, there are 3,315 stocks in total, including 1,749 Shanghai A-share stocks and 1,566 Shenzhen A-shares.

3.2 Rates of return calculation

After screening the stocks, the next step is to obtain the monthly trading price of each stock and calculate the corresponding rates of return. We perform the calculation based on Equation (1).

$$\text{Rate of Return}=\frac{\text{End of Month Price-Start of Month Price}}{\text{Start of Month Price}}*100\% \qquad (1)$$

Besides, since a total of more than three thousand stocks are selected, in order to quickly and uniformly calculate the monthly returns for each stock, we use the Visual Basic Edition (VBE) programming function in Excel to perform the calculations and the pivot window function to organize the calculated rates of returns into a panel data format, which can then be easily loaded into MATLAB for analysis.

3.3 Risk factors data

In this study, we have chosen the CSI 300 Index as the market index (Rm) for analysis. The earliest data for the CSI 300 can be traced back to December 2004 by comparing statistics from different databases. This is, therefore, the main reason why we set the sample period for our study to start with December 2004.

The CSI 300 Index has an important position in the Chinese and global equity markets, being one of the critical indicators of the Chinese stock markets and one of the most representative Chinese equity indices in the global market. This index covers 300 stocks in China's A-share market with large liquidity and market capitalization, which can better reflect the overall trend of China's A-share market. At the same time, the CSI 300 Index is also the underlying index for many derivative products, such as stock index futures and stock index options. Therefore, the importance and influence of the CSI 300 Index must be addressed in the Chinese stock markets.

According to the RESSET database, two different methods of calculating the risk-free rate of return (Rf) have been used in the Chinese stock market within the scope of our study covered in this paper. Specifically, from December 2004 to 7 October 2006, the coupon rate of three-month central bank notes was used for the risk-free rate of return. From 8 October 2006 to the present, the Shanghai interbank 3-month interbank offered rate was used as the risk-free rate of return measure.

As with the risk-free rate, the CAPM factor data and the Fama-French three-factor data used in this paper are taken from the RESSET database. The market premium return factor (RmRf) is the difference between the monthly return of the equity portfolio and the risk-free monthly return. The market capitalization factor (SMB) is the difference between the monthly return of a portfolio of small companies and the monthly return of a portfolio of large companies. And the book-to-market ratio factor (HML) is the difference between the monthly return of a portfolio of companies with a high book-to-market ratio factor and the monthly return of a portfolio of companies with a low book-to-market ratio factor.

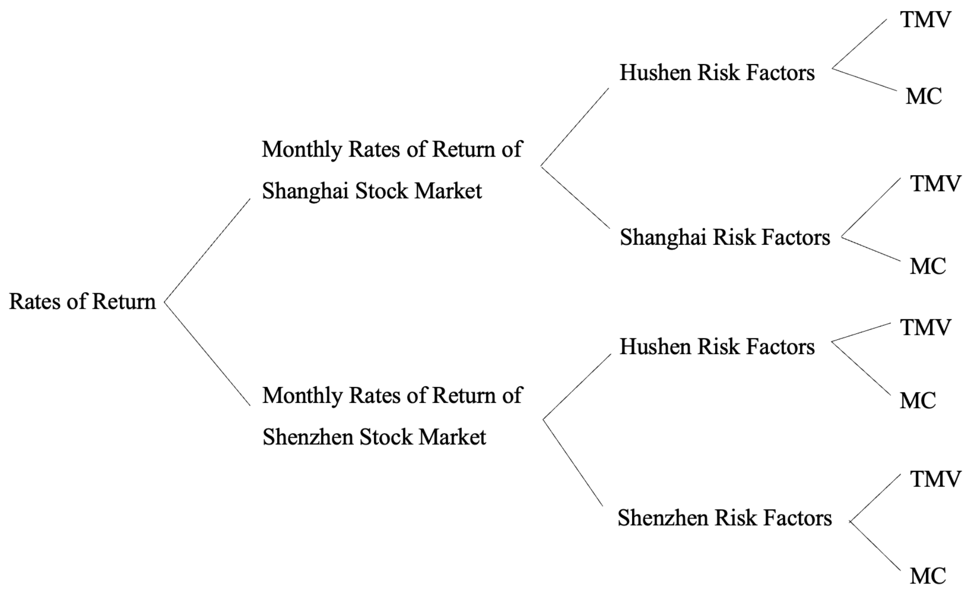
In collecting the factor data, three different types of factor data are used to complete the analysis: Hushen risk factor data, Shanghai risk factor data, and Shenzhen risk factor data. These factors are divided into two categories based on different asset weightings: market capitalization weighting (MC) and float-adjusted market capitalization weighting (TMV). Market capitalization weighting uses a company's market capitalization as a way of weighting its weight in the calculation, so companies with a larger market capitalization take up a greater weight in the index and have a more significant impact on the index. In contrast to market capitalization weighting, float-adjusted market capitalization weighting is the total market value of a company's outstanding shares. Therefore, companies with a larger market capitalization outstanding occupy a greater weight in the index and have a more significant impact.

As the two weightings are calculated differently, this, in turn, can lead to different results and may have a different impact on the performance of the index. In order to provide a more comprehensive and complete analysis of the data, this paper separately analyses the relationship between equity returns and real economic activity under different factor statistical approaches. The Fama-French three-factor model is analyzed in the way shown in Figure 1, based on different combinations of the eight data sets, and the CAPM model is also in the same way. Thus, a total of sixteen groups are analyzed, and for each group, we go through all eleven macroeconomic indices.

Figure 1

The Combination of Stock Returns and the Risk Factors

Where TMV and MC in the figure refer to two different weighting methods mentioned above.



3.4 To proxy the real economic activity

The most common index used to analyze this issue of China's macroeconomy or to proxy the real economic activity is the business index of macroeconomics, in addition to GDP and CPI. The business index of macroeconomics can provide a comprehensive picture of the economic growth rate, the economic cycle stage, and the likelihood of recession and recovery, by counting and analyzing changes in a range of macroeconomic variables. As the essential indicator of the fluctuation of macroeconomic activities, those indices are often used to analyze the macroeconomic development of China.

Table 3 summarizes some of the research literature focused on real economic activity, both on the real economy of China and on the economies of other countries. The table highlights a summary of the macroeconomic indicators chosen by this literature to study real economic activity.

Zhao and Zhou (2010) clearly state in their paper that, in addition to GDP, the business index of macroeconomics can also be used as an essential indicator of the macroeconomic situation in China and that there is a lagging relationship between the index and the consumer price index. Chen and Yang (2017), Zheng and Shang (2014), and Zhou, Xing, and Peng (2020) all choose the business index of macroeconomics to portray the trend of China's macroeconomic cycle when studying the relationship between macroeconomic and stock market volatility in China.

Table 3

Summary of Studies of the Index Selected

Study	Sample Period	Frequency	Selected Index
Zhao and Zhou (2010)	1995 to 2009	Annual	GDP, CPI, Business Index of Macroeconomics
Chen and Yang (2017)	2004-03 to 2015-05	Monthly	CPI, Business Index of Macroeconomics
Zheng and Shang (2014)	1992-01 to 2012-12	Monthly	IAV, Business Index of Macroeconomics
Zhou, Xing, and Peng (2020)	2005-01 to 2019-12	Monthly	CPI, M2, Export, Business Index of Macroeconomics, Completed Fixed Asset Investment, Unemployment rate, RMB to USD exchange rate
Auret and Golding (2012)	1969-12 to 2010-09	Quarterly and Annual	GDP, IPI
Zhu, Gao, and Sherman (2020)	1997-01 to 2013-12	Monthly	CPI deflator minus the growth rate of the Index of Industrial Production

At the same time, as an essential component of the diversification of the world economy, some scholars often use the index of industrial production to represent the real economic activity of some countries and regions, such as South Africa, the United Kingdom, and the United States, when studying the macroeconomic situation of this country or region. Auret and Golding (2012) look at the South African stock market and systematically analyze the ability of stock prices to predict real output growth and the overall economy by collecting quarterly and annual data, using GDP and the ability of stock prices to predict real output growth and the economy as a whole is systematically analyzed by collecting quarterly and annual data and using GDP and the index of real industrial production to represent the South African economy as a whole. This leads to the conclusion that in South Africa, the cycle of real GDP and the cycle of real industrial production actually lead to the cycle of stock prices, confirming Fama's (1981) findings. Zhu, Gao, and Sherman (2020) examine the relationship between future economic conditions and stock returns in the UK and the US. By using the Carhart four-factor model and the Carhart and Liquidity model, the analysis concludes there is strong evidence for the durability of the relationship between the returns of pro-cyclical. The authors have chosen the CPI deflator minus the growth rate of the index of industrial production to represent the real economic activity in the UK and the US.

Therefore, taking inspiration from previous studies such as Zhao and Zhou (2010), Auret and Golding (2012), and Zhu, Gao, and Sherman (2020), this paper has also chosen China's business index of macroeconomics and the industrial production index to represent the real economic activity in China.

Table 4

The Indexes to Proxy the Real Economic Activity in China

Categories	Index Name		Frequency
Monetary Indicators	Gross Domestic Product (GDP)		Quarterly
	Consumer Price Index (CPI)		Monthly
	Retail Sales Index (RPI)		Monthly
	Money Supply (MS)	M0	Monthly
		M1	Monthly
		M2	Monthly
Real Indicators	Producer Price Index (PPI)		Monthly
	Industrial Production Index (IPI)		Monthly
	Business Index of Macroeconomics	Consensus Index	Monthly
		Advance Index	Monthly
		Lagging Index	Monthly
	Import-Export Index (IE Index)		Monthly
	Import Index (II)		Monthly
	Export Index (EI)		Monthly
	Industrial Added Value Index (IAV)		Monthly

Inspired by previous studies, we have summarized some indicators that are representative of real economic activity in China and presented them in Table 4, which are eleven indices. These indices are useful for understanding the state of China's economy and predicting future economic trends. Table 4 shows the indices we summarized, all of which are monthly data except for GDP. It is worth noting that there are three categories of money supply indices, namely M0, M1 and M2, and three sub-categories of the business index of macroeconomics, which are consensus index, advance index and lagging index.

3.5 Dealing with GDP and missing value

Due to the availability of data, as shown in Table 4, the GDP data used in this paper are quarterly data. Therefore, in order to ensure the consistency of data frequencies in the regressions, we calculate Shanghai stocks' rates of return, Shenzhen stocks' rates of return and related Fama-French risk factors into quarterly data, respectively, when GDP is used to represent the real economic activity in China. This eliminates the frequency inconsistency due to different time intervals and allows us to perform the regression analysis more precisely.

In the compilation of other economic indices, it is found that starting in 2012, data from January and, in some years, February were missing each year. According to the announcement of the National Bureau of Statistics of China, in order to eliminate the impact of the irregularities of the Chinese Spring Festival holiday[7] and enhance the comparability of data, according to the national statistical system, from the 2012 final report, the survey of January statistics will not be conducted separately for some monthly reports, and the data of January and February will be surveyed and released together. That is, since 2012, the National Bureau of Statistics in February no longer release January industrial production above the scale, fixed asset investment, private fixed asset investment, real estate investment and sales, total retail sales of social consumer goods, and industrial economic efficiency data. Therefore, to ensure the continuity of the data, and after due consideration of the data characteristics, this paper uses the interpolation method to fill in the missing data.

In addition to this, when collecting stock price data and calculating monthly returns, missing stock returns are inevitable due to the fact that different stocks have been listed for different periods, and not all stocks can survive the market stably during the sample period. The software used in this study is MATLAB, so according to the characteristics of this software, we use "999999.00" to fill in the missing rates of return data.

[7] Chinese Spring Festival, also known as Lunar New Year or simply Spring Festival, is one of the most important traditional festivals in China. It is usually celebrated on the first day of the Chinese lunar calendar, which falls between January 21st and February 20th on the Gregorian calendar.

4. Methodology

This section mainly focuses on the discussion and enumerates this paper's research methodology. In this section, a wide-range review of the classical and contemporary literature is also conducted to gain a deeper understanding of the relationship between Chinese stock returns and real economic activity. This review encompasses the common models and research methods relevant to this area of research based on a thorough understanding of the relevant economic definitions. Also, based on a full analysis of the characteristics of the Chinese stock markets, we also elaborate on the reasons for the models used in this paper and evaluate the performance of the different models in the context of the reviewed literature. Based on this evaluation, we identify the most appropriate models for our analysis and the underlying economic data to be used. In addition, we elaborate on the data processing methods and their logic for constructing regression models and explain the backward-looking evaluation periods used in the study. At the same time, there are corresponding limitations for any study, and we will discuss the limitations as well. Overall, this section serves as the foundation of our research methodology, allowing us to effectively explore the interrelationship between the Chinese stock return and real economic activity.

4.1 The relationship between stock returns and real economic activity

The relationship between the macroeconomy activity and the stock market is closely linked, and the performance of the stock market is often seen as one of the critical indicators of the state of the macroeconomy. The macroeconomy serves as an overall indicator of the overall economic activity of a country or region. In contrast, the stock market is a stock exchange, a place where companies and investors buy and sell shares.

Generally speaking, if macroeconomic conditions are good and economic growth is stable, more people will invest in stocks, as corporate profits and stock prices are likely to rise. If the macro economy is unstable or in recession, this will lead to investors being worried about the economic outlook, investing less, and stock prices will fall. (e.g., Baker, Bloom and Davis, 2016; Jiang, Hu and Huang, 2021)

On the other hand, fluctuations in the stock market can also affect macroeconomic conditions. A rise in stock prices will increase companies' market capitalization and confidence, promoting business expansion and investment, which will boost economic growth. Conversely, a sharp fall in the stock market may trigger panic among investors and lead to capital withdrawal, thereby affecting the stable development of the real economy. (e.g., Liu and Liu, 2013) The inextricable relationship between the macroeconomy and the stock market has attracted many scholars to explore the relationship between the two.

4.2 The characteristics of the Chinese stock markets and reasons for model selection

In the previous literature review section, by comparing the advantages and disadvantages of the single-factor model (CAPM), multi-factor model (Fama-French three-factor model and Carhart four-factor model), and VAR model in regression analysis, we finally choose the single-factor model and Fama-French three-factor model to improve the prediction accuracy of the model by considering the impact of market risk and other factors on stock returns in an integrated manner. In this section, we are further detailly delve into the reasons for choosing the capital asset pricing model as well as the Fama-French three-factor model. It also explains the methodology of classifying Shanghai A-shares and Shenzhen A-shares as pro-cyclical stocks and counter-cyclical stocks. It should be noted that the reasons for model selection will be considered in this section in the context of the characteristics of the Chinese stock markets.

As Chen, Li and Zhai (2022) point out, compared to other emerging markets, China's stock markets are included in the MSCI Emerging Markets Index[8] late, and the market capitalization of foreign holdings as a proportion of the total market capitalization of A-shares is still emerging. In addition, due to the macroeconomic volatility in the world in recent years, as well as the overly stringent policy controls, the approval and licensing system, the high issuance threshold, and the low openness of the Chinese stock markets, the A-share market is generally undersupplied. It gradually shows some drawbacks compared to mature markets in Europe and the US and emerging markets in other countries.

Both the CAPM and the Fama-French three-factor model are practical tools for portfolio analysis when looking at the performance of the Chinese stock markets, both for the A-shares as a whole and for the SSE 50 Index[9]. Moreover, according to the results of the empirical study, the Fama-French three-factor model outperforms the CAPM in specific sectors, especially in explaining stock returns, and better reflects the different risk factors in the Chinese stock market. Zhang (2022), Yang (2022), and Xu (2022) all point out in their papers that the CAPM model is valid in the Chinese stock markets, and the market factor is still the most significant pricing factor. The Fama-French three-factor model outperforms the CAPM for some specific sectors of the Chinese stock markets, such as the science and technology innovation board, where the Fama-French three-factor model has improved explanatory power compared to the CAPM (Xu, 2022). The significant book-to-market effect is found in companies with large market capitalization, while the scale effect is found in smaller companies. Zhang

[8] The MSCI Emerging Markets Index (MSCI Emerging Markets Index) is an index published by Morgan Stanley Capital International (MSCI) that measures the performance of global emerging market equities. It is an important global investment indicator and is widely used to assess the economic development and stock market performance of emerging market countries. The index is also used as a benchmark by many portfolio managers and investors to assess the performance and risk of their portfolios.

[9] The SSE 50 Index is one of the key stock indices published by the Shanghai Stock Exchange and is jointly published by the Shanghai Stock Exchange and China Securities Index Co. The constituents of the index are the 50 largest and most liquid blue-chip stocks listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange, making it one of the largest, most representative, and most widely influential stock indices in the Chinese stock market. Due to the large market capitalization and trading volume of these companies, the SSE 50 Index is often regarded as one of the important wind indicators of the Chinese stock market and has a greater influence on the market.

(2022) studied the performance of China's A-shares before and after the outbreak of the novel coronavirus. Under the extreme stress test (specifically referring to the impact of the outbreak of the novel coronavirus on China's domestic economy and the world's overall economy). Although both models can explain the expected return rate of individual stocks of the SSE 50 index well, the explanatory ability of the Fama-French three-factor model is far superior to the CAPM.

$$R_{it} - R_{ft} = a_{it} + b_{it}RMRF + s_{it}SMB + h_{it}HML + m_{it}MOM12 + e_{it} \quad (2)$$

Where the Rit is the excess return of stock i over the risk-free rate, the market premium return factor (RmRf) is the difference between the monthly return of an equity portfolio and the risk-free monthly return. The market capitalization factor, SMB (small minus big), is the difference between the monthly return of a portfolio of small companies and the monthly return of a portfolio of large companies. The book-to-market factor, HML (small minus big), is the difference between the monthly return on a portfolio of companies with a high book-to-market factor and the monthly return on a portfolio of companies with a low book-to-market factor. MOM12 is the momentum factor, is the difference between the equal-option average return rate of the top 30% stocks in the past 12 months and that of the bottom 30% stocks in the past 12 months.

The Carhart four-factor model (Carhart, 1997), as shown above, is an extension of the capital asset pricing model (CAPM) used to explain stock returns. Compared with the single-factor model and the Fama-French three-factor model, the Carhart four-factor model introduces additional factors, including a market capitalization factor, a book-to-market ratio factor, and a momentum factor, to explain return volatility in the stock market more comprehensively. Although the Carhart four-factor model theoretically has a significant advantage over the single-factor and three-factor models, the four-factor model is far less effective than the single-factor and three-factor models, especially in the Chinese market. Besides, in practice, especially in the Chinese market, the four-factor model is much less capable of explaining the performance of the Chinese stock market than the one-factor and three-factor models.

Gao, O'Sullivan, and Sherman (2020) study the performance of a total of 419 open-end funds in the Chinese fund market under different asset pricing models from May 2002 to May 2014. To provide a clearer and more comprehensive test of the explanatory power of the models, they use weekly data frequencies in the study. They first evaluate the performance of unconditional models (including CAPM, the Fama-French three-factor model, and the Carhart four-factor model) in the fund market, and the results show that the Carhart four-factor model does not offer superior explanatory power in the Chinese open-end fund market, and the explanatory power of the Fama-French three-factor model is better than that of the Carhart four-factor model compared to the Fama-French three-factor model.

Moreover, some scholars have argued that instead of a significant momentum effect, average stock returns show an inverse impact on the Chinese capital market (e.g., Lu and Zou, 2007; Ning and Wang, 2012).

The study by Lu and Zou (2007) explores the momentum and reversal effects in the Chinese stock market. The study selects monthly stock data for a total of 96 months from January 1998 to December 2005 and concentrates on all A-share stocks listed in Shanghai and Shenzhen, excluding ST, PT and stocks with incomplete data, and finally includes data on 529 stocks. The researcher groups stocks of different sizes according to the ranking of their average monthly market capitalization outstanding from the limited rationality of investors and the policy characteristics of the Chinese stock market. Through empirical regression analysis, the study concludes that the Chinese stock market exhibits a more pronounced reversal effect relative to the momentum effect. In addition to the medium-term momentum effect and the long-term reversal effect, there are also ultra-short-term momentum effects and short-term reversal effects. In addition, small company stocks are more prone to reversals and have weaker inertial movement trends compared to large company stocks, while stocks with higher volume also have weaker inertial movement trends and are more prone to reversals compared to stocks with lower volume.

In contrast to Lu and Zou (2007), Ning and Wang's (2012) study expands the type of research object by using A-shares in the Chinese stock market as the main research object. In addition, they take several factors into full consideration when determining the sample interval for their study. To consider the limited number of listed companies, poor market efficiency, and information reflection in the Chinese stock market before 1997, and also considering that the stopping system was not implemented in the Chinese stock market before December 26, 1996. Thus, Ning and Wang set the full sample interval as January 1997 to March 2011. Using empirical models and residual comparison methods, the study discovers that the reversal effect is more pronounced in the Chinese stock market than the momentum effect. This finding is consistent with the findings of Ning and Wang (2012).

Combining the analysis of the three aforementioned papers, an observation can be made that there is no significant momentum effect present in the Chinese stock markets, which implies that the Carhart four-factor model cannot produce significant results in the Chinese stock markets. Therefore, the Carhart four-factor model was not chosen as the model for analysis in this study.

In addition to referring to the existing research literature, we conduct a number of experiments to select a model suitable for studying the link between stock returns and real economic activity in China. We first use the Fama-French three-factor model to test the correlation between stock returns and real economic activity. Unfortunately, our results are not significant, and no significant correlation is found. (The results will be discussed specifically in Section 5.) Therefore, we further test by using the CAPM. By comparing and evaluating these three models in theory and practice, we finally choose the capital asset pricing model and the Fama-French three-factor model to study the link between stock returns and real economic activities in China. Such a model selection approach can provide more reliable and precise results for our study.

4.3 Model description

As we discussed before, the two most used models to analyze the situation of the Chinese stock markets are the single-factor model, which is the capital asset pricing model (Jensen, 1968), and the Fama-French three-factor model (Fama and French, 1993).

The capital asset pricing model (CAPM), developed by Jensen (1968), is one of the essential models in financial theory and is often used in portfolio management and capital budgeting decisions.

$$R_{it} = \alpha_{it} + \beta_i[E(R_m) - R_f] \qquad (3)$$

Where the Rit is the excess return of stock i over the risk-free rate, the Rm is the return on the market portfolio of risky assets. And t denotes time.

The model primarily measures the relationship between risk and expected return and is often used to assess the expected return of a portfolio. An essential premise of the model is the assumption that markets are rational, that investors are risk averse, and that all investors in the market hold the same portfolio of risky assets. It is also assumed that stock returns are only linearly related to the systematic risk of the overall stock market. In essence, the one-factor model discusses the correlation between risk and return on capital assets, i.e., high risk is usually accompanied by a high return.

Building on the CAPM, Fama and French in 1992 examined the factors that determine the difference in returns of different stocks in the US stock market and found that beta does not explain the difference in returns of different stocks. However, the market capitalization, book-to-market ratio, and P/E ratio of listed companies could explain the difference well. Therefore, in the Fama and French (1993) paper, the pair constructed a three-factor model by modeling market risk, market capitalization risk, and book-to-market ratio risk.

$$R_{it} = \alpha_{it} + b_{it}RMRF + s_{it}SMB + h_{it}HML + e_{it} \qquad (4)$$

Where the Rit is the excess return of stock i over the risk-free rate, the market premium return factor (RmRf) is the difference between the monthly return of an equity portfolio and the risk-free monthly return. The market capitalization factor, SMB (small minus big), is the difference between the monthly return of a portfolio of small companies and *the monthly return of a portfolio of large companies. The book-to-market factor, HML (small minus big), is the difference between the monthly return on a portfolio of companies with a high book-to-market factor and the monthly return on a portfolio of companies with a low book-to-market factor. And t denotes time.*

The advantage of the Fama-French three-factor model over the CAPM is that it can explain multiple sources of equity returns, including market risk and factors such as company size and value. As such, the model can help investors better understand equity market volatility and returns and thus develop more effective investment strategies. Besides, As mentioned in Section 2 and earlier in this section, many scholars have confirmed that the three-factor model has a better performance in the Chinese stock market. Therefore, this is one of the main reasons why we use the Fama-French three-factor model first in this paper for analytical validation.

4.4 The reason to set the backward-looking evaluation periods (bp)

While reading the literature, it has been found that backward-looking periods are commonly used in macroeconomic studies (e.g., Fama, 1990; Zhu, Gao and Sherman, 2020). Backward-looking evaluation period refers to the range of past periods used in a study or analysis. It is usually based on historical data and is used to analyze or forecast future trends or movements.

In research, the setting of the backward-looking evaluation period has a significant impact on the results. A longer backward-looking evaluation period provides more data and trends but may also be too stale and inaccurate, while a shorter backward-looking evaluation period more accurately reflects current market changes and trends but may not reflect long-term trends. Therefore, with the intention of testing the forecasting ability of the model to assess its validity and accuracy, and also to be able to understand better economic cycles and fluctuations, as well as the relationship between macroeconomic variables. The backward-evaluation periods are also set in this paper. However, since the backward-evaluation periods may introduce errors, to avoid this, we make a careful trade-off when setting the bp to avoid too long or too short and set it to 48, 60 and 72, where bp equals 48,60 and 72. Also to improve the prediction accuracy and stability of the model, the minimum backward-looking evaluation period (min_bp_obs) is also set in the regression loop, where min_bp_obs is less than bp, and min_bp_obs = 36.

4.5 The regression methods to examine the relationship between stock returns and real economic activity

Once the model is selected, further processing and analysis of the data are necessary. In the following section, we will elaborate on the regression ideas step by step.

- **Step 1: Setting up some necessary variables**

Before formally starting the regression analysis, we first set up and specified some necessary variables. Firstly, we set the minimum observations required in each evaluation period for each stock. Since min_bp_obs needs to be less than or equal to bp, we set min_bp_obs to 36 and bp to 72. Besides, we also set the significant level for the beta on the output gap measure as 0.1.

- **Step 2: Calculating the rates of return and dealing with the missing data**

In order to make the data more convenient for subsequent analysis, we need to perform some necessary processing on the raw data in the second step. As the formula mentioned in Section 2, after calculating the monthly stock return data for each stock in Shanghai A-shares and Shenzhen A-shares, we filled the indeed data with "999999.00", such a filling method taking into account the characteristics of MATLAB. Therefore, in order to avoid the possible influence of missing data on the regression results and obtain more accurate regression results, we first count the monthly returns of missing stocks in Shanghai A-shares and Shenzhen A-shares to facilitate exclusion in the subsequent regression analysis. Through these steps, we can ensure the completeness and accuracy of the stock return dataset and reduce possible biases and errors in the regression results.

Since the GDP data collected are quarterly, thus, to ensure consistency in data frequency in the regression analysis, we convert the monthly returns of Shanghai A-share and Shenzhen A-share stocks into quarterly returns. This has the advantage of better reflecting seasonal changes and trends, while transforming quarterly data into monthly data may lose more information due to the increase in data frequency. In converting the data frequency, we used summation and averaging methods to make the conversion more adequate and reduce errors.

The transformation formula for the summation method is

Quarterly data = Monthly data 1 + Monthly data 2 + Monthly data 3

The transformation formula for the averaging method is

Quarterly data = (Monthly data 1 + Monthly data 2 + Monthly data 3) / 3

- **Step 3: Estimate the new pricing factor and the pre-determined output measure**

In the third step of the formal regression, we performed some continuity on the data.

After filling in the missing variables, we proceed to analyze and calculate the relationship between the market factor, value factor, and firm size factor and different indices that represent the real economic activity in China. The CAPM is a simple linear regression model that relates the excess returns of an asset to the excess return of the market portfolio, while the Fama-French three-factor model adds two additional factors, value and size, to capture the effects of these factors on stock returns.

For cyclical periods and stocks that meet the data volume requirements, regression analysis is performed using the CAPM and Fama-French three-factor model, respectively, and the beta coefficient and significance level (i.e., p-value) of the regression results are calculated for each stock in each cyclical period. We can gain insights into the relationship between stock returns and macroeconomic factors by analyzing the regression results. The beta coefficient measures the sensitivity of a stock's return to changes in the market factor (as well as the firm size factor and the value factor in the Fama-French three-factor model).

A beta greater than 1 indicates that the stock is more volatile than the market, while a beta less than 1 indicates that the stock is less volatile than the market. The p-value measures the statistical significance of the regression result, with a p-value less than 0.05 indicating statistical significance.

After obtaining the corresponding beta coefficients as well as p-values, stocks that can be used to construct a new portfolio are selected based on the positive or negative beta coefficients and the significance level of the p-values. The portfolios constructed by this method are those that have a positive or negative relationship between market returns and specific macroeconomic factors, thus more than enough to better utilize the portfolio theory in the CAPM and Fama-French three-factor model.

After identifying the stocks that can be used to construct a new portfolio and extracting their corresponding beta coefficients and p-values, it is necessary to calculate the returns of these stocks in order to obtain a new investment factor. This calculation process is based on the relationship between the positive and negative macroeconomic variables and the magnitude of the beta coefficient and p-value of each stock, which in turn leads to the calculation of the investment return for each stock. Specifically, if the macroeconomic variable is positive and the stock's beta coefficient and p-value are in line, its investment return is the excess return of the stock; if the macroeconomic variable is negative, its investment return is the opposite of the excess return of the stock. By calculating the investment return of each stock, the return of a series of portfolios can be obtained. The mean of these returns is then calculated to obtain a new investment factor.

$$R_{it} = \delta_i + \beta_{it}^{BS} * BS_t + \varphi_{it} * F_t^{O} + \varepsilon_{it} \qquad (5)$$

Where the R_{it} is the excess return of stock i over the risk-free rate, BS_t is the growth rate of producer price proxying for the business cycle, F^{o}_t is representing the new investment *factor and is a matrix of other risk factors for market, size, and value. And t denotes time.*

- **Step 4: Estimate the significance of alpha**

After obtaining the new investment factor, which is the average return of the stock portfolio, we need to determine its relationship with the market risk premium, as well as the firm size factor and the value factor in the Fama-French three-factor model. To do so, we conduct a linear regression analysis and calculate the corresponding alpha and p-values. This regression analysis is to assess the validity of the new factor, i.e., whether it explains the changes in the market risk premium. By calculating the regression coefficients, the direction and strength of the new factor's influence on the market risk premium can be determined, which can provide a basis for further investment decisions.

It's worth noting that calculating the p-value of the t-test are critical steps in the investment decision-making process. By analyzing the results of these tests, we can determine the effectiveness of the new investment factor and assess its potential impact on investment performance. Ultimately, these insights can help investors make informed decisions and allocate their resources more effectively.

4.6 Sub-sets of stocks testing for pro-cyclical and counter-cyclical stocks

- **Step 5: Classify the stock types and the sub-sets of stock testing**

In addition to classifying pro-cyclical and counter-cyclical stocks, we also need to perform linear regression analysis on both types of stocks to further explore the relationship between them and the market risk premium. Specifically, we need to calculate the linear relationship between excess return and production growth rate under each backward-looking evaluation period for pro-cyclical and counter-cyclical stocks and calculate the corresponding alpha and p-values accordingly. With these data, we can further determine whether the two stocks can explain the changes in the market risk premium, respectively, and thus provide more specific and targeted recommendations for investment decisions.

In order to classify stocks as pro-cyclical stocks and counter-cyclical stocks, we need to consider the relationship between excess returns and production growth rates during the backward-looking evaluation period. Specifically, we define those stocks that have a positive relationship between excess returns and production growth rates during the backward-looking evaluation period as pro-cyclical stocks, and those stocks that have a negative relationship between excess returns and production growth rates during the l backward-looking evaluation period as counter-cyclical stocks.

By classifying pro-cyclical and counter-cyclical stocks, we then need to perform a linear regression analysis to explore the relationship between them and the market risk premium (as well as the firm size factor and the value factor in the Fama-French three-factor model). Specifically, we need to calculate the linear relationship between excess returns and market risk premiums during each backward-looking evaluation period for pro-cyclical and counter-cyclical stocks, respectively, and calculate the corresponding alpha and p-values. With these data, we can further determine whether pro-cyclical stocks and counter-cyclical stocks can explain the changes in the market risk premium, thus providing more specific and targeted recommendations for investment decisions.

And in Section 5, we present the regression results and provide a comprehensive comparison with the relevant literature we reviewed earlier.

5. Empirical results

In this section, we separately delve into the regression results for the Fama-French three-factor model (Fama and French, 1993) and CAPM (Jensen, 1968). And after distinguishing between pro-cyclical and counter-cyclical stocks based on their historical relationship with the business cycle, then we examine the alpha of all stocks, pro-cyclical stocks and counter-cyclical stocks under different asset weighting statistics and backward-looking evaluation periods of 48, 60 and 72. Alpha measures an asset's risk-adjusted performance relative to a benchmark. A positive alpha indicates that an asset exceeds its benchmark, while a negative alpha indicates a lower return.

More importantly, to ensure that the tests are structured, we first start to test with the case where the beta significance is 10% (90% level of confidence). And if the results are significant, we continue to test the case where the beta significance is 5% (95% level of confidence).

At the same time, to ensure the accuracy of the regression test, we take special care to avoid choosing too long or too short a period when setting the backward-looking evaluation periods. The purpose of doing so is to maintain the reasonableness and validity of the return period. In the regression analysis, we first chose a time period with a look-back period of 72 for the test.

Several factors are taken into consideration when making the backward-looking evaluation period selection. Choosing too long a backward-looking evaluation period may include a large amount of outdated or irrelevant data, resulting in a loss of accuracy and usefulness of the analysis results. Conversely, choosing a backward-looking evaluation period too short may limit our complete understanding of the historical data and thus fail to capture long-term trends and correlations.

By choosing a backward-looking evaluation period of 72 when the test begins, we can obtain a relatively long window of historical data for in-depth research and analysis. This period can help us capture certain seasonal variations, cyclical trends, and other potential long-term influences.

We present the results in tables to facilitate a clear and comprehensive comparison of them. Using tables will allow us to illustrate the results in a more structured and organized manner. It can provide readers with a quick and easy way to compare the alpha values across different stock markets, asset weighting statistics, and evaluation periods. The results in Table 5 to Table 7 are the regression results for the Shanghai A-share market and Shenzhen A-share market collated from MATLAB, and four decimal places are retained.

The focus of our research will also be on pro-cyclical and counter-cyclical stocks. Pro-cyclical stocks tend to perform well during periods of economic growth, while counter-cyclical stocks perform better during economic downturns. Thus, following the treading strategy in Section 4 and mentioned by Zhu, Gao and Sherman (2020), we also hypothesize that if the trader expects the output to grow above the long-run average over the next year, he/or she would long stocks that have significantly positive betas (on the output) during the backward-looking period and then short the stocks which have significantly negative betas (on the output gap), and vice versa. Therefore, in this section, we will be more specific about the stock trading measures based on the regression results, i.e., the positivity and negativity of alpha.

By examining the alpha values under different asset weighting statistics and the backward-looking evaluation periods, we can also identify the patterns or trends in the performance of the stocks. This analysis can provide valuable insights for investors seeking to optimize their portfolios and make informed investment decisions.

5.1 The regression results of the Fama-French three-factor model for the Shanghai A-share market

The Fama-French three-factor model, developed by Fama and French in 1993, is one of the most classic models in economics used to explain the return of a stock or portfolio, containing a market factor, a market capitalization factor, and a book-to-market ratio factor. As mentioned in this section before, in this model, alpha specifically represents the excess return of a stock or portfolio relative to the expected return, i.e., the difference between the actual return and the expected return based on the market factor, the market capitalization factor, and the book-to-market ratio factor. Alpha can be used to measure whether a stock or portfolio is outperforming expectations. Specifically, suppose a portfolio's actual return is higher than the expected return. In that case, i.e., its alpha is positive, and the portfolio is performing well beyond what can be explained by market and economic factors. Conversely, if a portfolio's actual return is lower than the expected return, i.e., its alpha is negative, the portfolio is underperforming, below the range explained by market and economic factors.

Table 5 presents the comprehensive findings derived from applying the Fama-French three-factor model to analyze both pro-cyclical and counter-cyclical stocks in the Shanghai A-share and Shenzhen A-share markets. The results summarized in Panel A and Panel B correspond to the Shanghai market and the Shenzhen market, respectively. These results have been obtained considering a beta significance level of 90%.

It is important to note that due to the absence of statistically significant results in this particular case, we refrain from conducting further analysis at a higher beta significance level of 95%. Nevertheless, we proceed to explore the performance of these stocks across various backward-looking evaluation periods, and these additional outcomes are also presented in Table 5.

Including different backward-looking evaluation periods allows us to delve deeper into examining these stocks' performance over time. By assessing their performance across multiple timeframes, we aim to identify any potential patterns or trends that might emerge.

The results presented in Table 5 provide valuable insights into the behavior of pro-cyclical and counter-cyclical stocks in both the Shanghai and Shenzhen markets. While the beta significance level of 90% has not yielded statistically significant results, the examination of different backward-looking evaluation periods offers a broader perspective on the performance dynamics of these stocks.

Table 5

Trade based on future economic conditions for Shanghai and Shenzhen A-share markets, in the Fama-French three-factor model

*For all stocks in the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE), the sensitivity of the stock i's return to the business cycle can be estimated by regressing the stock i's return over the previous bp months on the Producer Price Index (PPI) and market, size and value factors. A stock's correlation with the business cycle can be measured by its beta on industrial production growth. A stock positively correlated with the business cycle over the backward-looking evaluation period is considered a pro-cyclical stock, while a negative correlation with the business cycle is a counter-cyclical stock. We short the pro-cyclical portfolio and/or long the counter-cyclical portfolio if production growth in the following month is anticipated to be above the steady state and vice versa. The portfolios are rebalanced on a monthly basis, and their time series are evaluated against market, size and value risk factors. The table presents the alpha values from these regression analyses, along with their corresponding levels of statistical significance: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.*

Panel A: Betas - 90% Level of Confidence for Shanghai A-share markets												
	Hushen Risk Factors						Shanghai Risk Factors					
	TMV			MC			TMV			MC		
	bp = 48	bp = 60	bp = 72	bp = 48	bp = 60	bp = 72	bp = 48	bp = 60	bp = 72	bp = 48	bp = 60	bp = 72
Alpha (All)	-0.0002	-0.0021	-0.007***	-0.0010	-0.0045*	-0.0070**	-0.0017	-0.0038	-0.0070***	-0.0006	-0.0043	-0.0060*
p-value	(0.9557)	(0.4000)	(0.0060)	(0.7401)	(0.0951)	(0.0180)	(0.5487)	(0.1774)	(0.0070)	(0.8622)	(0.1722)	(0.0520)
Alpha (Procyclical)	-0.0087	-0.0082	-0.0100*	-0.0085	-0.0086	-0.0090	-0.0094*	-0.0090	-0.0100*	-0.0098*	-0.0076	-0.0090
p-value	(0.1265)	(0.1757)	(0.0780)	(0.1423)	(0.1591)	(0.1180)	(0.0997)	(0.1328)	(0.0790)	(0.0860)	(0.2063)	(0.1110)
Alpha (Countercyclical)	0.0032	0.0015	0.0000	0.0031	0.0021	0.0010	0.0038	0.0019	0.0010	0.0049	0.0017	0.0030
p-value	(0.5775)	(0.7883)	(0.9590)	(0.5961)	(0.7106)	(0.8750)	(0.5103)	(0.7370)	(0.8380)	(0.399)	(0.7662)	(0.5490)

Panel B: Betas - 90% Level of Confidence for Shenzhen A-share markets												
	Hushen Risk Factors						Shenzhen Risk Factors					
	TMV			MC			TMV			MC		
	bp = 48	bp = 60	bp = 72	bp = 48	bp = 60	bp = 72	bp = 48	bp = 60	bp = 72	bp = 48	bp = 60	bp = 72
Alpha (All)	0.0021	-0.0014	-0.0030	0.0014	-0.0023	-0.0040	0.0017	-0.0004	0.0000	0.0013	0.0009	0.0000
p-value	(0.4653)	(0.5799)	(0.1910)	(0.6246)	(0.3856)	(0.1430)	(0.5277)	(0.8850)	(0.8660)	(0.6214)	(0.7135)	(0.9180)
Alpha (Procyclical)	-0.0077	-0.0081	-0.0100*	-0.0093	-0.0107*	-0.0110*	-0.0090	-0.0112*	-0.0120*	-0.0088	-0.0089	-0.0090
p-value	(0.2180)	(0.2120)	(0.0970)	(0.1374)	(0.0994)	(0.0770)	(0.1583)	(0.0912)	(0.0710)	(0.1748)	(0.1716)	(0.1450)
Alpha (Countercyclical)	0.0078	0.0065	0.0060	0.0081	0.0068	0.0060	0.0081	0.0057	0.0060	0.0070	0.0061	0.0040
p-value	(0.1907)	(0.2961)	(0.3540)	(0.1852)	(0.2794)	(0.3490)	(0.1836)	(0.3537)	(0.3340)	(0.2588)	(0.3283)	(0.4890)

Based on the results of Panel A in Table 5, it can be seen that in the context of the Shanghai A-share market, the alpha values of all stocks are negative and different from zero under the analysis of the Hushen risk factor and the Shanghai risk factor. However, it is important to note that the importance of these alphas is relatively low. Specifically, when considering evaluation periods of 48 and 60, the alpha values for all stocks are not statistically significant, except for a particular case where the statistical approach of the data is based on market capitalization weighting with a backward-looking evaluation period of 60 under the Hushin risk factor. In this special case, the alpha reaches statistical significance. These results indicate that the alpha values obtained by stocks in the Shanghai A-share market do not exhibit a high statistical significance. It does not prove a significant relationship between counter-cyclical stocks and the producer price index (PPI).

However, when the bp is extended to 72, the alpha values are significant for all stocks, at about -0.007%, both in the TMV and MC statistical methods. Although alpha values greater than zero are obtained for different evaluation periods for counter-cyclical stocks, these alphas do not reach significant levels regardless of the statistical approach, which also does not prove a significant relationship between counter-cyclical stocks and the producer price index (PPI). Pro-cyclical stocks show the opposite result to counter-cyclical stocks. The alphas of pro-cyclical stocks are negative for both the Hushen risk factors and Shanghai risk factors. And several are significant when the retrospective evaluation period is 48 and 72 and the significant level is at 10 percent.

Also, after a closer look at the results in Table 5, we can see that under either the Hushen risk factor or the Shanghai risk factor, their alpha values are not significant for either type of stock when bp=60 and the data statistic is TMV. The same situation occurs under the Shanghai risk factor when bp=60 and the data statistic is MC.

In addition, for those alpha values that obtained significance levels, they were not significant when viewed as a whole. And for the Shanghai A-share market, when using the Shanghai risk factor, the alpha values of all stocks are higher than those when using the Hushen risk factor, regardless of whether the statistical method of the float-adjusted market capitalization weighting (TMV) or the market capitalization weighting (MC) is used, as well as the different backward-looking evaluation periods. Therefore, from an overall perspective, Shanghai A-shares perform better under the influence of the Shanghai risk factor compared to the Hushen risk factor.

5.2 The regression results of the Fama-French three-factor model for the Shenzhen A-share market

Although the Shenzhen A-share market shows an entirely different return result from the Shanghai A-share market, some commonalities exist. Like the Shanghai A-share market, pro-cyclical stocks exhibit identical results in the Shenzhen A-share market. In Panel B, the alpha values for pro-cyclical stocks are all negative both under the Hushen risk factors and the Shenzhen risk factors. For that significant alpha, the significant levels are all at 10 percent. Also, for the counter-cyclical stocks have positive alpha values. However, they are still insignificant, and the equivalent alpha values for these stocks are all about 0.0067% per month under the Hushen risk factors and about 0.0062% per month under the Shenzhen risk factors.

However, all stock in the Shenzhen A-share market shows an entirely different result from the Shanghai market. The alpha values for the whole stock market are insignificant for both the Hushen risk factors and the Shenzhen risk factors. Also, in addition to the case where alpha is less than zero, there is also the case where this alpha is positive.

It is worth noting that in the Shenzhen A-share market, the alpha of all stocks as a whole underperformed when the Shenzhen risk factor is used, regardless of the data statistics and the length of the backward-looking evaluation periods. This is also the opposite of what happens in the Shanghai A-share market. At the same time, a closer analysis of the results in Table 5 also reveals that there are cases where the alpha value is zero in the results presented (e.g., in the Shenzhen A-share market when the risk factor is the Shenzhen risk factor and under the 60 and 72 backward-looking periods). But this alpha value of zero is not seen in the Shanghai A-share market.

The results in Table 5 show that when the Fama-French three-factor model was used to study the relationship between the Shanghai A-share market, Shenzhen A-share market and real economic activities, no significant results could be obtained. This indicates that there is no significant pricing effect between individual stock returns and real economic activity in this case, and we are not able to draw the corresponding stock trading methods. To further verify the relationship between stock returns and real economic activity and to avoid the bias of the Fama-French three-factor model in studying the Chinese stock market, we conduct the CAPM regression test and try to find some different results.

5.3 The regression results of the CAPM for the Shanghai A-share market

In this section, we analyze a total of 1,749 stocks in the Shanghai A-share market and investigate whether there is a significant relationship between each stock return and real economic activity, i.e., the producer price index. The tables display the alpha values under the different corresponding confidence intervals (90% and 95%). Through the regression analysis of the CAPM model, we obtain the relationship between the returns of each type of stock and the producer price index.

The CAPM is one of the most classic and original models used to evaluate the performance of a stock or portfolio. Despite the shortcomings of the CAPM relative to the Fama-French three-factor model in the Chinese stock market (e.g., recent studies such as Zhang, 2022; Yang, 2022; Xu, 2022, etc.), the results of the analysis in Sections 5.1 and 5.2 of this paper reveal that the Fama-French three-factor model does not yield significant results when exploring the relationship between the Shanghai A-share stocks return (Shenzhen A-share stocks return) and producer price index (PPI) does not yield significant results and there is no significant evidence of mutual influence and prediction between the two. Therefore, in this section, we continue our analysis by using the CAPM.

Table 6

Trade based on future economic conditions for Shanghai A-share markets, in the Capital Asset Pricing Model

*For all stocks in the Shanghai Stock Exchange (SSE), the sensitivity of the stock i's return to the business cycle can be estimated by regressing the stock i's return over the previous bp months on the Producer Price Index (PPI) and market factor. A stock's correlation with the business cycle can be measured by its beta on industrial production growth. A stock positively correlated with the business cycle over the backward-looking evaluation period is considered a pro-cyclical stock, while a negative correlation with the business cycle is a counter-cyclical stock. We short the pro-cyclical portfolio and/or long the counter-cyclical portfolio if production growth in the following month is anticipated to be above the steady state and vice versa. The portfolios are rebalanced on a monthly basis, and their time series are evaluated against market risk factor. The table presents the alpha values from these regression analyses, along with their corresponding levels of statistical significance: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.*

Panel A: Betas - 95% Level of Confidence

	Hushen Risk Factors						Shanghai Risk Factors					
	TMV			MC			TMV			MC		
	bp = 48	bp =60	bp = 72	bp = 48	bp =60	bp = 72	bp = 48	bp =60	bp = 72	bp = 48	bp =60	bp = 72
Alpha (All)	0.0008	-0.0016	-0.0050	0.0025	-0.0006	-0.0050	0.0027	-0.0005	-0.0030	0.0044	0.0011	-0.0040
p-value	(0.8533)	(0.6947)	(0.2750)	(0.5475)	(0.8757)	(0.3090)	(0.5731)	(0.8942)	(0.4410)	(0.3351)	(0.8067)	(0.3470)
Alpha (Procyclical)	-0.0100*	-0.0116*	-0.0150**	-0.0120**	-0.0129**	-0.0130**	-0.0051	-0.0087	-0.0130**	-0.0162**	-0.0116*	-0.0130**
p-value	(0.0903)	(0.0590)	(0.0180)	(0.0270)	(0.0332)	(0.0490)	(0.4269)	(0.1744)	(0.0430)	(0.0142)	(0.0671)	(0.0450)
Alpha (Countercyclical)	0.0041	0.0047	0.0030	0.0068	0.0060	0.0040	0.0058	0.0056	0.0020	0.0073	0.0069	0.0000
p-value	(0.5135)	(0.4568)	(0.6220)	(0.2513)	(0.3147)	(0.5820)	(0.3674)	(0.3849)	(0.7090)	(0.2245)	(0.2500)	(0.9540)

Panel B: Betas - 90% Level of Confidence

	Hushen Risk Factors						Shanghai Risk Factors					
	TMV			MC			TMV			MC		
	bp = 48	bp =60	bp = 72	bp = 48	bp =60	bp = 72	bp = 48	bp =60	bp = 72	bp = 48	bp =60	bp = 72
Alpha (All)	-0.0001	0.0000	-0.0050	0.0017	-0.0042	-0.0050	0.0013	0.0010	-0.0040	0.0039	-0.0005	-0.0020
p-value	(0.9687)	(0.9984)	(0.1690)	(0.7301)	(0.3389)	(0.1860)	(0.7506)	(0.8043)	(0.3000)	(0.4549)	(0.9213)	(0.7360)
Alpha (Procyclical)	-0.0113**	-0.0094*	-0.0120**	-0.0129**	-0.0111*	-0.0160**	-0.0115**	-0.0101**	-0.0130**	-0.0047	-0.0061	-0.0140**
p-value	(0.0363)	(0.0980)	(0.0230)	(0.0499)	(0.0776)	(0.0110)	(0.0398)	(0.0858)	(0.0150)	(0.4986)	(0.3650)	(0.0230)
Alpha (Countercyclical)	0.0054	0.0063	0.0010	0.0048	0.0057	0.0020	0.0050	0.0068	0.0020	0.0064	0.0077	0.0040
p-value	(0.3742)	(0.2883)	(0.8350)	(0.4595)	(0.4039)	(0.8000)	(0.4092)	(0.2637)	(0.7440)	(0.3301)	(0.2310)	(0.5310)

By looking at the results of Panel A and Panel B in Table 6, we can obtain that the alpha values of pro-cyclical stocks are all negative for Shanghai A-shares regardless of the confidence interval of 90% or 95%. In particular, when using the Hushen risk factors, the alpha values for pro-cyclical stocks are significant at the backward-looking evaluation periods of 48, 60 and 72 months. This is completely different from the findings of the Fama-French three-factor model. Also, in Table 6, when the risk factor is the Shanghai risk factor, for pro-cyclical stocks, although significant results are obtained for both TMV and MC statistical methods, continuous significant results are obtained only when the bp is 72 months, i.e., alpha remains significant when the confidence interval is shortened. Also, those pro-cyclical stock alphas that are not significant at bp = 48, and have significant results were obtained when the bp is extended to 72. This seems to indicate, on the other hand, the effect of the length of the backward-looking evaluation period on the results of the study.

In this study, we find differences between the alpha values of all stocks except pro-cyclical stocks and the results in Table 5. Although these alpha values are not significant, not all of them are negative, and we find some cases where they are greater than zero. In addition, our results show that the alpha of counter-cyclical stocks in the Shanghai A-share market is positive but insignificant when different risk factors and the length of the backward-looking evaluation periods are used. This is similar to the results of the Fama-French three-factor model in the Shanghai stock market.

In addition to this, we also find that in the Shanghai A-share market, the magnitude and significance of alpha values perform better when using the Shanghai risk factor than when using the Hushen risk factor. This may be due to the fact that the Shanghai risk factor is more suitable to reflect the characteristics of the Shanghai stock market, which in turn improves the explanatory power of the stock performance. It also illustrates the impact on the regression results under different risk factor categories.

Similar to Panel A in Table 5, Table 6 also shows that alpha values are zero in certain cases. Specifically, when utilizing the Hushen risk factors, employing the TMV statistical approach, and using a backward-looking period of 60, all stocks exhibit zero alpha values. Furthermore, only counter-cyclical stocks display zero alpha values when using the Shanghai risk factor, applying the MC statistic, and adopting a backward-looking period of 72. In contrast, alpha values for all stocks appear to be non-zero. These findings indicate that the interpretation of stock performance may be impacted by different risk factors, statistical approaches, and backward-looking evaluation periods. Unlike Table 5, in the Shanghai A-share market under the Fama-French three-factor model, only the alpha of counter-cyclical stocks is zero, while the alpha of all stocks is non-zero. However, under the CAPM, the alpha of all stocks also seems to be zero in the Shanghai A-share market.

5.4 The regression results of the CAPM for the Shenzhen A-share market

In this section, we analyze a total of 1,566 stocks in the Shenzhen A-share market and investigate whether there is a significant relationship between each stock return and the real economic activity, i.e., the producer price index. Through the regression analysis of the CAPM, we obtain the relationship between the returns of each type of stock and the producer price index.

Table 7

Trade based on future economic conditions for Shenzhen A-share markets, in Capital Asset Pricing Model

*For all stocks in the Shenzhen Stock Exchange (SZSE), the sensitivity of the stock i's return to the business cycle can be estimated by regressing the stock i's return over the previous bp months on the Producer Price Index (PPI) and market factor. A stock's correlation with the business cycle can be measured by its beta on industrial production growth. A stock positively correlated with the business cycle over the backward-looking evaluation period is considered a pro-cyclical stock, while a negative correlation with the business cycle is a counter-cyclical stock. We short the pro-cyclical portfolio and/or long the counter-cyclical portfolio if production growth in the following month is anticipated to be above the steady state and vice versa. The portfolios are rebalanced on a monthly basis, and their time series are evaluated against market risk factor. The table presents the alpha values from these regression analyses, along with their corresponding levels of statistical significance: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.*

Panel A: Betas - 95% Level of Confidence												
	Hushen Risk Factors						Shenzhen Risk Factors					
	TMV			MC			TMV			MC		
	bp = 48	bp =60	bp =72	bp = 48	bp =60	bp =72	bp = 48	bp =60	bp =72	bp = 48	bp =60	bp =72
Alpha (All)	0.0069	0.0006	0.0000	0.0076	0.0007	0.0000	0.0010	-0.0019	-0.0020	0.0009	-0.0032	-0.0030
p-value	(0.1326)	(0.8906)	(0.9730)	(0.1334)	(0.8837)	(0.9340)	(0.7885)	(0.5785)	(0.5540)	(0.7969)	(0.3894)	(0.4530)
Alpha (Procyclical)	-0.0126*	-0.0107	-0.0150**	-0.0145**	-0.0108	-0.0200***	-0.0110*	-0.0134**	-0.0190***	-0.0102	-0.0130*	-0.0170***
p-value	(0.0621)	(0.1323)	(0.0350)	(0.0348)	(0.1363)	(0.0060)	(0.0845)	(0.0422)	(0.0050)	(0.1039)	(0.0507)	(0.0090)
Alpha (Countercyclical)	0.0092	0.0062	0.0040	0.0085	0.0062	0.0050	0.0075	0.0049	0.0050	0.0078	0.0034	0.0060
p-value	(0.1457)	(0.3385)	(0.5630)	(0.1757)	(0.3421)	(0.4640)	(0.2488)	(0.4675)	(0.4310)	(0.2250)	(0.6143)	(0.3810)

Panel B: Betas - 90% Level of Confidence												
	Hushen Risk Factors						Shenzhen Risk Factors					
	TMV			MC			TMV			MC		
	bp = 48	bp =60	bp =72	bp = 48	bp =60	bp =72	bp = 48	bp =60	bp =72	bp = 48	bp =60	bp =72
Alpha (All)	0.0059	0.0024	0.0000	0.0077*	0.0022	0.0010	0.0013	0.0011	-0.0020	0.0008	0.0011	0.0000
p-value	(0.1508)	(0.5389)	(0.9930)	(0.0848)	(0.6259)	(0.7750)	(0.6678)	(0.7205)	(0.5230)	(0.8034)	(0.7265)	(0.9860)
Alpha (Procyclical)	-0.0107*	-0.0131**	-0.0140**	-0.0164***	-0.0153**	-0.0140**	-0.0110*	-0.0121**	-0.0190***	-0.0120**	-0.0111*	-0.0120*
p-value	(0.0816)	(0.0389)	(0.0220)	(0.0079)	(0.0157)	(0.0210)	(0.0675)	(0.0488)	(0.0020)	(0.0463)	(0.0709)	(0.0560)
Alpha (Countercyclical)	0.0089	0.0075	0.0040	0.0094	0.0083	0.0060	0.0079	0.0078	0.0090	0.0080	0.0086	0.0060
p-value	(0.1468)	(0.2291)	(0.4490)	(0.1212)	(0.1785)	(0.3540)	(0.1893)	(0.2148)	(0.1470)	(0.1903)	(0.1711)	(0.3210)

Table 7 shows the relationship between the returns of the three different types of stocks and the producer price index under the CAPM. As can be observed from the table, pro-cyclical stocks outperform under the Fama-French three-factor model in the Shenzhen A-share market and also outperform pro-cyclical stocks in the Shanghai A-share market, regardless of whether the confidence interval for beta is 90% or 95%. In addition, when the confidence interval of beta is 90%, the alpha of pro-cyclical stocks is significant under both the Hushen risk factors and the Shenzhen risk factor. This implies that in this case, the producer price index has a significant effect on the Shenzhen stock's return. However, when the confidence interval of beta is shortened to 95% and when the backward-looking evaluation periods are 48 and 60, it appears that the alphas of some pro-cyclical stocks are not significant.

In the Shenzhen A-share market, the relationship between returns and the producer price index for all stocks is similar to that of the Shanghai A-share market, but there are some differences. The alphas of counter-cyclical stocks are all greater than zero but insignificant. While most stocks have alphas greater than zero, there are some cases where it is less than zero. The difference is that, unlike the case for all stocks in the Shanghai market, the case where the alpha is less than zero for all stocks in the Shenzhen market occurs only under the Shenzhen risk factor. Under the Hushen risk factors, the alphas are greater than zero for all stocks. It is worth noting that alpha is also zero in the Shenzhen A-share market, and this occurs only when the bp is 72. This is different from the results under other backward-looking evaluation periods. This may imply that for stocks in the Shenzhen A-share market, an excessively long backward-looking evaluation period may not improve the predictive power of the model. Therefore, several factors need to be considered when choosing the backward-looking evaluation periods, including the reliability of historical data, the speed of market changes and current market conditions, to ensure the predictive power and accuracy of the model.

Finally, by further analyzing the results in Table 7 under the Hushen risk factors as well as the Shenzhen risk factor, it can be found that using the Shenzhen risk factor does not have a significant improvement on the regression results, i.e., it does not improve the explanatory power of the CAPM between stock returns and the real economic activity. This suggests that changing the type of risk factor in the Shenzhen A-share market has little improvement on the CAPM and that other factors or models may need to be considered to improve the predictive power.

Through the results presented in Tables 6 and 7, there are some commonalities between the two tables. It is easy to see that the alpha values of pro-cyclical stocks are negative and significant, and the alpha values of counter-cyclical stocks are positive and insignificant, both under the Hushen risk factors and the Shanghai risk factors/ or Shenzhen risk factors. For the pro-cyclical stocks shown in the regression results from Table 6 to Table 7, the alpha values are significantly significant.

However, the degree of significance of alpha is not high for all stocks as well as for counter-cyclical stocks, and some alpha is not significant and even has zero alpha value. This may imply that the assumed persistence of the relationship between stock returns and business cycles may only exist for pro-cyclical stocks and may not necessarily hold for counter-cyclical stocks. Therefore, in practice, we need to adapt our trading strategies to the business cycle characteristics of different industries rather than simply applying general stock trading rules.

Thus, when trading stocks, investors who wish to gain more excess returns can short the pro-cyclical portfolio and/ or long the counter-cyclical portfolio if production growth in the following month is anticipated to be above the steady state and vice versa. And our finding is similar to that obtained in the study by Chen (2021). In addition to this, based on the results in the tables, we can conclude that future economic conditions cannot price the individual stock returns properly. This conclusion is similar to the results of previous studies, such as those by Yang and Yang (2015) and Zhang, Yang and He (2016). However, we use completely different regression models from the previous study to further examine and illustrate this result from a new perspective.

Notably, this finding is also contrary to that reached by Zhu, Gao, and Sherman (2020) in their study of the US and UK stock markets. This suggests that different markets and different regional return data may lead to different conclusions. Therefore, investors need to make appropriate decisions when trading based on the markets and data they are dealing with, rather than blindly applying others' trading strategies.

When engaging in stock trading, it is crucial that investors carefully analyze market conditions and make informed decisions based on their investment strategy and risk appetite. In addition, the inherent risks associated with investing in stocks must be acknowledged, as these risks can potentially lead to investment losses. Therefore, before embarking on stock trading activities, individuals should take sufficient time to conduct thorough research and conduct a comprehensive risk assessment. By doing so, investors can develop a comprehensive and sound investment plan designed to reduce investment risk and maximize potential returns. This thorough approach will ultimately contribute to a more prosperous and rewarding investment journey.

Up to now, we have extensively discussed the results obtained from the regression analysis of Shanghai A-shares and Shenzhen A-shares using two different models. However, it is essential to recognize that the results discussed, and the corresponding stock trading methods are based on certain assumptions. First, we presuppose that all investors in the stock market are rational and rational in their forecasts of future economic conditions as well as in their judgments. Second, for individual stock returns, there is persistence in the relationship between them and the business cycle.

While our approach aligns with the research conducted by Fama (1990) and Schwert (1990) and draws valuable insights from the study by Zhu, Gao, and Sherman (2020), we must acknowledge that there could be some uncertainty when using future economic conditions as a proxy for investors' expectations of future economic conditions.

Understanding that these assumptions and potential uncertainties are inherent in any research methodology is important. Therefore, it is prudent for investors to approach stock trading with a comprehensive understanding of these factors and exercise caution when interpreting and applying the research findings to their investment decisions. This awareness will enable investors to navigate the stock market more effectively and make informed choices that align with their investment goals and risk tolerance.

5.5 Analysis of the possibility of the results

As mentioned earlier in this section, we note that there are no significant results are obtained when using the Fama-French three-factor model for the Shanghai A-share stocks and the Shenzhen A-share stocks. We conduct further analysis to identify the possible reasons for these results and find that the HML risk factor in the Fama-French three-factor model may not be applicable in the Chinese stock market. This is because the HML risk factor never obtains significant results, regardless of the macroeconomic variables and statistical approaches used in the analysis. This result highlights the limitations of the Fama-French three-factor model in explaining the relationship between stock returns and real economic activity in the Chinese stock market. It also underscores the need for deeper exploration into the characteristics and operational mechanisms of the Chinese stock market to gain a better understanding of its uniqueness in the global stock market landscape.

More importantly, our regression results overturn previous studies to some extent, demonstrating that the Fama-French three-factor model is not appropriate for the Chinese stock market (e.g., Chen and Kawaguchi, 2018; Wu and Xu, 2004). This suggests that when studying the Chinese stock market, there is a need to develop unique models applicable to this market for its specific characteristics and to conduct effective empirical studies in order to more accurately explain the volatility of stock returns in this market and further optimize the related investment decisions.

In addition, two different data statistical methods are used for regression analysis in this paper, which are float-adjusted market capitalization weighting (TMV) and market capitalization weighting (MC). Although we explore the difference between TMV and MC in Section 3 of our paper, the regression results presented in Tables 1 to 3 show that there is no significant effect on the regression results, regardless of the statistical method used, controlling for risk factors. There are many reasons for such results, but in the case of our study, it may be due to the large sample size. Our research covers 3,315 stocks, almost all A-share stocks in the Chinese market, and a study period over 214 months. These extensive data provide more accurate and comprehensive information. This is because in regression analysis, the size of the sample is very important for the stability and accuracy of the results. When the sample size is large, the results obtained are likely to converge even when different statistical methods are used.

The research results in Table 5 to Table 7 show that when the Fama-French three-factor model and CAPM are adopted, the regression results of the Shenzhen A-share market are relatively weak. In contrast, the Shanghai A-share market shows better regression results when considering its own risk factors. These results mean that analysis of the relationship between equity returns and actual economic activity in the A-share market may be subject to various risk factors and changes observed in different model factors.

To better understand and interpret these results, further investigation is warranted. It is essential to investigate the reasons for the difference between the regression results of the Shanghai and Shenzhen A-share markets. This exploration can include a comprehensive examination of market dynamics, industry-specific factors, investor behavior, and other relevant variables affecting the relationship between stock returns and real economic activity in each market.

By conducting A more detailed analysis, researchers can gain a deeper understanding of the complex interplay of risk factors and economic conditions in the A-share market. This knowledge will contribute to a complete understanding of the fundamental mechanisms driving stock returns and guide investors to develop more accurate investment strategies and risk management approaches based on each market's unique characteristics.

6. Conclusion

In recent years, there has been growing evidence that stock market returns are inextricably linked to changes in real economic activity and business cycles. Therefore, it becomes especially critical for investors who aspire to generate excess returns to make sound and timely investment decisions based on the available macroeconomic information.

In the current investment environment, investors should pay close attention to macroeconomic indicators and data to understand the economy's overall health. These common economic indicators include but are not limited to gross domestic product (GDP), consumer price index (CPI), inflation rates, employment data, and interest rate levels. Investors can gain critical insights into real economic activity and business cycles by analyzing those data. Also, in addition to economic indicators, investors should consider the impact of government policies. Government monetary policy, fiscal policy, and regulatory initiatives can have a significant effect on equity markets. Understanding government policy preferences and changes in policy may have a profound impact on investment decisions. Even to a certain extent, the operating conditions of companies, industry trends, and changes in technological factors may also impact the stock market to some extent.

Overall, it is critical for investors seeking excess returns to obtain accurate macroeconomic information and combine it with other factors for a comprehensive analysis. This helps them make timely and informed investment decisions to achieve better investment returns in the stock market.

Before synthesizing the findings of this paper, we need to clarify an essential hypothetical premise first. This study assumes that there may be a consistent and pervasive relationship between the returns of certain individual stocks and the business cycle. Based on this premise, we hypothesize that investors who are able to rationally and accurately predict actual future economic activity may be able to achieve excess returns. To explore whether there is a significant relationship between stock returns and real economic activity, our study extensively collects and analyzes monthly stock prices in the Chinese A-share markets while considering relevant indices that can represent the level of real economic activity in China.

In our study, we systematically examine the monthly returns of Shanghai A-shares and Shenzhen A-shares and provide an in-depth analysis of the findings. We collect monthly price data of all A-shares in the Shanghai Stock Exchange and Shenzhen Stock

Exchange, totaling 3315 stocks, for 214 months from December 2004 to September 2022, and 11 sets of economic indices that can represent the changes in China's macroeconomic development. The analysis is carried out using MATLAB by constructing matrices and regression functions. After calculating the monthly stock returns and processing the missing data, we systematically explore the relationship between stock returns and real economic activity in the Chinese stock market. Regression analysis is conducted on all macroeconomic indices listed in Section 3 of this paper respectively on the premise that the sample size and the sample interval are sufficient. By comparing the regression results, the producer price index (PPI) is finally selected to represent the actual economic development level of China[10]. It is worth noting that this is the first time that the producer price index (PPI) is used in the Chinese stock market to represent the development as well as the volatility of the Chinese real economy.

In addition, to study the relationship between stock returns and real economic activity in more depth, for the first time in the Chinese stock market, we also classify stocks in the SSE and SZSE into pro-cyclical and counter-cyclical stocks according to the different periods of the business cycle.

If a stock exhibits a positive correlation between its excess returns and production growth rates, we classify it as a pro-cyclical stock. On the other hand, if a stock shows a negative correlation between its excess returns and production growth rates during the evaluation period, we consider it a counter-cyclical stock. And then, we analyze the relationship between excess returns and production growth rates for these two groups of stock types in turn under different backward-looking evaluation periods. At the same time, we also follow up with stock trading recommendations based on the performance of these two stocks in different business cycles.

Through the research and analysis in this paper, we expect to provide investors and policymakers with insights into the relationship between stock returns and real economic activity. This has important implications for the development of investment

[10] The results of the remaining indices are presented in the appendix.

strategies, risk management, and economic forecasting. Our findings will help reveal the potential linkages between the stock market and the real economy and provide useful references for further research in related fields.

Besides, we find there is no significant relationship between stock returns and producer price index in either the Shanghai A-share market or the Shenzhen A-share market through regression analysis using no matter the capital asset pricing model (CAPM) and the Fama-French three-factor model. Although neither model yielded significant results, the overall performance level of the CAPM outperforms the three-factor model in the Chinese A-share markets.

In addition, we find that the regression results are affected by the type of risk factor to a greater extent in the Shanghai A-share market than in the Shenzhen A-share market. Specifically, under the Shanghai risk factor, the Shanghai A-share market outperforms the performance under the Hushen risk factor. However, the different statistical approaches, either TMV or MC, have a moderate impact on the regression results in either the Shanghai A-share or Shenzhen A-share markets.

Through this study, based on the data we've collected so far and the results of our analysis, the link between stock returns and the real economy in the Chinese market is not evident. However, we successfully classify stocks in the Shanghai A-share market as well as the Shenzhen A-share market into two categories: pro-cyclical stocks and counter-cyclical stocks. And our findings proved that pro-cyclical stocks perform better in the Shenzhen A-share market compared to counter-cyclical stocks.

The above findings provide an essential reference for investors. In contrast to the trading approach in Section 5, the regression analysis gives the following stock trading suggestions. For those investors who want to achieve excess returns can short the pro-cyclical portfolio and/or long the counter-cyclical portfolio if production growth in the following month is anticipated to be above the steady state and vice versa. However, the above stock trading recommendations are only for A-shares on the SSE and SZSE, not for the rest of the stocks on these two markets or the BSE.

In the present study, we also perform some innovative work.

The most innovative aspect of this study is the introduction of the producer price index (PPI), a macroeconomic index that has yet to be widely used in previous studies. By using the PPI, we fill a gap in the research field to explore the relationship between stock returns and real economic activity in the Chinese A-share markets. This innovative approach allows us to provide a new and comprehensive perspective to help investors understand the operation of the stock market in a more comprehensive manner. At the same time, our empirical study also gives a new stock trading scheme, which is a very different point from previous studies.

Besides, this paper has the following points in terms of innovation. First, this paper adopts an integrated research approach to ensure the comprehensiveness and accuracy of the study. This approach combines multiple research approaches, such as the literature review and the empirical research, thus providing a more holistic view. Second, the paper makes a broad selection of indicators that represent China's real economic activity and does not limit itself to the same type of economic indicators. Such a choice ensures a comprehensive analysis of multiple aspects of the Chinese economy. By considering various indicators, we can better understand and explain the dynamics of China's economy.

In addition, careful consideration has been given to the selection of the sample interval and sample size in this paper. The sample period is chosen to cover an appropriate time horizon to capture the Chinese economy's long-term trends and cyclical fluctuations. Meanwhile, the sample size is selected with due consideration to the statistical requirements to ensure that the sample size is large enough to generate reliable findings. Finally, this paper also pays special attention to the shortcomings in previous studies of the Chinese stock market and makes improvements and avoidances accordingly. By drawing on the experience and lessons learned from previous studies, this paper provides a more rigorous design in terms of methodology and empirical analysis to improve the reliability and reproducibility of the study.

With the results of this study, investors can predict future economic activities more rationally and accurately, resulting in higher abnormal returns. This has important implications for improving the accuracy and effectiveness of investment decisions.

Also, the methodology and findings of this study have important implications for exploring other studies on the relationship between stock returns and macroeconomics. Therefore, this study makes a positive contribution to the in-depth understanding of the operation of the Chinese stock market and improves the precision and effectiveness of investment decisions.

The research methods used in this paper have adequately considered many influencing factors, but there are inevitably some limitations and areas that could be improved.

One of the areas for improvement is in the handling of missing data. In practice, we find that some indices to proxy the real economic activities have missing data. To compensate for these missing data, we use interpolation to fill in the missing parts of the data. However, such methods may lead to a certain degree of bias, as the interpolation method may not fully reflect the true economic activity. Therefore, in future studies, other more accurate data processing methods can be considered to obtain more precise results.

In addition, the models used in this paper are relatively basic and need to be explored in further depth. We can consider using more complex models to study the factors influencing economic activities. Such as the conditional beta model or the conditional alpha-beta model. These two models consider the dynamic changes in capital markets and the impact of risk factors and can better capture the relationship between risk and return in different market environments. Also, they can take into account the effects of different economic factors and macro variables on risk and return to improve forecasting accuracy further. Furthermore, inspired by Goetzmann, Watanabe and Watanabe (2012), the Fama-French MacBeth model can also be used in subsequent studies.

However, it is important to note that the use of those complex models may also pose some additional challenges and difficulties, such as the estimation and selection of parameters for the models and how to interpret the model results effectively. Therefore, the use of these models needs to be considered in the context of the actual situation in order to obtain more accurate and reliable prediction results.

In conclusion, this paper systematically analyzes the relationship between monthly stock returns and real economic activity in the Chinese stock markets and gives corresponding trading recommendations by dividing stocks by cyclicality. It provides new research ideas for academic research in this field. In future research, the research methods should be continuously improved and enhanced, more accurate and comprehensive data should be used to study the influencing factors of economic activities, and more complex and advanced models should be explored to predict economic trends and changes, so as to help us better understand the nature and laws of economic activities and provide more accurate and effective references for financial decision-making.

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Appendix

Appendix 1

*Notes: The regression results shown in the table below were obtained from the CAPM. Significant results were not obtained when the beta was 90% in the Shanghai A-share market and Shenzhen A-share market. Since significance was not achieved at the 90% significance level, no further 95% test was performed. Panel A in the table shows the results for the Shanghai A-share market, while Panel B shows the results for the Shenzhen A-share market. In both markets, no significant results were observed for BP=72 with a beta of 90%. The table presents the alpha values from these regression analyses, along with their corresponding levels of statistical significance: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.*

Panel A: Betas - 90% Level of Confidence for Shanghai A-share market										
	CPI (Same month of the previous year = 100)	CPI (Same period of the previous year = 100)	RPI (YOY)	M0 (YOY)	M1 (YOY)	M2 (YOY)	IPI	BIME (Advance Index)	EI (Accumulation)	IAV (Accumulation)
	Hushen Risk Factors									
	TMV									
Alpha (All)	-0.0039	-0.0047	-0.0026	0.0013	-0.0039	0.0007	-0.0004	-0.0010	-0.0024	-0.0027
p-value	(0.1489)	(0.1456)	(0.3934)	(0.6714)	(0.2400)	(0.8507)	(0.8866)	(0.8084)	(0.4606)	(0.3577)
Alpha (Procyclical)	-0.0065	-0.0036	-0.0037	-0.0066	-0.0053	0.0001	0.0012	-0.0010	-0.0063	-0.0038
p-value	(0.2924)	(0.5368)	(0.5606)	(0.2616)	(0.3917)	(0.9838)	(0.8221)	(0.8499)	(0.2411)	(0.4523)
Alpha (Countercyclical)	0.0030	-0.0022	0.0004	0.0060	0.0037	-0.0010	-0.0055	-0.0007	-0.003	-0.0038
p-value	(0.6311)	(0.7226)	(0.9477)	(0.3376)	(0.5262)	(0.8442)	(0.3187)	(0.9022)	(0.5137)	(0.4467)
	MC									

Appendix 1 (continue)

Alpha (All)	-0.0024	-0.0033	-0.0027	0.0008	-0.0044	-0.0003	-0.0016	-0.0016	-0.0002	-0.0031
p-value	(0.4739)	(0.3347)	(0.3603)	(0.8151)	(0.2531)	(0.9397)	(0.6361)	(0.6896)	(0.9538)	(-0.2335)
Alpha (Procyclical)	-0.0065	-0.0036	-0.0041	-0.0065	-0.0058	0.0000	0.0001	0.0002	-0.0072	-0.0036
p-value	(0.3013)	(0.5339)	(0.5315)	(0.2670)	(0.3453)	(0.9987)	(0.9895)	(0.9744)	(0.2310)	(0.4772)
Alpha (Countercyclical)	0.0043	-0.0028	-0.0011	0.0060	0.0075	-0.0020	-0.0077	-0.0013	-0.0034	-0.0049
p-value	(0.5041)	(0.6486)	(0.8619)	(0.3344)	(0.2370)	(0.7332)	(0.1658)	(0.8145)	(0.5538)	(0.3356)
	Shanghai Risk Factors									
	TMV									
Alpha (All)	0.0014	0.0022	0.0033	0.0018	-0.0046	0.0014	0.0107	0.0022	-0.0056	-0.0131
p-value	(0.8433)	(0.7729)	(0.6424)	(0.6895)	(0.2852)	(0.7504)	(0.1275)	(0.7338)	(0.5497)	(0.1350)
Alpha (Procyclical)	-0.0021	0.0118	0.0079	-0.0004	-0.0052	0.0006	0.0073	-0.0065	-0.0111	0.0000
p-value	(0.8344)	(0.1809)	(0.5449)	(0.9530)	(0.4006)	(0.9190)	(0.4380)	(0.4038)	(0.3440)	(0.9971)
Alpha (Countercyclical)	0.0123	-0.0007	-0.0012	0.0062	0.0035	0.0000	0.0004	-0.0067	-0.0004	-0.0060
p-value	(0.2664)	(0.9437)	(0.9003)	(0.3451)	(0.5389)	(0.9994)	(0.9711)	(0.4017)	(0.9704)	(0.5973)
	MC									
Alpha (All)	-0.0012	0.0006	0.0001	0.0017	-0.0055	-0.0001	-0.0027	0.0004	0.0002	-0.0018
p-value	(0.8025)	(0.8945)	(0.9859)	(0.6473)	(0.2421)	(0.9782)	(0.4437)	(0.9337)	(0.9571)	(0.6273)
Alpha (Procyclical)	-0.0029	-0.0070	-0.0041	-0.0079	-0.0064	-0.0006	0.0006	0.0007	-0.0074	-0.0021
p-value	(0.6244)	(0.2716)	(0.5233)	(0.1695)	(0.3001)	(0.9128)	(0.9098)	(0.9041)	(0.2488)	(0.7194)
Alpha (Countercyclical)	-0.0001	0.0057	0.0016	0.0062	0.0074	0.0013	-0.0069	0.0013	-0.0030	-0.0025
p-value	(0.9843)	(0.3782)	(0.7951)	(0.3160)	(0.2268)	(0.8304)	(0.2161)	(0.8176)	(0.6202)	(0.6437)

Appendix 1 (continue)

Panel B: Betas - 90% Level of Confidence for Shenzhen A-share market										
	CPI (Same month of the previous year = 100)	CPI (Same period of the previous year = 100)	RPI (YOY)	M0 (YOY)	M1 (YOY)	M2 (YOY)	IPI	BIME (Advance Index)	EI (Accumulation)	IAV (Accumulation)
	Hushen Risk Factors									
	TMV									
Alpha (All)	0.0001	-0.0032	-0.0019	0.0050	-0.0020	-0.0007	-0.0023	0.0000	0.0038	-0.0034
p-value	(0.9827)	(0.4103)	(0.6545)	(0.1451)	(0.6395)	(0.8687)	(0.5047)	(0.9927)	(0.3194)	(0.3370)
Alpha (Procyclical)	-0.0048	-0.0039	-0.0039	-0.0071	-0.0025	0.0005	-0.0015	0.0011	-0.0001	-0.0038
p-value	(0.4508)	(0.5423)	(0.5587)	(0.2740)	(0.6923)	(0.9321)	(0.7729)	(0.8380)	(0.9913)	(0.4735)
Alpha (Countercyclical)	0.0040	0.0009	0.0000	0.0037	0.0055	-0.0014	-0.0070	-0.0001	0.0008	-0.0022
p-value	(0.5503)	(0.8968)	(0.9965)	(0.6124)	(0.4421)	(0.8326)	(0.2502)	(0.9851)	(0.8932)	(0.6837)
	MC									
Alpha (All)	0.0006	-0.0011	-0.0002	0.0053	-0.0032	-0.0003	-0.0032	-0.0020	0.0052	-0.0029
p-value	(0.8692)	(0.8028)	(0.9651)	(0.1273)	(0.5042)	(0.9435)	(0.3821)	(0.6873)	(0.1993)	(0.4067)
Alpha (Procyclical)	-0.0045	-0.0039	-0.0047	-0.0061	-0.0033	0.0012	-0.0022	-0.0004	-0.0006	-0.0032
p-value	(0.4972)	(0.5416)	(0.4974)	(0.3668)	(0.6004)	(0.8343)	(0.6887)	(0.9393)	(0.9208)	(0.5386)
Alpha (Countercyclical)	0.0040	0.0012	0.0000	0.0040	0.0031	-0.0014	-0.0091	-0.0011	0.0009	-0.0018
p-value	(0.5468)	(0.8539)	(0.9973)	(0.5834)	(0.6693)	(0.8353)	(0.1333)	(0.8540)	(0.8873)	(0.7447)
	Shenzhen Risk Factors									
	TMV									

Appendix 1 (continue)

Alpha (All)	-0.0012	-0.0039	-0.0015	0.0028	-0.0001	-0.0017	-0.0019	-0.0023	0.0050	-0.0007
p-value	(0.6315)	(0.1711)	(0.6460)	(0.3722)	(0.9797)	(0.5441)	(0.5146)	(0.5318)	(0.1797)	(0.8310)
Alpha (Procyclical)	-0.0042	-0.0040	-0.0014	-0.0058	-0.0024	0.0019	-0.0013	0.0000	0.0012	-0.0043
p-value	(0.5213)	(0.5216)	(0.8317)	(0.3892)	(0.7129)	(0.7348)	(0.8048)	(0.9966)	(0.8435)	(0.3951)
Alpha (Countercyclical)	0.0034	-0.0016	-0.0009	0.0052	0.0031	-0.0036	-0.0080	-0.0001	-0.0004	-0.0023
p-value	(0.5914)	(0.8079)	(0.8831)	(0.4703)	(0.6396)	(0.5365)	(0.1756)	(0.9801)	(0.9398)	(0.6518)
	MC									
Alpha (All)	-0.0018	-0.0043	-0.0024	0.0022	0.0000	-0.0025	-0.0023	-0.0036	0.0051	-0.0016
p-value	(0.4796)	(0.1240)	(0.4332)	(0.4692)	(0.9977)	(0.3894)	(0.4025)	(0.3607)	(0.1648)	(0.6099)
Alpha (Procyclical)	-0.0046	-0.0045	-0.0019	-0.0061	-0.0024	0.001	-0.0014	-0.0016	0.0016	-0.0040
p-value	(0.4849)	(0.4726)	(0.7724)	(0.3656)	(0.7162)	(0.7751)	(0.7932)	(0.7588)	(0.7876)	(0.4270)
Alpha (Countercyclical)	0.0028	-0.0020	-0.0013	0.0052	0.0035	-0.0037	-0.0065	-0.0014	-0.0005	-0.0028
p-value	(0.6545)	(0.7563)	(0.8344)	(0.4713)	(0.5976)	(0.5297)	(0.2724)	(0.8109)	(0.9349)	(0.5927)

Appendix 2

*Notes: The regression results shown in the table below were obtained from the CAPM. According to the table below, significant results are observed in both the Shanghai A-share market and the Shenzhen A-share market when the beta is set to 90%. panel A represents the results for the Shanghai A-share market, while panel B represents the results for the Shenzhen A-share market. For the case of BP=72, with a beta of 90%, we obtain significant results in both markets. The table presents the alpha values from these regression analyses, along with their corresponding levels of statistical significance: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.*

Panel A: Betas - 90% Level of Confidence for Shanghai A-share market									
	RPI (Aggregate)	BIME (Consensus Index)	BIME (Lagging Index)	IE Index (Current Period)	IE Index (Cumulative)	II (Current Period)	II (Accumulation)	EI (Current Period)	IAV (YOY)
	Hushen Risk Factors								
	TMV								
Alpha (All)			-0.0075		0.0001	0.0008	0.0000		
p-value			(0.0183)		(0.9800)	(0.8053)	(0.9951)		
Alpha (Procyclical)			-0.0109*		-0.0113**	-0.0111**	-0.0093*		
p-value			(0.0716)		(0.0417)	(0.0358)	(0.0851)		
Alpha (Countercyclical)			-0.0016		0.0047	0.0061	0.0007		
p-value			(0.8168)		(0.4142)	(0.2930)	(0.8998)		
	MC								
Alpha (All)			-0.0056**	0.0026	0.0009	0.0035		-0.0020	-0.0027
p-value			(0.0362)	(0.5288)	(0.8309)	(0.4166)		(0.5550)	(0.4075)
Alpha (Procyclical)			-0.0112*	-0.0111**	-0.0172**	-0.0096*		0.0019	-0.0003

Appendix 2 (continued)

p-value			(0.0708)	(0.0433)	(0.0058)	(0.0657)		(0.7673)	(0.9484)
Alpha (Countercyclical)			-0.0008	0.0038	0.0060	0.0072		-0.0109*	-0.0095*
p-value			(0.9051)	(0.4900)	(0.2979)	(0.2090)		(0.0811)	(0.0877)
	Shanghai Risk Factors								
	TMV								
Alpha (All)	-0.0107						-0.0195**	0.0029	0.0028
p-value	(0.1702)						(0.0274)	(0.6971)	(0.6887)
Alpha (Procyclical)	0.0038						-0.0356**	0.0191*	(0.0118)
p-value	(0.8040)						(0.0137)	(0.0591)	(0.2796)
Alpha (Countercyclical)	-0.0166*						-0.0099	-0.0116	-0.0163*
p-value	(0.0581)						(0.2918)	(0.3072)	(0.0981)
	MC								
Alpha (All)			-0.0032	0.0023	0.0015	0.0027			
p-value			(0.4974)	(0.5961)	(0.7459)	(0.5472)			
Alpha (Procyclical)			-0.0153**	-0.0101*	-0.0114*	-0.0092*			
p-value			(0.0225)	(0.0741)	(0.0614)	(0.0767)			
Alpha (Countercyclical)			0.0012	0.0035	0.0059	0.0056			
p-value			(0.8641)	(0.5444)	(0.3129)	(0.3342)			

Panel B: Betas - 90% Level of Confidence for Shenzhen A-share market

	RPI (Aggregate)	BIME (Consensus Index)	BIME (Lagging Index)	IE Index (Current Period)	IE Index (Cumulative)	II (Current Period)	II (Accumulation)	EI (Current Period)	IAV (YOY)
	Hushen Risk Factors								

Appendix 2 (continued)

	TMV				
Alpha (All)	0.0034		0.0017		0.0014
p-value	(0.4089)		(0.6786)		(0.7110)
Alpha (Procyclical)	-0.0112*		-0.0140**		-0.0140**
p-value	(0.0641)		(0.0250)		(0.0214)
Alpha (Countercyclical)	0.0093		0.0079		0.0069
p-value	(0.1432)		(0.1971)		(0.2478)
	MC				
Alpha (All)	0.0047		0.0039	0.0023	0.0029
p-value	(0.2883)		(0.3734)	(0.5761)	(0.4593)
Alpha (Procyclical)	-0.0131**		-0.0161**	-0.0107*	-0.0182***
p-value	(0.0330)		(0.0109)	(0.0817)	(0.0038)
Alpha (Countercyclical)	0.0095		0.0082	0.0068	0.0077
p-value	(0.1369)		(0.1792)	(0.2551)	(0.1922)
	Shenzhen Risk Factors				
	TMV				
Alpha (All)	0.0041	-0.0039	0.0034	0.0008	0.0023
p-value	(0.2226)	(0.2357)	(0.3649)	(0.7875)	(0.4907)
Alpha (Procyclical)	-0.0100*	-0.0132**	-0.0140**	-0.0115*	-0.0141**
p-value	(0.0993)	(0.0559)	(0.0177)	(0.0601)	(0.0172)
Alpha (Countercyclical)	0.0092	0.0037	0.0086	0.0080	0.0071
p-value	(0.1556)	(0.5967)	(0.1467)	(0.1944)	(0.2160)

Appendix 2 (continued)

	MC						
Alpha (All)		0.0028	-0.0047		0.0028	0.0001	0.0021
p-value		(0.3702)	(0.1304)		(0.4446)	(0.9803)	(0.5314)
Alpha (Procyclical)		-0.0110*	-0.0138**		-0.0139**	-0.0119*	-0.0139**
p-value		(0.0698)	(0.0439)		(0.0192)	(0.0535)	(0.0186)
Alpha (Countercyclical)		0.0087	0.0035		0.0076	0.0083	0.0083
p-value		(0.1784)	(0.6148)		(0.2010)	(0.1733)	(0.1484)

Appendix 3

*Notes: The regression results shown in the table below were obtained from the CAPM. According to the table below, we can see that significant results are obtained in both the Shanghai A-share market and the Shenzhen A-share market when the beta is set to 95%, both in Panel A and Panel B. For the case of BP=72, significant results were observed in both markets using a 95% significance level. The table presents the alpha values from these regression analyses, along with their corresponding levels of statistical significance: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.*

Panel A: Betas - 95% Level of Confidence for Shanghai A-share market									
	RPI (Aggregate)	BIME (Consensus Index)	BIME (Lagging Index)	IE Index (Current Period)	IE Index (Cumulative)	II (Current Period)	II (Accumulation)	EI (Current Period)	IAV (YOY)
	Hushen Risk Factors								
	TMV								
Alpha (All)			-0.0098**		0.0005	0.0009	0.0018		
p-value			(0.0081)		(0.9221)	(0.8108)	(0.6883)		
Alpha (Procyclical)			-0.0125*		-0.0110*	-0.0073	-0.0126**		
p-value			(0.0561)		(0.0709)	(0.1986)	(0.0358)		
Alpha (Countercyclical)			-0.0048		0.0068	0.0049	0.0064		
p-value			(0.5147)		(0.2862)	(0.4116)	(0.3212)		
	MC								
Alpha (All)			-0.0079**	0.0043	0.0017	0.0046		0.0011	-0.0024
p-value			(0.0475)	(0.3805)	(0.7458)	(0.3239)		(0.8003)	(0.5400)
Alpha (Procyclical)			-0.0146**	-0.0050	-0.0113*	-0.0087		0.0057	0.0009
p-value			(0.0421)	(0.4228)	(0.0537)	(0.1415)		(0.3990)	(0.8685)

Appendix 3 (continued)

Alpha (Countercyclical)			-0.0034	0.0032	0.0058	0.0059		-0.0078	-0.0143**
p-value			(0.6518)	(0.6035)	(0.3663)	(0.3383)		(0.2567)	(0.0448)
	Shanghai Risk Factors								
	TMV								
Alpha (All)	-0.0008						-0.0028	0.0021	-0.0031
p-value	(0.8464)						(0.5515)	(0.6123)	(0.4060)
Alpha (Procyclical)	0.0042						-0.0189**	0.0113	-0.0001
p-value	(0.5521)						(0.0018)	(0.1410)	(0.9796)
Alpha (Countercyclical)	0.0002						0.0038	-0.0074	-0.0082
p-value	(0.9787)						(0.5457)	(0.2845)	(0.1656)
	MC								
Alpha (All)			-0.0075	0.0162**	0.0000	0.0058			
p-value			(0.1536)	(0.0186)	(0.9944)	(0.2131)			
Alpha (Procyclical)			-0.0192**	0.0002	-0.0159*	-0.0026			
p-value			(0.0136)	(0.9869)	(0.0586)	(0.6990)			
Alpha (Countercyclical)			-0.0045	0.0138	0.0022	0.0067			
p-value			(0.5331)	(0.1300)	(0.7205)	(0.2692)			

Panel B: Betas - 95% Level of Confidence for Shenzhen A-share market

	RPI (Aggregate)	BIME (Consensus Index)	BIME (Lagging Index)	IE Index (Current Period)	IE Index (Cumulative)	II (Current Period)	II (Accumulation)	EI (Current Period)	IAV (YOY)
	Hushen Risk Factors								
	TMV								

Appendix 3 (continued)

Alpha (All)	0.0043		0.0027		0.0030
p-value	(0.3442)		(0.5729)		(0.4797)
Alpha (Procyclical)	-0.0089		-0.0188**		-0.0142**
p-value	(0.1737)		(0.0137)		(0.0445)
Alpha (Countercyclical)	0.0065		0.0057		0.0095
p-value	(0.3031)		(0.3924)		(0.1212)
MC					
Alpha (All)	0.0053		0.0050	0.0003	0.0055
p-value	(0.2691)		(0.3418)	(0.9494)	(0.2328)
Alpha (Procyclical)	-0.0123*		-0.0145*	-0.0130*	-0.0176**
p-value	(0.0682)		(0.0692)	(0.0503)	(0.0130)
Alpha (Countercyclical)	0.0069		0.0057	0.0078	0.0093
p-value	(0.2821)		(0.4047)	(0.1935)	(0.1255)
Shenzhen Risk Factors					
TMV					
Alpha (All)	0.0053	-0.0045	0.0035	-0.0004	0.0040
p-value	(0.1700)	(0.2265)	(0.4408)	(0.9191)	(0.3122)
Alpha (Procyclical)	-0.0113*	-0.0127*	-0.0184***	-0.0168**	-0.0142**
p-value	(0.0671)	(0.0922)	(0.0039)	(0.0121)	(0.0261)
Alpha (Countercyclical)	0.0077	0.0033	0.0068	0.0089	0.0095
p-value	(0.2315)	(0.6436)	(0.2897)	(0.1580)	(0.1066)
MC					

Appendix 3 (continued)

Alpha (All)	0.0044	-0.0047	0.0023	-0.0005	0.0041
p-value	(0.2338)	(0.2011)	(0.5999)	(0.8959)	(0.3008)
Alpha (Procyclical)	-0.0126**	-0.0139*	-0.0203***	-0.0157**	-0.0140**
p-value	(0.0417)	(0.0600)	(0.0014)	(0.0169)	(0.0259)
Alpha (Countercyclical)	0.0080	0.0026	0.0074	0.0094	0.0041
p-value	(0.2187)	(0.7137)	(0.2543)	(0.1432)	(0.3008)

Appendix 4

*Notes: The regression results shown in the table below were obtained from the Fama-French three-factor model. According to the regression results in the table below, the regression results of the Fama-French three-factor model are not significant in both the Shanghai A-share market and the Shenzhen A-share market when the beta is set to 90%. This means that no significant conclusion can be drawn for a beta of 90% in these two markets. The table presents the alpha values from these regression analyses, along with their corresponding levels of statistical significance: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level.*

Panel A: Betas - 90% Level of Confidence for Shanghai A-share market										
	CPI (Same month of the previous year = 100)	CPI (Same period of the previous year = 100)	RPI (YOY)	RPI (Aggregate)	M0 (YOY)	M1 (YOY)	M2 (YOY)	IPI	BIME (Consensus Index)	BIME (Advance Index)
	Hushen Risk Factors									
	TMV									
Alpha (All)	-0.0013	-0.0051	0.0001	-0.0025	-0.0011	-0.0014	-0.0033	0.0021	-0.0018	-0.0016
p-value	(0.5516)	(0.0312)	(0.9658)	(0.2710)	(0.5912)	(0.4641)	(0.1226)	(0.3708)	(0.5064)	(0.5474)
Alpha (Procyclical)	-0.0024	-0.0024	-0.0010	-0.0004	-0.0070	-0.0030	0.0043	0.0016	-0.0085	0.0003
p-value	(0.6820)	(0.6878)	(0.8825)	(0.9460)	(0.2532)	(0.6101)	(0.4348)	(0.7521)	(0.1339)	(0.9481)
Alpha (Countercyclical)	0.0018	-0.0031	0.0004	-0.0033	0.0064	0.0032	-0.0080	-0.0016	0.0026	-0.0018
p-value	(0.7611)	(0.6279)	(0.9475)	(0.6035)	(0.3142)	(0.5992)	(0.1252)	(0.7461)	(0.6432)	(0.7281)
	MC									
Alpha (All)	-0.0012	-0.0047*	-0.0004	-0.0005	-0.0008	-0.0033	-0.0033	0.0012	-0.0015	-0.0018

Appendix 4 (continued)

p-value	(0.5934)	(0.0553)	(0.8899)	(0.8754)	(0.5775)	(0.3205)	(0.2265)	(0.6445)	(0.6163)	(0.6040)
Alpha (Procyclical)	-0.0021	-0.0024	-0.0027	-0.0002	-0.0057	-0.0032	0.0048	0.0012	-0.0085	0.0023
p-value	(0.7291)	(0.6919)	(0.6791)	(0.9753)	(0.3496)	(0.5854)	(0.3743)	(0.8050)	(0.1499)	(0.6744)
Alpha (Countercyclical)	0.0017	-0.0030	0.0004	-0.0025	0.0059	-0.0005	-0.0077	-0.0019	0.0028	-0.0002
p-value	(0.7848)	(0.6239)	(0.9526)	(0.7001)	(0.3536)	(0.9335)	(0.1531)	(0.7134)	(0.6419)	(0.9755)
	Shanghai Risk Factors									
	TMV									
Alpha (All)	-0.0030	-0.0060**	-0.0026	-0.0034	-0.0007	-0.0023	-0.0039**	-0.0014	-0.0029	-0.0022
p-value	(0.1796)	(0.01740)	(0.2508)	(0.1544)	(0.7777)	(0.2356)	(0.0382)	(0.5223)	(0.3145)	(0.3978)
Alpha (Procyclical)	-0.0043	-0.0044	-0.0048	-0.0014	-0.0076	-0.0033	0.0038	0.0000	-0.0083	0.0015
p-value	(0.4745)	(0.4549)	(0.4662)	(0.8270)	(0.1916)	(0.5621)	(0.4743)	(0.9970)	(0.1449)	(0.7778)
Alpha (Countercyclical)	0.0021	-0.0038	-0.0003	-0.0026	0.0060	0.0029	-0.0087*	-0.0046	0.0039	0.0005
p-value	(0.7283)	(0.5433)	(0.9608)	(0.6783)	(0.3500)	(0.6264)	(0.0915)	(0.3817)	(0.4996)	(0.9178)
	MC									
Alpha (All)	-0.0019	-0.0052**	-0.0030	-0.0035	-0.0015	-0.0026	-0.0046**	-0.0013	-0.0008	-0.0012
p-value	(0.4083)	(0.0318)	(0.1826)	(0.1579)	(0.5094)	(0.3005)	(0.0336)	(0.5967)	(0.7966)	(0.6919)
Alpha (Procyclical)	-0.0033	-0.0034	-0.0052	-0.0022	-0.0070	-0.0034	0.0028	-0.0003	-0.0085	0.0024
p-value	(0.5966)	(0.5694)	(0.4234)	(0.7350)	(0.2266)	(0.5513)	(0.6078)	(0.9460)	(0.1512)	(0.6689)
Alpha (Countercyclical)	0.0018	-0.0044	-0.0012	-0.0031	0.0061	0.0023	-0.0089*	-0.0037	0.0060	0.0024
p-value	(0.7717)	(0.4738)	(0.8479)	(0.6226)	(0.3439)	(0.7108)	(0.0882)	(0.4853)	(0.3267)	(0.6152)

Appendix 4 (continued)

Panel B: Betas - 90% Level of Confidence for Shenzhen A-share market										
	CPI (Same month of the previous year = 100)	CPI (Same period of the previous year = 100)	RPI (YOY)	RPI (Aggregate)	M0 (YOY)	M1 (YOY)	M2 (YOY)	IPI	BIM (Consensus Index)	BIME (Advance Index)
	Hushen Risk Factors									
	TMV									
Alpha (All)	0.0019	-0.0033	-0.0012	-0.0045	0.0009	0.0002	-0.0029	0.0004	0.0022	-0.0048*
p-value	(0.4127)	(0.2270)	(0.6275)	(0.1177)	(0.7354)	(0.9240)	(0.2363)	(0.8762)	(0.3939)	(0.0627)
Alpha (Procyclical)	0.0003	-0.0011	-0.0004	0.0003	-0.0050	-0.0005	0.0040	0.0000	-0.0086	0.0009
p-value	(0.9604)	(0.8567)	(0.9505)	(0.9643)	(0.4483)	(0.9336)	(0.4575)	(0.9952)	(0.1361)	(0.8581)
Alpha (Countercyclical)	0.0018	-0.0029	0.0000	-0.0038	0.0036	0.0016	-0.0077	-0.0064	0.0102	-0.0036
p-value	(0.7787)	(0.6509)	(0.9970)	(0.5577)	(0.6234)	(0.8234)	(0.1861)	(0.3165)	(0.1275)	(0.5578)
	MC									
Alpha (All)	0.0016	-0.0029	-0.0017	-0.0043	0.0003	0.0004	-0.0043	-0.0018	0.0016	-0.0034
p-value	(0.4967)	(0.2553)	(0.5256)	(0.1490)	(0.9085)	(0.8696)	(0.1232)	(0.4956)	(0.5500)	(0.2739)
Alpha (Procyclical)	-0.0011	-0.0009	-0.0005	0.0008	-0.0067	-0.0004	0.0041	-0.0008	-0.0097	0.0020
p-value	(0.8601)	(0.8803)	(0.9433)	(0.9062)	(0.2946)	(0.9501)	(0.4697)	(0.8805)	(0.1065)	(0.6958)
Alpha (Countercyclical)	0.0019	-0.0026	-0.0013	-0.0051	0.0033	0.0011	-0.0092	-0.0087	0.0091	-0.0012
p-value	(0.7692)	(0.6862)	(0.8377)	(0.4477)	(0.6627)	(0.8790)	(0.1168)	(0.1980)	(0.1732)	(0.8387)
	Shenzhen Risk Factors									
	TMV									
Alpha (All)	0.0028	-0.0023	0.0005	-0.0024	0.0000	0.0014	-0.0039	0.0015	0.0043	-0.0038

Appendix 4 (continued)

p-value	(0.2416)	(0.3531)	(0.8557)	(0.3584)	(0.9946)	(0.4300)	(0.1601)	(0.5679)	(0.1192)	(0.2056)
Alpha (Procyclical)	0.0011	-0.0011	-0.0005	0.0002	-0.0042	-0.0005	0.0035	0.0007	-0.0082	-0.0018
p-value	(0.8645)	(0.8652)	(0.9476)	(0.9736)	(0.5411)	(0.9398)	(0.5472)	(0.9049)	(0.1771)	(0.7262)
Alpha (Countercyclical)	0.0012	-0.0040	0.0018	-0.0034	0.0036	0.0031	-0.0090	-0.0025	0.0092	-0.0022
p-value	(0.8560)	(0.5381)	(0.7740)	(0.6072)	(0.6244)	(0.6535)	(0.1317)	(0.6690)	(0.1522)	(0.7050)
	MC									
Alpha (All)	0.0027	-0.0012	-0.0004	-0.0030	-0.0013	0.0007	-0.0038	0.0012	0.0031	-0.0035
p-value	(0.2383)	(0.5951)	(0.8712)	(0.3186)	(0.3746)	(0.7648)	(0.2093)	(0.6507)	(0.2138)	(0.2484)
Alpha (Procyclical)	0.0012	0.0000	-0.0001	0.0006	-0.0051	0.0010	0.0041	0.0012	-0.0084	0.0001
p-value	(0.8482)	(0.9945)	(0.9895)	(0.9311)	(0.4622)	(0.8774)	(0.4774)	(0.8331)	(0.1679)	(0.9789)
Alpha (Countercyclical)	0.0018	-0.0036	-0.0022	-0.0049	0.0032	0.0008	-0.0121**	-0.0051	0.0089	-0.0033
p-value	(0.7835)	(0.5861)	(0.7271)	(0.4621)	(0.6668)	(0.9089)	(0.0404)	(0.4271)	(0.1652)	(0.5703)

Panel C: Betas - 95% Level of Confidence for Shanghai A-share market

	BIME (Lagging Index)	IE Index (Current Period)	IE Index (Cumulative)	II (Current Period)	II (Accumulation)	EI (Accumulation)	EI (Current Period)	IAV (Accumulation)	IAV (YOY)
	Hushen Risk Factors								
	TMV								
Alpha (All)	-0.0060	-0.0004	0.0024	-0.0021	-0.0025	-0.0012	-0.0010	0.0016	0.0024
p-value	(0.0026)	(0.8779)	(0.3222)	(0.3914)	(0.3074)	(0.6178)	(0.6658)	(0.5039)	(0.3222)
Alpha (Procyclical)	-0.0082	-0.0080	0.0028	-0.0092*	-0.0118**	-0.0002	0.0056	-0.0002	0.0028
p-value	(0.1973)	(0.1314)	(0.5786)	(0.0923)	(0.0376)	(0.9626)	(0.3507)	(0.9735)	(0.5786)
Alpha (Countercyclical)	-0.0007	0.0016	-0.0062	0.0026	0.0020	-0.0042	-0.0107*	-0.0012	-0.0062

Appendix 4 (continued)

p-value	(0.9127)	(0.7762)	(0.2221)	(0.6523)	(0.7069)	(0.4433)	(0.0832)	(0.8127)	(0.2221)
	MC								
Alpha (All)	-0.0072**	0.0002	-0.0047*	-0.0003	-0.0023	-0.0012	-0.0005	0.0009	0.0016
p-value	(0.0034)	(0.9326)	(0.0750)	(0.9228)	(0.4231)	(0.6640)	(0.8514)	(0.6970)	(0.5404)
Alpha (Procyclical)	-0.0105	-0.0075	-0.0112**	-0.0091	-0.0117**	-0.0006	0.0048	-0.0006	0.0028
p-value	(0.1060)	(0.1643)	(0.0404)	(0.1026)	(0.0404)	(0.9107)	(0.4269)	(0.9004)	(0.5730)
Alpha (Countercyclical)	-0.0011	0.0023	0.0005	0.0037	0.0021	-0.0058	-0.0115*	-0.0009	-0.0073
p-value	(0.8702)	(0.6811)	(0.9299)	(0.5199)	(0.7122)	(0.3039)	(0.0688)	(0.8573)	(0.1661)
	Shanghai Risk Factors								
	TMV								
Alpha (All)	-0.0084	-0.0010	-0.0051*	-0.0015	-0.0027	-0.0010	0.0000	0.0000	-0.0002
p-value	(0.0000)	(0.7204)	(0.0796)	(0.6152)	(0.3821)	(0.7057)	(0.9880)	(0.9980)	(0.9091)
Alpha (Procyclical)	-0.0101	-0.0073	-0.0120**	-0.0097*	-0.0112**	-0.0002	0.0053	-0.0001	0.0011
p-value	(0.1070)	(0.1614)	(0.0275)	(0.0777)	(0.0427)	(0.9666)	(0.3729)	(0.9849)	(0.8283)
Alpha (Countercyclical)	-0.0018	0.0009	0.0032	0.0038	0.0021	-0.0038	-0.0097	-0.0010	-0.0052
p-value	(0.7938)	(0.8655)	(0.5737)	(0.5131)	(0.7136)	(0.4940)	(0.1213)	(0.8431)	(0.3036)
	MC								
Alpha (All)	-0.0069***	0.0007	-0.0031	0.0012	-0.0010	0.0000	-0.0003	-0.0003	0.0000
p-value	(0.0004)	(0.8288)	(0.3152)	(0.7631)	(0.7784)	(0.9997)	(0.9015)	(0.8981)	(0.9876)
Alpha (Procyclical)	-0.0105*	-0.0068	-0.0126**	-0.0091	-0.0127**	-0.0004	0.0040	-0.0022	0.0014
p-value	(0.0948)	(0.2053)	(0.0256)	(0.1067)	(0.0272)	(0.9363)	(0.4995)	(0.6455)	(0.7749)
Alpha (Countercyclical)	-0.0002	0.0021	0.0045	0.0047	0.0036	-0.0039	-0.0092	0.0003	-0.0049
p-value	(0.9726)	(0.7090)	(0.4430)	(0.4155)	(0.5197)	(0.4725)	(0.1301)	0.9520)	(0.3441)

Appendix 4 (continued)

Panel D: Betas - 95% Level of Confidence for Shenzhen A-share market

	BIME (Lagging Index)	IE Index (Current Period)	IE Index (Cumulative)	II (Current Period)	II (Accumulation)	EI (Accumulation)	EI (Current Period)	IAV (Accumulation)	IAV (YOY)
	Hushen Risk Factors								
	TMV								
Alpha (All)	-0.0040*	-0.0003	-0.0018	-0.0015	0.0001	0.0028	0.0011	0.0005	0.0027
p-value	(0.0888)	(0.9174)	(0.5406)	(0.5192)	(0.9726)	(0.3420)	(0.7159)	(0.8731)	(0.2976)
Alpha (Procyclical)	-0.0108	-0.0085	-0.0123**	-0.0098	-0.0108*	0.0038	0.0083	-0.0002	0.0022
p-value	(0.1263)	(0.1479)	(0.0425)	(0.1107)	(0.0708)	(0.5262)	(0.1833)	(0.9637)	(0.6680)
Alpha (Countercyclical)	0.0034	0.0066	0.0064	0.0057	0.0089	-0.0029	-0.0102	-0.0021	-0.0034
p-value	(0.6281)	(0.2837)	(0.2818)	(0.3602)	(0.1464)	(0.6095)	(0.1054)	(0.6916)	(0.5732)
	MC								
Alpha (All)	-0.0047**	0.0011	-0.0017	0.0000	0.0007	0.0015	0.0025	0.0000	0.0003
p-value	(0.0297)	(0.7060)	(0.5478)	(0.9923)	(0.7947)	(0.6166)	(0.3604)	(0.9954)	(0.9238)
Alpha (Procyclical)	-0.0115*	-0.0070	-0.0123**	-0.0106*	-0.0111*	0.0022	0.0082	0.0005	0.0007
p-value	(0.0986)	(0.2308)	(0.0422)	(0.0862)	(0.0631)	(0.7175)	(0.1956)	(0.9241)	(0.8948)
Alpha (Countercyclical)	0.0047	0.0062	0.0064	0.0069	0.0094	-0.0037	-0.0091	-0.0034	-0.0068
p-value	(0.5101)	(0.3116)	(0.2756)	(0.2765)	(0.1223)	(0.5191)	(0.1583)	(0.5271)	(0.2906)
	Shenzhen Risk Factors								
	TMV								
Alpha (All)	-0.0035	0.0030	0.0008	0.0004	0.0015	0.0032	0.0009	0.0017	0.0015
p-value	(0.1510)	(0.3048)	(0.7909)	(0.8815)	(0.5713)	(0.2764)	(0.7863)	(0.5579)	(0.6093)

Appendix 4 (continued)

Alpha (Procyclical)	-0.0115	-0.0074	-0.0125**	-0.0111*	-0.0113*	0.0024	0.0066	-0.0014	0.0009
p-value	(0.1035)	(0.2170)	(0.0466)	(0.0753)	(0.0656)	(0.7070)	(0.2986)	(0.7807)	(0.8744)
Alpha (Countercyclical)	0.0027	0.0061	0.0059	0.0061	0.0079	-0.0019	-0.0079	-0.0010	-0.0012
p-value	(0.7019)	(0.3086)	(0.3145)	(0.3066)	(0.1775)	(0.7398)	(0.2159)	(0.8592)	(0.8429)
	MC								
Alpha (All)	-0.0037*	0.0007	0.0001	-0.0017	0.0010	0.0019	0.0015	0.0020	0.0021
p-value	(0.0958)	(0.7930)	(0.9647)	(0.4938)	(0.7288)	(0.5032)	(0.5962)	(0.5106)	(0.4876)
Alpha (Procyclical)	-0.0115	-0.0073	-0.0117*	-0.0113*	-0.0117*	0.0009	0.0071	-0.0001	0.0023
p-value	(0.1083)	(0.2341)	(0.0585)	(0.0728)	(0.0604)	(0.8871)	(0.2711)	(0.9822)	(0.6847)
Alpha (Countercyclical)	0.0043	0.0048	0.0062	0.0057	0.0071	-0.0045	-0.0100	-0.0021	-0.0037
p-value	(0.5431)	(0.4381)	(0.2918)	(0.3625)	(0.2313)	(0.4427)	(0.1192)	(0.6977)	(0.5627)