

2018 Doctoral Thesis

**The profitability effect in asset pricing model performance:
An empirical study on Chinese and Japanese equity market**

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Abstract

The question of what drives stock returns is perennial in modern finance. The *Fama-French-three-factor* model has been the benchmark to explain expected returns during the past two decades because the book-to-market ratio (a measure of value) and market capitalization (size) have strong explanatory power in empirical analysis. Value and size premium are always the most important factor in asset pricing model.

However, recently more and more papers question the *Fama-French-three-factor* model, (eg, Chen & Zhang (2010); Hou et al. (2015); Fama & French (2015)), because it has been difficult to explain the cross-sectional variation in expected returns recently, especially value factor which is a redundant factor on the US market (Fama & French (2015)). People hope to find new factors that replace size and value premium.

Profitability effects have attracted attention of researchers seeking to explain cross-sectional variations in stock returns. Researchers attend to profitability effects because they can be used to assess the quality of firms and investment decisions. Based on Novy-Marx (2013), gross profitability is associated with risk that cannot be captured by the value factor, the size factor. The profitability strategies belong to large growth strategies. In fact, the profitability strategy, despite generating significant returns on its own, loads strongly and negatively on the size and value factors. Highly gross profitable firms earn higher excess returns and significantly higher abnormal returns than those with lower gross profitability firms. That reveals gross profitability have possibility to replace size and value premium.

Most of the literature is based on the US stock market and limited on the Japanese and Chinese stock market. Due to political and cultural differences, each capital

market embraces different investment environment. Therefore, the price formation process and risk factors might be different. Hence, we try to provide additional evidence for the literature concerning the search for a better asset pricing model.

In the chapter 3, on the Japanese market, we follow Ball et al. (2015) to investigate and compare firms' gross profit, operating profit, and net income as predictors of returns for a cross-section of publically traded Japanese equities spanning 1994-2016. We test the predictive power of profit measures on cross-sectional stock returns using portfolio tests and Fama-MacBeth regressions, find that gross-profit-to-book-equity ratios significantly predict returns on sampled stocks. Consistent with Novy-Marx (2013), we also find that sorting portfolios by gross profitability and book-to-market ratios outperforms on the Japanese market. Hence, we create a *Market-Profitability-Value* model that captures value and profitability premium among returns of sampled stocks. Based on Gibbons-Ross-Shanken test and economic value, we demonstrate that our enhanced model outperforms Fama-French multiple-factor model in isolating influences on equity returns.

In the chapter 4, on the Chinese market, we follow Novy-Marx (2011, 2013) to investigate and compare firms' gross profit, operating leverage as predictors of returns for a cross-section of traded Chinese equities spanning 1996-2016. We use portfolio tests and Fama-MacBeth regressions, find that gross-profit-to-market-capitalization ratios significantly predict returns on sampled stocks. We also find that sorting portfolios by gross profitability and size outperforms on the Chinese market. Hence, we create a *Market-Size-Profitability* model that captures profitability and size premium among returns of sampled stocks. Based on Gibbons-Ross-Shanken test and economic value, we demonstrate that our enhanced model outperforms Fama-French multiple-factor model in isolating influences on equity returns.

The research contributes to the international literature on profitability effect. The evidence of Japanese and Chinese stock market also provides out-of-sample tests for the existing contradicting studies which mainly focus on US market.

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Chapter 1

Introduction

Chapter 1 includes a comprehensive introduction of the study. Section 1.1 describes the Research background. Section 1.2 is research problem statement. Section 1.3 explains research objectives. Section 1.4 introduces contributions of study. Section 1.5 presents the outline of the study.

1.1 Research background

The question of whether asset prices are predictable is as central as it is old. From Harry Markowitz model (1959) to *Fama-French-five-factor model* (2015). Until in the *AFA Annual 2018 Meeting* (most famous finance distinguished meeting), still have 1/3 papers focus on the topics (see Daniel et al. (2018)). A lot of researches have been done to trace the evidence of anomaly made by the effect of security returns.

People keen on researching asset pricing model, because they can put into use the evaluating mutual fund performance, measuring abnormal returns in event studies, estimating expected returns for portfolio choice, obtaining cost of equity estimates for capital budgeting, stock valuation and so on.

Fama-French-three-factor model has been popular in the last two decades, because the book-to-market ratio (value) and market capitalization (size) factors indeed have strong explanation power in empirical analysis. However, size and book-to-market ratio directly involve in market equity price information. Using price information

to explain price itself is full of controversy. Meanwhile, it is important to note that although *Fama-French-three-factor* models have been tested on the international markets, they show less explanatory power compared with the US evidence.

We believe that there are many anomalies affecting stock returns, and different regions have different asset pricing model to explain expected returns.

1.2 Research problem statement

There are several studies on the asset pricing impact on profitability.

Firstly, profitability has important impacts for real-world investment practices. For example, value investors such as Benjamin Graham, Warren Buffett mainly attend to profitability effects because they can be used to judge the quality of firms and investment decisions.

Secondly, size and value effect are losing their power in many empirical researches recently, while, profitability effect play important roles in generating the cross-sectional variation of expected returns. Novy-Marx (2013) shows that gross profitability is the other side of the value. Fama & French (2015), and Ball et al. (2015) reveal that profitability earns a high positive premium and helps to capture most asset-pricing anomalies that plague the *Fama-French-three-factor* model.

Thirdly, profitability premium provides an excellent hedge for the size and value premiums and expand the investor's investment opportunity. In addition, the forecasting power of profitability is economically and statistically strong compared to the well-known size, value and momentum effects.

We research profitability effect, and present a new framework that allows for multiple tests and derive recommended statistical significance levels for current research in asset pricing.

1.3 Research objective

There is ample literature focused on the profitability of stock returns especially in the developed markets. However, most of the literature is based on the US stock market and limited on the Japanese and Chinese stock markets.

China and Japan are ranked second and third, regarding GDP and stock market value in the world. The research for the two main markets are good supplement for asset pricing model theory. After all, these factors are just proved effective on the US market, which is lack of persuasion. Compared to US market, Chinese and Japanese equity markets' performance will give us more interesting stories. Meanwhile, we can also compare the differences between emerging markets and emerged markets.

1.4 Research motivation

Profitability effect is widely used in US since Novy-Marx (2011,2013) and Fama & French (2015) in the last few years. However, profitability is not directly observable, so there exists little supporting empirical evidence, especially in Japanese and Chinese equity markets. Hence, we try to provide additional evidence for the literature concerning the search for a better asset pricing model.

Firstly, to examine whether profitability factor is effective on the Japanese and Chinese stock markets. Secondly, to examine which profitability variable is a better proxy for predicting stock returns. Thirdly, to check whether the value factor and size factor are effective from the academic viewpoint. Fourthly, there is no unique factor model that explains stock returns. We try to add to profitability factor that explains stock returns well on the Japanese and Chinese market based on recent research on factor model.

1.5 Contribution of the study

The key concepts and major tasks of the dissertation are summarized as follows. The research contributes to the international literature on profitability effect. The evidence of Japanese and Chinese stock markets also provides out-of-sample tests for the existing contradicting studies which mainly focuses on US market.

Firstly, we test all kinds of profitability, operating leverage and other variables, which are not tested before on the Japanese and Chinese markets. We confirm the role of gross profitability. The research revealed gross profitability strong explained power.

Secondly, we are replacing the ineffective factors, such as book-to-market ratio (B/M) factor in China and size factor in Japan. We mirror the most famous three factor model, the *Fama-French-three-factor* model (1993) and *Hou-Xue-Zhang-factor* model (2015) and create local factor models on the Japanese and Chinese markets to explain returns respectively. The results prove that our enhanced *MKT-GP-B/M-factor* model outperforms in Japan and *MKT-Size-GP-factor* model outperforms in China.

Thirdly, we testified of the application of new factor model, using *MSCI* smart-beta index, including Large cap, Small cap, Minimum Volatility, High Dividend Yield, Risk Weighted, which can evaluate our enhanced factor model performance comprehensively. Our central contribution is to provide a new workhorse factor model for estimating expected returns.

1.6 Outline of the research

The thesis is as follows. Chapter 1 presents the introduction, the problem statement, and the motivation of the research. Chapter 2 presents an overview of the relevant literature. Chapter 3 discusses the Japanese stock market. Chapter 4 discusses the Chinese stock market. Chapter 5 summaries the major findings and implications, followed by the limitation of the research and recommendations for future research.

Chapter 2

Overview of the relevant literature

Chapter 2 includes a comprehensive theoretical and empirical literature review of the study. Section 2.1 discusses the CAPM theory. Section 2.2 reviews the evidence of factors in the prior study. Section 2.3 explains multifactor model theory. Section 2.4 introduces Japanese stock market and Chinese stock market. Section 2.5 presents the research methods used in the study. Section 2.6 explains calculation of factors. Section 2.7 explains *GRS* test. Section 2.8 provides a summary of the chapter 2.

2.1 The logic of the CAPM theory

The CAPM builds on the model of portfolio choice developed by Harry Markowitz (1959). In Markowitz's model, investors choose "mean-variance-efficient" portfolios, in the sense that the portfolios minimize the variance of portfolio return, given expected return, and maximize expected return, given variance. Thus, the Markowitz approach is often called a "mean-variance-model". Sharpe (1965) and Lintner (1965) add two key assumptions to the Markowitz model to identify a portfolio that must be mean-variance-efficient. That is The Capital Asset Pricing Model (CAPM).

The CAPM assumes that all investors have the same investing behaviour. Therefore, by aggregating utilities, a securities market line can be defined and an optimal investment portfolio can be determined. The CAPM is associated with two types of returns: risk free return of the government bonds and beta times the return on the market portfolio.

Tests of the CAPM are based on three implications of the relation between expected return and market beta implied by the model. Firstly, expected returns on all assets are linearly related to their betas, and no other variable has marginal explanatory power. Secondly, the beta premium is positive, meaning that the expected return on the market portfolio exceeds the expected return on assets whose returns are uncorrelated with the market return. Thirdly, in the Sharpe-Lintner version of the model, assets uncorrelated with the market have expected returns equal to the risk-free interest rate, and the beta premium is the expected market return minus the risk-free rate.

The formular is described as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + e_{it}. \quad (2.1)$$

If the markets are efficient and the Sharpe-Litner version of the CAPM is the correct model, then alpha should be zero. Statistical inference to test the hypothesis $\alpha = 0$ is the basis of many empirical tests of the validity of the CAPM. The theory of the CAPM is that it offers powerful and intuitively pleasing predictions about how to measure risk and the relation between expected return and risk.

Fama & MacBeth (1973) reveals that there is a positive cross-sectional relation between market risks and expected stock returns. The authors test the relationship between average return and risk in the New York Stock Exchange. Their result shows that the risk-return regressions are consistent with the “efficient capital market” hypothesis in which the prices of securities fully reflect the available information in the market.

However, Roll (1977) argued CAPM for two reasons. Firstly, the mean-variance efficiency of the market portfolio is equivalent to the CAPM equation where the stock’s unconditional α depends primarily on the covariance between its β and the market risk premium. This statement is a mathematical intuition and does not require model assumptions. Given a proxy for the market portfolio, testing the CAPM equation is equivalent to testing the mean-variance efficiency of the portfolio. Secondly, the validity of the CAPM is equivalent to the market being mean-variance efficient with respect to all the investment opportunities. Without looking into all

the investment opportunities, it is not possible to test whether the portfolio is mean-variance efficient. Therefore, it is not possible to test the CAPM.

Unfortunately, the empirical record of the model is also poor-poor enough to invalidate the way it is used in applications. The CAPM's empirical problems may reflect theoretical failings, the result of many simplifying assumptions.

2.2 Evidence of factors in the prior study

2.2.1 Market capitalization and value premium

Following this, many other researchers have found that the market beta alone cannot fully capture all the dimensions of risk such as the book to market effect and the size effect.

The size effect was first tested by Banz (1981) on the US stock market and both found a return premium on small market capital stocks. The size effect considers that market equity has significant marginal explanatory power on security returns. Blume & Stambaugh (1983) confirmed the size effects using US data with the size of the bias in daily returns on stocks of small firms which is sufficient to alter the conclusions about the size effect. The biases can arise in any study that forms equally weighted rebalanced portfolios and the biases can be greatly reduced by using returns implicit in a buy and hold strategy. Moreover, Hawawini & Keim (1995) research results showed a size effect in Japan and several European markets.

Rosenberg et al. (1985) was the first who discovered a positive relationship between a return premium on the US stock markets and the high ratio of a firm's book to market value. Since then, subsequent researchers such as Chan et al. (1991), K. Daniel & Titman (1997) have shown that the book to market effect does play an important role in explaining the cross sectional variation of the Japanese stock market.

2.2.2 Momentum effect

There are some other cross sectional explanatory variables used to test the relationship with the stock returns. The momentum effect is the empirically observed

tendency for rising asset prices to keep rising further and falling prices to keep falling. Jegadeesh & Titman (1993) showed that stocks with strong past performance continue to outperform stocks with poor past performance in the next period with an average excess return of about 1 % per month on US market.

Fama & French (2012) examined North America, Europe, Japan, and Asia Pacific market, indicated that the factors that lead to the momentum effect in the US are not prominent in the Asian markets including Japan.

2.2.3 Profitability effect

Regarding profitability effect, first, we should learn about how to cause the profitability effect. Inspired by valuation theory, Fama & French (2006) concludes that why these variables are related to average returns can be explained via the dividend discount model.

$$M_t = \sum_1^n E(D_{t+n})/(1+r)^n \quad (2.2)$$

The equation (2.2), M_t means market value of a share of stock, is expected dividend per share in period $t+n$, r is internal rate of return on dividends. Equation (2.2) says that if at time t the stocks of two firms have the same expected dividends but different prices, the stock with a lower price has a higher expected return.

$$M_t = \sum_1^n E(Y_{t+n} - dB_{t+n-1,t+n})/(1+r)^n \quad (2.3)$$

The equation (2.3), D_{t+n} can be rewrite as $Y_{t+n} - B_{t+n-1,t+n}$, Y_{t+n} is total equity earnings for period $t+n$, stands for expected profitability and $dB_{t+n} = B_{t+n} - B_{t+n-1}$ is the change in total book equity, stands fot expected investment. r is internal rate of return on dividend,stands for expected return.

The equation (2.4), dividing by time t book equity gives

$$\frac{M_t}{B_t} = \frac{\sum_1^n (Y_{t+n} - B_{t+n-1,t+n})/(1+r)^n}{B_t} \quad (2.4)$$

Firstly, fix everything in (2.4) except B_t/M_t and r , a higher book-to-market equity

ratio, B_t/M_t , implies a higher expected return. Then fix everything in (2.4) except Y_t/B_t , will have positive relationship with the expected stock return, we call Y_t/B_t as profitability. Then, fix everything in (2.4) except $dB_{t+n-1,t+n}/B_t$, will have negative relationship with the expected stock return. We call investment pattern.

Earnings in equation (2.4) represents a firm's true economic profitability. That is theory of size, book to market ratio, profitability effect and investment pattern effect.

Regarding profitability premium, we consider three types of profitability, that is gross profitability, operating profitability, and net income.

Fama & French (2008) find that gross profits-to-assets has far more power than earnings. However, predicting the cross section of returns. Novy-Marx (2013) concludes that gross profit scaled by book value of total assets outperforms other measures of profitability such as earnings, cash flows, and dividends. Gross profits-to-assets is another dimension of value. They find that profitability firms measured by gross profits-to-assets (sales minus cost of goods sold and scaled by total book assets) have historically generated significantly higher returns than firms having low profitability.

Regarding the operating profitability premium, Fama & French (2015) defines the measure of operating profitability, OP , as annual revenues minus the cost of goods sold, interest expense, selling, and general and administrative expenses during the previous fiscal year divided by the end book value of equity. Operating profitability has power predicting the cross section of returns.

Ball et al. (2015) also test profitability effect, but more refining. The analysis proceeds in two stages. Firstly, they re-evaluate whether gross profitability has greater predictive power than net income, also investigate the predictive power of operating profitability. They find that operating profitability explains the cross section of expected returns better than other commonly used measures. Secondly, they compare gross profitability effect, operating profitability effect, and net income effect by same denominator, like by book value of total assets, book equity and the market value of equity.

2.3 Multifactor model theory

Except Capital Asset Pricing Model (CAPM), there are several famous multifactor models. The *Fama-French-three-factor* model, *Carhart-four-factor* model, *Hou-Xue-Zhang-factor* model and *Fama-French-five-factor* model.

Fama & French (1992) were the first to prove that market beta cannot explain the cross-sectional variation of expected returns on US stocks using the non-financial stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ during the 1963-1990 periods. Further, *Fama-French-three-factor* model (1993) was created.

Chen & Zhang (2010) say that the market factor, an investment factor, and a return-on-assets factor summarize the cross-sectional variation of expected stock returns. The new three-factor model substantially outperforms traditional asset pricing models in explaining anomalies associated with short-term prior returns, financial distress, net stock issues, asset growth, earnings surprises, and valuation ratios. The model's performance, combined with its economic intuition based on q -theory, suggests that it can be used to obtain expected return estimates in practice. The new factor model outperforms traditional asset pricing models in explaining a wide range of anomalies in the cross-section of returns.

Also inspired by q -theory, Hou et al. (2015) proposed a four-factor model which includes a market factor, size factor, investment factor and a profitability factor. Research which applies data to test the performance of such models has shown that both models work well on the American share market.

Fama & French (2015) summarize these theories, add profitability and investment pattern to model, find that the five-factor model outperforms the three-factor model in explaining the cross section of stock returns.

2.4 Overview of the Japanese and Chinese stock markets

Japan is third of the world's largest economies and one of the most important financial hubs in Asia. The Japanese GDP growth rate in Japan averaged 0.50 % from 1980 until 2017, reaching a high of 3.20 % in the second quarter of 1990 and a record low of -4.90 % in the first quarter of 2009.

The Tokyo Stock Exchange (TSE) is the main stock exchange of the Japanese stock market. It is the world's third largest by market capitalization. The TSE trades through two primary indexes which are *Nikkei 225* and the *TOPIX*. Currently, there are four stock exchanges operating in other Japanese cities including Osaka, Nagoya, Fukuoka and Sapporo.

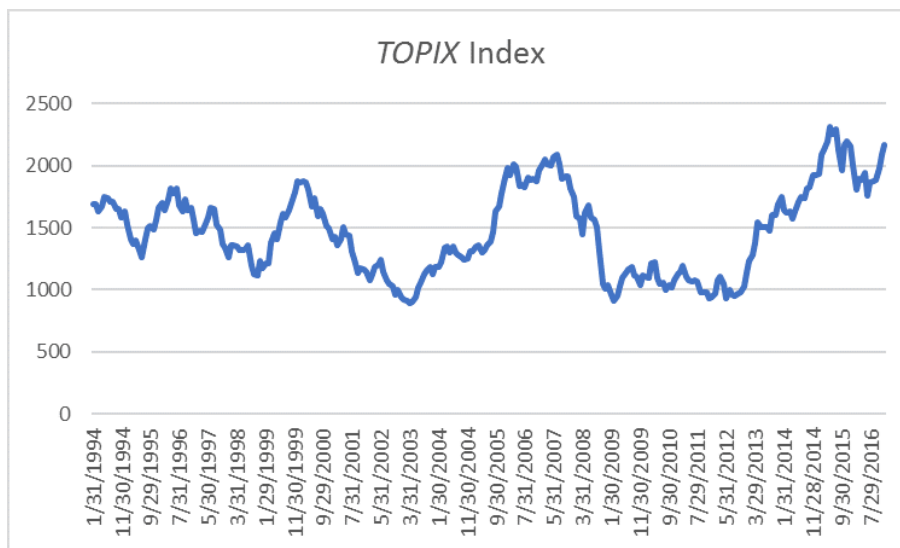


Figure 2.1: The *TOPIX* index fluctuation (1994-2016).

After experiencing last decade's intense reforms and development, Chinese market has increased significantly and is even comparable with that of US. The Gross Domestic Product (*GDP*) in China was worth 11199.15 USD Billions in 2016. The *GDP* value of China represents 18.06 % of the world economy. *GDP* in China averaged 1790.50 USD Billions from 1960 until 2016, reaching an all-time high of 11199.15 USD Billions in 2016 and a record low of 47.21 USD Billions in 1962.

Starting from ground zero in 1990, the Chinese stock market is one of the fastest growing markets of all times. China established Shanghai and Shenzhen Stock

Exchanges at the end of 1990. Starting with only eight stocks listed on Shanghai and six listed on Shenzhen, the number of stocks on the two exchanges rose to 311 by the end of 1995, 720 by 1997, 1,060 by 2000 and 2,868 by 2016. Combined the two exchanges together, the total market capitalization reached 57 trillion RMB (9 trillion USD) by the end of 2017, putting China in second place globally, only after the United States (from the World Federation of Exchanges monthly report of Dec 2017), even bigger than Japan.

There are three different types of shares in China's stock market: A, B and H shares. A shares are dominated in renminbi (RMB) and are open mostly to domestic investors. B shares, usually dominated in U.S. dollars on the Shanghai Stock Exchange and Hong Kong dollars on the Shenzhen Stock Exchange, are mainly for foreign investors. Domestic investors are restricted from investing abroad and foreign investors are also restricted from investing in the A-share market in mainland China.

Based on Professor Robert Schiller (winner of Nobel economic award in 2013), the market is significantly underestimated when the market capitalization is below 50% or less compared to the country's *GDP* scale. 50% to 75 % means somewhat underestimated, 75% to 90% means reasonable, over 90% is overvalued. From this point of view, Chinese equities are underestimated in the long term.

According to the World Bank database, China is 14.9% of global *GDP*, 11.7% of total exports (goods and services) and 10.0% of total imports (goods and services), but Chinese equities' weight in the *MSCI AC* World Index is only 2.3%. One possible reason for such under-representation of Chinese equities may be the restrictions in market accessibility for Chinese A-shares. From this point of view, Chinese equities are under-represented in the global equity market universe relative to its economic influence. The current opening up of Chinese A-share markets allows global investors to capture China's growth in a more direct and efficient manner.

Chinese stock market has its characteristics and attract our attention. Since the number of stocks is small and the statistical information of each issue is often cut off in the middle, the maintenance of the data is incomplete. This makes the detailed analysis on the Chinese stock market difficult. At the same time, on the

stock market, it is thought that there are many accounting information dressed up, there is a spread of speculative behavior, the rational institutional investors are few, and general investors in the secondary market occupy more than 70%. Because of these problems, the factors influencing the Chinese stock market may differ from the Western countries and the mature markets such as Japan.



Figure 2.2: Shanghai A-share index fluctuation 1996-2016.

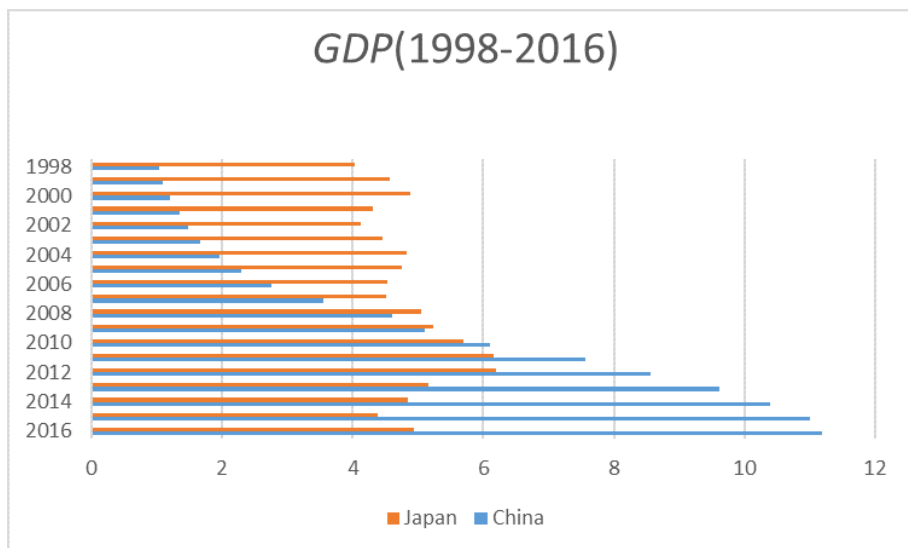


Figure 2.3: GDP growth rate in Japan and China 1998-2016.

2.5 Research methods used in the study

2.5.1 Single sorting

Following Novy-Marx (2013), five portfolios were formed every month, at the beginning of each month, based on profitability in order to test the relationship between the profitability and the expected stock return. All firms in the sample size were sorted based on profitability and divided equally into five groups. Portfolio 1 is the lowest fifth of all firms with the highest profitability, while portfolio 2 is the four fifth of all firms, etc. Portfolio 5 is the highest fifth of all firms with profitability. A portfolio of value weighted raw return will be computed.

2.5.2 Double sorting method

Following Fama & French (1993), the portfolios are formed to study the impact of asset pricing over the idiosyncratic risk and cross-sectional effects such as size, book to market, profitability. A portfolio strategy is the most common method used in asset pricing research because it is easy to analyze and interpret the stock returns.

First of all, we sort the stocks into 5 portfolios according to its characteristics (for example: size) in the previous month at the beginning of each month. Secondly, the stocks are sorted again into 5 portfolios according to the stocks IV within each stock portfolio control variable such as size. Thirdly, 25 stock portfolios are formed which accommodate the same amount of stocks. Besides that, value-weighted portfolio raw returns for the current month were computed.

For example, by using size as the control variable, the stocks are first sorted into 5 portfolios according to the stock's size. Therefore, the size 1 portfolio contains the first top 20 % stocks with the highest size; the size 2 portfolio contains the second top 20 % stocks, the size 3 portfolio contains the third top 20 % stocks, the size 4 portfolio contains the fourth top 20 % stocks, the size 5 portfolio contains the lowest 20 % of all stocks with low size values. After that, stocks are further sorted into 5 portfolios according to the stocks IV within each size portfolio. On the other hand, size-IV portfolios accommodate same amount of stocks. Finally, 25 portfolios were formed and can be identified as size 1-IV Low, size 1-IV 2, size 1-IV 3, size 1-IV

4, and size 1-IV-High, size 2-IV Low, size 2-IV2 and so on. This method was also appropriate for other control variables.

2.5.3 Fama-MacBeth-two-step regression

Fama & MacBeth (1973) propose a method for addressing the inference problem caused by correlation of the residuals in cross-section regressions. Instead of estimating a single cross-sectional regression of average monthly returns on beta. The Fama-MacBeth-two-step regression is a practical way of testing how these factors describe portfolio or asset returns. The goal is to find the premium from exposure to these factors. In the first step, each portfolio's return is regressed against one or more factor time series to determine how exposed it is to each one (factor exposures).

In the second step, the cross-section of portfolio returns is regressed against the factor exposures, at each time step, to give a time series of risk premia coefficients for each factor. The insight of Fama-MacBeth is to then average coefficients, once for each factor, to give the premium expected for a unit exposure to each risk factor over time.

Finally, we follow the same method to explicitly test whether these variables are priced risk factor using the simple rolling cross-sectional regression methodology.

2.6 Calculation of asset pricing model

Following Fama & French (2015), we calculate the following five asset pricing factors for each region: MKT (market factor), SMB (small minus big) factor, HML (high minus low) factor, RMW (robust minus weak) factor.

Regarding of calculations of SMB, HML, RMW, we firstly classify the largest market capitalization stocks as big stocks. All remaining stocks are classified as small stocks. Then, for the region's big stocks, we determine the usual 30 % (growth), middle 40 % (neutral), and the top 30 % (value) breakpoints for the B/M ratio and apply these breakpoints to big and small stocks. These classifications allow us to form the six value-weighted portfolios which we denote by SG , SN , SV , BG , BN , and BV where S and B refers to small and big, and G , N , and V indicate

growth, neutral, and value. SMB is the value-weighted average of the returns for the three small stock portfolios minus the average of returns for the three big stock portfolios. We construct value minus growth returns for small and big stocks, $HML_s = SV - SG$, $HML_b = BV - BG$, and HML is the value-weighted average of HML_s and HML_b .

The calculation of the RMW is identical to the calculation of the HML factor except that the second sort at time t is made not on the stock's B/M ratio but on the prior year's gross profitability. The intersection of the independent size and gross profitability sorts produces six value-weighted portfolios, SR , SN , SW , BR , BN and BW , where S and B indicate small or big, and R , N , and W indicate robust, neutral, and weak (top 30 %, middle 40 % and bottom 30 %, respectively). We form robust minus weak returns for small and big stocks, $RMW_s = SR - SW$ and $RMW_b = BR - BW$, and RMW is the value-weighted average of RMW_s and RMW_b .

2.7 GRS test

About evaluating model performance, Gibbons et al. (1989) propose the most widely used statistical test of empirical validity for asset-pricing models (GRS test). The null hypothesis (H_0) of the *GRS* test is that $a_i=0$ jointly for all i , while the alternative hypothesis (H_1) is that at least one a_i is non-zero. Under the assumption that the error term (e_i) is normally and independently distributed with zero means and nonsingular covariance matrix σ , the GRS test is a finite-sample F -test whose statistic is given by such analysis completely ignores the power of the test.

We assume that we test equation (2.1) using GRS test. The GRS Test is described as follows:

1. The GRS test is a statistical test of the hypothesis that $a_i = 0$.
2. Equivalently, it is a test that some linear combination of the factor portfolios is on the minimum variance boundary.
3. Equivalently, it is also a test that each factor portfolio is multifactor minimum variance.

Kim & Shamsuddin (2016) consider that proportion between the maximum sharpe ratio of the three factor portfolios and the slope of the efficient frontier based on all assets is an important index, which reflect economic importance. Although a perfectly efficient portfolio with the value of exactly and literally equal to one cannot exit in practice, the proportion the higher, the economic value is higher. We call the proportion as economic value.

In the other hand, Lewellen et al. (2010) critique the usual practice of using cross-sectional R^2 s and pricing errors to judge success and show that the explanatory power of many previously documented factors are spurious.

Overall, our work follow Gibbons et al. (1989), Kim & Shamsuddin (2016), and Lewellen et al. (2010), use GRS P value and economic value not cross-sectional R^2 , focuses on evaluating the statistical and economic significance of a factor.

2.8 Conclusion

This chapter presented the research methods used in the study which includes the single portfolios sorting, the double portfolios sorting and the Fama and Macbeth approach. The chapter also describes overview of Japanese and Chinese stock markets. Further, this study investigates book to market ratio, momentum size and profitability effect. And the detail empirical analysis will be presented in Chapter 3 and Chapter 4.

Chapter 3

Capturing profitability in asset pricing models for Japanese equities 1994-2016

This chapter discusses the Japanese equity market. Section 3.1 describes background. Section 3.2 is literature review. Section 3.3 describes the data collection process and the definitions of the control variables used in the study. Section 3.4 is empirical results. Section 3.5 discusses conclusions. Section 3.6 discusses Notes.

3.1 Introduction

Fama & French (2012), Fama & French (2017) say that Japanese market is always an exception compared to US, Europe, Asia pacific market. Like, the size premium is not so effective, but value premium is stronger than other markets.

In Japan, several studies have tested asset pricing model, from three-factor model to five-factor model. Many factors own strong theory base and have been proved effective on the US equity market, but not addressed on the existing literature on the Japanese equity markets. Actually, the *Fama-French-three-factor* model on the Japanese market is the main issue about its failure to capture size premium.

Based on Novy-Marx (2013), gross profitability is associated with risk that cannot be captured by the value factor and the size factor. That gives us courage to find

the new factors, making an appropriate asset pricing model on the Japanese market.

This study tests whether the profitability predicts expected excess market returns on the Japanese equity market. Also, this study determines which profitability proxy performs best on the Japanese equity market. Our results are robust to alternative factor definitions, proxies for profitability. We confirm that gross-profit-to-book-equity is a superior proxy for predicting equity returns. Our results endorse those of Novy-Marx (2013) and support existence of a gross profitability premium for Japanese equities. In addition, we mirror *Fama-French-three-factor* and five-factor models, delete the redundant factor, and create a *Market-Profitability-Value (MKT-RMW-HML)* model to explain expected returns on Japanese equities.

3.2 Literature review

This study originates with Novy-Marx (2013), who shows that gross profitability relates significantly to equity returns after controlling for book-to-market ratio. Profitability earns a high positive premium and helps to capture most asset-pricing anomalies that plague the *Fama-French-three-factor* model. Fama & French (2015) add operating profitability to create a five-factor model that outperforms their three-factor model in explaining cross-sections of equity returns. Ball et al. (2015), Ball et al. (2016) present a more refined test for profitability effects. Firstly, they re-evaluate whether gross profitability has greater predictive power over returns than net income and operating profitability. Secondly, they compare the effects of gross profitability, operating profitability, and net income using identical denominators (book value of total assets, book equity, and market capitalization).

These literatures on the Japanese equities are as follows. Firstly, retesting *Fama-French-five-factor* model by examining years of monthly data for shares on the first and second sections of the Tokyo Equity Exchange (*TSE*), Kubota & Takehara (2018) find that operating profitability is not a statistically significant predictor of Japanese equity returns. Maeda (2017) tests *q-factor* (Note 1) model (market, profitability, and investment), finds that profitability (net income) is not a significant predictor of returns on Japanese equities. These studies, however, merely

retest whether an asset-pricing model is appropriate for the Japanese market. By ignoring profitability effects, their conclusions lack force. This study resolves this deficiency in earlier literature. In order to provide comprehensive characterization about profitability and ensure robustness, we employ three different measures for profitability, including gross profitability (GP), operating profitability (OP) and net income (NP). We characterize firms' profits comprehensively using gross profit, operating profit, and net income to assure robustness in predicting equity returns.

3.3 Data and variable

Financial statement data are from the FactSet database (Note 2). Financial statements are disclosed by Japanese firms following Japanese *GAAP* (Generally accepted accounting principles). Empirical research covers Japanese equities listed on the first section of the Tokyo Stock Exchange (*TSE*). Financial firms (industry codes: 7050, 7010, 7100, and 7150) are excluded for their distinctive high-leverage/low-equity capital structures. We also exclude firms with negative book value of equity to get rid of financial distressed firms. Our samples covered 834 companies in 1994, and, adjusted yearly, reached 1,658 in 2016. The observation period was from August 1994 to March 2016. We use software SAS 9.2 to do the following data processing.

We use monthly return series to measure stock return, portfolio returns, use monthly market capitalization and annual frequency data for financial statement data. For the risk free interest rate, the monthly average of the overnight call-money rate without collateral as reported by Bank of Japan.

To construct factors that might influence equity returns, we assemble annual financial statement data for sales ($SALE$), cost of goods sold ($COGS$), sales-general-administrative expenses (SGA), book value of total assets (AT), and book equity (BE) measured as AT minus total liabilities (LT). We measure investment patterns (INV) as changes in total assets (AT) every year. $\text{Log}(ME)$ is the log of market capitalization. B/M indicates the book-to-market ratio (BE/ME). Gross profit (GP) is $SALE$ minus $COGS$. Operating profit (OP) is $SALE$ minus $COGS$ and SGA . Bottom-line profit (NP) is net income.

GP (Gross Profitability) equals (Gross Profits)/(Book Equity or Total Assets or market value).

OP (Operating Profitability) equals (Operating Profits)/(Book Equity or Total Assets or market value).

NP (Net income) equals (Net income)/(Book Equity or Total Assets or market value).

$Log(ME)$ equals \log (Market capitalization).

B/M equals Book Equity/Market capitalization.

INV equals $(Assets(t) - Assets(t-1))/Total\ Assets$.

3.4 Methods and empirical results

3.4.1 Fama-MacBeth univariate regressions on measures of profitability

We use monthly Fama and MacBeth regressions to examine whether profitability convincingly forecasts stock returns. The goal is to find the premium from exposure to these factors. In the first step, the cross-section of portfolio returns is regressed against the factor exposures, at each time step, rolling regression, to give a time series of risk premia coefficients for each factor. In the second step, collect all the risk premia coefficients, to average these coefficients, calculate t value.

Table 3.1 shows regressed monthly returns of individual stocks on lagged profitability. We focus on t -values to compare the explanatory power of measures of profitability.

Deflating by total assets, GP , OP , and NP have no significant predicting power, while deflating by book equity, GP and NP have significant predicting power.

Deflating by market capitalization, GP and OP also have power in predicting return significant. Note, however, we admit that a market capitalization-based measure conflates a productivity proxy with B/M ratios. Hence, based on empirical tests for the sampled equities, we choose profit deflated by book equity as a proxy variable.

3.4.2 Fama-MacBeth multivariate regression

Controlling for other important determinants of stock returns. In this subsection, we utilize the monthly Fama and MacBeth (1973) cross-sectional regressions to further examine the forecasting ability of profitability to predict future stock returns. We regress monthly stock returns of individual stocks on lagged profitability (measured by GP , OP and NP) for each month over 1994:08-2016:03.

Table 3.2 reports model (1)-(3) specifications for multivariate regressions including controls for book-to-market ratio (B/M), size ($\log(ME)$), and INV (investment patterns). When controlled accordingly, the B/M is strong for the sampled equities. We reconfirm the existence of strong value effects among Japanese equities per Kubota & Takehara (2007), Kubota & Takehara (2018). The size premium sheds predictive power. Investment patterns show no effect on returns of sampled equities, consistent with Kubota & Takehara (2018) and unlike US equities.

GP exhibits significant power to predict returns, whereas the predictive power of OP is not significant. Results show NP has negative power to explain returns, however, motivated by valuation theory, Fama & French (2006) explore the positive relation between profitability and expected returns. Hence, we abandon net income as an investigative variable.

Based on Fama-MacBeth cross-sectional regressions, gross-profit-to-book-equity exerts the most significant power over expected returns alone or when controlled for size, B/M , and INV . Novy-Marx (2013) concludes that gross profit is the cleanest accounting measure of true economic profitability and therefore outperforms other measures of profitability. Items farther down the income statement are more attenuated measures of profitability and less cogent with respect to true economic profitability.

3.4.3 Sorts on profitability

We perform portfolio tests as a more predictive exercise that escapes bias of Fama-MacBeth regressions. We compare results of gross-profit-to-book-equity, and operating-profit-to-book-equity for the sampled equities.

Specifically, at the beginning of each month, we form five deciles portfolios based

on the ranked values of profitability computed with the most recently announced annually earnings, measured by gross profitability.

Earnings data in Factset financial statements files are used in the months immediately after the most recent public annually earnings announcement dates. Following Hou et al. (2015), to avoid look-ahead bias as well as ensure the accounting information of firms has been publicly known when we use it, we allow for a 5-month lag between stock returns and accounting variables.

The monthly value-weighted returns of these profitability deciles are calculated for the current month, and the portfolios are rebalanced monthly.

Particularly, decile 1 refers to firms in the lowest profitability decile, and decile 5 refers to firms in the highest profitability decile. The ‘ High-Low ’ profitability spread portfolio is computed as long the highest profitability decile and short the lowest decile. We then compute the abnormal returns of the profitability deciles using the *Fama-French-three-factor* model, and examine whether standard risk factors could explain the positive profitability-return relationship. The *Fama-French-three-factor* model includes the market factor (MKT), the size factor (small minus big, SMB), which is the difference between the return on small and big-capitalization firms, and the value factor (high minus low, HML), which is the difference between the return on high and low book-to-market value firms. These monthly factor returns are extracted from Factset Financial Research Database.

Table 3.3 documents that the monthly average abnormal returns (*Fama-French-three-factor* , in percentage) of the single sorts on gross profitability, and their corresponding t-statistics (in squared brackets) from regressing the time series of excess returns of the double sorts on the Fama-French (1993) three-factors over 1994:08-2016:03 sample period.

In the *GP* formulation, sorting portfolios’ average excess returns are generally increasing with *GP*. for the *Fama-French-three-factor* model increase with *GP*, although not monotonically. The high-minus-low quintile portfolio earns a statistically insignificant average excess return of 10 basis points per month (t -value = 0.56). Alpha for the three-factor model is 26 basis points per month (t -value = 1.41). Loading for *HML* is negative significant. That reveals high gross-profit-to-

book-equity portfolio generates more excess returns, meanwhile there exists negative relation between GP and B/M ratio.

In the OP formulation, in contrast with GP , the high-minus-low quintile portfolio does not spread excess returns (see **Table 3.4**). In fact, comparison reveals that a strategy of pursuing gross profitability generates more excess returns than pursuing operating profitability.

3.4.4 Construction of mimicking factors

We find that gross profitability is negatively correlated with book-to-market ratio. That reveals the profitability strategy is a growth strategy, and it provides a great hedge for value strategies. We can explore the performance of portfolios double-sorted by profitability and B/M ratio to generate more excess return.

For comparison, we sort $GP-B/M$ portfolios, $OP-B/M$ portfolios, $Size-GP$ portfolios, and $Size-OP$ portfolios for the sampled equities. Average excess portfolio returns appear.

Portfolios are rebalanced monthly and formed by performing independent double sorts on book-to-market ratio and profitability. Specifically, at the beginning of each month, we independently sort firms into five B/M groups (growth to value) using the 20th, 40th, 60th, and 80th B/M percentiles and five profitability quintiles based on GP , OP . Separately, using the most recently announced annually accounting information. We compute the monthly value-weighted abnormal returns of these 25 ($5*5$) $GP-B/M$, and ($5*5$) $OP-B/M$ portfolios.

In the $GP-B/M$ formulation in **Table 3.5**, except in row 1, GP and average return are positively related in all remaining rows. R-W portfolios (gross profitability premium) in rows 3 and 5 are significant. Value premium is evident in columns 2 through 5. Large value and robust profitability portfolios perform best with 1.37% monthly returns. We confirm that controlling for GP improves performance of value strategies and controlling for B/M ratio improves performance of profitability strategies.

In the $OP-B/M$ formulation in **Table 3.6**, the R-W portfolio (operating profitability premium) is positive in rows 2, 4, 5. However, only in row 2 is significant.

Value premium is effective in columns 2 through 4. Overall, *GP* quintiles outperform *OP* quintiles.

Portfolios are rebalanced monthly and formed by performing independent double sorts on size and profitability. Specifically, at the beginning of each month, we independently sort firms into five size groups (small to big) using the 20th, 40th, 60th, and 80th size percentiles and five profitability quintiles based on *GP*, *OP*. Separately, using the most recently announced annually accounting information. We hold these portfolios for one month, and compute the monthly value-weighted abnormal returns of these 25 (5*5) *Size-GP*, and (5*5) *Size-OP* portfolios.

In the *Size-GP* formulation in **Table 3.7**, holding *GP* roughly constant, average return typically falls as size increases. Only the S-B portfolio (size premium) in column 4 is significant. Holding size roughly constant, average return typically increases with *GP*, but R-W portfolios (gross profitability premium) are not significant. That finding reveals *Size-GP* sorting underperforms *GP-B/M* sorting.

In the *Size-OP* formulation in **Table 3.8**, holding *OP* roughly constant, average return typically falls as size increases. Only the S-B portfolio (size premium) in column 4 is significant. Holding size roughly constant, average return typically increases with profitability. No R-W portfolio (operating profitability premium) is significant. That finding reveals *Size-OP* sorting underperforms *OP-B/M* sorting.

Overall, value quintiles outperform size quintiles. Sorting of *GP* and *B/M* portfolios outperform among the sampled equities.

3.4.5 Summary of factor model

The *Fama-French-three-factor* model is an empirical asset pricing model. The *Fama-French-three-factor* model is designed to capture the relation between average return and size and the relation between average return and price ratios like the book-to-market ratio, which were the two well-known patterns in average returns. The model's regression equation is

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_iSMB_t + h_iHML_t + e_{it}. \quad (3.1)$$

In this equation, R_{it} is the return on security or portfolio i for period t , R_{ft} is the risk free return, R_{mt} is the return on the value-weighted (VW) market portfolio of all samples, SMB_t is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML_t is the difference between the returns on diversified portfolios of high and low B/M stocks, and e_{it} is a zero-mean residual. The three factor model says that the sensitivities β_i , s_i , and h_i to the portfolio returns capture all variation in expected returns, so the expected value of the intercept α_i is zero for all securities and portfolios i .

We eliminate redundant factors to boost the model's explanatory power. Based on Fama-MacBeth regressions and tests of combination portfolios, we define two main factor premiums: HML (high minus low B/M) and RMW (robust minus weak GP). New factor model is

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + r_iRMW_t + h_iHML_t + e_{it}. \quad (3.2)$$

In this equation, R_{it} is the return on security or portfolio i for period t , R_{ft} is the riskfree return, R_{mt} is the return on the value-weighted (VW) market portfolio, RMW_t is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML_t is the difference between the returns on diversified portfolios of high and low B/M stocks, and e_{it} is a zero-mean residual. The sensitivities β_i , r_i , and h_i to the portfolio returns capture all variation in expected returns, so the expected value of the intercept α_i is zero for all securities and portfolios i .

We suggest a way to interpret the zero-intercept hypothesis, the factors are just diversified portfolios that provide different combinations of exposures to the unknown state variables. And, along with the market portfolio and the risk free asset, the factor portfolios span the relevant multifactor efficient set. In this scenario, the role of the valuation equation (2.3) is to suggest factors with risk premiums that allow us to capture the expected return effects of state variables without naming them.

To construct factor, we sort independently to assign stocks to two size groups, three B/M groups, and three profitability groups (GP). The size breakpoint is

median market cap. B/M or GP breakpoints are the 30th and 70th percentiles. MKT ($R_m - R_f$) is the value-weighted return on the market portfolio of all sampled stocks minus the risk-free rate. SMB is the return on a diversified portfolio of small-cap stocks minus the return on a diversified portfolio of big-cap stocks. HML is the difference between returns on diversified portfolios of high and low B/M stocks. In addition, RMW_{GP} is the difference between returns on diversified portfolios of stocks with robust and weak gross profitability.

In **Table 3.9**, the 2*3 sorts used to construct RMW and HML to produce two size factors SMB , we call SMB_{GP} and $SMB_{B/M}$. Equivalently, we consider that SMB is the average of the returns on the six small stock portfolios minus the average of the returns on the six big stock portfolios.

3.4.6 Evaluating model performance

If a characteristic is significant in cross-sectional regressions, we hypothesized that its factor will be significant in time-series regressions. Hence, we created a new model $MKT-RMW(GP)-HML$ model for the sampled equities and compared time-series regressions with the *Fama-French-three-factor* model.

About evaluating model performance, we use GRS test. Meanwhile, we follow Kim & Shamsuddin (2016), add to economic value to evaluate model performance.

About GRS test, the detail is as follows. For example, if we are testing the Fama-French-three-factor model, equation 3.1.

Step 1, we would run time series regressions for all test portfolios, like 5*5 $GP-B/M$ portfolios.

Step 2, form the estimated intercepts into a 25*1 vector (α).

$$\hat{\alpha} = \begin{bmatrix} \hat{\alpha}_1 \\ \vdots \\ \hat{\alpha}_{25} \end{bmatrix} \quad (3.3)$$

Step 3, calculate the residual for each regression, form the residuals into a T*N (260*25) matrix (note, T = total number of time period, N = Number of portfolios, L = Number of factors in the model).

$$e_{it} = R_{it} - R_{ft} - \alpha_i - \beta_i(R_{mt} - R_{ft}) - s_iSMB_t - h_iHML_t. \quad (3.4)$$

Step 4, compute an unbiased estimate of the covariance matrix of residuals,

$$\hat{\Sigma} = \hat{\varepsilon}'\hat{\varepsilon} / (T-N-1), \hat{\Sigma} \text{ is } N \times N \text{ matrix.}$$

Step 5, calculate the sample means of the factor portfolios and form a $L \times 1$ vector of sample means, L stands for numbers of factors.

$$\bar{\mu} = \begin{bmatrix} \bar{F}_1 \\ \vdots \\ \bar{F}_L \end{bmatrix}$$

Step 6, form the factor portfolio (excess) returns into a $T \times N$ matrix

$$F = \begin{bmatrix} F_{11} & F_{12} & \cdots & F_{1N} \\ F_{21} & F_{22} & \cdots & F_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ F_{T1} & F_{T2} & \cdots & F_{TN} \end{bmatrix}$$

Step 7, compute an unbiased estimate of the covariance matrix of the factors (the dimension of the covariance matrix is $N \times N$).

$$\hat{\Omega} = \frac{(F - \hat{F})'(F - \hat{F})}{T - 1}$$

where,

$$\hat{F} = \begin{bmatrix} \hat{F}_1 & \hat{F}_2 & \cdots & \hat{F}_N \\ \hat{F}_1 & \hat{F}_2 & \cdots & \hat{F}_N \\ \vdots & \vdots & \ddots & \vdots \\ \hat{F}_1 & \hat{F}_2 & \cdots & \hat{F}_N \end{bmatrix}$$

Step 8, compute the GRS statistic.

$$\left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{\mu}'\hat{\Omega}^{-1}\bar{\mu}}\right] \sim F(N, T-N-L)$$

where,

1. $\hat{\alpha}$ is a $N \times 1$ vector of estimated intercepts.
2. $\hat{\Sigma}$ is an unbiased estimate of the residual covariance matrix.
3. $\bar{\mu}$ is a $L \times 1$ vector of the factor portfolios' sample means.
4. $\hat{\Omega}$ is an unbiased estimate of the factor portfolios' covariance matrix.

if $\alpha_i = 0$, then the GRS statistic equals zero; the larger the α s are in absolute value the greater the GRS statistic will be.

The test models include a *Fama-French-three-factor* model and our *MKT-RMW(GP)-HML* factor model. The test samples include *GP-B/M* portfolios, *OP-B/M* portfolios, *Size-GP* portfolios, *Size-OP* portfolios, and *Size-B/M* portfolios.

Through the **Table 3.10**, for GRS P value, except 5×5 *Size-B/M* sorting portfolios, our *MKT-RMW(GP)-HML* factor model outperforms the *Fama-French-three-factor* model. For economic value, our *MKT-RMW(GP)-HML* model always provides optimum. Overall, we show our *MKT-RMW(GP)-HML* model outperforms both the statistical and economic significance for the sampled equities.

3.5 Conclusion

McLean & Pontiff (2016) argue that some stock market anomalies are less anomalous after being published. Repeatedly cited size and value factors naturally are less anomalous over time. That also impels us to seek new effective factors and new-factor models. Our conclusions are as follows.

We find that gross profitability surpasses operating profitability and net income in power to predict returns on the sampled equities. This finding explains why Kubota & Takehara (2018)) and Maeda (2017) say profitability is not a significant factor in the Japanese equity market: they choose a flawed proxy for profitability.

As a measure of profitability, gross-profit-to-book-equity explains the sampled cross-section of expected returns better than operating profitability and net income.

We extend Novy-Marx’s intuition about focusing on gross profitability rather than current revenue and construct a measure of gross profit with a stronger link to expected returns on Japanese equities.

Size premium for the sampled equities shed predictive power over time and become redundant. Value premium remains strong among our sampled equities. Hence, we created a new *MKT-RMW(GP)-HML* factor model and investigated the applicability of a *Fama-French-three-factor* model on our sampled equities. Tests reveal that the model featuring gross profitability outperforms the *Fama-French-three-factor* model.

3.6 Note(s)

Note1. *q-factor*, based on *q-theory* (Tobin (1969)) predicts that investment frictions steepen the relation between expected returns and firm investment.

Note 2. FactSet integrates third-party data for 16,000+ active companies. It provides financial information and analytical applications to global buy and sell-side professionals. FactSet is popular among Japanese financial analysts and portfolio managers and the world’s third-largest provider of financial data behind Bloomberg and Thomson Reuters.

Note 3. We use Kim and Shamsuddin (2016) R package to do the GRS test.
Package: GRS.test.

Title: GRS Test for Portfolio Efficiency and Its Statistical Power .

Version: 1.0.

Date: 2016-09-11.

Author: Jae H. Kim.

Description: Computational resources for test proposed by Gibbons, Ross, Shanken (1989) (DOI:10.2307/1913625).

The GRS test code will be published in Appendix B.

Table 3.1: Fama-MacBeth univariate regressions of firm returns 1994-2016.

| variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|--------------|----------------------|---------|---------|---------------------|---------|---------|--------------------|--------|---------|
| | Sort by total assets | | | Sort by book equity | | | Sort by market cap | | |
| <i>GP</i> | 0.45 | | | 0.1 | | | 0.47 | | |
| (<i>t</i>) | (0.99) | | | (2.09) | | | (3.62) | | |
| <i>OP</i> | | -0.52 | | | -0.24 | | | 1.18 | |
| (<i>t</i>) | | (-0.25) | | | (-0.83) | | | (2.71) | |
| <i>NP</i> | | | -1.57 | | | -0.62 | | | -0.02 |
| (<i>t</i>) | | | (-0.58) | | | (-2.13) | | | (-0.03) |

To assess profitability as a predictive measure we focus on its numerator. Deflating *GP*, *OP*, and *NP* individually by total asset (1-3), book equity (4-6), and market capitalization (7-9), respectively.

Slope coefficients (*100) β and (*t*-statistics) from regressions are shown. Numbers in parentheses (.) are *t* test statistics, which is adjusted by white (1980) adjust. *t*-statistics are based on the time-series variability of slope estimates, incorporating a white adjust for possible autocorrelation and heteroscedasticity in the slopes.

Fiscal year-end for more than 90% of firms in the *TSE* first section is March 31. Accordingly, sampled firms were sorted at the end of August each year, five months after fiscal year-end, to assure public availability. We estimate regressions monthly spanning August 1994 to March 2016. Following Novy-Marx (2013), (*GP*) is computed with the most recently announced annually firm's gross profit (calculated by revenue minus cost of goods sold (*COGS*) both in annual *t*). Following Fama and French (2015), we define the measure of operating profitability, (*OP*), as annual revenues minus the cost of goods sold, selling, and general and administrative expenses. (*NP*) is net income.

Table 3.2: Fama-MacBeth multivariate regressions of firm returns 1994-2016.

| variables | Model (1) | Model (2) | Model (3) |
|-----------------|-----------|-----------|-----------|
| <i>GP</i> | 0.19 | | |
| (<i>t</i>) | (3.98) | | |
| <i>OP</i> | | 0.15 | |
| (<i>t</i>) | | (0.59) | |
| <i>NP</i> | | | -0.51 |
| (<i>t</i>) | | | (-1.99) |
| <i>INV</i> | 0.37 | 0.26 | 0.48 |
| (<i>t</i>) | (1.03) | (0.7) | (1.37) |
| <i>B/M</i> | 0.43 | 0.37 | 0.38 |
| (<i>t</i>) | (3.53) | (3.24) | (3.36) |
| <i>Log (ME)</i> | -0.02 | -0.05 | -0.04 |
| (<i>t</i>) | (-0.34) | (-0.73) | (-0.63) |

When other variables are controlled, like *INV*, *B/M*, and *Log(ME)*, we compare *GP* (Model 1), *OP* (Model 2), and *NP* (Model 3) effect respectively. Multivariate slope coefficients (*100) β s and (*t*-statistics) from regressions are shown. Numbers in parentheses (.) are t test statistics, which is adjusted by white adjust. *t*-statistics are based on the time-series variability of slope estimates, incorporating a white adjust for possible autocorrelation and heteroscedasticity in the slopes.

Fiscal year-end for more than 90% of firms in the *TSE* first section is March 31. Accordingly, sampled firms were sorted at the end of August each year, five months after fiscal year-end, to assure public availability. We estimate regressions monthly spanning August 1994 to March 2016. Following Novy-Marx (2013), (*GP*) is computed with the most recently announced annually firm's gross profit (calculated by revenue minus cost of goods sold (*COGS*) both in annual *t*). Following Fama & French (2015), we define the measure of operating profitability, (*OP*), as annual revenues minus the cost of goods sold, selling, and general and administrative expenses. (*NP*) is net income. *LOG(ME)* is the log of market capitalization (*ME*). The *B/M* variable is defined as the book value of common equity at the end of previous fiscal year (year $t-1$) divided by the market capitalization by the end of month $t-1$. *INV* is the change in the book value of total assets from the beginning to the end of the previous period divided by the previous end book value of total assets.

Table 3.3: Sorts on gross profitability 1994-2016.

| Portfolio | Sort by gross profit / book equity | | | | |
|--------------|------------------------------------|---|---------|---------|---------|
| | Excess return | Fama-French-three-factor model α | SMB | HML | MKT |
| 1 (low) | 0.13 | -0.03 | 0.07 | 0.02 | 1.00 |
| (<i>t</i>) | (0.39) | (-0.27) | (2.07) | (0.63) | (44.47) |
| 2 | 0.14 | -0.10 | -0.07 | 0.10 | 0.96 |
| (<i>t</i>) | (0.42) | (-1.06) | (-2.48) | (3.28) | (52.98) |
| 3 | 0.17 | 0.01 | 0.02 | 0.02 | 0.93 |
| (<i>t</i>) | (0.55) | (0.11) | (0.77) | (0.81) | (57.55) |
| 4 | 0.09 | -0.23 | 0.04 | 0.22 | 1.00 |
| (<i>t</i>) | (0.27) | (-2.78) | (1.83) | (8.39) | (63.43) |
| 5 | 0.24 | 0.23 | 0.06 | -0.19 | 1.08 |
| (<i>t</i>) | (0.64) | (2.06) | (1.97) | (-5.67) | (52.24) |
| High-Low | 0.10 | 0.26 | -0.01 | -0.22 | 0.08 |
| (<i>t</i>) | (0.56) | (1.41) | (-0.17) | (-3.81) | (2.34) |

The table reports value-weighted excess returns and *Fama-French-three-factor* model α and MKT, SMB and HML loadings. We sort stocks into deciles based on *TSE* first section breakpoints at the end of each March and hold the portfolio for the August. Our sample period starts in August 1994 and ends in March 2016. The monthly value-weighted returns of these profitability deciles are calculated and the portfolios are rebalanced monthly.

Earnings data in Factset financial statements files are used in the months immediately after the most recent public annually earnings announcement dates. Following Hou et al. (2015) to avoid look-ahead bias as well as ensure the accounting information of firms has been publicly known when we use it, we allow for a minimum 5-month lag between stock returns and accounting variables. Specifically, at the beginning of each month, we form five deciles portfolios based on the ranked values of profitability computed with the most recently announced annually earnings and hold for one month, measured by gross profitability.

Particularly, decile 1 refers to firms in the lowest profitability decile, and decile 5 refers to firms in the highest profitability decile. The ' High-Low ' profitability spread portfolio is computed as long the highest profitability decile and short the lowest decile. Numbers in parentheses (.) are *t* test statistics.

Table 3.4: Sorts on operating profitability 1994-2016.

| Portfolio | Sort by operating profit / book equity | | | | |
|--------------|--|---|---------|---------|---------|
| | Excess return | Fama-French-three-factor model α | SMB | HML | MKT |
| 1 (low) | 0.23 | -0.07 | 0.47 | 0.25 | 1.11 |
| (<i>t</i>) | (0.58) | (-0.39) | (9.7) | (4.72) | (34.19) |
| 2 | 0.21 | -0.01 | 0.03 | 0.07 | 1.03 |
| (<i>t</i>) | (0.58) | (-0.06) | (0.86) | (1.73) | (39.4) |
| 3 | 0.10 | -0.13 | -0.04 | 0.10 | 0.95 |
| (<i>t</i>) | (0.32) | (-1.38) | (-1.5) | (3.35) | (53.36) |
| 4 | 0.15 | -0.07 | -0.05 | 0.10 | 0.91 |
| (<i>t</i>) | (0.5) | (-0.84) | (-1.81) | (3.55) | (54.55) |
| 5 | 0.16 | 0.15 | 0.00 | -0.19 | 1.06 |
| (<i>t</i>) | (0.45) | (1.38) | (0.15) | (-5.89) | (52.78) |
| High-Low | -0.07 | 0.22 | -0.47 | -0.45 | -0.06 |
| (<i>t</i>) | (-0.26) | (0.89) | (-6.87) | (-5.97) | (-1.25) |

The table reports value-weighted excess returns and *Fama-French-three-factor* model α and MKT, SMB, HML loadings. We sort stocks into deciles based on *TSE* first section breakpoints at the end of each March and hold the portfolio for the August. Our sample period starts in August 1994 and ends in March 2016. The monthly value-weighted returns of these profitability deciles are calculated, and the portfolios are rebalanced monthly.

Earnings data in Factset financial statements files are used in the months immediately after the most recent public annually earnings announcement dates. Following Hou et al. (2015), to avoid look-ahead bias as well as ensure the accounting information of firms has been publicly known when we use it, we allow for a minimum 5-month lag between stock returns and accounting variables. Specifically, at the beginning of each month, we form five deciles portfolios based on the ranked values of profitability computed with the most recently announced annually earnings and hold for one month, measured by operating profitability.

Particularly, decile 1 refers to firms in the lowest profitability decile, and decile 5 refers to firms in the highest profitability decile. The ‘ High-Low ’ profitability spread portfolio is computed as long the highest profitability decile and short the lowest decile. Numbers in parentheses (.) are *t* test statistics.

Table 3.5: Panel A-1. Double sort by GP and B/M .

| A-1 B/M | Weak | 2 | 3 | 4 | Robust | R-W | (t) |
|------------|--------|--------|--------------|--------|--------|-------|---------|
| | | | GP quintiles | | | | |
| Low | 0.16 | -0.04 | -0.04 | -0.19 | 0.04 | -0.13 | (-0.42) |
| 2 | -0.03 | 0.02 | 0.18 | 0.16 | 0.47 | 0.50 | (2.23) |
| 3 | 0.13 | 0.18 | 0.33 | 0.50 | 0.82 | 0.69 | (2.73) |
| 4 | 0.39 | 0.49 | 0.70 | 0.73 | 0.88 | 0.49 | (1.89) |
| High | 0.55 | 1.04 | 1.10 | 1.17 | 1.37 | 0.82 | (2.41) |
| H-L | 0.39 | 1.09 | 1.14 | 1.36 | 1.33 | | |
| (t) | (0.82) | (2.62) | (3.12) | (3.55) | (2.57) | | |

Panel A-1 shows average excess returns for 25 value-weighted (VW) portfolios, from independent (5*5 GP-B/M sorting). We sort stocks into deciles based on *TSE* first section breakpoints at the end of each March and hold the portfolio for the August. Our sample period starts in August 1994 and ends in March 2016.

Portfolios are rebalanced monthly and formed by performing independent double sorts on book-to-market ratio and profitability. Specifically, at the beginning of each month, we independently sort firms into five B/M groups (growth to value) using the 20th, 40th, 60th, and 80th B/M percentiles and five profitability quintiles based on GP . Separately, using the most recently announced annually accounting information. We hold these portfolios and compute the monthly value-weighted abnormal returns of these 25 (5*5) B/M - GP portfolios.

The “R-W” profitability spread portfolio is computed as long the most robust profitability decile and short the weakest decile. The “H-L” profitability spread portfolio is computed as long the highest B/M decile and short the lowest decile. Numbers in parentheses (.) are t test statistics.

Table 3.6: Panel A-2. Double sort by OP and B/M

| A-2 B/M | Weak | 2 | 3 | 4 | Robust | R-W | (t) |
|------------|--------|--------|--------------|--------|--------|-------|---------|
| | | | OP quintiles | | | | |
| Low | 0.09 | -0.27 | 0.03 | 0.02 | -0.02 | -0.12 | (-0.21) |
| 2 | -0.06 | 0.03 | 0.14 | 0.09 | 0.65 | 0.71 | (2.05) |
| 3 | 0.47 | 0.17 | 0.24 | 0.71 | 0.43 | -0.03 | (-0.09) |
| 4 | 0.52 | 0.60 | 0.76 | 0.61 | 0.69 | 0.17 | (0.56) |
| High | 0.77 | 0.80 | 0.92 | 1.26 | 1.37 | 0.61 | (1.34) |
| H-L | 0.67 | 1.07 | 0.88 | 1.24 | 1.40 | | |
| (t) | (1.13) | (2.02) | (1.97) | (2.67) | (2.19) | | |

Panel A-2 shows average excess returns for 25 value-weighted (VW) portfolios, from independent (5×5 OP - B/M sorting). We sort stocks into deciles based on TSE first section breakpoints at the end of each March and hold the portfolio for the August. Our sample period starts in August 1994 and ends in March 2016.

Portfolios are rebalanced monthly and formed by performing independent double sorts on book-to-market ratio and profitability. Specifically, at the beginning of each month, we independently sort firms into five B/M groups (growth to value) using the 20th, 40th, 60th, and 80th B/M percentiles and five profitability quintiles based on OP . Separately, using the most recently announced annually accounting information. We hold these portfolios and compute the monthly value-weighted abnormal returns of these 25 (5×5) B/M - GP portfolios.

The “R-W” profitability spread portfolio is computed as long the most robust profitability decile and short the weakest decile. The “H-L” profitability spread portfolio is computed as long the highest B/M decile and short the lowest decile. Numbers in parentheses (.) are t test statistics.

Table 3.7: Panel B-1. Double sort by size and GP .

| B-1 Size | Weak | 2 | 3 | 4 | Robust | R-W | (t) |
|-------------|--------------|-------|--------|--------|--------|-------|---------|
| | GP quintiles | | | | | | |
| Small | 0.66 | 0.60 | 0.72 | 0.81 | 0.85 | 0.19 | (1.07) |
| 2 | 0.34 | 0.28 | 0.31 | 0.33 | 0.31 | -0.03 | (-0.19) |
| 3 | 0.15 | 0.22 | 0.18 | 0.26 | 0.33 | 0.18 | (1.07) |
| 4 | 0.06 | 0.16 | 0.17 | 0.38 | 0.38 | 0.32 | (1.89) |
| Big | 0.22 | 0.14 | 0.20 | 0.08 | 0.22 | 0.01 | (0.02) |
| S-B | 0.44 | 0.46 | 0.52 | 0.73 | 0.63 | | |
| (t) | (1.07) | (1.2) | (1.62) | (2.18) | (1.51) | | |

Panel B-1 shows average excess returns for 25 value-weighted (VW) portfolios from independent ($5*5$ *Size-GP* sorting). We sort stocks into deciles based on *TSE* first section breakpoints at the end of each March and hold the portfolio for the August. Our sample period starts in August 1994 and ends in March 2016.

Portfolios are rebalanced monthly and formed by performing independent double sorts on size and profitability. Specifically, at the beginning of each month, we independently sort firms into five size groups (small to big) using the 20th, 40th, 60th, and 80th size percentiles and five profitability quintiles based on GP . Separately, using the most recently announced annually accounting information. We hold these portfolios and compute the monthly value-weighted abnormal returns of these 25 ($5*5$) *Size-GP* portfolios.

The “S-B” profitability spread portfolio is computed as short the biggest size decile and long the smallest decile. The “R-W” profitability spread portfolio is computed as long the most robust profitability decile and short the weakest decile. Numbers in parentheses (.) are t test statistics.

Table 3.8: Panel B-2. Double sort by size and OP .

| B-2 Size | Weak | 2 | 3 | 4 | Robust | R-W | (t) |
|-------------|--------|--------------|--------|--------|--------|-------|---------|
| | | OP quintiles | | | | | |
| Small | 0.78 | 0.54 | 0.66 | 0.77 | 0.83 | 0.05 | (0.23) |
| 2 | 0.33 | 0.33 | 0.28 | 0.27 | 0.35 | 0.01 | (0.07) |
| 3 | 0.17 | 0.22 | 0.23 | 0.31 | 0.20 | 0.03 | (0.14) |
| 4 | 0.22 | 0.26 | 0.18 | 0.14 | 0.31 | 0.09 | (0.63) |
| Big | 0.31 | 0.20 | 0.14 | 0.16 | 0.17 | -0.14 | (-0.47) |
| S-B | 0.47 | 0.34 | 0.52 | 0.61 | 0.66 | | |
| (t) | (1.16) | (0.88) | (1.51) | (1.96) | (1.67) | | |

Panel B-2 shows average excess returns for 25 value-weighted (VW) portfolios from independent ($5*5$ *Size-OP* sorting). We sort stocks into deciles based on TSE first section breakpoints at the end of each March and hold the portfolio for the August. Our sample period starts in August 1994 and ends in March 2016.

Portfolios are rebalanced monthly and formed by performing independent double sorts on size and profitability. Specifically, at the beginning of each month, we independently sort firms into five size groups (small to big) using the 20th, 40th, 60th, and 80th size percentiles and five profitability quintiles based on OP . Separately, using the most recently announced annually accounting information. We hold these portfolios and compute the monthly value-weighted abnormal returns of these 25 ($5*5$) *Size-OP* portfolios.

The “R-W” profitability spread portfolio is computed as long the most robust profitability decile and short the weakest decile. The “S-B” profitability spread portfolio is computed as short the biggest size decile and long the smallest decile. Numbers in parentheses (.) are t test statistics.

Table 3.9: Factor definitions

| Sort | Breakpoint | Factors |
|------------------|--------------------------|---|
| 2x3 sorts | | |
| | Size: Median | $SMB_{B/M} = (SH + SN + SL)/3 - (BH + BN + BL)/3$ |
| <i>Size-B/M,</i> | | $SMB_{GP} = (SR + SN + SW)/3 - (BR + BN + BW)/3$ |
| <i>Size-GP,</i> | | $SMB = (SMB_{B/M} + SMB_{GP})/2$ |
| <i>GP-B/M</i> | <i>B/M</i> : 30th & 70th | $HML = (SH + BH)/2 - (SL + BL)/2 = [(SH - SL) + (BH - BL)]/2$ |
| | <i>GP</i> : 30th & 70th | $RMW = (SR + BR)/2 - (SW + BW)/2 = [(SR - SW) + (BR - BW)]/2$ |

The table shows SMB, HML, RMW's definitions. We follow Fama-French (2015) definitions, use independent sorts to assign stocks to two size groups, and three *B/M*, profitability (*GP*) groups. The value-weighted (VW) portfolios defined by the intersections of the groups are the building blocks for the factors. We label these portfolios with two letters. The size breakpoint is the median market cap, and the *B/M*, *GP* breakpoints are the 30th and 70th percentiles of *B/M*, *GP* for stocks. The first always describes the size group, small (S) or big (B). In the 2*3 sorts, the second describes the B/M group, high (H), neutral (N), or low (L), also the second describes the *GP* group, robust (R), neutral (N), or weak (W).

Table 3.10: GRS Test (Gibbons et al. (1989), Kim & Shamsuddin (2016)).

| Test portfolios | Model | GRS P | Economic Value |
|-----------------|---------------------------------|-------|----------------|
| <i>B/M-GP</i> | <i>Fama-French-three-factor</i> | 0.02 | 0.51 |
| | <i>MKT-RMW(GP)-HML(B/M)</i> | 0.05 | 0.55 |
| <i>B/M-OP</i> | <i>Fama-French-three-factor</i> | 0.73 | 0.66 |
| | <i>MKT-RMW(GP)-HML(B/M)</i> | 0.75 | 0.68 |
| <i>Size-GP</i> | <i>Fama-French-three-factor</i> | 0.00 | 0.47 |
| | <i>MKT-RMW(GP)-HML(B/M)</i> | 0.00 | 0.48 |
| <i>Size-OP</i> | <i>Fama-French-three-factor</i> | 0.09 | 0.55 |
| | <i>MKT-RMW(GP)-HML(B/M)</i> | 0.13 | 0.58 |
| <i>Size-B/M</i> | <i>Fama-French-three-factor</i> | 0.02 | 0.51 |
| | <i>MKT-RMW(GP)-HML(B/M)</i> | 0.01 | 0.52 |

The table reports *GRS P* value and Economic value (Gibbons et al. (1989); Kim & Shamsuddin (2016)). Comprehensively, the *GRS P* value indicates statistical significance. The bigger the *P* value, the greater the model performance. Economic value indicates proportion between the maximum sharpe ratio of the three factor portfolios and the slope of the efficient frontier based on all assets. The bigger the economic value, the greater the dual economic and market efficiency.

We test this hypothesis for combinations of 5*5 portfolios and factors. Here we compare the *Fama-French three-factor* model and our *MKT-RMW(GP)-HML* factor model. The test samples include *GP-B/M* portfolios, *OP-B/M* portfolios, *Size-GP* portfolios, *Size-OP* portfolios, and *Size-B/M* portfolios.

Chapter 4

Profitability in asset pricing models for Chinese equities 1996-2016

This chapter discusses the asset pricing model on the Chinese stock market. Section 4.1 discusses background. Section 4.2 discusses literature review. Section 4.3 describes the data collection process and the definitions of the control variables used in the study. Section 4.4 discusses empirical results. Section 4.5 discusses conclusions and limitations.

4.1 Introduction

Fama(2015) cast a view that the value (book to market ratio) factor becomes redundant in US market, which really subverts our cognition. Actually, the regression loadings of book-to-market ratio is not statistically significant, the value factor may not have reflected fundamentals on the Chinese markets (see Wang & Xu (2004), Hu et al. (2018)). Hence, finding a new factor which is closely related to value factor, and can explain cross-sections of stock returns better is the motivation of the paper.

This research also links to the growing asset pricing model. The studies show that operating leverage and profitability exert power in predicting returns. Meanwhile, This can replace value factor among US equities, but scant literature investigates

Chinese equities.

Firstly, Liu (2015) finds that operating leverage effect exists in China (2003-2013). We will keep on researching operating leverage effect expanding timeline samples. Secondly, Liu (2017) finds empirical evidence of profitability effect in China. Profitability premium exists on the Chinese stock market, where profitability is measured by gross profit (GP). Firms with high profitability generate substantially higher future stock returns than those with low profitability. The profitability premium is robust when controlling for various alternative anomalies and risks in the literature such as size, book-to-market, operating leverage.

Our study characterizes firms' profits comprehensively using gross profit, operating leverage to assure robustness in predicting equity returns. We confirm that gross-profit-to-market capitalization is a superior proxy for predicting equity returns. Our results endorse those of Novy-Marx (2011), Novy-Marx (2013) and support the existence of operating leverage, and gross profitability premium for Chinese equities. In addition, we mirror *Fama-French-three-factor* (1993) model and *Hou-Xue-Zhang-factor* (2015) model, delete the redundant factor, and create a *Market-Size-Profitability (MKT-SMB-RMW)* model to explain expected returns on Chinese equities, our enhanced local factor model is more appropriate than *Fama-French-three-factor* model.

4.2 Literature review

4.2.1 Book to market ratio and size effect

Hilliard & Zhang (2015) find the existence of size effect in China. However, while the regression loadings of book-to-market are not statistically significant, confirming the weak cross-sectional returns predictability of B/M ratio.

Hu et al. (2018) also test the *Fama-French-three-factor* model, they find a significant size effect but no robust value effect. Neither the market portfolio nor the zero-cost high-minus-low (HML) portfolio has average premiums statistically different from zero. Although this contradicts most of the existing literatures, it is consistent with my research. The literature also explains that why their research

contradicts with prior research, because the difference comes from the extreme values in a few months in the early years of the market (1995 to 1996), which turns out to have a heavy impact on the average premiums given the relatively short history of the Chinese stock market. Hence, based on the experience, this time we also remove the extreme months, from 1995 to 1996.

Overall, we summarise that book to market ratio and size effect, which cannot explain the expected returns in China at the same time.

4.2.2 Floating ratio

For the market characteristics of the Chinese market, the first research factor is floating ratio (The percentage of tradable shares). A unique characteristic of the listed Chinese companies is that most of the A shares are prohibited from trading. These shares include the state-owned shares. They are not tradable publicly at the stock exchanges.

Higher floating ratio means less risk as to government policies toward non-tradable shares. Therefore, firms with higher floating ratios own better corporate governance. These firms should have higher expected returns when other things being equal. Wang & Xu (2004) found a phenomenon that the higher the floating ratio, the higher the expected return is.

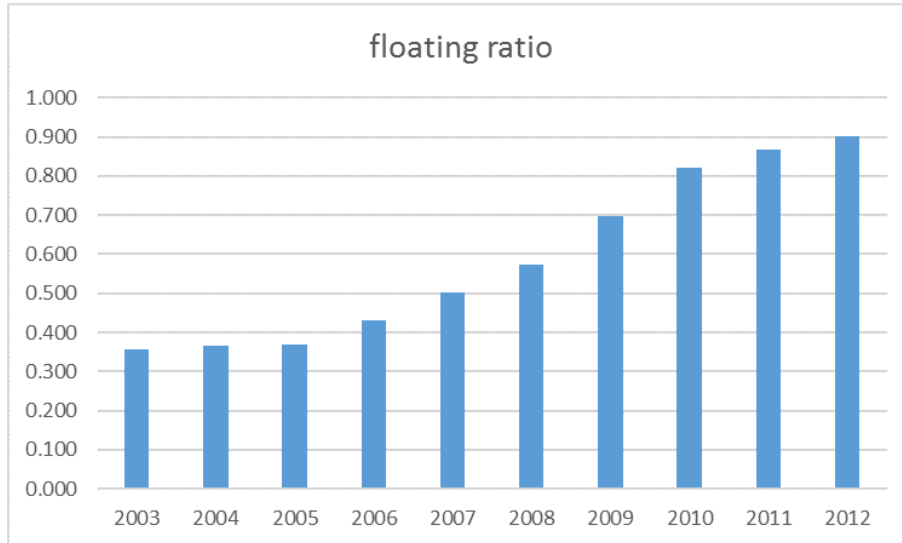


Figure 4.1: Floating ratio (2003-2012).

(Source) Derived from the data of the market capitalization and total market capitalization of the distribution stock recorded in the database, 2003-2012.

From the viewpoint of Figure 4.1, the average floating ratio is relatively stable in 2003, 2004, and 2005, and since 2006, the average floating ratio has increased significantly. The literature tells us that floating ratio effect, is indeed effective before 2005 because at that time most of the stock's floating ratio were low. The change of floating ratio has significant power to the expected returns. But after floating ratio reform in 2005, most stocks' floating ratio has risen close to 90% or more. The effect has vanished then.

4.2.3 Momentum effect

Li et al. (2010) examine the relationship between momentum and Chinese stock returns from 1994-2007. They follow Jegadeesh & Titman (1993) approach to explore momentum strategies in China. They do not find momentum profitability in any of the 25 sorts strategies. The results exist for stocks listed on Shanghai Stock Exchange as well as Shenzhen Stock Exchange. Unlike evidence for the other markets (e.g. U.S), the momentum fails to qualify as a useful predictor in the portfolio method. Hence, we do not discuss momentum effect on the Chinese market.

4.2.4 Operating leverage effect

It focuses on the “operating leverage hypothesis” literaturred by Carlson et al. (2004). The hypothesis using real option theory prove operating leverage generate a value premium generally. His hypothesis is that, as with any real options model, a firm’s value consists of two pieces: currently deployed asset and growth options. $V_i = V_{iA} + V_{iG}$, where i denotes the firm and the subscript A and G signify assets-in-place and growth options, respectively. The firm’s expected excess returns depend on its exposure to the underlying risk factors.

This exposure can be shown as a value weighted sum of the loadings of the firm’s assets-in-place and the firm’s growth options on these risks,

$$\beta^i = \frac{v_A^i}{v^i} \beta_A^i + \frac{v_G^i}{v^i} \beta_G^i. \quad (4.1)$$

Just as the value of equity equals the value of assets minus the value of debt, the value of deployed assets consists of the capitalized value of the revenues they generate minus the capitalized cost of operating the assets, $V_{iA} = V_{iR} - V_{iC}$. The exposure of the assets to the underlying risks is then a value weighted average of the exposures of the capitalized revenues and the capitalized operating costs,

$$\beta_A^i = \beta_R^i + \frac{v_C^i}{v_A^i} (\beta_R^i - \beta_C^i). \quad (4.2)$$

While growth options are almost always riskier than revenues from deployed capital in real options models, the presence of operating costs allows for deployed assets that are riskier than growth options. This is the operating leverage hypothesis. Combining equations (4.1) and (4.2) gives

$$\beta^i = \frac{v_A^i}{v^i} (\beta_R^i + \frac{v_C^i}{v_A^i} (\beta_R^i - \beta_C^i)) + \frac{v_G^i}{v^i} \beta_G^i. \quad (4.3)$$

If variation in book-to-market is driven primarily by difference in growth-options, not rents to deployed capital. Operating costs-to-assets is a good proxy for V_{iC}/V_{iA} . If firms’ positions in the cross-section of operating margins (operating profits-to-operating revenues) are persistent over time. The hypothesis starts to be focus on

because Novy-Marx (2011). He rewrites the equation in (4.4), finds the direct empirical evidence for the “operating leverage hypothesis”. underlying most theoretical models of value premium.

$$\beta^i = BM^i(OL^i(\beta_R^i - \beta_C^i) - (\beta_G^i - \beta_R^i)) + \beta_G^i. \quad (4.4)$$

where BM^i is firm i 's book-to-market and OL^i is the firm's annual operating costs divided by book assets (multiplied by an arbitrary scale constant). And based on (4.4), we learn that the operating leverage hypothesis thus predicts that high book-to-market firms earn higher returns because they are relatively more exposed to assets-in-place, and assets-in-place are riskier than growth options. It also predicts that high operating leverage firms earn higher returns, because their assets-in-place are more levered (through operations), and thus riskier. Overall, operating leverage can be considered as a risk premium.

4.2.5 Gross profitability effect

Liu (2017), Jiang & Tang (2018)) finds that gross profitability is a statistically significant predictor of Chinese equity returns. Profitability premium, hence appears to be complementary for the famous size and value premiums and expand the investor's investment opportunity set. Especially there is no value premium in China. In addition, the forecasting power of profitability is economically and statistically strong compared to the well-known size, value and momentum effects.

4.3 Data and variable

Financial statement data are from the FactSet database. Financial statements are disclosed by Chinese firms following Chinese accounting standards. Empirical research covers Chinese equities listed on shanghai A share and Shenzhen A share (*SSE* and *SZSE*). Our sample covered 281 companies in 1996, and, adjusted yearly, reached 2,258 in 2016. The observation period was from April 1996 to March 2016, and, adjusted quarterly.

We obtain the accounting data and monthly stock returns from the China Stock Market and Accounting Research (Factset). We obtain the Chinese risk-free rate. our sample consists of all of the Chinese A-share stocks with accounting and returns data available traded on the main boards of Shanghai and Shenzhen, we exclude firms in financial industry according to the industry classification of China. We also exclude firms with negative book value of equity to get rid of financial distressed firms.

We use monthly return series to measure stock return, portfolio returns, use monthly market capitalization, and quarterly frequency data for financial statement data. Because samples are relative small in China, using the most recently announced quarterly reports' information is more efficient to find abnormal returns in Chinese stock market than rebalancing portfolios annually by using annual reports' data. We use software SAS 9.2 to do the data processing.

To construct factors that might influence equity returns, we assemble quarterly financial statement data for sales (*SALE*), cost of goods sold (*COGS*), sales-general-administrative expenses (*SGA*), book value of total assets (*AT*), and book equity (*BE*) measured as *AT* minus total liabilities (*LT*). $\text{Log}(\text{ME})$ is the log of market capitalization (*ME*). *B/M* indicates the book-to-market ratio (BE/ME). Gross profit (*GP*) is *SALE* minus *COGS*. Operating costs (*OL*) is *SALE* plus *COGS*. Based on Novy-Marx (2011, 2013), we define operating leverage as operating costs divided by market capitalization, gross profitability as gross profit divided by market capitalization.

4.4 Methods and empirical results

4.4.1 Fama-MacBeth univariate regressions

We use monthly Fama-MacBeth regressions to examine whether profitability convincingly forecasts stock returns.

Table 4.1 shows regressed monthly returns of individual stocks on lagged operating leverage, profitability, market capitalization, the book-to-market ratio. We focus on *t*-values to compare the explanatory power of variables. Gross profitability, oper-

ating leverage have significant predicting power, while book-to-market ratio (B/M) have no significant predicting power. Gross profitability has most power to predict expected return, because the Fama-MacBeth regressions to the gross profitability with a high t test-statistic of 3.24.

4.4.2 Fama-MacBeth multivariate regression

Table 4.2 reports model (1)-(4) specifications for multivariate regressions including controls for book-to-market ratio (B/M), size ($\log(ME)$). When controlled accordingly, model (1) implies Fama-French's *Size-B/M* is not ideal combination. Because size effect is effective although, value effect sheds predictive power. Model (2) and model (3) reveal that operating leverage and gross profitability effects are strong for the sampled equities. Model (4) shows that when controlled operating leverage, gross profitability still shows strongest effect, with a test-statistic of 4.14. However, operating leverage loses much of its power to predict returns. Based on Novy-Marx (2013), the operating leverage on its power is absorbed by profitability. Hence, we abandon operating leverage as our factor candidate.

Overall, we reconfirm the existence of strong gross profitability effects among Chinese equities per Jiang & Tang (2018). Size premium still have power. However, due to the speculative nature of the Chinese capital markets and low quality in the accounting information, the B/M shows no effect on returns of sampled equities, consistent with prior study. Signaling that the risk OL represents can already be captured by other controls, namely GP .

4.4.3 Construction of mimicking factors

We perform portfolio tests as a more predictive exercise that escapes bias of Fama-MacBeth (1973) regressions. We can explore the performance of portfolios double-sorted by profitability and size to generate more excess return. For comparison, we sort *Size-B/M* portfolios, *Size-GP* portfolios and *GP-B/M* portfolios for the sampled equities. Average excess portfolio returns appear.

In the *Size-B/M* formulation in **Table 4.3**, holding B/M roughly constant, average return typically falls as size increases. The S-B portfolios (size premium) in

column 1, 2, 3 are significant. Holding size roughly constant, only H-L portfolios in row 4, 5 increases with B/M . No H-L portfolio is significant. That finding reveals size quintiles outperform B/M quintiles.

In the *Size-GP* formulation in **Table 4.4**, holding GP roughly constant, average return typically falls as size increases. The S-B portfolios (size premium) in column 1, 2, 3 are significant. Holding size roughly constant, average return typically increases with GP . R-W portfolios (gross profitability premium) in row 2, 3, 4, 5 are significant. Small size and robust profitability portfolios perform best with 2.16% monthly returns. That finding reveals GP quintiles outperform size quintiles.

In the *GP-B/M* formulation in **Table 4.5**, GP and average return are positively related in all rows. R-W portfolios (gross profitability premium) in rows 4 are significant. Value premium has no evident in columns 1 through 5. That finding reveals GP quintiles outperform B/M quintiles.

Overall, we confirm that controlling for GP improves performance of size strategies and controlling for size improves performance of profitability strategies. Results suggest sorting of gross profitability and size portfolios outperform among the sampled equities.

4.4.4 Summary of factor model

To construct factor, we sort independently to assign stocks to two size groups, three B/M groups, and three profitability groups (GP). The size breakpoint is median market cap. B/M or GP breakpoints are the 30th and 70th percentiles. MKT ($R_m - R_f$) is the value-weighted return on the market portfolio of all sampled stocks minus the risk-free rate. SMB is the return on a diversified portfolio of small-cap stocks minus the return on a diversified portfolio of big-cap stocks. HML is the difference between returns on diversified portfolios of high and low B/M stocks. In addition, RMW is the difference between returns on diversified portfolios of stocks with robust and weak gross profitability.

Firstly, we analyse the correlation among the factor premium. That is MKT (market premium), SMB (size premium), HML (value premium) and RMW (profitability premium). We show the factor means, standard error numbers and correlations ma-

trix for each set of factors.

In **Table 4.6**, RMW has negative relation with MKT, HML, SMB, this is consistent with US equities. The strong negative relation between RMW and SMB is interesting for any kind of investment strategy. Value premium (HML) is almost zero.

The *Fama-French-three-factor* model is an empirical asset pricing model. The *Fama-French-three-factor* model is designed to capture the relation between average return and size (market capitalization, price times shares outstanding) and the relation between average return and price ratios like the book-to-market ratio, which were the two well-known patterns in average returns. The model's regression equation is

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_iSMB_t + h_iHML_t + e_{it}. \quad (4.5)$$

In this equation, R_{it} is the return on security or portfolio i for period t , R_{ft} is the risk free return, R_{mt} is the return on the value-weighted (VW) market portfolio, SMB_t is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML_t is the difference between the returns on diversified portfolios of high and low B/M stocks, α_i is the intercept, and e_{it} is a zero-mean residual. The three factor model says that the sensitivities β_i , s_i , and h_i to the portfolio returns capture all variation in expected returns, so the expected value of the intercept α_i is zero for all securities and portfolios i .

We eliminate redundant factors to boost the model's explanatory power. Based on Fama-MacBeth regressions and tests of combination portfolios, we define two main factor premiums: SMB (small minus big size) and RMW (robust minus weak GP). Hence, we create a new model *MKT-RMW-SMB* model for the sampled equities and compare time-series regressions with the *Fama-French-three-factor* model. New factor model is

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_iSMB_t + r_iRMW_t + e_{it}. \quad (4.6)$$

Where R_{it} is the return of portfolio in month t . R_{ft} is risk free rate. α_i is the intercept, β_i , s_i , r_i are factor coefficients for time-series regression, e_{it} is the error term.

If a characteristic is significant in cross-sectional regressions, we hypothesize that its factor will be significant in time-series regressions. Hence, we create a new model *MKT-SMB-RMW* model for the sampled equities and compare time-series regressions with the *Fama-French three-factor* model.

Table 4.7 and **Table 4.8** shows results from time series regressions for monthly percent excess returns on 25 *Size-GP* portfolios. The test models include a *Fama-French-three-factor* model (Panel A) and *MKT-SMB-RMW-factor* model (Panel B). The test sample is *Size-GP* portfolios.

In Panel A, R^2 s vary from 91% to 97% with an average of 95%. In Panel B, R^2 s vary from 92% to 97% with an average of 96%. Using visual comparison methods R^2 s, *MKT-SMB-RMW* model outperforms *Fama-French-three-factor* model.

4.4.5 Evaluating model performance

Gibbons et al. (1989) propose the most widely used statistical test of empirical validity for asset-pricing models (GRS test). It tests for the null hypothesis that the intercept terms of empirical asset-pricing model portfolios jointly equal 0. Failure to reject the null hypothesis is evidence the model adequately captures portfolio returns. Meanwhile, we follow ?, add to economic value to evaluate model performance.

If the new 3 sensitivities to the new three factors, β_i , s_i , r_i , capture all variation in expected returns, the expected value of the intercept α_i is zero for all portfolios i .

The test models include a *Fama-French-three-factor* model and *MKT-SMB-RMW* factor model. The test samples include *GP-B/M* portfolios, *Size-GP* portfolios, and *Size-B/M* portfolios.

For *GRS P* value in **Table 4.9**, *MKT-SMB-RMW* factor model outperforms the *Fama-French-three-factor* model. For economic value, *MKT-SMB-RMW* factor model obviously provides optimum. Overall, we show *MKT-SMB-RMW* factor

model outperforms both the statistical and economic significance for the sampled equities.

4.5 Conclusion

The conclusions are as follows. Gross-profit-to-market-capitalization explains the sampled cross-section of expected returns better than other variables on Chinese equities. Value premium for the sampled equities shed predictive power over time and become redundant. Operating leverage premium loses powers when add to profitability factor. Size premium remain strong among our sampled equities. Hence, we create a new *MKT-SMB-RMW* factor model and investigate the applicability of a *Fama-French-three-factor* model on our sampled equities. Tests reveal that the model featuring gross profitability outperforms the *Fama-French-three-factor* model.

Table 4.1: Fama-MacBeth univariate regressions of firm returns 1996-2016.

| variables | 1 | 2 | 3 | 4 |
|----------------|--------|--------|--------|---------|
| <i>OL</i> | 0.48 | | | |
| (<i>t</i>) | (2.51) | | | |
| <i>GP</i> | | 1.70 | | |
| (<i>t</i>) | | (3.24) | | |
| <i>B/M</i> | | | 0.03 | |
| (<i>t</i>) | | | (0.27) | |
| <i>log(ME)</i> | | | | -0.33 |
| (<i>t</i>) | | | | (-1.85) |

In model1-model4, we test operating leverage, gross profitability, book-to-market ratio, and size effect, respectively. Slope coefficients (*100) β and (*t*-statistics) from regressions are shown. Numbers in parentheses (.) are t test statistics, which is adjusted by white adjust. *t*-statistics are based on the time-series variability of slope estimates, incorporating a white adjust for possible autocorrelation and heteroscedasticity in the slopes.

Following Novy-Marx (2013), (*GP*) is computed with the most recently announced quarterly firm's gross profit (calculated by revenue minus cost of goods sold (*COGS*) both in quarterly *t*). Following Novy-Marx (2011), we define the measure of operating leverage, (*OL*), as *SALE* plus *COGS* divided by market capitalization. *LOG(ME)* is the log of market capitalization (ME). The *B/M* variable is defined as the book value of common equity at the end of previous quarterly year (quarterly year *t*-1) divided by the market capitalization by the end of month *t* - 1. The sample period starts in April 1996 and ends in March 2016.

Table 4.2: Fama-MacBeth multivariate regressions of firm returns 1996-2016.

| variables | 1 | 2 | 3 | 4 |
|-----------------|---------|---------|---------|---------|
| <i>OL</i> | | 0.53 | | 0.04 |
| (<i>t</i>) | | (2.98) | | (0.23) |
| <i>GP</i> | | | 2.16 | 2.12 |
| (<i>t</i>) | | | (4.62) | (4.14) |
| <i>B/M</i> | -0.06 | -0.04 | -0.04 | -0.03 |
| (<i>t</i>) | (-0.63) | (-0.34) | (-0.36) | (-0.32) |
| <i>Log (ME)</i> | -0.36 | -0.33 | -0.40 | -0.40 |
| (<i>t</i>) | (-1.98) | (-1.83) | (-2.26) | (-2.22) |

In model1-model4, we test *B/M-Size*, *B/M-Size-OL*, *B/M-Size-GP*, and *B/M-Size-GP-OL* effect, respectively. Multivariate slope coefficients (*100) β and (*t*-statistics) from regressions are shown. Numbers in parentheses (.) are *t* test statistics, which is adjusted by white adjust. *t*-statistics are based on the time-series variability of slope estimates, incorporating a white adjust for possible autocorrelation and heteroscedasticity in the slopes.

Following Novy-Marx (2013), (*GP*) is computed with the most recently announced quarterly firm's gross profit (calculated by revenue minus cost of goods sold (*COGS*) both in quarterly *t*). Following Novy-Marx (2011), we define the measure of operating leverage, (*OL*), as *SALE* plus *COGS* divided by market capitalization. *LOG(ME)* is the log of market capitalization (ME). The *B/M* variable is defined as the book value of common equity at the end of previous quarterly year (quarterly year $t - 1$) divided by the market capitalization by the end of month $t - 1$. The sample period starts in April 1996 and ends in March 2016.

Table 4.3: Panel A. Double Sort by *Size-B/M*.

| Panel A | Low | 2 | 3 | 4 | High | H-L | <i>t</i> |
|----------|---------------|--------|--------|--------|--------|-------|----------|
| Size | B/M quintiles | | | | | | |
| Small | 2.22 | 2.16 | 2.05 | 1.80 | 1.56 | -0.66 | (-2.62) |
| 2 | 1.41 | 1.72 | 1.78 | 1.69 | 1.25 | -0.16 | (-0.71) |
| 3 | 1.47 | 1.47 | 1.66 | 1.40 | 1.28 | -0.16 | (-0.62) |
| 4 | 0.91 | 1.16 | 1.46 | 1.32 | 1.21 | 0.25 | (0.68) |
| Big | 0.75 | 1.04 | 0.86 | 0.90 | 0.86 | 0.10 | (0.21) |
| S-B | 1.46 | 1.12 | 1.16 | 0.88 | 0.77 | | |
| <i>t</i> | (2.79) | (2.16) | (2.49) | (1.68) | (1.32) | | |

Panel A shows average excess returns for 25 value-weighted (*VW*) portfolios from independent (5×5 *Size-B/M* sorting). We sort stocks into deciles based on Shanghai A share and Shenzhen A share (*SSE* and *SZSE*) breakpoints at the end of each December and hold the portfolio for the April. Our sample period starts in April 1996 and ends in March 2016.

Portfolios are rebalanced monthly and formed by performing independent double sorts on size and book-to-market ratio. Specifically, at the beginning of each month, we independently sort firms into five size groups (small to big) using the 20th, 40th, 60th, and 80th size percentiles and five value quintiles based on *B/M*. Separately, using the most recently announced quarterly accounting information. We hold these portfolios and compute the monthly value-weighted abnormal returns of these 25 (5×5) *Size-B/M* portfolios.

The “S-B” profitability spread portfolio is computed as short the biggest size decile and long the smallest decile. The “H-L” profitability spread portfolio is computed as long the highest *B/M* decile and short the lowest decile. Numbers in parentheses (.) are *t* test statistics.

Table 4.4: Panel B. Double Sort by *Size-GP*.

| Panel B | Weak | 2 | 3 | 4 | Robust | | |
|----------|--------------|--------|--------|--------|--------|----------|--------|
| Size | GP quintiles | | | | R-W | <i>t</i> | |
| Small | 1.93 | 1.95 | 1.83 | 2.05 | 2.16 | 0.23 | (0.94) |
| 2 | 1.23 | 1.52 | 1.61 | 1.63 | 1.85 | 0.62 | (2.83) |
| 3 | 1.16 | 1.33 | 1.48 | 1.58 | 1.73 | 0.70 | (2.53) |
| 4 | 0.92 | 0.83 | 1.16 | 1.34 | 1.84 | 0.71 | (2.54) |
| Big | 0.42 | 0.82 | 0.64 | 1.04 | 1.36 | 0.96 | (2.55) |
| S-B | 1.51 | 1.13 | 1.26 | 0.97 | 0.90 | | |
| <i>t</i> | (3.22) | (2.23) | (2.61) | (1.76) | (1.54) | | |

Panel B shows average excess returns for 25 value-weighted (VW) portfolios, from independent (5*5 *Size-GP* sorting). We sort stocks into deciles based on Shanghai A share and Shenzhen A share (*SSE* and *SZSE*) breakpoints at the end of each December and hold the portfolio for the April. Our sample period starts in April 1996 and ends in March 2016.

Portfolios are rebalanced monthly and formed by performing independent double sorts on size and profitability. Specifically, at the beginning of each month, we independently sort firms into five size groups (small to big) using the 20th, 40th, 60th, and 80th size percentiles and five profitability quintiles based on GP. Separately, using the most recently announced quarterly accounting information. We hold these portfolios and compute the monthly value-weighted abnormal returns of these 25 (5*5) *Size -GP* portfolios.

The “S-B” profitability spread portfolio is computed as short the biggest size decile and long the smallest decile. The “R-W” profitability spread portfolio is computed as long the most robust profitability decile and short the weakest decile. Numbers in parentheses (.) are *t* test statistics.

Table 4.5: Panel C. Double Sort by GP - B/M .

| Panel C | Weak | 2 | 3 | 4 | Robust | | |
|---------|--------|--------|--------------|--------|--------|------|--------|
| B/M | | | GP quintiles | | | R-W | t |
| Low | 0.58 | 0.74 | 0.86 | 0.71 | 1.11 | 0.53 | (1.16) |
| 2 | 0.85 | 0.93 | 0.94 | 1.27 | 1.49 | 0.63 | (1.68) |
| 3 | 0.90 | 0.92 | 0.95 | 1.18 | 1.50 | 0.58 | (1.55) |
| 4 | 0.92 | 0.95 | 1.20 | 1.30 | 1.89 | 0.97 | (2.29) |
| High | 0.92 | 0.80 | 0.95 | 0.82 | 1.14 | 0.17 | (0.43) |
| H-L | 0.33 | 0.06 | 0.08 | 0.13 | 0.04 | | |
| t | (0.87) | (0.16) | (0.18) | (0.29) | (0.09) | | |

Panel C shows average excess returns for 25 value-weighted (VW) portfolios, from independent (5*5 GP - B/M sorting). We sort stocks into deciles based on Shanghai A share and Shenzhen A share (SSE and $SZSE$) breakpoints at the end of each December and hold the portfolio for the April. Our sample period starts in April 1996 and ends in March 2016.

Portfolios are rebalanced monthly and formed by performing independent double sorts on book-to-market ratio and profitability. Specifically, at the beginning of each month, we independently sort firms into five B/M groups (growth to value) using the 20th, 40th, 60th, and 80th B/M percentiles and five profitability quintiles based on GP . Separately, using the most recently announced quarterly accounting information. We hold these portfolios and compute the monthly value-weighted abnormal returns of these 25 (5*5) B/M - GP portfolios.

The “H-L” profitability spread portfolio is computed as long the highest B/M decile and short the lowest decile. The “R-W” profitability spread portfolio is computed as long the most robust profitability decile and short the weakest decile. Numbers in parentheses (.) are t test statistics.

Table 4.6: Correlation among the factor premiums 1996-2016.

| Factor | MKT | RMW | SMB | HML |
|--------|-------|-------|-------|-------|
| Mean | 1.00 | 0.54 | 0.62 | -0.01 |
| STD | 9.51 | 2.44 | 3.46 | 2.68 |
| CORR | MKT | RMW | SMB | HML |
| MKT | 1.00 | -0.26 | 0.06 | -0.10 |
| RMW | -0.26 | 1.00 | -0.58 | -0.18 |
| SMB | 0.06 | -0.58 | 1.00 | -0.27 |
| HML | -0.10 | -0.18 | -0.27 | 1.00 |

The table reports factor premiums conditions. Mean stands for average of the factor premiums, STD stands for standard deviation of the factor premiums, CORR stands for the Pearson correlation between the factor MKT, SMB, HML, and RMW premiums.

MKT ($R_m - R_f$) is the value-weighted return on the market portfolio of all sampled equities minus the risk-free rate. SMB is the return on a diversified portfolio of small-cap equities minus the return on a diversified portfolio of big-cap equities. HML is the difference between returns on diversified portfolios of high and low B/M equities. In addition, RMW is the difference between returns on diversified portfolios of equities with robust and weak gross profitability. Our sample period starts in April 1996 and ends in March 2016.

Table 4.7: Panel A. Time series regressions for 25 *Size-GP* Portfolios.

| Panel A | | | | | | | | | | | |
|---------|------------|-------|-------|-------|-----------------|---------------|-------|-------|-------|--------|--|
| | Weak | 2 | 3 | 4 | Robust | Weak | 2 | 3 | 4 | Robust | |
| Size | α_i | | | | GP quintiles | $t(\alpha_i)$ | | | | | |
| Small | -0.09 | -0.51 | -0.52 | -0.44 | -0.55 | -0.47 | -3.34 | -3.48 | -2.33 | -2.93 | |
| 2 | -0.15 | -0.18 | -0.30 | -0.56 | -0.23 | -0.90 | -1.15 | -1.90 | -3.31 | -1.56 | |
| 3 | 0.07 | 0.07 | 0.01 | -0.08 | -0.10 | 0.45 | 0.50 | 0.04 | -0.52 | -0.66 | |
| 4 | 0.36 | 0.04 | 0.02 | 0.04 | 0.18 | 2.37 | 0.25 | 0.11 | 0.24 | 1.49 | |
| Big | 0.30 | 0.34 | 0.48 | 0.84 | 0.94 | 2.18 | 2.06 | 2.26 | 3.93 | 4.35 | |
| | β_i | | | | $t(\text{MKT})$ | | | | | | |
| Small | 1.08 | 1.09 | 1.10 | 1.11 | 1.10 | 56.46 | 68.85 | 70.60 | 57.08 | 56.53 | |
| 2 | 1.04 | 1.05 | 1.05 | 1.04 | 1.00 | 60.86 | 66.00 | 63.54 | 59.35 | 66.60 | |
| 3 | 1.01 | 1.05 | 1.08 | 1.04 | 1.00 | 61.06 | 73.06 | 62.73 | 62.66 | 65.32 | |
| 4 | 1.02 | 1.05 | 1.03 | 1.07 | 0.97 | 64.19 | 65.81 | 64.33 | 63.50 | 76.27 | |
| Big | 1.00 | 1.05 | 1.04 | 0.96 | 0.94 | 69.78 | 61.85 | 47.31 | 43.39 | 41.90 | |
| | s_i | | | | $t(\text{SMB})$ | | | | | | |
| Small | 1.62 | 1.33 | 1.12 | 0.66 | 0.04 | 29.72 | 29.44 | 25.19 | 11.97 | 0.65 | |
| 2 | 1.56 | 1.19 | 0.93 | 0.66 | -0.21 | 32.19 | 26.32 | 19.86 | 13.29 | -5.01 | |
| 3 | 1.35 | 0.98 | 0.67 | 0.46 | -0.32 | 28.72 | 23.91 | 13.64 | 9.85 | -7.33 | |
| 4 | 1.22 | 0.91 | 0.57 | 0.25 | -0.48 | 26.96 | 20.16 | 12.55 | 5.16 | -13.22 | |
| Big | 1.19 | 0.60 | 0.23 | -0.12 | -0.97 | 29.24 | 12.58 | 3.73 | -1.96 | -15.26 | |
| | h_i | | | | $t(\text{HML})$ | | | | | | |
| Small | 0.06 | 0.06 | 0.04 | 0.05 | 0.24 | 0.82 | 1.09 | 0.65 | 0.68 | 3.29 | |
| 2 | -0.08 | -0.06 | -0.06 | -0.08 | 0.22 | -1.28 | -0.98 | -0.94 | -1.18 | 4.00 | |
| 3 | -0.21 | -0.12 | -0.37 | -0.16 | 0.11 | -3.51 | -2.22 | -5.90 | -2.63 | 1.99 | |
| 4 | -0.26 | -0.14 | -0.29 | -0.24 | -0.04 | -4.51 | -2.47 | -4.96 | -3.90 | -0.82 | |
| Big | -0.08 | -0.26 | -0.45 | -0.46 | -0.16 | -1.45 | -4.21 | -5.50 | -5.65 | -1.99 | |
| | R^2 | | | | | | | | | | |
| Small | 0.96 | 0.97 | 0.97 | 0.95 | 0.94 | | | | | | |
| 2 | 0.96 | 0.96 | 0.96 | 0.95 | 0.96 | | | | | | |
| 3 | 0.96 | 0.97 | 0.96 | 0.95 | 0.96 | | | | | | |
| 4 | 0.96 | 0.96 | 0.96 | 0.95 | 0.97 | | | | | | |
| Big | 0.97 | 0.95 | 0.92 | 0.91 | 0.91 | | | | | | |
| Average | 0.95 | | | | | | | | | | |

Table 4.8: Panel B. Time series regressions for 25 *Size-GP* Portfolios.

| Panel B | Weak | 2 | 3 | 4 | Robust | Weak | 2 | 3 | 4 | Robust |
|---------|-------|-------|------------|-------|--------------|-------|-------|-----------------|-------|--------|
| Size | | | α_i | | GP quintiles | | | $t(\alpha_i)$ | | |
| | 0.17 | -0.17 | -0.19 | 0.08 | 0.17 | 0.87 | -1.08 | -1.21 | 0.44 | 0.97 |
| 2 | -0.08 | -0.06 | -0.10 | -0.21 | 0.16 | -0.45 | -0.38 | -0.62 | -1.22 | 1.02 |
| 3 | -0.10 | 0.03 | -0.24 | -0.13 | 0.11 | -0.54 | 0.21 | -1.27 | -0.71 | 0.69 |
| 4 | 0.06 | -0.14 | -0.22 | -0.11 | 0.05 | 0.35 | -0.84 | -1.25 | -0.62 | 0.34 |
| Big | 0.13 | -0.16 | -0.36 | 0.02 | 0.31 | 0.90 | -0.93 | -1.74 | 0.10 | 1.45 |
| | | | β_i | | | | | $t(\text{MKT})$ | | |
| Small | 1.07 | 1.07 | 1.08 | 1.07 | 1.04 | 54.83 | 69.27 | 71.39 | 59.38 | 61.92 |
| 2 | 1.03 | 1.04 | 1.03 | 1.02 | 0.97 | 58.51 | 63.69 | 61.85 | 59.49 | 64.85 |
| 3 | 1.03 | 1.06 | 1.10 | 1.04 | 0.98 | 58.60 | 70.00 | 58.03 | 59.80 | 62.84 |
| 4 | 1.04 | 1.06 | 1.05 | 1.08 | 0.98 | 62.80 | 64.32 | 60.92 | 60.29 | 75.43 |
| Big | 1.01 | 1.08 | 1.11 | 1.02 | 0.98 | 69.04 | 65.83 | 54.27 | 48.92 | 47.08 |
| | | | s_i | | | | | $t(\text{SMB})$ | | |
| Small | 1.49 | 1.16 | 0.95 | 0.41 | -0.33 | 23.56 | 23.03 | 19.36 | 6.97 | -6.05 |
| 2 | 1.54 | 1.14 | 0.84 | 0.51 | -0.43 | 26.71 | 21.43 | 15.51 | 9.12 | -8.68 |
| 3 | 1.46 | 1.01 | 0.84 | 0.51 | -0.43 | 25.59 | 20.59 | 13.51 | 8.89 | -8.46 |
| 4 | 1.39 | 1.02 | 0.72 | 0.35 | -0.41 | 25.77 | 18.87 | 12.84 | 6.02 | -9.63 |
| Big | 1.28 | 0.87 | 0.69 | 0.32 | -0.65 | 26.78 | 16.26 | 10.40 | 4.76 | -9.57 |
| | | | r_i | | | | | $t(\text{RMW})$ | | |
| Small | -0.30 | -0.39 | -0.39 | -0.60 | -0.80 | -3.19 | -5.35 | -5.45 | -6.99 | -9.98 |
| 2 | -0.09 | -0.14 | -0.24 | -0.42 | -0.41 | -1.12 | -1.84 | -3.03 | -5.18 | -5.77 |
| 3 | 0.16 | 0.03 | 0.23 | 0.02 | -0.22 | 1.94 | 0.35 | 2.58 | 0.27 | -3.01 |
| 4 | 0.31 | 0.19 | 0.23 | 0.14 | 0.16 | 3.96 | 2.35 | 2.76 | 1.63 | 2.51 |
| Big | 0.18 | 0.54 | 0.92 | 0.88 | 0.71 | 2.65 | 6.83 | 9.42 | 8.88 | 7.19 |
| | | | R^2 | | | | | | | |
| Small | 0.96 | 0.97 | 0.97 | 0.96 | 0.96 | | | | | |
| 2 | 0.96 | 0.96 | 0.96 | 0.96 | 0.96 | | | | | |
| 3 | 0.96 | 0.97 | 0.95 | 0.95 | 0.96 | | | | | |
| 4 | 0.96 | 0.96 | 0.95 | 0.95 | 0.97 | | | | | |
| Big | 0.97 | 0.96 | 0.94 | 0.92 | 0.92 | | | | | |
| Average | 0.96 | | | | | | | | | |

Panel A model is *Fama-French-three-factor (MKT-SMB-HML)* model. The table shows coefficient from time series regressions for monthly percent excess returns on (5*5) *Size-GP* portfolios. R_{it} is the return of portfolio in month t. R_{ft} is risk free rate. α_i is the intercept, β_i , s_i , h_i are factor coefficients for time-series regression. $t(\alpha_i)$ is the intercept, $t(MKT)$, $t(SMB)$, $t(HML)$ are the t -statistics, provided on the right-hand side. R^2 is explanation power of time regressions. Our sample period starts in April 1996 and ends in March 2016.

Panel B model is *MKT-SMB-RMW* factor model. The table shows coefficient from time series regressions for monthly percent excess returns on (5*5) *Size-GP* portfolios. R_{it} is the return of portfolio in month t. R_{ft} is risk free rate. α_i is the intercept, β_i , s_i , r_i are factor coefficients for time-series regression. $t(\alpha_i)$ is the intercept, $t(MKT)$, $t(SMB)$, $t(RMW)$ are the t -statistics, provided on the right-hand side. R^2 is explanation power of time regressions. Our sample period starts in April 1996 and ends in March 2016.

Table 4.9: Gibbons-Ross-Shaken Test (Gibbons et al. (1989), Kim & Shamsuddin (2016)).

| Test portfolios | Model | GRS P value | Economic value | R^2 |
|-----------------|---------------------------------|-------------|----------------|-------|
| <i>B/M-GP</i> | <i>Fama-French-three-factor</i> | 0.01 | 0.37 | 0.95 |
| | <i>MKT-SMB(Size)-RMW(GP)</i> | 0.22 | 0.73 | 0.96 |
| <i>Size-GP</i> | <i>Fama-French-three-factor</i> | 0.00 | 0.32 | |
| | <i>MKT-SMB(Size)-RMW(GP)</i> | 0.82 | 0.81 | |
| <i>Size-B/M</i> | <i>Fama-French-three-factor</i> | 0.00 | 0.32 | |
| | <i>MKT-SMB(Size)-RMW(GP)</i> | 0.00 | 0.60 | |

The table reports *GRS P* value and Economic value (Gibbons et al. (1989), Kim & Shamsuddin (2016)). Comprehensively, the *GRS P* value indicates statistical significance. The bigger the *P* value, the greater the model performance. Economic value indicates proportion between the maximum sharpe ratio of the three factor portfolios and the slope of the efficient frontier based on all assets. The bigger the economic value, the greater the dual economic and market efficiency. We also show the model's R^2 .

We test this hypothesis for combinations of 5*5 portfolios and factors. Here we compare the *Fama-French-three-factor* model and our *MKT-RMW-HML* factor model. The test samples include *Size-GP* portfolios, *B/M-GP* portfolios, and *Size-B/M* portfolios. Our sample period starts in April 1996 and ends in March 2016.

Chapter 5

Conclusion

This chapter discusses the conclusion. Section 5.1 is the model's application. Section 5.2 explains anomaly on the Japanese and Chinese market Section. 5.3 compares Japanese and Chinese markets. Section 5.4 discusses conclusions, limitations.

5.1 Application to smart-betas

We hope our model can perform well in real market, and close to trading strategy. Hence, we use *MSCI* index return to test new factor model and *Fama-French-three-factor* model. We use Morgan Stanley Capital International (*MSCI*) index, a float-adjusted index that global investors can use as a benchmark to try to do global comparison. We believe this is a useful analysis because there are many vendors of "smart beta" strategies.

Through Table 5.1, Table 5.2, we compare *Fama-French-three-factor* model and *MKT-HML-RMW* factor model in Japan. We find that use of *MKT-HML-RMW* factor model makes absolute α smaller except in small cap index. For adjust R^2 , the two models have similar result, from 70%-95%. 5 indexes have significant power for RMW factor, also 5 indexes have significant power for SMB factor, but 3 of them are negative, that means SMB has been an unstable factor.

Through Table 5.3, Table 5.4, we compare *Fama-French-three-factor* model and *MKT-SMB-RMW* factor model in China. We find that use of *MKT-SMB-RMW* factor model makes absolute α smaller except in small cap index and MSCI A 50.

For adjust R^2 , the two models have similar result, from 81%-97%. All indexes have significant power for SMB factor, but Just 1 index have significant power for RMW factor, that means RMW has not sufficiently explain index return.

Through the sample, we can conclude that our sample in China is relatively shorter because of the lack of data. Therefore, the performances on the Chinese markets are not ideal.

In summary, new factor model performs better than *Fama-French three-factor* model for explaining *MSCI* smartbetas on the Japanese market, and on the Chinese markets, due to the data lack missing, we can not get definite results.

Table 5.1: Time series regression with MSCI Japanese index returns and factor model 1994-2016.

| Panel A Fama-French-three-factor | | | | | | |
|-------------------------------------|-------|------|-------|------|-------|--------|
| MSCI index | a | MKT | SMB | HML | R^2 | sample |
| MSCI Japan Enhanced Value | 0.18 | 0.97 | 0.06 | 0.40 | 0.85 | 206 |
| MSCI Japan Quality Tilt | 0.10 | 0.93 | -0.19 | 0.06 | 0.95 | 206 |
| MSCI Japan Minimum Volatility (JPY) | 0.21 | 0.73 | -0.06 | 0.02 | 0.86 | 172 |
| MSCI Japan High Dividend Yield | 0.09 | 0.73 | -0.03 | 0.45 | 0.69 | 206 |
| MSCI Japan Risk Weighted | 0.07 | 0.80 | 0.13 | 0.32 | 0.86 | 262 |
| MSCI Japan Momentum | 0.14 | 0.90 | -0.29 | 0.01 | 0.72 | 262 |
| MSCI Japan | 0.03 | 0.95 | -0.19 | 0.14 | 0.89 | 262 |
| MSCI Japan Small Cap | -0.04 | 0.94 | 0.71 | 0.03 | 0.88 | 182 |

| MSCI index | t(a) | t(MKT) | t(SMB) | t(HML) | sample |
|-------------------------------------|-------|--------|--------|--------|--------|
| MSCI Japan Enhanced Value | 1.19 | 33.81 | 0.91 | 6.14 | 206 |
| MSCI Japan Quality Tilt | 1.20 | 59.59 | -5.40 | 1.63 | 206 |
| MSCI Japan Minimum Volatility (JPY) | 1.69 | 31.40 | -1.15 | 0.26 | 172 |
| MSCI Japan High Dividend Yield | 0.50 | 21.38 | -0.38 | 5.70 | 206 |
| MSCI Japan Risk Weighted | 0.68 | 38.63 | 3.16 | 6.49 | 262 |
| MSCI Japan Momentum | 0.77 | 25.33 | -4.16 | 0.15 | 262 |
| MSCI Japan | 0.27 | 44.66 | -4.47 | 2.81 | 262 |
| MSCI Japan Small Cap | -0.03 | 34.87 | 11.76 | 0.58 | 182 |

In Table 5.1, we list 8 smart-betas' monthly returns, *MSCI* Japan Enhanced Value, *MSCI* Japan Quality Tilt, *MSCI* Japan Minimum Volatility, *MSCI* Japan High Dividend Yield, *MSCI* Japan Risk Weighted, *MSCI* Japan Momentum, *MSCI* Japan, *MSCI* Japan small cap. And we do time-series regression with *Fama-French-three-factor* model. α stands for intercept, *MKT* stands for market factor, *SMB* stands for size factor, *HML* stands for value factor, *RMW* stands for profitability factor, and R^2 stands for regression adjust R^2 . $t(a)$, $t(MKT)$, $t(SMB)$, $t(HML)$, $t(RMW)$ stands for factors' t value, and sample size stands for test month numbers.

Table 5.2: Time series regression with MSCI Japanese index returns and factor model 1994-2016.

| Panel B MKT-HML-RMW-factor | | | | | | |
|-------------------------------------|-------|------|-------|-------|-------|--------|
| MSCI index | a | MKT | RMW | HML | R^2 | sample |
| MSCI Japan Enhanced Value | 0.09 | 0.99 | 0.28 | 0.49 | 0.85 | 206 |
| MSCI Japan Quality Tilt | 0.06 | 0.93 | -0.04 | 0.03 | 0.94 | 206 |
| MSCI Japan Minimum Volatility (JPY) | 0.00 | 0.77 | 0.38 | 0.16 | 0.87 | 172 |
| MSCI Japan High Dividend Yield | -0.07 | 0.76 | 0.37 | 0.55 | 0.70 | 206 |
| MSCI Japan Risk Weighted | -0.06 | 0.84 | 0.48 | 0.46 | 0.87 | 262 |
| MSCI Japan Momentum | 0.15 | 0.87 | -0.14 | -0.06 | 0.70 | 262 |
| MSCI Japan | -0.04 | 0.95 | 0.12 | 0.15 | 0.88 | 262 |
| MSCI Japan Small Cap | -0.05 | 0.98 | 0.70 | 0.29 | 0.82 | 182 |

| MSCI index | t(a) | t(MKT) | t(RMW) | t(HML) | sample |
|-------------------------------------|-------|--------|--------|--------|--------|
| MSCI Japan Enhanced Value | 0.56 | 33.59 | 2.70 | 6.88 | 206 |
| MSCI Japan Quality Tilt | 0.62 | 53.16 | -0.66 | 0.77 | 206 |
| MSCI Japan Minimum Volatility (JPY) | -0.02 | 33.10 | 4.73 | 2.48 | 172 |
| MSCI Japan High Dividend Yield | -0.36 | 21.75 | 2.98 | 6.52 | 206 |
| MSCI Japan Risk Weighted | -0.60 | 41.75 | 6.27 | 9.07 | 262 |
| MSCI Japan Momentum | 0.76 | 23.28 | -0.99 | -0.64 | 262 |
| MSCI Japan | -0.30 | 42.06 | 1.45 | 2.65 | 262 |
| MSCI Japan Small Cap | -0.31 | 28.14 | 5.82 | 3.34 | 182 |

In Table 5.2, we list 8 smart-betas' monthly returns, *MSCI* Japan Enhanced Value, *MSCI* Japan Quality Tilt, *MSCI* Japan Minimum Volatility, *MSCI* Japan High Dividend Yield, *MSCI* Japan Risk Weighted, *MSCI* Japan Momentum, *MSCI* Japan, *MSCI* Japan small cap. And we do time-series regression with *MKT-GP-BM* factor model respectively. α stands for intercept, *MKT* stands for market factor, *SMB* stands for size factor, *HML* stands for value factor, *RMW* stands for profitability factor, and R^2 stands for regression adjust R^2 . $t(a)$, $t(MKT)$, $t(SMB)$, $t(HML)$, $t(RMW)$ stands for factors' t value, and sample size stands for test month numbers.

Table 5.3: Time series regression with MSCI Chinese index returns and factor model 1996-2016.

| Panel C Fama-French-three-factor | | | | | | |
|----------------------------------|------|------|-------|-------|-------|--------|
| MSCI index | a | MKT | SMB | HML | R^2 | sample |
| MSCI China A | 0.68 | 0.93 | -0.44 | 0.11 | 0.95 | 181 |
| MSCI China A 50 | 1.23 | 0.81 | -0.78 | 0.42 | 0.82 | 143 |
| MSCI China A Minimum Volatility | 0.57 | 0.88 | -0.19 | 0.07 | 0.97 | 113 |
| MSCI China A Large Cap | 1.07 | 0.86 | -0.74 | 0.25 | 0.86 | 142 |
| MSCI China A Large Cap Value | 0.25 | 1.04 | 0.55 | -0.38 | 0.97 | 142 |
| MSCI China A Small Cap | 1.26 | 0.95 | -0.49 | 0.92 | 0.89 | 82 |

| MSCI index | t(a) | t(MKT) | t(SMB) | t(HML) | sample |
|---------------------------------|------|--------|--------|--------|--------|
| MSCI China A | 4.77 | 61.08 | -10.03 | 1.89 | 181 |
| MSCI China A 50 | 3.57 | 24.35 | -7.84 | 3.29 | 143 |
| MSCI China A Minimum Volatility | 3.54 | 58.03 | -3.71 | 1.25 | 113 |
| MSCI China A Large Cap | 3.48 | 28.90 | -8.37 | 2.23 | 142 |
| MSCI China A Large Cap Value | 1.58 | 66.29 | 11.69 | -6.37 | 142 |
| MSCI China A Small Cap | 3.80 | 24.30 | -4.02 | 7.54 | 82 |

In Table 5.3, we list 6 smart-betas' monthly returns, *MSCI China A*, *MSCI China A 50*, *MSCI China A Minimum Volatility*, *MSCI China A Large Cap*, *MSCI China A Large Cap Value*, *MSCI China A small cap*. And we do time-series regression with *Fama-French-three-factor* model. α stands for intercept, *MKT* stands for market factor, *SMB* stands for size factor, *HML* stands for value factor, *RMW* stands for profitability factor, and R^2 stands for regression adjust R^2 . $t(a)$, $t(MKT)$, $t(SMB)$, $t(HML)$, $t(RMW)$ stands for factors' t value, and sample size stands for test month numbers.

Table 5.4: Time series regression with MSCI Chinese index returns and factor model 1996-2016.

| Panel D MKT-SMB-RMW factor | | | | | | |
|---------------------------------|----------|------|-------|-------|-------|--------|
| MSCI index | α | MKT | SMB | RMW | R^2 | sample |
| MSCI China A | 0.64 | 0.93 | -0.45 | 0.08 | 0.95 | 181 |
| MSCI China A 50 | 1.27 | 0.81 | -0.89 | 0.02 | 0.81 | 143 |
| MSCI China A Minimum Volatility | 0.51 | 0.89 | -0.20 | 0.12 | 0.97 | 113 |
| MSCI China A Large Cap | 1.00 | 0.87 | -0.77 | 0.12 | 0.86 | 142 |
| MSCI China A Large Cap Value | 0.07 | 1.06 | 0.70 | 0.17 | 0.96 | 142 |
| MSCI China A Small Cap | 2.18 | 0.84 | -1.23 | -0.93 | 0.83 | 82 |

| MSCI index | t(α) | t(MKT) | t(SMB) | t(RMW) | sample |
|---------------------------------|---------------|--------|--------|--------|--------|
| MSCI China A | 4.18 | 56.06 | -9.14 | 1.08 | 181 |
| MSCI China A 50 | 3.30 | 21.33 | -7.82 | 0.09 | 143 |
| MSCI China A Minimum Volatility | 3.06 | 54.64 | -3.99 | 1.61 | 113 |
| MSCI China A Large Cap | 2.99 | 26.23 | -7.79 | 0.82 | 142 |
| MSCI China A Large Cap Value | 0.37 | 54.66 | 12.21 | 1.91 | 142 |
| MSCI China A Small Cap | 5.09 | 15.72 | -9.43 | -3.24 | 82 |

In Table 5.4, we list 6 smart-betas' monthly returns, *MSCI China A*, *MSCI China A 50*, *MSCI China A Minimum Volatility*, *MSCI China A Large Cap*, *MSCI China A Large Cap Value*, *MSCI China A small cap*. And we do time-series regression with *MKT-Size-GP* factor model. α stands for intercept, *MKT* stands for market factor, *SMB* stands for size factor, *HML* stands for value factor, *RMW* stands for profitability factor, and R^2 stands for regression adjust R^2 . $t(\alpha)$, $t(MKT)$, $t(SMB)$, $t(HML)$, $t(RMW)$ stands for factors' t value, and sample size stands for test month numbers.

5.2 Anomaly explain on Japanese and Chinese market

Based on the previous study, we summarise and explain these anomalies on the Japanese and Chinese markets.

5.2.1 Why gross profitability surpasses other profitability proxy on the Japanese market

Gross profit is the cleanest accounting measure of true economic profitability. The farther down the income statement one goes, the more polluted profitability measures become, and the less related they are to true economic profitability. For example, a firm that has both lower production costs and higher sales than its competitors are unambiguously more profitable. Even so, it can easily have lower earnings than its competitors.

The predictive power of operating profit and gross profit is puzzling for two reasons. Firstly, Japanese shareholders focus on corporate gross profit. Secondly, prior research finds that some of the items between gross profit and operating profit, such as selling, general, administrative expenses and expenditures on research and development, predicts expected returns. On the other hand, selling, general and administrative expenses (*SGA*), which together represent a decomposition of gross profits. Hence operating profitability effect become weaker when lose selling, general and administrative expenses (*SGA*) effect. An international comparison of return on equity (*ROE*)-a metric that investors regard as an important profitability indicator shows that Japanese companies have had a low *ROE* over the long-term despite a recent increasing trend. The *ROE* in Japan is far lower than in other developed nations. By calculations, only about 50 percent of Japanese companies would meet the 8 percent threshold recommended. Hence, *ROE* is not appropriate on the Japanese market.

5.2.2 Why do not choose momentum factor as research variable

Momentum (Jegadeesh & Titman (1993), Carhart (1997)) is another important factor, which we did not discuss at this time. Because momentum is included in the price information. We do not hope to bring in a factor including price information. As Novy-Marx (2012) shows that momentum is primarily driven by firms' performance prior to portfolio formation, not by a tendency of rising and falling equities to keep rising and falling.

On the other hand, Fama & French (2012), Cakici et al. (2015) have tested that the momentum has no power in Japan and China respectively. Hence, it is unnecessary to discuss about momentum.

5.2.3 Why choose floating ratio as research variable on the Chinese market

We conclude that stock returns are considered related to corporate governance. Corporate governance plays an important role for improvement of profitability effect. Good governance leads to good gross profitability effect.

ESG (Environmental, Social and Governance) factor has been a popular research filed in asset pricing model. Floating ratio reflects the expected corporate governance in China, which help to predict a firm's future cash flow. (Gompers & Metrick, 2003) consider that corporate governance affects firm performance, the floating ratio may serve as a better proxy the fundamental risks in China than the book-to-market variable.

Overall, we want to develop a multi-factor model including *ESG* (corporate governance) factor, floating ratio is proxy variable for corporate governance, which is worth researching.

5.2.4 Why choose operating leverage as research variable on the Chinese market

Carlson et al. (2004) discovered an economic role of operating leverage in explain-

ing the value premium effect: when demand drops by some certain reasons, market value of equity declines due to the unfavorable performance of the firm while book value of equity remains basically the same, leading to a higher book-to-market ratio. And operating leverage can further amplify this dynamic by adding to the demand volatilities.

Zhang (2005) shows that increased operating leverage, in the form of higher fixed costs of production, leads to a higher value premium. Novy-Marx (2011), for the first time, finds the direct empirical evidence for the operating leverage hypothesis underlying most theoretical models of value premium.

Kisser (2014) finds a positive relationship between operating leverage and the gross profitability premium, but a negative relationship between operating leverage and the value premium. High operating leverage indeed can cause high B/M as the higher risk required by investors decreases the market value of equity, therefore, increasing B/M. It would make sense that the value premium would not exclusively price the risk emanating from operating leverage. Hence, we consider operating leverage as intermediate variables.

Overall, operating leverage, value premium, and gross profitability have a tri-angle relationship. Operating leverage is intermediate variable, can supply direct evidence to explain value premium, gross profitability premium.

5.3 Comparing Japanese and Chinese markets

We consider that Japanese and Chinese markets have somethings in common, but there a lot of differences. Firstly, we could see the relationship which exsits between Japanese and Chinese markets.

Figure 5.1 The correlation between china and other regions.

| China A-shares displays low correlation with other regions | | | | | | | | |
|--|---------|---------|-------|------|------|--------|-------|---------|
| 3-Year correlation (2012-14) | China A | China H | World | EM | USA | Europe | Japan | AC APxJ |
| China A | 1 | | | | | | | |
| China H | 0.59 | 1 | | | | | | |
| World | -0.01 | 0.47 | 1 | | | | | |
| EM | 0.15 | 0.71 | 0.8 | 1 | | | | |
| USA | -0.03 | 0.36 | 0.94 | 0.68 | 1 | | | |
| Europe | -0.01 | 0.45 | 0.94 | 0.74 | 0.8 | 1 | | |
| Japan | 0.01 | 0.36 | 0.67 | 0.58 | 0.55 | 0.58 | 1 | |
| Asia-Pacific ex-Japan | 0.14 | 0.74 | 0.78 | 0.97 | 0.64 | 0.72 | 0.58 | 1 |

Sources: SSGA; MSCI; FactSet, as of December 31 2014

(Source) from factset as of December 31th, 2014.

From Figure 5.1, we can conclude that Chinese index has no significant correlation with other regions, however, Japanese index has highly correlated with US, EU, and EM markets. We will analyse the differences from multi-angles.

Firstly, the two countries have different economic systems. Although China is a market economy system, it is differences from the western market economy. For example, Japan implemented the free market economy and China implemented the socialist market economy with a high degree of macroeconomic control. This means that in China, when the “invisible hand” of the market lapses, the ”visible hand” of the government can demonstrate its power and implement the government’s macro-control. Japan’s “visible hand” did not play its due role on the stock market crash before the “bubble economy” burst. Hence, in China, we should focus on government power.

Secondly, the two countries have different economic structures. China is dominated by the state-owned economy, the majority of blue chip themselves are state-owned assets or related background, while in Japan and other western countries, the majority are private companies. On the Chinese stock market, when index is threatened or damaged, the government will take measures to protect market, because the stock price is directly related to performance of state-owned assets.

Thirdly, the two countries have different stages of economic and social development. Japan had entered a developed society, while China is still a developing

country. Therefore, the investment demand and potential consumer demand are extremely different.

5.4 Conclusions and limitations

5.4.1 Conclusions

McLean & Pontiff (2016) argue that some stock market anomalies are less anomalous after being published. Repeatedly cited size and value factors naturally are less anomalous over time. That also impels me to seek new effective factors and new-factor models.

Due to political and cultural differences, each capital market embraces different investment environment. Therefore, the price formation process and risk factors might be different.

On the Japanese market, we follow Ball et al. (2015) to investigate and compare firms' gross profit, operating profit, and net income as predictors of returns for a cross-section of publically traded Japanese equities spanning 1994-2016. We test the predictive power of profit measures on cross-sectional stock returns using portfolio tests and Fama-MacBeth regressions, it was found out that gross-profit-to-book-equity ratios significantly predict returns on sampled stocks. Consistent with Novy-Marx (2013), we also find that sorting portfolios by gross profitability and book-to-market ratios outperforms in the Japanese market. Hence, we create a Market-Profitability-Value model that captures value and profitability premium among returns of sampled stocks. Based on Gibbons-Ross-Shanken test and economic value, we demonstrate that our enhanced model outperforms *Fama-French-multiple-factor* model in isolating influences on equity returns.

On the Chinese market, we follow Novy-Marx (2011,2013) to investigate and compare firms' gross profit, operating leverage as predictors of returns for a cross-section of traded Chinese equities spanning 1996-2016. We use portfolio tests and Fama-MacBeth regressions, and finds out that gross-profit-to-market-capitalization ratios significantly predicts returns on sampled stocks. We also find that sorting portfolios by gross profitability and size outperforms in the Chinese market. Hence, we create a

Market-Size-Profitability model that captures profitability and size premium among returns of sampled stocks. Based on GRS test and economic value, we demonstrated that my enhanced model outperforms *Fama-French-multiple-factor* model in isolating influences on equity returns.

The latest popular concept is that it is far better to buy a wonderful company at a fair price than to buy a fair company at a wonderful price. Profitability helps isolate “good growth” and “bad value” stocks. We should keep on research the interesting profitability factor. Overall, through lots of validations, we find gross profitability have same effect whatever in US, Japan or China.

5.4.2 Limitations

Usually, there are three types of factor models to explain expected return.

1. Macroeconomic factor model-Factors are observable economic and financial time series.
2. Fundamental factor model-Factors are created from observable asset characteristics.
3. Statistical factor model-Factors are unobservable and extracted from asset returns.

In this paper, we mainly focus on fundamental factor model, however, these models have their demerits, it is very difficult to determine the appropriate model, include the number of factors and what the factors are. Data mining technique, like PCA, ICA (Cha & Chan (2000)) can automatically identify the hidden factors from historical data and confirm the number of factors.

Technical analysis (see K. (2014)) has been widely applied by practitioners to analyze financial data and make trading decisions for decades. With machine learning development, we should focus on big data and the cross-section of stock returns in the future study.

Combining traditional financial theory and big data analysis is the future research trend. We will devote myself to researching the newest financial theory and try to using data analysis to simulate financial market, extracting hidden factor from stock returns.

Appendix A

Definitions

This appendix provides a brief survey of the empirical literature as it relates to the cross-sectional predictive power of the firm characteristics used in this paper. The variables appear in the literature.

Risk free rate: The risk free rate used in this research is the 1-month Gensaki bond, obtained from Factset at the beginning of each month. The risk free rate is used to calculate the monthly excess market returns and the monthly excess portfolio returns.

Market capitalization of individual stocks (MV): Market capitalization measure firm size. The firm size is measured by the logarithm of the market value of equity (the number of total shares outstanding multiplied by market share price at the end of month $t-1$ for each stock). The concept of market capitalization is simple where different size companies perform differently. Most of the empirical studies show that firms with small market capitalization tend to outperform large firms.

Beta: Fama & MacBeth (1973), and others provide evidence that beta is positively related to expected stock returns, though not as strongly as the CAPM predicts. More recent work shows that beta has no predictive power after 1960 and no predictive power back to 1926 after controlling for its correlation with size and B/M (e.g., Fama & French (1992), Fama & French (2006)).

Dividend yield: The relation between dividends and expected stock returns has a long history in the empirical literature. The bottom line seems to be that dividend yield has little predictive power for future returns.

Momentum: Jegadeesh & Titman (1993) show that past 3 to 12 month returns are positively related to subsequent 3 to 12 month returns. This relation has been confirmed by many others (e.g., Fama & French (2008)).

Profitability: Many studies have shown that earnings surprises, earnings-to-price, and earnings-to-book-value are positively related to subsequent returns (e.g., Fama & French (2006), Fama & French (2008) , Novy-Marx (2013)).

Asset growth (*INV*): A variety of variables that measure a firm's investment and growth seem to be negatively related to expected stock returns.

Appendix B

Code on the Japanese market

Appendix B gives the code of calculations. We take Japanese samples as examples.

1. Fama-MacBeth univariate regressions of firm returns 1994-2016.

```
/* a1a11 is a database include all the financial statements.*/  
data jap.a1a11;  
set jap.a1a11;  
op1=(sale-cogs-sga)/asset;  
op2=(sale-cogs-sga)/book1;  
op3=(sale-cogs-sga)/me1;  
gp1=(sale-cogs)/asset;  
gp2=(sale-cogs)/book1;  
gp3=(sale-cogs)/me1;  
netincome1=netincome/asset;  
netincome2=netincome/book1;  
netincome3=netincome/me1;  
keep code1 code2 date return inv lnmel bemel  
    rf gp1 gp2 gp3 op1 op2 op3 netincome1  
    netincome2 netincome3 ;run;  
% macro mac;  
% do i=37 % to 296;  
data jap.b &i .;  
set jap.a1a11;
```

```

if date= &i .;run;
proc reg data=jap.b & i.
outest = jap.d & i. noprint;
by date ;
model return= gp1/white;
model return= gp2/white;
model return= gp3/white;
model return= op1/white;
model return= op2/white;
model return= op3/white;
model return= netincome1/white;
model return= netincome2/white;
model return= netincome3/white;
run; /*fama-macbeth regression */
% End;
% MEND mac;
% mac;
data jap.ajune4;
set jap.d37;
run;
% macro mac;
% do i=37 % to 296;
data jap.ajune4;
merge jap.ajune4 jap.d & i.;
by date ;
run;
% End;
% MEND mac;
% mac; /*fama-macbeth regression */
proc sort data=jap.ajune4;
by _MODEL_ date;

```

```
run ;/*rank*/  
data jap.ajune5;  
set jap.ajune4;run;  
proc means data=jap.ajune5 mean std t probt ;  
var bemel lnme1 inv1 netincome1 netincome2 netincome3 ;  
by _MODEL_ ;  
output out=jap.ajune6;  
quit; /*calculate coeffieint and t value */
```

2. Double Sort by B/M and Profitability

```
proc rank data=jap.ala11 out=jap.g1 groups=5;
by date;
ranks p1;
var beme2;
run ;
proc sort data=jap.g1; by date p1;run;
proc rank data=jap.g1 out=jap.g2 groups=5;
by date p1;
ranks p2;
var gp2;
run ;
data jap.g;
set jap.g2;
if p1=0 then p=p2+1;
if p1=1 then p=p2+6;
if p1=2 then p=p2+11;
if p1=3 then p=p2+16;
if p1=4 then p=p2+21;
run;
data jap.g;
set jap.g;
ref=return-rf;
run;
proc sort data=jap.g;
by p date ;run;
proc means data = jap.g noprint;
var me1; by p date;
output out = jap.g4 sum = sumcap;
run;
data jap.g5;
```

```

merge jap.g  jap.g4(drop = _TYPE_);
by p date;
run;
data jap.g6;
set jap.g5;
wt = mel/sumcap;
run;
proc sort data = jap.g6; by p date; run;
proc means data = jap.g6 noprint;
var ref ;
weight wt;
by p date;
output out = jap.g8 mean = ref ;
run;
data jap.g8(drop =_TYPE_  FREQ_); set jap.g8;
run;
/* Calculate value weighted returns */
proc univariate data=jap.g8  noprint;
var ref;
by p ;
output out=jap.gp2
mean=ref ;
run; /* Calculate 5*5 GP-B\M portgolio excess return monthly
*/
proc univariate data=jap.g  noprint;
var ref;
by p date;
output out=jap.g8e
mean=ref ;
run; /* Calculate 5*5 GP-B\M portfolio average excess return */

```

3. Factor constructions-SMB, HML, RMW

```
libname jap 'h:\sas';
/* sort the factor into 10 groups */
proc rank data=jap.a1a11 out=jap.a1a7 groups=10;
by date;
var me1 beme1 gp2 op2;
ranks p1 p2 p3 p4;
run ;
data jap.a1a8;
set jap.a1a7;
keep code1 date return rf me1 beme1 gp2 op2 p1 p2 p3 p4;
run;
data jap.a1a8;
set jap.a1a8;
mv = p1+1;
bm = p2+1;
gp = p3+1;
op = p4+1;
drop p1 p2 p3 p4;
run;
data jap.a1a9;
set jap.a1a8;
if bm <=3 then b='1';
else if bm<=7 then b='2';
else b='3';
if gp <=3 then R='1';
else if gp <=7 then R='2';
else R='3';
if op <=3 then o='1';
else if op <=7 then o='2';
else o='3';
```



```

if in <=3 then i='1';
else if in <=7 then i='2';
else i='3';
if mv <=5 then s='1';
else s='2';
SB=s || b;
SR=s || r;
So=s || o;
Si=s || i;
keep date code1 return rf me1 SB SR So Si;
run;
proc sort data=jap.a1a9; by date ;run;
/* SMB, HML construcion*/
data jap.a1b1;
set jap.a1a9;
ref= return-rf;
by date;
keep date code1 ref me1 SB;
run;
proc sort data=jap.a1b1;
by date SB ;run;
proc means data = jap.a1b1 noprint;
var me1; by date SB;
output out = jap.a1b2 sum = sumcap;
run;
data jap.a1b3;
merge jap.a1b2 jap.a1b1;
by date SB;
run;
data jap.a1b4;
set jap.a1b3;

```

```

wt = mel/sumcap;
run;
proc sort data = jap.a1b4; by date SB; run;
proc means data = jap.a1b4 noprint;
var ref ;
weight wt;
by date SB;
output out = jap.a1b5 mean = ref ;
run;
data jap.a1b5(drop =_TYPE_ FREQ); set jap.a1b5;
run;
proc sort data = jap.a1b5; by SB date; run;
/* Calculate value weighted returns */
proc univariate data=jap.a1b5 noprint;
var ref;
by SB date ;
output out=jap.a1b6
mean=meanreturn;

run; /* 5*5 portfolios excess return */
proc sort data=jap.a1b6;
by date ;run;
data jap.a1b7;
set jap.a1b6;
SMB=(lag5(meanreturn)+lag4(meanreturn)+lag3(meanreturn))/3
-(lag2(meanreturn)+lag(meanreturn)+meanreturn)/3;
HML=(lag3(meanreturn)+meanreturn)/2
-(lag2(meanreturn)+lag5(meanreturn))/2;
if SB <'23' then delete; drop meanreturn ;
run;
data jap.a1b7;

```

```

set jap.a1b7;
drop SB;
run; /*smb1 hml */
data chi.jfac1;
set jap.a1b7;
run;
data chi.jfac2;
set jap.a1b7;
run;
data chi.jfac3;
set jap.a1b7;
run;
/* SMB, RMW construcution*/
data jap.a1b1;
set jap.a1a9;
ref= return-rf;
by date;
keep date code1 ref me1 SR;
run;
proc sort data=jap.a1b1;
by date SR;run;
proc means data = jap.a1b1 noprint;
var me1; by date SR;
output out = jap.a1b2 sum = sumcap;
run;
data jap.a1b3;
merge jap.a1b2 jap.a1b1;
by date SR;
run;
data jap.a1b4;
set jap.a1b3;

```

```

wt = mel/sumcap;
run;
proc sort data = jap.a1b4; by date SR; run;
proc means data = jap.a1b4 noprint;
var ref ;
weight wt;
by date SR;
output out = jap.a1b5 mean = ref ;
run;
data jap.a1b5(drop =_TYPE_ _FREQ_); set jap.a1b5;
run;
proc sort data = jap.a1b5; by SR date; run;
/* Calculate value weighted returns */
proc univariate data=jap.a1b5 noprint;
var ref;
by SR date ;
output out=jap.a1b6
mean=meanreturn;

run; /* 5*5 portfolios excess return */
proc sort data=jap.a1b6;
by date ;run;
data jap.a1b7;
set jap.a1b6;
SMB=(lag5(meanreturn)+lag4(meanreturn)+lag3(meanreturn))/3
-(lag2(meanreturn)+lag(meanreturn)+meanreturn)/3;
RMW=(lag3(meanreturn)+meanreturn)/2-
(lag2(meanreturn)+lag5(meanreturn))/2;
if SR <'23' then delete; drop meanreturn ;
run;
data jap.a1b7;

```

```
set jap.alb7;  
drop SR;  
run; /*SMB RMW*/  
data chi.jfac1;  
set jap.alb7;  
run;  
data chi.jfac2;  
set jap.alb7;  
run;  
data chi.jfac3;  
set jap.alb7;  
run;
```

4. Gibbons-Ross-Shaken Test

```
afac1<-read.csv("C:/Users/lenovo/Desktop/data/ch4factor.csv")
afac<-read.csv("C:/Users/lenovo/Desktop/data/chfactor.csv")
agpme<-read.csv("C:/Users/lenovo/Desktop/data/chgpme.csv")
amebe<-read.csv("C:/Users/lenovo/Desktop/data/chmebe.csv")
agpbe<-read.csv("C:/Users/lenovo/Desktop/data/chgpbe.csv")
afac<-afac[,c(1,2)]
afac<-merge(afac,afac1,by="date")
names(agpme)[1]<-c("p")
names(agpme)[2]<-c("date")
names(amebe)[1]<-c("p")
names(amebe)[2]<-c("date")
names(agpbe)[1]<-c("p")
names(agpbe)[2]<-c("date")
names(afac)[1]<-c("date")
names(afac1)[1]<-c("date")
ag5<-cast(agpme,date~p)
ag6<-cast(amebe,date~p)
ag7<-cast(agpbe,date~p)
total5<-merge(ag5,afac,by="date")
total6<-merge(ag6,afac,by="date")
total7<-merge(ag7,afac,by="date")
f61=total7[1:205,c(27,29,28)] # OP-ME-3-factor model
r61=total7[1:205,2:26]# 25 OP-ME portfolio returns
GRS.MLtest(r61,f61)
g61<-GRS.test(r61,f61)$R2
g61<-matrix(g61,nrow=5,ncol=5)
gg61<-mean(g61)
g62<-GRS.test(r61,f61)$coef
g621<-matrix(g62[,c(1)],nrow=5,ncol=5)
gg621<-abs(g621)
```

```

ggg621<-mean(gg621)
g631<-matrix(g63[,c(1)],nrow=5,ncol=5)
g65<-GRS.test(r61,f61)$se
g651<-matrix(g65[,c(1)],nrow=5,ncol=5)
gg651<-mean(g651)
g61<-GRS.test(r61,f61)$R2
g62<-GRS.test(r61,f61)$coef
g63<-GRS.test(r61,f61)$tstat
g61<-matrix(g61,nrow=5,ncol=5)
g621<-matrix(g62[,c(1)],nrow=5,ncol=5)
g622<-matrix(g62[,c(2)],nrow=5,ncol=5)
g623<-matrix(g62[,c(3)],nrow=5,ncol=5)
g624<-matrix(g62[,c(4)],nrow=5,ncol=5)
g631<-matrix(g63[,c(1)],nrow=5,ncol=5)
g632<-matrix(g63[,c(2)],nrow=5,ncol=5)
g633<-matrix(g63[,c(3)],nrow=5,ncol=5)
g634<-matrix(g63[,c(4)],nrow=5,ncol=5)

```

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