The “Value” Effect and the Market
For Chinese Stocks

by

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Abstract: A long literature in empirical finance has isolated both a "value" and a small-capitalization effect in asset pricing. This study confirms the existence of these "style" effects both in new types of equity indexes and in the stocks of Chinese companies traded in international markets. We then present a new nonparametric method of portfolio construction that enables investors to extract the predictive power of these style effects, without diluting their efficacy through an unintended weighting distribution that closely resembles capitalization weighting. We then develop a simple method to isolate periods where style tilts are likely to be particularly effective.

1. Introduction

A long literature in empirical finance has isolated a "value" effect in asset pricing. Studies such as Basu (1983) and Keim (1983) have shown that stocks selling at low prices relative to their earnings and book values have generated higher returns for investors. Similar results have been shown for stocks selling at low multiples to their sales. Fama and French (1992) confirmed a strong "value" effect in the United States stock market from the early 1960s through 1990. A particularly strong "value" effect characterized the U.S. stock market during the early 2000s as market prices adjusted from the levels that existed at the height of the "Internet Bubble." Fama and French (1998) have also documented a strong "value" effect in international stock markets.

One can interpret such findings as being inconsistent with efficient markets. Portfolios made up of stocks with low market values (MV) relative to book values (BV) earn excess risk-adjusted returns when risk is measured by beta from the Capital Asset Pricing Model (CAPM). But any test of market efficiency is a joint test of the relationship of returns to MV/BVs and the efficacy of CAPM's beta to fully measure risk. According to Fama and French, the ratio of market value to book value itself is a risk measure, and therefore the larger returns generated by low MV/BV stocks are simply a compensation for risk. Low MV/BV stocks are often those in some financial distress.

Investigators such as Banz (1981) and Fama and French (1992) have also found a strong relationship between company size (measured by total market capitalization) and returns. Smaller firms appear to generate higher returns than larger firms. Again, the interpretation of these results is controversial. The excess returns of small firms can be interpreted as inefficiency, but they also may represent compensation for bearing risk. Smaller companies may be far more sensitive to economic shocks than are larger firms.

Some studies of the stocks of Chinese companies over limited periods of time have confirmed the existence of style effects. For example, Wong, Tan and Liu (2006) found that smaller firms and "value" stocks produced excess returns in the Shanghai Stock Exchange "A" share market over the period 1993 through 2002. Similar results have been reported by Bo and Krige (2008), Drew, Naughton, and Veeraraghaven (2003), Wong and DiIorio (2007), and Lam and Spyros (2003). But as we have shown for the United States stock market, style effects are not dependably consistent.[1] Wong and DiIorio (2007) conclude that "there is no factor that has a persistent effect on stock returns."[2] There is also evidence that "momentum" strategies can yield excess returns in the Chinese market over the period 1995 through 2005.[3] Brown, Du, Rhee, and Zhang (2008) find that both "value" and "momentum" strategies produced excess returns in four Asian markets (Hong Kong, Korea, Singapore, and Taiwan). They conclude, however, that a combination of the best value and momentum strategies does not provide a significant improvement over the best value strategy evaluated separately.

2. Indexes and Funds with Style Tilts

Many investment portfolios, whether actively managed or indexed, employ such style or factor tilts in composing their portfolios. For example, some mutual funds specialize in smaller companies, those whose market capitalizations are below the average capitalization for companies that comprise the major stock-market indexes. Other funds concentrate on so-called "value" stocks, those stocks that sell at relatively low multiples of their book values and earnings. Some indexed market mutual funds and exchange-traded funds (ETFs) are broken up into "value" and "growth" components. For example, the Standard and Poor's 500 Stock Index has been broken up into "value" and "growth" components and investors can buy mutual fund shares and ETFs representing these components.

Considerable recent interest has been shown in a new set of indices that are weighted by certain fundamental factors such as sales, earnings, dividends, or book values, rather than by capitalization. The

[1] See Jun and Malkiel (2008).

[2] See Naughton, Truong, and Veeraraghavan (2008).

[3] See also, Lam and Spryrou (2003).

best known of the new “fundamentally weighted” indices that claim to improve upon cap-weighted indexes is the Research Affiliates Fundamental Index™ (“RAFI,” FTSE RAFI US 1000-Ticker PRF). The RAFI index contains 1,000 stocks weighted by fundamental measures of book value, earnings, etc. It has outperformed traditional large-cap indices such as the Standard and Poor’s 500 index and the Russell 1000 index by substantial margins during the early 2000s. Such performance has emboldened the proponents of the Fundamental Index ™ (FI) to claim that this new method of indexing could replace the ‘old paradigm’ of capitalization weighted indexing. See, for example, Arnott et. al. (2008).

In our judgment the reason for the ability of FI portfolios to outperform certain market benchmarks during the period from 2000 through 2005 is that FI relies in part on the “value” and “size” effects that researchers have understood for years. To the extent that earnings and book values are some of the factors used to weight stocks in the portfolio, FI will systematically overweight “value” stocks and underweight “growth” stocks. Moreover, since FI underweights stocks with high market capitalizations relative to fundamental factors, there will be a tendency for an FI portfolio to contain smaller-capitalization stocks than those in a traditional capitalization-weighted index.

Over the period from 2000 through 2005 there was a particularly strong “value” effect as well as a “small firm” effect. The bursting of the Internet bubble in early 2000 produced extremely poor returns for the overpriced large-cap growth stocks that were the market leaders during the late 1990s. FI portfolios were not alone in performing very well over the early 2000s. Managed as well as indexed portfolios focusing on “value” and “small-cap” stocks all tended to outperform the broad market indexes.

One direct method of measuring the factor tilts inherent in FI portfolios is to perform a regression analysis of the monthly FI returns in the United States against a Fama-French three-factor model. Fama and French (1993) argue that the Capital Asset Pricing Model (CAPM) should be augmented by two additional risk factors, which are company size and the market price to book (MV/BV) ratio. Thus, risk is captured by CAPM’s beta, MV/BV, and an equity capitalization (size) measure.

We estimate the equation:

$$R_{FI} - R_F = \hat{a} + \hat{b}(R_M - R_F) + \hat{c}\ \text{SMB} + \hat{d}\ \text{HML} + \mu, \qquad (1)$$

where R_{FI}, R_M and R_F stand for the returns on the FI portfolio, the market portfolio, and the risk free rate; SMB measures the difference in returns of small firms (S) and big firms (B) as measured by market capitalization, and HML measures the difference in returns of expensive firms and cheap firms when market value relative to book value is used to measure relative expensiveness. Excess risk-adjusted returns of the FI portfolio will be measured by $\hat{a}$.

If one performs such regressions over the periods from January 1962 and from January 1979 through December 2008, it is possible to show that the FI return can be fully explained by the Fama-French risk factors as has been shown for a shorter period by Jun and Malkiel (2008). The coefficients of determination of regressions of FI returns and the three Fama-French risk factors are 0.97 and 0.96 and all of the coefficients of the factors are highly significant. In addition, a zero "alpha" or excess return is generated by the FI method of weighting the portfolio. The regression results are shown in Table 1.

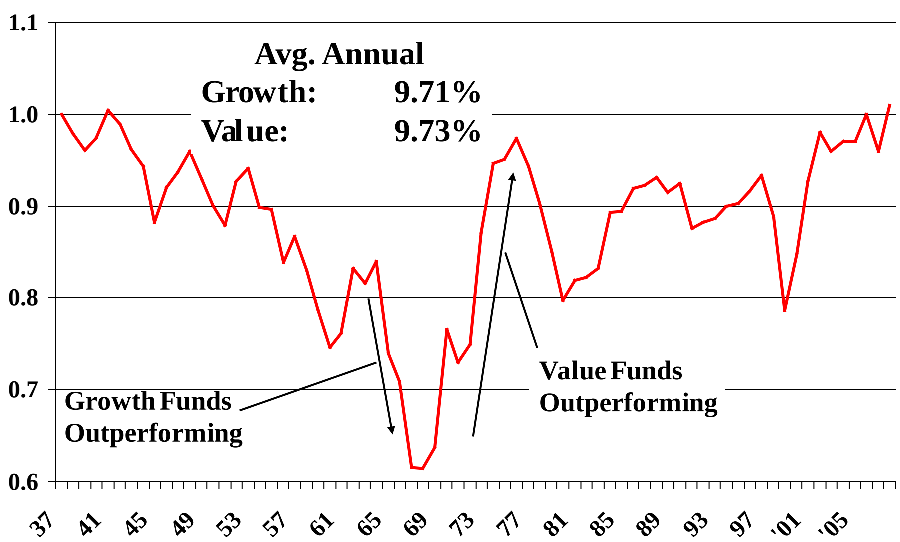
Table 1: FI Returns versus Fama-French Risk Factors

Regression results from monthly excess returns on the fundamental index are explained by the Fama-French factors of Beta (excess returns on the S&P 500), MV/BV Risk Factor (the value premium), and Size Risk Factor (the small-cap premium) in two sample periods are presented starting in (1) January 1962, and (2) January 1985, and ending in December 2008. The y-intercept of the regression is presented as α below. T-statistics for the coefficient of factors are presented in parenthesis. Significant test statistics at 5% significance level are marked with *.

Period	Beta	M/B Risk Factor	Size Risk Factor	α_{Fi}	R^2	F-stat
Jan 1962 – Dec 2008	1.016 (131.37)*	0.344 (28.72)*	-0.073 -(6.90)*	0.000 (0.55)	0.97	6100.99*
Jan 1985 – Dec 2008	1.022 (81.09)*	0.385 (19.50)*	-0.101 -(6.01)*	0.001 (1.32)	0.96	2250.11*

We also need to maintain some degree of skepticism concerning the long-term productivity of value and size portfolio tilts. From the mid-1960s to the present, "value" mutual fund managers have usually outperformed "growth" managers (although not during the late 1990s). In earlier periods, however, from the late thirties to the mid-sixties, growth funds appeared to be the persistent winners. There appears to be considerable mean reversion evident in the time series when measured over a very long time period. Indeed, Fig. 1, which measures the relative performance of mutual funds with "growth" and "value" mandates, shows that, over more than a 70-year period, the performance of both types of funds was essentially the same. A similar kind of mean reversion can be found between large- and small-capitalization stocks as shown in Fig. 2. Large-cap stocks are represented by the Russell 1000 index of the largest 1,000 companies by capitalization. Small-cap stocks are represented by the Russell 2000 index, which measures the returns of the next 2,000 companies ranked by company size.

Fig. 1: How Persistent is the Value Effect?
Reversion to the Mean: Growth Funds vs. Value Funds, 1937-2008



Growth = Lipper Growth
Value = Lipper Growth & Income

Fig. 2: Reversion to Mean: The “Small-Cap” Effect

Note: Data are as of January 31, 2008. The indices are unmanaged. An investor cannot invest directly in an index. Indexes are shown for illustrative purposes only and do not represent the performance of any specific investment. Past performance is no guarantee of future results.

Source: Russell Mellon Analytical Solutions, Morgan Stanley Global Wealth Management Asset Allocation Group.

3. Factor Tilts in Chinese Stocks Available to International Investors

In this paper, we will examine the existence of style or factor tilts in an important emerging market—China. During the period 1982 through 2008, China has been the most rapidly growing country in the world. Since Deng Xiaoping instituted his free market reforms during the early 1980s, China has grown at a compounded rate of almost 10 percent through 2008. The annual growth rate has exceeded 10 percent from 2005 through mid-2008. In such a growth environment we ask first if factor tilts have been effective during the 2000s, a period for which data are readily available for Chinese companies traded in markets that are accessible to international investors.

Perhaps the best known index of Chinese company stocks available to world investors is the FTSE/Xinhua index of 25 Chinese company stocks traded on the Hong Kong stock exchange. An ETF indexed to the FTSE/Xinhua 25 trades under the ticker symbol FXI. In this study we use an initial sample of the 25 largest Chinese-company stocks each year as measured by their equity capitalization.[4] Our

[4] These stocks are so-called “H” shares, where H stands for Hong Kong. We have not studied the “A” shares traded on the Shanghai Stock Exchange, which are available without restrictions only to local mainland residents.

sample is highly correlated with FXI and is essentially the same as the FTSE/Xinhua 25 stock index. We will refer to this sample as the "25 Largest Chinese H Shares."

We will examine the effectiveness of various style tilts by measuring the returns of a portfolio that is long the 25 stocks in the index weighted by book values, earnings, and sales (the weightings often used in fundamentally-weighted portfolios).

The traditional criterion used to define a "value" stock has been the ratio of the stock's market price to book value. Stocks selling at relatively low multiples of book value per share have always been considered to be "value stocks." But book values can be inflated by goodwill and they can be greatly affected by the accounting policies used to value inventories, to account for mergers and acquisitions, and by write-offs. The ratio of market price to earnings per share is another criterion used to define a value stock. But earnings per share can easily be manipulated through accounting policies with respect to depreciation, pension fund contributions, reserves, etc. Perhaps the cleanest accounting statistics that can be used are the sales or revenues reported by the firm. Sales data are much harder to manipulate than book values and earnings. Therefore, it will be interesting to examine if the use of a statistic such as price per share divided by sales (or revenues) per share can produce similar results to the ones we have found using more traditional value methods.

In Table 2 we present a comparison of the results using different fundamental measures of book value, earnings, and sales. We compare the annual mean return, the standard deviation of the return, and the growth of one dollar invested in January 2000 to its final value at the end of December 2008. Annual rebalancing is assumed.

We find that the book value weighting appears to do best among the three valuation metrics. While earnings weighting and sales weighting produce slightly lower returns than book value weighting, both metrics do appear to improve substantially upon capitalization weighting. We conclude that the preferred single metric for composing a value portfolio is book value. There appears to be support, then, for the traditional book-value metric to define a value stock.

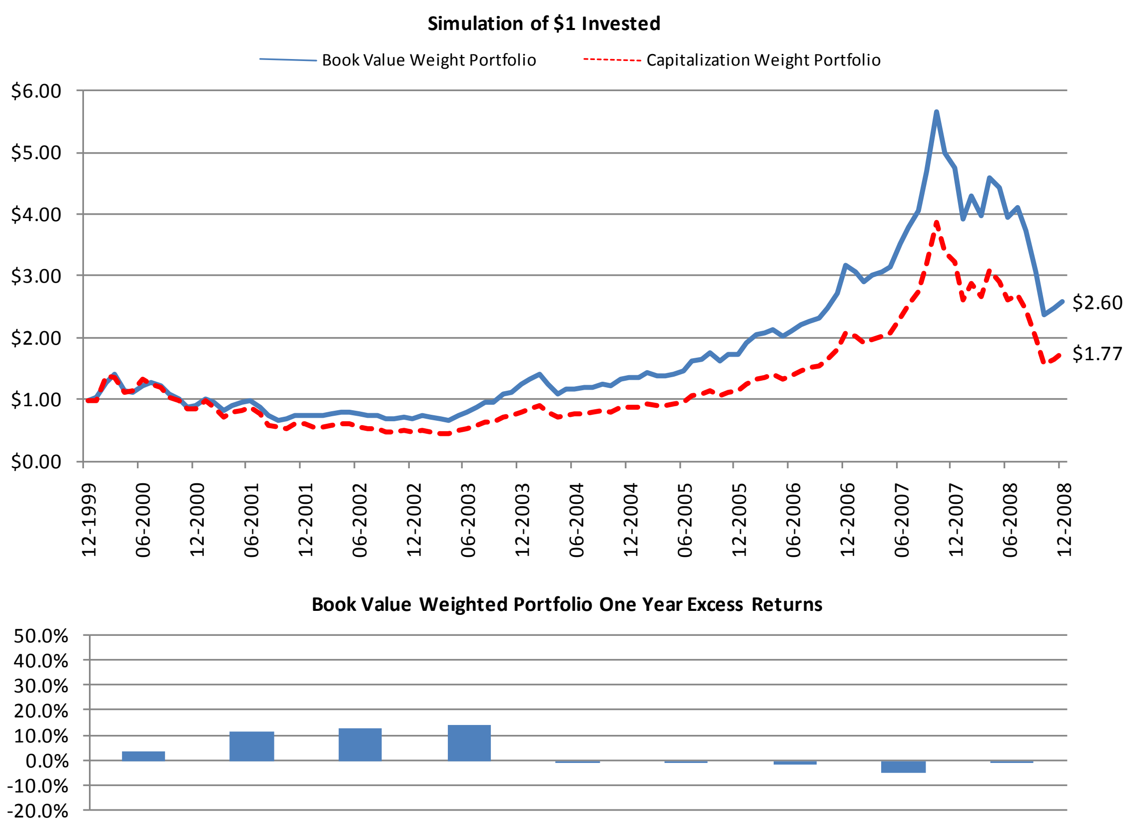
Table 2: Comparison of Returns

Valuation Metric	Annual Mean Return	Standard Deviation	Value of $1.00 Invested at Start of Period
Capitalization Weighting	6.5%	45.3%	$1.77
Book Value Weighting	11.1	44.0	2.60
Earnings Weighting	10.8	44.3	2.54
Sales Weighting	10.5	45.7	2.47

25 Largest Chinese H Shares. 100% Long Positions Only. January 2000 through December 2008.

Fig. 3 presents the time series comparison of the book value weighted portfolio and the capitalization weighted portfolio from January 2000 through December 2008.

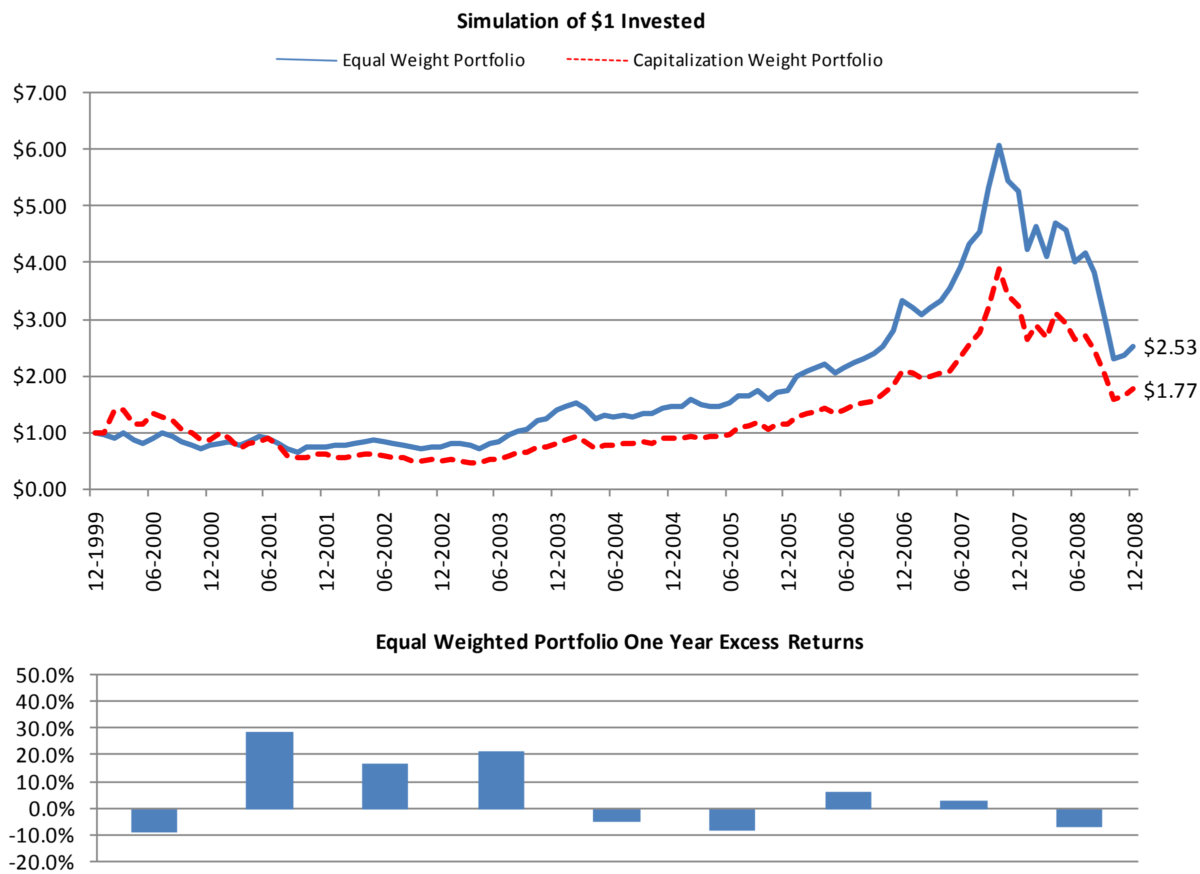
Fig. 3: Fundamental Weighted Portfolio (by Book Value)



25 Largest Chinese H Shares. 100% Long Positions Only. January 2000 through December 2008

We note that a one dollar investment grows to $2.60 by using book values to weight the long portfolio, compared with a final value of only $1.77 for a capitalization-weighted portfolio. Note, however, in Fig. 4 that there appears to be a very simple way to capture some of the advantages of a value tilt (as well as a tilt towards smaller-capitalization stocks). All we need to do is to weight all the stocks in the portfolio equally. Equal weighting produces a final value of $2.53, substantially greater than the final value of the capitalization-weighted portfolio.

Fig. 4: Equal Weighted Portfolio



25 Largest Chinese H Shares. 100% Long Positions Only. January 2000 through December 2008.

There is another striking finding evident in Figs. 3 and 4: There is an obvious pattern of mean reversion. We see, from an examination of the differences between style weighting and capitalization weighting (shown in the bottom panels of the Figures), that style tilting produces positive returns during the early part of the sample period. In the later years, however, the strategy often loses money. Style tilts do not consistently produce excess returns. This is similar to the experience in the United States. Fundamentally weighted investment strategies produced returns well above market benchmarks in the early years of the 2000s, but below benchmark returns from 2006 through 2008.

4. A Rank Weighting Method to Capture Style Tilts

An examination of Figs. 3 and 4 suggests that at least some of the advantages of style tilts may be quite simply captured by an equal weighting of the stocks in the portfolio. We noted in Fig. 4 that an equal- weighted portfolio of the same 25 Chinese stocks appears to have somewhat similar return characteristics to the "value" weighted portfolios in Fig. 3.

In fact, historical studies of U.S. equity performance show that equal-weighted portfolios often outperform capitalization-weighted ones. Such findings are entirely consistent with the Fama-French (1992) paper documenting the existence of size and value excess returns for U.S. equities during a long period from 1960 to the 1990s. An equally-weighted portfolio would give more weight to smaller and more inexpensively priced stocks, relative to a capitalization-weighted portfolio.

Fundamentally-weighted indexes are no different from capitalization- weighted indexes in one respect: larger companies are more heavily weighted than smaller ones. Whether the "economic footprint" is measured by total capitalization, sales, earnings, or book value, ExxonMobil will carry a larger weight than other stocks in the U.S. market. The methodology of applying the fundamental variables to the actual weighting of the portfolio preserves a highly skewed distribution, and hence the weighting distribution that is more akin to capitalization weighting. The same is true for the Chinese stock market.

Fig. 5: Distribution of Variables

25 Largest Chinese H Shares
January 2008

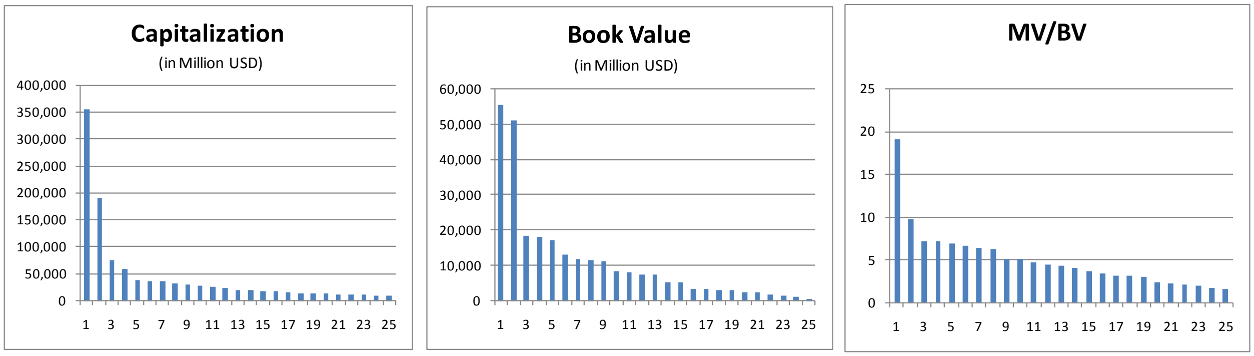


Fig. 5 shows the distribution of the following variables: Market Capitalization, and two fundamental variables; Book Value and the Market Value to Book Value for the 25 Chinese stocks used in our analysis. The weighting of the stocks using the variables in Fig. 5 is calculated as shown below, where *n* is the number of stocks in the portfolio.

$$\text{Capitalization Weighting of Stock}_{\,i} = \frac{\text{Market capitalization of Stock}_{\,i}}{\sum_{n}^{i} \text{Market capitalization of Stock}_{\,i}} \qquad (2)$$

$$\text{Fundamental Weighting of Stock}_{\,i} = \frac{\text{Fundamental Measure of Stock}_{\,i}}{\sum_{n}^{i} \text{Fundamental Measure of Stock}_{\,i}} \qquad (3)$$

Let us now consider an alternative weighting method that will allow us to extract the predictive power of the fundamental variables, without diluting their efficacy through an unintended weighting distribution that closely resembles capitalization weighting. One can create a less skewed weighting distribution by ranking the stocks in the portfolio by the fundamental variables in question, rather than using the absolute values of the fundamental factors.

To conceptualize the rank weighting method, we first visualize a portfolio where the stocks are equally weighted. Then, we will adjust the weight based on the rank of the fundamental variables of each stock. The most highly ranked stock will have the highest weighting and the lowest ranked stock will have the lowest weighting. In this method we will let the absolute deviation of any two stocks be equal. The highest ranked stock will have as much additional weighting compared to the 2nd ranked stock, as the 2nd ranked stock does compared to the 3rd ranked stock, etc. Furthermore, we can control and calibrate the degree to which the variation from stock to stock occurs. The equation for the weighting of each stock $_i$ will be:

$$\text{Rank Weighting of Stock}_{\text{i}} = \left(\text{Rank (Stock}_{\text{i}}) - \frac{\sum_{n}^{i} \text{Rank (Stock}_{\text{i}})}{n} \right) \times \Delta + \frac{1}{n} \quad (4)$$

Note that Δ is the sensitivity of the divergence of the weighting. For example, if the value of Δ is zero, then the rank weighting method would be so insensitive to the information of the stock's fundamental measure that it would remain equal weighted. If the value of Δ is higher, we can see how the bracketed part of the equation would introduce some imbalance to the equal weight portfolio. By applying this methodology, we can create a fundamentally weighted portfolio, using the equal weighted portfolio as a base. We can then test the unbiased predictive power of the fundamental variables, without unintended effects of the capitalization-weighted-like skewed distribution of the constituent stocks. Table 3 illustrates the distribution of stocks with respect to two different types of weighting methods representing values of $\Delta = 0.3$ and $\Delta = 1.0$. Note that in all three distributions, the median stock is given a 1/25th or 4 percent weight.

Table 3: Weighting Distribution of Stocks by Rank Weighting Sensitivity

In this example stocks are ranked by the value of market to book (MV/BV).
The stock ranked number one has the highest MV/BV ratio.

n	Equal	Rank, Δ = 0.3%	Rank, Δ = 1.0%
1	4.0%	0.4%	-8.0%
2	4.0%	0.7%	-7.0%
3	4.0%	1.0%	-6.0%
4	4.0%	1.3%	-5.0%
5	4.0%	1.6%	-4.0%
6	4.0%	1.9%	-3.0%
7	4.0%	2.2%	-2.0%
8	4.0%	2.5%	-1.0%
9	4.0%	2.8%	-0.0%
10	4.0%	3.1%	1.0%
11	4.0%	3.4%	2.0%
12	4.0%	3.7%	3.0%
13	4.0%	4.0%	4.0%
14	4.0%	4.3%	5.0%
15	4.0%	4.6%	6.0%
16	4.0%	4.9%	7.0%
17	4.0%	5.2%	8.0%
18	4.0%	5.5%	9.0%
19	4.0%	5.8%	10.0%
20	4.0%	6.1%	11.0%
21	4.0%	6.4%	12.0%
22	4.0%	6.7%	13.0%
23	4.0%	7.0%	14.0%
24	4.0%	7.3%	15.0%
25	4.0%	7.6%	16.0%
LONG	100%	100%	136%
SHORT	0%	0%	-36%

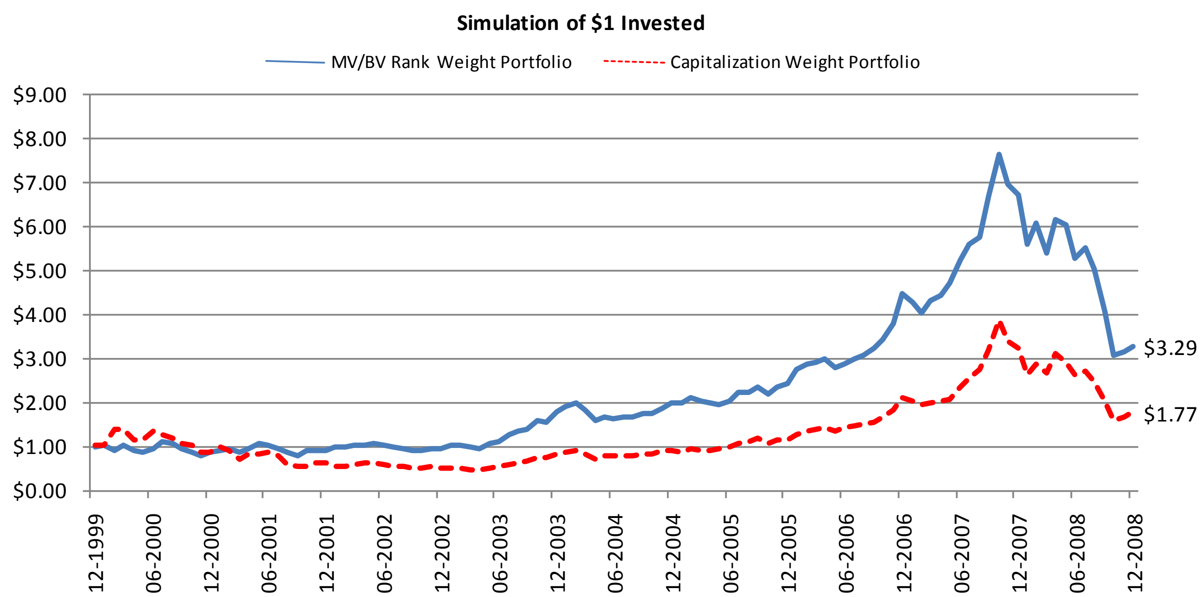
There are, of course, an infinite number of rank-weighted portfolios that can be produced depending upon the value of Δ chosen, as well as whether the portfolio is constrained to have only long positions. With a Δ of 0.3%, the portfolio contains only long positions and is well diversified. The minimum holding has a weight just under half of one percent, and the highest weighted stock has a weight just over 7½ percent of the portfolio. Such a portfolio would fit within the requirements of the U.S. Securities and Exchange Commission to be considered a "diversified" portfolio.

When Δ is set at one percent, short as well as long positions are allowed. The largest holding makes up 16 percent of the portfolio. The Δ = 1.0% produces a portfolio very close to the popular 130/30 portfolios sold by hedge funds. 136% of the portfolio is held as long positions, while 36% of the portfolio (the least value-oriented stocks) is sold short. We could also produce an exact 130/30 portfolio by setting Δ = 0.9125%.

Figs. 6 and 7 show the results of the rank-weighted portfolios. In Fig. 6, Δ is set at 0.3% and only long positions are allowed.

Fig. 6: Rank Weighted Portfolio (by MV/BV)

25 Largest Chinese H Shares
100% Long Positions Only (Δ = 0.3%)
January 2000 through December 2008



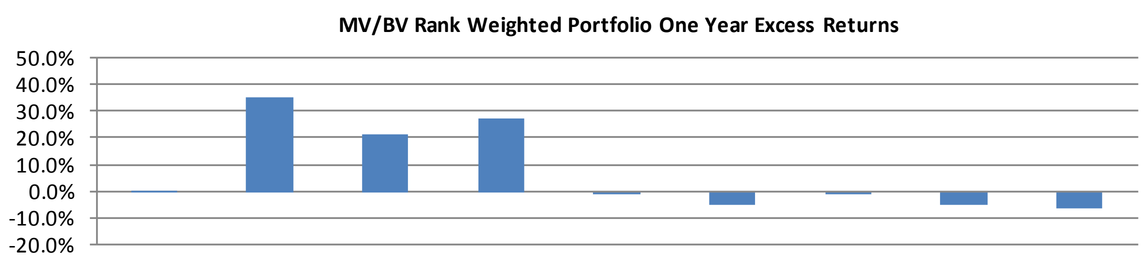
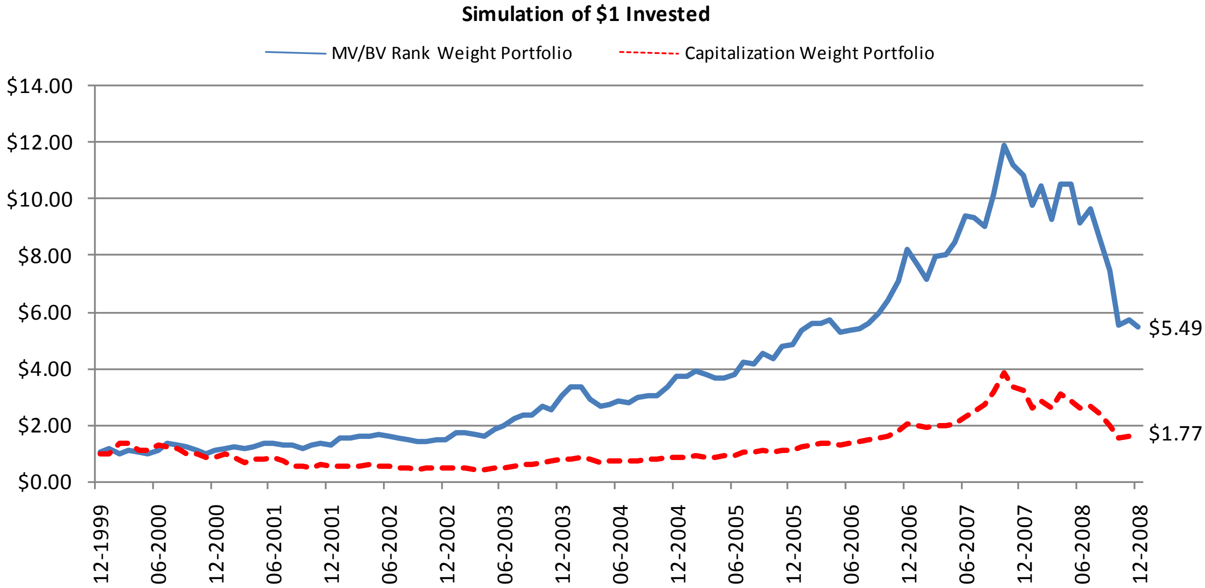
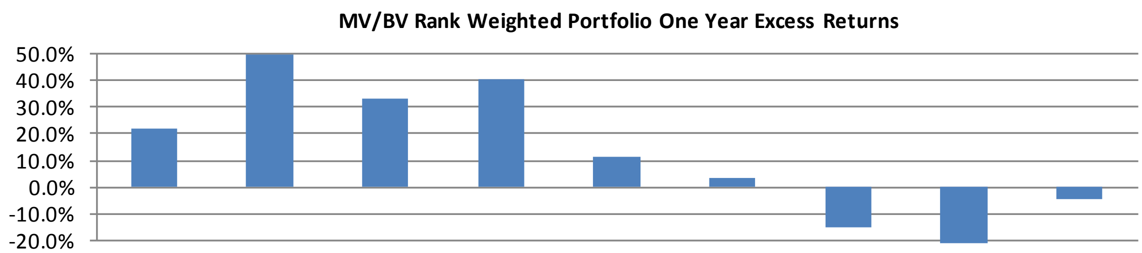


Fig. 7: Rank Weighted Portfolio (by MV/BV)

25 Largest Chinese H Shares
136% Long Positions / 36% Short Positions (Δ = 1.0%)
January 2000 through December 2008





Comparing Figs. 6 and 3 we see that the rank-weighted method produces higher rates of return and a higher final value. Fig. 7 shows, however, that the illustrated hedged portfolio (136% long, 36% short) produces even larger returns and a final value over 150% as great as the unhedged portfolio. We conclude that asset pricing in the market for the stocks of Chinese companies does seem to conform to the patterns found both in the United States market and in the foreign markets studied by Fama and French (1998).[5] Moreover, we suggest that a rank weighting can substantially improve the portfolio returns relative to fundamental weighting.

[5] Eugene Fama and Kenneth R. French, "Value versus Growth: The International Evidence." Journal of Finance 53 (December, 1998), 1975-1999.

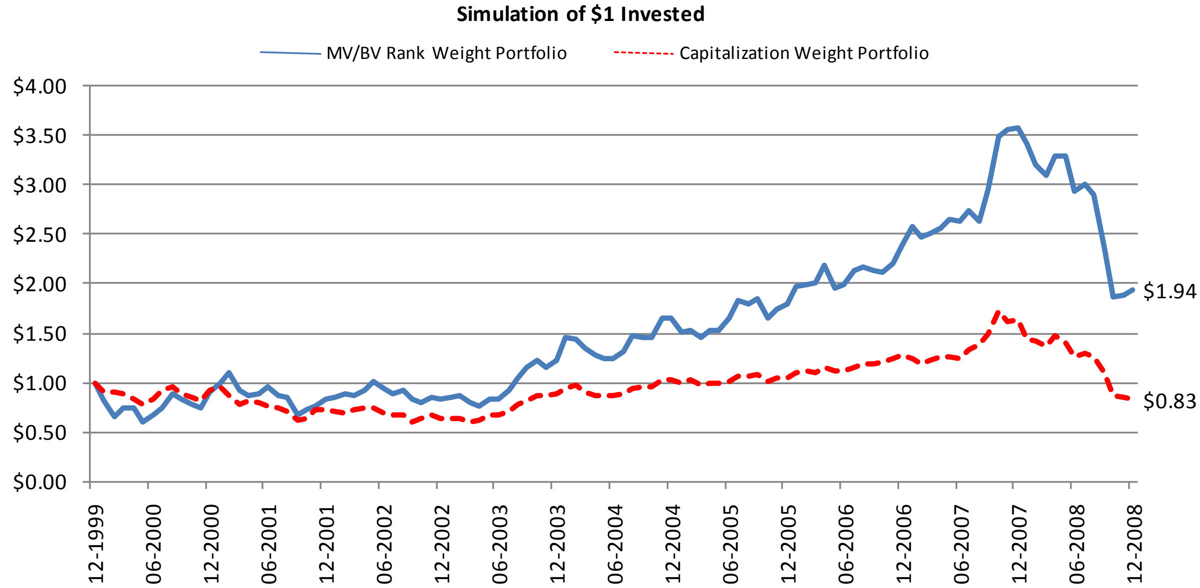
5. Ex Sample Tests

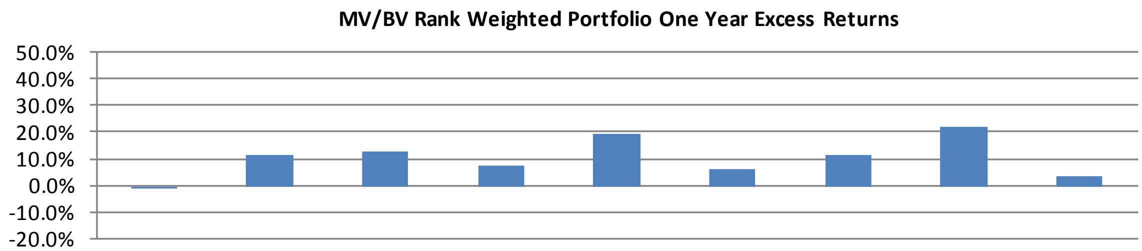
While these results are quite encouraging, we need to be concerned with whether the returns we have achieved above the benchmark could be the result of data mining. Since we have examined a number of historical simulations, there can always be a suspicion that we have simply commended the best performing historical model, without regard to whether the above-benchmark performance is likely to continue into the future. Moreover, we need to determine that our rank method of portfolio construction is an effective method to exploit the “value” effect in a different sample of companies. We therefore report here some ex sample tests on a different sample of Chinese company stocks.

Fortunately, data are available for much broader stock indexes. We use the Hang Seng Index of Chinese Companies traded on the Hong Kong Exchange (HSI). While there is overlap with the FXI Index, and with our sample of 25 H Shares, the majority of the companies in these indexes are different. In our ex sample tests we will use 25 companies from the HSI index that are not included in our original sample. Our comparison portfolio will be a capitalization weighted index of the same 25 ex sample stocks. The ex sample stocks have roughly the same capitalization and have a similar industry breakdown as was the case in the original sample. Fig. 8 presents the simulations over the same time period. The capitalization weighted and rank weighted returns from new sample of 25 stocks are smaller than that for the original sample. The final value of one dollar invested in the MV/BV rank weighted portfolio is $1.94 versus a final value of $0.86 for the capitalization weighted HSI portfolio. But the results, while not as dramatic as they were in the original sample, are qualitatively the same. The value portfolio is established by a rank weighting using a book to market value metric. The final dollar amount from implementing our value strategy is over 100 percent higher than a long investment in the capitalization-weighted portfolio. Moreover, the rank-weighted portfolio outperforms the capitalization-weighted portfolio in all but one year. The ex sample tests confirm the usefulness of the rank-weighted portfolio strategy we have suggested.

Fig. 8: Rank Weighted Portfolio (by MV/BV)

Ex Sample 25 Stocks in the Hang Seng Index (HSI)
136% Long Positions / 36% Short Positions (Δ = 1.0%)
January 2000 through December 2008





6. Predicting Differential Returns from "Value" and "Growth" Stocks

In the first part of this paper, we showed that the subset of "value" stocks has outperformed the broader indexes of Chinese equities. We also showed that there appeared to be considerable mean reversion in the outperformance of a value-tilted portfolio versus a capitalization weighted portfolio in our sample period. Value tilts do not produce excess returns consistently either in the United States or in China. In this section we test for time-series predictability. Can we predict those periods where style tilts are likely to be most effective?

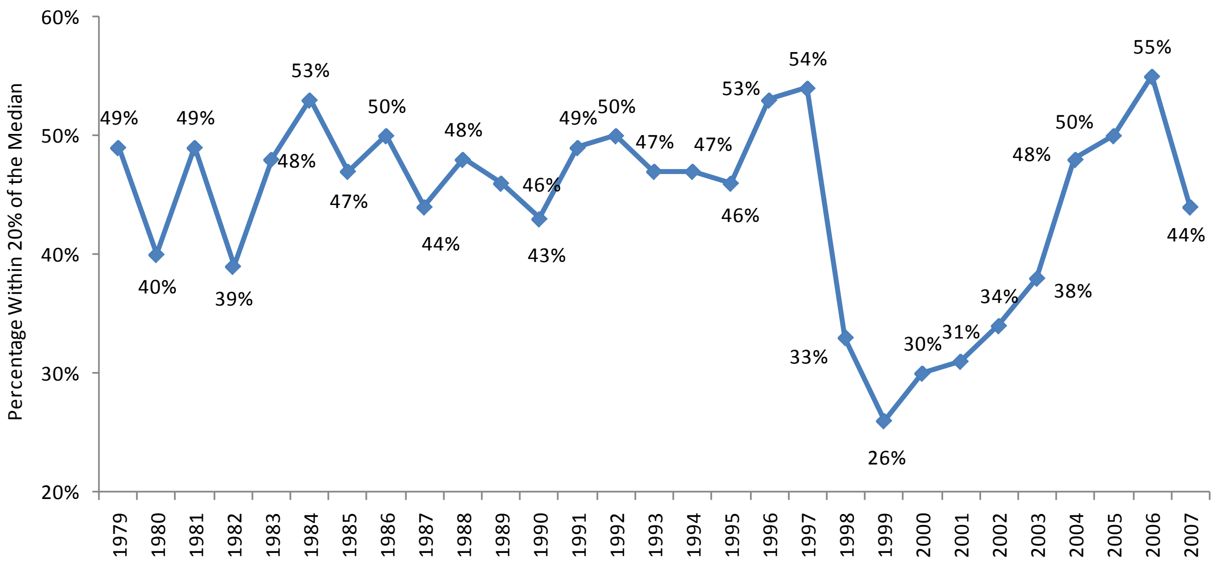
Our hypothesis, as suggested earlier, is that value-tilt strategies will tend to outperform capitalization-weighted portfolios when the valuation of equities in the market as a whole is quite dispersed. Value strategies are less likely to outperform when valuations are compressed. The compression of multiples can be measured in several ways. First, we can consider two types of valuation metrics: the price-to-earnings ratio (P/E), and the price-to-book value ratio (MV/BV). Then, we can consider two ways to measure the compression in the market. First, we can measure the level of dispersion of various valuation metrics by calculating the standard deviation. Second, we can measure compression by examining how close the valuation metrics are to the median market metric at various points in time.

There are problems, however, with the use of standard deviation methods of dispersion. First, if we use P/E multiples as our metric of value, there is the issue of how to deal with negative earnings. This issue can be resolved by using market-to-book measures, since book values are unlikely to be negative. But a second issue is that the standard deviation measure can give misleading estimates of dispersion when there are a few large outliers. Market-to-book and price-earnings ratios may all be very close together, but a few outliers could make measures of the standard deviation of the valuation metric quite large. Hence, we have chosen to measure compression by looking at the percentage of companies in the sample with valuation metrics reasonably close to the market median.

We begin by examining whether we can predict periods of excess returns from value portfolios in the United States market. During the period from 2000 through 2005, value-tilted portfolios substantially outperformed broad capitalization-weighted indexes. This was the period when stock prices adjusted from levels that, at least in retrospect, were widely considered to be “bubble” levels. Moreover, there was a substantial divergence between the valuation of “growth” stocks and “value” stocks. Growth stocks, such as Cisco Systems, sold at over 100 times earnings and at huge multiples of book value at the turn of the century, while “value” stocks, such as Public Service of New Jersey, sold at a multiple of earnings that was in the low teens and with market values close to the book values of the shares. The dispersion of price-earnings multiples (and MV/BV multipliers) was extraordinarily large. Moreover, as Fig. 9 shows, only about one quarter of the stocks in the Standard and Poor's 500 Stock Index sold at P/E multiples that were within 20 percent of the median multiple for the market as a whole during December 1999.

Fig. 9: Percentage of S&P 500 Stocks Within 20% of the Median P/E

December 1979 through December 2007



This line of reasoning suggests a very simple way to isolate periods where value tilts are likely to be very effective and those periods where they are less likely to produce superior returns. Value tilts are likely to be most effective when valuation ratios (whether P/E or MV/BV Ratios, or other valuation metrics) are very dispersed. They should be less effective when multiples are very compressed since in those situations, growth is relatively more attractively priced in the market and capitalization weighting will not be very different from value weighting. Note that by 2006, over half of the stocks in the S&P 500 sold at P/E multiples within 20 percent of the median P/E multiple. According to our hypothesis, value tilts should then be less effective in 2006 and 2007 than was the case earlier in the decade.

An easy way to test the hypothesis that compressed P/E multiples predict that value tilts will be less effective is to regress excess returns from "value" investing on a measure of P/E compression. The S&P 500 Index is divided into its value and growth components on the basis of BV/MV ratios and these value and growth components ($S\&P_V + S\&P_G$) serve as the basis for both mutual (index) funds and Exchange Traded Funds. Defining excess returns (ER) as the value premium we can estimate the following equation:

$$ER_t = S\&P_{V,t} - S\&P_t = \hat{a} + \hat{b}(COMP)_{t-1} + \mu, \qquad (5)$$

where $COMP_{t-1}$ (compression) is measured by the percentage of stocks in the S&P 500 that sell at P/E multiples within 20 percent of the median multiple at the start of the period. Excess returns each year are regressed on our compression measure at the beginning of the year.[6] Table 4 presents the results. Note that the signs of the regression coefficient are negative and statistically significant. The more compressed are P/E multiples, the lower the value premium. The Figure presents results for three different methods of composing a value portfolio. The S&P value portfolio is comprised of the half of the capitalization of the S&P 500 with the lowest ratios of MV/BV. The RAFI results use the returns from the Research Affiliates fundamentally weighted portfolios. The DFA results use the actual results achieved by the "deep value" portfolios managed by Dimensional Fund Advisors.

Table 4: Regressions Results of Future Excess Returns against Multiple Compressions

Selected U.S. Value Tilt Portfolios
January 1994 through December 2008

The table shows the coefficient, T-statistic, R^2, and F-statistic of regressions of excess returns on a measure of P/E compression. Significant test statistics at 5% significance level are marked with *.

	RA Fundamental Portfolio - S&P 500				S&P Value Portfolio - S&P 500				DFA Value Portfolio - S&P 500			
Independent Variable	Coeff	T-stat	R^2	F-Stat	Coeff	T-stat	R^2	F-Stat	Coeff	T-stat	R^2	F-Stat
Average P/E Compression	-0.58	-2.82*	0.38	7.96*	-0.37	-1.84*	0.21	3.38*	-0.50	-1.54	0.15	2.38

Note: Durbin Watson statistics allow us to reject the hypothesis of positively autocorrelated disturbances.

[6] Because the compression data tend to be very noisy, our compression measure is averaged over two years rather than taken at one point in time.

The DFA portfolios are constructed according to the Fama-French value metrics. We see that whatever method is used to construct a value-tilt portfolio, the more compressed the price-earnings multiplies, the lower the excess returns of the portfolio. Value tilts are far more productive when valuation relationships are dispersed. While we do not show the results here, the same findings hold when compression is measured by a price /book value metric.

Unfortunately, we do not have a long time series of Chinese company stocks so we do not have a large number of degrees of freedom. Nevertheless, using compression measures of price/book value and price/earnings, we find similar results for Chinese companies. The more compressed are valuation metrics, the less productive are value-tilted portfolios.

The results are shown in Table 5. The value-tilted portfolios considered are our 100% long portfolios composed by the P/E rank and MV/BV rank methods of portfolio selection described earlier. Because valuation metrics are more widely dispersed in the Chinese stock market than in the U.S. market, and because our stock sample is so small (25 stocks versus 500 stocks in the S&P 500 Stock Index), we took as our compression measure the proportion of stocks within 100 percent of the median market valuation. We use the P/E multiple as our “value” measures. We confirm that the one-year excess return from “value-style” investing tends to be larger as valuation ratios are more disbursed in the market. The findings are generally similar to those shown for the United States market, shown in Table 4. Value strategies in the Chinese stock market are more effective when valuation metrics are dispersed.

Table 5: Excess One-Year Returns of China Value-Tilted Portfolio vs. P/E Compression

Rank Weighted Portfolios (By MV/BV and P/E)
25 Largest Chinese Company H Shares
100% Long Positions Only (Δ = 0.3%)
January 2000 through December 2008

The table shows the coefficient, T-statistic, R^2, and F-statistic of regressions of excess returns on a measure of P/E compression. Significant test statistics at 5% significance level are marked with *.

	P/E Rank Weight – Cap Weight				MV/BV Rank Weight – Cap Weight			
Independent Variable	Coeff	T-stat	R^2	F-Stat	Coeff	T-stat	R^2	F-Stat
Average P/E Compression	-3.21	-3.05*	0.65	9.32*	-2.39	-4.76*	0.82	22.62*

Note: Durbin Watson statistics allow us to reject the hypothesis of positively autocorrelated disturbances.

Our measure of value compression was less successful in the ex sample set of 25 companies taken from the Hang Seng Index but not included in the original sample of 25 H-share companies. Table 6 presents the results. While the signs are correct, the coefficients of determination were small and the coefficients of the regressions were not statistically significant.

Table 6: Excess One-Year Returns of Ex Sample China Value-Tilted Portfolio vs. P/E Compression

Rank Weighted Portfolios (By MV/BV and P/E)
Ex Sample 25 Stocks in the Hang Seng Index (HSI)
100% Long Positions Only (Δ = 0.3%)
January 2000 through December 2008

The table shows the coefficient, T-statistic, R^2, and F-statistic of regressions of excess returns on a measure of P/E compression. Significant test statistics at 5% significance level are marked with *.

	P/E Rank Weight – Cap Weight				MV/BV Rank Weight – Cap Weight			
Independent Variable	Coeff	T-stat	R^2	F-Stat	Coeff	T-stat	R^2	F-Stat
Average P/E Compression	-0.89	-1.10	0.19	1.21	-0.43	-0.50	0.05	0.25

Note: Durbin Watson statistics allow us to reject the hypothesis of positively autocorrelated disturbances.

7. Concluding Comments

We have shown that “value” tilted portfolios appear to produce higher than market returns in the market for Chinese company stocks in most time periods from the late 1990s through mid-2008. But value-tilted portfolios do not consistently outperform capitalization-weighted portfolios. There appears to be evidence of mean reversion over time. Periods of lower relative returns for value-tilted portfolios often follow periods when value tilts have been effective.

The rank method of portfolio construction described in this paper appears to be a particularly effective way to enhance the returns from a value style of investing. Rank weighting also appears to reduce the degree of mean reversion during periods when “value” stocks underperform the market. We have also shown that periods when value tilting is most effective correspond to periods when valuation metrics are very dispersed. The degree of compression of price-earnings multiples is a good predictor of the differences in returns between value-tilted and capitalization-weighted equity portfolios for a portfolio of the 25 largest H-share companies. The relationship is weaker, however, for an alternative set of 25 companies taken from the Hang Seng Index.

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