

MONITORING THE FIVE RISKS:

Analytical Risk Measurement for Retail Investors and Wealth Managers

By James T. Chong, PhD, William P. Jennings, PhD, and G. Michael Phillips, PhD

Retail investors and wealth managers typically face constraints and risks that short-term traders don't. Short-term traders are usually in and out of the marketplace so quickly that the overall economy is relatively unchanged. Traditionally, most risk measurements have focused on the needs of traders that are quickly in and out of the market and of institutional money managers that rebalance portfolios day to day as cash flows in and out of funds. However, retail investors and wealth managers need more detailed information about more types of risk because of the much longer average holding periods they maintain for their portfolios. This article reviews the "five risks" approach to analytical risk measurement with specific applications to retail investors and wealth managers.¹

Returns-Based Measures

Traditional short-term measures of risk are usually returns-based, measuring the volatility of returns and various measures of the correlation of asset or portfolio returns with benchmark returns. It is common for a standard deviation of returns to be a measure of total volatility of an asset or portfolio and the popular beta coefficient of the capital asset pricing model (CAPM) to measure the units of nondiversifiable risk present in the investment. Similarly, the Value at Risk reflects a two-standard-deviation confidence band of a pricing model, typically the CAPM, expressed as a percentage of the asset value.

We begin this review by looking at alternative short-term risk measures that may be more useful for individual investors and wealth managers. In the early academic discussions of what became modern portfolio

theory, it was agreed that the standard deviation methods were heavy-handed in that they confuse potential upside gain with downside loss and count them both as risk (Chong et al. 2011; Chong and Phillips 2012a). However, one-sided risk measurements were too difficult to estimate given the limited computer resources available. With today's free computational power, the short-term measures of lower semideviation and downside beta become practical as day-to-day analytical risk measurements. These capture the first of our five risks, market risk.

Downside Risk Measures

The lower semideviation for a portfolio is computed using those returns that are below the overall portfolio mean return. This can be done with regular day-to-day returns, but it is also frequently computed using excess returns relative to a riskless rate such as the federal funds rate or a U.S. Treasury yield. The average of a series' lower semideviation and upper semideviation together would be the series standard deviation. The value of using the lower semideviation is that it does not confuse return and loss as risk.

In a similar way, the downside beta is computed using returns from those days when the benchmark return (or the benchmark excess return relative to a riskless rate) is negative. Investors often are surprised that the downside beta and its corresponding upside beta, from those days when the benchmark return is positive, are not symmetric (Chong et al. 2013; Chong, Halcoussis et al. 2012). About half the time the CAPM beta is larger than both the upside and downside betas or smaller

than both the upside and downside betas (Chong et al. 2014). When using downside beta as a filter, we use a value of 0.7 as a threshold rather than 1.0. Over the long term, the median downside beta has been closer to 0.7 while the average (arithmetic mean) has been closer to 1.0.²

Momentum and Behavioral Risk

The second of the five risks is a behavioral risk related to momentum. The version we use is simple to implement. It is the ratio of the asset price to its 52-week high (George and Hwang 2004). When a price is substantially off its 52-week high, especially when the overall market hasn't also collapsed, this could indicate there was negative information about the stock or it could mean that the stock is out of favor in the public eye. Regardless, stocks trading near their 52-week highs demonstrate positive momentum and outperform market averages than those stocks less in favor. We use a ratio of greater than 85 percent.

Economic Risk

The third of the five risks is sensitivity to the economy. Various forms of the arbitrage pricing theory relate assets' market performance to economic variables. Most of these are returns-based and hence have short-term applicability by focusing on high-frequency information; but some, such as the MacroRisk Eta[®] pricing model, focus on cointegration-style long-term price relationships (Chong, Jennings et al. 2012a). The MacroRisk Index (MRI, also known as "Composite MacroRisk Index") is computed from the estimated factor loadings from the Eta[®] pricing model and provides an overall measure of the economic risk present in

the asset. Money market funds have single-digit MRI values and large well-diversified indexes, most mutual funds have double-digit MRI values, and most common stocks have triple-digit and higher MRI values. We suggest that MRI values should be less than 350 for individual investments and closer to 100 or less for a well-diversified portfolio.

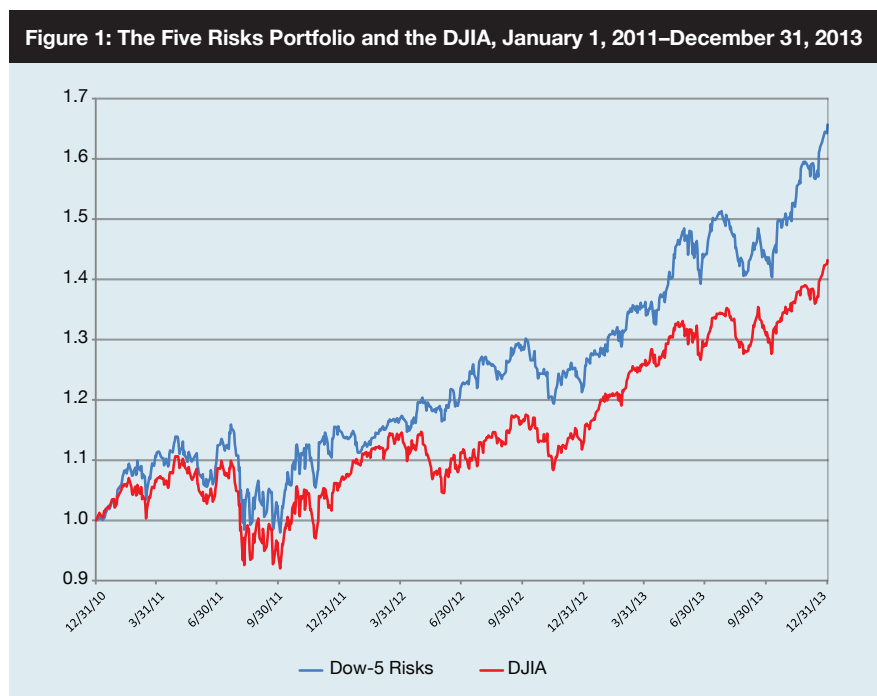
In addition there are quantitative measures of potential price appreciation based on a top-down analysis of the impact of the economy on investments. The “Economic Climate Rating” is a number between one and five that statistically estimates whether the economy is a strong headwind (1), neutral (3), or a strong tailwind (5).³

Attribution Instability Risk

The fourth of the five risks is attribution instability. When investors purchase an asset for a longer holding period, they must be concerned with the possibility of the asset changing its basic relationship to the market. As an extreme, suppose you purchased shares in a computer company and then discovered the company was divesting its laptop and printer lines. Or, suppose you purchased shares in a popular restaurant chain that closed its doors and changed its focus to retail grocery products. Or, suppose you purchased shares of a mutual fund that over time changed its investing focus from domestic consumer cyclicals to Asian real estate holdings. The consistency of the investment’s relationship to the overall economy over time is attribution stability. One measurement of attribution stability is the R-squared statistic from the Eta® model, which measures the extent of the economy’s influence in determining current market value. The related value, 1 minus R-squared, is the measure of attribution instability risk (Chong and Phillips 2012b). When the economy has little consistent relationship with the stock value, the R-squared is low and the attribution instability risk is high. We limit attribution instability to only 5 percent to 15 percent.

Residual Risk

The final quantitative measure is the Residual Risk Index, also known as Eta® Value at Risk. A traditional Value at Risk



(VaR) is computed by taking the two-standard-deviation value for the residuals from an asset pricing model expressed in dollars as a percentage of the historical average price of the model’s target variable; popular models for VaR computation include the capital asset pricing model, the arbitrage pricing model, and various multiple index models. The Eta® Value at Risk uses the Eta® pricing model. Like traditional VaR computations, one would take the two-standard-deviation value of its residuals and express that as a percentage of the average stock price for the issue being modeled (Chong, Jennings et al. 2012b). The Eta® Value at Risk measures the percentage impact on the stock price expected from a shock due to idiosyncratic factors that are not captured by the economic variables in the model. We find that, in investment periods up to 18 months to two years out, maintaining Eta® Value at Risk at less than 20 percent is associated with more stable performance and higher risk-adjusted return.

A Five Risks Portfolio

As an example, consider applying the five risks analytical measurements to the 30 Dow Industrials. The Dow stocks are among the most closely watched and efficient assets

Table 1: Fama-French Three-Factor and Carhart Four-Factor Regressions

| | Dow-5 Risks | DJIA |
|---|-------------|--------|
| Annualized Return | | |
| 2011 | 14.98% | 5.53% |
| 2012 | 6.80% | 5.70% |
| 2013 | 31.83% | 23.59% |
| Standard Deviation | | |
| 2011 | 20.95% | 21.02% |
| 2012 | 9.76% | 11.88% |
| 2013 | 13.21% | 10.16% |
| Ratio of Annualized Return to Standard Deviation | | |
| 2011 | 0.715 | 0.263 |
| 2012 | 0.697 | 0.480 |
| 2013 | 2.410 | 2.321 |

sold in open markets. Since 2010, we have applied the five risks method to select a low-volatility portfolio of Dow 30 stocks as part of an annual economy in review.⁴

Figure 1 shows the results. The portfolio comprises seven to 10 of the Dow 30 stocks purchased at the beginning of the year and

Table 2: Fama-French Three-Factor and Carhart Four-Factor Regressions

| | Fama-French 3-Factor | Carhart 4-Factor |
|-------------------------|----------------------|------------------|
| Annual Alpha | 3.89% | 2.18% |
| MKT – RF | 0.8522** | 0.8583** |
| SMB | -0.2541** | -0.2290** |
| HML | 0.0903* | 0.2386** |
| MOM | — | 0.2477** |
| Adjusted R ² | 0.8129 | 0.8352 |
| | * p < 0.05 | **p < 0.01 |

Table 3: A Five Risks Portfolio of Dow 30 Stocks, as of December 31, 2013

| Company Name | Coca-Cola | Johnson & Johnson | Pfizer | Verizon Communications | Wal-Mart Stores |
|--------------------------------|-----------|-------------------|--------|------------------------|-----------------|
| Ticker | KO | JNJ | PFE | VZ | WMT |
| Downside Beta | 0.6957 | 0.6324 | 0.6419 | 0.4125 | 0.3326 |
| Price to High Price | 97.91% | 95.78% | 95.12% | 93.12% | 97.46% |
| MacroRisk Index | 79 | 91 | 99 | 94 | 115 |
| Economic Climate Rating | 2 | 3 | 3 | 4 | 3 |
| Attribution Stability | 96.01% | 98.57% | 98.40% | 97.06% | 96.31% |
| Eta [®] Value at Risk | 4.12% | 4.09% | 5.15% | 5.77% | 6.32% |

sold at the end of the year and replaced with a new portfolio. The annually rebalanced five risks portfolio returned 18.32 percent per year compared to the overall Dow 30, which returned 12.71 percent per year. The Sharpe ratio for the five risks portfolio was 1.195 and for the Dow 30 was 0.842. Using the lower semideviation as the divisor, we also computed the Sortino ratios.⁵ For the five risks portfolio, the Sortino ratio was 1.157 and for the Dow 30 it was 0.821.

Table 1 provides further insight into the performances of the five risks portfolio and the Dow Jones Industrial Average (DJIA) by year. In 2011 and 2012, the low-volatility portfolio of Dow 30 stocks outperformed the DJIA for annualized return and standard deviation, which resulted in a favorable ratio. In 2013, the five risks portfolio is also preferred, with a favorable ratio as a

result of its higher return compensating for its higher risk.

Next, we conduct an analysis of factor exposures of the five risks portfolio by utilizing the Fama-French three-factor model and the Carhart four-factor model (see table 2). The Fama-French three factors are related to the market (i.e., market return minus the risk-free rate, MKT – RF), size (SMB), and value (HML). Carhart introduced the fourth factor, momentum (MOM). Both the three- and four-factor models are fairly powerful (with adjusted R-squared statistics of 81.29 percent and 83.52 percent, respectively) in explaining the sources of returns of the five risks portfolio, which has statistically significant loadings on all four factors. With only a slight increase in adjusted R-squared, this would suggest there are other factors not accounted for, such as

those related to quality of firms and volatility of stocks, among others.

Applying the five risks analytical risk measurement tools identifies a handful of Dow 30 stocks that meet these criteria. Table 3 shows a variety of these statistics for the Dow 30 as of December 31, 2013, when this analysis was performed. Were we to rebalance the above portfolio now, it would likely select KO, JNJ, PFE, VZ, and WMT for an equally weighted portfolio.

The methods described here have been researched and successfully applied to a wide range of assets including most types of common stocks, exchange-traded funds, mutual funds, preferred stocks, and closed-end funds. They also have been implemented using indexes and subportfolios for asset allocation purposes. The Dow 30 was selected for this research because those stocks are among the most efficiently traded and widely analyzed and consequently provided a stronger demonstration of these methods.

Conclusion

Retail investors and wealth managers often face longer holding periods and longer planning horizons than institutional fund managers and stock traders. While many of the analytical measurements of risk used by short-term traders provide some information to retail investors, the unique needs resulting from the longer planning horizons introduce several areas where additional analytical risk measurements are appropriate. Besides traditional market risk, investors must know momentum and behavioral risk, changing economic conditions, changing attribution, and idiosyncratic risk components. The “five risks” paradigm we have demonstrated here could be built from scratch, using spreadsheets and common regression programs, or by using available tools such as those on the MacroRisk Analytics platform. Either way, the “five risks” paradigm we have demonstrated provides an accessible and easily implemented approach to analytical risk measurement for retail investors and wealth managers. ●

Continued on page 24 ➔

MONITORING THE FIVE RISKS

Continued from page 19

James T. Chong, PhD, is a professor of finance at California State University, Northridge, and a research economist at MacroRisk Analytics. He earned a PhD in finance from The University of Reading. Contact him at jchong@macrorisk.com.

William P. Jennings, PhD, is dean emeritus of the College of Business and Economics at California State University, Northridge, where he was chair of the Department of Finance, Financial Planning, and Insurance. He earned a PhD in economics from the University of California, Los Angeles. Contact him at bjennings@macrorisk.com.

G. Michael Phillips, PhD, is director of the Center for Financial Planning and Investment and a professor of finance, financial planning,

and insurance at California State University, Northridge. He also serves as chief scientist for MacroRisk Analytics. He earned a PhD from the University of California, San Diego, with specializations in econometrics and applied economics. Contact him at mphillips@macrorisk.com.

Endnotes

1. This method was described in Chong, Jennings et al. (2012b).
2. As of October 25, 2013, the mean downside beta for common stocks was 1.12 while the median was 1.09.
3. <http://www.macrorisk.com/how-it-works/examples/>
4. In January 2011, the review was provided to ProducersEsource.com as a column. In January 2012 and 2013, it was provided to the T3-Technology Tools for Today newsletter as a supplement for readers.
5. <http://www.forbes.com/sites/phildemuth/2013/10/24/what-is-risk-everything-you-need-to-know-about-the-sortino-ratio/>.

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