An exploration of momentum-sorted cross section return in Chinese stock market

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Abstract

We apply a functional principal component analysis on momentum-sorted cross section return controlled by Fama-French three factors in Chinese "A" share market. We find that the momentum effect is not as weak as evidenced in existing literature, in precondition of rich risk patterns explored. On the basis of extracted risk patterns, we construct two functional momentum factors. Firstly, an elaborate version of conventional momentum factor. Secondly, an extreme minus mediocre risk factor which is explained by the disposition effect. Additionally, we conduct static and dynamic eigenfunction portfolio using risk pattens. Our finding shows the static portfolio outperforms conventional contrarian strategy, and can be further reinforced by adjusting positions as long as achieving the prediction in functional scores.

Keywords: Momentum, Functional principal component analysis, Chinese "A" share stock return, Eigenfunction portfolio

JEL Classification: F30, G11, G12, G15

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1. Introduction

To model cross sectional equity return, Fama and French (1992) and Carhart (1997) developed well-known factors of market premium, size, value and momentum. Despite, numerous empirical studies being carried out using these models world-wide[1], arguments that the variation in cross sectional return cannot be fully explained by these four factors have been on the rise. Theoretically, these four factors should be able to obtain insignificant risk-adjusted return in both of developed and emerging stock markets. Interestingly, while all the other three factors explain cross section stock returns in China, momentum factor presents insignificant interpretation in Chinese stock market (Wong et al. (2006), Wu (2011), Cheung et al. (2014) and Cakici et al. (2015), amongst others). The possible arguments for the failure of momentum factor in Chinese market are extreme high market volatility and explosion of systematic risk.

In the domestic "A" share market[2], the investor is mainly consisted by households rather than institutions in developed markets, for instant in the U.S market. Given the composition of "A" share market, it is obviously that risk is higher compared with U.S. market. The standard deviation of Shanghai stock composite index is as high as 973.17 during 2005 to 2015, compared with 336.65 for S&P 500 in U.S. Is this really making investors stop to invest in such a risky market? The answer apparently is 'No'. The striking interesting role of Chinese government explains this phenomenon. For the purpose of keeping economic growth, Chinese regulators target to increase wage level and therefore boost domestic demands. However, a crash in stock market would directly reduce total wealth of households, which goes against policy target. As a result, Chinese government have to bail the market out during financial crises. Thus, investors' expectation is largely formulated by government commitment, and the stock market becomes very volatile and liquid. Although, this might be beneficial to household investors, it is probably not helpful for building a healthy financial system in the future.

Another possible reason for insignificant momentum factor in China is the explosion of systematic risk. Market anomalies can vanish or totally reverse during a specific period in the stock market, especially during sys-

[1]See Blitz et al. (2011), Fama and French (2015), Gandhi and Lustig (2015), amongst others.

[2]Chinese A share market is dominated in Chinese Yuan/CNY, and is mainly accessible for local investors.

tematic risk exploding period. For instant, the crash of momentum strategy has been a concern of the U.S. hedge fund industry for many years (Grundy and Martin (2001), De Groot et al. (2012), Daniel et al. (2012), Daniel and Moskowitz (2013), amongst others.). The hedge fund industry plays a relative safety assurance role for investors, by taking advantage of a market neutral strategy, but a crash would lead to disruptions in the market, which could lead investors into a vicious circle. Thus, this situation might happen in China and momentum strategy may crash frequently. The hedge fund is still an emerging industry in China, strong herding behavior exists in equity market neutral strategies[3]. Due to high idiosyncratic risk, the market neutral strategies earns significant profits since 2013. The common practice of alpha harvesting, however quickly produced an over-crowded industry that finally crashed in late 2014. More severely, this crash does not only concentrate on momentum anomaly, but for all market anomalies because of high contagion effect. It is clear to see that Chinese market is difficult to predict and is full of noises. Therefore, instead of excessive reliance on the traditional four factors mentioned above, the real challenge should be how to explore cross-sectional risk patterns in such a volatile market.

This study explores firm specific momentum-sorted cross section stock returns in China. We collect entire "A" share monthly price data of the period January 2005 to December 2015. Firstly, we find the results show that firm specific size and value contain strong market anomalies information in China, but momentum is relatively weak, and the value effect nearly disappears after controlling for momentum. This is consistent with existing literature. Secondly, as the main contribution, we find two functional momentum factors to interpret the momentum-sorted cross section returns which the Fama-French three factor and Carhart four factor models cannot fully explain. Specifically, rich risk patterns can be extracted from residuals of the Fama-French three factor model through using Functional principal component analysis —FPCA, so that these two functional factors are orthogonal to each other and uncorrelated with Fama-French three factors. The first functional momentum factor is a more detailed version of momentum —winner minus loser (also known as UMD, Up minus Down) factor; and the second functional momentum factor is an "Extreme minus Mediocre –EMM" factor. This further supports that "V" shaped disposition effect found by Ben-David and Hirshleifer (2012) in existence within China. In the end, as a trading application of functional momentum risk factors, we construct two versions

[3]Followed by public accessibility of CSI 300 (initialed from 2013) and CSI 500 (initialed from 2015) future indexes, the short position of a market neutral strategy is able to be approximated by short positions on futures.

–static and dynamic eigenfunction portfolios, the static portfolio improves the sharpe ratio of conventional contrarian strategy from 0.6 to 0.9. Furthermore, using loadings of risk patterns provided by FPCA, we extend the static portfolio to the dynamic one. These loadings –functional scores represent the direction and magnitude of risk patterns at each time point. Thus, the dynamic eigenfunction portfolio give a mechanism to capture tailed risk and avoid unexpected loss during systematic risk exploding, in precondition that these loadings can be predicted. However, we unfortunately fail to forecast the loadings through neither self-dependence nor leading indicators, which lead to a further research in the future.

The rest of paper is structured as follows. Firstly, the related literature is reviewed. Secondly, we exploit market anomalies in the Chinese stock market from two aspects: constructing portfolios based on firm specific information and regressing cross-sectional return on market common factors. In section 4, we apply FPCA to exploit the residual from the Fama-French three factor model and propose two functional momentum factors. The corresponding explanations of these two factors are elaborated in the section 5. Section 6 displays the performances of static and dynamic eigenfunction portfolios, as a trading implementation of functional momentum risk factors. A conclusion is provided at the end, and the prediction of functional scores is worth for a further investigation.

2. Literature review

The cross-sectional asset pricing is a study on verifying market anomaly according to firm specific historical characteristics, including size, value, momentum and dividend payment, etc., (Fama and French (1996), Daniel and Titman (1997), Fama and French (2015), etc.). Fama and French (2012) test the size, value and momentum factors in international developed stock markets –(North America, Europe, Japan and Asia Pacific), and the authors assert that these factors exist everywhere, except for insignificant momentum factor in Japan. Contrarily, Cheung et al. (2014) study emerging Chinese stock market which actually plays the most important role in Asia Pacific region, and their finding suggests an insignificant momentum factor, whilst size and value factors remain significant between 2002 and 2013 (also see Wong et al. (2006) and Cakici et al. (2015)). Thus, emerging Chinese domestic "A" share market behave differently with other developed market in Asia Pacific area. According to "Bloomberg Business", Chinese stock market has reached

10 trillion USD market capitalization in 2015, which is equivalent to Japanese stock market, and the fact that the failure of momentum in domestic "A" shares motivates many researches[4]. To study momentum effect in China, it is noteworthy to start with constructing momentum related portfolios.

Generally, there are two well-known strategies to build portfolios with firm specific momentum information, momentum strategy–winner minus loser (Jegadeesh and Titman, 1993) and contrarian strategy–loser minus winner (Bondt and Thaler, 1985). Applications of momentum and contrarian strategies has been richly discussed in literature[5]. Kang et al. (2002) investigate Chinese "A" shares between 1993 and 2000, and they find that momentum strategy is not profitable in China in short-term, while contrarian strategy does make profit(also see Wu (2011)). This is different from the situation happened in U.S. market. The preliminary research of momentum strategy can be traced back to Levy (1967), who suggests that following stock prices momentum can make unusual profits in U.S. market. But this market anomaly draws less attentions until Jegadeesh and Titman (1993). When investors long past winner stocks and short past loser stocks —WML effect in the short-run, would lead to abnormal returns (Jegadeesh and Titman, 1993). Meanwhile in the long-run, Bondt and Thaler (1985) find that winner stocks underperform losers so that investors should long past losers and short past winners —LMW effect. The source of these market anomalies in U.S. market has been systematically determined, and this can help to understand the opposite performance occurred in China.

Theoretical explanations for a profitable momentum or contrarian strategy mainly rely on behavior finance or investors' psychology. Investors have different behavior in short-term and long-term. Barberis et al. (1998) propose an investor sentiment model and their finding suggests people always underreact to the information they receive in the short-run, but overreact to the information in the long-run. This can be one of the reasons explaining why cross-sectional return is always behaved as contrarian beyond 12 months. Similarly, Chan et al. (1995) and Jegadeesh and Titman (2001) state that stock returns can always be predicted by past returns and earnings, as people in equity market have a nature of sluggishness in the short-term, while the mean reversion mechanism would lead to a contrarian effect in the long run.

[4]See Kang et al. (2002), Wong et al. (2006), Naughton et al. (2008), Wu (2011), Cheema and Nartea (2014), Cheung et al. (2014), amongst others

[5]See Griffin et al. (2003), De Groot et al. (2012), Cheema and Nartea (2014) for momentum; Chang et al. (1995), Baytas and Cakici (1999), Balvers et al. (2000) and Wu (2011) for contrarian.

Furthermore, some literature argue that momentum or contrarian profits are stemmed from other reasons[6]. For instant, regarding to contrarian effect, investors' sentiment is not the only explanation, Lo and MacKinlay (1990) highlight that lead-lag effect cause a profitable contrarian strategy due to the positive cross-serial correlation among small and big firms. Borrowing these explanations, Kang et al. (2002) confirm the existence of both overreaction and lead-lag effect in Chinese stock market, but in short-run, resulting a short-term profitable contrarain strategy. High level of uncertainty makes investors in this market more sensitive to recent news, which leads to the insignificant momentum-wml factor in Chinese market.

On the other hand, the failure of market anomaly in cross section asset pricing cannot be simply attributed to investors' behavior, the tailed risk of risk factors is also important to study. For example, it is inevitable to notice that momentum effect cannot bring an evergreen strategy, even in developed market, since it crashes occasionally. Griffin et al. (2003) find net negative returns occur occasionally with applying price and earnings momentum strategies in international stock markets. Grundy and Martin (2001) claim momentum strategy always experiences negative market beta during down-ward market. This indicates the crash of momentum strategy is due to market systematic risk. Also, Daniel and Moskowitz (2013) document historical momentum crashes in U.S. from 1927 to 2010, and the results show crashes almost only happen during financial crisis or bear market. Thus, the failure of momentum factor in Chinese stock market can be caused by frequent explosions of systematic risk, which is not a surprise in such a volatile market. Meanwhile, measuring and predicting systematic risk can improve the profit of momentum strategy through adjusting portfolio position. As one possible solution, Daniel et al. (2012) adopt two-state hidden Markov model to classify market states, thereby heavily loss can be avoided in momentum strategy. Aiming to solve the same problem, our paper use the loading of extracted risk patterns —functional score as an indicator to measure tailed risk on momentum-related strategies.

In this paper, we exploit momentum-sorted cross sectional returns in Chinese "A" shares, aiming to find significant momentum-related risk factors, in addition to construct portfolios based on risk patterns exploited. In the term of methodology, Gandhi and Lustig (2015) use a similar method with ours, they apply principal component analysis –PCA on size-sorted cross section U.S. bank returns, and the orthogonal nature of principal com-

[6]See Chordia and Shivakumar (2002), Lo and MacKinlay (1990), amongst others.

ponents suggests a size effect in highly leveraged bank shares. Different with their work, we adopt functional principal component analysis —FPCA on 12 months momentum-sorted cross-sectional returns controlled by Fama-French three factors. The beauty of FPCA is it provides an intrinsic framework to decompose variability of stock return. FPCA extracts a set of basis function that maximally explains variation of objectives –functional curves (Ramsay, 2006). Meanwhile, it can be beneficial from dimensionality reduction and feasibility of missing data, as a result, less computations meet in functional data analysis –FDA. As a technique mainly applied in mechanic engineering, seldom applications have been done in finance. Kokoszka et al. (2014) apply FDA in U.S. high-frequency intra-day data and discuss the property of functional scores. In another paper, Kokoszka et al. (2014) propose functional dynamic factor model to model intra-day curve with functional risk factors. But they have not tried to apply FDA into cross-sectional data. Our paper, as another attempt, contributes the literature of applied FDA in cross section stock returns. We contribute a new methodology to study cross section risk patterns in a high volatile market. Lastly, as a contribution to behavior finance, beside the different behavior between past winner and losers, we also empirically highlight that different behavior between past extremes and mediocre shares, verifying that "V" shaped disposition effect existed in China as well.

3. Market anomalies in China

Existing literature (Wu (2011), Cheung et al. (2014) and Cakici et al. (2015), etc.) document that momentum effect is very weak in China, with the accompanying strong size effect. In this section, in order to confirm this statement with our data set, we run equally weighted portfolios according to firm specific information: market capitalization, B/M ratio and 12 months momentum. If these portfolios obtained significant abnormal return, the corresponding common risk factors should be significant in this market. Hence, three factor (Fama and French, 1992) and four factor (Carhart, 1997) models are applied to re-assess these common risk factors in Chinese "A" share market.

3.1. The data set

The reform in Chinese stock markets always aims to build a more open, more liberalized and more powerful supervised financial environment. In the end of 2005, Chinese government approved the "Eleventh Five-Year Plan", which represents the economic return started to undergo a shift from extensive growth to intensive growth. In stock market, hundreds of companies launched stock splits in 2005, and the authority started a new wave of IPO in 2006. Hence, we study monthly adjusted price data of entire Chinese "A" share data set from the beginning of 2005[7] to the end of 2015. Meanwhile, the last decade experiences a standard business cycle: booms, financial crisis, recession, oscillation and recovery. In total, there are 836 listed shares in January 2005, which increased to 2755 listed shares in December 2015. Similar with other asset pricing studies in U.S. markets, we exclude financial shares and new listed shares who cannot provide 12 month momentum information. To study U.S. market, it always need to filter very small shares to get rid of bias from very small valued shares in U.S. market. Our study, however, do not exclude small listed stocks because there is no particularly small capitalized shares in Chinese stock markets under Chinese strict financial regulations. We use log return transformation on raw price data.

$$R_t = log(\frac{P_t}{P_{t-1}}) \tag{1}$$

Meantime, to construct common risk factors ((Fama and French, 1992), (Carhart, 1997)), we collect Shanghai stock exchange composite index as the market index r_t^m, 3 months treasure bill rate (January 2005 –October 2006) and SHIBOR [8] (November 2006 –December 2015) as the risk free rate r_t^f. The market risk premium factor gives as $rmrf = r^m - r^f$. To construct size and value factors, we collect total market capitalization and book to market ratio for each stock. And the firm specific momentum factor is calculated

[7] Because firm specific momentum information is calculated from past returns, it is necessary to collect monthly adjusted price data between January 2000 and December 2015, for computing short-term and long-term 48 months momentum factors for January 2005.

[8] SHIBOR: Shanghai interbank offered rate, initiated from November 2006, and initiated to public from January 2007.

according to previous K month past returns through following formula,

$$Mom_{i,t} = \sum_{j=t-K}^{t-2} R_{i,j} \tag{2}$$

where i denotes stock i. Similarly, the long run K month momentum factor formulated as,

$$Mom_{i,t} = \sum_{j=t-K}^{t-12} R_{i,j} \tag{3}$$

Following Fama and French (1992) and Carhart (1997), one period lag sorting is applied that cross section returns are sorted into decile at t in ascending order according to firm specific information from $t-1$. Lastly, equal weighted small minus big —SMB factor is obtained using the first decile to minus the last decile, high minus low —HML and winner minus loser —WML common factors using the last decile to minus the first decile. In this paper, we use 12 month firm specific momentum factor to construct standard WML factor. All the data is collected from WIND database.

3.2. Firm specific information

To construct single factor portfolio on the basis of firm specific size, value and momentum information, we set the holding period J varying from 3 months to 24 months. Cross-sectional returns are sorted into ten deciles in ascending order. The size, value and momentum strategy follow the rule of small minus big, high minus low and winner minus loser. At each time t, we launch a portfolio and hold it for J month, where J equals to 3, 6, 9, 12 and 24. Table 1 displays the average monthly returns, and it presents that size and value portfolios outperform to momentum portfolios. To be specific, size portfolio is significantly profitable regardless of holding for a short or long periods, and value portfolio is significantly profitable if holding period was longer than 9 months. This result definitely makes sense in China, especially in the term of size. Instead of based on registration like U.S. market, the IPO system in China is based on examination and approval by China Securities Regulatory Commission —CSRC. Thus, it results an oversupply to Chinese IPO system. More importantly, once a company is approved to be listed, it always has a highly probability to be taken over or merged and acquired, simply because the new approval by CSRC provides a suitable object to invest. Therefore, new listed small companies always own higher risk premiums, resulting size effect is very strong in Chinese market. On the other hand, the momentum strategy cannot produce significant profitable portfolios in Chinese stock market, which is consistent with existing literature. The reason of this result can be attributed to that Chinese “A” share is too volatile and investors behavior is hardly to captured.

[Insert Table 1 Here]

To study the interaction between these factors, we conduct double sorted portfolio through controlling firm specific momentum. Controlling momentum into quintile, the Table 2 presents that size effect is significant but value effect is not. In detail, the panel A shows that smb effect provides positive significant portfolio return, and this effect is stronger in the loser quintile compared with the winner quintile. Meanwhile, the panel B demonstrates a surprise result that significant value effect nearly vanishes when momentum is controlled although it still brings positive returns. The only one significant under 95% level is occurred in the winner quintile. This result reveals that the value –hml effect in China is a result of the difference between past return performances.

Moreover, as a robust confirmation of momentum–WML strategy in Chinese stock market, we also sort cross section returns by momentum after controlling size and value factors. Table 3 presents the results of double sorted portfolios. In panel A, the cross-sectional returns were firstly sorted by size in quintile, and then further sorted by momentum in quintile, obtaining a 5×5 portfolio strategy. The WML strategy is unprofitable in all size quintiles because losers outperformed winners in any size quintile. However, only the portfolio average return in small quintile is significant under 5% level, which indicates that WML effect is stronger in small companies. In panel B, momentum quintiles portfolios are constructed after controlled value. The WML strategy is statistically unprofitable in first three value quintiles, statistically significant at 10%, 5% and 10% level, respectively. Hence, the WML effect in low value quintiles is stronger than the one in high value quintiles. On the other hand, the size and value anomalies exist as usual after controlling momentum. Therefore, the WML effect does exist in China, but only significantly exists in small size and low value shares. Besides, the loss of momentum-WML strategy points out a profitable contrarian-LMW strategy.

[Insert Table 2 Here]

[Insert Table 3 Here]

To assess the performance of momentum and contrarian strategies, our work follow (Jegadeesh and Titman, 1993) to construct relative strength portfolios. We sort cross-sectional returns in ascending order by firm specific past return with different looking back periods K, where K could be short-term 3, 6, 9, 12 months, or long-term 60 months. And five types of holding periods, 3, 6, 9, 12 and 24 months, are considered. Thus, there are 50 portfolios in total, where 25 for the momentum strategy and 25 for the contrarian strategy. By rolling portfolios with different holding periods, we compute average monthly returns in Table 4. Table 4 shows consistent results with existed works(Kang et al. (2002), Wu (2011), etc.). Momentum strategy does not make any profit under any formation period and holding period; while, contrarian strategies earned positive profits in all scenarios although with insignificant t-statistics. According to Kang et al. (2002), this is due to the short-run over-reaction effect in Chinese stock market. Once again, firm specific past return weakly explains risk patterns for cross section returns. The fact of high volatile Chinese stock market causes investors' behavior not just stick on distinguishing the difference between winners and losers, but also other behavior patterns.

[Insert Table 4 Here]

3.3. Market common factor

The conventional common risk factors have been studied in developed markets (Fama and French (1992), Carhart (1997), etc). It is worth to evaluate whether these common risk factors still work in Chinese markets with our data set. Because the difference between past winner and past loser is distinct enough, in this paper, we concentrate on explaining momentum-sorted portfolio returns. Two standard factor models will be applied to explain cross-sectional portfolio returns: Fama-French three factor model and Carhart four factor model. According to Fama and French (1992), three factor model is constructed as,

$$r_t^i - r_t^f = \alpha^i + \beta_1^i rmrf_t + \beta_2^i smb_t + \beta_3^i hml_t + \epsilon_t^i \tag{4}$$

where r_t^i denotes i^{th} decile portfolio monthly return and r_t^f denotes risk free rate. Meanwhile, we run Carhart four factor model (Carhart, 1997),

$$r_t^i - r_t^f = \alpha^i + \beta_1^i rmrf_t + \beta_2^i smb_t + \beta_3^i hml_t + \beta_4^i wml_t + \epsilon_t^i \tag{5}$$

Theoretically, a good explanatory factor model should produce insignificant risk adjusted return –the intercept α, hence we apply GRS test (Gibbons et al., 1989) to jointly test the significance of intercepts in 10 portfolio regressions. The null hypothesis is $H_0 : \alpha_i = 0 \quad \forall i \in [1 : 10]$, the more insignificant of GRS statistics, the better factor model will be implied. Table 5 lists regression and test results.

[Insert Table 5 Here]

The panel A shows that rmrf and smb factors are almost significant to explain all decile portfolio excess returns, while hml factor is insignificantly to explain these returns. This result does not contain too much surprise, because it is basically consistent with Table 2, where the size strategy is profitable and the value strategy becomes unprofitable after controlling momentum. Moreover, cross-sectionally, we find that 3 factor model has better explanatory ability in upper deciles, which indicates three factor model is more efficient to explain shares with better past performances. This can be also supported by intercept terms, only $9th$ and $10th$ decile portfolios give insignificant risk-adjusted returns. Meanwhile, none of three factors can explain wml portfolio excess return. This result is consistent with Fama and French (1993), thereby requiring the Carhart four factor model. In the panel B, adding momentum-wml factor, the Carhart four factor model explains ten decile portfolio with R^2 approximately 0.75, which is roughly equivalent with R^2 obtained in panel A. Regarding to the first three factors–rmrf, smb and hml, it provides similar results with panel A. Thus, the key variable investigated here is wml, which is significant in the last two deciles but insignificant in other deciles. Like panel A, Carhart four factor model is also more efficient to interpret excess return on better performed portfolio, where R^2 in upper deciles are greater than counterparts in lower deciles. In the term of wml portfolios, only wml factor can significantly explain wml portfolio, with R^2 0.84. Furthermore, Even though three factor and four factor models can obtain a relatively high R^2 statistics, there are still some risk patterns cannot be explained as the P values of GRS test are 0.0233 and 0.0226 for Fama-French and Carhart model, which cannot reject the null under 5% level but reject under 1% level. Therefore, to explore the risk patterns in residuals would be a possible solution to further explain cross-sectional returns.

4. The functional momentum risk factor

In last section, we regress momentum-sorted cross-sectional returns on Fama-French three factor and Carhart four factor model, and results express both of these two models cannot fully explain the cross-sectional portfolio excess returns, and the wml and hml factors are significantly weak in these factor models. This results that the risk-adjusted return in each factor model is still significant, thereby implying more risks need to be explained. Therefore, in this section, we apply functional principal component analysis –FPCA to exploit variation patterns of residuals from Fama-French three factor model, and then construct functional momentum risk factors on the basis of extracted risk patterns.

4.1. Exploiting variations in residuals

Residuals from Fama-French three factor models represents the cross-sectional portfolio returns for controlling rmrf, smb and hml. The variation of residuals should be the cross-sectional risk that Fama-French three factors cannot explain, which is worth to analyze whether meaningful risk patterns exist within residuals. That is to say, if these residuals behave regularly with specific rankings, this sorting algorithm offers meaningful potential risk patterns. Meanwhile, because the residuals are stemmed from momentum-sorted portfolio return, these risk patterns should be connected with investors' behavior on firm specific momentum information.

In consideration of these risk patterns, we adopt a functional approach aiming to decompose the total variation of residuals. One barrier to apply FPCA is cross-sectional portfolio returns cannot be smoothed into functional objects if cross-sectional returns are grouped into deciles, because the number of knots (or breakpoints) is not enough for smoothing (Ramsay, 2006). Hence, we sort cross section returns into 100 groups and set 11 knots. Still, the sorting follows the ascending order, where the 1st group contains all loser shares, and the 100th group includes all winner shares. In each percentage, we regress portfolio excess return on Fama-French three factors, and store the residuals. Our sample spans over January 2005 to December 2015, which gives a 132 by 100 residual matrix. In order to emphasize variation measure and reduce noise, we demean and standardize residual matrix, similar method applied in Blitz et al. (2011). Then, using fda package in R, we smooth cross section non-cyclical residual series to functional objects by a cubic B-Spline smoother at each time month t. To be specific, at each time point t, we set 11 knots in cross-sectional 100 residuals, and then adopt 13 cubic B-Spline to smooth these knots to a functional curve. Since the data across over 132 months, we get 132 functional curves eventually. The left panel of Figure 1 displays these functional objects.

[Insert Figure 1 Here]

Decomposing the total variation of this functional system based on FPCA, we find a set of eigenfunctions (13 in our case[9]) with nonzero functional eigenvalues, formulated as $\Psi = \{\psi_i | \lambda_i \neq 0\}$, where ψ_i is eigenfunction i and λ_i is eigenvalue on *ith* eigenfunction. Similar with the principal component analysis–PCA in multivariate data analysis, the sum of functional eigenvalues represents the total variation of this system, thus, the proportion explained by each eigenfunction i is given as $\frac{\lambda_i}{\sum_{i=1}^{13} \lambda_i}$. Because of the property of orthogonality, there is no overlapping explained by each eigenfunction. One advantage of eigenfunction is it provides a more visualized variation pattern to uncover potential risk compared with PCA. Moreover, FPCA also give functional scores as loadings for each eigenfunction at each time period, where the sign and value interpret the direction and magnitude of corresponding eigenfunctions at each time period. If the sign of loading at t is positive, it indicates risk pattern at this month patterned as forward; If the sign of loading is negative, the picture turns to the contrary way. The right panel in Figure 1 illustrates main eigenfunctions exploited by FPCA. The first four eigenfunctions —efs explain approximate 87.2% of the total variation. We may concentrate the first two eigenfunctions because the third and fourth eigenfunction only take into account approximately 10% variation and patterned as noise. Specifically, the first eigenfunction –$ef1$ explains 64% variation, and it shows an upward trend, which is consistent with momentum-sorted ascending order. This patten may implies the difference between past winners and past losers, which is similar but not exactly same with the wml effect, because it provides a non-linear function to describe such difference. The second eigenfunction –$ef2$, plotted as a quadratic —V/U shape curve, takes into account 13.3% of total variation. This risk pattern suggests different investor behavior on extreme and mediocre stocks [10]. Lastly, in order to show the patten of these eigenfunctions are convinced,

[9]The number of eigenfunctions depends on the number of knots in B-spline smoother.

[10]This V shape risk pattern also significantly exists in cases that cross-sectional returns are sorted by momentum factor with other looking back periods, e.g. 3 months, 6 months, 9 months; while the pattern becomes weak when it comes to long-run past return, e.g. 60 months with 1 year gap.

we compute confidence intervals of main eigenfunctions through bootstrap with 2000 replications, which is a standard empirical way to study property of eigenfunctions (Hall and Hosseini-Nasab, 2006). Figure 2 illustrates the 95% confidence intervals of main eigenfunctions. The patterns are consistent with our result obtained above, and bootstrapping results provide consistent proportional variations as well –64.2% for $ef1$ and 13.4% for $ef2$. Therefore, the discussions on risk patterns above are reliable and provide meaningful frames to build new risk factors in next subsection.

[Insert Figure 2 Here]

4.2. The functional momentum risk factor

In this section, we construct functional risk factors given as cross section momentum-sorted portfolio returns weighted by the value of eigenfunctions. As discussed in last sub-section, the third and fourth eigenfunction are patterned as noises, it is difficult to use them to construct common risk factor. Information coefficient can help to measure the correlation between eigenfunctions and cross-sectional portfolio returns at each time t, which gives 132 cross-sectional correlation coefficients for each eigenfunction. Moreover, we take absolute value of correlations to evaluate the strength of correlation, because the direction of eigenfunctions does not affect the magnitude of correlation. Figure 3 plots cross-sectional information coefficients on $ef1$, $ef2$, $ef3$ and $ef4$. Over the whole sample period, the information coefficient on $ef1$ is the highest in average, which is visually higher than information coefficients on $ef2$. Compared with the first two, $ef3$ and $ef4$ are flatter and close to zero, combined with little variation proportions contributed, it is convinced that these two eigenfunctions are not suitable to construct functional risk factors.

[Insert Figure 3 Here]

Hence, we build the first functional momentum risk factor by $re_t \times ef1'$, denotes as FPC1, and $re_t \times ef2'$, denotes as FPC2. As a standard test on common risk factors, we apply Fama-MacBeth regression (Fama and MacBeth, 1973) with FPC1 and FPC2, and Table 6 documents regression results. By running cross-sectional regressions on portfolio risk exposures which obtained from individual time series regression, the result indicates FPC1 has significant risk premium on momentum-sorted portfolio returns at 1% significant level. This factor is even stronger in January, which means the existence of January effect. Thus, the difference behavior on past winners and past losers fairly exists, and it can significantly explain cross-sectional risk premium. Compared with FPC1, FPC2 has less significant risk premium at 10% level, but surprisingly, FPC2 is insignificant during January. It indicates that in January, cross-sectional risk patterns are main dominated by the difference between winner and losers instead of the difference between extreme and mediocre. The last column shows two factors regression, and both of FPC1 and FPC2 are significant under 1% and 5% level. Due to the fact of orthogonality, the risk premium coefficients on FPC1 and FPC2 do not change, and adjusted R square simply equals to a linear combination of single factor regressions, which means combining FPC1 and FPC2 can definitely improve the explanation of cross-sectional risk patterns. Both of FPC1 and FPC2 factors can be used as common risk factors for Chinese stock market.

[Insert Table 6 Here]

In order to confirm the role of FPC1 and FPC2 in Chinese "A" share, we re-regress decile momentum-sorted portfolio returns [11] on Fama-French three factor, as well as adding functional momentum factors. Table 7 represents estimation results. Compared with Table 5, functional risk factors improves the explanatory power on cross-sectional portfolio returns, supported by less significant risk-adjusted return and higher value of adjusted R^2. To be particular, in panel A, rmrf, smb and FPC1 factors are highly significant with adjusted R^2 above 0.8. The significance of FPC1 improves the explanatory ability, confirming this factor is a non-ignorable factor in China. Another remarkable fact is coefficients on FPC1 are opposite signed from loser group to winner group. It indicates different behaviors existed in lower deciles and upper deciles, which is exactly same with the risk patten indicated by FPC1. While, in middle panel, even though adjusted R^2 did not increase too much compared with Fama-French or Carhart factor models, FPC2 performs significantly in loser and winner deciles. This makes sense because the risk premium explained by FPC2 is mainly stemmed from extreme stocks. Unlike coefficients of FPC1 in panel A, the sign of coefficients on FPC2 are same in loser and winner deciles, both are positive. It reveals extreme stocks have different investor behavior with mediocre stocks to some extent, and this is also same with the risk patten implied by FPC2. Benefited from othogonality, FPC1 and FPC2 factors reinforce interpretation ability of Fama-French

[11] Here we sort cross section returns into decile, simply because it is unnecessary to display 100 regression results, and easier to compare with results form previous four factor models.

three factor model without any overlapping, supported by higher adjusted R^2 and the P value of GRS test in panel C equals to 0.0159, which outperform Fama-French and Carhart models in Table 5. Therefore, based on all discussions in this section, the risk factor FPC1 and FPC2 do exist in Chinese stock market.

[Insert Table 7 Here]

5. Explanations on functional momentum risk factors

For further understanding the economic meaning of functional momentum factors, we explain them in detail in this section. The FPC factors are constructed by momentum-sorted cross-sectional return, they interpret different investment preferences on stocks' past performances. The first eigenfunction mainly retains a pattern of monotonicity, indicating the different behaviors between losers and winners. The conventional momentum (winner minus loser) or contrarian (loser minus winner) strategy can be seen as a completed linear version of FPC1. Thus, it is reasonable to use explanations on momentum strategy to explain FPC1. While, the asymmetric "V" shape in the second eigenfunction indicates different behaviors between extreme stocks and mediocre ones. This risk pattern is due to the fact of disposition effect of Chinese investors. Beside, in order to investigate the relationship between FPC factors and market state, we also borrow the concept of "up and down" market states[12] defined in Cooper et al. (2004), and seek any connection. Unfortunately, we do not find any remarkable relationship among them.

5.1. What is FPC1?

The FPC1 factor is actually an elaborated form of wml factor. According to FPCA, the first eigenfunction is the main variation pattern of cross-sectional momentum-sorted portfolio returns for controlling Fama-French three factors. Corresponding weights give to sorted portfolio returns through selling shares with relatively poor performances and buying shares with relatively good performances. Hence, the wml factor, as an extreme spread portfolio,

[12] In Cooper et al. (2004), they define an UP market can be identified with positive three years market return, while the negative for a DOWN market. In this paper, we set the looking back period as 6 months and 12 months because Chinese stock market is more volatile.

can be seen as a simple approximation of FPC1. This also can be confirmed by the last column in Table 7, FPC1 is the only significant explanatory variable in panel A and panel C, and it almost fully explains wml portfolio return with 0.95 adjusted R^2. From significant FPC1 factor and insignificant wml factor, we can see that, in high volatile stock market, investment behavior on momentum-sorted portfolio is not as regular as developed markets. Momentum-related risk factor becomes significant to interpret cross-sectional return once enough risk is captured. Thus, what really makes FPC1 factor exists in China? From Table 4, we know that momentum –wml strategy earned negative profit during last decades, while contrarian –lmw strategy profits positively. Thus, we can deduce that FPC1 profits negatively, and if we reverse the weight of FPC1, the contrarain–FPC1´strategy is profitable, which will be empirically proved by Table 9 in next section. Here, we aim to investigate the reason of a profitable FPC1´and a non-profitable FPC1. As the detailed version of momentum and contrarian strategy, the profitability of FPC1 and FPC2 can be explained from the perspective of these two conventional strategy[13].

Bondt and Thaler (1985) show that the loser portfolio outperforms to the winner portfolio in long run leading to a contrarain strategy because of the long-term overreaction in U.S. stock markets[14], and the overreaction effect exists if the autocorrelation coefficient in portfolio returns are negative. This results that investors always conduct contrarian or reversal strategy in the long-run and momentum strategy in the short-run. Moreover, the overreaction is not the only source for contrarian effect, where cross effect also causes such an effect (Lo and MacKinlay, 1990). The cross effect asserts that a higher return for stock i at period t generally implies a higher return for stock j at period $t + 1$. A standard case is the lead-lag structure, it says that big capitalized stocks may lead small capitalized stocks, or in the opposite way. Hence, positive cross-serial correlations is the evidence for the cross effect.

We empirically test the overreaction and cross effect with our data set. Table 8 documents the self-cross autocorrelation results. To test overreaction and cross effect, we rank entire A shares according to their market capitalization, and equally weighted sort them into quintiles, notate as S1 –S5. In panel A, we calculate first four lags of autocorrelation coefficients for these portfo-

[13]Kang et al. (2002) study the profitability of contrarain strategy in Chinese "A" share from 1993 to 2000.

[14]It is worth to mention that the short-term underreaction explains the profitability of short-term momentum strategy in U.S. market (Barberis et al., 1998)

lios, and 3 out of 20 correlation coefficients are positive, which points out that overreaction effect exists in China, but in the short-run. In panel B, we compute cross-autocorrelations with lag 1 and 2. The cross-autocorrelations are mainly negative, which suggests that lead-lag structure generally contributes more on FPC1 or momentum strategy, rather than on FPC1´or contrarian strategy in U.S. market, and this result is against with Lo and MacKinlay (1990). However, there is an exceptional case in lag 1 table. The cross autocorrelation from S1 to S5 is 0.2131, and then it becomes to −0.0490 from S5 to S1. This means that the lead-lag structure does cause FPC1´or contrarian effect if we only consider smallest and biggest stocks. Once more, different with U.S. market, smallest firms lead biggest firms in China, and this result is consistent with Kang et al. (2002). Therefore, the profitability of FPC1´or contrarian strategy in China is mainly stemmed from overreaction in short run, in addition some contributions from cross effect between smallest firms and biggest firms. As the final result, these make a significant FPC1 factor in Chinese market.

[Insert Table 8 Here]

5.2. What is FPC2?

Compared with FPC1, the second FPC factor is more interesting. Because the second eigenfunction implies the difference investment behavior between extreme stocks and mediocre stocks, along with the property of asymmetry —refer to Figure 1 and Figure 2. This risk pattern can be explained by the disposition effect in investors' behavior. The disposition effect, identified by Shefrin and Statman (1985), asserts that investors are always willing to sell winner stocks too early and to ride loser stocks too long, which is an expression of prospect theory in investment. Recently, Ben-David and Hirshleifer (2012) argued that the selling/buying function of traditional disposition effect should be a "V or U" shaped toward to past returns, and this statement is further supported by An (2015) with more than 70 thousands accounts in U.S. market. Ben-David and Hirshleifer (2012) explains that such "V" shaped trading function is a result of the overconfidence in investors. Many speculative investors hold too much confidence on their own information source, and this results they are more likely to trade those stocks with big news. Apparently, mediocre stocks have low probabilities to have any big news, but stocks become to extreme performed ones always due to some big news. Hence, with the faith that they know better than the market, speculative investors are more inclined to trade extreme performed stocks, leading more risks to extreme shares. Mediocre stocks, on the contrary, absorb less attention, which gains higher liquidity premium, and therefore incurs the spread between extreme and mediocre stocks. Regard to the asymmetry in "V" shaped risk pattern, investors are more willing to trade winner extreme shares because they have achieved the profit they expected, while the counterpart in loser extreme shares have not been realized. An (2015) provides another possible reason for the asymmetry in "V" shaped trading activity, which is investors are inclining to re-examine the positions or to update their beliefs on stocks with higher profits. In this paper, we empirically prove that asymmetric "V" shaped trading activities also exist in Chinese stock market, and it significantly explains the risk pattern in cross section momentum-sorted stock returns.

[Insert Figure 4 Here]

6. The eigenfunction portfolio

Since the total variation pattern in cross-sectional return has been decomposed into finite K number of eigenfunctions –($ef1 = \psi_1$; $ef2 = \psi_2$; $ef3 = \psi_3$, etc), the cross section momentum-sorted return curve at t can be expressed as,

$$r(t) = \mu_t + \sum_{i=1}^{K} \xi_{i,t}\psi_i^*(t) + \varepsilon_t \tag{6}$$

where $r(t)$ is a cross-sectional functional return object, μ_t is the functional mean and $K = 13$ in this study. We define the eigenfuntion portfolio —EFP as a portfolio policy allocates capital across return object according to the risk pattern revealed by eigenfunction, thus the return on this portfolio r_t^p is essentially the inner product of portfolio weights $w(t)$ and cross-sectional return $r(t)$.

$$r_t^p = \langle w(t), r(t) \rangle \tag{7}$$

The EFP can assign weights perfectly concordant with one of eigenfunctions. Remind that cross-sectionally, we sorted return into 100 groups based on firm-specific momentum, and the value of ef_i on each group i can be obtained from FPCA, hence, we can then simply calculate weights w_i for group i as,

$$w_i = \frac{ef_i}{\sum_{i=1}^{100} |ef_i|} \tag{8}$$

Substituting Equation 6 into Equation 8, and then the portfolio return is expressed as,

$$\begin{aligned} r_t^p &= \langle w(t), \mu_t + \sum_{i=1}^{K} \xi_{i,t}\psi_i + \varepsilon(t)\rangle \\ &= \langle w(t), \mu_t\rangle + \langle w(t), \sum_{i=1}^{K} \xi_{i,t}\psi_i\rangle + \langle w(t), \varepsilon(t)\rangle \end{aligned} \tag{9}$$

According to equation above, the EFP return is contributed by three parts. The first part is stemmed from the inner product between portfolio weights and functional mean, which implies a realization of positive return as long as the trend of eigenfunctions describes the pattern of cross-sectional functional mean. We call this part ″static eigenfunction portfolio ″return. The second part, $\langle w(t), \sum_{i=1}^{K} \xi_i\psi_i\rangle$, realizes only if we can capture functional scores ξ_i at time t. The sign and magnitude of functional loadings represent the direction and strength of corresponding eigenfunctions at each time period: signs decide the direction of this eigenfunction realizes forward or reverse; and magnitudes decide how strong of risk pattern indicated by this eigenfunction at time (t). We call this part ″dynamic eigenfunction portfolio ″return, because it contains varying risk uncertainties in each month. Lastly, the error term $\varepsilon(t)$ is uncorrelated with eigenfunctions according to Equation 6, i.e. $E\langle\psi_i, \varepsilon(t)\rangle = 0$.

In this section, we assess the performance of EFPs weighted by first and second eigenfunction —$ef1$ and $ef2$. The portfolio weights either be static or be dynamically adjusted. In static portfolio, once weights have been decided, this weights will be applied until the end. However, for an eigenfunction´risk pattern, it is difficult to maintain it exists at each single month, and once it violates from determined weights, static portfolio has to be confronted with a certain loss. For instance, any contrarian strategy cannot guarantee to be ever profitable, and occasionally momentum strategy makes profit in short-term in China while contrarian does not. Wu (2011) has shown that a mixing portfolio between momentum and contrarian strategy highly outperforms pure contrarian strategy in Chinese stock market. In other words, the unexpected loss in static portfolio can be avoided as long as the loading of eigenfunctions —functional scores in next time period can be predicted.

6.1. Static eigenfunction portfolio

To conduct static eigenfunction portfolio, according to firm specific momentum, we sort cross-sectional returns into 100 groups. Then, portfolio weights on these 100 groups are fixed given as standardized value of eigenfunctions –$ef1$ and $ef2$. We assess the portfolio performance of both forward and reverse directions of these eigenfunctions. In order to compare with conventional momentum/contrarian strategies, the conventional winner minus loser and loser minus winner portfolios are also implemented. Last but not the least, because $ef1$ and $ef2$ are naturally orthogonal, we apply mean variance optimization to mix them, using 3 months length rolling window to avoid using any future information. In total, there are seven types of strategies.

The portfolio performances are tested from January 2005 to December 2015. Table 9 presents statistics of monthly average return, sharpe ratio and maximum drawdown for these portfolios [15]. The first eigenfunction strategies show similar performances with conventional strategies, where momentum is similar with $ef1$ and contrarian is similar with $-ef1$; and once more, results support that contrarian or $-ef1$ strategy is profitable in China. This result is consistent with the explanation in section 5.1. The $-ef1$ strategy outperforms to conventional contrarian strategy because it interprets more elaborate risk pattern, which the sharpe ratio increase to 0.76 from 0.69. Regard to the second eigenfunction strategy, $ef2$ is unprofitable while $-ef2$ is profitable, and $-ef2$ underperform $-ef1$ because it explains less proportion of total risk. Based on the explanation in section 5.2, investors are more likely to trade extreme stocks, which represents that the liquidity on extreme stocks is higher than liquidity on mediocre stocks, thereby giving liquidity risk premiums to mediocre stocks. Lastly, through mean-variance optimization, the mixing portfolio of $-ef1$ and $-ef2$ presents slightly lower average monthly return 0.03, compared with $-ef1$ strategy who earns 0.06 per month. However, because more risk are explained by combining $-ef1$

[15] The comparable results are robust when 3 months, 6 months and 9 months momentum factors considered.

and $-ef2$, the mixing strategy obtains lowest maximum drawdown and the highest sharpe ratio among these seven portfolio strategies. The cumulative return of these portfolios are plotted in Figure 5, and monthly performance panels shows that January effect fairly exists in all positive profitable strategies.

[Insert Table 9 Here]

[Insert Figure 5 Here]

6.2. Dynamic eigenfunction portfolio

The static eigenfunction portfolio would undergo a loss or low profitability when the real risk pattern in some periods are not consistent with the weight set initially, for example, momentum crashes in U.S. market and the crash of alpha strategy in November 2014 in Chinese hedge fund industry. The changing on cross-sectional risk pattern cause some of market anomalies no longer exist or even become the contrary. Hence, managers should dynamically adjust weights on static portfolio if dynamic risk pattern can be predicted. Under the eigenfuntion strategy framework, functional scores is an ideal index to measure the direction and strength of risk patterns, statistically verified by Table 10. Once functional score $\xi_{i,t+1}$ can be predicted, we can maximum EFP return via realizing the part of $E\sum_{j=1}^{K}\langle\psi_i, \xi_{i,t+1}\psi_j\rangle$ in Equation 14, as a result of timely adjustment on trading positions to avoid accidental loss from systematic risk. Specifically, we can adjust the position or levers of EFP according to the sign and magnitude of $\hat{\xi}_{i,t+1}$. The sign of $\hat{\xi}_{i,t+1}$ decides we should give EFP as weights ef_i or $-ef_i$. The high value of $\hat{\xi}_{i,t+1}$ implies that the risk pattern suggested by ef_i will be strong at period of $t+1$, leading to an increase to buy-in position. On the contrary, the position should be reduced if the value of $\hat{\xi}_{i,t+1}$ is close to from zero.

[Insert Table 10 Here]

To forecast a time series in finance, it is either to use its own past information to predict itself if such self-dependent exists, or finding some related leading indicators to forecast. Fortunately, we are not the only one to try to predict functional loadings on eigenfunctions. The weak dependence of functional scores can be tested by adopting Kokoszka and Reimherr (2013)'s approach. They test a null hypothesis that a functional score series is not a weakly auto-correlated sequence, and provide a limiting distribution for a functional score related statistics,

$$\wedge^{(k)} = (N-1)^{-\frac{1}{2}} \sum_{i-1}^{N-1} I_{N,n}^{(k)} I_{N,n+1}^{k} \xrightarrow{d} N(0,1) \tag{10}$$

where $I_{N,n}^{(k)} = sign(\hat{\xi})$. Once we can reject the null hypothesis, functional loadings can be self-predicted via adopting an AR(p) process, which reads,

$$\hat{\hat{\xi}}_{i,t+1} = \sum_{j=0}^{p} \hat{\gamma}_i \xi_{i,t-j} \tag{11}$$

According to Equation 10, statistics $\wedge^{(k)}$ should follow standard normal distribution. Hence, we can simply compare the statistics with ± 1.96 under 95% significant level. No accident, such elegant property is difficult to be valid in real world, also fails in Kokoszka and Reimherr (2013). Our results show statistics on $ef1$ equals to -0.87 and -0.70 for $ef2$, which means functional scores on $ef1$ and $ef2$ are not serial-correlated.

Apart from self-dependence, functional scores can be correlated with some leading indicators associated with economic meaning. Similar work has been done by Daniel and Moskowitz (2013), they find that the sign of index return in past one year has predictability on the strength of momentum strategy. Thus, inspired by their work, it is practicable if we can find some variables χ_i as a leading indicator for functional scores.

$$\hat{\hat{\xi}}_{i,t+1} = \hat{\alpha} + \hat{\beta} \cdot \chi_{i,t} \tag{12}$$

Chordia and Shivakumar (2002) find that several macroeconomic variables have interpretation ability for cross-sectional returns. In this paper, we apply three of these macroeconomic variables as potential leading indicators, expressed as DP –dividend payment, Y3B –yield on 3 months treasury bill and SSL –spread between 3 months short-term and 10 years long-tern treasury bill. Besides, market index is another potential leading indicator to explore, thereby we calculating rolling time-varying four moments of market index with six months window length. Table 11 displays results of regression model 12 on these potential variables. Unfortunately, the majority of these variables are failed to forecast functional scores. Although DP, market index mean and standard deviation series obtain significant β, it is still inaccurate to predict functional scores because of extreme low value of R^2.

[Insert Table 11 Here]

7. Conclusion

The momentum effect is significantly weak in China, and this can be due to the fact that Chinese stock market is highly volatile and frequent systematic risk. Instead of concentrating on explanations of this phenomenon, this paper exploits cross section risk patterns in Chinese stock market. Hence, compared with conventional four common risk factors –rmrf, smb, hml and wml, the rich risk patterns can better interpret cross-sectional stock return. Before we exploit cross-sectional returns, we first re-assess market anomalies in China on the basis of size, value and momentum information. The results show that size effect is strong while momentum is not, which is consistent with existing literature. It indeed implies conventional wml factor does not work in China and more risks need to be captured for interpreting Chinese stock cross-sectional return. As the main part, we then apply functional principal component analysis to extract risk patterns from cross section momentum-sorted portfolio returns after controlling for Fama-French three factors. Among 13 types of eigenfunctions, the first and second eigenfuntion point out meaningful risk patterns, thereby building two functional principal component risk factors —FPC1 and FPC2. The FPC1 factor is an elaborate version of the wml factor which explains more risk in cross section portfolio return, and FPC2 factor describes the difference between extreme and mediocre shares. Adding FPC1 and FPC2 to Fama-French three factor model, we obtain high value of adjusted R^2 and less jointly significant risk adjusted return. Meanwhile, as a standard method to test the existence of common risk factor, the Fama-MacBeth regression shows that FPC1 and FPC2 factors do exist in China. The existence of these two factors can be explained by following reasons: the FPC1 is caused by short-term overreaction and cross lead-lag effect; the FPC2 exists because of the "V" shaped disposition effect in behavior finance. Lastly, as an empirical trading application of exploited rick patterns, we construct an eigenfunction portfolio with two versions: static and dynamic. The static portfolio outperforms conventional momentum or contrarain portfolios. This is because a greater risk proportion from total cross-sectional variation is explained by eigenfuntions. The dynamic eigenfunction portfolio provides a mechanism for adjusting trading positions by predicting the loadings of eigenfunction –functional scores. This can avoid unexpected loss from static portfolios. However, it is difficult to accurately predict functional scores through neither self-dependence nor macroeconomic leading indicators, and this can lead to a further research in the future.

Appendix A. The inference of eigenfunction portfolio

A.1. Static eigenfunction portfolio

Since predicting functional scores is an intractable issue, it is better to discuss the property of static portfolio first. Consider a static basis portfolio is constructed through the risk pattern suggested by eigenfunction ϕ_i. Hence, its weights should be defined as a function of this eigenfunction, one case is equation 8, and then we have,

$$w_i = k\psi_i = sign(E\langle\psi_i, \mu_t\rangle)\psi \tag{13}$$

If $\int \psi_i ds = 0$, it ensures that our portfolio is a market-neutral strategy. Letting $r_t = \mu_t + \sum_{j=1}^{K}\langle r_t, \psi_j\rangle\psi_j + \varepsilon(t)$ and $\mu_t \neq 0$, its expected return is,

$$\begin{aligned} Er_t^i = E\langle k\psi_i, \mu_t + \sum_{j=1}^{K}\xi_i\psi_j + \varepsilon(t)\rangle \\ = k(E\langle\psi_i, \mu_t\rangle + E\sum_{j=1}^{K}\langle\psi_i, \xi_i\psi_j\rangle + E\langle\psi_i, \varepsilon(t)\rangle) \\ = k(E\langle\psi_i, \mu_t\rangle + E\xi_i) \\ = kE\langle\psi_i, \mu_t\rangle = |E\langle\psi_i, \mu_t\rangle| = \theta_i \end{aligned} \tag{14}$$

Because functional scores in static version cannot be predicted, here we use a general assumption that expected functional score is zero. We can confirm that the portfolio with respect to some eigenfunction delivers strictly positive return in precondition that the eigenfunction describes the functional mean. Further more, the risk associated with it is

$$Var(r_t^i) = Var(\langle k\psi_i, r_i\rangle) = \lambda_i \tag{15}$$

Sharpe ratio should be

$$SR_S^i = \frac{(\theta_i - r^f)}{\lambda_i} \tag{16}$$

where θ_i is projection of eigenfunction on functional mean and r^f is risk-free ratio.

Furthermore, due to the fact that eigenfunctions are orthogonal intrinsically, it is reasonable to adopt optimal portfolio theory (e.g. mean-variance theory) to construct the best mixed static portfolio according to first and second eigenfunctions simultaneously. By Equation 14, FMP return expresses as,

$$Er_t^b = (|E\langle\psi_1, \mu_t\rangle|, ..., |E\langle\psi_K, \mu_t\rangle|)' - \gamma\mathbf{1} \tag{17}$$

A.2. dynamic eigenfunction portfolio

In dynamic eigenfunction portfolio, we assume that functional scores can be predicted as $\hat{\xi}_t$. Thus, instead of letting $E(\xi_{i,t}) = 0$, Equation 14 can be re-estimated as,

$$\begin{aligned} Er_t^i &= E\langle k\psi_i, \mu_t + \sum_{j=1}^{K} \xi_i\psi_j + \varepsilon(t)\rangle \\ &= k(E\langle\psi_i, \mu_t\rangle + E\sum_{j=1}^{K}\langle\psi_i, \xi_i\psi_j\rangle + E\langle\psi_i, \varepsilon(t)\rangle) \\ &= k(E\langle\psi_i, \mu_t\rangle + E(\hat{\xi}_{i,t}\langle\phi_i, \phi_i\rangle)) \\ &= kE\langle\psi_i, \mu_t\rangle + E(\hat{\xi}_{i,t}) \\ &= |E\langle\psi_i, \mu_t\rangle| + E(\hat{\xi}_{i,t}) = \gamma_i \end{aligned} \tag{18}$$

To dynamically adjust the direction of eigenfunction ϕ_i, it is reasonable to keep $E(\widehat{\xi_i, t})$ strictly positive, resulting γ_i is greater than θ_i. Hence, the sharpe ratio SR_D^i is superior to SR_S^i, where SR_D^i formulated as below.

$$SR_D^i = \frac{(\gamma_i - r^f)}{\lambda_i} \tag{19}$$

Appendix B. Tables

Table 1: **Single factor portfolios performances**

The table shows the average monthly profitability of SMB, HML, and WML portfolio from Jan. 2005 to Dec. 2015 with different holding periods. Each column represents different holding periods varied from 3 to 24 months. The value in brackets are t-statistic through the average return divided by the Newey-West robust standard errors.

	3	6	9	12	24
size-(smb)	0.0137	0.0135	0.0134	0.0131	0.0134
	(3.45)	(3.32)	(3.34)	(3.21)	(2.97)
value-(hml)	0.0067	0.0070	0.0069	0.0070	0.0070
	(0.63)	(1.59)	(1.95)	(1.83)	(2.51)
momentum-(wml)	-0.0049	-0.0047	-0.0046	-0.0046	-0.0048
	(-1.41)	(-0.83)	(-0.67)	(-0.80)	(-0.96)

Table 3: **Double sorted portfolio (control size and value)**

The table presents the average monthly return of 5×5 double sorted portfolios. In panel A, the cross-sectional returns are firstly sorted by firm specific market capitalization in ascending order into quintiles from small to big, and then further sorted by momentum also in ascending order into quintiles. The last row displays the average monthly return of winner minus loser portfolio for each size quintile. In right panel B, similarly, the cross-sectional returns are firstly sorted by firm specific B/M ratio into quintiles, and then to be sorted by momentum into quintiles. The holding periods for each portfolio are entire sample from Jan. 2005 to Dec. 2015. The value in brackets are Newey-West robust t-statistics.

		Panel A: Size					Panel B: Value				
		Small	2	3	4	Big	Low	2	3	4	High
Momentum	Loser	0.0307	0.0292	0.0315	0.0327	0.0196	0.0151	0.0163	0.0126	0.0059	0.0036
		(2.80)	(2.53)	(2.75)	(2.95)	(1.76)	(1.39)	(1.45)	(1.29)	(0.58)	(0.33)
	2	0.0292	0.0327	0.0188	0.0174	0.0120	0.0163	0.0059	0.0143	0.0139	0.0050
		(2.53)	(2.95)	(1.63)	(1.54)	(1.12)	(1.45)	(0.58)	(1.26)	(1.25)	(0.46)
	3	0.0315	0.0188	0.0181	0.0166	0.0081	0.0126	0.0143	0.0101	0.0175	0.0117
		(2.75)	(1.63)	(1.55)	(1.44)	(0.74)	(1.29)	(1.26)	(0.92)	(1.58)	(1.08)
	4	0.0327	0.0174	0.0166	0.0122	0.0058	0.0059	0.0139	0.0175	0.0174	0.0138
		(2.95)	(1.54)	(1.44)	(1.08)	(0.54)	(0.58)	(1.25)	(1.58)	(1.56)	(1.21)
	Winner	0.0196	0.0120	0.0081	0.0058	0.0029	0.0036	0.0050	0.0117	0.0138	0.0174
		(1.76)	(1.12)	(0.74)	(0.54)	(0.26)	(0.33)	(0.46)	(1.08)	(1.21)	(1.54)
	WML	-0.0056	-0.0034	-0.0038	-0.0032	-0.0023	-0.0057	-0.0047	-0.0029	-0.0018	-0.0012
		(-2.38)	(-1.80)	(-1.87)	(-1.57)	(-0.77)	(-1.67)	(-1.99)	(-1.72)	(-1.09)	(-0.66)

Table 2: **Double sorted portfolio (control momentum)**

The table exhibits the average monthly return of 5×5 double sorted portfolios. Firstly, the cross-sectional returns are sorted by firm specific momentum in ascending order obtaining 5 quintiles from loser to winner. Secondly, they are further sorted to quintiles by size–market capitalization in panel A, and by value –B/M ratio in panel B. The last row in panel A and B present the average monthly return of small minus big and high minus low portfolios. The holding periods for each portfolio are entire sample from Jan. 2005 to Dec. 2015. The value in brackets are Newey-West robust t-statistics.

		Momentum				
		Loser	2	3	4	Winner
Panel A						
Size	Small	0.0319	0.0199	0.0151	0.0132	0.0097
		(2.86)	(1.74)	(1.32)	(1.15)	(0.83)
	2	0.0199	0.0132	0.0319	0.0159	0.0077
		(1.74)	(1.15)	(2.74)	(1.41)	(0.71)
	3	0.0151	0.0319	0.0159	0.0211	0.0103
		(1.32)	(2.74)	(1.35)	(1.87)	(0.95)
	4	0.0132	0.0159	0.0211	0.0246	0.0060
		(1.15)	(1.41)	(1.87)	(2.20)	(0.55)
	Big	0.0097	0.0077	0.0103	0.0060	0.0020
		(0.83)	(0.71)	(0.95)	(0.55)	(0.18)
	SMB	0.0111	0.0121	0.0120	0.0093	0.0060
		(3.87)	(5.54)	(4.72)	(3.92)	(1.91)
Panel B						
Value	Low	0.0158	0.0156	0.0184	0.0199	0.0200
		(1.42)	(1.37)	(1.65)	(1.71)	(1.75)
	2	0.0156	0.0199	0.0143	0.0227	0.0208
		(1.37)	(1.71)	(1.25)	(2.03)	(1.80)
	3	0.0184	0.0143	0.0210	0.0173	0.0202
		(1.65)	(1.25)	(1.80)	(1.55)	(1.82)
	4	0.0199	0.0227	0.0173	0.0105	0.0170
		(1.71)	(2.03)	(1.55)	(1.05)	(1.45)
	High	0.0200	0.0208	0.0202	0.0170	0.0136
		(1.75)	(1.80)	(1.82)	(1.45)	(1.30)
	HML	0.0021	0.0032	0.0026	0.0032	0.0065
		(1.02)	(1.88)	(1.57)	(1.93)	(2.70)

Table 4: **Relative strength portfolio with momentum and contrarian strategies**

The table shows average monthly returns of relative strength portfolio with momentum and contrarian strategies. Each row stands for formation periods on K, the first four rows considered the short-run past return; and the last row considered the long-run past return. Each column represents different holding periods varied from 3 to 24 months. We refer the method from (Jegadeesh and Titman, 1993) to construct these equal weighted portfolios with over-lapping holding periods. The value in brackets are Newey-West robust t-statistics.

	Momentum					Contrarian				
	3	6	9	12	24	3	6	9	12	24
3 months	-0.0036	-0.0033	-0.0033	-0.0035	-0.0040	0.0035	0.0031	0.0032	0.0034	0.0037
	(-0.57)	(-0.55)	(-0.68)	(-0.67)	(-0.84)	(0.36)	(0.55)	(0.64)	(0.62)	(0.82)
6 months	-0.0038	-0.0039	-0.0039	-0.0041	-0.0046	0.0038	0.0038	0.0038	0.0040	0.0045
	(-0.54)	(0.81)	(-1.59)	(-0.92)	(-0.86)	(0.73)	(0.54)	(0.83)	(0.83)	(0.82)
9 months	-0.0042	-0.0041	-0.0040	-0.0039	-0.0042	0.0041	0.0040	0.0038	0.0038	0.0040
	(-0.11)	(-0.92)	(-0.82)	(-0.82)	(-0.82)	(0.22)	(0.57)	(0.62)	(0.80)	(0.77)
12 months	-0.0049	-0.0047	-0.0046	-0.0046	-0.0047	0.0046	0.0044	0.0043	0.0042	0.0044
	(-0.83)	(-0.84)	(-0.70)	(-0.80)	(-0.97)	(1.24)	(0.93)	(0.67)	(0.75)	(0.91)
60 months	-0.0009	-0.0012	-0.0015	-0.0017	-0.0020	0.0011	0.0014	0.0017	0.0020	0.0022
	(-0.08)	(-0.27)	(-0.33)	(-0.41)	(-0.64)	(0.54)	(0.06)	(0.17)	(0.27)	(0.49)

Table 5: **Factor models on momentum-sorted portfolio cross section return**

The table shows estimation results of OLS regressing on momentum-sorted equal-weighted portfolio excess return toward to common risk factors. The columns represent portfolio excess returns, from the first decile —loser to the last decile —winner, and we also consider winner minus loser portfolio return. In panel A, Fama French three risk factors (Fama and French, 1992) are adopted; and in panel B, an extra wml factor is added as Carhart four factor model (Carhart, 1997). The last two columns show the F statistics and P values of GRS test (Gibbons et al., 1989). *, ** and *** indicate statistical significant level at 10%, 5% and 1% level, respectively.

	Loser	2	3	4	5	6	7	8	9	Winner	WML	F(GRS)	p(GRS)
Panel A: Fama-French model													
α	0.01^{**}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{**}	0.00	0.00	0.00		
rmrf	-0.27	-0.27	-0.32^{*}	-0.32^{*}	-0.33^{*}	-0.33^{***}	-0.41^{***}	-0.38^{***}	-0.41^{***}	-0.46^{***}	-0.09		
smb	-1.25^{***}	-1.25^{***}	-1.31^{***}	-1.29^{***}	-1.28^{***}	-1.28^{***}	-1.35^{***}	-1.33^{***}	-1.31^{***}	-1.33^{***}	-0.04	2.18	0.0233
hml	-0.04	0.02	0.05	0.08	0.12	0.11	0.17	0.20^{*}	0.24^{*}	0.21	0.13		
$Adj R^2$	0.72	0.75	0.78	0.77	0.79	0.80	0.80	0.83	0.82	0.73	0.02		
Panel B: Carhart model													
α	0.01^{**}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{**}	0.00	0.00	0.00^{*}		
rmrf	-0.28	-0.28	-0.33^{*}	-0.32^{*}	-0.33^{*}	-0.33^{***}	-0.41^{***}	-0.38^{***}	-0.40^{***}	-0.45^{***}	-0.09		
smb	-1.28^{***}	-1.26^{***}	-1.31^{***}	-1.28^{***}	-1.27^{***}	-1.28^{***}	-1.35^{***}	-1.32^{***}	-1.28^{***}	-1.27^{***}	0.00	2.19	0.0226
hml	0.13	0.09	0.09	0.05	0.09	0.08	0.13	0.11	0.02	-0.21	-0.17^{*}		
wml	-0.21^{*}	-0.09	-0.05	0.03	0.04	0.04	0.06	0.10	0.27^{***}	0.51^{***}	0.36^{***}		
$Adj R^2$	0.73	0.76	0.78	0.77	0.79	0.81	0.81	0.84	0.84	0.77	0.84		

Table 6: **Fama-MacBeth Regression with FPC1 and FPC2 factors**

To assess how functional principal component factors describe momentum-sorted value weighted portfolio returns, we apply Fama-MacBeth regression on FPC1 and FPC2. The first step is to obtain factor risk exposures on each portfolio through running time series regression between risk factor and individual portfolio returns. Then, the risk premium coefficients are obtained from the second step by regressing cross-sectional portfolio return on risk exposures from month to month. Because we are aiming to confirm the existence of significant risk premium instead of assess positive or negative signs, we take absolute value of risk premium coefficients. The value in brackets are t-statistics.

	Jan.2005-Dec.2015				Jan.2005-Dec.2015				Jan.2005-Dec.2015			
	Entire	Jan	Dec	Feb-Nov	Entire	Jan	Dec	Feb-Nov	Entire	Jan	Dec	Feb-Nov
FPC1	0.15	0.18	0.15	0.15					0.15	0.18	0.15	0.16
	(4.41)	(5.81)	(4.25)	(4.69)					(4.87)	(6.13)	(4.70)	(5.40)
FPC2					0.07	0.06	0.07	0.08	0.07	0.06	0.07	0.08
					(1.65)	(1.43)	(1.65)	(1.82)	(2.17)	(2.09)	(2.13)	(2.66)
$Adj R^2$	0.21	0.30	0.21	0.21	0.06	0.04	0.06	0.07	0.28	0.34	0.28	0.29

Table 7: **Factor models with FPCs on momentum-sorted portfolio cross section return**

The table exhibits estimation results of OLS regressing momentum-sorted portfolio excess return toward on Fama-French risk factors, in addition with functional momentum factors FPC1 and FPC2. The columns represent portfolio excess returns, from the first decile —loser to the last decile —winner, as well as winner minus loser portfolio return. In panel A, there are four factors, Fama French three risk factors and FPC1; in panel B, the FPC1 is replaced by the FPC2; and in panel C, both FPC1 and FPC2 are considered, forming as a five factor model. The last two columns present the F statistics and P values of GRS test (Gibbons et al., 1989). *, ** and *** indicate statistical significant level at 10%, 5% and 1% level, respectively.

	Loser	2	3	4	5	6	7	8	9	Winner	WML	F(GRS)	p(GRS)
					Panel A: Fama-French with FPC1								
α	0.00	0.01*	0.01**	0.01**	0.01**	0.01**	0.01	0.01*	0.01	0.01	0.00*		
rmrf	−0.39***	−0.37***	−0.41***	−0.39***	−0.39***	−0.37***	−0.44***	−0.39***	−0.37***	−0.38***	0.00		
smb	−1.30***	−1.29***	−1.34***	−1.32***	−1.30***	−1.30***	−1.36***	−1.33***	−1.29***	−1.30***	0.00	2.48	0.0170
hml	0.12	0.15	0.16	0.18	0.20	0.17	0.21	0.21	0.19	0.10	-0.01		
FPC1	−0.19***	−0.16***	−0.14***	−0.12***	−0.10***	−0.07***	−0.05*	-0.01	0.07***	0.13***	0.16***		
$Adj R^2$	0.83	0.83	0.83	0.81	0.82	0.82	0.81	0.83	0.84	0.79	0.95		
					Panel B: Fama-French with FPC2								
α	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01*	0.01*	0.00	0.00	0.00		
rmrf	-0.31	-0.28	−0.33*	−0.31*	−0.33*	−0.32**	−0.40***	−0.37***	−0.40***	−0.50***	-0.10		
smb	−1.30***	−1.26***	−1.31***	−1.28***	−1.27***	−1.26***	−1.34***	−1.31***	−1.30***	−1.38***	−0.04***	2.21	0.0217
hml	0.02	0.03	0.06	0.07	0.11	0.09	0.15	0.17	0.22	0.29	0.13		
FPC2	0.17***	0.04	0.02	-0.03	-0.03	-0.06	-0.06	-0.07	-0.05	0.21***	0.02		
$Adj R^2$	0.74	0.75	0.77	0.77	0.78	0.80	0.80	0.83	0.82	0.76	0.02		
					Panel C: Fama-French with FPCs								
α	0.00	0.01*	0.01*	0.01*	0.01*	0.01*	0.01	0.01	0.01	0.01*	0.00*		
rmrf	−0.42***	−0.38***	−0.41***	−0.38***	−0.39***	−0.36***	−0.43***	−0.38***	−0.36***	−0.42***	0.00		
smb	−1.34***	−1.30***	−1.35***	−1.31***	−1.30***	−1.28***	−1.35***	−1.31***	−1.28***	−1.35***	0.00		
hml	0.18	0.16	0.17	0.17	0.20	0.15	0.19	0.18	0.17	0.18	0.00	2.52	0.0159
FPC1	−0.19***	−0.16***	−0.14***	−0.12***	−0.10***	−0.07***	−0.05*	-0.01	0.07***	0.13***	0.16***		
FPC2	0.17***	0.04	0.02	-0.03	-0.02	-0.06	-0.06	-0.07	-0.05	0.21***	0.02***		
$Adj R^2$	0.85	0.83	0.83	0.81	0.82	0.82	0.81	0.83	0.84	0.82	0.95		

Table 8: **Own and cross serial correlations**

This table displays own and cross-serial correlations within size-sorted portfolio returns with contrarian strategy. Each column represents size quintile from smallest size group to biggest one, denoted as S1 - S5. In panel A, the autocorrelation is looked back four periods on each quintile portfolio return. In panel B, we examine the cross-serial correlations with two lags periods. Notice that the sample included stock without any missing data from Jan.2005 to Dec.2015, there are 1269 stocks in total.

Panel A: Own-serial correlation					
	S1	S2	S3	S4	S5
lag1	0.0215	0.0480	-0.0718	-0.0568	-0.1076
lag2	-0.0823	-0.1462	-0.1199	-0.0176	-0.1442
lag2	-0.0161	-0.2109	-0.0137	-0.0488	0.0259
lag4	-0.0865	-0.0602	-0.0293	-0.0168	-0.0531
Panel B: Cross-serial correlation					
Lag1	S1	S2	S3	S4	S5
S1	0.0943	0.0313	-0.0017	0.0244	0.2131
S2	-0.0413	0.0820	-0.1166	0.0838	0.0349
S3	-0.0443	-0.0457	0.0080	-0.0649	-0.0102
S4	-0.0568	0.0079	-0.0811	0.0286	-0.0671
S5	-0.0490	0.0071	0.1256	0.0100	-0.0789
Lag2	S1	S2	S3	S4	S5
S1	-0.1985	-0.0736	0.0959	0.0523	-0.0208
S2	0.1109	-0.1109	-0.0684	-0.1701	-0.2025
S3	-0.0125	0.1296	-0.0742	-0.0016	0.0396
S4	0.0046	-0.0377	-0.1364	0.0071	-0.1057
S5	0.0142	-0.0297	-0.1216	-0.0939	-0.1032

Table 9: **The statistics of static portfolios**

The table shows the average monthly return, sharpe ratio and maximum drawdown statistics for 7 types of portfolio strategies. The first two columns are conventional strategies –wml and lmw. The following five columns represent portfolios weighted by the first or second eigenfunctions, or mixing two of them for optimization.

	Conventional strategy		Eigenfunction strategy				
	Momentum	Contrarian	ef1	-ef1	ef2	-ef2	mixing
return	-0.0508	0.0508	-0.0602	0.0602	-0.0172	0.0172	0.0318
sharpe ratio	-0.6988	0.6988	-0.7561	0.7561	-0.4546	0.4546	0.8912
maximum drawdown	-0.6751	-0.1389	-0.7804	-0.1311	-0.2358	-0.0961	-0.0429

Table 10: **The fitting of functional scores on EFP return**

The table presents results that regressing static eigenfunction function portfolio returns on the loadings of each eigenfunction. $-ef1$ and $-ef2$ represent static portfolio returns weighted by $-ef1$ and $-ef2$, and their functional loadings are $fs1$ and $fs2$.

		$fs1$			$fs2$
$-ef1$	α	-0.0405^{***}	$-ef2$	α	-0.0091^{***}
	β	1.0369^{***}		β	1.0895^{***}
	R^2	0.94		R^2	0.92

Table 11: **Leading indicator tests on functional scores**

This table shows estimation results of regressions between a functional score and kinds of potential leading indicators. We consider three macroeconomic variables (Chordia and Shivakumar, 2002), DP –dividend payment, Y3B –yield on 3 months treasury bill and SSL –spread between 3 months short-term and 10 years long-tern treasury bill; as well as four moments of market index. We compute time-varying moment series through rolling market index with 6 months window. As a forecast regression model, we regress functional scores on first lag of potential leading indicators. It is notable that $fs1$ is functional scores for the first eigenfunction, and $fs2$ is functional scores for the second eigenfunction. *, ** and *** indicates statistical significant level at 10%, 5% and 1% level, respectively.

Macroeconomic Variables				
		α	β	R^2
DP	fs1	-0.0686	0.038^{*}	0.02
	fs2	0.0097	-0.0053	0.002
Y3B	fs1	-0.0536	0.0222	0.01
	fs2	0.0063	-0.0026	0.00
SSL	fs1	0.0303	-0.0242	0.01
	fs2	-0.0001	0.0001	0.00
Market index				
Mean	fs1	0.10^{**}	-0.001^{**}	0.05
	fs2	-0.0063	0.0001	0.00
Standard Deviation	fs1	0.051^{**}	-0.001^{***}	0.05
	fs2	-0.0039	0.0000	0.00
Skewness	fs1	0.0031	-0.0185	0.00
	fs2	0.0016	-0.0093	0.00
Kurtosis	fs1	-0.0868	0.044	0.02
	fs2	-0.0042	0.0021	0.00

Appendix C. Figures

Figure 1: **The functional residual curves and decomposed eigenfunctions**

In order to explore variation patterns of residuals in three factor model, cross-sectional residuals have to be smoothed to functional curves before adopting functional principal component analysis. Therefore, we apply 13 cubic B-spline smoother to smooth the 132 by 100 residual matrix, and get 132 functional curves. In right panel, the FPCA extracts 13 eigenfunctions, where the first four take into account 87.2% from the total variation, plotted in the figure. The first eigenfunction is colored in black, explaining 64%; the second eigenfunction is colored in red, interpreting 13.3% variation; the third eigenfunction is colored in green, taking account 5.9%; and the fourth one is colored in blue, only taking account 4% from total variation.

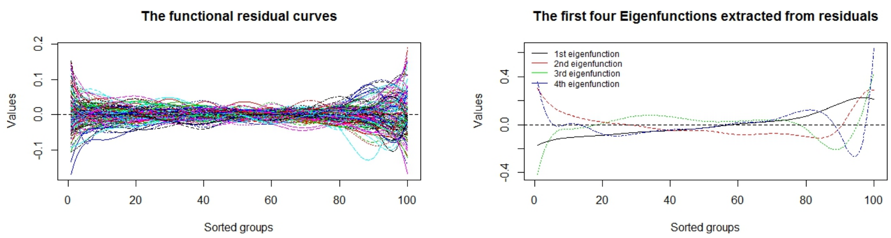


Figure 2: **Confidence intervals of first four functional eigenfunctions**

Refer to Hall and Hosseini-Nasab (2006), the best way to investigate numerical properties of FPCA´s eigenfunctions is to use bootstrapping. Bootstrapping cross-sectional residual functional curves with 2000 times, we construct 95 % confidence intervals for the first four functional eigenfunctions. In average, the first eigenfucntion takes into account 64.2%, followed with 13.4% of the second eigenfunction, and last two eigenfunctions explain 6.0% and 4.0%, respectively.

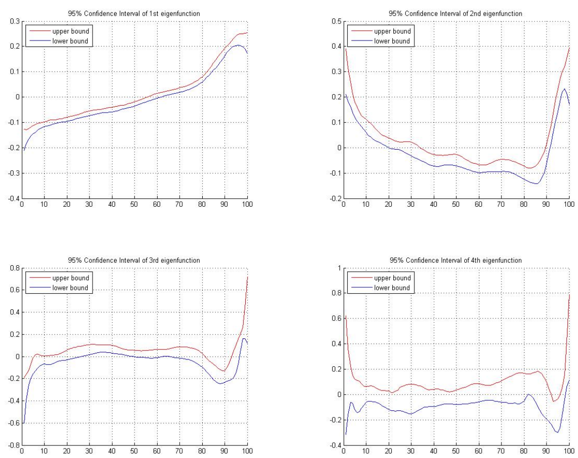


Figure 3: **The Information Coefficients**
The first and second eigenfunctions suggest upward-trend and quadratic risk patterns on cross-sectional momentum sorted portfolio returns. The information coefficients between eigenfunction and cross-sectional portfolio returns are computed from month to month. In total, we get 132 information coefficients from Jan. 2005 to Dec. 2015. In order to assess the strength of correlation, we set the domain of correlation coefficients is between 0 and 1 by taking absolute of correlation coefficients.

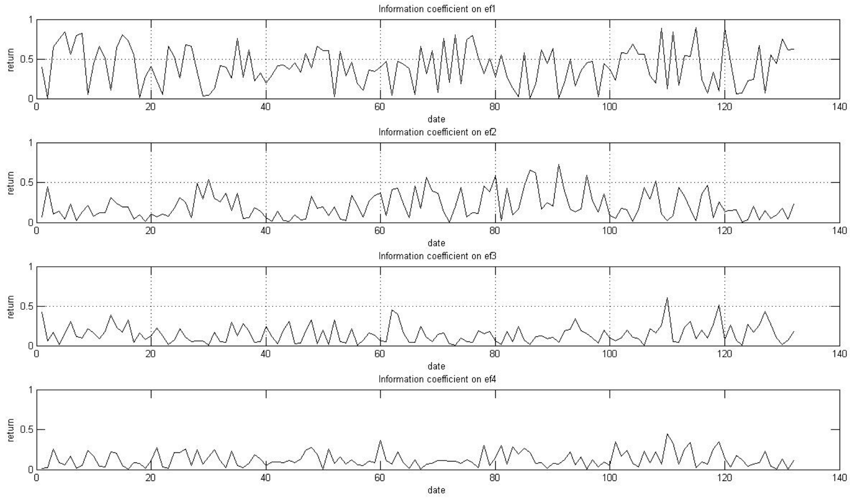


Figure 4: **The V shaped selling activity toward to profit**
The figure is cited from (Ben-David and Hirshleifer, 2012), they find the V shaped selling behavior in response to the profit. They find investors are inclining to trade those shares with extreme performances.

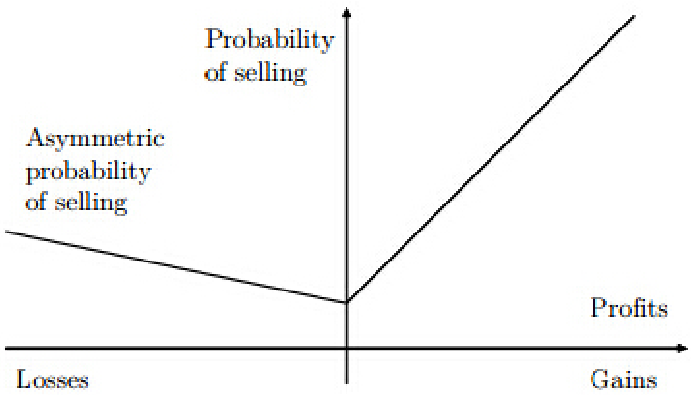
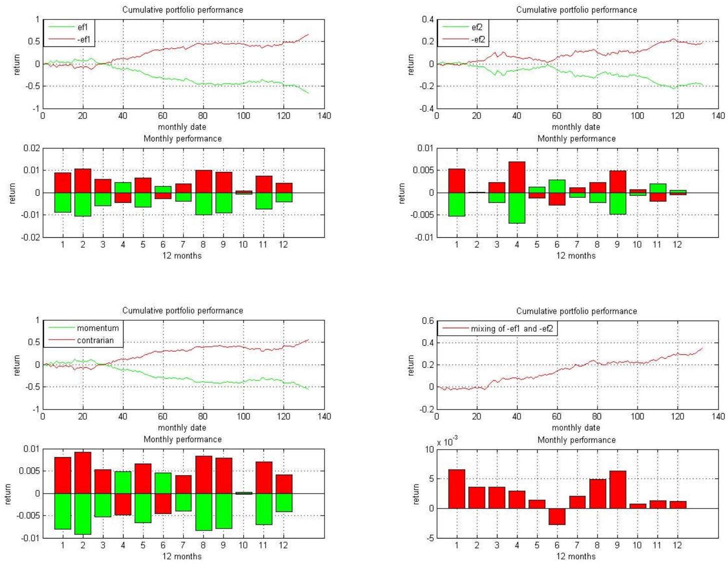


Figure 5: **The performance of static portfolio strategies**
Following four figures show cumulative portfolio returns and monthly average return for different static portfolios. The figure at the top left corner shows performances of $ef1$ and $-ef1$ portfolios, and the counterparts for $ef2$ are plotted at top right corner. The sub-figure at left bottom corner shows performances of conventional winner minus loser and loser minus winner portfolio. The last sub-figure displays the performance of a mixing portfolio between $-ef1$ and $-ef2$.



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