The evolvement of momentum effects in China: evidence from functional data analysis

The Evolvement of Momentum Effects in China: Evidence from Functional Data Analysis

Bo Li[a], Zhenya Liu[b,c,d,*], Hanen Teka[e], Shixuan Wang[f]

[a] *Business School, Beijing International Studies University, Beijing, 100024, China*
[b] *School of Finance, Renmin University of China, Beijing, 100872, China*
[c] *China Financial Policy Research Center, Renmin University of China, Beijing, 100872, China*
[d] *CERGAM, Aix-Marseille University, 13090 Aix-en-Provence Cedex 02, France*
[e] *Department of Basic Sciences, Deanship of Preparatory Year and Supporting Studies, Imam Abdulrahman Bin Faisal University, P. O. Box 1982, Dammam, Saudi Arabia*
[f] *Department of Economics, University of Reading, UK*

Abstract

Using an approach based on functional data analysis, we address the controversy that momentum or reversal effect disputes exist in China's A-shares markets. It finds patterns of nonlinear cross-sectional variation and the dynamic change of average stock returns over time. After the global financial crisis of 2008, our empirical results show that momentum effects in the middle term went away and reversal effects took over. We also find substantial reversal effects for the short- (1-6 months) and long-term (3 years), respectively, but no evidence of permanent momentum effects in China.

Keywords: Momentum anomaly, China's A-shares market, Functional Data Analysis, Circular Block Bootstrap
JEL classification: C31, C32, C51, G12

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Email addresses: libo@bisu.edu.cn (Bo Li), zhenya.liu@ruc.edu.cn (Zhenya Liu), shixuan.wang@reading.ac.uk (Shixuan Wang)

1. Introduction

Evidence of momentum effects is well-established in industrialized securities markets (Erb & Harvey, 2006; Miffre & Rallis, 2007; Asness et al., 2013; He et al., 2018). However, the results of this research are inconclusive regarding momentum effects in China. Even studies on anomalies in China's stock market, the world's second-largest behind the United States, can assist both global and local investors in allocating their money more effectively (Girardin & Liu, 2019). Kang et al. (2002), Su (2011), and Hu & Liu (2013) confirm the presence of momentum effects, whereas Wang (2004), Zhou et al. (2010), Hsu et al. (2018), Gao et al. (2021), and Jansen et al. (2021) indicate the existence of reversal effects. Furthermore, Chui et al. (2010) and Goyal & Wahal (2015) found no major momentum impact in China. According to Hsu et al. (2018), these inconsistent outcomes result from frequent policy alterations that cause quick changes in the structure of the market economy. Yang et al. (2019) investigated the inconsistencies in momentum effects in China by segmenting A-shares monthly data into five sub-periods. They suggest that contrarian profits observed across the entire sample period are mostly driven by results in the sub-periods 2005–2008 and 2009–2012. The inconsistent results motivate us to explore the momentum effects dynamically in China.

Another focus of this paper is to include nonlinear information in the analysis. Fama & French (2008) indicate that theoretical explanations for anomalous returns do not predict linear relations between average returns and anomaly variables. Freyberger et al. (2020) convert cross-sectional returns into functions using quadratic splines to describe the cross-sectional nonlinearity. They suggest a nonparametric technique to address the difficulty of determining anticipated returns from company characteristics. Boubaker et al. (2021) use a functional data analysis (FDA) procedure to investigate asset pricing anomalies and characterize the nonlinear spectrum of anomalous returns. As a result, this paper expands on Boubaker et al. (2021)'s work by examining the dynamic evolution of momentum effects in China using the FDA.

Our research methodology is as follows: First, we decompose portfolio returns sorted on various momentum variables into empirical functional principal components (EFPCs). This decomposition identifies both nonlinear cross-sectional varying patterns and the dynamic time-series evolution of momentum effects. Thus, the decomposition is compatible with Cochrane (2011)'s prediction "combining time series with cross-sectional data will give further insights."

Second, we conduct a dynamic study of momentum effects. Because the cross-section of the second EFPC shows a monotonic trend, we propose showing the time-varying change in momentum effects by using the partial means of its harmonic loadings, which are more efficient and easier to understand when doing dynamic analysis. We empirically verify that the univariate sorting results are incorporated into ours.

Finally, we use a circular block bootstrap to determine the robustness of the momentum effects (Politis & Romano, 1992). The conclusion is that a resilient impact should produce consistent findings across datasets. As a result, the confidence interval for the expectation of second harmonic loadings should be on the origin point's side. Alternatively, the second EFPCs' cross-sectional projections should have monotone functional confidence bands.

This paper contributes to the growing body of knowledge about momentum effects in three ways, particularly in China's A-shares market. First, we suggest a new way to study how momentum effects change over time in China by extending the FDA procedure, which can find both nonlinear cross-sectional patterns and how time series change over time. Related research on China's A-shares market is Cao et al. (2019). However, our paper is significantly different from theirs in one critical aspect. Cao et al. (2019) decomposed the cross-sectional Fama–French three-factor model residuals in China's A-shares market to derive two data-driven factors that describe the behavioral biases in the market's historical performance. At the same time, we provide compelling evidence to reconcile the previous debate in China on momentum/reversal effects. After the global financial crisis of 2008, our empirical results show that the mid-term momentum effects turned around, and the reversal effects took over the market. Also, we don't find much evidence of sustained momentum effects across settings. However, there is much evidence of both short-term and long-term reversal effects in China. Our findings concur with Zhou et al. (2010), Hsu et al. (2018), and Gao et al. (2021), but successfully complement them. Third, from the point of view of an investor, we find that the main cause of reversal effects in China is the return from the month before. So, we suggest that investors who use trading strategies based on reversal effects include the return from the previous month (i.e., without waiting a month).

This paper is structured as follows: Section 2 reviews the pertinent literature. Section 3 presents the mathematical framework of our FDA approach. Section 4 contains information about the dataset used in this study and how to calculate momentum variables. Section 5 presents the functional principal component analysis results. Section 6 performs the dynamic analysis and exihbits the outcomes of the bootstrapping. Section 7 summarizes our findings.

2. Literature Review

Momentum effects in the global securities markets have been studied ever since Jegadeesh & Titman (1993) demonstrated that buying stocks with good past performance and selling stocks with poor past performance generated significant positive returns over holding periods of 3 to 12 months. In a later study, Jegadeesh & Titman (2001) added the data from 1990 to 1998 and repeated their previous research. Their results showed that a momentum strategy could still yield significant profits. Scholars refer to momentum with a 1-year look-back period and a 1-month cooling-off period as JT momentum.

Studies have devoted great efforts to explaining the JT momentum effect. Fama & French (1996) found that—except for the continuation of short-term return anomalies related to size, earnings/price, cash flow/price, book-to-market equity, past sales growth, and long-term past returns largely disappear in a three-factor model. However, Carhart (1997), Novy-Marx (2013), and Fama & French (2020) considered JT momentum to be one source of systemic risk factors. Besides, the source of momentum effects is still debated. Guo et al. (2021) evaluated and ranked numerous competing explanations for the momentum anomaly. They found that all explanations account for 31% of the momentum effect, while 69% remains unexplained.

Meanwhile, literature has found that momentum effects exist almost everywhere, including in different formations, markets, and financial instruments. For different formation periods, Conrad & Kaul (1998) assert that a momentum strategy is usually profitable over the medium-term (3- to 12-month) horizon, while a contrarian strategy would have statistically significant profits over long periods but only during the 1926–1947 sub-period. For developed and emerging markets, Rouwenhorst (1998) used the monthly return data of 12 OECD countries from 1980 to 1995, confirming that momentum effects existed in all OECD countries with different formation periods and holding periods. In a subsequent study, Rouwenhorst (1999) verified that the securities markets of 20 emerging economies also show momentum effects. Griffin et al. (2003) analyzed returns obtained with the momentum strategy in global markets and found significant positive returns in most markets but only a weak correlation. Bhojraj (2006) demonstrated momentum effects in the stock indices. In addition to the stock market, Erb & Harvey (2006), Miffre & Rallis (2007), Asness et al. (2013), and Jia et al. (2022) studied cross-sectional momentum effects in foreign exchange, commodity, global bond markets, and cryptocurrencies, respectively. Kim (2019) employed the deep learning method to promote the profit of momentum strategy.

Unlike in developed countries, the momentum effect controversy has persisted in China's stock market. The literature on this topic falls into three categories. The first category consists of studies that confirm the presence of momentum effects. Kang et al. (2002) found statistically significant abnormal profits for some short-horizon contrarian and intermediate-horizon momentum strategies. Su (2011) documented significant abnormal profits for industry momentum strategies. Hu & Liu (2013) reported that momentum effects are much stronger among firms with low R^2. Li et al. (2018) showed various winner minus loser WML factors are significant positives.

The second category suggests the reversal effects. Wang (2004) found a negative average return compared to the relative strength strategy over a horizon of 6 months to 2 years. Zhou et al. (2010) show that momentum strategies generate significant and negative returns in the Chinese stock market over one month, nine months, and longer investment horizons. Hsu et al. (2018) suggested that the traditional medium-term momentum effect does not exist in China, while the short-term reversal effect can produce significant profits. Gao et al. (2021) found a strong short-term return reversal effect in China. But when these authors varied the length of the formation period (3, 6, 9, and 12 months), there were no momentum-based return premiums. Jansen et al. (2021) presented out-of-sample evidence for the momentum anomaly, with excess returns of 0.42% (t-statistic 2.79), 0.81% (t-statistic 3.28), and 0.89% (t-statistic 4.16) for seasonal, seasonal reversal, and the combination of both, respectively.

Studies in the third category find no significant momentum effects in China.

Chui et al. (2010) suggested that momentum profits are insignificant in China. Goyal & Wahal (2015) discovered no strong evidence for momentum effects in China. Yao et al. (2022) proposed an individual investor preference index (IIPI) and argued that the momentum effect decreases to zero as the IIPI increases.

To investigate the inconsistent conclusions, Yang et al. (2019) analyzed the existing empirical studies on momentum and contrarian strategies in China. They employ monthly data on A-shares from DataStream for the period January 1991–December 2012 and divide it into five sub-periods: 1993–1996, 1997–2000, 2001–2004, 2005–2008, and 2009–2012. They suggest that the contrarian profits observed in the whole sample period are driven primarily by results in the sub-periods 2005–2008 and 2009–2012. Another interesting finding is that for the sub-period from 2001 to 2004, most of the momentum strategies yield positive returns.

The research that has already been done on momentum effects uses fixed-sample data. This may be "data sniffing," which means that they only use the sample period that leads to the results they want. Therefore, conducting a dynamic study with an anchor start and updating data phase by phase is necessary. At the same time, the cross-sectional nonlinearity is not taken into account by traditional methods, so we use the FDA smoothing method to avoid this.

Novel FDA approaches have become increasingly popular in financial studies. Ramsay & Ramsey (2002) used FDA to analyze the dynamics of a monthly non-seasonally adjusted production index. Hall & Hosseini-Nasab (2006) showed how the properties of FPCA can be elucidated through stochastic expansions and related results. Chaudhuri et al. (2016) developed the semi-parametric functional auto-regressive modeling approach to the density forecasting analysis of national inflation rates by using sector inflation rates. To test the significance of risk factors for cross-sectional returns, Kokoszka et al. (2017) developed an inferential framework that involves function-on-scalar regression. Cao et al. (2019) used a two-step FPCA to study the momentum factor driven by data in China's stock market and the related dispersion effect. Horváth et al. (2020a) proposed a functional asset pricing model with function-on-function regression to study the dynamic beta of multiple assets. Horváth et al. (2020b) subsequently studied forward curves formed from commodity futures prices using the developed tools in functional time-series analysis. Boubaker et al. (2021) proposed an FDA procedure to decompose pricing anomalies in the U.S. market. Bouri et al. (2021) studied cumulative intraday return curves in the Bitcoin market by FDA approaches. Boubaker et al. (2022a) proposed a method for detecting bubble phases and the timing of bursts in global stock markets based on functional central limit law. Boubaker et al. (2022b) studied the effect of corporate social responsibility (CSR) and customer relationships on the stock price during the COVID-19 pandemic by FPCA.

In particular, we argue that the main reason momentum effects are so hard to predict is that conventional methods are limited to linear patterns and can't accurately show how they change over time in their entirety. The FDA procedure addresses these disadvantages well by decomposing the panel returns into cross-sectional orthogonal EFPCs and time-series harmonic loadings simultaneously, where the EFPCs help avoid unrelated noises and the loadings provide conditions for dynamic analysis. Therefore, we adopt the FDA procedure to explore the momentum controversy in China's A-shares market.

3. Methodology

Compared with conventional approaches, such as portfolio sorting and Fama & MacBeth (1973) cross-sectional regression, the FDA procedure can characterize the nonlinear (as well as linear) patterns of cross-sectional returns, which is crucial in momentum effects research. The portfolio sorting approach usually sorts the individual assets into 5 or 10 portfolios by their characteristics in the lagged period and calculates a hedge portfolio return as the difference between the excess returns of two extreme portfolios on each cross-section side, and tests its significance or its intercept by asset pricing model regressions. The Fama & MacBeth (1973) cross-sectional regression regresses the excess returns of individual assets on their lagged characteristic to obtain the exposures and then tests whether the exposures are significantly non-zero. Freyberger et al. (2020) prove that the portfolio sorting is equivalent to the Fama & MacBeth (1973) cross-sectional regression. To attain cross-sectional nonlinearity, the FDA procedure sorts the stocks by their previous characteristics and transforms the sorted cross-sectional returns into functions by B-splines. Then, it adopts FPCA to decompose the functions into EFPCs and performs statistical inferences.

3.1. Smoothing cross-sectional returns

Consider a large set of stocks in the market which are sorted by an ex-ante momentum variable $\{MOM^i_{t-1}, i = 1, 2, \ldots, N_t\}$ into P groups, and let $\{r_{t,p},\ 1 \leq p \leq P\}$ denotes the value-weighted portfolio excess return of the p^{th} group of stocks at period t.

The first step smooths the T-period discretely panel returns $\{r_{t,p}, 1 \leq t \leq T,\ 1 \leq p \leq P,\ t, p \in \mathbb{N}\}$ into T functional curves $\{r_t(u),\ 1 \leq t \leq T,\ 0 \leq u \leq 1,\ t \in \mathbb{N},\ u \in \mathbb{R}\}$ by B-splines, where $u = \frac{rank(MOM_{t-1})}{N_t}$ denotes the normalized rank of MOM^i_{t-1} into the interval $(0, 1]$.

Assuming $r_t(u)$ is in the Hilbert space $L^2(0, 1]$ with inner product

$$\langle x(u), y(u)\rangle = \int_0^1 x(u)y(u)du,$$

and norm

$$\|x(u)\| = (\int_0^1 x^2(u)du)^{1/2}.$$

By Karhunen-Loéve Theorem, we can write $r_t(u)$ as:

$$r_t(u) = \sum_{k=1}^{\infty} c_{t,k}\varphi_k(u) \approx \sum_{k=1}^{K} c_{t,k}\varphi_k(u), 0 \leq u \leq 1. \tag{1}$$

where $\varphi_k(u)$ is the k^{th} given basis function and $c_{t,k}$ is the k^{th} fitted coefficient.

3.2. Decomposing the functions

Assume that $\{r_t(u)\}$ is a stationary sequence of functions defined in $L^2(0, 1]$, and satisfies the moment condition $\mathbb{E}\|r_t(u)\|^4 < \infty$. Then, the covariance function $COV(u, v)$ of $r_t(u)$ is given by:

$$COV(u, v) = \mathbb{E}\big(r_t(u) - \mu(u)\big)\big(r_t(v) - \mu(v)\big), \tag{2}$$

where $\mu(u) = \mathbb{E}\big(r_t(u)\big)$ is the mean function.

The Karhunen-Loéve Theorem provides a basic tool to describe the random functions $\{r_t(u), 1 \leq t \leq T\}$. With $\lambda_1 \geq \lambda_2 \geq \cdots$ and $\phi_1(t)$, $\phi_2(t)$, $\ldots$ denoting eigenvalues and correspond orthonormal EFPCs of the covariance function $C(u, v)$, we obtain

$$r_t(u) = \sum_{m=1}^{\infty} \xi_{t,m}\phi_m(u), \tag{3}$$

where $\xi_{t,m} = \langle r_t(u), \phi_m(u) \rangle = \int_0^1 r_t(u)\phi_m(u)\,du$. With the increase of m, the eigenvalue λ_m becomes smaller and smaller, and the importance of the m^{th} principal component is getting lower and lower. Therefore, the structure and dynamics of the random functions $r_t(u)$ can be assessed by analyzing the M functional principal components $\{\phi_m,\ 1 \leq m \leq M\}$ of the first M largest eigenvalues as well as the harmonic loadings $\{\xi_{t,m},\ 1 \leq m \leq M\}$.

In many applications, a small number of principal components approximate the functions $\{r_t(u), 1 \leq t \leq T\}$ with a high degree of accuracy. Indeed, FPCA plays a more substantial role than its well-known analog in multivariate analysis (Benko et al., 2009). In multivariate analysis, the interpretation of the principal components is the correlation between principal components and original variables. In the functional context, $\phi_1(u), \phi_2(u), \dots$ represents the major variation patterns of $r_t(u)$ as functions of u.

For a given T-period functional sample, the empirical sample covariance function of $r_t(u)$ is:

$$COV_T(u,v) = \frac{1}{T}\sum_{t=1}^{T}\big(r_t(u) - \mu_T(u)\big)\big(r_t(v) - \mu_T(v)\big), \tag{4}$$

where $\mu_T(u) = \sum_{t=1}^{T} r_t(u)/T$ is the sample mean function. The unknown eigenfunction ϕ_m and eigenvalue λ_m are estimated by the empirical eigenfunction $\hat{\phi}_m$ and its eigenvalue $\hat{\lambda}_m$, which satisfy the integral equation

$$\hat{\lambda}_m\hat{\phi}_m(u) = \int_0^1 COV_T(u,v)\hat{\phi}_m(v)\,dv,\ \ m = 1, 2, \dots, M. \tag{5}$$

Using the M-dimensional space spanned by the $\hat{\phi}_1(u), \dots, \hat{\phi}_M(u)$ corresponding to the M biggest eigenvalues, $r_t(u)$ can be approximated by

$$r_t(u) \approx \hat{r}_t(u) = \sum_{m=1}^{M}\hat{\xi}_{t,m}\hat{\phi}_m(u) \tag{6}$$

where $\hat{\xi}_{t,m} = \langle r_t(u), \hat{\phi}_m(u) \rangle = \int_0^1 r_t(u)\hat{\phi}_m(u)du$ is the harmonic loading at month t of m^{th} EFPC. We refer the reader to Horváth & Kokoszka (2012) for more details.

3.3. Analyzing the EFPCs

This section shows why we dynamically analyze the momentum effect using the partial mean sequence of $\hat{\xi}_{t,m}$. From Section 3.2, the functions can be decomposed into orthonormal EFPCs ($\phi_m(u), m = 1, 2, \dots$) and corresponding harmonic loadings $\{\hat{\xi}_{t,m}, t = 1, 2, \dots, T\}$. An EFPC is a continuous function of u. Thus it represents a possible cross-sectional return variation pattern. The harmonic loadings are discrete, representing the effect magnitude of $\hat{\phi}_m(u)$ in month t. The variance contributions are captured by eigenvalue $\hat{\lambda}_m$.

We use the following statistics for analysis:

1) The variance contribution of $EFPC_m$ equals

$$\frac{\hat{\lambda}_m}{\sum_{m=1}^{\infty} \hat{\lambda}_m} \tag{7}$$

2) The expectation of $\xi_{t,m}\phi_m(u)$ on u:

$$\mathbb{E}_u[\hat{\xi}_{t,m}\hat{\phi}_m(u)] = \hat{\xi}_{t,m}\mathbb{E}_u[\hat{\phi}_m(u)]$$

is a discrete sequence and stands for m^{th} estimated time-series return variation pattern.

3) The expectation of $\xi_{t,m}\phi_m(u)$ on time t:

$$\mathbb{E}_t[\hat{\xi}_{t,m}\hat{\phi}_m(u)] = \mathbb{E}_t[\hat{\xi}_{t,m}]\hat{\phi}_m(u)$$

is a function of u and stands for m^{th} estimated cross-sectional return variation pattern.

Our insights can be obtained as follows: a momentum effect implies cross-sectional average return variation on momentum variable MOM. When $\hat{\phi}_m(u)$ is fixed, the momentum effect related to m^{th} EFPC relies on the mean of $\{\hat{\xi}_{t,m}, t = 1, \dots, T\}$, e.g. $\mathbb{E}_T[\hat{\xi}_{t,m}]$. This inspires us to use the partial mean sequence $\{\mathbb{E}_s[\hat{\xi}_{t,m}], t = 1, \dots, s,\ \ s = 1, \dots, T\}$, to analyze the momentum effect dynamically. Moreover, a robust effect should have consistent results for all situations, which means $\mathbb{E}_s[\hat{\xi}_{t,m}]\hat{\phi}_m(u)$ should have the same sign for all resampled datasets. In other words, for a robust effect, the functional confidence intervals of $\mathbb{E}_s[\hat{\xi}_{t,m}]\hat{\phi}_m(u)$ should have similar shapes or the confidence intervals of $\mathbb{E}_s[\hat{\xi}_{t,m}]$ on one side of the origin point. Thus we can estimate the confidence intervals by circular block bootstrapping to test for robustness.

4. Data and variable definition

We rely on the monthly returns of all A-shares and the market premiums [1] from the China Stock Market and Accounting Research Database (CSMAR). To avoid survival bias, our analysis includes delisted stocks. Because 1997 was the first that the daily price limit (10%) policy was in effect, our sample period is from January 1997 to December 2020.

Scholars generally calculate cumulative returns over different formation periods. The typical look-back periods used in the literature are 1, 3, 6, 12, 24, and 36 months (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993; Rouwenhorst, 1998; Wang, 2004; Gao et al., 2021). In addition, De Bondt & Thaler (1985) used a 12-month cooling-off period to study the long-term reversal effect for a 3-year formation period. Jegadeesh & Titman (1993) also set the last month as the cooling-off period when studying momentum effects in a 1-year holding period.

We define the momentum variable of stock s on month t as:

$$MOM^{s}_{L-C} = \sum_{l=t-L}^{t-C} r^{s}_{l} \tag{8}$$

where L is the length of the formation period and C is the length of the cooling-off period. To examine the pattern among various formations, we choose L as 1, 3, 6, 12, 24, and 36 while designating C as 1 (no cooling-off), 2 (1-month cooling-off), and 13 (1-year cooling-off). For example, Jegadeesh & Titman (1993) momentum for stock s can be written as MOM^{s}_{12-2}.

Table 1 shows the descriptive statistics of momentum variables on various formations. The momentum variables containing the cooling-off period have higher minimum values when L is greater than 12. Moreover, as L increases, the difference between the momentum variables with and without the cooling-off period becomes larger, indicating that most return volatility occured recently.

[1] We exclude the periods when a stock is marked with ST, *ST, SST, and S*ST. These markers represent listed companies in deficit for at least two consecutive fiscal years. All these companies confront the risk of being delisted, and their daily price change limit is 5%, which is half of the normal ones.

Table 1: Descriptive statistics of momentum variables on various formations

L-C	N(obs.)	Min.	Max.	Median	KS test
1-1	487721	-0.7819	22.0526	-0.0021	0
3-1	484781	-1.2425	22.3348	0.0026	0
6-1	475921	-1.6741	22.3348	0.0244	0
6-2	475271	-1.6741	22.3348	0.0178	0
12-1	455928	-1.9218	22.3348	0.0669	0
12-2	455867	-1.7544	22.3348	0.0591	0
24-1	413007	-2.7448	22.3348	0.2076	0
24-13	412511	-1.9405	22.3348	0.0753	0
36-1	372133	-3.6367	22.3348	0.4227	0
36-13	371884	-1.8831	22.3348	0.2429	0

1. This table reports descriptive statistics of momentum variables on various formations. The first column, "L-C", shows the formation coefficients L and C in Eq.(8). The second to sixth columns show the number of observations, minimum, maximum, median, and KS test p-values.

5. Empirical results

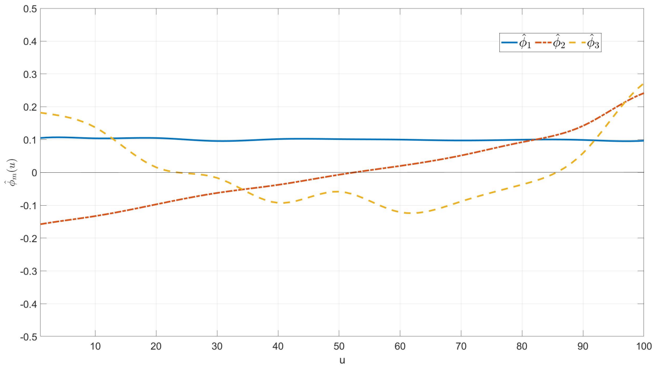
In this section, we first examine the importance of the EFPCs, dissect their economic implications, and compare our results with the conventional portfolio sorting approach. Table 2 lists the individual and total variance contributions (in percent) of the first eight EFPCs.

Table 2: Individual and total variance contributions of the first eight EFPCs

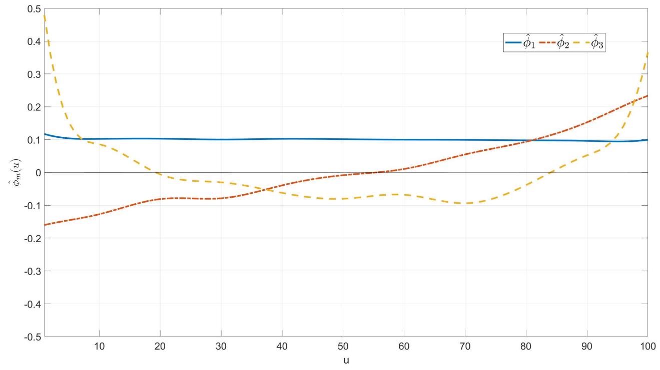
L-C	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	6^{th}	7^{th}	8^{th}	Total
1-1	89.57	4.79	2.19	0.77	0.55	0.39	0.36	0.31	98.92
3-1	90.25	4.59	1.39	0.99	0.64	0.50	0.33	0.30	98.98
6-1	89.38	5.41	2.01	0.64	0.55	0.38	0.32	0.29	98.98
6-2	89.46	4.96	2.26	0.72	0.52	0.41	0.37	0.30	98.99
12-1	90.41	5.09	1.17	0.87	0.48	0.37	0.34	0.26	99.00
12-2	89.65	4.83	1.78	1.03	0.71	0.39	0.32	0.27	98.97
24-1	90.47	4.63	2.10	0.52	0.43	0.39	0.28	0.26	99.08
24-13	90.78	4.40	2.08	0.63	0.46	0.31	0.27	0.25	99.16
36-1	89.48	4.93	1.80	1.19	0.48	0.46	0.38	0.31	99.03
36-13	91.45	3.30	1.90	0.91	have5	0.38	0.31	0.28	98.99

This table reports the individual variance contributions (in percent) of the first eight EFPCs in the second to ninth columns. The variance contribution of the m^{th} EFPC is captured by Eq.(7). The first column, "L-C", shows the formation coefficients L and C in Eq.(8). The last column shows the summations.

The total variance contributions of the first eight EFPCs are approximately 99%, which means we can recover the portfolio returns from them with high accuracy. The variance contributions of the first three EFPCs are nearly 90%, 3.30-5.41%, and 1.39-2.26%, respectively. For the second EFPCs, the formations without a cooling-off period have higher variance contributions than the ones with the same start coefficient. The fourth to eighth EFPCs have substantially low-level variance contributions, so we have regarded them as noise.



(a) 1-1



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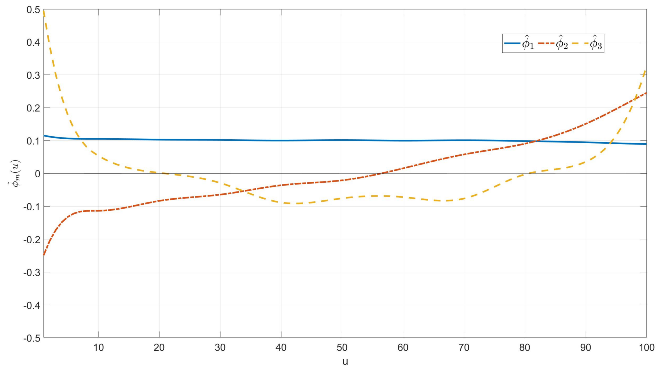

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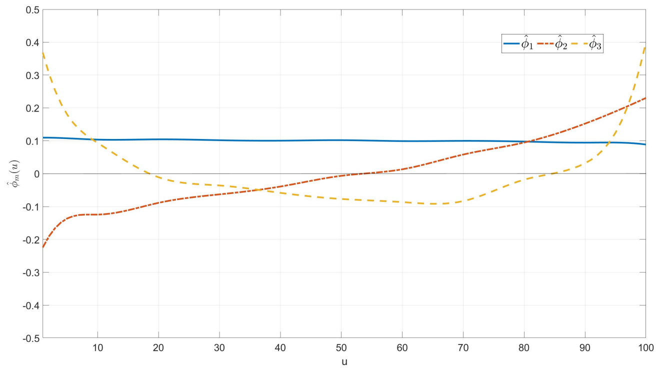
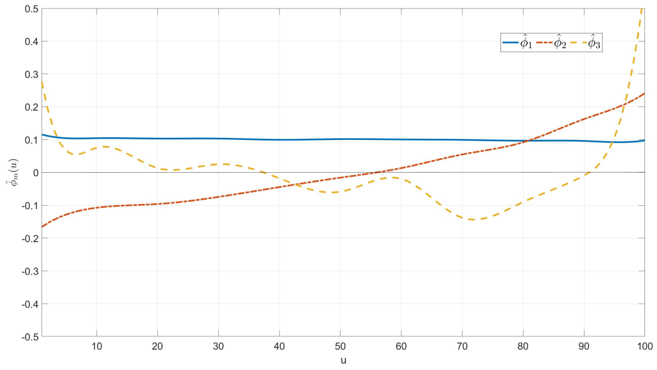
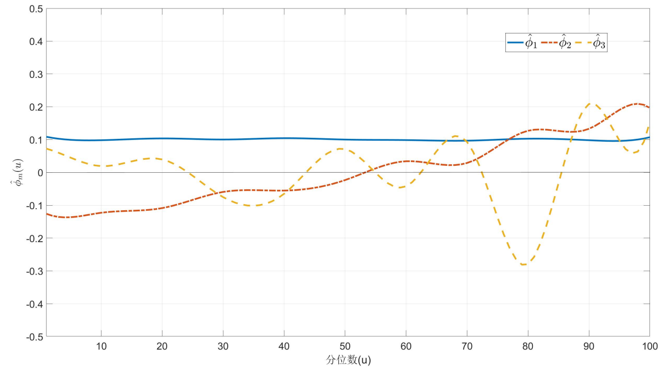


(d) 6-2

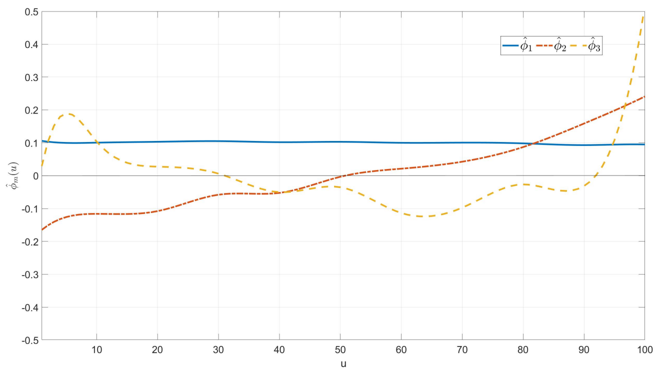
Figure 1: The first three EFPCs for various formations



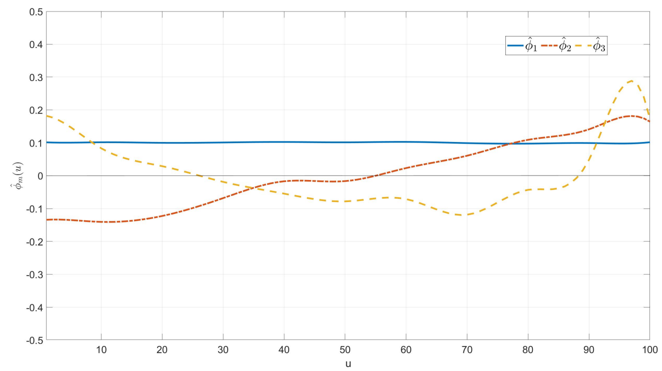
(e) 12-1



(f) 12-2

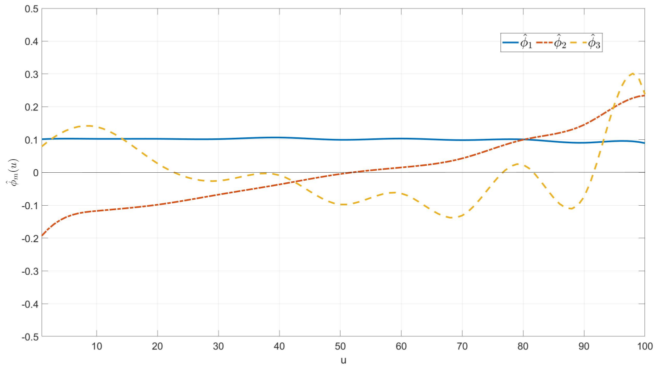


(g) 24-1

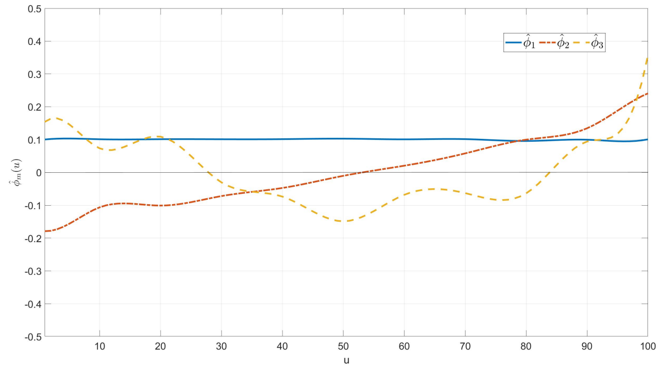


(h) 24-13

Figure 1: The first three EFPCs for various formations (Cont.)



(i) 36-1



(j) 36-13

Figure 1: The first three EFPCs for various formations (Cont.)

Figure 1 illustrates the first three EFPCs ($\hat{\phi}_m(u), m = 1, 2, 3$) for all momentum formations. The curves represent potential return variation patterns on the cross-section:

1) The first EFPCs present nearly horizontal straight lines with an insignificant variation in cross-section, indicating that they primarily reflect the stock return fluctuation in time series rather than cross-sections.

2) The second EFPCs exhibit monotonic lines on cross-section, indicating the dominant parts of the momentum effects[2].

3) Finally, the third EFPCs do not show a unified pattern, and their variance contributions are much lower than those of the first two. Because they are orthogonal to other EFPCs, we consider them noise to the momentum effects.

5.1. The analysis of the first EFPC

Literature suggests the first statistical factor is the value-weighted market index. Thus, we dissect the first EFPC by regressing it on the market factor Mkt by

$$\hat{\xi}_{t,1}\mathbb{E}_u[\hat{\phi}_1(u)] = \hat{\alpha} + \hat{\beta}(R_{Mkt,t} - R_{f,t}) + \hat{\epsilon}_t \tag{9}$$

Table 3 presents the regression results. For all formation periods, the Newey & West (1987) robust t-statistics are larger than 2, the intercept $\hat{\alpha}$ is approximately 0, and the coefficient $\hat{\beta}$ and adjusted R^2 are nearly 1. The empirical results demonstrate that $\hat{\xi}_{t,1}\mathbb{E}_u[\hat{\phi}_1(u)]$ can be explained by the market premium. Along with the shape of $\hat{\phi}_1(u)$, the $\hat{\xi}_{t,1}\hat{\phi}_1(u)$ can be regarded as an expansion of the market factor, which in line with the U.S. market.

5.2. The analysis of the second EFPC

All the second EFPCs exhibit monotonicity in Figure 1, consistent with the effect concepts. Thus, they indicate a momentum or reversal effect in our context,

[2]Whether the monotonic relationship is increasing or decreasing depends on both the EFPCs and their corresponding harmonic loadings.

Table 3: Regression results of the first EFPCs on the market factor

L-C	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\beta}$	$t(\hat{\beta})$	Adj.R^2	MSE
1-1	0.00	(2.64)	1.07	(46.90)	0.88	0.0009
3-1	0.01	(2.76)	1.08	(46.23)	0.88	0.0010
6-1	0.00	(2.58)	1.07	(47.32)	0.89	0.0009
6-2	0.00	(2.64)	1.08	(47.56)	0.89	0.0009
12-1	0.00	(2.19)	1.07	(47.09)	0.89	0.0009
12-2	0.00	(2.17)	1.07	(47.02)	0.89	0.0009
24-1	0.00	(2.25)	1.09	(42.79)	0.87	0.0011
24-13	0.01	(2.63)	1.08	(43.78)	0.87	0.0010
36-1	0.00	(2.02)	1.09	(40.06)	0.86	0.0012
36-13	0.00	(2.35)	1.09	(40.96)	0.86	0.0014

This table reports the regression summary of Eq.(9). The first column, "L-C", shows the formation coefficients L and C in Eq.(8). The numbers in parentheses are Newey & West (1987) robust t-statistics.

depending on the sign of the average harmonic loadings. Table 4 shows the results of regressing the time-averaging second EFPC on u,

$$\mathbb{E}_T[\hat{\xi}_{t,2}]\hat{\phi}_1(u) = \hat{\alpha} + \hat{\beta}u + \hat{\epsilon}_t \tag{10}$$

The numbers in parentheses are Newey & West (1987) robust t-statistics. If $\hat{\beta}$ is positive, there is a momentum effect (Mom.), otherwise a reversal effect (Rev.).

Because only the JT momentum (formation "12-2") has a distinguished positive $\hat{\beta}$, we can infer that only the momentum effect of formation "12-2" exists in China's A-shares stock market of the entire sample. We apply the portfolio sorting approach with the same formations to test this. Table 5 presents the expected returns (in percent) of the deciles and hedge portfolios. The data in parentheses are Newey & West (1987) robust t-statistics. Using the portfolio sorting approach, some momentum effects (formations by "6-2", "12-1", "12-2", "24-1", and "24-13") do not pass the significance test; thus, these effects do not exist in the conventional sense. However, using the FDA procedure, all the projections of the second EFPCs on the cross-section are monotonic, which implies that momentum effects exist but are overshadowed by the noise. We contend that the hedge portfolios

Table 4: Regression results of the time-averaging second EFPCs on u

L-C	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\beta}$	$t(\hat{\beta})$	Adj.R^2	Effect
1-1	0.0038	(48.51)	-0.0077	(-56.93)	97.04%	Rev.
3-1	0.0044	(46.46)	-0.0090	(-54.70)	96.80%	Rev.
6-1	0.0030	(38.04)	-0.0061	(-45.01)	95.34%	Rev.
6-2	0.0006	(49.12)	-0.0013	(-58.03)	97.14%	Rev.
12-1	0.0008	(39.60)	-0.0018	(-46.87)	95.69%	Rev.
12-2	-0.0013	(-41.02)	0.0027	(48.41)	97.95%	Mom.
24-1	0.0030	(39.48)	-0.0061	(-46.53)	95.63%	Rev.
24-13	0.0016	(61.92)	-0.0032	(-72.12)	98.13%	Rev.
36-1	0.0042	(43.17)	-0.0086	(-50.88)	96.32%	Rev.
36-13	0.0033	(46.80)	-0.0066	(-54.76)	96.80%	Rev.

This table reports the regression results of Eq.(10). The first column, "L-C", shows the formation coefficients L and C in Eq.(8). The numbers in parentheses are Newey & West (1987) robust t-statistics. If $\hat{\beta}$ is positive, there is a momentum effect (Mom.), otherwise a reversal effect (Rev.).

eliminate only the cross-sectional average return and cannot cancel the noise orthogonal to momentum effects. The FDA procedure separates all disturbances unrelated to momentum effects and obtains pure effects.

6. Dynamic analysis and Robust test

This section presents a dynamic analysis framework of momentum effects and tests their significance by circular block bootstrap.

6.1. Dynamic analysis

As in Section 5.2, $\mathbb{E}_T[\hat{\xi}_{t,2}]\hat{\phi}_2(u)$ determines whether momentum or reversal effect for the entire sample. Since $\hat{\phi}_2(u)$ is fixed and exhibits monotonic increasing as the momentum variable increases (Figure 1), $\mathbb{E}_T[\hat{\xi}_{t,2}]$ will determine whether the effect is momentum or reversal at any T.

Note that we can substitute the entire sample subscript T with the subsample subscript S. Thus, we propose using the sequence $\{\mathbb{E}_S[\hat{\xi}_{t,2}], t = 1, \ldots, S,\ S = 1, \ldots, T\}$, named the "partial mean sequence" of $\hat{\xi}_{t,2}$, to perform the dynamic

Table 5: Returns of deciles and the hedge portfolios

L-C	1	2	3	4	5	6	7	8	9	10	10-1
1-1	1.51	1.39	1.59	1.05	1.16	1.13	1.22	0.98	1.26	0.61	-0.90
	(2.45)	(2.29)	(2.50)	(1.77)	(1.76)	(1.80)	(2.02)	(1.62)	(1.75)	(0.89)	(-2.33)
3-1	1.62	1.38	1.69	1.27	1.34	1.23	1.02	0.95	0.62	0.53	-1.09
	(2.56)	(2.09)	(2.47)	(1.96)	(1.98)	(1.87)	(1.65)	(1.56)	(1.01)	(0.77)	(-2.56)
6-1	1.56	1.45	1.19	1.03	1.04	1.12	1.31	1.08	0.94	0.49	-1.07
	(2.20)	(2.15)	(1.83)	(1.56)	(1.66)	(1.84)	(2.02)	(1.68)	(1.48)	(0.82)	(-2.07)
6-2	1.18	1.34	1.12	1.23	1.10	1.26	0.88	1.24	0.78	0.98	-0.20
	(1.78)	(1.93)	(1.74)	(1.86)	(1.70)	(2.02)	(1.54)	(1.95)	(1.24)	(1.70)	(-0.45)
12-1	1.15	1.12	1.06	0.78	0.84	0.88	0.93	0.96	1.23	0.98	-0.17
	(1.68)	(1.69)	(1.66)	(1.28)	(1.39)	(1.36)	(1.55)	(1.73)	(1.84)	(1.53)	(-0.37)
12-2	0.84	0.88	1.06	0.83	1.02	0.93	0.94	1.21	1.07	1.22	0.38
	(1.27)	(1.41)	(1.48)	(1.31)	(1.55)	(1.61)	(1.56)	(2.07)	(1.91)	(1.92)	(0.91)
24-1	1.08	1.24	1.26	1.30	1.18	1.14	0.84	0.94	0.68	0.75	-0.33
	(1.64)	(1.87)	(1.84)	(1.99)	(1.73)	(1.72)	(1.33)	(1.45)	(1.16)	(1.10)	(-0.86)
24-13	1.26	1.18	1.08	1.15	1.16	1.10	1.17	1.28	0.72	0.94	-0.32
	(1.90)	(1.80)	(1.69)	(1.66)	(1.78)	(1.78)	(1.78)	(1.81)	(1.22)	(1.36)	(-0.87)
36-1	1.47	1.68	1.46	1.27	1.39	0.96	1.10	0.56	0.72	0.68	-0.79
	(2.07)	(2.37)	(2.15)	(1.98)	(1.90)	(1.48)	(1.62)	(0.89)	(1.16)	(1.00)	(-2.08)
36-13	1.72	1.34	1.12	1.36	1.08	1.64	1.10	0.95	0.89	0.69	-1.03
	(2.30)	(2.01)	(1.72)	(2.23)	(1.70)	(2.26)	(1.63)	(1.49)	(1.39)	(1.01)	(-2.48)

This table shows the returns of deciles and the hedge portfolios by the conventional method. The first column named "L-C" shows the formation coefficients L and C in Eq.(8). Columns "1"-"10" show the value-weighted decile portfolio mean returns (in percent) from the lowest to the highest past returns. The column "10-1" shows the winner minus loser hedge portfolio mean returns (in percent). The Newey & West (1987) adjusted t-statistics are in parentheses.

analysis of the momentum or reversal effect up to S. The positive value implies a momentum effect at time S, and vice versa.

Figure 2 illustrates the partial mean sequences from January 2003 to December 2020[3]. Only the curve of formation "12-2"(the JT momentum) is above zero in December 2020, which is consistent with the results shown in Table 4. The curves by formation "6-2", "12-1", "12-2", "24-1", and "24-13" —whose hedge portfolio returns are insignificant in Table 5—pass through the zero line (the dashed line) multiple times.

Before the 2008 global financial crisis, the curves corresponding to the medium-term (6-12 months) momentum effects were above zero, indicating that China's A-shares market presented medium-term momentum effects. The JT momentum effect was the strongest of these effects. The short-term (1-3 months) and long-term (24-36 months) momentum show reversal effects. When the global financial crisis erupted and the bull market collapsed, stocks with high past returns experienced much more significant declines than those with low past returns, turning momentum effects into reversal effects. Thus, the momentum effects turned into reversal effects at this time point. The curve corresponding to JT momentum passes through the zero line (the dashed line) numerous times. This explains why much of the recent literature is inconclusive regarding the momentum effect of formation "12-2".

Furthermore, the curves on formations "6-2", "12-2","24-13", and "36-13" are always much higher than "6-1", "12-1","24-1", and "36-1". Alternatively, the formations without cooling-off periods would lead to stronger reversal effects. This implies that short-term past returns, especially 1-month past returns, are the main sources of all the reversal effects. This result also verifies the importance of the 1-month reversal effect in China. Therefore, investors using trading strategies based on the reversal effects should include the last month's return (without the cooling-off period). This is dramatically different from the conventional literature, which includes the one month for the momentum strategy (Chui et al., 2010; Goyal &

[3]We chose to begin with January 2003 for two main reasons. First, our dataset starts in January 1997, and the first $\hat{\xi}_{t,2}$ values for the 36-month formation period appear in January 2000. Second, calculating the mean values requires some initial values. We choose the number of initial values as 36.

Wahal, 2015).

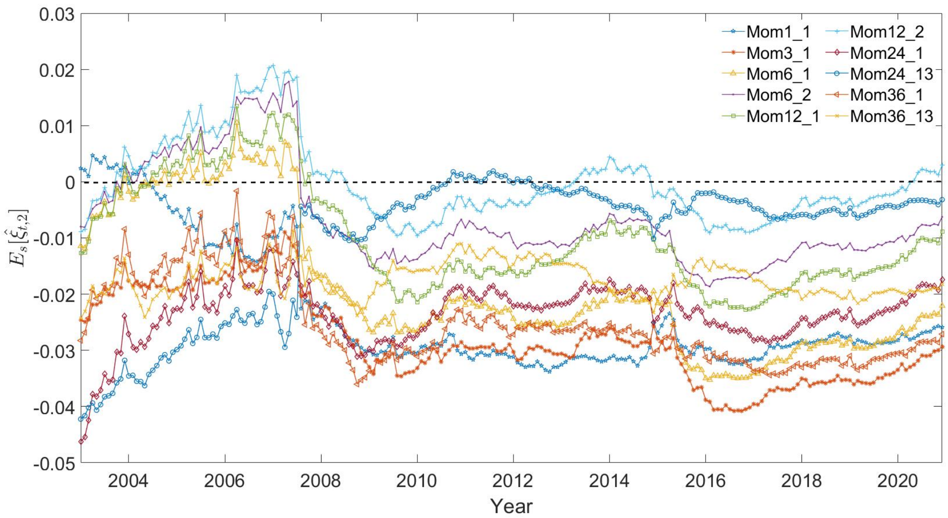


Figure 2: Time-varying $\mathbb{E}_s[\hat{\xi}_{t,2}]$

We suggest the partial mean sequence fluctuates between positive and negative in different periods, indicating switchings between the momentum and reversal effects. In the following section, we deploy a Politis & Romano (1992) circular block bootstrap procedure to examine the significance of the partial mean sequence to determine the significant effects.

6.2. Circular block bootstrap

The partial mean sequences determine the effect types (momentum or reversal). Therefore, if their values repeatedly switch between positive and negative with different samples, we cannot reach a consistent conclusion about the effect.

Because the partial mean values are random variables for different samples, we suggest testing the momentum effect by their confidence intervals. If the effect is persistent, the partial mean values should stay positive or negative for all samples. Therefore, the confidence interval should be on one side of the origin point.

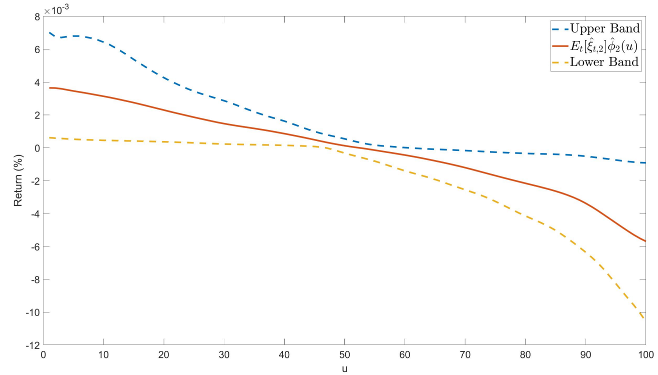
Table 6 presents the circular block bootstrap results of the partial mean sequences. The second and fourth columns show the lower and upper bands of 95% confidence intervals, respectively. The five formations ("6-2", "12-1", "12-2", "24-1", and "24-13") that have insignificant hedge portfolio returns still cannot satisfy the above condition given above. Furthermore, although the formation period "6-1" has significant hedge portfolio returns, its Newey & West (1987) robust t-statistics is very close to the critical value. Thus, its upper band is expected to be close to the origin point.

Table 6: The circular block bootstrap results of the partial mean sequences

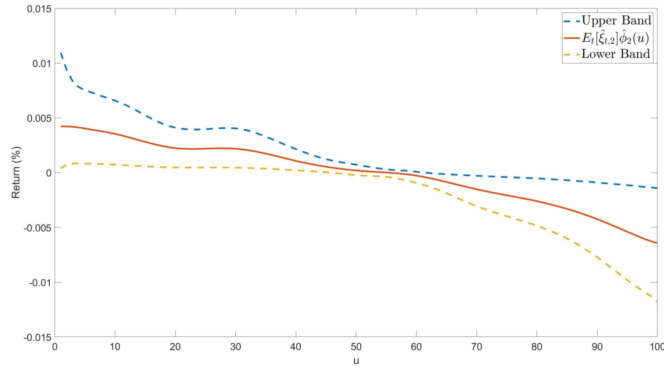
L-C	Circular Block Bootstrap			Real data
	Lower Band	Median	Upper Band	
1-1	-0.0444	-0.0240	-0.0038	-0.0243
3-1	-0.0507	-0.0279	-0.0058	-0.0284
6-1	-0.0420	-0.0188	0.0034	-0.0191
6-2	-0.0253	-0.0050	0.0152	-0.0050
12-1	-0.0287	-0.0053	0.0177	-0.0055
12-2	-0.0140	0.0078	0.0294	0.0077
24-1	-0.0408	-0.0175	0.0055	-0.0178
24-13	-0.0268	-0.0090	0.0084	-0.0092
36-1	-0.0482	-0.0245	-0.0015	-0.0250
36-13	-0.0377	-0.0193	-0.0006	-0.0195

This table shows the circular block bootstrap results of the partial mean sequences. The first column named "L-C" shows the formation coefficients L and C in Eq.(8). The "Lower Band" and "Upper Band" columns present the 95% confidence intervals of the partial mean sequences estimated by bootstrapping. The "Median" column states the median value of the partial mean sequences estimated by bootstrapping. The "Real Data" column exhibits the partial mean sequence estimated by the original dataset.

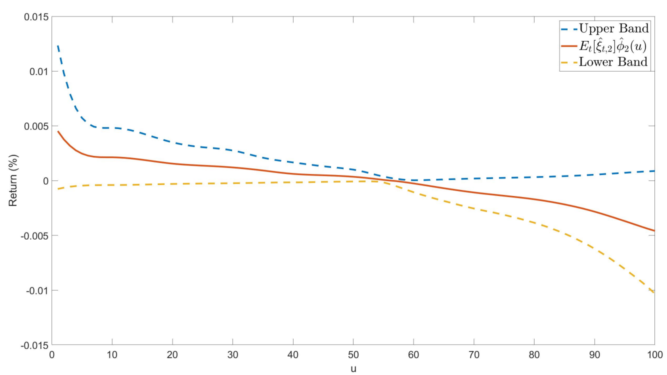
One advantage of the FDA is that it facilitates examining non-linearity in momentum effects. Thus, Figure 3 shows the confidence bands for the partial mean sequences. The 95% functional confidence bands corresponding to the formation "6-2", "12-1", "12-2", "24-1", and "24-13" are no longer monotonous, indicating that the medium-term reversal effects are not robust. This result is consistent with the previous analyses presented in Table 4 and 5 and Figure 2.



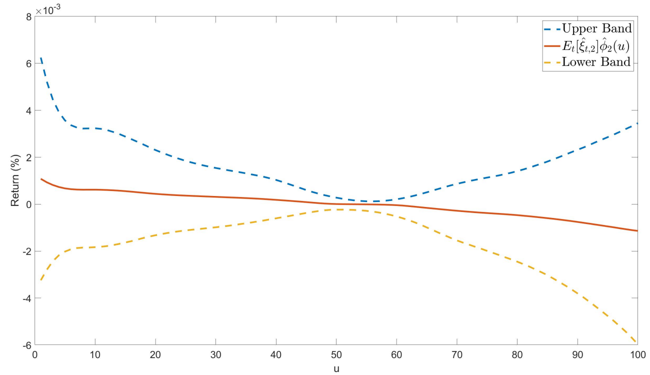
(a) 1-1



(b) 3-1

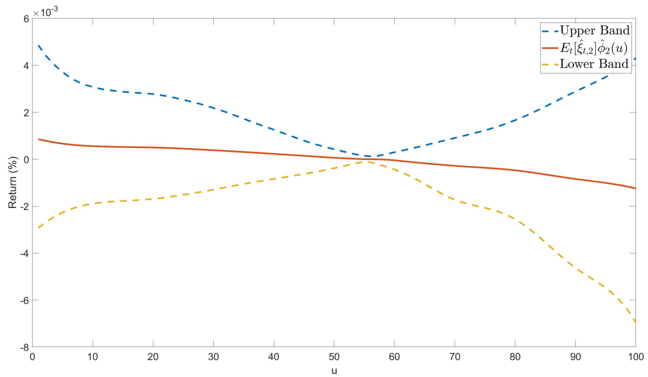


(c) 6-1

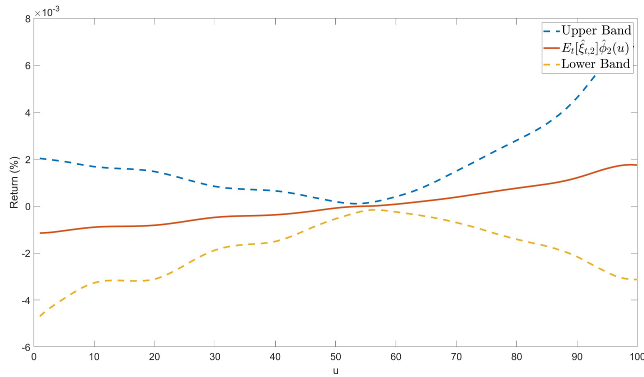


(d) 6-2

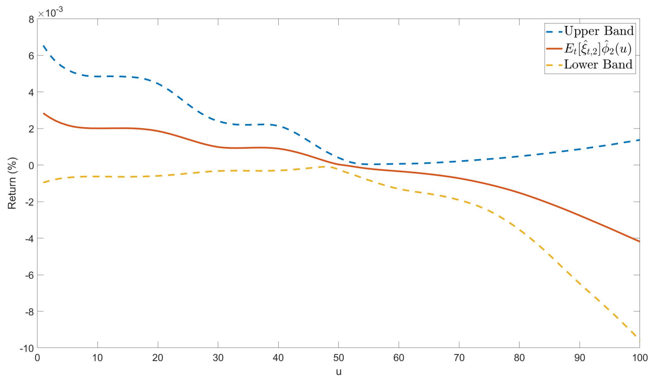
Figure 3: The functional 95% confidence bands of $\mathbb{E}_t[\hat{\xi}_{t,2}]\hat{\phi}_2(u)$



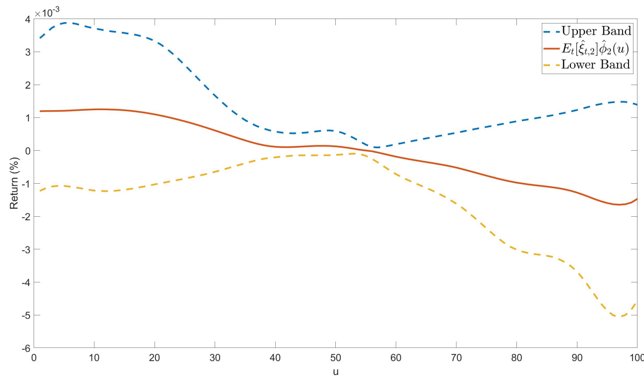
(e) 12-1



(f) 12-2

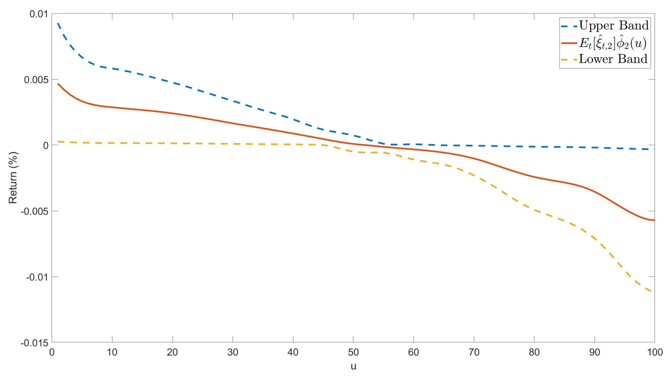


(g) 24-1

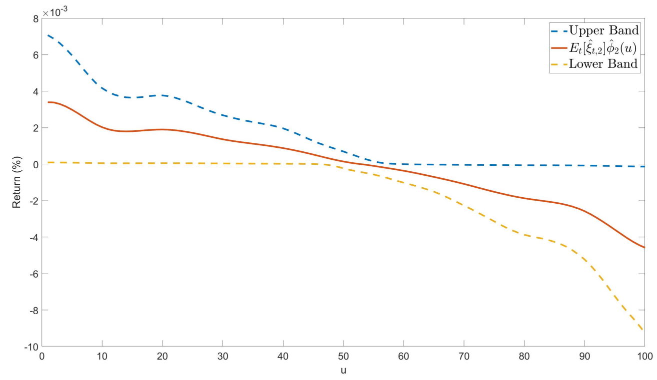


(h) 24-13

Figure 3: The functional 95% confidence bands of $\mathbb{E}_t[\hat{\xi}_{t,2}]\hat{\phi}_2(u)$ (Cont.)



(i) 36-1



(j) 36-13

Figure 3: The functional 95% confidence bands of $\mathbb{E}_t[\hat{\xi}_{t,2}]\hat{\phi}_2(u)$ (Cont.)

7. Conclusions

This research uses the FDA approach to resolve the momentum/reversal controversy in the prior literature on China's A-shares stock market. The FDA benefits from the ability to identify nonlinear cross-sectional patterns. The empirical evidence indicates that the first two EFPCs account for more than 94% of return variation. The first is significantly correlated with the market factor, while the second reflects the momentum or reversal effects.

We shed insight on China's momentum/reversal controversy by proposing a dynamic analysis framework for the second EFPCs. First, the empirical findings demonstrate that after the 2008 global financial crisis, mid-term momentum effects vanished and the market became dominated by reversal effects. The formation "12-2" curve goes through the zero line (the dashed line) several times, which explains why the current literature on the JT momentum effect is conflicting.

Second, we argue a robust momentum effect should satisfy the confidence intervals of the partial mean sequence values located on one side of the origin point (or the product of the second EFPC and the mean of its harmonic loadings has monotonic functional confidence bands). The circular block bootstrap results indicate significant short-term (1-6 months) and long-term (3-year) reversal effects in China.

Third, we find that formations without cooling-off periods resulted in higher reversal effects, implying that short-term past returns, particularly 1-month past returns, are the primary cause of all reversal effects observed.

Based on the above conclusions, we suggest investors in China's A-shares markets focus on developing strategies based on the reversal effects, especially 1-month formation. Secondly, with updated data, participants can also utilize the bootstrap procedure in this paper to examine the future momentum/reversal effects.

Since Liu et al. discussed the heterogeneous effects of the COVID-19 outbreak on stock prices, our future research should investigate the global or industrial momentum effects under special events like CovID-19 or the Russia-Ukraine Conflict. Another line of future research could use high-frequency data to investigate intraday momentum effects by deploying the tools in FDA.

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