Low-Volatility Portfolio Construction: *Ranking Versus Optimization*

AYE M. SOE

AYE M. SOE
is director of Index Research & Design at S&P Dow Jones Indices in New York, NY.
aye_soe@spdji.com

Among the long-standing anomalies in modern investment theory, perhaps none is as puzzling and compelling as the low-volatility effect. It challenges the traditional equilibrium asset pricing theory that an asset's expected return is directly proportional to its beta or systematic risk, or, in other words, higher-risk securities should be rewarded with higher expected returns while lower-risk assets receive lower expected returns.

Contrary to that theory, the empirical evidence of numerous academic studies has illustrated that low-volatility or low-risk investing outperforms the broad market as well as high-risk strategies over a long-term investment horizon with much less realized volatility (see section on academic literature). In the U.S. equity market, the S&P 500 Low Volatility Index returned 6.95% (10.75% standard deviation) and the MSCI USA Minimum Volatility Index returned 5.1% (12.32% standard deviation) on an annualized basis over the 10 years that ended March 31, 2012, with 23% to 30% lower volatility than a market cap-weighted benchmark such as the S&P 500, which returned 4.12% (15.99% standard deviation).

Low-volatility investing is not a new concept, but the financial crisis of 2008 and the market's see-sawing volatility during the second half of 2011 have brought it back to the investment community's attention for risk management purposes. The resurgence of low-volatility investing has also reignited the theoretical debate on the properties of a true market portfolio. In a textbook world of Modern Portfolio Theory, a "market portfolio" is an optimal portfolio (that is, no other can exist with higher return for a given level of risk). However, the market portfolio is unobservable, so a market cap-weighted broad market benchmark is typically used as a proxy. Low-volatility strategies' outperformance compared to a market cap-weighted benchmark over a long-term investment horizon has raised the question of whether the superior performance is due to an anomalous behavior or an incompletion in the single-factor asset pricing model.

In this article, we analyze the low-volatility effect in the U.S. equity market with a focus on the common properties of various low-volatility strategies. Drawing from the extensive academic literature that exists on the topic, we examine the two major approaches to constructing low-volatility portfolios and apply them to the U.S. equity market: mean variance optimization-based versus the rankings-based approaches. Our analysis shows that both approaches are equally effective in reducing portfolio volatility over a long-term investment horizon. We then extend our analysis to the international and emerging markets. Our findings confirm that the low-volatility effect is not unique to the U.S. equity markets; it is present on a global scale.

THE LOW-VOLATILITY EFFECT IN ACADEMIC LITERATURE

Substantial academic literature exists on low-volatility investing. Black, Jensen, and Scholes [1972] demonstrated that the expected excess return on a security was not linearly related to its beta. The authors found that the alphas of high-beta securities were negative while the alphas of low-beta securities were positive. Fama and French [1992] also observed that the positive relationship between average return and beta was weak. The returns of high-beta portfolios had average returns that were close to or less than those of low-beta portfolios. Black [1993] suggested that even if Fama and French are correct in their conclusions, investors should consider a strategic tilt toward low-beta portfolios.

Ang, Hodrick, Xing, and Zhang [2006] found that stocks with high idiosyncratic volatility tended to have normal returns during bull periods in the U.S. and in international markets. However, their returns were lower during bear market periods or recessions. On average, the returns were negative, earning –0.02% per month during the 1963-to-2000 study period. The pattern of negative returns associated with the volatility factor was equally noted by Kang [2012], indicating that portfolios tilted to low-risk securities had higher returns than those tilted to high-risk stocks.

The mean-variance framework pioneered by Markowitz [1952] serves as the foundation of the optimization-based low-risk investing strategies.[1] Haugen and Baker [1991], using the minimum-variance portfolio based on the 1,000 largest U.S. stocks, illustrated that market cap-weighted portfolios were inefficient because there were alternative portfolios with lower volatility and higher returns. Using data from January 1968 to December 2005, Clark, de Silva, and Thorley [2006] constructed minimum-variance portfolios that had annualized realized volatility at three-fourths that of the broad market [11.7% versus 15.4%]. At 0.55, the Sharpe ratio of the minimum-variance portfolio was higher than the market cap-weighted benchmark's Sharpe ratio of 0.36.

Blitz and van Vliet [2007] created decile portfolios based on the rankings of stocks by their three-year realized volatility. Their study showed that the volatility of the top decile portfolio was about two-thirds of the market volatility, while the volatility of the bottom decile portfolio had a standard deviation that was almost twice that of the market. Another important finding in their study was that stocks with low volatility exhibited low beta, while stocks with high volatility exhibited high beta. In other words, using beta or variance as a measure of volatility should produce the same impact on the portfolio's returns and risk profile.

Baker, Bradley, and Wurgler [2011] demonstrated that whether risk was defined as beta or volatility, low-risk portfolios consistently outperformed high-risk portfolios over a long-term investment horizon. Using data from January 1968 to December 2008, stocks were divided into five groups based on their five-year trailing volatility or trailing beta. The results showed that the bottom quintile beta and volatility portfolios outperformed the top quintile portfolios. Applying the principles of behavioral finance and institutional benchmarking limitations, the authors attributed the low-risk anomaly to average investors' preference for positive skewness or lottery-like payoffs with high-volatility stocks and the institutional limitation on using leverage. Carvalho, Lu, and Moulin [2012] proposed that a rankings- or quantile-based low-volatility construction approach could be considered as an equal-risk budget strategy that does not account for the impact of correlations between stocks.

A CLOSER LOOK AT TWO LOW-VOLATILITY STRATEGIES

Based on existing research, there are two principal ways to construct low-volatility strategies. The first is the mean-variance optimized approach, as proposed by Markowitz [1952], in which a portfolio's variance is minimized by considering the correlations among stocks.[2] The second approach involves dividing a universe of securities into quantiles by a measure of volatility, either beta or standard deviation, and forming a portfolio based on the least-volatile stocks. Unlike using the minimum-variance approach to create a low-volatility portfolio, the rankings-based approach, in theory, forms a portfolio of low-volatility stocks. Blitz and van Vliet [2011] concurred with the earlier academic studies that using a simple and more transparent quantile- or rankings-based approach for low-volatility portfolio construction is equally as effective at reducing volatility as the mean-variance optimized approach.

We evaluated the low-volatility effect in the U.S. equity market using both the quantile- or rankings-based approach and the minimum-variance optimization approach. We divided the U.S. equity market into three market cap ranges (large cap, mid cap and small cap) and applied the low-volatility strategy construction approaches to all three. The division allowed us to determine whether low-volatility effect was present in all three market caps.

Rankings-Based Approach

In the rankings-based approach, we divided each market cap segment, as represented by the S&P 500, S&P MidCap 400, and S&P SmallCap 600, into quintiles based on the standard deviation of the trailing 252 trading days' price changes. Securities in the bottom quintile constitute the low-risk strategy and were weighted by the inverse of their standard deviation,[3] thereby giving the least-volatile stock the highest weight. The maximum weight of a security is capped at 5% while no sector constraint is set. Each group is rebalanced on a quarterly basis.

Minimum-Variance Approach

The Northfield U.S. Fundamental Model[4] and the Northfield Open Optimizer are utilized to construct minimum-variance portfolios. In a standard Markowitz framework, a minimum-variance portfolio resides on the farthest-left corner of the efficient frontier. It has the lowest risk among all possible portfolios, given the covariance matrix among securities.

We constructed two minimum-variance–based strategies for each market cap range: the base unconstrained case and the constrained case. Both are limited to long-only. In the base case, there are no restrictions on the maximum weight of a security or a sector. In the constrained case, we limited the maximum weight of a security to 5%, the minimum weight of a sector to 50% of the benchmark sector's weight, and the maximum weight of a sector to 150% of the benchmark sector's weight. Similar to the rankings-based approach, the minimum-variance–based strategies are rebalanced on a quarterly basis.

We constructed a base portfolio and a constrained portfolio for minimum-variance–based strategies because a pure minimum-variance portfolio can produce concentrated, unrepresentative stock and sector weights if left unconstrained. For example, in our base minimum-variance portfolio, the number of stocks in a portfolio at rebalancing ranged from 17 to 54 and their weights ranged from 0.001% to 26.52% with sector weight differences as great as 54% of the underlying benchmark sector weights. The extreme concentration can be attributed to the presence of estimation errors in the minimum-variance approach, in which risk is underestimated for some stocks, as highlighted by Monnier and Rulik [2011]. Additional constraints such as maximum weights of the stock, sector and country exposures can be imposed on the portfolio weights to reduce the concentration problem.

COMMON PROPERTIES OF LOW-VOLATILITY STRATEGIES

In this section, we highlight two key common properties shared by rankings-based and minimum-variance–based low-volatility strategies. The properties stem from the risk-return behaviors of the strategies observed during different market environments.

Better Risk-Adjusted Returns

Low-volatility strategies deliver superior risk-adjusted returns compared to market cap-weighted market benchmarks over a long-term investment horizon. Exhibits 1 to 3 present the risk-return profiles of the rankings-based and the constrained and unconstrained minimum-variance–based low-volatility portfolios for the U.S. large-cap, mid-cap, and small-cap equity market segments. Returns are presented as annualized geometric averages.

In the large-cap segment, we split the 21-year sample periods into 10-year and 11-year subperiods. All three low-volatility strategies, despite their varying risk-return profiles, outperformed the benchmark over the long-term with much lower realized volatility. Average risk reduction amounted to approximately 30% over the most recent 10-year period and 20% over a 21-year period for all three strategies. With the exception of January 1991–December 2000 performance figures,

Exhibit 1
Comparisons of Large-Cap Low-Volatility Strategies

	Minimum Variance			
	Base Case—Unconstrained	Constrained	Ranking Based	S&P 500
January 1991–December 2011				
Return	11.51%	11.29%	10.39%	8.80%
Standard Deviation	11.98%	12.82%	11.37%	15.08%
Sharpe Ratio	0.681	0.620	0.619	0.361
January 1991–December 2000				
Return	13.53%	16.57%	14.26%	17.46%
Standard Deviation	12.34%	12.83%	11.90%	13.37%
Sharpe Ratio	0.700	0.910	0.787	0.939
January 2001–December 2011				
Return	9.71%	6.70%	6.98%	1.48%
Standard Deviation	11.68%	12.72%	10.82%	16.28%
Sharpe Ratio	0.663	0.372	0.463	–0.030

Source: S&P Dow Jones Indices LLC. Data current as of December 31, 2011. The Minimum Variance Constrained and Unconstrained Strategies were constructed using the Northfield Portfolio Optimizer and Simulator. The Rankings Based Low Volatility Strategy (S&P 500 Low Volatility Index) was launched on April 4, 2011, and constructed based on the S&P 500 Index. Past performance is no guarantee of future results. All data referenced in the chart prior to April 4, 2011, reflects hypothetical historical performance.

Exhibit 2
Comparisons of Mid-Cap Low-Volatility Strategies

	Minimum Variance			
	Base Case—Unconstrained	Constrained	Ranking Based	S&P MidCap 400
January 1992–December 2011				
Return	8.07%	9.20%	12.15%	10.96%
Standard Deviation	12.62%	12.95%	11.09%	17.45%
Sharpe Ratio	0.382	0.459	0.803	0.442
January 1992–December 2001				
Return	7.99%	12.56%	13.79%	15.02%
Standard Deviation	12.93%	12.47%	10.66%	16.31%
Sharpe Ratio	0.255	0.631	0.854	0.633
January 2002–December 2011				
Return	8.16%	5.94%	10.53%	7.04%
Standard Deviation	12.35%	13.41%	11.52%	18.53%
Sharpe Ratio	0.512	0.306	0.755	0.281

Source: S&P Dow Jones Indices LLC. Data current as of December 31, 2011. The Minimum Variance Constrained and Unconstrained Strategies were constructed using the Northfield Portfolio Optimizer and Simulator. The Rankings Based Low Volatility Strategy (a/k/a S&P MidCap 400 Low Volatility Index) has not been launched by S&P Dow Jones Indices but has been constructed based on the S&P MidCap 400 Index. Past performance is no guarantee of future results. All data referenced in the chart reflects hypothetical historical performance.

the unconstrained minimum-variance portfolio produced higher risk-adjusted returns than its constrained counterpart and the rankings-based portfolio. This is to be expected because the truly unconstrained minimum-variance portfolio should be the optimal Sharpe portfolio.

The risk-return profiles of the low-volatility strategies were mixed for mid-cap equities when measured over different periods. Over the full 20-year sample period, the constrained minimum-variance–based and the rankings-based strategies produced the higher Sharpe ratios than the market portfolio. The rankings-

Exhibit 3
Comparisons of Small-Cap Low-Volatility Strategies

	Minimum Variance			
	Base Case—Unconstrained	Constrained	Ranking Based	S&P SmallCap 600
January 1996–December 2011				
Return	10.39%	10.89%	12.13%	9.04%
Standard Deviation	14.12%	14.95%	14.19%	20.16%
Sharpe Ratio	0.523	0.528	0.643	0.299
January 1996–December 2003				
Return	12.34%	13.97%	16.00%	11.48%
Standard Deviation	14.25%	15.13%	13.06%	19.97%
Sharpe Ratio	0.581	0.655	0.914	0.372
January 2004–December 2011				
Return	8.48%	7.90%	8.40%	6.65%
Standard Deviation	14.04%	14.80%	15.25%	20.43%
Sharpe Ratio	0.464	0.401	0.422	0.230

Source: S&P Dow Jones Indices LLC. Data current as of December 31, 2011. The Minimum Variance Constrained and Unconstrained Strategies were constructed using the Northfield Portfolio Optimizer and Simulator. The Rankings Based Low Volatility Strategy (a/k/a S&P SmallCap 600 Low Volatility Index) has not been launched by S&P Dow Jones Indices but has been constructed based on the S&P SmallCap 600 Index. Past performance is no guarantee of future results. All data referenced in the chart reflects hypothetical historical performance.

based strategy appears to have produced the best risk-adjusted performance among the three when measured over the full sample period and two 10-year subperiods. Depending on the subperiod being measured, both constrained and unconstrained minimum-variance–based strategies fared worse than the market portfolio on risk-adjusted basis.

Using the Russell 1000 as the underlying large-cap universe and the Russell 2000 for the small-cap universe, Mezrich and Ishikawa [2011] found that, while low-volatility alpha is present in the large-cap space, it is absent in the small-cap space. The authors attributed the absence to the Russell 2000's less-concentrated market cap distribution feature, unlike its large-cap counterpart, which allows for the elimination of the large-cap "fat tail."[5] Nevertheless, our results indicate that the low-volatility effect is indeed present in the small-cap space. The finding could be partly attributed to the choice of underlying small-cap universe and the methodology differences between the S&P SmallCap 600 and the Russell 2000 (Soe [2009]). Nevertheless, our analysis shows that all three low-volatility strategies achieved higher Sharpe ratios than that of the benchmark over the entire 16-year sample period and the two eight-year subperiods.

Asymmetric Payoffs

Another property of low-volatility strategies is their upside and downside capture abilities. Although low-volatility strategies outperform the market with lower risk in general over the long-term, their behaviors in different environments over the short term can vary greatly. In other words, the strategies generate a consistent risk-return pattern in the aggregate; however, on a micro level, they may not always outperform, depending on the market conditions.

On average, low-volatility strategies outperformed their respective market benchmarks in 47% to 50% of the months studied in our analysis (see Exhibit 4). All three strategies tended to outperform less frequently when the market trended upward. This pattern reversed when the market faced headwinds. All three strategies outperformed the markets approximately 73% to 87% of the times when market returns were negative. This asymmetric response to market movements highlights the ability of low-volatility strategies to provide downside protection in uncertain times.

All three strategies consistently underperformed by approximately 0.55% to 1.7% during up market periods, depending on the market cap segment. The results indi-

EXHIBIT 4

Hit Rate—Percent of Months with Outperformance of the Low-Volatility Strategies over a Market Portfolio

	MV—Base	MV—Constrained	Rankings Based
Hit Rate—Percent of Months with Outperformance—Large Cap			
All Periods	51.37%	52.16%	49.41%
Up Months	38.79%	40.61%	31.52%
Down Months	74.44%	73.33%	82.22%
Hit Rate—Percent of Months with Outperformance—Mid Cap			
All Periods	46.56%	47.37%	48.18%
Up Months	25.97%	27.27%	24.68%
Down Months	80.65%	80.65%	87.10%
Hit Rate—Percent of Months with Outperformance—Small Cap			
All Periods	47.32%	48.29%	49.27%
Up Months	26.92%	26.92%	30.77%
Down Months	82.67%	85.33%	81.33%

Source: S&P Dow Jones Indices LLC. Data current as of December 31, 2011. The Minimum Variance Constrained and Unconstrained Strategies were constructed using the Northfield Portfolio Optimizer and Simulator. The Rankings Based Low Volatility Strategies (a/k/a S&P 500 Low Volatility Index, S&P MidCap 400 Low Volatility Index, and S&P SmallCap 600 Low Volatility Index) have been constructed based on the S&P 500, S&P MidCap 400, and S&P SmallCap 600 Indices, respectively. Past performance is no guarantee of future results. The data referenced in this chart may reflect hypothetical historical performance.

cate that low-volatility strategies did not participate fully in up markets and lagged benchmark returns. An opposite pattern emerged during down markets. All three strategies outperformed by 1.4% to 2.5%, depending on the market cap segment (Exhibit 5). Taken together with the results shown in Exhibit 4, it can be noted that low-volatility strategies possess asymmetric risk-return profiles: they outperform the market more frequently and with larger magnitude when it is down.

Across all three market cap segments, relative to the minimum-variance strategies, the rankings-based strategy outperformed the least frequently when the market was rallying but outperformed the most frequently when the market was trending down. With regard to the magnitude of outperformance, the rankings-based strategy outperformed the most during down markets. The difference in market risk level among the three strategies accounts for this behavior.

RISK COMPOSITION

As shown above, all three low-volatility strategies deliver superior risk-adjusted returns relative to a market cap-weighted benchmark portfolio despite significant differences in portfolio construction. However, even with the common thread of their risk-return behavior, they vary greatly in their risk composition.

Exhibit 6 presents the average risk exposure compositions of the low-volatility strategies over the past 21 years. Using the Northfield U.S. Fundamental Equity Risk Model, the contribution to ex ante total risk of each strategy in any given year was broken into systematic or market risk, factor risk, and stock-specific risk. Market risk is measured by the contribution of beta factor to total risk, factor risk is measured by the contribution of the remaining 11 factors and 55 industry variables to total risk, with the remaining portion making up the idiosyncratic risk.[6] The risk in each market cap segment was computed against the respective benchmark on a quarterly basis and averaged to create an annual figure.

Of the three low-volatility strategies, the rankings-based approach appears to have generated the lowest level of systematic or market risk. The levels of systematic risk for the two minimum-variance approaches were similar, with very little discernible difference, even though they were both higher than that of the rankings-

EXHIBIT 5

Average Monthly Outperformance of the Low-Volatility Strategies over a Market Portfolio

	MV—Base	MV—Constrained	Rankings Based
Average Monthly Outperformance over a Market Portfolio—Large Cap			
All Periods	0.14%	0.14%	0.05%
Up Months	–0.84%	–0.55%	–0.98%
Down Months	1.93%	1.40%	1.94%
Average Monthly Outperformance over a Market Portfolio—Mid Cap			
All Periods	–0.31%	–0.24%	–0.02%
Up Months	–1.69%	–1.36%	–1.54%
Down Months	1.96%	1.60%	2.50%
Average Monthly Outperformance over a Market Portfolio—Small Cap			
All Periods	–0.06%	–0.01%	0.13%
Up Months	–1.34%	–1.08%	–1.15%
Down Months	2.15%	1.86%	2.34%

Source: S&P Dow Jones Indices LLC. Data current as of December 31, 2011. The Minimum Variance Constrained and Unconstrained Strategies were constructed using the Northfield Portfolio Optimizer and Simulator. The Rankings Based Low Volatility Strategies (a/k/a S&P 500 Low Volatility Index, S&P MidCap 400 Low Volatility Index and S&P SmallCap 600 Low Volatility Index) have been constructed based on the S&P 500, S&P MidCap 400, and S&P SmallCap 600 Indices, respectively. Past performance is no guarantee of future results. The data referenced in this chart may reflect hypothetical historical performance.

Exhibit 6
Average Contribution to Total Risk of the Low-Volatility Strategies

	Systematic Risk	Factor Risk	Stock Specific Risk
Average Contribution to Total Risk—Large Cap			
Minimum Variance—Base	53.63	33.87	12.51
Minimum Variance—Constrained	45.23	37.79	17.24
Rankings Based	41.43	43.28	15.30
Average Contribution to Total Risk—Mid Cap			
Minimum Variance—Base	58.87	25.97	15.15
Minimum Variance—Constrained	56.70	25.36	17.93
Rankings Based	33.86	44.02	22.12
Average Contribution to Total Risk—Small Cap			
Minimum Variance—Base	63.24	24.96	11.80
Minimum Variance—Constrained	62.01	24.81	13.18
Rankings Based	43.84	45.89	10.27

Source: S&P Dow Jones Indices LLC. Data current as of December 31, 2011. The Minimum Variance Constrained and Unconstrained Strategies were constructed using the Northfield Portfolio Optimizer and Simulator. The Rankings Based Low Volatility Strategies (a/k/a S&P 500 Low Volatility Index, S&P MidCap 400 Low Volatility Index, and S&P SmallCap 600 Low Volatility Index) have been constructed based on the S&P 500, S&P MidCap 400, and S&P SmallCap 600 Indices, respectively. Past performance is no guarantee of future results. The data referenced in this chart may reflect hypothetical historical performance.

based strategy. This was consistent across all three market cap segments. Based on the results, we can conclude that the rankings-based strategy's return behavior can diverge significantly from market returns, as well as from the returns of the minimum-variance strategies. This supplements our analysis in the previous section on the hit rate and the magnitude of outperformance in various market environments (see Exhibits 4 and 5). The rankings-based strategy outperformed the least frequently in rising markets but outperformed the most frequently and by the largest magnitude in falling markets.

The design differences among the three approaches are also responsible for divergence in the level of factor risk taken. The rankings-based strategy has a substantially larger exposure to factor risk than the minimum-variance strategies. This is consistent across all three market cap segments. Similarly, Kang [2012] found that the non-optimized low-volatility strategies exhibited higher active risk and lower market beta compared to a minimum-variance strategy. Active constraints on factors and other risk exposures are typically placed on an optimized minimum-variance portfolio, so unlike the absence of those in the rankings-based strategy, the minimum-variance strategy has controlled exposure to factor risk but higher exposure to market risk. The differences in risk composition have implications on the sources of portfolio returns.

The levels of stock-specific risk taken by all three strategies differ as well, but not as much as the differences observed with market risk and factor risk.

KEY CONSIDERATIONS IN SELECTING AN APPROPRIATE LOW-VOLATILITY STRATEGY

Both rankings-based and mean-variance-optimization–based low-volatility strategies effectively provide volatility reduction of approximately one-third relative to a capitalization-weighted market index over a long-term investment horizon. However, due to differences in portfolio design and construction, each strategy may take on substantially different factor risk (see the section on risk composition), sector weights, and portfolio turnover. As we noted earlier, the rankings-based strategy does not impose active constraints on factor exposures or sector weights, and may at times deviate significantly from the weights of the underlying market capitalization-weighted portfolio. Minimum-variance strategies, on the other hand, typically place sector and factor constraints in order to yield representative portfolios or to maintain tight tracking error with respect to the market-cap weighted index.

Therefore, the selection of a low-volatility strategy for a benchmark would depend on the type of investor, his or her investment objectives, and risk tolerance. For example, an investor who lacks an understanding of the complex technique behind the mean-variance-optimization–based low-volatility strategy but is concerned with achieving lower total risk than a market portfolio may prefer a simpler and more transparent rankings-based strategy. On the other hand, a more sophisticated investor whose investment policy statement is mandated to maintain a tighter tracking error relative to a cap-weighted benchmark may prefer a mean-variance-optimization–based low-volatility strategy.

Turnover plays an important role in selecting a suitable low-volatility strategy. While no explicit constraint on turnover was imposed in our construction for the mean-variance–based strategies for all three market cap ranges, the average annual two-way turnovers remain lower than those of the rankings-based strategies. For example, the average annual two-way turnover of the U.S. Large Cap optimization-based strategy over the test period is 44.04%, while that of the rankings-based strategy is 60.67%. Tax efficiency of a strategy, therefore, would be of concern to a taxable investor.

Another key consideration in selecting an appropriate low-volatility strategy is to determine the right benchmark to measure the effectiveness of such strategy. Blitz and van Vliet [2011] theorized that at the end of the day, the purpose of low-volatility investing is to establish a risk-return profile that is superior to an investment in the market cap-weighted market portfolio. Simply comparing returns is not appropriate because low-volatility portfolios exhibit significantly lower risk than the benchmark. A performance measure that adjusts returns appropriately for risk is more relevant to evaluating the effectiveness of the strategy relative to a benchmark. The authors proposed using simple risk-adjusted performance metrics such as a Sharpe ratio or Jensen's alpha, depending on how risk is being defined (total risk versus beta). In our article, we used the Sharpe ratio as a benchmark to compare the results and to evaluate the effectiveness of both types of low-volatility strategies.

THE LOW-VOLATILITY EFFECT IN DEVELOPED AND EMERGING MARKETS

Studies have shown that low-volatility investing is equally effective on a global and regional scale. Based on a universe of European and Japanese large-cap stocks observed from 1986 to 2006, Blitz and van Vliet [2007] noted a 5.9% difference in average returns between the top and bottom decile portfolios. Regression results from the monthly returns of decile portfolios against the monthly market returns indicated a negative relation between estimated betas and alphas. On a regional level, the results showed alpha spreads of 10.2% for Europe and 10.5% for Japan. Blitz, Pang, and van Vliet [2012] extended the study to emerging equity markets and concluded that the empirical relationship between risk and return was negative and was much stronger when volatility rather than beta was used as a measure of risk to rank securities. Based on the universe of S&P/IFCI Investable Emerging Markets Index constituents, the authors found that the Sharpe ratio of the low-volatility portfolio was more than twice that of the high-volatility portfolio (0.69 versus 0.29).

We extended our analysis of the low-volatility effect to a global scale by examining low-volatility strategies in international developed and emerging markets. Similar to our analysis of the U.S. equity markets, we compared the results from the rankings-based and the mean-variance-optimization–based low-volatility strategies to the broader regional benchmarks. The methodology for the rankings-based strategy for the international developed and emerging markets differs slightly from the one we used for the U.S. markets. While we quantile the domestic universe and hold the lowest quintile of stocks ranked by volatility, we hold a fixed number of securities (200 for each market) for our international analysis. The number of stocks in our underlying universe of international developed and emerging market securities varies greatly from period to period, whereas the number of constituents is fixed for the domestic universe.[7] In addition, we use the MSCI EAFE Minimum Volatility Index to represent the international developed minimum-variance–based strategy and the MSCI Emerging Markets Minimum Volatility Index to represent the minimum-variance–based strategy for emerging markets. It should be noted that the MSCI EAFE and Emerging Markets Minimum Volatility Indices place restrictions on the maximum and minimum weights of stocks, sectors, factor exposures, turnover, countries, and regions. In contrast, the rankings-based international developed and emerging markets low-volatility strategies do not impose any constraint.

Comparing the risk-return profiles of portfolios in the international developed and emerging markets shows the effectiveness of low-volatility strategies (see Exhibits 7 and 8). In the developed markets, both low-volatility strategies reduced realized volatility by 29% to 30% compared to the market cap-weighted regional benchmarks over the 10-year full sample period and 5-year subperiods. In the emerging markets, depending on the strategy, low-volatility portfolios had 20% to 33% lower volatility compared to market cap-weighted benchmarks over a 10-year period. The rankings-based low-volatility strategy had the highest level of risk reduction (almost 33%) among all the strategies we have examined in the various regional equity markets, which is significant because emerging market returns are typically accompanied by even higher volatility.

Exhibit 7

Comparisons of the International Developed Markets Low-Volatility Strategies

	Rankings Based	Minimum Variance	MSCI EAFE Index	S&P BMI International Developed LargeMid Index
January 2002—December 2011				
Return	12.37%	9.85%	5.12%	5.60%
Standard Deviation	13.10%	13.17%	18.75%	18.71%
Sharpe Ratio	0.805	0.609	0.176	0.201
January 2002—December 2006				
Return	24.23%	20.08%	15.43%	15.34%
Standard Deviation	9.23%	9.74%	13.51%	13.36%
Sharpe Ratio	2.359	1.809	0.961	0.964
January 2007—December 2011				
Return	1.65%	0.49%	–4.26%	–3.32%
Standard Deviation	15.65%	15.56%	22.68%	22.73%
Sharpe Ratio	0.028	–0.047	–0.242	–0.200

Source: S&P Dow Jones Indices LLC and MSCI. Data current as of December 31, 2011. The Minimum Variance Constrained and Unconstrained Strategies are represented by the MSCI EAFE Minimum Volatility Index. The Rankings Based Low Volatility Strategies are represented by the S&P BMI International Developed Markets Low Volatility Index, which was launched on December 5, 2011, and constructed based on the S&P BMI International Developed Markets Index. Past performance is no guarantee of future results. All data referenced in this chart prior to December 5, 2011, reflects hypothetical historical performance.

Exhibit 8

Comparisons of the Emerging Markets Low-Volatility Strategies

	Emerging Markets Low-Volatility Strategies		Emerging Markets Benchmarks	
	Rankings Based	Minimum Variance	MSCI Emerging Markets Index	S&P BMI Emerging Plus LargeMid Index
January 2002—December 2011				
Return	18.84%	18.23%	14.20%	13.69%
Standard Deviation	16.38%	19.31%	24.28%	23.87%
Sharpe Ratio	1.039	0.850	0.509	0.497
January 2002—December 2006				
Return	26.91%	28.65%	26.97%	25.46%
Standard Deviation	12.06%	14.40%	18.08%	17.85%
Sharpe Ratio	2.028	1.819	1.356	1.289
January 2007—December 2011				
Return	11.29%	8.66%	2.70%	3.02%
Standard Deviation	19.73%	23.12%	29.10%	28.60%
Sharpe Ratio	0.511	0.322	0.051	0.063

Source: S&P Dow Jones Indices LLC and MSCI. Data current as of December 31, 2011. The Minimum Variance Constrained and Unconstrained Strategies are represented by the MSCI Emerging Markets Minimum Volatility Index. The Rankings Based Low Volatility Strategies is represented by the S&P BMI Emerging Markets Low Volatility Index, which was launched on December 5, 2011, and constructed based on the S&P BMI International Developed Markets Index. Past performance is no guarantee of future results. All data referenced in this chart prior to December 5, 2011, reflects hypothetical historical performance.

CONCLUSIONS

Consistent with the findings of earlier academic research, our study shows that both principal approaches to constructing low-volatility strategies are equally effective in their ability to reduce realized volatility relative to market cap-weighted portfolios over an intermediate- to long-term investment horizon. Using the Sharpe ratio to measure the effectiveness of each strategy on a risk-return tradeoff basis, our analysis shows low-volatility strategies possess superior risk-adjusted performance over a benchmark portfolio. This desirable risk-return characteristic could have a profound portfolio management implication because the portfolio with a higher Sharpe ratio provides better diversification.

Extending the study to the developed and emerging markets also shows the effectiveness of low-volatility strategies on a global scale. In fact, the level of risk reduction over the long term is even higher than that observed in the U.S. equity markets (particularly in the emerging markets).

Lastly, it is nearly impossible to analyze the low-volatility effect without discussing the role of traditional equilibrium asset pricing theory. Hence, in addition to providing above-mentioned risk management capabilities, low-volatility effect has reignited the debate on what constitutes a market portfolio or an optimal Sharpe portfolio, a tangency portfolio for which there is no other portfolio with the same or higher expected return with lower volatility. In doing so, it brings new light to the CAPM criticism, as posited by many academic studies, that cross-sectional variation in average returns of stocks cannot be explained by the market risk factor alone.

ENDNOTES

[1]The minimum-variance portfolio is the portfolio with the lowest risk for a given level of expected return.

[2]Portfolio variance is formulaically expressed as

$$\sigma_p^2 = \sum_i w_i^2 \sigma_p^2 + \sum_i \sum_{i \neq j} w_i w_j \sigma_i \sigma_j \rho_{ij}$$

[3]

$$w_i = \frac{\frac{1}{Volatility}}{\sum_{i=1}^{n} \frac{1}{Volatility}}$$

Volatility = standard deviation of the trailing 252 trading day price changes.

[4]The Minimum Variance Constrained and Unconstrained (Base) Strategies were constructed using the Northfield Portfolio Optimizer and Portfolio Simulator in FactSet. The Northfield U.S. Fundamental Equity Risk Model is a multi-factor risk model designed to help control the portfolio's exposure to endogenous factors. It is a relaxed Capital Asset Pricing Model (CAPM) construct; while acknowledging the importance of beta in measuring the risk of a portfolio, it also acknowledges that certain groups of securities have covariances that are not related to CAPM beta. The model is based on 67 factors: beta, 11 fundamental characteristics, and 55 industry groups. Mathematically, a multi-factor model can be expressed as

$$R_i = \beta_{1i} f_1 + \cdots\cdots\cdots + \beta_{ni} f_n + \varepsilon_i$$

[5]For example, the largest 5% of stocks in the Russell 1000 amount to 43% of the total market cap of the Russell 1000, whereas the largest 5% of stocks in the Russell 2000 amount to 18% of the total market cap of the Russell 2000.

[6]The 11 factors are Earnings/Price, Book/Price, Dividend Yield, Trading Activity, 12-Month Relative Strength, Log of Market Capitalization, Earnings Variability, EPS Growth Rate, Revenue/Price, Debt/Equity, and Price Variability. For more information on detailed factor definitions and the industry variables, please visit www.northinfo.com/documents/8.pdf.

[7]We use the S&P BMI International Developed ex. U.S. and South Korea LargeMid Index as our universe for the international developed markets low volatility strategy and the S&P BMI Emerging Markets Plus LargeMid Index as our universe for the emerging markets low volatility strategy. Volatility is computed using daily one-year price changes in local currency.

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