Accessing the China A-Shares Market via Minimum-Variance Investing

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The instrumental work of Sharpe [1964] on the capital asset pricing model suggests that by drawing the tangent line from the point of risk-free asset to the efficient frontier the market portfolio is obtained. In the past few decades, the market portfolio has received significant attention, and the popularity of passive investing has increased in parallel. At the same time, another portfolio on the efficient frontier has been quietly enjoying a rise in fame: the minimum-variance (MV) portfolio. In the last 10 years, the concept of the MV portfolio has successfully evolved from an academic topic of discussion to an implementable investment theme. Currently, a significant number of investment mandates or products have embraced the concept and allocated financial resources to MV investing.

The concept of MV investing is applicable in a variety of geographical regions. A number of researchers, such as Haugen and Barker (1991) and Chow, Kose, and Li (2016), have investigated the characteristics of MV investing in the U.S. and European markets and on broader global markets. These researchers mainly conclude that MV investing is capable of reducing portfolio volatility compared with its corresponding market-cap-weighted portfolio.

Despite its wide application, MV investing is still a relatively new topic in the China A-shares market. This research aims to fill the knowledge gap in this direction. The China A-shares market is receiving more attention from international investors, as highlighted by Pong, Perrett, and Chan (2014), because of its expanding market size and improved access. Investors will increasingly need to understand more about the China A-shares market and make the necessary allocation in their global portfolio. In addition to a market-cap-weighted approach, investors should be given more choices on different portfolio solutions for their China A-shares allocation, and MV investing can be one of the options.

This research aims to serve as a comprehensive guide for MV investing in the China A-shares market. The article first discusses some of the important features of the China A-shares market and its implications for MV investing. We then focus on the construction of a pure theoretical MV portfolio without any implementation constraints. We study its characteristics in terms of historical performance, tracking error, turnover, diversification, liquidity, and industry exposure. The results enable us to understand the practical issues that arise when implementing MV investing in the China A-shares market and provide directions on how to handle them. We then construct MV portfolios with different constraints and study the impact of these constraints on the implementation. The China A-shares market has a high rate of stock trading suspension, and our portfolio construction methodology takes this feature into account. The simulation results show that MV investing is capable of reducing volatility in the China A-shares market for the period of 2007–2017. We also compare and document the characteristics of the China A-shares MV portfolio with those of other regions. As a result of its popularity, market participants have concerns about the potential crowding effect resulting from recent capital flows into the strategy. We investigate whether this is the case for China A-shares by studying valuation and quality aspects of the MV portfolio. Subsequently, two approaches for controlling the factor exposure of the MV portfolios are considered.

CHINA A-SHARES MARKET AND MV INVESTING

Several features specific to the China A-shares market have potential implications for MV investing. The first feature concerns the high percentage of state-owned enterprises (SOEs) in the market. Hsu et al. [2017] estimated that over 50% of the A-shares market cap was derived from SOEs as of the end of 2016. They posited that a significant proportion of holdings in these SOEs is static and may cause the shares of SOEs to exhibit relatively low levels of liquidity and volatility. Consequently, particular attention must be paid to liquidity and capacity aspects when constructing a variance-related portfolio. The second feature relates to stock suspensions. The level of stock suspensions in the China A-shares market is relatively high, partly because of the option for companies to carry out voluntary suspension. The suspension issue has two dimensions, the first being that no rebalancing transactions can be performed on suspended stocks and the second that the lack of trading caused by suspension can be mistaken easily for real static prices. These two cases must be distinguished for covariance estimation. The third feature relates to the participation rate of retail investors. It is well known that trading volumes in the China A-shares market are mainly driven by retail investors. Retail investors tend to be less patient, to be more focused on short-term profit, and to favor stocks with lottery-like payoffs.

What attracts significant debate around MV investing is not only observed reductions in volatility but also that such reductions have been accompanied by market-like or even higher returns. The MV portfolio is heavily exposed to low-volatility stocks, and thus the low-volatility anomaly is closely related to MV investing. Several hypotheses have been suggested to explain the low-volatility anomaly. The leverage aversion hypothesis (Frazzini and Pedersen 2014) and the delegated-agency model (Brennan, Cheng, and Li 2012) propose leverage constraints and agency issues, respectively, as the main explanations. The preference-for-gambling hypothesis (Baker, Bradley, and Wurgler 2011) argues that investors irrationally use high-volatility stocks as lotteries and are willing to accept lower expected returns by paying a premium to gamble with high-volatility stocks.

The high level of state ownership relative to that of the institutional investors in the China A-shares market is less likely to favor the leverage aversion hypothesis and the delegated-agency model. However, the high retail investor participation rate is consistent with the lottery preference theory. On balance, it is reasonable to expect that the low-volatility anomaly could exist in the China A-shares market.

DATA

The constituents of the FTSE China A Index serve as the underlying universe for constructing the MV portfolio. The universe represents the large and mid-size segments of the China-A shares market. The return data and the fundamental data of individual stocks are sourced from FTSE Russell. All returns are in Chinese renminbi. The sample period is from March 2007 to March 2017.

The 10-year sample period can be considered a relatively short time span compared with the research for the U.S. market. For example, the U.S. MV study by Clarke, de Silva, and Thorley (2006) used a sample period of 37 years, and greater confidence can naturally be placed in the results. Ideally, a longer sample period should be chosen for a China A-shares study for greater statistical power. However, the fact that the China A-shares market started in the early 1990s limits the sample data period. In addition, as pointed out by Hsu et al. (2017), there are certain structural differences regarding the regulatory framework and financial reporting standards before and after 2007. The China Securities Regulatory Commission carried out a split-share structure (SSS) reform in 2005 to relax trading restrictions on shares of listed SOEs. Under the SSS, nontradable shares accounted for more than two-thirds of the stock market. With its purpose being to bring nontradable shares to market, the result of the reform was a significant enhancement in stock liquidity. A majority of the listed companies had gone through the process by 2007. China's Ministry of Finance announced in 2006 that all listed A-share firms were required to comply with a new set of accounting standards that substantially conform to International Financial Reporting Standards Foundation by 2007. The new accounting reform produced a set of new auditing standards and internal control reporting requirements. Considering that the reform led to a reduction in accruals-based earnings management, as suggested by Ho, Liao, and Taylor (2015), it can cause potential issues when constructing factors, especially those related to the quality aspect. Both the regulatory and accounting standard changes prompted us to choose 2007 as the starting point of the sample period. The data length limitations should be borne in mind when evaluating empirical results of any China A-shares smart beta study.

A notable feature of the China A-shares market is the high level of stock suspensions and the prolonged length of suspensions. Exhibit 1 provides a general idea of the suspension situation during the sample period. The exhibit shows the average proportion of stocks being suspended, the average aggregate weightings of stocks suspended, and the average length of suspension for each calendar year.[1] The results show that the stock suspensions can be a significant issue in the China A-shares market. The direct impact of trading suspensions is that one cannot trade the suspended stocks during portfolio rebalancing. Therefore, our construction methodology allows only stocks that are not suspended to be traded during rebalancing, and the weightings of the suspended stocks in the portfolio are unchanged before and after rebalancing.

BASE-CASE MV PORTFOLIO

In this section, we introduce the base-case MV portfolio. The base-case MV portfolio is a long-only portfolio that is obtained from Equation (1):

$$\text{Minimize } \sigma^2(w) = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i C_{ij} w_j \;\; \text{s.t. } w_i \geq 0 \text{ and } \sum_{i=1}^{N} w_i = 1 \tag{1}$$

where σ^2 is the portfolio variance, w_i is the weight of the ith stock, and C is the covariance matrix. The variance and covariance estimates in C are calculated using two years of daily return observations throughout this article.[2] The covariance matrix calculation and the portfolio optimization are performed on the third Friday of March and September to match the rebalance schedule of the FTSE China A Index.

EXHIBIT 1
Summary Statistics of Suspensions in the FTSE China A Index

Year	Average Proportion of Suspensions	Average Aggregate Weighting of Suspensions	Average Suspended Days/ Trading Days
2007	5.4%	4.5%	13/242
2008	4.8%	5.1%	12/246
2009	2.1%	2.3%	5/244
2010	2.7%	2.8%	6/242
2011	3.1%	2.3%	7/244
2012	1.8%	1.3%	4/243
2013	1.8%	1.5%	12/238
2014	3.4%	2.4%	19/245
2015	7.7%	6.2%	28/244
2016	5.4%	4.7%	29/244
Average	**3.8%**	**3.3%**	**14/243**

Notes: The average proportion of suspensions is calculated as the average of the daily proportion of index constituents being suspended on each business day within the specified year. The average aggregate weighting of suspensions is calculated as the average of the daily aggregate weightings of index constituents being suspended on each business day within the year. The average suspended days is the average suspension length for each index constituent within the specified year; index constituents with no suspension within the year are excluded from the calculation.

[1] The suspension data are sourced from WIND.

[2] To ensure a robust comparison of volatilities, stocks with fewer than 360 daily return observations in each estimation period are excluded. Likewise, to reduce the distortion caused by missing values in the correlation calculation, stocks with fewer than 300 coincident daily return observations are also excluded from the analysis. This is achieved in the following steps. First, we count for each stock the number of stocks with which it has at least 300 coincident observations. The stock with the minimum count is then removed. This process is repeated until the correlation between any two remaining stocks can be calculated using at least 300 coincident returns. The covariance matrix is estimated using principal component analysis. For more details on the construction of the covariance matrix, please refer to the methodology of the FTSE Global Minimum Variance index ground rules.

EXHIBIT 2

Return–Risk Characteristics of the Base-Case and Constrained MV Portfolios (2007–2017)

	FTSE China A Index	Base-Case MV Portfolio	MV, Max Wgt = 1%	MV, Diversification Target = 100	MV, Diversification Target = 200	Industry Neutral Base-Case MV Portfolio	Industry Neutral MV, Diversification Target = 100
Average Number of Holdings	498	20	106	168	301	27	177
Average Maximum Weighting (%)	2.6	22.7	1.3	2.4	1.2	21.1	2.8
Average Median Weighting (%)	0.1	3.3	1.0	0.5	0.3	2.4	0.4
Volatility (% p.a.)	32.3	24.3	28.6	27.8	30.4	24.2	29.7
Volatility Reduction (%)	–	24.7	11.3	14.0	5.9	24.9	8.0
Maximum Drawdown (%)	–72.5	–54.6	–65.0	–63.9	–67.4	–60.3	–66.7
Return (% p.a.)	2.6	10.5	9.8	10.1	9.8	7.2	8.0
Net Return (% p.a.) (LDV model)	2.6	10.1	9.6	9.8	9.6	6.8	7.7
Net Return (% p.a.) (100 bps trading cost)	2.5	8.9	8.6	9.0	8.9	5.7	6.9
Tracking Error (% p.a.)	–	18.4	10.6	10.9	9.4	13.1	7.7
Information Ratio	–	0.4	0.7	0.7	0.7	0.3	0.7
Average Liquidity (%)	93.3	12.5	51.1	55.4	72.8	17.1	61.8
Turnover (% p.a.)	17.0	142.3	111.5	98.3	80.4	145.7	96.5

Notes: Net return (LDV model) is calculated as the gross return after transaction costs, where transaction costs are estimated using the limited dependent variable (LDV) model proposed by Lesmond, Ogden, and Trzcinka (1999) at each semiannual rebalancing for illustration purposes. Net return (100 bps trading cost) is calculated assuming transaction costs to be 100 bps one-way during semiannual rebalancing. Liquidity is defined as the portion of the portfolio that can be implemented in a day, assuming a notional US$1 billion portfolio traded with a maximum of 20% of the three-month average daily traded value of each stock. Tracking error is calculated as the annualized historical standard deviation of the difference in daily returns between the MV portfolio and the FTSE China A Index. The turnover figures represent the two-way turnover. The information ratio is calculated as the ratio of annualized active portfolio return and tracking error.

CHARACTERISTICS OF THE BASE-CASE MV PORTFOLIO

Exhibit 2 shows the average number of stocks in the base-case MV portfolio. The results indicate that on average only 20 stocks are required to construct an MV portfolio. That number is relatively low compared to the number of constituents in the underlying benchmark. The risk–return characteristics of this MV portfolio are shown in the same exhibit. The historical volatility of the base-case MV portfolio is 24.3% across the 10-year sample period whereas that of the capitalization-weighted benchmark is 32.3%. This finding illustrates that the objective of variance reduction is achieved. The performance of the MV portfolio is also shown in Exhibit 2. Over the same sample period, the return from the MV portfolio is higher than that of the market-cap-weighted index: 10.5% per annum versus 2.6% per annum, respectively.

The small number of stocks in the base-case portfolio raises practical concerns in terms of stock concentration and levels of diversification. Exhibit 2 indicates the degree of concentration by showing the average maximum and median stock weightings in the base-case portfolio. The average maximum stock weighting is extremely large at 22.7%. The median stock weighting is on average 3.3%. This indicates that constructing a theoretical MV portfolio without any constraints can cause implementation issues in terms of excessive stock weights and a lack of diversification.

Another related issue concerns the ease with which the strategy may be implemented. We define liquidity as the proportion of the portfolio that may be implemented in one day, assuming a notional US$1 billion portfolio traded with a maximum of 20% of the three-month average daily traded value of each stock. We compare the liquidity of the market-cap index and the base-case MV portfolio in the bottom section of Exhibit 2. The liquidity of the base-case MV portfolio is very low, with only 12.5% of the portfolio implemented in a day. This highlights the need to enhance the strategy design to facilitate portfolio implementation.

STOCK WEIGHT CONCENTRATION AND DIVERSFICATION

The findings just presented show that unconstrained optimization results in a concentrated MV portfolio with low investment capacity. One possible solution to overcome these concentration issues is to limit the maximum weighting of individual stocks. A maximum weight constraint can be used in the optimization to ensure that stock weightings do not exceed a certain threshold. As an illustration, we apply a maximum stock weight constraint of 1%. Exhibit 2 shows the number of stocks in this constrained portfolio across the sample period: The number of holdings increases compared to that of the base-case portfolio, to approximately 106 stocks on average.

An alternative approach to increasing diversification is to impose a requirement for a minimum number of stocks in the portfolio. Following DeMiguel et al. (2009), we use a diversification target to control the level of diversification. The diversification target is defined as $\Sigma w_i^2 = 1/N$ where N is the parameter for controlling the level of diversification and is used as a two-norm constraint in the portfolio optimization. It is equivalent to the Herfindahl index, and its inverse represents the effective number of stocks in the portfolio. Two cases are used in the empirical study, with N set to 100 and 200, respectively.[3] Exhibit 2 indicates that the number of stocks increases significantly (on average 168 for $N = 100$ and 301 for $N = 200$) compared with the base-case MV portfolio.

RETURN–RISK, LIQUIDITY, AND TURNOVER OF THE MV PORTFOLIOS

Exhibit 2 summarizes the return–risk characteristics of alternative formulations of the MV portfolio and aims to illustrate the trade-off between volatility reduction and the application of constraints. Maximum stock weights and diversification constraints affect levels of volatility reduction. A more binding set of constraints results in smaller reductions in volatility. Despite this, all MV portfolio formulations are still able to achieve volatility reductions. Another notable feature of China A-shares MV investing is the enhanced level of return. All the MV portfolios examined in this article generate higher historical returns than the market-cap index, with excess returns ranging 7.2%–7.9% per annum. The use of constraints has a limited impact on the portfolio returns.

Portfolio liquidity improves as higher levels of diversification are employed, as shown in Exhibit 2. The percentage of the portfolio implemented reaches 55.4% and 72.8%, on average, when the diversification target equals 100 and 200, respectively, and represents a significant improvement compared to the base-case portfolio. The base-case MV portfolio requires the highest levels of turnover, and the required turnover decreases as the diversification level increases. When the diversification target is set at 200, the average annual turnover is approximately 80.4% and is nearly half the unconstrained levels. Despite this improvement, turnover remains relatively high, resulting in concerns regarding the effect of transaction costs on performance outcomes. We use the transaction cost model proposed by Lesmond, Ogden, and Trzcinka (1999) to estimate the trading cost for each stock on the trading list at the rebalancing dates. This model uses the incidence of zero returns to estimate the marginal trader's effective transaction costs. We therefore calculate net returns of the MV portfolios based on the estimated transaction costs. The results in Exhibit 2 indicate that the simulated return decreases by 0.2% to 0.4% per annum, depending on the portfolio formulation.[4] For reference, we also use a more prudent transaction cost assumption of 100 bps one-way for all stocks, and the simulated return decreases by 0.9% to 1.6% per annum.

INDUSTRY EXPOSURE

The base-case portfolio optimization does not apply industry exposure control, so active industry

[3] There is no theoretical framework to choose the optimal level of the diversification target. The parameters $N = 100$ and $N = 200$ are chosen for illustration. Higher diversification targets may be selected, but we show later that the choice of diversification target affects the level of volatility reduction.

[4] Daily returns of the previous year are used as inputs for the limited dependent variable (LDV) model to estimate the trading cost. The average of the median trading cost estimate at each rebalancing is found to be 15 bps, and the magnitude is consistent with the median bid–ask spread that we calculate separately for comparison purposes.

exposure is expected. Panels A and B of Exhibit 3 show the industry exposure of the market-cap benchmark and the base-case MV portfolio using the FTSE Industry Classification Benchmark industry classification. A comparison of the two reveals two characteristics regarding the base-case MV portfolio: (1) its industry exposure can be extreme (e.g., the weighting of the financial industry reaches 60% as of September 2012), and (2) its industry exposure is not stable across time. Panel C of Exhibit 3 shows the industry exposure of the MV portfolio with a diversification target of 100. In comparison with the base-case MV portfolio, the industry exposure of this diversified MV portfolio is more stable and less extreme.

Following Asness, Frazzini, and Pedersen (2014), we examine the MV portfolio characteristics with and without active industry positions. We construct two industry-neutral portfolios using the base-case MV portfolio and the portfolio with diversification target equal to 100 as reference points. Exhibit 2 shows that the volatility reduction is only marginally affected for the base-case industry-neutral portfolio. However, applying the industry-neutral constraint to the diversified MV portfolio results in a decrease in the volatility reduction from 14.0% to 8.0%. This illustrates that the volatility reduction may be attributed to both the industry and stock-selection effects.

COMPARISON AGAINST OTHER MARKETS

The study so far shows that MV investing is capable of fulfilling the objective of volatility reduction in the China A-shares market. It is worthwhile to study how this compares to other regions. Here we compare the results from the China A-shares market to those of four other representative markets, including the United States, Japan, Developed Europe, and Emerging Markets.[5] The currencies used for the analysis are local currencies for the United States and Japan, the euro for Developed Europe, and the U.S. dollar for Emerging Markets. The same optimization setup with a diversification target of 100 and identical rebalancing schedules are applied to all five markets. Exhibit 4 shows the volatility reduction levels for the five different markets and reveals an intriguing finding: The volatility reduction level in the China A-shares market is the smallest among the five.

To investigate why the variance reduction is less effective in the China A-shares market, we explore two angles. First, we examine the level of ex ante volatility reduction. The effectiveness of volatility reduction on an ex ante basis should have a bearing on the ex post results. Exhibit 4 shows the ex ante volatility reduction of the MV portfolios for each region: On average the ex ante volatility reduction in the China A-shares market is lower than that of other markets.

The second perspective is to study the predictive power of the volatility forecasts. For each market, we calculate the cross-sectional rank correlation between each stock's ex ante standard deviation (calculated from its trailing 24-month daily total returns) and its subsequent ex post standard deviation (calculated from its leading 12-month daily total returns) at each rebalancing. A higher rank correlation indicates that the ex ante volatility can forecast its ex post counterpart more accurately, and the ex post volatility reduction should be more effective. This argument is supported by the results in Exhibit 4. The average correlation between historical volatility and future volatility for the China A-shares market is equal to 0.5 and is the lowest among the equity markets examined; the correlation of the developed market is around the level of 0.7.[6]

Despite the lower levels of volatility reduction, the simulated excess return is high compared to other markets. The excess return of 7.4% per annum is significantly higher than that found in the U.S. and Developed European markets. Turnover numbers for each of the MV portfolios in the United States, Japan, Developed Europe, and Emerging Markets are also shown in Exhibit 4. The results highlight that MV investing in China A-shares is a relatively high turnover strategy compared to in other developed markets. As a result, the impact of trading costs on the portfolio characteristics must be carefully considered and would be a suitable direction for future research.

FACTOR EXPOSURE OF THE MV PORTFOLIO

In addition to the metrics studied in previous sections, we examine the cross-sectional factor exposures to gain a deeper understanding of the characteristics

[5] The FTSE USA Index, FTSE Japan Index, FTSE Developed Europe Index, and FTSE Emerging Index are used to represent the underlying universes, respectively.

[6] A detailed analysis of the time series shows that the rank correlation for the China A-shares market can be as low as 0.2 at certain points, whereas correlations in other markets are consistently above 0.5.

Exhibit 3
Industry Exposure of the FTSE China A Index and the Base-Case and Diversification-Constrained MV Portfolios

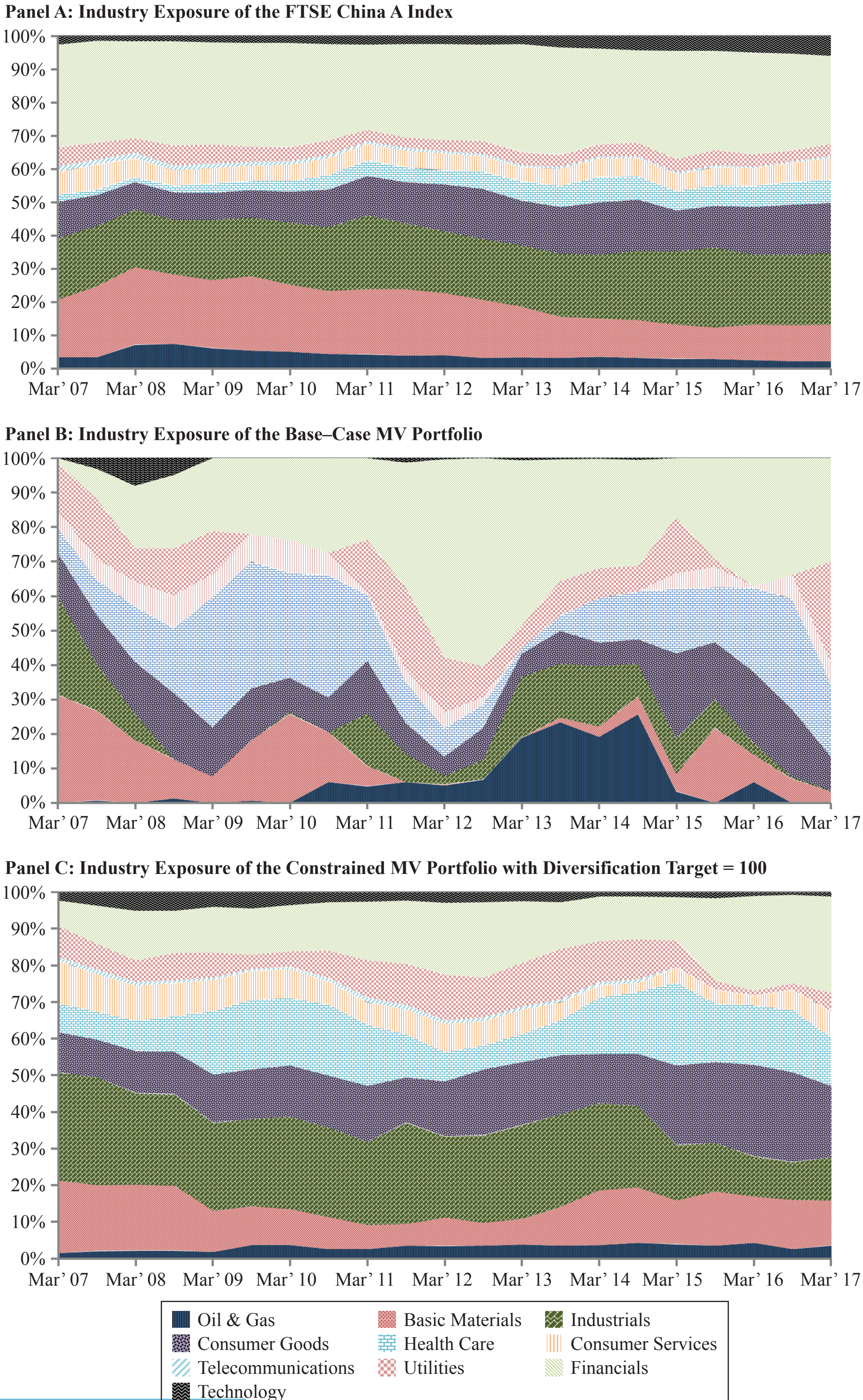


EXHIBIT 4

Portfolio Characteristics of Minimum-Variance Portfolios for China A-Shares, U.S., Japan, Developed Europe, and Emerging Markets (2007–2017)

	China A	U.S.	Japan	Developed Europe	Emerging
Excess Return (% p.a.)	7.4	2.3	6.4	2.5	5.7
Volatility (% p.a.)	27.8	11.2	13.0	10.8	15.8
Volatility Reduction (% p.a.)	14.0	27.0	34.2	31.1	32.9
Ex-Ante Volatility Reduction (% p.a..)	23.4	37.5	36.8	43.1	52.3
Rank Correlation Between Ex Ante and Expost Volatility (% p.a.)	0.5	0.7	0.7	0.7	0.7
Annual Turnover (%)	98.3	84.0	84.6	82.3	116.6
Tracking Error (% p.a.)	10.9	7.8	11.9	7.8	10.6
Information Ratio	0.7	0.3	0.5	0.3	0.5

Notes: Tracking error is calculated as the annualized historical standard deviation of the difference in daily returns between the MV portfolio and the corresponding benchmark. The FTSE USA Index, FTSE Japan Index, FTSE Developed Europe Index, and FTSE Emerging Index are used to represent the underlying universes. The currencies used for the analysis are local currencies for the United States and Japan, the euro for Developed Europe, and U.S. dollar for Emerging Markets. The cross-sectional rank correlation is calculated using stock-level ex ante standard deviation (calculated from its trailing 24-month daily total returns) and its subsequent ex post standard deviation (calculated from its leading 12-month daily total returns) at each rebalancing. The information ratio is calculated as the ratio of annualized active portfolio return and tracking error.

of China A-shares MV investing. The MV portfolio is expected to have exposure to the low-volatility stocks by construction, but there may be unintended exposures to other factors. The increasing popularity of MV investing has prompted some sections of the investment community to voice concerns about overcrowding. Jacobs (2015) stated that price pressure on factors may be exacerbated by the fact that assets under management in generic factors cannot be controlled and factor overvaluation can result. Ang, Madhavan, and Sobczyk (2017) studied the change in the valuation levels of a portfolio with a background of high inflows to the strategy. In particular, one may argue that the capital inflow can cause the portfolio to become more expensive and poorer in quality. Value and quality are then the natural factor candidates to be studied.

We follow the mechanism proposed by FTSE Russell (2017) to construct factors.[7] To define the value factor, we use the average *z*-scores of the earnings yield, cash flow yield, and sales-to-price ratio. To define quality, we calculate the average *z*-scores of profitability (measured as the average *z*-scores of return on assets, change in asset turnover, and accruals) and leverage (measured as operating cash flow to total debt).[8] Size is defined as the natural logarithm of the company's full market capitalization.

For illustration purposes, we use the MV portfolio with a diversification target of 100 as the reference portfolio. Exhibit 5 shows the portfolio active exposure (calculated as the excess weighted average *z*-scores) on value, quality, and size factors each month.[9] Panel A of Exhibit 5 indicates that the active value exposure fluctuates around zero in the sample period and does not exhibit any systematic value trend in recent years. In contrast, the MV portfolio displays positive active quality exposure, as shown in Exhibit 5, Panel B. Panel C of Exhibit 5 shows the active size exposure of the MV portfolio across time. The positive size exposure indicates a small size bias in the China A-shares MV portfolio that decreases through time.

FACTOR EXPOSURE OVERLAY ON THE MV PORTFOLIO

The explicit objective of MV investing is to minimize portfolio volatility, so exposure to the

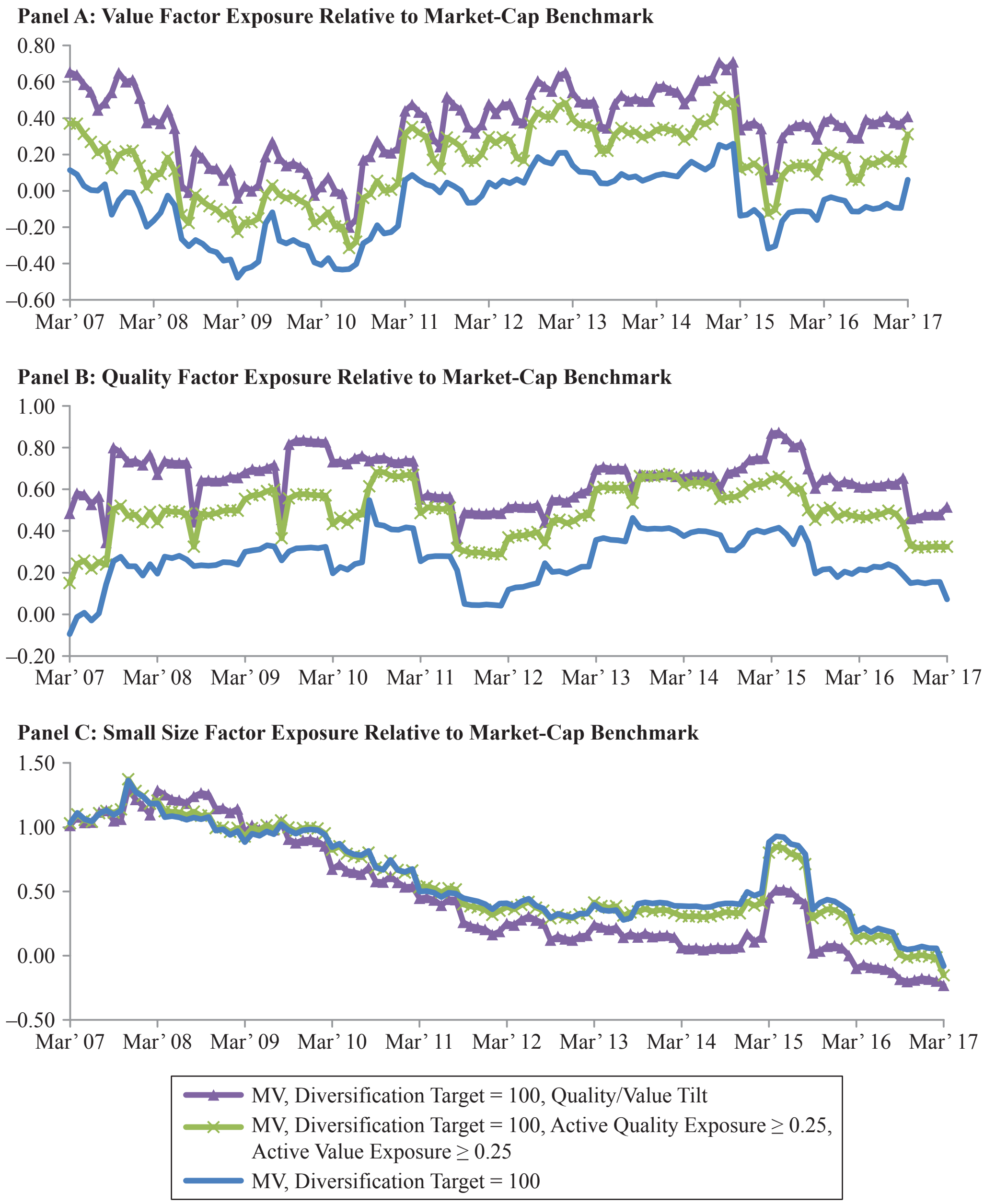
[7] The first step in calculating factor exposure is to transform the raw factor scores into a standardized z-score for each stock. Multiple measures can be used to represent a single factor.

[8] For more discussion on the quality factor definition, please refer to FTSE Russell (2014).

[9] The factor exposure values are calculated on a monthly basis on the third Friday of each month, chosen to coincide with the rebalancing day during each rebalancing month.

Exhibit 5

Factor Exposure of Minimum-Variance Portfolios Relative to Market-Cap Benchmark



low-volatility factor is expected. The existence of other factor exposures in the MV portfolio is unintentional. A natural question is whether it is possible to control unintended factor exposures while preserving the volatility reduction capability. Extensive research has shown that value (Zhang 2005) and quality factors (Asness, Frazzini, and Pedersen 2013) exhibit a positive long-run risk premium. In this section, we consider two approaches to controlling value and quality factor exposures on the MV portfolio and evaluate their effectiveness. The value and quality factors are of particular interest in light of concerns regarding overcrowding.

The first method involves restricting the exposures using constraints in the optimization. Clarke, de Silva, and Thorley (2006) applied a zero factor constraint on various factors when constructing a U.S. MV portfolio.

EXHIBIT 6

Return–Risk Characteristics of Factor-Titled MV Portfolios (2007–2017)

	MV, Diversification Target = 100	MV, Diversification Target = 100, Active Quality Exposure ≥ 0.25, Active Value Exposure ≥ 0.25	MV, Diversification Target = 100, Quality/Value Tilt
Return (% p.a.)	10.1	10.6	11.3
Volatility (% p.a.)	27.8	28.1	28.1
Volatility Reduction (%)	14.0	13.0	13.0
Maximum Drawdown (%)	–63.9	–63.9	–63.0
Tracking Error (% p.a.)	10.9	10.3	10.4
Information Ratio	0.7	0.8	0.8

Notes: Tracking error is calculated as the annualized historical standard deviation of the difference in daily returns between the MV portfolio and the FTSE China A Index. Information ratio is calculated as the ratio of annualized active portfolio return and tracking error.

Goldberg, Leshem, and Geddes (2014) imposed a positive active factor constraint to control the value exposure of the portfolio. This approach allows us to identify the MV portfolio using traditional optimization techniques, given some required level of factor exposure. There is no theoretical framework for determining the optimal level of factor exposure. Here we impose the constraint that the active value and quality exposure of the MV portfolio must be at least 0.25 to achieve a positive factor tilt.

The second approach aims to soften the role of factor constraints on optimization while achieving factor exposure control. The approach involves the use of a factor tilting mechanism proposed by FTSE Russell (2017) to overlay factor exposures on top of a portfolio. The FTSE Russell factor tilting methodology converts the *z*-scores to a number between 0 and 1 via the cumulative normal distribution function, referred to as *s*-scores. The *s*-scores are then multiplied by the original portfolio weights. The tilted stock weight $\hat{W}_i$ is calculated using Equation (2):

$$\hat{W}_i = \frac{S_i * W_i}{\sum_{j=1} S_j * W_j} \tag{2}$$

where S_i is the *s*-score and W_i is the weight of stock *i* in the MV portfolio. When there are *n* factors to be tilted, Equation (3) is used to obtain the tilted stock weight:

$$\widehat{W}_i = \frac{\Pi_{k=1}^{n} S_{ik} * W_i}{\sum_{j=1} (\Pi_{k=1}^{n} S_{jk} * W_j)} \tag{3}$$

where S_{ik} is the s-score of stock *i* on the *k*th factor. The MV portfolio with diversification target equal to 100 is used as the underlying portfolio.

The time series of active factor exposures using both techniques are shown in Exhibit 5. Both approaches result in positive active quality and value exposures. The factor tilt approach results in smaller levels of active size exposure compared to the original MV portfolio and the constrained factor portfolio.

We investigate whether the ability to reduce volatility is maintained after the factor exposure overlay is applied. The findings in Exhibit 6 illustrate that both approaches retain the ability to reduce volatility. The original diversified MV portfolio displays volatility reduction of 14.0% compared to 13% for both exposure-controlled portfolios. Exhibit 6 provides the annualized returns and shows the performance impact of the factor overlay. The higher excess returns, especially for the factor-tilt portfolio, echo the findings of the factor risk premium literature.

CONCLUSION

MV has received ever-increasing attention from both academics and industry practitioners. There are two reasons for its popularity: The first relates to its ability to achieve reductions in volatility, and the second concerns the observed historical outperformance relative to a market-cap benchmark. Previous research has shown that the concept can be applied to various markets, including the United States, Europe, and Japan. This study shows that MV investing can also be applied to the China A-shares market. Our research results are particularly useful for investors with an emphasis on controlling risk exposure and capturing the low-volatility premium. However, we highlight that the implementation can be challenging, and our analysis offers insights for practitioners who have concerns about China-specific challenges. We provide a step-by-step guide to explain how a China A-shares MV portfolio can be constructed with practical requirements in terms of concentration, diversification, liquidity, and industry exposure. Our methodology takes into account the special feature of stock suspensions, and the simulated results show that MV investing is capable of reducing volatility and enhancing portfolio returns in the China A-shares market over the sample period. However, volatility reduction is lower than similar MV strategies in other major global equity markets. This can be attributed to both the lower ex ante volatility reduction and the weaker forecasting power over ex post volatility. Finally, we examine the valuation and quality aspects of the China A-shares MV portfolio and consider whether they have deteriorated because of its increasing popularity. The empirical results suggest otherwise. We apply two methods to overlay factor characteristics on the MV portfolio. The analysis shows that a value and quality factor overlay to an MV portfolio does not significantly affect the levels of volatility reduction and simultaneously successfully captures the associated factor risk premium, though similar results must be found in other major markets to ensure robustness. These findings indicate that MV investing can be considered an important alternative to market-cap-weighted approaches for accessing the China A-shares market.

REFERENCES

Ang, A., A. Madhavan, and A. Sobczyk. 2017. "Crowding, Capacity, and Valuation of Minimum Volatility Strategies." *The Journal of Index Investing* 7 (4): 41–50.

Asness, C. S., A. Frazzini, and L. H. Pedersen. 2013. "Quality minus Junk." Working paper, October 2013, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2312432.

——. 2014. "Low-Risk Investing without Industry Bets." *Financial Analyst Journal* 70 (4): 24–41.

Baker, M., B. Bradley, and J. Wurgler. 2011. "Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility Anomaly." *Financial Analysts Journal* 67 (1): 40–54.

Brennan, M., X. Cheng, and F. Li. 2012. "Agency and Institutional Investment." *European Financial Management* 18 (1): 1–27.

Chow, T. M., E. Kose, and F. Li. 2016. "The Impact of Constraints on Minimum-Variance Portfolios." *Financial Analysts Journal* 72 (2): 52–70.

Clarke, R. G., H. de Silva, and S. Thorley. 2006. "Minimum-Variance Portfolios in the U.S. Equity Market." *The Journal of Portfolio Management* 33 (1): 10–24.

DeMiguel, V., L. Garlappi, F. J. Nogales, and R. Uppal. 2009. "A Generalized Approach to Portfolio Optimization: Improving Performance by Constraining Portfolio Norms." *Management Science* 55 (5): 798–812.

FTSE Russell. "Factor Exposure Indexes." 2014, http://www.ftse.com/products/downloads/FTSE_Quality_Factor_Paper.pdf.

——. 2017. "Factor Exposure and Portfolio Concentration." Research paper, April 2017.

Frazzini, A., and L. H. Pedersen. 2014. "Betting against Beta." *Journal of Financial Economics* 111 (1): 1–25.

Goldberg L., R. Leshem, and P. Geddes. 2014. "Restoring Value to Minimum Variance." *Journal of Investment Management* 12 (2): 32–39.

Haugen, R. A., and N. L. Barker. 1991. "The Efficient Market Inefficiency of Capitalization-Weighted Stock Portfolios." *The Journal of Portfolio Management* 17 (3): 35–40.

Ho, J., Q. Liao, and M. Taylor. 2015. "Real and Accrual-Based Earnings Management in the Pre- and Post-IFRS Periods: Evidence from China." *Journal of International Financial Management & Accounting* 26 (3): 294–335.

Hsu, J., V. Viswanathan, M. Wang, and P. Wool. "Anomalies in China A-Shares." 2017. Working paper, April 2017, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2955144.

Jacobs, B. I. 2015. "Is Smart Beta State of the Art?" *The Journal of Portfolio Management* 41 (4): 1–3.

Lesmond, D. A., J. P. Ogden, and C. A. Trzcinka. 1999. "A New Estimate of Transaction Costs." *The Review of Financial Studies* 12 (5): 1113–1141.

Pong, E., J. Perrett, and E. Chan. 2014. "Preparing for China's Inclusion in Global Benchmarks." *The Journal of Index Investing* 5 (3): 33–45.

Sharpe, W. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *The Journal of Finance* 19 (3): 425–442.

Zhang, L. 2005. "The Value Premium." *The Journal of Finance* 60 (1): 67–103.