Dynamic Asset Allocation in Chinese Stock Market

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Abstract

While numerous studies have analyzed the dynamic asset allocation in the U.S. stock market, little attention has been paid to that of the Chinese stock market. In this paper, we investigate the dynamic asset allocation strategies in Chinese stock market to explore the Chinese stock market return predictability. We find significant out-of-sample forecasting power of several return predictors, and the downside risk measure performs particularly well. We then examine the performance of dynamic portfolio strategies in the Chinese stock market such as aggregate market timing strategy, and industry, size, and value rotation strategies. We provide strong evidence that the dynamic portfolio strategies deliver superior outperformance relative to the passive buy-and-hold portfolio strategies. Specifically, the dynamic portfolio strategies can beat the buy-and-hold benchmarks by about 600 basis points per annum, and almost double the Sharpe ratios.

JEL classifications: C22, C53, G11, G12, G17

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Dynamic asset allocation strategies designed to explore stock return predictability are of great interest to portfolio managers and financial economists. Voluminous studies report positive evidence that dynamic portfolio strategies, which incorporate the forecasting power of return predictors, can strongly beat the passive buy-and-hold benchmark and deliver economically and statistically significant gains for the investors in the U.S. stock market, e.g., Kandel and Stambaugh (1996), Campbell and Thompson (2008), Cochrane (2008, 2011), Kong et al. (2011), among many others. However, there is little research analyzing the dynamic asset allocation choices in the Chinese stock market context, which recently has attracted considerable attention from the portfolio managers due to its huge economic size and rapid economic growth in the past two decades. Chinese stock market now ranks the largest among all emerging stock markets and the second-largest among all national stock markets.

This paper aims to design dynamic asset allocation strategies to explore the Chinese stock market return predictability. Specifically, we examine whether a hypothetical mean-variance portfolio manager can take advantage of the return predictability of Chinese stock market, and whether the accordingly constructed dynamic portfolio strategies such as aggregate market timing strategy and component portfolios rotation strategies can outperform the corresponding passive buy-and-hold benchmark investment strategies.

The dynamic portfolio investment strategies are constructed as follows. First, at the end of each month, the mean-variance portfolio manager forecasts out-of-sample both the mean and covariance of excess Chinese stock returns in the coming month. Second, portfolio managers allocate the weights of their investment in the stocks in proportion to the forecasted mean to covariance ratio of excess returns, and then they hold the portfolio for the whole month until they rebalance their portfolios at the end of next month. We assess the performance of the dynamic asset allocation strategies with four performance criteria: the Sharpe ratio, the certainty equivalent return (CER) gain, the CER gain net of transactions costs, and the turnover for each portfolio strategy, which are commonly used in the existing studies, e.g., Campbell and Thompson (2008) and DeMiguel et al. (2009).

To implement the dynamic investment strategies, we employ eight popular return predictors to forecast the next month Chinese stock returns. Specifically, the intertemporal CAPM of Merton (1980) theoretically proposes that stock market risk measures are related to stock returns. Barro (2006), Bali et al. (2009), and Huang et al. (2012) provide evidence that downside risk can forecast future stock returns, which summarizes the worst loss of the stock market over a target horizon with a given level of confidence. Bali and Peng (2006), Guo and Neely (2008), and Rossi and Timmermann (2011) show that realized volatility is related to future stock returns. Moreover, a number of existing studies find that many economic variables also can forecast stock market returns. In this paper, we hence consider eight predictive variables including the downside risk, realized volatility, and six economic variables such as valuation ratios and inflation rates proposed by Welch and Goyal (2008) that are available in Chinese stock market. We aim to examine whether the portfolio manager could utilize the forecasting power of these eight predictors to improve portfolio investment performance in Chinese stock market.

Our analysis shows that Chinese stock market indeed presents both statistically and economically significant return predictability which a portfolio manager can exploit through dynamic portfolio strategies to make significant profits. Based on aggregate market timing strategies, we find four predictors (downside risk, realized volatility, dividend-payout ratio, and book-to-market ratio) generate positive certainty equivalent return (CER) gains for the investors. The downside risk performs the best, and generates sizable annualized CER gains of 594 basis points. That is to say, the mean-variance portfolio managers can earn economically high profits up to 594 basis points per annum, relative to the passive buy-and-hold benchmark, using the forecast generated by downside risk.

We then explicitly take into account the trading costs of implementing the dynamic portfolio strategies. Assuming a proportional transactions cost of 50 basis points per transaction, because the low share turnover of the market timing strategies (about 2.68% per month for downside risk), the transaction costs are relatively small. After we deduct these trading costs, the dynamic portfolios strategies still deliver superior performance. For example, downside risk based market timing strategy generates net of transaction cost CER gain of about 593 basis points. Realized volatility and book-to-market ratio also generate economically large profits of about 300 basis points comparing to the buy-and-hold benchmark. In addition, the aggregate market timing portfolio strategies also generate high Sharpe ratios. For example, the market timing strategy based on downside risk produces high monthly Sharpe ratio of 0.24, more than two times larger than that of the buy-and-hold strategy (0.09) which ignores the return predictability.

Industry, size, and value portfolios rotation investment strategies also show that the investors can gain significant profits by exploring Chinese stock market predictability. For example, the industry portfolios rotation strategy based on downside risk delivers a remarkable Sharpe ratio of 0.15, almost doubles the Sharpe ratio of the equal-weighted buy-and-hold strategy (0.08) for 13 industries. It also generates economically large CER gain and the net-transaction-cost CER gain of about 600 basis points, substantially beating the passive benchmark. Industry rotation strategies based on realized volatility and book-to-market ratio also generate economically large gains for the portfolio managers. We obtain similar findings of strong economic value of Chinese stock market predictability for size and value rotation strategies as well.

The remainder of this paper is organized as follows. Section 2 briefly introduces the dynamic asset allocation framework. Section 3 describes the data used in this paper. Section 4 reports the out-of-sample return predictability evidence. Section 5 presents the performance of dynamic asset allocation strategies including aggregate market timing and component rotation strategies. Section 6 concludes this paper.

Dynamic Asset Allocation Strategy

In this paper, we investigate whether the hypothetical mean-variance portfolio managers are able to make profitable investments in Chinese stock market and beat the passive buy-and-hold benchmark, taking advantage of the empirical evidence that Chinese stock returns are predictable. For that purpose, we assume that the portfolio managers adopt a dynamic mean-variance portfolio investment strategy as follows. At the end of each month, the managers first forecast out-of-sample both the mean and covariance of excess Chinese stock returns in the coming month. They then use the forecasts to make asset allocation decisions across the risky Chinese stocks and the risk-free bills. The managers hold the portfolios until they rebalance their portfolios in next month.

Specifically, the mean-variance portfolio managers choose the weights of equities in the portfolio at the end of month t as follows:

$$w_t = \frac{1}{\gamma}\hat{\Sigma}_{t+1}^{-1}\hat{R}_{t+1}^{j} , \tag{1}$$

where γ is the risk aversion coefficient of five, $\hat{R}_{t+1}^{j}$ is the vector of out-of-sample forecasts of excess stock returns, and $\hat{\Sigma}_{t+1}^{-1}$ is the forecast of the variance-covariance matrix of excess stock returns.[1] The econometric methodology of out-of-sample return prediction is described in the Appendix. When there are only two assets involved, the managers then allocate $1-w_t$ of the portfolio to risk-free bills.

Following Campbell and Thompson (2008) and DeMiguel et al. (2009), to evaluate the performance of asset allocation, we consider four criteria: (i) the Sharpe ratio; (ii) the certainty equivalent return (CER) gain for a mean-variance investor; (iii) the CER gain net of transactions costs; and (iv) the share turnover for each portfolio strategy.

The CER of a portfolio is calculated by

$$CER_p = \hat{\mu}_p - 0.5\,\gamma\hat{\sigma}_p^2 , \tag{2}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ are the sample mean and variance, respectively, for the portfolio manager's portfolio over the forecast evaluation period. The CER can be interpreted as the risk-free return that an investor is willing to accept instead of adopting the given risky portfolio. The CER gain is the difference between the CER for the investor who uses a particular predictive regression forecasting model of excess stock returns and that for an investor who uses the historical average forecasts. We multiply this difference by 12 so that it can be interpreted as the annual portfolio management fee that an investor would be willing to pay to have access to the predictive regression forecasts instead of the historical average forecasts.

The monthly Sharpe ratio is the mean portfolio return in excess of the risk-free rate divided by the standard deviation of the excess portfolio return. The average monthly turnover is the percentage of wealth traded each month. For the CER gain net of transactions costs, the costs are calculated using the monthly turnover measures and assuming a proportional transactions cost equal to 50 basis points per transaction.

Data

We obtain the value-weighted monthly aggregate Chinese stock market return from the C-SMAR, which includes all the China A-share stocks listed in Shanghai and Shenzhen stock exchanges. Our return data extends from January 2002 to December 2012.[2] The excess stock return is calculated as the difference between the stock return and the risk-free rate, which is also obtained from CSMAR.

We get the monthly stock returns for 13 industry portfolios, formed on the industry classification of China Securities Regulatory Commission (CSRC): AGRIC (Agriculture, Forestry, and Fishing), MINES (Mining), MANUF (Manufacturing Industries), UTILS (Electric, Gas, Water production, and Supply), CNSTR (Construction), TRANS (Transportation and storage), INFTK (Information technology), WHTSL (wholesale and Retail store), MONEY (Finance and insurance), PROPT (Real estate), SRVC (Service industry), MEDIA (Communication and cultural industry), MULTP (conglomerate and other industry). The industry portfolios are constructed at the end of June of each year, according to the industry classification data at the end of June of this year. The 10 size portfolios are constructed at the end of each June, using the market equity data at the end of June with equal number of firms in each portfolio. Similarly, we construct 10 value (book-to-market) portfolios, formed on book-to-market ratio at the end of each June with equal number of firms in each portfolio. The book value is the firm's book equity of previous fiscal year, and market value is the market equity data at the end of this June.

In this paper, we consider two market risk measures including *downside risk* and *realized volatility* as predictors in forecasting the Chinese stock returns. We measure the downside risk using the value-at-risk (*VaR*) of aggregate stock market returns, which summarizes the worst loss over a target horizon with a given level of confidence and indicates the overall extreme market risk faced by the investors. In this paper, we employ a rolling window of five-year daily returns to estimate the 95-percentile *VaR* based on extreme value theory. Appendix provides detailed description on how to calculate the downside risk. The realized volatility is measured using the squared daily returns over a five-year rolling window, since Harrison and Zhang (1999) and Ghysels et al. (2005) suggest that the predictability of conditional variance is stronger over relatively longer estimation intervals due to estimation error.

In addition, following Welch and Goyal (2008), we consider a group of six Chinese economic variables in predicting Chinese stock market returns that are popular predictors in the return predictability literature and are available for the Chinese market.

- Dividend-price ratio (log), D/P: difference between the logarithm of dividends and that of prices for all A-share stocks listed in Shanghai and Shenzhen stock exchanges, where dividends are measured using a one-year moving sum.

- Dividend yield (log), D/Y: the difference between the logarithm of dividends and that of lagged prices, where dividends are measured using a one-year moving sum.

- Dividend-payout ratio (log), D/E: difference between the log of dividends and log of earnings for A-share stocks listed in Shanghai and Shenzhen stock exchanges, where dividends and earnings are measured using a one-year moving sum.

- Book-to-market ratio (log), B/M: the difference between the logarithm of book value and that of market value for A-share stocks listed in Shanghai and Shenzhen stock exchanges.

- Earnings-price ratio (log), E/P: the difference between the logarithm of earnings and that of prices on all A-share stocks listed in Shanghai and Shenzhen stock exchanges, where earnings are measured using a one-year moving sum.

- Inflation, INF: calculated according to the CPI from the National Bureau of Statistics. Following Welch and Goyal (2008), since the inflation rate data are released in the following month, we use the lagged two-month inflation in regression.

[Insert EXHIBIT 1 about here]

China's stock market has experienced tremendous growth and development in the last two decades. While the Chinese stock market on average delivers relatively high return, it also presents high volatility. As displayed in Exhibit 1, the Chinese stock market returns fluctuate wildly over time. The standard deviation over our sample period is 9.11%, which is much larger than that of U.S. stock market reported in the literature. For example, Huang et al. (2013) report the standard deviation of S&P500 index over 1965:07-2010:12 to 4.46%, and Bali et al. (2009) also show a similar magnitude for the aggregate U.S. stock market. [Insert EXHIBIT 2 about here]

Panel A of Exhibit 2 provides descriptive statistics for the value-weighted excess stock returns of the aggregate Chinese stock market (MKT). The average of monthly excess Chinese stock market return is 0.86%, and the standard deviation is 9.11%, which indicates a highly volatile stock market over our sample periods in China. Nonetheless, the aggregate Chinese market has a high Sharpe ratio of 0.09 for a buy-and-hold investor, which is about 40% higher than that of U.S. stock market reported in the literature. In addition, the excess returns of aggregate Chinese market have negative skewness and high kurtosis greater than 3, suggesting a left-skewed and leptokurtic distribution of Chinese stock returns. Therefore, it is important for the portfolio managers to manage both the market variance risk and downside risk actively when investing in the Chinese stock market.

Panel A also presents the descriptive statistics for the downside risk (*DR*), the realized volatility (*RV*), and the six Chinese economic variables. The mean of downside risk for the aggregate Chinese stock market is 12.04%, which implies a possible extreme loss of 12.04 RMB in one month at the 95% confidence level when investing 100 RMB in the aggregate Chinese stock market. The average realized volatility is 7.81% which captures the variation risk of the stock market. Moreover, both downside risk and realized volatility are highly persistent with the first-order autocorrelation coefficients of 0.92. The summary statistics of the six Chinese economic variables are largely consistent with literature: the mean values range from -2.90 for D/P and D/Y to 0.02 for INF, and all economic predictors are highly persistent. Panel B shows that both downside risk and realized volatility have low correlation with the economic variables.

Out-of-sample Prediction

In this section, we report the empirical results for out-of-sample prediction.[3] As shown in Panel A of Exhibit 3, four predictors generate positive out-of-sample R^2_{OS} for the monthly excess aggregate Chinese market return over the 2005:01 to 2012:12 forecast evaluation period. Specifically, the downside risk deliveries an economically large R^2_{OS} statistic of 5.99%, the realized volatility results in a sizable R^2_{OS} statistic of 1.40%, B/M of 3.45%, and E/P of 0.95%. Three of these four positive R^2_{OS} statistics (*DR*, B/M, and E/P) are statistically significant according to the *MSFE-adjusted* statistics. Therefore, the predictive regression forecasts produce a substantially smaller MSFE than the historical average benchmark. Remarkably, the R^2_{OS} of downside risk is much larger than the other predictors, and hence, the downside risk presents superior real-time forecasting power for the Chinese stock market than the other predictors in term of MSFE.

[Insert EXHIBIT 3 about here]

The remaining four economic variables generate negative out-of-sample R^2_{OS} over the 2005:01 to 2012:12 forecast evaluation period. Thus, they fail to outperform the historical average benchmark in terms of MSFE, which is consistent with the findings of Welch and Goyal (2008) that individual economic variables display limited out-of-sample predictive ability.

Panel B further shows that adding information in the downside risk in conjunction with economic variables can substantially improve the out-of-sample performance of all of the forecasts based on economic variables alone. Six forecasts generate positive R^2_{OS} statistics, ranging from 0.84% to 4.45%. The bivariate forecast of combining the downside risk with B/M realizes the largest R^2_{OS} statistic of 4.45%. In addition, the MSFE for all of the six combining forecasts are significantly smaller than that of historical average, according to the *MSFE-adjusted* statistics.

Asset Allocation Performance

Next, we proceed to assess the performance of dynamic portfolio strategies implemented by the mean-variance portfolio managers to explore the Chinese stock market return predictability. We assume that the managers use market downside risk, realized volatility, and the six economic variables to construct the out-of-sample forecasts of excess returns on the Chinese aggregate stock market and its various component portfolios including the industry, size, and value portfolios. Then they perform dynamic asset allocations according to the return forecasts.

Market timing portfolio performance

Exhibit 4 reports the performance of the market timing portfolio strategy, where the portfolio managers dynamically invest in the Chinese aggregate market and risk-free bill based on return forecasts for excess aggregate stock market returns. As shown, five predictors including downside risk, realized volatility, dividend-payout ratio, book-to-market ratio, and earnings-price ratio, generate positive annualized certainty equivalent return (CER) gains, ranging from 25 to 594 basis points. The active portfolio managers hence can earn larger profits than the passive buy-and-hold investor ignoring return predictability. Remarkably, the downside risk has the largest CER gain of 594 basis points per annum for the portfolio managers. That is to say, the portfolio manager can exploit the forecasting power of downside risk through dynamic portfolio strategies to make significant investment profits up to 594 basis points in China stock market, relative to the passive buy-and-hold benchmark. The realized volatility also produces large CER gain of 309 basis points per annum, and B/M produces 299 basis points per annum.

[Insert EXHIBIT 4 about here]

After taking into account the trading costs of implementing the market timing strategies, we calculate the net-of-transactions-costs CER gains for all predictors. The market timing investment strategies based on downside risk, realized volatility, book-to-market ratio, and dividend-payout ratio still deliver superior performance with CER gains of 593, 260, 264, and 38 basis points, respectively. In particular, the share turnover for downside risk based strategy is 2.68% per month and smaller than those of other predictors. This implies that the transaction costs for this strategy are relatively small. In addition, among the predictors with positive CER gains, the market timing portfolio based on downside risk produces the largest monthly Sharpe ratio of 0.24, more than two times larger than that of the buy-and-hold strategy (0.09). Realized volatility, book-to-market ratio, and dividend-payout ratio also generate economically large Sharpe ratios for the portfolio managers.

In summary, the aggregate market timing strategies based on downside risk, realized volatility, and the economic variables such as book-to-market ratio outperform the passive buy-and-hold portfolio strategies in the Chinese stock market, and these predictors deliver substantial economic profits for the portfolio managers.

Component rotation portfolio performance

Next, we examine the performance of component rotation portfolio strategies, where the portfolio manager dynamically rebalance his portfolio between the 13 Chinese industry portfolios (10 size portfolios; 10 value portfolios) and risk-free bill based on the corresponding forecasts of Chinese industry (size; value) portfolio returns.

We start with the industry rotation portfolio strategy. Exhibit 5 presents the summary statistics and correlation matrix for excess returns of 13 Chinese industry portfolios. As shown in Panel A of Exhibit 5, the average returns of the industry portfolios range from 0.34% (CNSTR) to 1.20% (MINES), while the standard deviations range from 8.82% (TRANS) to 11.49% (MEDIA). The maximum Sharpe ratio is as large as 0.12 for MINES, while the minimum Sharpe ratio is 0.04 for CNSTR. Panel B reports the correlation matrix for 13 Chinese industry portfolios. The correlation coefficients between industry portfolios range from 0.42 to 0.96. We also construct an equal-weighted buy-and-hold portfolio based on 13 industry portfolios, which is a string benchmark for the optimal portfolio strategies as argued by DeMiguel et al. (2009). Panel A shows that the equal-weighted portfolio has lower risk and higher Sharpe ratios than many industries due to diversification, with the average return of 0.68 and the Sharpe ratio of 0.08.

[Insert EXHIBIT 5 about here]

The results for industry rotation portfolio performance are reported in Exhibit 6. Consistent with results of the market timing strategy in Exhibit 4, predictors such as downside risk, realized volatility, and book-to-market ratio generate positive and economically sizable CER gains for the portfolio managers, up to 659, 391, and 324 basis points per annum, respectively. It implies that the portfolio manager can earn large profits from theindustry rotation investment strategies when exploiting the forecasting power of these predictors for industry portfolios, relative to the passive buy-and-hold industry strategies. After accounting for transactions costs, the net-of-transactions-costs CER gains of industry rotation strategies are still positive. Again, the downside risk based portfolio has the largest CER gains and lowest share turnover, and substantially outperforms the other predictors.

[Insert EXHIBIT 6 about here]

Both the downside risk and book-to-market ratio generate large Sharpe ratios of 0.15, almost double that of equal-weighted industry portfolio strategy (0.08). Therefore, in terms of the criteria of Sharpe ratio, downside risk and book-to-market ratio based industry rotation strategies substantially beat the passive buy-and-hold strategies, and outperform those based on the other predictors.

In summary, our empirical results for industry rotation portfolio are in line with those for market timing portfolio. The mean-variance industry rotation strategies based on the forecasting power of downside risk, realized volatility and the economic variable such as book-to-market ratio substantially beat the passive buy-and-hold industry strategy. In particular, the downside risk performs the best among all the predictors.

[Insert EXHIBIT 7 about here]

Exhibit 7 presents the results for the size and value rotation portfolios. The average CER gains for downside risk, realized volatility, and book-to-market ratio are positive again. Specifically, the downside risk based dynamic rotation strategies deliver CER gains of 534 basis points and 541 basis points per annum for the size and value rotation portfolios, respectively; the realized volatility presents 395 basis points and 392 basis points per annum for the size and value rotation portfolios, respectively; while, the book-to-market ratio generates 98 and 92 basis points CER gains for the size and value rotation portfolios, respectively. After considering the transaction costs, strategies based on downside risk, realized volatility, and book-to-market ratio still produce positive profits. In addition, portfolios constructed according to these predictors generate economically large Sharpe ratios as well. Therefore, the dynamic size and value rotation portfolio strategies based on the downside risk, realized volatility, and book-to-market ratio outperform the corresponding passive buy-and-hold size and value portfolio strategies.

Conclusion

This paper investigates the dynamic asset allocation in Chinese stock market. Specifically, we examine which the mean-variance portfolio managers can explore the Chinese stock market return predictability to improve their investment performance, and whether the designed market timing and component rotation portfolio strategies can generate statistically and economically superior performance relative to the passive investment strategy of buying and holding the stock market. To implement the mean-variance dynamic portfolio strategies, we consider eight predictors including the downside risk, realized volatility, and six Chinese economic variables. Then, the portfolio managers employ these predictors to out-of-sample forecast the future stock returns, and accordingly allocate the weight of their investments in Chinese stocks dynamically based on time-varying expected stock returns.

We assess the performance of asset allocation using four criteria: the out-of-sample Sharpe ratio, the certainty equivalent return (CER) gain, the CER gain net of transactions costs, and the turnover for each portfolio strategy. Empirical results show that, for both the market timing and the component rotation strategies, the dynamic portfolio strategies based on predictors such as downside risk, realized volatility, and book-to-market ratio consistently beat the corresponding passive buy-and-hold benchmark strategies, and generate economically large Sharpe ratios and CER gains. Among the eight predictors considered, the downside risk performs the best and generates the largest profits for the portfolio managers.

Appendix

Out-of-sample Forecast Construction

Following Campbell and Thompson (2008) and Welch and Goyal (2008), we construct the out-of-sample forecasts for the Chinese excess stock returns based on recursive predictive regressions, in which the predictive regression slopes are estimated recursively by using information available up to the period of forecast formation, t, to avoid the use of future data not available at the time of forecast to investors.

Specifically, the out-of-sample excess return forecast at period $t+1$ and information available through period t is generated by

$$\hat{R}^{j}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t X^{k}_{1:t;\, t}\,, \tag{A.1}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates from regressing $\{R^{j}_{s+1}\}_{s=1}^{t-1}$ on a constant and $\{X^{k}_{1:t;\, s}\}_{s=1}^{t-1}$, in which R^{j}_{t+1} represents the monthly excess stock returns of the aggregate Chinese stock market portfolio, 13 industry portfolios, 10 size portfolios, and 10 value portfolios, respectively; and X^{k}_{t} denotes the return predictors at period t.

We divide the total sample of length T into n initial estimation sub-sample and q out-of-sample evaluation sub-sample, where $T = n+q$, and get q out-of-sample forecasts: $\{\hat{R}^{j}_{t+1}\}_{t=n}^{T-1}$. In this paper, we use 2001:12 to 2004:12 as the initial estimation period so that the forecast evaluation period spans 2005:01 to 2012:12. The length of the initial in-sample estimation period balances having enough observations for precisely estimating the initial parameters with the desire for a relatively long out-of-sample period for forecast evaluation.

We employ the widely used Campbell and Thompson (2008)'s R^2_{OS} statistic and Clark and West (2007)'s *MSFE-adjusted* statistic to evaluate the out-of-sample forecasts. The R^2_{OS} statistic is akin to the familiar in-sample R^2, and measures the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast relative to the historical average benchmark,

$$R^2_{OS} = 1 - \frac{\sum_{t=n}^{T-1}(R^j_{t+1} - \hat{R}^j_{t+1})^2}{\sum_{t=n}^{T-1}(R^j_{t+1} - \bar{R}^j_{t+1})^2}\,, \tag{A.2}$$

where $\bar{R}^j_{t+1}$ denotes the historical average benchmark corresponding to the constant expected return model ($R^j_{t+1} = \alpha + \varepsilon_{t+1}$),

$$\bar{R}^j_{t+1} = \frac{1}{t}\sum_{s=1}^{t} R^j_s\,. \tag{A.3}$$

Welch and Goyal (2008) show that the historical average is a very stringent out-of-sample benchmark, and economic variables typically fail to outperform the historical average. The R^2_{OS} statistic lies in the range $(-\infty, 1]$; when $R^2_{OS} > 0$, the predictive regression forecast $\hat{R}^j_{t+1}$ outperforms the historical average $\bar{R}^j_{t+1}$ in term of MSFE.

We use the *MSFE-adjusted* statistic to test the null hypothesis that the historical average MSFE is less than or equal to that of the predictive regression forecast against the one-sided (upper-tail) alternative hypothesis that the historical average MSFE is greater than that of the predictive regression forecast, corresponding to H_0: $R^2_{OS} \leq 0$ against H_A : $R^2_{OS} > 0$. The Clark and West (2007)'s *MSFE-adjusted* statistic is conveniently calculated by first defining

$$f_{t+1} = (R^j_{t+1} - \bar{R}^j_{t+1})^2 - [(R^j_{t+1} - \hat{R}^j_{t+1})^2 - (\bar{R}^j_{t+1} - \hat{R}^j_{t+1})^2]\,, \tag{A.4}$$

then regressing $\{f_{t+1}\}_{t=n}^{T-1}$ on a constant, and finally calculating the t-statistic corresponding to the constant. A p-value for a one-sided (upper-tail) test is then computed using the standard normal distribution. Clark and West (2007) demonstrate that the *MSFE-adjusted* statistic performs reasonably well in terms of size and power when comparing forecasts from nested linear models for a variety of sample sizes.

Downside Risk Calculation

We measure the downside risk of stock market using the the *VaR* which summarizes the worst loss over a target horizon with a given level of confidence. Specifically, we calculate the *VaR* based on the extreme value theory (EVT), which models the distribution patterns of the tail component of stock returns, independently on the assumption of entire return distribution. Therefore, it provides a fairly powerful and robust framework to estimate the *VaR*. Following Gençay and Selçuk (2004) and Gupta and Liang (2005), value-at-risk (*VaR*) based on the extreme value theory (EVT) is determined by

$$VaR = u + \frac{\sigma}{\xi}\left[\left(\frac{N}{n}p\right)^{-\xi} - 1\right], \tag{B.1}$$

where N is the length of a rolling window of stock returns, u is a determined loss threshold, n is the number of extreme losses out of N observations that exceed the loss threshold u, ξ and σ are shape and scale parameters of a generalized Pareto distribution, and p represents the probability of occurrence of extreme loss.

The downside risk measure based on *VaR* captures the extreme losses of stock returns from a generalized Pareto distribution; and when $\xi = 0$, the generalized Pareto distribution reduces to the exponential distribution. Empirically, the parameters ξ and σ of generalized Pareto distribution can be estimated using maximum likelihood methods. With the estimated parameters and determined loss threshold u, *VaR* estimates can be obtained at any confidence level p based on Eq. (B.1).

Endnotes

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[1]The weights on stocks in the investor's portfolio are restricted to lie between 0 and 1.5 to prevent extreme investments and limit the impact of estimation error.

[2]The Shanghai Stock Exchange was opened in 1990 and the Shenzhen Stock Exchange in 1991. Since December 16, 1996, both markets have used a daily price limit of 10 percent based on the previous day's closing price. Therefore, this paper only focuses on the post-1996 sample. As a rolling window, the data from 1997 through 2001 is used to calculate the realized volatility and the downside risk, and the sample from January 2002 is employed to construct the return forecast.

[3]To save space, we only show the out-of-sample forecasting results for the aggregate market. In an unreported results, the return predictors used in this paper show similar predictive powers for in-sample market returns and out-of-sample returns of industry, size, and value portfolios.

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EXHIBIT 1. Aggregate Chinese Stock Market Returns

This figure plots the aggregate Chinese stock market returns over the period from January 2002 through December 2012.

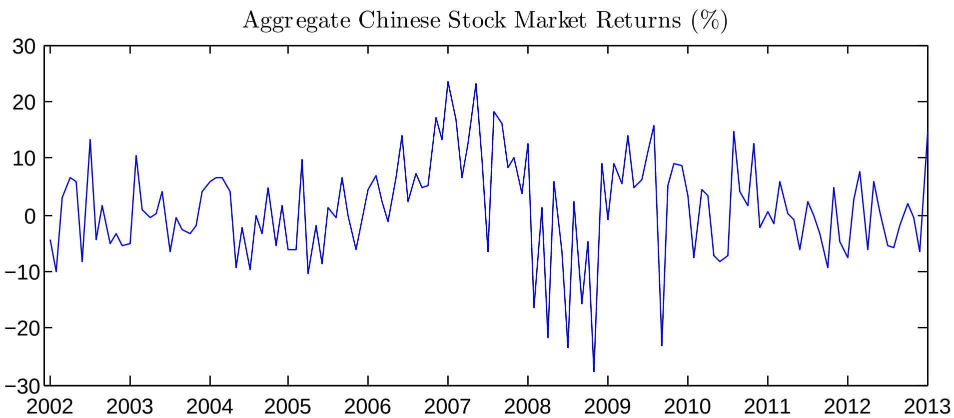

EXHIBIT 2. Summary Statistics

Panel A reports the mean, standard deviation (Std. Dev.), skewness (Skew.), kurtosis (Kurt.), minimum (Min.), maximum (Max.), first-order autocorrelation coefficient (AR(1)), and Sharpe ratio (SR) for the monthly excess returns (in percentage) of the aggregate Chinese stock market portfolio (MKT), market downside risk (DR), realized volatility (RV), and six economic variables. Panel B reports the correlation matrix for market downside risk (DR), realized volatility (RV), and six economic variables. Our data sample period extends from January 2002 through December 2012.

Panel A: Descriptive statistics

	Mean	Std. Dev.	Skew.	Kurt.	Min.	Max.	AR(1)	SR
MKT (%)	0.86	9.11	-0.34	3.88	-27.77	23.34	0.14	0.09
DR (%)	12.04	1.37	0.21	3.78	9.19	16.04	0.92	
RV (%)	7.81	1.12	-0.23	1.90	5.23	9.67	0.92	
D/P	-2.90	0.41	1.76	5.47	-3.35	-1.66	0.95	
D/Y	-2.90	0.42	1.76	5.42	-3.35	-1.64	0.95	
D/E	-1.58	0.44	1.01	3.43	-2.26	-0.49	0.95	
B/M	-0.89	0.36	-0.44	2.31	-1.69	-0.29	0.96	
E/P	-1.32	0.23	-0.38	1.78	-1.71	-0.93	0.96	
INF	0.02	0.03	0.45	2.43	-0.02	0.09	0.96	

Panel B: Correlation between downside risk, realized volatility, and economic variables

	DR	RV	D/P	D/Y	D/E	B/M	E/P	INF
DR	1	0.78	-0.09	-0.08	0.17	-0.58	-0.29	0.05
RV	0.78	1	-0.16	-0.15	-0.03	-0.40	-0.06	0.14

EXHIBIT 3. Out-of-sample Prediction

This table reports the out-of-sample predictability of the aggregate Chinese stock market. Each forecast in Panel A is generated by the recursive univariate predictive regression using the market downside risk, realized volatility, or one of the six economic variables given in the first column; and the forecasts in Panel B are based on the recursive bivariate predictive regressions by combining the downside risk with one of the six economic variables given in the fourth column. R^2_{OS} is the Campbell and Thompson (2008)'s out-of-sample R^2 statistic, which measures the reduction in mean squared forecast error (MSFE) for the competing predictive regression forecast relative to the historical average benchmark forecast. *MSFE-adjusted* is the Clark and West (2007)'s statistic for testing the null hypothesis that the historical average forecast MSFE is less than or equal to the competing predictive regression forecast MSFE against the one-sided (upper-tail) alternative hypothesis that the historical average forecast MSFE is greater than the competing predictive regression forecast MSFE. All of the predictive regression slopes in out-of-sample forecasts are estimated recursively using the data available through period of forecast formation t. The out-of-sample evaluation period extends from January 2005 through December 2012.

Panel A: Univariate forecasts			Panel B: Bivariate forecasts		
Predictor	R^2_{OS}	*MSFE-adjusted*	Predictor	R^2_{OS}	*MSFE-adjusted*
DR	5.99%	2.44			
RV	1.40%	1.16			
D/P	-4.43%	1.58	*DR* + D/P	1.90%	2.18
D/Y	-5.70%	1.49	*DR* + D/Y	0.84%	2.12
D/E	-2.78%	-0.01	*DR* + D/E	1.79%	1.50
B/M	3.45%	1.71	*DR* + B/M	4.45%	1.91
E/P	0.95%	1.54	*DR* + E/P	4.10%	1.87
INF	-3.33%	-0.47	*DR* + INF	1.75%	1.51

EXHIBIT 4. Market Timing Portfolio Performance

This table reports the asset allocation performance measures for the mean-variance portfolio manager with a risk aversion coefficient of five, who allocates monthly between the aggregate Chinese stock market and risk-free bill using the out-of-sample forecasts for excess aggregate Chinese stock market returns. Each forecast is based on the market downside risk, realized volatility, or one of the six economic variables given in the first column. Δ is the annualized certainty equivalent return (CER) gain for an investor who uses the predictive regression forecast instead of the historical average benchmark forecast. The monthly Sharpe ratio is the average return of the portfolio formed on the predictive regression forecast in excess of the risk-free rate divided by its standard deviation. Turnover is the average monthly turnover for the portfolio based on the predictive regression forecast. Δ, tc = 50bps is the CER gain assuming a proportional transactions cost of 50 basis points per transaction. The out-of-sample evaluation period is over 2005:01–2012:12.

	Δ (ann.)	Sharpe ratio	Turnover	Δ (ann.), tc = 50bps
DR	5.94%	0.24	2.68%	5.93%
RV	3.09%	0.17	9.56%	2.60%
D/P	-4.99%	0.16	5.51%	-5.22%
D/Y	-5.15%	0.16	5.54%	-5.38%
D/E	0.66%	0.12	6.23%	0.38%
B/M	2.99%	0.24	7.32%	2.64%
E/P	0.25%	0.24	7.69%	-0.11%
INF	-1.09%	0.07	3.68%	-1.25%

EXHIBIT 5. Summary Statistics for Industry Portfolios

Panel A reports the mean, standard deviation (Std. Dev.), first-order autocorrelation coefficient (AR(1)), and Sharpe ratio (SR) for the monthly excess returns (in percentage) of the 13 Chinese industry portfolios and the equal-weighted buy-and-hold portfolio (*EW Portfolio*). Panel B reports the correlation matrix for the 13 industry portfolios. Our data sample period extends from January 2002 through December 2012.

Panel A: Statistics description for industry portfolios (%)

	Mean	Std. Dev.	AR(1)	SR		Mean	Std. Dev.	AR(1)	SR		Mean	Std. Dev.	AR(1)	SR
AGRIC	0.69	10.45	0.04	0.07	TRANS	0.36	8.82	0.08	0.04	PROPT	1.01	11.12	0.15	0.09
MINES	1.20	9.70	0.09	0.12	INFTK	0.49	8.94	0.04	0.05	SRVC	0.98	9.77	0.15	0.10
MANUF	0.90	9.76	0.11	0.09	WHTSL	0.81	9.98	0.16	0.08	MEDIA	0.78	11.49	-0.07	0.07
UTILS	0.47	9.17	-0.01	0.05	MONEY	0.88	10.19	0.01	0.09	MULTP	0.76	10.61	0.11	0.07
CNSTR	0.34	9.63	0.04	0.04										
EW portfolio	0.68	8.89	0.08	0.08										

Panel B: Correlation matrix

	AGRIC	MINES	MANUF	UTILS	CNSTR	TRANS	INFTK	WHTSL	MONEY	PROPT	SRVC	MEDIA	MULTP
AGRIC	1	0.58	0.88	0.78	0.83	0.75	0.84	0.90	0.45	0.68	0.83	0.83	0.86
MINES		1	0.77	0.77	0.69	0.82	0.71	0.68	0.74	0.71	0.67	0.54	0.66
MANUF			1	0.91	0.90	0.91	0.92	0.96	0.64	0.82	0.93	0.85	0.94
UTILS				1	0.88	0.89	0.82	0.86	0.60	0.74	0.85	0.76	0.88
CNSTR					1	0.82	0.81	0.89	0.57	0.81	0.88	0.81	0.91
TRANS						1	0.82	0.84	0.69	0.74	0.82	0.74	0.84
INFTK							1	0.89	0.60	0.75	0.86	0.83	0.87
WHTSL								1	0.55	0.78	0.93	0.88	0.94
MONEY									1	0.65	0.56	0.42	0.55
PROPT										1	0.86	0.65	0.82
SRVC											1	0.83	0.94
MEDIA												1	0.86
MULTP													1

EXHIBIT 6. Industry Rotation Portfolio Performance

This table reports the asset allocation measures for the mean-variance portfolio manager with a risk aversion coefficient of five, who allocates monthly between 13 Chinese industry portfolios and risk-free bill using the out-of-sample forecasts for the excess industry portfolio returns. Each forecast is based on the market downside risk, realized volatility, or one of the six economic variables given in the first column. Δ is the annualized certainty equivalent (CER) return gain for an investor who uses the predictive regression forecast instead of the historical average benchmark forecast. The monthly Sharpe ratio is the average return of the portfolio formed on the predictive regression forecast in excess of the risk-free rate divided by its standard deviation. Turnover is the average monthly turnover for the portfolio based on the predictive regression forecast. Δ, tc = 50bps is the CER gain assuming a proportional transactions cost of 50 basis points per transaction. The out-of-sample evaluation period is over 2005:01–2012:12.

	Δ (ann.)	Sharpe ratio	Turnover	Δ (ann.), tc = 50bps
DR	6.59%	0.15	9.63%	6.31%
RV	3.91%	0.08	21.54%	2.87%
D/P	-2.97%	0.03	16.43%	-3.72%
D/Y	-3.66%	0.02	17.52%	-4.46%
D/E	-2.52%	0.04	18.75%	-3.40%
B/M	3.24%	0.15	19.64%	2.33%
E/P	-3.81%	0.08	17.85%	-4.63%
INF	-2.69%	0.03	13.37%	-3.33%

EXHIBIT 7. Size and Value Rotation Portfolios Performance

This table reports the asset allocation measures for the mean-variance portfolio manager with a risk aversion coefficient of five, who allocates monthly between 10 Chinese size (value) portfolios and risk-free bill using the out-of-sample forecasts for the excess size (value) portfolio returns. Each forecast is based on the downside risk, realized volatility, or one of the six economic variables given in the first column. Δ is the annualized certainty equivalent (CER) return gain for an investor who uses the predictive regression forecast instead of the historical average benchmark forecast. The monthly Sharpe ratio is the average return of the portfolio formed on the predictive regression forecast in excess of the risk-free rate divided by its standard deviation. Turnover is the average monthly turnover for the portfolio based on the predictive regression forecast. Δ, tc = 50bps is the CER gain assuming a proportional transactions cost of 50 basis points per transaction. The out-of-sample evaluation period is over 2005:01–2012:12.

	Δ (ann.)	Sharpe ratio	Turnover	Δ (ann.), tc = 50bps
Panel A: Size rotation portfolio performance				
DR	5.34%	0.11	10.28%	5.17%
RV	3.95%	0.05	23.50%	2.92%
D/P	-4.05%	0.03	16.71%	-4.69%
D/Y	-4.92%	0.02	17.42%	-5.60%
D/E	-2.94%	0.01	15.86%	-3.49%
B/M	0.98%	0.12	21.16%	0.21%
E/P	-1.07%	0.11	18.59%	-1.68%
INF	-1.77%	0.02	14.72%	-2.32%
Panel B: Value rotation portfolio performance				
DR	5.41%	0.12	10.27%	5.24%
RV	3.92%	0.05	23.36%	2.89%
D/P	-4.10%	0.03	16.79%	-4.74%
D/Y	-4.98%	0.02	17.51%	-5.66%
D/E	-3.06%	0.01	15.83%	-3.61%
B/M	0.92%	0.12	21.19%	0.15%
E/P	-1.17%	0.11	18.63%	-1.79%
INF	-1.87%	0.02	14.70%	-2.43%