DO FUNDAMENTAL INDEXES PRODUCE HIGHER RISK-ADJUSTED RETURNS THAN MARKET CAP INDEXES? EVIDENCE FOR CHINESE STOCK MARKET

BY

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THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science in Finance
in the Graduate School of Business
Nazarbayev University, 2023

Astana, Kazakhstan

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Abstract

The proponents of fundamental indexing ('FI') theorize that a traditional value weighted portfolio is characterized by a return drag due to overweighting

overvalued stocks and underweighting undervalued stocks. A number of empirical studies found an extra return for an FI strategy compared to a value weighted benchmark. However, the critics argue that the primary driver of FI's superior performances reflects not the drag avoided but a style shift towards value strategy. Hence the analytical comparison of an FI alternative should control for a style shift when testing for the drag effect. The 2018 study of an FI strategy for the U.S. stock market by De Moor, Liu & Sercu employs a vigintile portfolio analysis to control for style shift and do not find any economically or statistically significant benefit from drag avoidance. I employ the conventional factor analysis and the proposed double-sorted bucket analysis to test the FI strategy using Chinese stock market data. Like others before, I conclude that the FI's extra return is primarily due to its value bias rather than avoidance of the drag effect.

Do Fundamental Indexes Produce Higher Risk-Adjusted Returns Than Market Cap Indexes? Evidence For Chinese Stock Market

The concept of fundamental indexation ('FI') was first introduced by Arnott, Hsu and Moore (2005). The main idea behind FI is to create an index in which stocks are weighted by economic fundamentals, such as sales, book value, cash flows, and dividends, instead of market capitalization. The argument by proponents of FI is that cap-weighting in traditional indexes leads to a performance drag due to systematically overweighting overvalued stocks and underweighting undervalued stocks in a portfolio.

Literature Review

Arnott, Hsu and Moore (2005) found that their use of fundamentals in weighting the top thousand U.S. stocks benefited from an average annual excess return of 1.97% (with 0.1 pp. higher standard deviation and Sharpe ratio of 0.44 versus the cap-weighted benchmark's 0.32) compared to the S&P 500 from 1962 to 2004. Clare, Motson and Thomas (2013) constructed an FI index for the entire U.S. market from 1969 to 2011 and found an average annual excess return of 1.56% (with 0.1 pp. higher standard deviation and Sharpe ratio of 0.41 versus the cap-weighted benchmark's 0.32).

Back-testing based studies using historical stock market data have also suggested the superiority of FI in Europe. Hemminki and Puttonen (2008) build an FI version of the DJ Euro Stoxx50 Index from 1996 to 2006 and show an average annual excess return of 1.74% (with 0.3 pp. lower standard deviation

and Sharpe ratio of 0.55 versus the cap-weighted benchmark's 0.48). Houwer and Plantinga (2009) construct an FI version of the DJ Euro Stoxx 600 Index between 1993 and 2007 and find an annual excess return of 2.4% (with 0.1 pp. lower standard deviation and Sharpe ratio of 0.79 versus the cap-weighted benchmark's 0.69).

Meanwhile, the critics argue that the strong value tilt accounts for most of the outperformance of FI portfolios. The FI weighting tends to favor companies whose fundamental values are high in relation to their market values, resulting in overweighting value stocks and underweighting growth stocks (whose perceived growth prospects justify high prices relative to current fundamentals). In other words, FI's excess returns is possibly explained by the well-known value premium rather than by the pricing noise in the stock markets and the related cap drag.

The alphas are found to be either negative or no longer significant when risk factor models (Fama-French 3-factor model or Carhart 4-factor model) are implemented for the fundamental indices. Such were the findings for equity markets in the United States (Jun and Malkiel, 2007; Blitz and Swinkels, 2008; Chow, Hsu, Kalesnik and Little, 2011), Europe (Mihm and Locarek-Junge, 2010; Bolognesi and Pividori, 2015), and Australia (Mar, Bird, Casavecchia and Yeung, 2007). In a broader study, Walksausl and Lobe (2009) found that fundamental indices can outperform their cap-weighted counterparts on a global

level and in 44 countries (including China) but show that the abnormal returns can be greatly explained by an augmented exposure to value stocks.

Benchmark Study

In their literature review on FI, De Moor, Liu and Sercu (2018) observe that while most studies find that a substantial part of the gain is accounted by the risk factors, there is far less consensus as to whether there is any net alpha left due to avoiding the drag. In order to estimate the benefits from drag avoidance while controlling for style shifts, the authors sorted stocks in the U.S. equity market into twenty buckets by marketcap and weighted each stock in a vigintile based on FI (sales, book value, cash flows), EW (equal-weighting), and LW (weighting by lagged marketcap). They also concluded that the extra return delivered by FI is essentially all about style shift – primarily the value bias – rather than drag avoidance.

De Moor, Liu and Sercu (2018) first compared VW/VW portfolio (where each vigintile is sorted by marketcap and each stock per vigintile is also value weighted) with the VW/EW portfolio (where each vigintile is sorted by marketcap and each stock per vigintile is weighted equally). Since value weighting each bucket controls for the size bias of an EW/EW portfolio and equal-weighting in each bucket ensures that the weights are not correlated with pricing errors, the difference between the VW/VW and the VW/EW portfolios should provide the estimate of a drag effect, which the authors find to be economically and statistically insignificant.

Meanwhile, the difference between the VW/EW and the VW/FI portfolios (where each vigintile is sorted by marketcap and each stock per vigintile value weighted by one of the FI metrics) should provide the estimate of FI's style shift. De Moor, Liu and Sercu (2018) illustrate decomposition of the extra return of a VW/FI portfolio relative to the VW/VW benchmark through the following formula: $E(r^{vw/fi} - r^{vw/vw}) = E(r^{vw/fi} - r^{vw/ew}) + E(r^{vw/ew} - r^{vw/vw})$. Here the first component accounts for the residual style shift and the second one accounts for the drag avoided. Examining FI's monthly return over the VW monthly return, the authors estimated that FI's excess exposure to value bias is roughly 0.3%, while the highest excess exposure estimate to size bias is just 0.075%.

Chinese Stock Market

As a contribution to the FI literature, I apply the research strategy designed by De Moor, Liu and Sercu (2018) to China, which has the world's second-largest stock market. Indeed, I found no previous study (at least in English) that has tested fundamental indexing strategy focusing on the Chinese equity market. There is a university paper (which has not been published in an academic journal) by Naylor and Dai (2016) which compares performance of fundamental indexation in the BRICs (Brazil, Russia, India, China). Yet they simply compare return characteristics of a cap-weighted reference portfolio with those of FI (with the latter producing higher return but also higher volatility) and do not conduct deeper analysis.

A possible explanation for the lack of China-focused study of an FI strategy could be that it largely prohibits participation by foreign investors in its domestic stock market as well as participation by its domestic investors in foreign markets. According to Liu, Stambaugh, and Yuan (2019), "at the end of 2016, 197 foreign institutions were authorized to invest in A-shares, China's domestically traded stocks, but with a quota of just 0.6% of total market value (and even less in earlier years). Chinese domestic investors can invest in international financial markets only through a limited authorized channel" (p. 48).

Given the separation of China's market and investors from the rest of the world and the substantial differences in its economic and financial systems, Liu, Stambaugh, and Yuan (2019) develop three-factor (CH-3) and four-factor (CH 4) models for Chinese equities in a way that is analogous to - but not a simple replica of - the Fama and French (1993) procedure for the U.S. factors. In my factor analysis, I use the risk-free rate (rf), the CH-3 (mktrf,[1] SMB, and VMG) and CH-4 (mktrf, SMB, VMG, and PMO) factors the authors have published on the University of Pennsylvania website. The factor data is available from January 2000 to December 2021 and summarized in Table 1.

[1] The market factor, i.e. return on the market less the risk-free rate

Table 1. Summary statistics for the CH-3 and CH-4 factors. The means and standard deviations are expressed in percent per month. Unlike the other factors, it is not clear why the numbers for SMB change once the fourth factor is added.

When building the size factor (SMB), Liu, Stambaugh, and Yuan (2019) exclude the smallest 30% of firms, which account for 7% of the stock market's total capitalization. Given the restrictive IPO regulations in China, the authors estimated that a typical stock in the bottom 30% derives roughly 30% of its market value from its potential shell value in a reverse merger. For the construction of the value factor (VMG), they run a Fama-MacBeth regression including four different valuation ratios and opt to use the earnings-price ratio instead of the book-to-market used by Fama and French (1993).

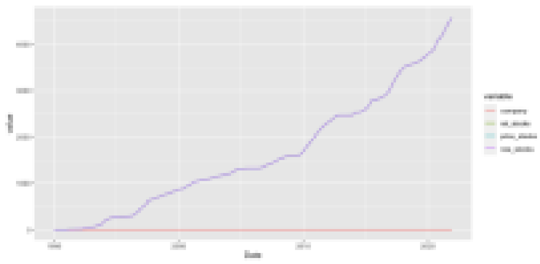
The authors also propose a fourth factor, PMO (pessimistic minus optimistic), as the sentiment factor based on abnormal turnover. Similar in its logic to the Carhart momentum, this factor is meant to capture the dominance of the Chinese market by individual retail investors: "As of the year 2015, over 101 million individuals had trading accounts, and individuals held 88% of all free-floating shares" (p. 62).

Methodology and Data

In order to capture the universe of Chinese stocks, I look at 5,090 A shares listed on the Shanghai, Shenzhen and Beijing stock exchanges and use a period from January 1990 to December 2021 when downloading the data. Of the 5,090 Chinese equities, 4,930 stocks are active and 160 stocks were delisted, which prevents the survivorship bias. All the data was retrieved from Refinitiv DataStream in Chinese Yuan (CNY): monthly data for total returns ('ret'), stock prices ('price'), and number of shares outstanding ('nos'); and quarterly data for company sales ('sales'), book value of equity ('bve'), free cash flow ('fcf'), and dividends ('div').

My first step before cleaning the data is to visualize the number of stocks for which variable data is available each month or quarter. The left-hand side of Figure 1 shows that the number of stocks for which the monthly data (ret, price, nos) is available remains the same each month and hence the lines overlap and grow steadily over time. Indeed, the first ret, price, and nos data become available only in March 1991. The right-hand side of Figure 1 shows the number of stocks for which the quarterly data (sales, bve, fcf, div) is available. While steady increase can be observed in the number of stocks for which sales, fcf, and div data is available, there is a clear seasonality in the availability of bve data.

Figure 1: The number of stocks for which data is available for the monthly variables (on the left) and quarterly variables (on the right)



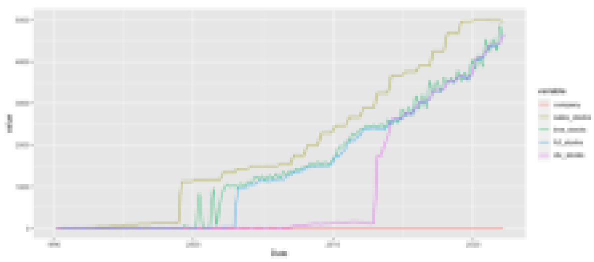


Figure 2 shows visualization of missing values for each stock in each variable dataset. To ensure that, when joined later with the monthly variables, an actively traded stock for which a quarterly data has simply not been published for a given quarter will not necessarily drop out, I use the last observation carried forward ('locf') function in R for the 4,930 active stocks. I then join the locf-filled quarterly data for 4,930 stocks with the 160 delisted stocks, thus making sure that the locf function is applied to the actually delisted stocks.

Figure 2: Displaying the missing values for the monthly (ret, price, nos) and quarterly variables (sales, bve, fcf, div) and quarterly variables with locf

sales bve

ret

fcf
sales with locf bve with locf fcf with locf

price nos

div div with locf

Figure 3 shows how carrying forward the last available quarterly data for the 4,930 active stocks addresses the seasonality in the availability of the bve data. I then join the monthly and quarterly variables (but only sales, bve, and fcf – not dividends, to be explained in the next paragraph), create a marketcap variable and lag the marketcap and quarterly variables by one month. For example, ret data for the end of January 2012 is matched with marketcap, bve, sales, and fcf data for the end of December 2011. In other words, the end-of month return is matched with data available at the beginning of the month. For the rebalancing frequency of the portfolios, I use monthly revisions, which seems realistic for both institutional and private investors who need to weigh transaction costs against tracking error.

Figure 3: The number of stocks for which data is available for the quarterly variables (sales, bve, fcf, div) before (left-hand-side) and after (right-hand-side) the locf function

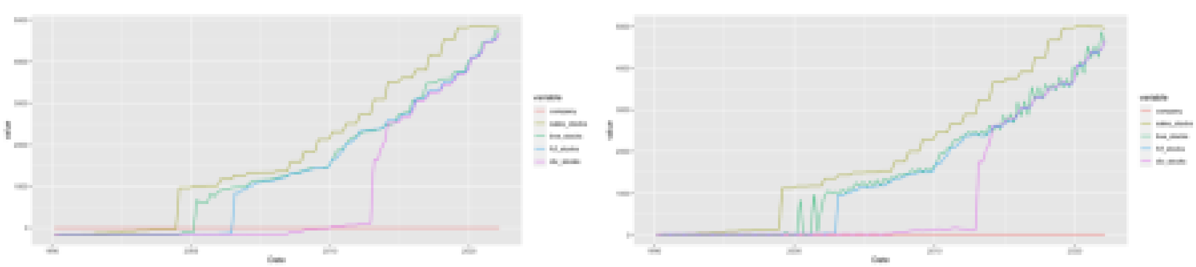


Figure 4 shows the monthly sum of the number of stocks for which data is available in the joined dataset. From April 2000 to March 2002, only one stock has data for all the variables (ret, marketcap, sales, bve, fcf). From February 2002 to March 2002, only two stocks have data for all the variables. This number jumps to nine in April 2002 and to 884 in April 2003. Therefore, I cut data rows with dates older than April 2003 and thus work with 225 months for the rest of the analysis. In the joined dataset, the average cross-section contains about 2,187 stocks. Had I included the dividends, I would have had to start from June 2007, when the dividend data availability for stocks increases from 20 companies to 65, or June 2008, when this number grows to 118, as shown in Figure 5. Thus, I do not include the dividends in my analysis in order to work with a longer time horizon.

Figure 4. The number of stocks for which data is available for the monthly (ret, marketcap) and quarterly variables (sales, bve, fcf) in the joined dataset used for further analysis

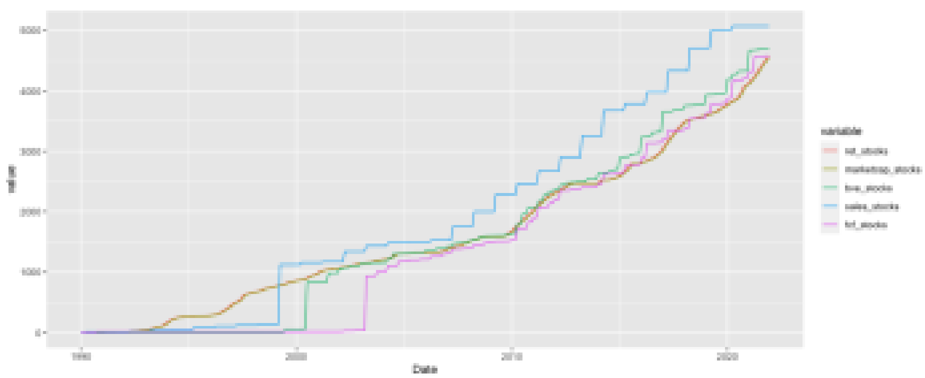
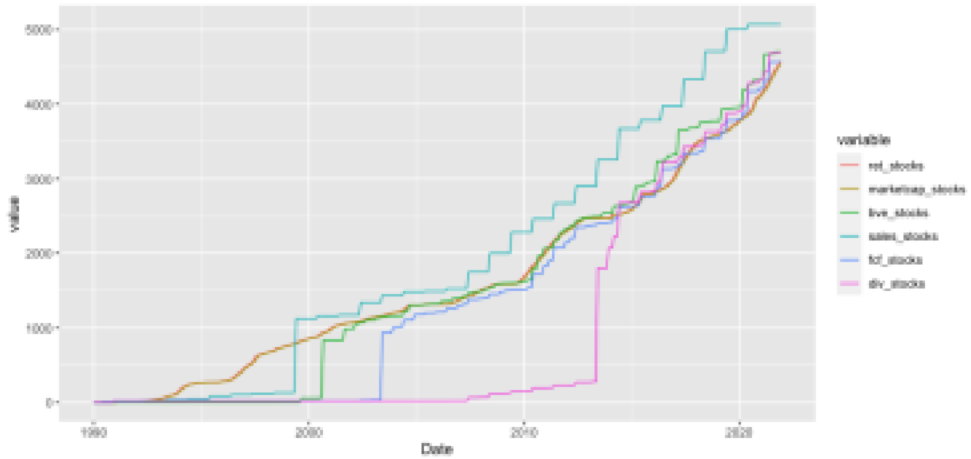


Figure 5. The number of stocks for which data is available for the monthly (ret, marketcap)

and quarterly variables (sales, bve, fcf, div) in the joined dataset with dividends which is not used for further analysis due to shortened time horizon of data availability for all variables



Before moving on to the analysis of the joined dataset, I first check my return data. To draw the comparison, I plot the return data together with the market return data, which I derived by adding the risk-free rate to mktrf factor in the CH3 three factors. Figure 6 shows that the average market return in the

CH3 dataset is 0.9497% and the average monthly return in my dataset is 1.558% between April 2003 and December 2021. The discrepancy is most likely due to Liu et al.'s (2019) exclusion of the smallest 30% of firms, when building the Chinese factor model.

Figure 6. Checking the return data in the joined dataset by juxtaposing it with the total market return (rf+mktrf) data

```
> summary(ret4_monthly_mean_ff)
      Date            avg_ret_per_month  mkt_total_ret
 Min.   :2003-04-01   Min.   :-28.704   Min.   :-25.1400
 1st Qu.:2007-12-01   1st Qu.: -4.458   1st Qu.: -2.8100
 Median :2012-08-01   Median :  1.388   Median :  0.9900
 Mean   :2012-07-31   Mean   :  1.558   Mean   :  0.9497
 3rd Qu.:2017-04-01   3rd Qu.:  6.399   3rd Qu.:  4.8400
 Max.   :2021-12-01   Max.   : 31.607   Max.   : 24.8100
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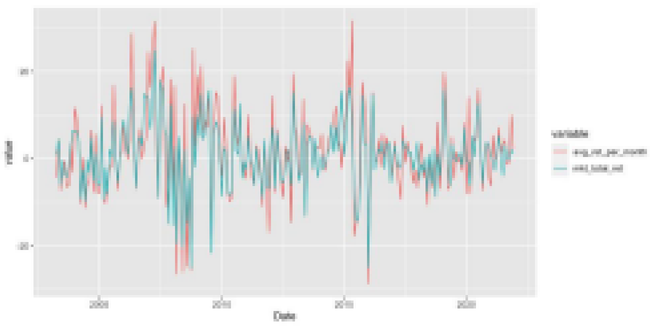


I clean the joined dataset further by setting to zero the rows with negative bve (1.63% of the total bve data) or negative sales (0.16% of the total sales data). I also take the absolute value of the negative free cash flows (52.15% of the total fcf data), assuming that a hugely negative cash flow tends to occur only in big firms. According to De Moor, Liu and Sercu (2018), absolute cash flow works better than the standard versions, fcf itself or max(fcf,0). **Simple summary of VW, FI, EW, and LW returns**

Table 1 shows the prima facie benefits from FI, in percent per month, when portfolio weights are based on relative sales, bve, and the absolute value of fcf, compared to portfolios that are value-weighted (VW), equal-weighted

(EW), or value weights lagged by one-month, three-months, or six-months (LW1, LW3, LW6). The reason for the inclusion of the latter three is due to the logic underlying FI, whereby older weights are supposed to provide better returns, consistent with lower drag. Table 2 shows monthly excess returns and Sharpe ratios for these portfolios. The Sharpe ratios are not annualized. Table 3 shows the differences in the monthly returns for the VW index and FI/EW/LW weighted portfolios and t-stats of these differences.

Table 1: Performance of VW, FI, EW, and LW portfolios, in percent per month

	variable	mean	sd	ann_ret
1	ret_VW	0.8113643	7.961796	10.18283
2	ret_BV	1.0775340	7.848385	13.72492
3	ret_SL	1.2984646	8.404502	16.74394
4	ret_CF	1.1682773	8.264379	14.95616
5	ret_EW	1.5577584	9.910257	20.38082
6	ret_LW1	0.8400571	7.969999	10.55974
7	ret_LW3	0.8578213	7.989820	10.79368
8	ret_LW6	0.8707288	8.096099	10.96395

Consistent with previous studies in other equity markets, I find that the FI returns exceed the VW returns for the Chinese stock market. Monthly returns increase on average by 0.266% (with t-statistic of 2.35) when weighting is based on bve, and by 0.487% (with t-statistic of 3.98) and 0.357% (with t statistic of 1.87) when weighting is by sales and the absolute value of fcf, respectively. Annualized this means 3.54% - 6.56% extra for FIs. Except for

bve, this comes with a small increase in risk, but the Sharpe ratios are still higher for all FIs compared to VW.

Table 2: The monthly excess returns and Sharpe ratios

	variable	mean	sd	sharpe_ratio
1	excess_ret_VW	0.6205643	7.965988	0.07790174
2	excess_ret_BV	0.8867340	7.851734	0.11293480
3	excess_ret_SL	1.1076646	8.408098	0.13173782
4	excess_ret_CF	0.9774773	8.266351	0.11824773
5	excess_ret_EW	1.3669584	9.912447	0.13790322
6	excess_ret_LW1	0.6492571	7.974182	0.08141990
7	excess_ret_LW3	0.6670213	7.993838	0.08344194
8	excess_ret_LW6	0.6799288	8.099753	0.08394440
9	mktrf	0.7588889	7.614749	0.09966039

Table 3: The differences in the monthly returns for the VW index and portfolios weighted with FI, EW and LW

	mean diff	t stat	p value
diff_BV_VW	0.26616969	2.353129	0.01948214460
diff_SL_VW	0.48710029	3.984119	0.00009161812
diff_CF_VW	0.35691297	1.870462	0.06272383481
diff_EW_VW	0.74639413	2.845794	0.00484100756
diff_LW1_VW	0.02869277	1.772968	0.07759293133
diff_LW3_VW	0.04645703	1.626536	0.10524151170
diff_LW6_VW	0.05936452	1.483603	0.13932003946

EW pays an even more generous extra return of 0.75% (with t-statistic of 2.85), with a predictably larger standard deviation, but its Sharpe ratio is as good as the sales-based one. LW barely and insignificantly beat VW in terms of mean return and Sharpe ratio, although the extra return grows with the lag

length in accordance with the FI prediction: the older the weights, the less their error should correspond to the current level of mispricing and should thus generate a better return. The statistical significance of extra returns from FI and the statistical insignificance of extra returns from LW imply that the FI's extra return probably has more to do with style shifts than drag avoided. **Factor regressions on VW, FI, EW, LW returns**

I regress returns on the FI, EW, and LW portfolios on the CH-3 and CH-4 factors and do the standard Newey-West t-test for a zero value of the intercept, alpha. The results are summarized in Table 4. The alpha is insignificant for VW, FI, and LW portfolios, meaning that the risk factors account well for changes in returns for these portfolios.

For the VW portfolio, on average, there is a small and negative exposure of 0.05-0.03 (with 0.86-0.53 t-statistic) towards the value factor (VMG). While the value exposure is also small and negative for the LW portfolio, it is large and negative for the EW portfolio: 0.18-0.27 (with 2.68-3.91 t-statistic). Meanwhile, we see that the fundamental indexation strategy has, on average, a large and positive exposure towards VMG: 0.20-0.23 (with 2.94-2.79 t-statistic) for bve-based FI; 0.18-0.22 (with 2.33-2.48 t-statistic) for sales-based FI; 0.18-0.22 (with 2.33-2.48 t-statistic) for sales-based FI; and 0.31-0.32 (with 3.54-3.27 t-statistic) for fcf-based FI. Thus, these regression results provide strong empirical support for the theoretical observation that fundamental indices are tilted towards value stocks.

Table 4. CH-3 regressions on monthly returns on the left and CH-4 regressions on monthly returns on the right

In regard to the SMB factor, FIs and LW retain a large and positive exposure to the small-cap stocks similar to VW, with the exception of fcf-based portfolio. It is possible that taking the absolute value of fcf when constructing

this portfolio has eroded the size signal contained in negative cash flows, contrary to our assumption that a hugely negative cash flow tends to occur only in big firms. As expected, EW is especially exposed to SMB. A direct consequence of investing the same proportion in small and large cap stocks will be a small-cap market bias in comparison with VW.

Unlike VW, EW, and LW portfolios, the FIs show a significant negative exposure to momentum (PMO), which is consistent with previous studies (Stotz, Dohnert & Wanzenried, 2010; Clare, Motson and Thomas, 2013; Basu & Forbes, 2014; De Moor, Liu & Sercu, 2018). The negative momentum coefficient is likely a result of the FI's contrarian strategy of selling winner stocks and buying loser stocks.

Factor regressions on FI, EW, LW excess returns relative to VW As an alternative, for the FI, EW, and LW portfolios I compute returns in excess of the VW return, regress them on the CH-3 and CH-4 factors, and do the standard Newey-West t-test for a zero value of the intercept, alpha. The results are summarized in Table 5. Since the left-hand side variable is a return in excess of the VW return, the coefficients estimate the exposures to mktrf, SMB, VMG, and PMO as differentials relative to those of VW. Consistent with the regression results on the total returns, these numbers also indicate a style shift. Specifically, relative to VW, FI imparts a large and significant upward boost to the portfolio's sensitivity to VMG: 0.25-0.26 (with 5.19-4.77 t-statistic) for bve-based FI; 0.23-0.25 (with 4.31-4.34 t-statistic) for sales-based FI; and

0.35-0.36 (with 4.74-5.12 t-statistic). FI's relative exposure to SMB is less consistent. The small-cap sensitivity increases insignificantly for the FIs based on bve and sales, with respective relative coefficients of 0.01-0.02 (with 0.29-0.59 t-statistic) and 0.09-0.10 (with 1.68-2.13 t-statistic). Meanwhile, the SMB sensitivity falls insignificantly for the fcf-based FI, with negative coefficient of 0.08-0.09 (and 1.31-1.52 t-statistic).

Compared to VW, EW has stronger exposure to SMB with the coefficient of 0.66-0.67 (and 14.67-15.51 t-statistic). The EW portfolio has significantly smaller exposure to VMG than the VW portfolio with the negative coefficient of 0.15-0.22 (and 3.41-5.83 t-statistic). Using LW affects style far less than adopting FI or EW, again as expected, although their greater exposure to both SMB and VMG is statistically significant.

Table 5: The results from regressions on the difference of FI and EW returns over VW returns with the CH-3 (on the left) and CH-4 (on the right) factors

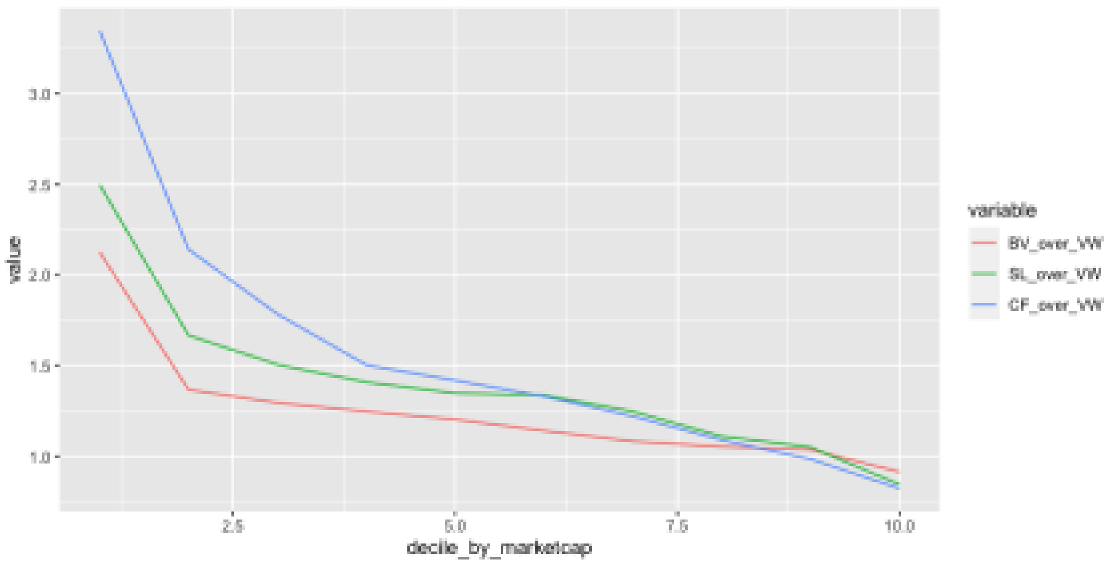
Coefficient	(Intercept)	mktrf	SMB	VMG
BV_est	−0.0417	0.0093	0.0117	0.2530
BV_NW_t_val	−0.3721	0.4631	0.2886	5.1872
SL_est	0.1132	0.0646	0.0857	0.2286
SL_NW_t_val	0.9246	2.7511	1.6793	4.3090
CF_est	−0.0308	0.0561	−0.0939	0.3559
CF_NW_t_val	−0.1819	1.7461	−1.5216	5.1068
EW_est	0.5119	0.0264	0.6582	−0.2172
EW_NW_t_val	5.8859	1.4711	15.5127	−5.8343
LW1_est	0.0092	0.0002	0.0134	0.0085
LW1_NW_t_val	0.6299	0.0811	2.4625	1.5369
LW3_est	−0.0094	0.0022	0.0303	0.0283
LW3_NW_t_val	−0.3577	0.4020	2.9031	2.6770
LW6_est	−0.0407	0.0126	0.0529	0.0459
LW6_NW_t_val	−1.1608	1.7481	4.2398	2.7070

Coefficient	(Intercept)	mktrf	SMB	VMG	PMO
BV_est	0.0148	−0.0008	0.0241	0.2617	−0.0756
BV_NW_t_val	0.1192	−0.0441	0.5894	4.7672	−1.3448
SL_est	0.1888	0.0519	0.1038	0.2484	−0.0991
SL_NW_t_val	1.3709	2.3095	2.1261	4.3425	−1.4478
CF_est	0.0387	0.0424	−0.0806	0.3543	−0.0967
CF_NW_t_val	0.1994	1.4946	−1.3072	4.7399	−1.1315
EW_est	0.5143	0.0348	0.6659	−0.1453	0.0264
EW_NW_t_val	5.3573	1.7995	14.6650	−3.4071	0.6008
LW1_est	0.0013	0.0018	0.0120	0.0091	0.0109
LW1_NW_t_val	0.0822	0.6541	2.1976	1.5499	1.4685
LW3_est	0.0013	0.0007	0.0325	0.0327	−0.0124
LW3_NW_t_val	0.0430	0.1342	3.2146	3.1191	−0.8323
LW6_est	−0.0427	0.0137	0.0528	0.0512	0.0056
LW6_NW_t_val	−1.0773	1.8765	4.2491	2.8933	0.2795

Decile portfolio analysis

Before proceeding with the analysis for the double-sorted portfolios, I first visualize what weight adjustments might be recommended by an FI strategy. Every month I sort stock on size and put each of them into one of ten size buckets (from the smallest decile 1 to the largest decile 10). Figure 7 shows for every decile and FI strategy the ratio of average FI-recommended weight over average market weight. For the smallest stocks the FI weights are, on average, 2.2-3.3 times the market weights. In fact, even at the 75th size percentile the FI weights are still 1.2 times their market counterparts.

Figure 7. Average relative fundamental size divided by the average relative market value of the size buckets



Following the mixed portfolio test strategy proposed by De Moor, Liu and Sercu (2018) to avoid a style shift when testing for the drag, I allocate portfolio

capital to stocks in two steps. Every month, all stocks are assigned to one of ten equally-populated size buckets (deciles). Capital is allocated to each decile on the basis of market weight (VW), but within deciles I use weights based on either bve (BV), sales (SL), free cash flow (CF), or equal weights (EW). I then compare performance of these mixed portfolio strategies (VW/BV, VW/EW, VW/CF, VW/EW) and their pure versions, i.e., when the weights are only based either on marketcap (VW/VW), bve (BV/BV), sales (SL/SL), free cash flow (CF/CF), or equal weights (EW/EW).

Figure 8 shows how the average monthly return on these portfolios co move over time, while Figure 9 displays the cumulative return on CNY1 from each portfolio strategy. Table 6 summarizes the mean monthly return and standard deviation of each portfolio strategy. Table 7 shows the difference in mean monthly returns and standard deviations of each mixed portfolio and pure FI and EW portfolio from the pure VW portfolio. Table 8 shows the t-statistic for the difference in these means.

The performance of the pure portfolio strategies is the same as the earlier summary of prima facie benefits from VW, BV, SL, CF and EW. Among the pure strategies, the EW/EW portfolio had the largest monthly average return of all the pure strategies (1.56% with 9.91% standard deviation). Now when stocks are first sorted into VW deciles and only then equally weighted, VW/EW's mean monthly return of 0.85% is closer to the VW/VW's 0.81%, while delivering a substantially larger standard deviation of 9.14% compared to

VW/VW's 7.96%. In other words, after controlling for size by first sorting stocks into VW deciles, the EW strategy became very close in performance to the VW/VW: the mean difference is just 0.04% with 0.31 t-statistic.

Consistent with the findings of De Moor, Liu & Sercu (2018) for the U.S. equity market, I thus find no economically or statistically significant drag avoidance effect for the Chinese equity market when comparing VW/VW to VW/EW at the level of total portfolio return. The VW/FI portfolios should not do better or worse than the VW/EW in terms of drag: if they do generate higher returns, this means direct evidence of style shifts, even at the within-bucket level.

Among the mixed portfolios, VW/SL has the largest mean monthly return

(1.21% with 8.29% standard deviation), followed by VW/CF (1.16% and 8.24% standard deviation) and VW/BV (1.04% with 7.82% standard deviation). Indeed, these FI strategies mixed with VW have only slightly lower returns than their pure counterparts and the difference in VW/FI's mean returns relative to VW/VW (and VW/EW) remains both economically and statistically significant. In other words, after controlling for size by first sorting stocks into VW deciles, the FI strategies remain very close in performance to their pure counterparts, implying that FI's are mostly value-biased rather than size-biased.

Figure 8. The average monthly return on each pure and mixed portfolio

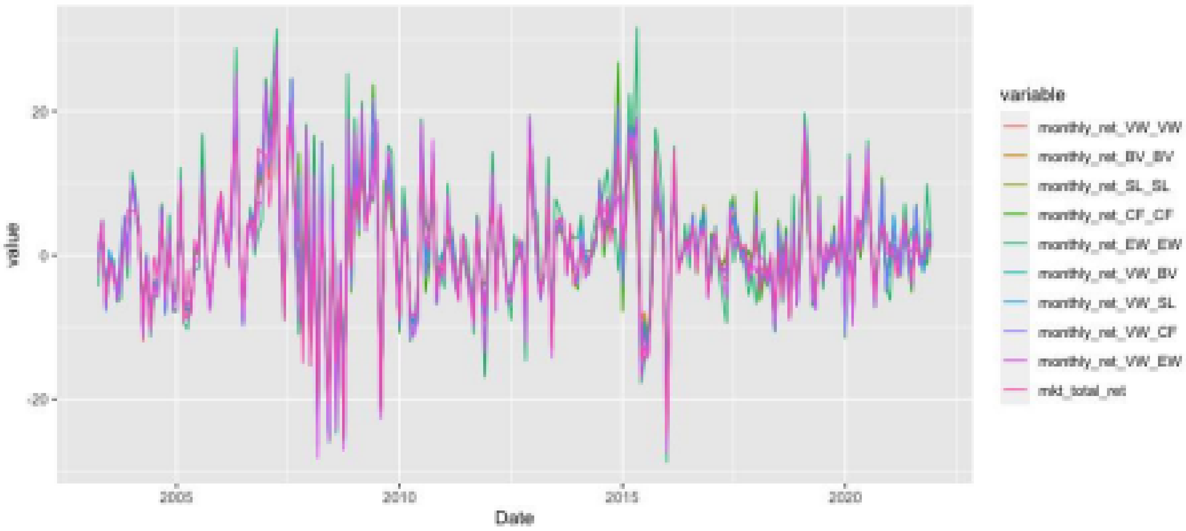
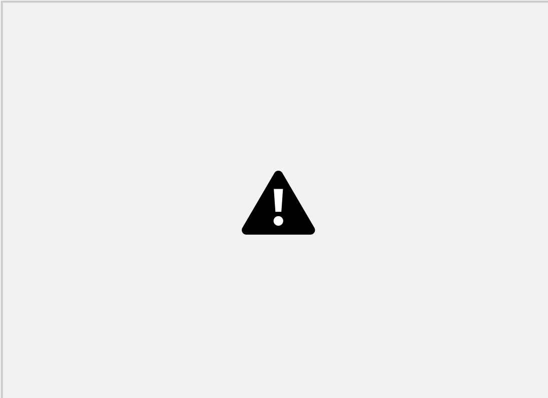


Figure 9. The cumulative return on CNY1 from each pure and mixed portfolio strategy

Table 6. The mean monthly return and standard deviation of each pure and mixed portfolio strategy.

Table 7. The difference in mean monthly returns and standard deviations of BV/BV, SL/SL, CF/CF, EW/EW, VW/BV, VW/SL, VW/CF and VW/EW portfolios from the VW/VW portfolio

Table 8. The t-statistic for the difference in mean monthly returns of BV/BV, SL/SL, CF/CF, EW/EW, VW/BV, VW/SL, VW/CF and VW/EW portfolios from the VW/VW portfolio



Analysis per bucket

I now turn to bucket-by-bucket analysis. Table 9 summarizes the average monthly return per bucket for each of the pure and mixed weighting schemes. Table 10 and Figure 10 show each portfolio's average monthly return per bucket in excess of the corresponding VW/VW-weighted bucket.

The pure FIs have lower mean returns than VW/VW for smaller deciles. They begin to exceed VW/VW's monthly average return per bucket starting from bucket five (BV/BV), seven (SL/SL), and nine (CF/CF). By contrast, the EW/EW portfolio exceeds VW/VW for buckets 1-9 and generates lower return

relative to VW/VW only for the largest decile. This is consistent with the earlier observations in factor regressions with the EW having the strongest size exposure, followed by – in the descending degree of size bias - SL, BV, VW, and CF.

Among the mixed portfolios, the extra returns realized by VW/EW within each decile relative to its VW/VW-weighted counterpart are essentially zero. The implication is that there is no economically and statistically meaningful benefit from drag avoidance at the bucket level either for the Chinese equity market, which is again consistent with the bucket-level findings of De Moor, Liu & Sercu (2018) for the U.S. equity market.

The VW/FI portfolios all have a positive extra return relative to their VW/VW (and VW/EW) benchmark for each decile and the difference grows larger starting from bucket seven. The VW/FI's difference relative to VW/EW suggests that there must have been extra sources of return over and above drag avoidance, like style changes.

Table 9. The mean monthly return per bucket for each pure and mixed portfolio

Table 10. The average excess returns per bucket relative to the VW/VW return for the same bucket

Figure 10. The average excess returns per bucket relative to the VW/VW return

for the same bucket

Total return on a bucket portfolio

Having obtained similar results from decile portfolio analysis as De Moor, Liu & Sercu (2018), I now add a new type of FI analysis by estimating total return per bucket. Every month, I sort stocks into size deciles based on either marketcap, bve, sales, or fcf. I then weight each stock in a decile based on its size or use equal weights. I thus estimate average monthly return of a portfolio wholly invested in one of the buckets. The average monthly returns are summarized in Table 11 and Figure 11. The average standard deviations are summarized in Table 12 and Figure 12. The Sharpe ratios are summarized in Table 13 and Figure 13. As expected, smaller deciles have higher average monthly return and higher standard deviation than the larger deciles.

The average monthly return on buckets 1-4 is higher when sorted by marketcap compared to those sorted by FI: from 3% for bucket 1 to 1.7% for bucket 4 versus 1.5-1.8% return average for these buckets when sorted by one of the FI metrics. The higher return on marketcap-sorted buckets 2-4 also comes with slightly lower volatility compared to bve- and sales-sorted buckets. The Sharpe ratios of the marketcap-sorted buckets 1-4 grow larger than the FI-sorted buckets 1-4 with each smaller decile.

The average monthly return on buckets 5-10 gets lower when sorted by marketcap compared to those sorted by FI: from 1.4% for bucket 1 to 0.7% for bucket 10 versus 1.3-1.6% average for these buckets when sorted by one of the FI metrics. Meanwhile, the difference gets smaller in volatility buckets 5-9 sorted by either marketcap or an FI metric. For the largest decile 10, the lowest standard deviation of 7.5%-7.6% can be observed for buckets first sorted by marketcap or bve and then value-weighting each stock within the bucket by corresponding size metric instead of equal weighting. The Sharpe ratios of the marketcap-sorted buckets 5-10 grow smaller than that of the FI-sorted buckets 5-10 with each larger decile.

These results are consistent with the findings observed earlier. The marketcap-weighting is more sensitive to stock size, hence the larger deviation of its mean monthly returns per bucket from the average monthly returns on FI weighted buckets. Compared to the marketcap-weighted buckets, the FI weighted buckets have less variation in mean monthly returns and standard

deviations across deciles, indicating their greater immunity to the size bias. In contrast to the average Sharpe ratio of 0.13-0.15 for the FI-weighted buckets, the marketcap-weighted bucket portfolios have the highest Sharpe ratio (0.26-

0.27) for the smallest deciles and the smallest Sharpe ratio (0.06-0.07) for the largest deciles.

Table 11. The average monthly return of a portfolio wholly invested in one of the buckets

Figure 11. The average monthly return of a portfolio wholly invested in one of the buckets

Table 12. The average standard deviation of a portfolio wholly invested in one of the buckets

Figure 12. The average standard deviation of a portfolio wholly invested in one

of the buckets

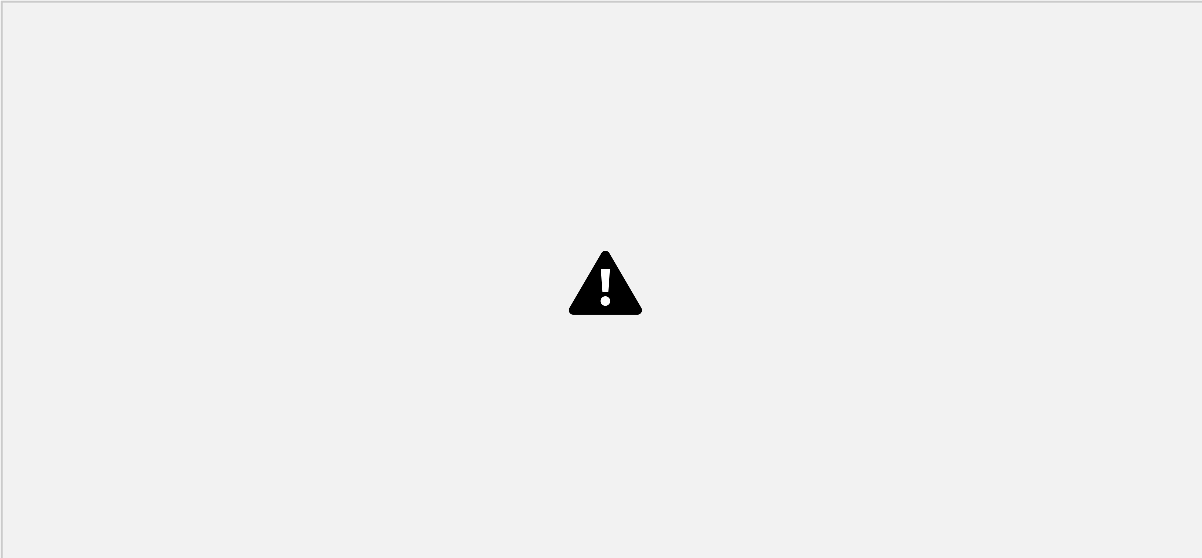


Table 13. The Sharpe ratio of a portfolio wholly invested in one of the buckets

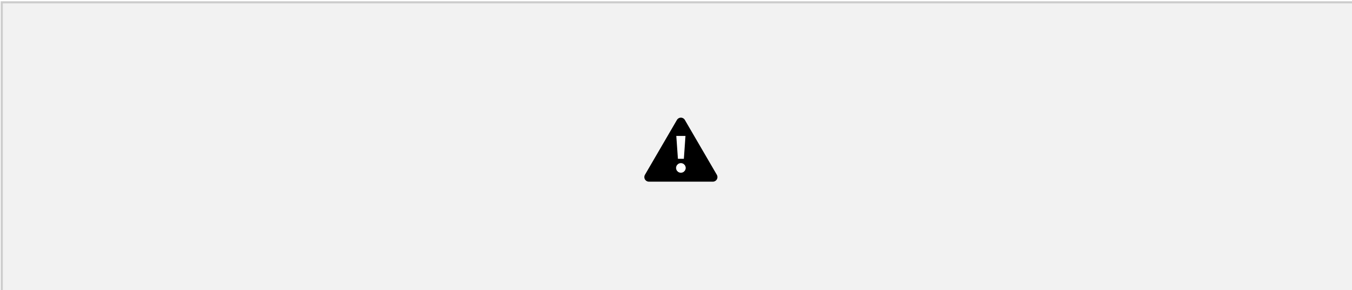
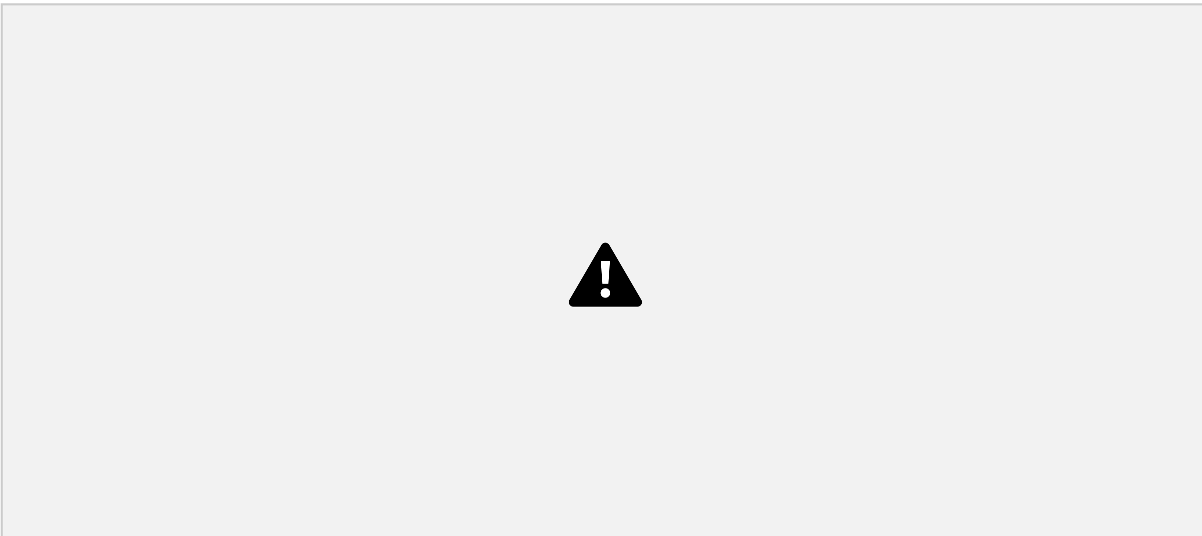


Figure 13. The Sharpe ratio of a portfolio wholly invested in one of the buckets



Conclusion

The debate in the literature on FI is whether it derives its extra return from drag avoidance, as theorized by its proponents, or style shifts towards value stocks, as argued by its critics. Using the Chinese stock market data, I first conduct a conventional factor regression analysis and then apply the double sorting research methodology outlined in the benchmark study by De Moor, Liu and Sercu (2018). In line with their conclusion for the U.S. stock market, I find that the FI's extra return is primarily from its value bias rather than avoidance of the drag effect.

As a final step, I add per-bucket return summary for an investor who would like to invest wholly in only one of the buckets, sorted by either marketcap or an FI metric. Given the larger sensitivity of marketcap-weighting to stock size, such an investor would gain the highest Sharpe ratio from

investing in the smallest decile sorted by marketcap. Meanwhile, the FI-sorted buckets are more immune to the size bias and hence their average monthly return and standard deviation remains largely similar across different deciles.

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