HORIZON

THE BARRA NEWSLETTER

Portfolio Construction in Europe:

Screening vs. Optimization

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Welcome to Horizon.

This issue of Horizon focuses on international equity markets and the effect of dramatic and sudden changes in the level of volatility in emerging and developed markets. These trends have given rise to customer requirements for more dynamic risk modeling, effective portfolio construction tools, and additional inside in understanding the different methods of forecasting risks.

We study changes in the Japanese equities market and their impact on active management. Guy Miller, Vice President Equity Research, and Edouard Sénéchal, address current concerns of Japanese active managers, who experience low levels of tracking error by historical standards. Guy and Edouard discuss how portfolio managers may want to react to the changing environment and show the negative impact of long only constraints as well as transaction costs.

Our second article describes recent improvements to our emerging markets equity block within the Barra Integrated Model. Most of these markets experienced severe turbulence in the late 1990s and many are now showing their lowest volatility levels in a decade. Risk models based on monthly data have difficulty following such strong variations. To address this problem Barra is now applying daily index returns data to several emerging market models and Guy Miller quantifies the improvements in risk forecasts.

Elizabeth Penades, Senior Associate Research Consulting, and Leonid Kopman, Associate, Research Analytics, compare Screening and Optimization approaches to portfolio construction for the European market. In a perfect world, mean-variance optimization will outperform any other portfolio construction method. If, however, the forecasts contain a lot of noise it is not so clear that optimization will be superior. Liz and Leonid compare different portfolio construction methods in a more realistic set up of uncertain risk and return forecasts. They confirm results of similar studies for the US market: Portfolio optimization outperforms different screening methods and delivers higher information ratios even in the case of uncertainty.

Stock specific risk accounts for the majority of the volatility of a single stock and is a good gauge of the return potential and uncertainty around the expected return of a single stock. Accurate specific risk forecasts are therefore critical for any bottom up portfolio manager. Guy Miller and Elizabeth Penades compare three different methods of estimating stock specific risk and find that a structural model for forecasting specific risk is superior to a simple historical and a more complex specific risk modeling approach.

Horizon's regular features include a pullout calendar of Barra's upcoming events and a section highlighting recent publications by Barra's research group. As announced in our last Barra Horizon this release is only available on the web at http://www.barra.com/horizon.

Frank Nielsen

Frank Nielsen, CFA, MSCIBarra

Declining Active Risk in Japanese Equity Portfolios

Guy Miller
Vice President
Barra Equity Research

Edouard Sénéchal
Senior Associate
Barra Research Consulting

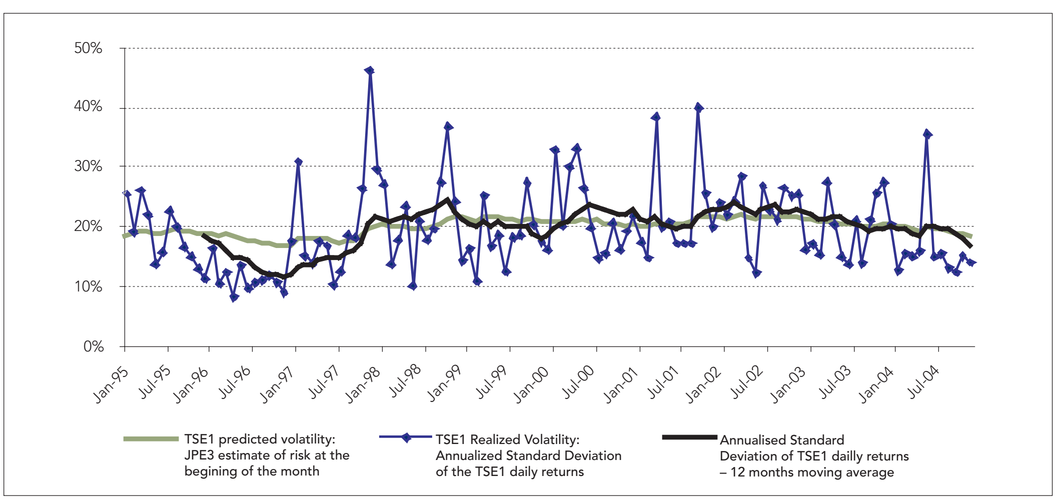
Since the collapse of the Internet bubble, many Japanese portfolio managers have observed a surprising contrast between trends in tracking error and market volatility: tracking errors have fallen dramatically for many portfolios, while the volatility of the TSE1 index has declined much more gradually. The decrease in tracking error is related to a phenomenon occurring in markets around the globe. The cross-sectional dispersion of asset returns within these markets is much smaller today than it was a few years ago. The low level of cross-sectional dispersion makes the art of active portfolio management more difficult than it was before. It demands a considered response from managers.

Section I of this paper examines the evolution of market and cross-sectional volatilities in the Japanese equity market. The impact of declining cross-sectional volatility on portfolio tracking error is the subject of Section II. Section III discusses how portfolio managers should adapt to this new environment. Should active managers take more aggressive positions in order to maintain a given level of expected return? Or should they accept smaller active returns –and perhaps smaller management fees? Section IV summarizes.

I. Declining Volatility of Japanese Equities

Figure 1 displays the history of risk in the Japanese TSE1 equity market index.

Figure 1
The Evolution of Market Volatility



Trailing month-long windows of daily returns data are used to estimate the risk in the figure, expressed as an annualized standard deviation in return. The sudden rise in volatility that follows the 1997 Asian crisis is one of the most notable features of the history. Following this rise, the risk of the TSE1 Index hovered around 20% for several years. Since 2001, market risk has undergone a slow decline. Measurement error and volatility clustering in the history make it difficult to describe the monthly changes precisely, but a 12-month moving average shows a prolonged decline in market risk. The average risk for the index in 2004 was close to 17%, compared with 22% in 2001.

Over the same period, cross-sectional volatility experienced more extreme changes, as illustrated in Figure 2. Like market volatility, cross-sectional volatility jumped after the Asian crisis of 1997, and continued rising through the 1998 Russian crisis and the Internet bubble. It reached a high of 23% in February 2000. Cross-sectional volatility subsequently fell sharply, dwindling to 10% by mid-2000. By December 2004 it had sunk to 5%.

While the behaviors of market and cross-sectional volatility are linked, cross-sectional volatility has a special influence on active risk and return. This measure of returns dispersion is a good gauge of the opportunities available to managers for generating active returns. If all assets had the same return, their cross-sectional dispersion would be zero and there would be no opportunity to generate active returns. As the cross-sectional dispersion of asset returns rises, so does the opportunity to outperform (or under-perform) a benchmark. In general, the active risk of a portfolio is expected decline as cross-sectional volatility falls, and active managers find that their task has become more difficult.

II. The Impact of Reduced Cross-sectional Volatility on Tracking Error

To see how the change in market conditions affects portfolio active risk, consider the behavior of two style indices benchmarked against the TSE1 Index. Figure 3 shows histories of forecast and realized active risks in value and growth tilts. The tilt portfolios are the Russell Nomura Large-cap Value and Growth indices. The risk forecasts are from JPE3 and JPE3S, Barra's models for Japanese equity risk. Realized risk is measured using a 12-month forward-looking standard deviation.

Figure 2
Cross-sectional Volatility of TSE1 Assets

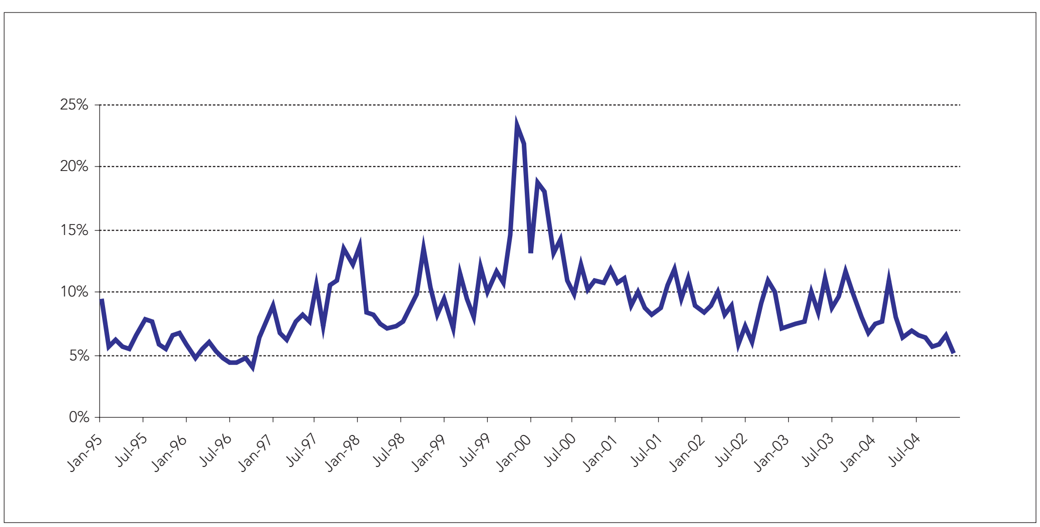
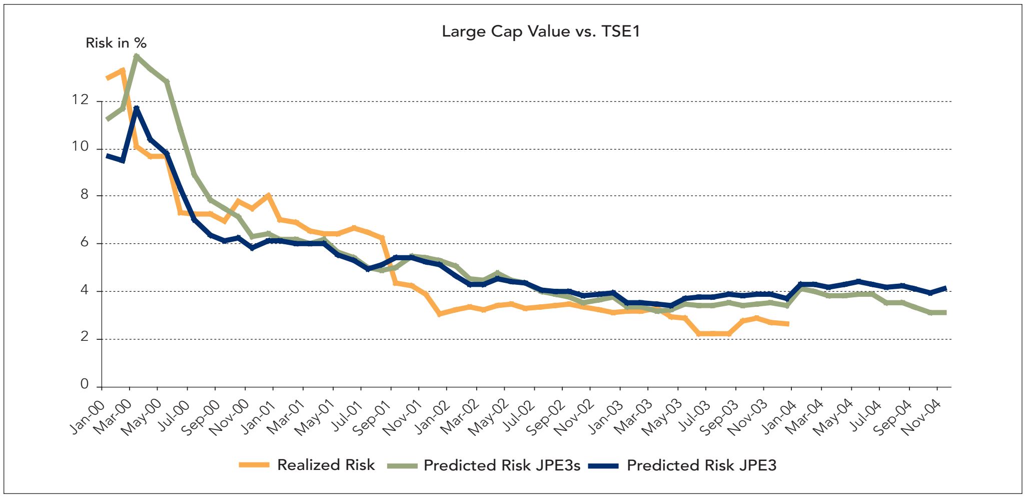
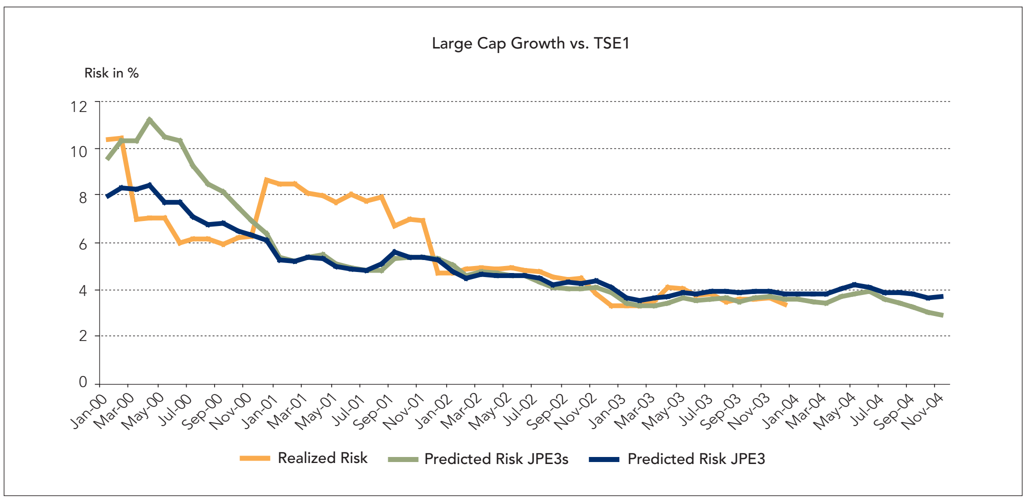


Figure 3

Evolution of Tracking Error for Japanese Growth and Value Indices





Active risk levels fell significantly with the collapse of the technology bubble. The realized tracking error of Russell Nomura Value Index plummeted from a peak value of approximately 12% in 2000 to 4% in 2004. Despite the severity of the change, the forecasts follow the realized tracking error reasonably well. Both risk models reacted satisfactorily to the changing risk environment.

Tracking error in the Value and Growth portfolios comes from a mixture of common factor and asset-specific risk. In style tilts such as these, common factors are usually the dominant source of active risk. While cross-sectional dispersion also reflects both sources of risk, it is more strongly influenced by specific risk. (Recall that about two-thirds of asset-level variance is specific risk and that market risk accounts for a significant fraction of common factor risk; c.f. the relative contributions to adjusted r-squared described in the JPE3 Research Notes, available on Barra's client website.) Thus it is most directly relevant to asset selection strategies, for which asset-specific returns play a leading role. Comparing the evolution of market-residual common factor risk with that of specific risk will help in understanding what is happening to opportunities for active management in the Japanese equity market.

Market-residual volatility is defined as the volatility of a given factor not explained by its market exposure:

$$\sigma_{residual\ factor\ f} = \sqrt{\sigma^2_{factor\ f} - \beta^2_{factor\ f}\,\sigma^2_{TSE1}}$$

Figures 3 and 4 show the average market-residual volatility of JPE3 style and industry factors from 1995 through 2004[1]. Both styles and industries exhibit strongly declining market-residual volatility after 2000. If portfolio positions (and hence factor exposures) remained similar throughout this period, common factor contributions to active risk would have fallen proportionately.

Figure 3

Equal Weighted Average Residual Volatility of Style Factors

Figure 4

Equal Weighted Average Residual Volatility of Industry Factors

Figure 5 shows the history of predicted and realized average specific risk for Japanese equities. The downward trend for specific risk resembles the trend among the residual common factors; both decline from their peaks to about half of their peak values over a 5-year period. This implies that strategies based on stock picking (sensitive to stock-specific risk) and on factor rotations (sensitive to common factor risk) have been affected to similar extents as the risk environment has changed.

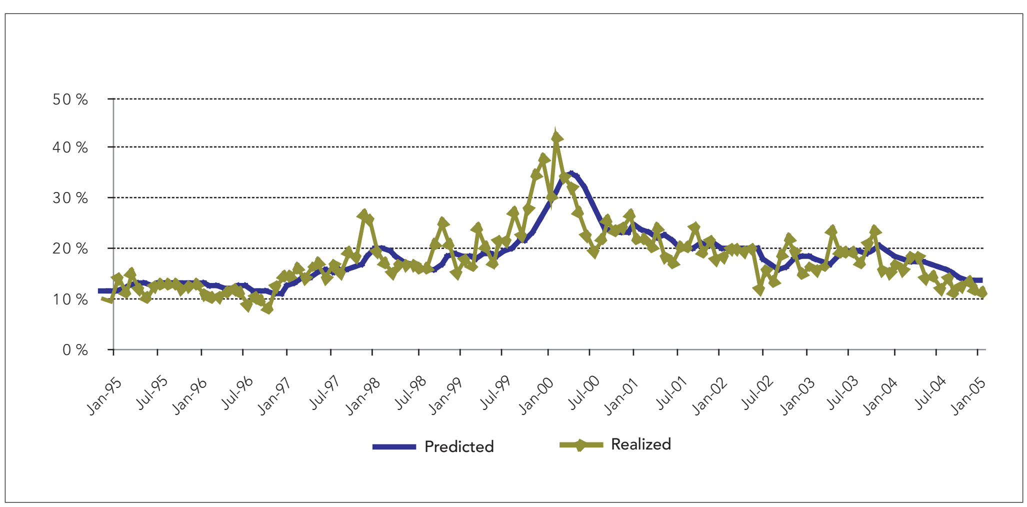
III. Implications for Active Portfolio Management

The historical decline in non-market risks has narrowed the range of active returns that any given portfolio might produce. Consequently it is now harder for an active manager to distinguish his or her portfolio from the benchmark. The active return a plan sponsor might expect from investing with a skilled portfolio manager has diminished. In this environment, the crucial thing for fund managers and plan sponsors alike is to understand how and to what extent opportunities can be preserved.

In Section II, we examined active risk in large-cap growth and value portfolios. By construction, these indices have roughly constant Growth and Value exposures. Also, although the weights of individual assets may vary over time, the population of active position sizes is relatively stable. The exposure to stock-specific risk can therefore be expected to be roughly constant. Because specific and common factor risk exposures do not respond to changing risk levels, risk in the portfolios is essentially

Figure 5

Evolution of Average Specific Risk for Japanese Equitiess



[1]The volatilities were extracted from our short term Japanese model, JPE3S. They are computed using daily factor returns and a 90-day half-life. For more information on JPE3S, consult http://www.barra.com/support/library/JPE3S_research_notes.pdf.

unmanaged.

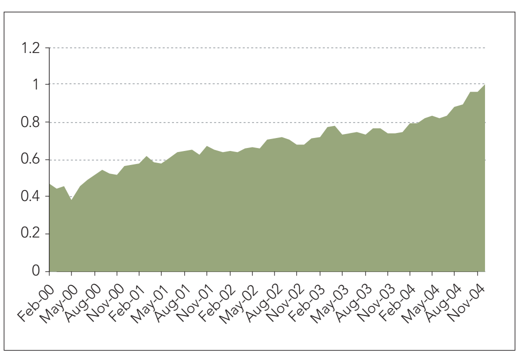
In order to maintain a constant level of active risk - and therefore preserve the potential for active return - a portfolio manager must increase active exposures as volatility declines. We use a simple example to illustrate this point.

Imagine a long-only portfolio manager who believes that large-cap stocks will out-perform the benchmark. To over-weight the Size factor, the manager uses each stock's Size exposure to construct asset-level alphas – the alpha of each stock is simply proportional to its Size exposure. The portfolio is rebalanced each month to maintain a constant forecast tracking error of 4%. Thus, every month optimization maximizes the portfolio's overall Size exposure while maintaining a constant tracking error.

This simple strategy, when implemented with JPE3S over the 5-year period 2000–2004, produced an annualized active return of 0.15% and a realized tracking error of 3.85% (15 bps below the target of 4%). To maintain a constant level of active risk, the portfolio's active Size exposure more than doubled over the study period to offset the precipitous decline in cross-sectional volatility. Figure 5 shows the historical development of the Size exposure.

Figure 5

Size Exposure History for a Constant Ex-ante Tracking Error Portfolio



So far the discussion has focused on the need to manage risk rather than allowing it to drift amidst changing circumstances. Fixing the level of active risk implies control over risk, but it does not mean that the risk is being deployed in the best possible way. In addition to controlling active risk, a manager must justify that risk with expected active returns: the goal of active management is to maximize the risk-adjusted return of the portfolio, not to maintain a constant level of risk. In order to adapt a strategy to the new financial environment one must take into account not only the decline in residual volatility but also how expected returns have changed.

Consideration of a simplified investment problem provides some insight into how to best manage exposures. In general, a quantitative manager strives to maximize the risk-adjusted portfolio return,

$$V = h^T\alpha - \lambda h^T V h - TC.$$

Here α is the vector of forecast alphas, h is the vector of active asset weights in the portfolio, V is the residual returns covariance matrix, and TC is the trading cost of establishing and unwinding positions, expressed as a return — that is, as a fraction of portfolio wealth, amortized over the lifetime of the active positions. The "cost of risk" is described by the risk-aversion parameter λ. The manager chooses the active position sizes h to maximize the risk-adjusted active return U, subject to any policy constraints (e.g., long-only) that might be in force. Some of the optimized positions are clearly driven by forecast returns, while others help hedge the portfolio's risk. Computer-aided portfolio construction (as offered, for example, by Barra's Aegis Portfolio Optimizer) is usually required to calculate optimal positions sizes.

In the absence of transactions costs and position constraints, the solution for the optimal positions can be written very simply.

$$H = \frac{1}{2\lambda} V^{-1}\alpha.$$

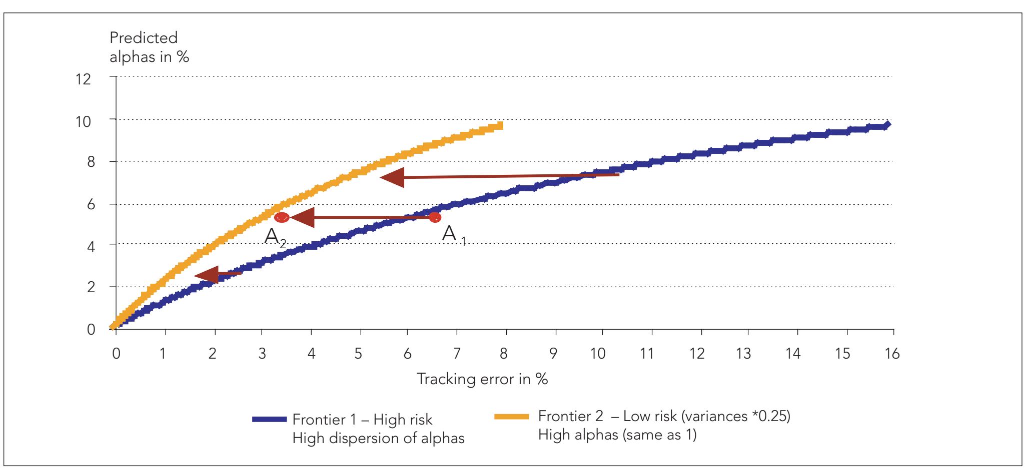
How do positions react when the financial environment changes? The risk aversion λ describes the risk preferences of the manager or asset owner; it can be expected to stay fixed. If risk (expressed as a standard deviation) halves then the variances and covariances in *V* will shrink to one quarter of their previous values, and the inverse covariance matrix V^{-1} will quadruple. If forecast alphas remain unchanged, position sizes should quadruple as well! The target tracking error of the portfolio would then double, justified by the superior risk-reward relationship in the new low-volatility environment. The active return of the portfolio would increase by a factor of four, and so would the risk-adjusted active return. The portfolio's information ratio, the ratio of portfolio active return to active risk, would double. But it is unlikely that alphas actually remain unchanged in the new environment. Few Japanese equity managers have seen their information ratios double as volatility has fallen.

It is more likely that the information coefficient, the ratio of forecastible alpha to risk, remains approximately constant. In this case, alpha and risk scale in the same way. When risks halve, asset-level alphas also decline by a factor of two. In response, the optimal position sizes should double. When this is done, the portfolio's tracking error target stays the same in both environments, and so does its expected risk-adjusted active return. Its information ratio therefore remains unchanged. For a portfolio with no constraints and negligible transactions costs, nothing has been lost, but neither has anything been gained. The simple policy of maintaining a fixed tracking error target has turned out to be precisely the right thing to do. Needless to say, if alphas had decreased more drastically than risk levels had the best course would be to actually reduce the tracking error target.

Maintaining a constant tracking error seems like a reasonable course of action, but policy constraints and transactions costs can make it less optimal than it appears at first sight. Before turning to the impact of transactions costs, consider first the effect of a long-only policy constraint. The long-only constraint is always damaging, since it reduces the set of information on which a manager can freely act (see for example Chapter 15 in *Active Portfolio Management*, 2nd Edition, by Richard Grinold and Ronald Kahn). It can become an even greater handicap in a low-volatility environment. Suppose asset volatilities decline by 50%, while asset alphas and residual return correlations remain unchanged. The long-only efficient frontier shifts to the left, as shown in Figure 6.

Figure 6

Impact of Declining Volatility and Constant Alphas on the Efficient Frontier



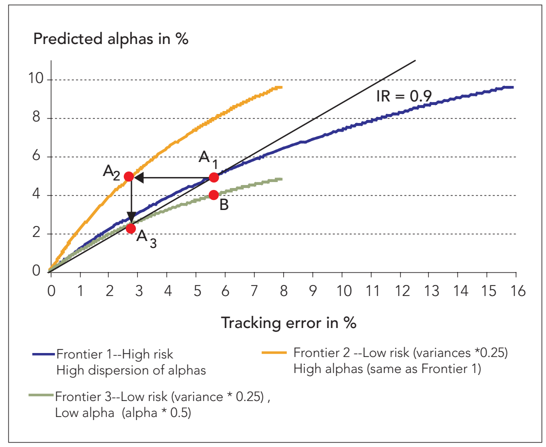
Because only the overall level of non-market risk has changed, the portfolios located on the efficient frontier remain the same. Each portfolio still yields the maximum return for a given amount of active risk, although its active risk is halved.

Suppose that a manager selected portfolio A when risk was high, and that at that time it was located at point A_1 in the risk-return space of Figure 6. After volatility has fallen, the same portfolio occupies point A_2 on Frontier 2, the new low-volatility efficient frontier. Although the risk-adjusted active return of portfolio A has improved, under the new circumstances it is no longer optimal. Since risk is now better rewarded, the manager should enlarge his exposures to increase his active returns. Keeping the same portfolio exposures would only make sense if the manager had become much more risk-averse. The manager therefore moves away from the old portfolio at A_2, choosing instead a higher risk portfolio on the new frontier.

In increasing the active positions and their associated risk, note that the manager can freely enlarge only the long active positions. Positions that are under-weighted relative to the benchmark are constrained, since the asset weight in the portfolio must be zero or greater. The expected return of portfolios on the long-only frontier does not increase in proportion to risk, but more slowly. The information ratio decreases with increasing risk. Thus, even if transactions costs are negligible and asset-level alphas remain the same, the information ratio will not double as it would without a long-only constraint. The long-only constraint is eliminating more information than it did in the high-volatility regime.

Now consider a more realistic example in which asset-level alphas and volatilities decline together (for simplicity we assume that residual return correlations remain constant). Figure 7 illustrates the resulting risk-reward tradeoff.

Figure 7
Impact of Declining Volatility and Proportionately Declining Alphas on the Efficient Frontier



As we saw before, when risk levels are cut in half, the long-only efficient frontier moves leftward from Frontier 1 to Frontier 2. If asset-level alphas also halve, the efficient frontier shifts downward from Frontier 2 to Frontier 3. The initial portfolio A now occupies point A_3 on the risk-reward diagram. Because both active risks and active returns have been reduced, the information ratios at point A_1 and point A_3 are identical. Once again however, portfolio A is not optimal, given the manager's risk preferences. The manager should choose to increase risk-adjusted return by selecting a higher risk portfolio on Frontier 3. The optimal portfolio lies between points A_3 and B, and has a lower risk-adjusted return than in the high-volatility regime. Note that it will also have a lower information ratio than the one the manager previously enjoyed. Under the same scenario, a long-short manager would simply double the size of all active positions to maintain the same risk-adjusted return and information ratio. One again, there is less usable information in the low-volatility environment, because of the long-only constraint.

We now turn to the role of transactions costs in the new environment of lower risk. It is simplest to discuss costs in the context of small orders, for which commissions and the loss on the spread remove a fixed fraction f from the value from each trade, independent of the exact size of the trade (typically for small orders, f might be a few dozen basis points; when orders become very large the fraction f will start to depend on order size and will increase as orders become larger). If an active position is held for a time τ, the act of setting up and unwinding an active position reduces the return rate on the position from α to the cost-adjusted value

$$\tilde{\alpha} = \alpha - \frac{2f}{\tau}\,\mathrm{sign}\,(h).$$

(Unless a position is taken purely for hedging, the sign of h should be the same as the sign of α.) The cost-adjusted value can be used to estimate optimal active position sizes in the absence of policy constraints:

$$h = \frac{1}{2\lambda} V^{-1}\tilde{\alpha}.$$

Now suppose that residual risk levels and forecast returns fall to half of their previous values. If the trading cost rate f fails to decease along with the expected residual return α, the cost-adjusted residual return will decrease by more than half; indeed, many cost-adjusted alphas will become equal to zero.

As an example consider a very plausible situation in which, prior to the decrease in volatility, a manager used to lose a third of his forecast alpha to transactions costs. Then, the financial environment changes and both risk and asset-level alphas are halved. If commissions and spreads remain unchanged, the manager now loses two thirds of the asset-level alpha and so is left with cost-adjusted alphas that are one-quarter of their previous sizes (1/3 of 1/2 as opposed to 2/3 of 1). Taking transactions costs into account, the correct response on the part of the manager is to allow tracking error to fall and, roughly speaking, keep position sizes the same. Managers with less burdensome costs can afford to increase their position sizes somewhat, partially compensating for the loss in risk-adjusted return. Obviously transactions costs have a dramatic effect on the decision of how best to proceed in the new environment, and should be carefully considered.

IV. Conclusions

Although the risk of the TSE1 index has been relatively stable since the end of the Internet bubble, cross-sectional volatility levels have declined sharply. As a result, many Japanese equity managers have seen their strategies weaken as their tracking errors have decreased. Active management has become a harder game.

Taking more aggressive positions in order to compensate for the decline in tracking errors should help address the problem, but transactions costs and policy constraints imply that the compensation need not be complete; indeed, some reduction in targeted tracking error is probably optimal. The reduced tracking error is accompanied by a lower risk-adjusted return, an inevitable consequence of the harsher environment. Performance will suffer most in portfolios with long-only constraints or other strong constraints on position sizes, and in portfolios with high turnover. Long-short portfolios and portfolios with low turnover can compensate more completely and should be less severely affected.

Improved Emerging Market Risk Forecasts

Guy Miller
Vice President
Barra Equity Research

Equity risk in the emerging markets is extremely dynamic. Most of these markets experienced severe turbulence in the late 1990s, and many are now showing their lowest volatility levels in a decade. Risk models based on monthly data have difficulty following such strong variations. To address this problem Barra is now applying daily index returns data to several emerging market equity risk models.

Introduction

Equity risk levels around the world rose violently in the late 1990s, under the combined influences of a technology bubble and of debt crises in the Asian and Russian markets. Since that volatility outburst, the development of risk in the various emerging markets has followed no single pattern, but many now find themselves in states of relative quiescence. These extreme variations have had strong implications for risk forecasting.

Risk forecasts are based on the past, through observation and interpretation. Rapidly changing conditions make it difficult to appraise the current situation and make reliable forecasts.

Barra's response to rapid change has been to move from equity returns data acquired at monthly intervals to daily data. Monthly returns data have been viewed traditionally as natural sources of information about risk over investment horizons of a month or longer, but are too sparse to be effective when significant changes in risk occur within a few years or less. Daily data provide a denser, more detailed view of what is happening in the markets, and form the basis of risk forecasts that are more responsive. The program of applying daily returns data to risk forecasts has been implemented in equity risk models for most of the larger developed markets. In some models, for example USE3L and JPE3S, the implementation is very deep and daily returns at the asset level are employed. In others (e.g. JPE3, UKE7, and EUE2), daily index returns data are used to improve forecasts of market or systematic risk. In all cases, the application of daily data has been found to improve the quality of risk forecasts. Accompanying progress in models for the developed markets, the agenda has broadened to include emerging markets.

Daily asset-level data for emerging markets are often either unavailable or limited by illiquidity, and so the most practical approach is to monitor changing risk levels through the daily returns of a market index. This report describes the main results of our research to improve risk forecasts for emerging equity markets with daily data.

Recent Trends in Emerging Market Risk

Figure 1 depicts the recent history of equity risk in the US S&P 500. Risk histories in the emerging markets are represented in Figures 2–4, which show the realized risk of equity indices in Russia, China, and Chile. Each figure uses a forward-looking 3–month window of daily index returns to construct the estimated level of risk, presented as an annualized standard deviation. In all of the figures the risk levels vary significantly over time. Although the individual histories differ, they generally show the period from 2003 onward to be a quiescent one.

The dramatic movements in risk reflected in the figures pose particular difficulties for risk models based on monthly data, since in order to have enough data for a reasonable appraisal of realized risk, many months of returns are necessary. Using a long data history imparts a long memory to a model's risk forecasts. Periods of high risk continue to influence forecasts long after they have ended. In markets where risk levels have declined sharply, models based on monthly data tend to over-forecast risk, sometimes severely.

DEWIV Scaling for Market Risk Forecasts

Within the context of a factor model for risk the problem of strongly dynamic risk naturally separates into two components, factor and specific risk. Factor risk involves returns that are com-

Figure 1
Historically realized risk in the US equity market

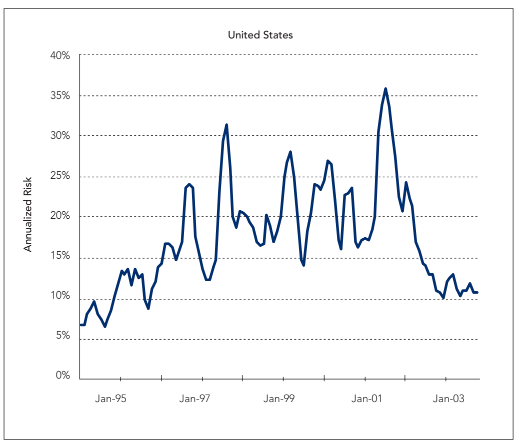


Figure 2
Historically realized risk in the Russian equity market

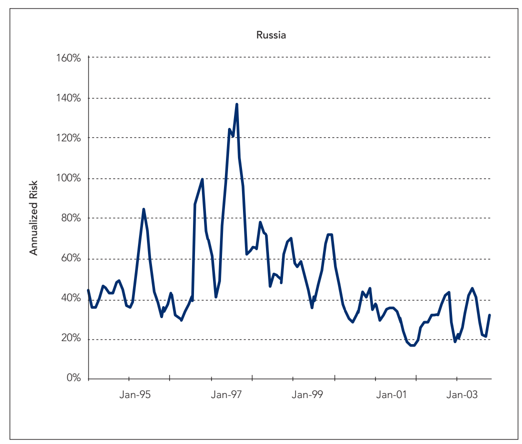


Figure 3
Historically realized risk in the Chinese equity market

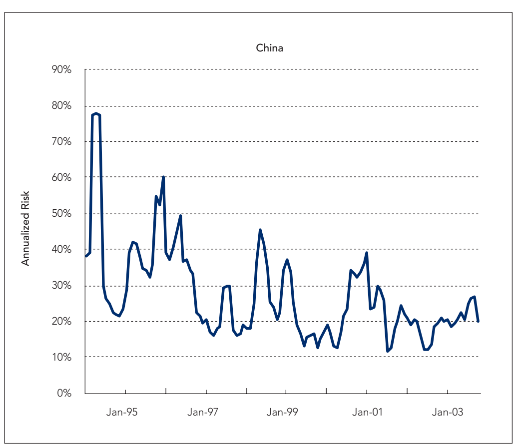
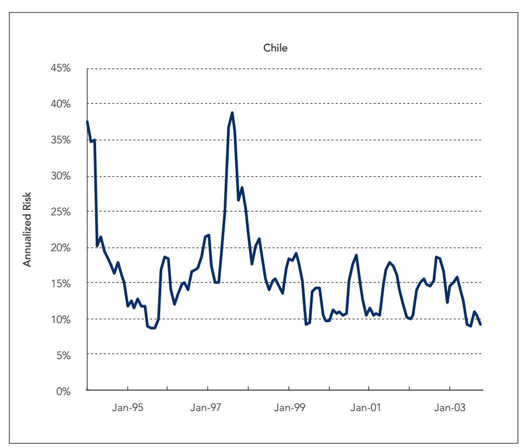


Figure 4
Historically realized risk in the Chilean equity market



[1] Parkinson, Michael. "The Extreme Value Method for Estimating the Variance of the Rate of Return," Journal of Business, 53 , pp. 61-65, 1980.

mon to a group of related assets; common price movements in energy stocks provide one example. Factor risk does not diversify away as the number of names in a portfolio is increased. It must be hedged. Specific risk arises from return that is particular to each individual company. It cannot be hedged but is reduced by diversification.

Monthly data can support very responsive specific risk forecasts. Put simply, the reason for this is that assets may be pooled into representative categories that have similar specific risks. Each month, the returns collected from all of the assets in a given category may be thought of as independent samples from the single returns distribution common to the category. A relatively small number of months may be adequate to characterize the specific risk of the category, and hence of each asset in it. To put this in less abstract terms, by using Nissan's specific returns to inform an estimate of the specific risk to Toyota, a good idea of Toyota's risk emerges more quickly than if Toyota's returns had been considered in isolation. The result is that specific risk forecasts can be based successfully on monthly returns data even in very dynamic risk environments.

Factor risk forecasting, on the other hand, can reap considerable benefits from higher frequency data, particularly daily data. If asset-level daily returns data are available, daily factor returns can be calculated and applied to forecasts of longer-term risk (e.g., quarterly or annual risk; for a discussion see the USE3L equity risk model research notes, available from the client support site at www.barra.com). If asset-level data are unavailable, or if the market is so illiquid that though available the data are difficult to interpret and apply, improvement may still be possible. Specifically, it may be possible to use daily index returns to produce a responsive forecast for the single most important source of common risk, the market itself.

The market risk forecast is based on an exponentially weighted moving average of historical daily risk, adjusted for serial correlations between the daily returns. The exponential weighting causes recent returns to influence the average more strongly than returns in the distant past. For brevity such a forecast is often called a DEWIV, where the acronym stands for "daily exponentially weighted index volatility."

Table 1 lists the 25 emerging market equity models that appear in Barra's Integrated Model. Of the 25, daily index returns were available for 19. Of these, half enjoyed improvements when DEWIV modifications were applied to their factor covariance forecasts.

Table 1
DEWIV status of the emerging market models. Highlighted models are being released in DEWIVed versions.

Model	Country	Source of Data Daily Index	DEWIV Applied?
ARE1	Argentina	MSCI	No
BHE1	Bahrain	None	No
CHE1d	China	GTA	Yes
CLE1d	Chile	MSCI	Yes
COE1d	Colombia	MSCI	Yes
CZE1	Czech Republic	MSCI	No
EGE1	Egypt	MSCI	No
HUE1d	Hungary	MSCI	Yes
ILE1	Israel	MSCI	No
INE1	India	MSCI	No
JOE1	Jordan	MSCI	No
LKE1	Sri Lanka	MSCI	No
MOE1	Morocco	MSCI	No
NGE1	Nigeria	None	No
OME1	Oman	None	No
PEE1d	Peru	MSCI	Yes
PHE1	Philippines	MSCI	No
PKE1	Pakistan	MSCI	No
PLE1d	Poland	MSCI	Yes
RUE1d	Russia	MSCI	Yes
SKE1	Slovakia	None	No
SUE1	Saudi Arabia	None	No
TRE1d	Turkey	MSCI	Yes
VEE1d	Venezuela	MSCI	Yes
ZWE1	Zimbabwe	None	No

The 9 models that benefited from the procedure are being released as part of the upcoming Barra Integrated Model release, BIM 204. The remaining 10 models have been left in their original states.

The improved Chinese Equity Model, CHE1d, underwent one modification in addition to the introduction of DEWIVed market risk forecasting. A strong and isolated volatility spike occurred in China in August 1994. This is now removed from the time series of monthly factor returns before calculating factor covariances.

Forecast Quality

To gauge the effect of DEWIV on forecast quality, we employ bias statistics. A bias statistic is the standard deviation of normalized returns called z-scores, which in this case are the monthly returns to the cap-weighted country specific estimation universes (ESTU), each divided by its risk forecast for that month: $z_t = r_t/\hat{\sigma}_t$. Ideally, the bias statistic should have a value close to 1. If we sample normally distributed z-scores over T months, an unbiased forecast should produce a bias statistic between $1-\sqrt{2/T}$ and $1+\sqrt{2/T}$, with 95% probability. If the returns distribution is fat-tailed (usually the case in financial markets), the "no bias" confidence interval can be somewhat wider. Thus, the range $1-\sqrt{2/T}$ and $1+\sqrt{2/T}$ is conservative. Bias statistics for the old and new model versions are shown in Table 2. The table also includes the Indian equity model, INE1, as an example of a model that was not improved by the DEWIV procedure and therefore was not revised. The "no bias" range for these 3-year intervals lies between 0.76 and 1.24.

Generally, introducing a DEWIV forecast modification confers a substantial performance improvement. Although many of the models over-forecasted risk significantly without DEWIV, most forecasts fell within the unbiased range after modification. As expected for markets in which risk has fallen by a large amount, the bias statistics still tend to lie in the lower part of the range (implying forecasts that are slightly high), since the forecasts retain some memory of the earlier high volatility epoch and decrease conservatively.

Table 2

Forecast bias statistics with and without DEWIV. Statistically significant biases are highlighted.

	March 1999–February 2002		March 2002–February 2005	
Country	No DEWIV	DEWIVed	No DEWIV	DEWIVed
China	0.60	0.96	0.56	0.78
Chile	0.60	0.85	0.62	0.88
Columbia	0.81	1.21	0.68	0.91
Hungary	0.68	0.88	0.57	0.77
Peru	0.57	0.69	0.56	0.64
Poland	0.65	0.87	0.59	0.77
Russia	0.58	0.68	0.42	0.50
Turkey	0.88*	1.05 *	0.60	0.78
Venezuela	0.63	0.75	0.83	0.85
India	1.01	1.22	0.86	1.15

* *In calculating the bias statistics for Turkey, the 85% return to the market that occurred in December 1999 has been omitted.*

The one market that poses particular problems is Russia. Its forecast is improved slightly by the DEWIV, which has therefore been implemented, but the forecast for the March 2002 - February 2005 period is still too high. The earlier high-volatility epoch in the Russian equity market was particularly protracted and violent; much time is needed for a model to "forget" volatility of that magnitude, and this is arguably not inappropriate. To lower the forecast one would have to excise the period through 2001 from the model's memory, or at least shorten the half-life of the DEWIV so it is forgotten very rapidly. The first of these alternatives seems too extreme, and the second would produce unacceptably volatile risk forecasts - a very short memory means that the model frequently makes complete revisions in its views. In the most recent year the forecast appears finally to have approached the existing volatility level; the bias statistic for the 12-month period ending in February 2005 is 0.76. We therefore have decided to adopt the DEWIV modification for Russia, but are continuing to explore the possibilities for more extensive improvements in this and the other emerging market models.

By its nature, DEWIV changes only the forecast level of market risk. Betas to the market are unaffected, both at the asset and portfolio level. Therefore, the implementation of the DEWIV methodology will be significant for managers who consider the relative risks of national markets. The changes will not affect managers who are market-neutral or who select assets within a market without taking active market risk.

Table 3 shows risk forecasts for several portfolios before and after the DEWIV revisions. The forecast risks are given as annualized return standard deviations, in percent.

Note that the change in forecast varies substantially from one market to another. In some, for example Peru and China, the change is modest. In others, such as Turkey and Hungary, it is dramatic. In all cases, the revised forecast is lower than the pre-DEWIV forecast. The high market volatilities of the late 1990s, which still strongly influence forecasts based on monthly returns data, affect the DEWIVed forecasts much more moderately.

Table 3

Forecast annualized portfolio risks for April 2005, with and without DEWIV.

Portfolio	No DEWIV	DEWIV
MSCI Chile	24.08	18.84
MSCI Columbia	30.10	25.57
MSCI Hungary	32.74	24.53
MSCI Peru	26.71	26.60
MSCI Poland	31.45	26.26
MSCI Russia	45.73	38.83
MSCI Turkey	57.61	38.49
MSCI Venezuela	50.40	45.41
MSCI China	36.30	32.49
IFC EMM World	17.01	16.00

Summary

Strongly variable risk levels are common in emerging equity markets, and complicate modeling their risks. Applying daily index returns to a model through the DEWIV methodology often enhances the quality of market risk forecasts - DEWIV has long been a feature of models for developed markets such as Japan and the UK. Our research indicates that in about half of the 19 emerging markets for which we could obtain daily index returns, implementing DEWIV significantly improved model performance. This feature has consequently been added to all of those models.

The new DEWIV models become available to users of the upcoming Barra Integrated Model release, BIM 204.

Appendix: DEWIV Modification of the Factor Covariance Forecast

A DEWIV covariance forecast modification aims to improve forecasts for market risk. In this application the market will be defined as the capitalization-weighted estimation universe. Ideally the market risk forecast would be based on daily returns to the estimation universe itself, but since daily data for each of its constituents are generally unavailable, the daily returns of a broad equity index form a convenient substitute.

Only a few steps are necessary to integrate an improved estimate of market risk into a factor risk forecast. First, historical market risk is estimated from daily index returns. The specific risk model is used to calculate the specific risk of the market (usually quite small in comparison with the overall market risk), and this is removed from the market risk estimate to obtain the "pure factor" portion of the market risk. Factor betas identify the market contribution to each factor's behavior. They are calculated and used to separate the factor covariance matrix into market and non-market components. Finally, the risk of the market piece of the covariance matrix is adjusted to bring it into agreement with the pure factor market risk estimate, and the market and non-market pieces are recombined to complete the improved factor covariance forecast.

Now consider each of the steps in turn. The average daily volatility of the index is

$$\sigma_d^2 = \sum_t w_t \,(r_t - \bar{r})^2$$

where r denotes the average of the daily returns r_t. Trading days are labeled by consecutive integers t. The weights are given by

$$w_t = \frac{e^{t/\tau}}{\sum_{t'} e^{t'/\tau}}$$

Here $\tau = t_{half}/\ln 2$, where $\tau_{half} = 250$ is the half-life in trading days of the exponential weighting scheme. These weights ensure that the most recent trading year influences the estimation of volatility more heavily than the previous year, and that the previous year is in turn more influential than earlier epochs.

The correction for serial correlation is based on the assumption that the return of the index over any n-day period is independent of its return over the subsequent n days, to an adequate approximation. Various "independence lengths" n were considered for the emerging market model DEWIVs. The value $n = 11$ generally produced good results, and was finally selected for all of the models.

To a sufficient level of accuracy, the n-day return is just the sum of individual daily returns:

$$R = \sum_{t=1}^{n} r_t$$

If the statistical properties of the daily returns are approximately homogeneous, so that the variances of all the daily returns can be assumed equal and all the correlations ρ_m between the return on a given day and the return m days earlier can be assumed equal as well, then the variance of R may be written as

$$\sigma_R^2 = \sigma_d^2 \left[n + 2(n-1)\rho_1 + 2(n-2)\rho_2 + \ldots + 2\rho_{n-1} \right]$$

Note that if the returns on different days are independent, the correlations vanish and we recover the familiar prescription for aggregating variances, $\sigma_R^2 = n\sigma_d^2$.

Under the stated assumptions, the variance of the return over a longer interval of N days is N/n times σ_R^2. Thus, a "daily-based" market variance estimate over a month of N trading days is $\hat{\sigma}_R^2 = (N/n)\,\sigma_R^2$.

To modify the forecast of factor risk, the factor part of the monthly index variance $\hat{\sigma}_M^2$ is necessary. This is just the difference between the total market variance and the model forecast for the market's specific variance,

$$\hat{\sigma}^2_{M,\text{ factor}} = \hat{\sigma}^2_M - \hat{\sigma}^2_{M,\text{ specific}}$$

The specific variance is typically small compared to the total variance, so this step represents a minor adjustment.

Finally, the new market volatility must be built into the factor covariance matrix. First betas with respect to the factor component of the market return are prepared from the market asset holdings vector h_M, the matrix X of asset exposures to the factors, and the original (pre-DEWIV) forecast factor covariance matrix, V_0 :

$$\beta = \frac{V_0 X^T h_M}{h_M^T X V_0 X^T h_M}$$

The revised factor covariance forecast simply replaces the original market forecast with the new one:

$$V = V_0 + (\hat{\sigma}^2_{M\text{ , factor}} - h_M^T X V_0 X^T h_M)\,\beta\beta^T$$

Portfolio Construction in Europe: Screening vs. Optimization

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A money manager possessing return forecasts has a choice of several techniques to apply when constructing a portfolio. Portfolios can be constructed using heuristics, such as screening, where stocks are simply ranked by their alphas: depending on its alpha ranking, a stock ends up on a buy, sell, or hold list. Optimization methods for portfolio construction consider alphas and risk forecasts, combining them into a maximization problem, e.g. maximizing risk-adjusted return via quadratic programming.

If return and risk forecasts are perfect, the quadratic programming approach will outperform any other portfolio construction method: if one has perfect knowledge, one cannot do better than the optimum. If, however, the forecasts contain a lot of noise it is not so clear that quadratic programming will outperform other portfolio construction approaches. Quadratic programming is particularly susceptible to errors in risk and return forecasts in that it can attempt to take advantage of noise in the forecasts, which has the effect of "error amplification".

Earlier research (Grinold and Kahn [1999] and Muller [1993]) suggests that, when the cross-sectional correlation of forecasted and realized asset returns (the information coefficient, or IC) is 0.1 and the risk model is adequate, the quadratic programming approach consistently outperforms heuristics. Given the changes in equity markets in the past decade, for instance rapidly changing levels of risk, which have challenged risk models' ability to respond, it is not obvious that portfolio construction by optimization should still be preferable to a heuristic approach. In the light of this, we replicated the tests in Grinold and Kahn [1999] and Muller [1993] with current data for the US market. The new test results produced similar results to those in the earlier publications, with quadratic programming still outperforming screening approaches to portfolio construction.

The question remains of whether the conclusions are applicable to other models for other markets. This article describes implementation of the tests to the European market. If quadratic programming does not outperform screening when constructing portfolios for the European market, the quality of the risk model could be called into question, since the alpha forecasts are excellent by construction. Thus, this test gives us another opportunity to confirm the descriptive strength of Barra's Europe Equity Model, EUE2.

Methodology

To compare the performance of quadratic optimization against screening approaches to portfolio construction, we designed the following experiment. We considered four portfolio construction cases: January 2000, January 2001, January 2002 and January 2003. Active portfolios were constructed, relative to the MSCI Europe benchmark, which was also the universe from which the members of the portfolios were drawn. We ignored transaction costs, and constrained the portfolios to be fully invested and long-only. Return forecasts were constructed as follows. For each case, we started with the realized asset return over the subsequent 12 months (January to December), and added random noise drawn from a uniform distribution with variance 99 times higher than the cross-sectional variance of the true returns, resulting in an IC of about 0.1. The resulting return forecasts are scaled and shifted—preserving the value of IC—so that they have the same mean and variance as the realized returns. The covariance matrix and exposures from EUE2 for January are used in the optimizations.

The following portfolio construction methods were implemented:

- Equal-Weight Screening: select 50, 100 or 150 assets with highest alphas and assign them equal weights.
- Cap-Weight Screening: select 50, 100 or 150 assets with highest alphas and weight them by capitalization.
- Optimization: optimize with three different targets for portfolio active risk, to span the range of active risk levels of the portfolios constructed by screening

For each of the three methods above, the resulting portfolios were compared on the basis of their realized active risks, realized active returns and information ratios (IRs: realized active return divided by realized active risk). Realized risks were estimated as the standard deviation of the subsequent year's (January to December) monthly returns. For the given level of active risk, the best construction method will produce portfolios with the biggest active returns and hence the highest information ratios.

Results

Active returns, risks, and IRs for the four years 2000-2003 are presented in Table 1. Optimization had the highest IR 10 out of 12 times. In the two times it did not, it had the second highest. Equal-Weighted Screening

Table 1

Active risk and active return data given by portfolio construction methods

Method	Equal-Weighted Screening (50)	Equal-Weighted Screening (100)	Equal-Weighted Screening (150)	Cap-Weighted Screening (50)	Cap-Weighted Screening (100)	Cap-Weighted Screening (150)	Optimization-High Risk	Optimization-Medium Risk	Optimization-Low Risk
2000 Risk, %	5.55	4.25	3.61	4.13	4.71	5.21	6.09	4.51	2.52
2000 Return, %	13.65	13.9	12.71	0.37	-0.26	1.19	30.05	17.45	9.4
2000 IR	2.46	3.27	3.52	0.09	-0.06	0.23	4.93	3.87	3.73
2001 Risk, %	11.93	9.28	10.13	8.69	7.68	6.64	10.24	7.98	5.43
2001 Return, %	1.71	13.31	10.55	8.68	5.94	5.29	12.62	11.31	8.51
2001 IR	0.14	1.43	1.04	1.00	0.77	0.80	1.23	1.42	1.57
2002 Risk, %	6.25	6.06	6.74	14.82	10.86	8.62	11.58	8.4	4.96
2002 Return, %	7.72	6.1	9.12	-0.08	-3.68	-2.07	22.64	14.81	8.33
2002 IR	1.24	1.01	1.35	-0.01	-0.34	-0.24	1.96	1.76	1.68
2003 Risk, %	8.18	7.25	6.9	5.57	4.06	2.68	8.09	6.15	4.29
2003 Return, %	31.91	20.26	16.8	12.78	7.19	3.34	31.28	21.26	10.85
2003 IR	3.90	2.79	2.43	2.29	1.77	1.25	3.87	3.46	2.53

Table 2

Number of nonzero positions in QP portfolios

Risk Level	High	Medium	Low
2000	32	45	79
2001	23	40	80
2003	22	32	49
2004	24	41	72

came in second since it had the IR ratio twice and the second highest 9 out of 12 times. Cap-Weighted Screening had the lowest IR 11 out of 12 times.

In Table 2, we list the number of nonzero positions in portfolios constructed by optimization. It is easy to see that, in addition to having higher information ratio most of the time, optimized portfolios have about 50% fewer positions, which is often desirable as it may reduce costs.

Conclusion

We compared Screening and Optimization approaches to portfolio construction for the European market using the methodology found in Grinold and Kahn [1999] and Muller [1993]. We obtained similar results to those we previously saw in the US market. Optimization clearly outperformed the screening methods, producing the best IRs in 10 out of 12 cases. The worst-performing method was Cap-Weighted Screening. This is because the wide variation in market capitalization within the constructed portfolios leads to a large imbalance in the portfolio's composition.

Optimized portfolios also had a smaller number of positions. It is important to note optimization can easily take into account various user requirements, such as constraints on maximum holdings, risk, turnover etc.

Finally, optimization is only as good as the risk model it uses to perform its maximization problem. The results from this study reaffirm the accuracy and utility of Barra's Europe Equity Model, EUE2.

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Comparing Specific Risk Forecasting Methodologies

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Introduction

Specific risk is the idiosyncratic risk of a company, the component of risk that is not due to broader influences and is not shared across companies. Consider a simple example. High oil prices adversely affect all airlines, but although all airlines are vulnerable to labor disputes, a strike by pilots is usually confined to a single company. When airline share prices fall because of rising energy costs, the behavior is captured by their common industry membership—their joint exposure to a common factor return. When an individual airline's pilots strike and its shares fall, the company experiences a negative specific return. Specific risk can be diluted through diversification but common factor risk can only be reduced through hedging.

The risk σ_p of a portfolio p with n assets is expressed as the standard deviation of its return. Expressed in terms of portfolio holdings and asset return covariances, the portfolio risk is

$$\sigma_p = \sqrt{h^T V h}.$$

Here h is the $n \times 1$ vector of asset weights in the portfolio, h^t is its $1 \times n$ transpose, and V is the $n \times n$ matrix of asset return covariances. To forecast risk, one must forecast V.

In multi-factor models asset returns r are written as sums of a common factor contribution r_{cf} that produces covariances between assets, and a specific return s that is statistically independent of the factor return:

$$r = r_{CF} + s.$$

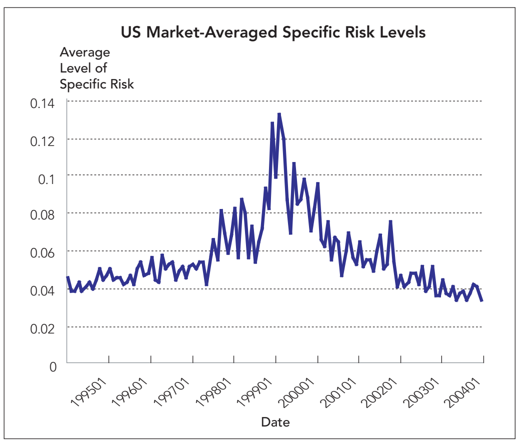
Following this division, the covariance matrix itself is the sum of common-factor and specific components:

$$V = V_{CF} + \Delta.$$

The specific risk contribution is represented by Δ, an $n \times n$ diagonal matrix of specific return variances. The matrix Δ is diagonal because specific returns are uncorrelated across assets.

Since specific risk is the only risk that can be reduced through diversification, it is crucial to obtain an accurate specific risk forecast. Stock pickers target specific returns, and the active return on which they base their businesses primarily bears specific risk. When a PM manages risk, a forecast that is flawed can cause the portfolio to miss its risk targets. A low forecast will cause the manager to take positions that are larger and more risky than they should be. Alternatively, high forecasts result in overly conservative positions that reduce the manager's active return. Specific risk models are especially vulnerable to misforecasting during periods of rapidly changing risk. Figure 1 graphs the US Market-Averaged Specific Risk Levels over a ten-year period from January 1995 through December 2004. In the middle of the period, specific risk rises quickly and then falls precipitously. Are there specific risk models that can follow such large variations and produce forecasts that do not mislead?

Figure 1



This paper explores the relative merits of different methods for forecasting Δ, i.e., for forecasting the specific return risk of individual assets. The methods include what we will term historical estimation, the Parkinson technique, and structural modeling

Types of Specific Risk Models

The historical estimate of an asset's specific risk is simply the historical standard deviation of its specific returns. Perhaps the simplest implementation of the historical method is to estimate the historical standard deviation in an equally weighted trailing window:

$$\sigma_s = \sqrt{\frac{1}{T}\sum_{1}^{T}(s-\bar{s})^2}.$$

Here T is the number of time periods in the sample, and $\bar{s}$ is the time-series average specific return.

This method of estimating specific risk is appealing because it is very straightforward. However, it has several disadvantages. A long history of returns is required to reduce statistical errors in the estimate of standard deviation. If the goal is to forecast risk on monthly and longer horizons, several years of monthly returns are required. If risk levels change rapidly, this can introduce large systematic errors into the forecast. Daily data offer only modest opportunities to increase the data density and shorten the time needed to estimate the returns standard deviation, since daily specific returns tend be serially correlated—successive days are not statistically independent. The historical method also fails to take advantage of what is known about the specific risks of similar companies. Imagine what would happen to an insurance company that ignored the health risks shared by people who smoke.

The **Parkinson estimate** for forecasting specific risk is based on the Parkinson volatility estimator, an approach derived from the mathematics of Brownian motion[1]. The Parkinson method differs from the historical method in that it uses intra-month high and low prices rather than monthly returns. If the log of the stock price is considered to follow a continuous random walk process, the monthly high and low prices can be used to estimate the diffusion rate of the random walk and hence the monthly asset-level risk. For each month in the historical window, the difference l between the log of the month's maximum price and the log of its minimum price is recorded. The estimated Brownian diffusion coefficient is

$$D_1 = 0.361 \times E\,[l^2] \cong 0.369 \times \frac{1}{T}\sum_{1}^{T} l_i^2.$$

[1] Parkinson, Michael. "The Extreme Value Method for Estimating the Variance of the Rate of Return," Journal of Business, 53 , pp. 61-65, 1980.

The diffusion coefficient D_l is an estimate of the monthly return variance. To transform this to a forecast of specific risk, the forecast common factor contribution to the asset variance is subtracted.

Under the stated assumptions, this estimate of risk is more accurate than an historical estimate using the same number of months. Sampling the monthly highs and lows lets the volatility process itself select the instant a price is sampled, thus obtaining more information than if the sampling time is fixed.

Nevertheless, the Parkinson method relies on asset prices following continuous random walks, which implies that the log returns are normally distributed. Financial reality departs violently from this requirement. It is important to ascertain how seriously the inaccuracy of its underlying returns model compromises the Parkinson method. Is it usable nonetheless? For example, could we replace the theoretical value of 0.361 for the coefficient in the Parkinson estimate with an empirically determined number?

The **structural estimate** was developed at Barra and exploits similarities between assets in characterizing their specific risks. By pooling assets, it allows information about the specific risk of Ford to influence the risk forecast of General Motors. The structural specific risk forecast is composed of three pieces: (1) a forecast level $\hat{S}_t$ of average absolute specific returns across the entire market, (2) a relative departure V_{it} of an individual asset from the market-wide average risk level, and (3) a "kurtosis correction" k_{it}. The complete specific risk forecast σ_{it} for asset i at time t is

$$\sigma_{it} = k_{it}\,(1+V_{it})\,\hat{S}_t\,.$$

The average risk level is meant to capture rapid changes in the overall sensitivity of the market to asset-level news. It is based on several trailing months of realized market-averaged specific risk, and the market return m_{t-1} over the previous month.

$$\hat{S}_t = \alpha + \gamma_1 S_{t-1} + \gamma_2 S_{t-2} + \gamma_3 S_{t-3} + \gamma_m m_{t-1}\,.$$

The coefficient γ_m of the market return is negative, so that the model responds to a down month by increasing its risk forecast

The relative risk V_m is extracted from regressions on the ratios of absolute asset specific returns to the market-averaged risk. The relative risk depends on an asset's industry membership, historical residual volatility, the lagged 6-month moving average of its absolute specific returns, its lagged realized return, and several risk index exposures. The relative risk thus makes computer software stocks more risky than utility stocks, and more leveraged companies more risky than less leveraged ones. The dependence on historical returns allows the model to increase risk forecasts for assets that, even within their industry and style cohorts, are unusually volatile.

The kurtosis correction k_{it} converts average absolute returns to return standard deviations. In most Barra implementations of the structural model it is a function of capitalization decile.

Implementation of the Different Specific Risk Models

To see how each of the forecasting methods fares in practice, we produced a suite of several different monthly specific risk forecasts for a ten-year period extending from January 1995 through December 2004. The forecasts used as input data monthly and daily specific returns from the Barra USE3 model, as well as intra-month high and low prices. The forecast types included historical estimates, Parkinson estimates, historical and Parkinson hybrids, and structural model forecasts.

Historical models were estimated from monthly and daily specific returns, using 30-month and 60-month data windows. For models that used daily specific returns, specific risks were estimated with and without corrections to account for serial correlations.

The Parkinson models were constructed using high and low prices monthly prices within 30- and 60-month trailing windows. Applications of the original Parkinson method systematically under-forecasted specific risk, which suggested that a better approach would be to adopt a coefficient different from the theoretically derived value of 0.361. We selected an empirical value, 0.39, to be discussed later.

A hybrid forecast was generated by combining the monthly-based historical and Parkinson estimates. Both component models use data windows of the same length. The hybrid "plays it safe" by comparing the values obtained from the historical and Parkinson forecasts and choosing the higher forecast.

The structural specific risk model is taken from the Barra US Equity model. It is described in detail in the USE3 Model Handbook.

Performance Comparisons

Model performance was evaluated through bias statistics. A bias statistic is the standard deviation of normalized returns called z-scores, which in this case are the monthly returns to a trial portfolio, each divided by its risk forecast for that month: $z_t = r_t / \hat{\sigma}_t$ Ideally, the bias statistic should have a value close to 1. If we sample normally distributed z-scores over T months, an unbiased forecast should produce a bias statistic between $1-\sqrt{2/T}$ and,$1+\sqrt{2/T}$ with 95% probability. If the returns distribution is fat-tailed (usually the case in finance), the "no bias" confidence interval can be somewhat wider. Thus, the range $1-\sqrt{2/T}$ and $1+\sqrt{2/T}$ is conservative. A number greater than 1 and outside the no-bias confidence interval indicates that realized risk exceeded the forecasts, while a number outside the interval and less than 1 indicates that realized risk was smaller than the forecast.

We assessed the bias statistics of total and active specific risk in 50 random portfolios, 40 style portfolios, and one sector tilt portfolio, all with constituents drawn from the Barra USE3 estimation universe.

Bias test results for random and style portfolios are provided for the whole test period, January 1, 1995 - December 31, 2004. Note that although a good model will necessarily perform well in a long-term bias test, a less desirable model may also do well, since over-prediction in part of the period can compensate for under-prediction in another part and yield a bias statistic close to 1. It is therefore good practice to exercise caution and also to break the test period down into sub-periods. We reported bias statistics for 3 sub-periods: January 1995 –April 1998, May 1998 –August 2001, and September 2001–1December 2004.

Table 1 contains bias statistics for the random portfolios. The table displays average bias statistics for the active and total specific risk forecasts for 50 random portfolios, broken down by time period. Adjacent to each average, we report the number of portfolios that over-predicted risk, under-predicted risk, or were within the no-bias confidence interval at the 95% level.

Table 2 contains bias statistics for style tilt and sector tilt portfolios. Four styles were represented by log of capitalization, relative strength, the book-to-price ratio, and analyst-predicted earnings growth. The top 1000 assets in the USE3 Estimation Universe were divided into style deciles to form 10 portfolios of 100 stocks each. A tech portfolio was also created that includes all assets exposed to the technology sector in the Barra US model.

Table 1

Dates: 19950101 to 20041201	Specific Risk	Over	Under	In	Active Specif Risk	Over	Under	In
Simple estimate: 30 months of Monthly Returns	0.98	1	0	49	1.01	1	2	47
Simple estimate: 60 months of Monthly Returns	0.99	4	2	44	1.02	1	3	46
Parkinson estimate: 30 months of Intra-month Hi/Lows	0.99	1	1	48	0.96	4	0	46
Parkinson estimate: 60 months of Intra-month Hi/Lows	1.01	1	3	46	0.98	3	1	46
Combined Simple and Parkinson Estimates: 30 months	0.89	17	0	33	0.87	24	0	26
Combined Simple and Parkinson Estimates: 60 months	0.91	13	0	37	0.90	19	0	31
Simple estimate: 30 months of Daily Returns	0.88	17	0	33	0.91	14	0	36
Simple estimate: 60 months of Daily Returns	0.88	19	0	31	0.92	13	0	37
Simple estimate: 30 months of Daily Returns with Correction	0.91	13	0	37	0.93	10	0	40
Simple estimate: 60 months of Daily Returns with Correction	0.91	14	0	36	0.94	7	0	43
Structural Model: Based on Monthly Returns	0.95	5	0	45	0.97	3	0	47

Dates: 19950101 to 19980401	Specific Risk	Over	Under	In	Active Specific Risk	Over	Under	In
Simple estimate: 30 months of Monthly Returns	1.01	2	2	46	0.99	1	0	49
Simple estimate: 60 months of Monthly Returns	0.96	4	2	44	0.95	2	0	48
Parkinson estimate: 30 months of Intra-month Hi/Lows	1.07	1	3	46	1.02	1	3	46
Parkinson estimate: 60 months of Intra-month Hi/Lows	1.03	1	3	46	0.98	1	0	49
Combined Simple and Parkinson Estimates: 30 months	0.93	4	0	46	0.89	5	0	45
Combined Simple and Parkinson Estimates: 60 months	0.90	5	0	45	0.87	7	0	43
Simple estimate: 30 months of Daily Returns	0.89	5	0	45	0.87	8	0	42
Simple estimate: 60 months of Daily Returns	0.84	12	0	38	0.82	17	0	33
Simple estimate: 30 months of Daily Returns with Correction	0.91	5	0	45	0.90	6	0	44
Simple estimate: 60 months of Daily Returns with Correction	0.86	6	0	44	0.85	11	0	39
Structural Model: Based on Monthly Returns	0.96	2	2	46	0.95	2	0	48

Dates: 19980501 to 20010801	Specific Risk	Over	Under	In	Active Specific Risk	Over	Under	In
Simple estimate: 30 months of Monthly Returns	1.12	0	11	39	1.20	0	19	31
Simple estimate: 60 months of Monthly Returns	1.20	0	20	30	1.30	0	29	21
Parkinson estimate: 30 months of Intra-month Hi/Lows	1.05	0	6	44	1.05	0	7	43
Parkinson estimate: 60 months of Intra-month Hi/Lows	1.16	0	17	33	1.17	0	17	33
Combined Simple and Parkinson Estimates: 30 months	0.98	1	2	47	1.00	0	3	47
Combined Simple and Parkinson Estimates: 60 months	1.08	0	7	43	1.11	0	11	39
Simple estimate: 30 months of Daily Returns	1.00	0	1	49	1.10	0	9	41
Simple estimate: 60 months of Daily Returns	1.07	0	5	45	1.17	0	16	34
Simple estimate: 30 months of Daily Returns with Correction	1.03	0	2	48	1.12	0	11	39
Simple estimate: 60 months of Daily Returns with Correction	1.10	0	6	44	1.20	0	17	33
Structural Model: Based on Monthly Returns	0.95	2	0	48	1.04	0	4	46

Dates: 20010901 to 20041201	Specific Risk	Over	Under	In	Active Specific Risk	Over	Under	In
Simple estimate: 30 months of Monthly Returns	0.79	23	0	27	0.78	26	0	24
Simple estimate: 60 months of Monthly Returns	0.75	30	0	20	0.73	35	0	15
Parkinson estimate: 30 months of Intra-month Hi/Lows	0.82	17	0	33	0.78	26	0	24
Parkinson estimate: 60 months of Intra-month Hi/Lows	0.78	26	0	24	0.73	36	0	14
Combined Simple and Parkinson Estimates: 30 months	0.73	34	0	16	0.70	41	0	9
Combined Simple and Parkinson Estimates: 60 months	0.70	41	0	9	0.67	45	0	5
Simple estimate: 30 months of Daily Returns	0.73	33	0	17	0.72	39	0	11
Simple estimate: 60 months of Daily Returns	0.69	42	0	8	0.68	44	0	6
Simple estimate: 30 months of Daily Returns with Correction	0.75	29	0	21	0.74	33	0	17
Simple estimate: 60 months of Daily Returns with Correction	0.71	38	0	12	0.69	43	0	7
Structural Model: Based on Monthly Returns	0.93	4	0	46	0.90	5	0	45

Table 2

Dates: 19950101 to 20041201	Over	Under	In	Active Over	Active Under	Active In
Simple estimate: 30 months of Monthly Returns	3	3	35	1	4	36
Simple estimate: 60 months of Monthly Returns	4	3	34	1	6	34
Parkinson estimate: 30 months of Intra-month Hi/Lows	4	6	31	4	1	36
Parkinson estimate: 60 months of Intra-month Hi/Lows	3	7	31	3	2	36
Combined Simple and Parkinson Estimates: 30 months	14	0	27	16	0	25
Combined Simple and Parkinson Estimates: 60 months	12	1	28	9	0	32
Simple estimate: 30 months of Daily Returns	14	2	25	5	1	35
Simple estimate: 60 months of Daily Returns	18	1	22	6	0	35
Simple estimate: 30 months of Daily Returns with Correction	11	2	28	3	2	36
Simple estimate: 60 months of Daily Returns with Correction	14	2	25	3	1	37
Structural Model: Based on Monthly Returns	5	6	30	1	5	35

Dates: 19950101 to 19980401	Over	Under	In	Active Over	Active Under	Active In
Simple estimate: 30 months of Monthly Returns	2	2	37	2	3	36
Simple estimate: 60 months of Monthly Returns	5	1	35	3	1	37
Parkinson estimate: 30 months of Intra-month Hi/Lows	2	5	34	2	3	36
Parkinson estimate: 60 months of Intra-month Hi/Lows	2	5	34	2	1	38
Combined Simple and Parkinson Estimates: 30 months	6	0	35	6	0	35
Combined Simple and Parkinson Estimates: 60 months	6	0	35	8	0	33
Simple estimate: 30 months of Daily Returns	7	0	34	6	0	35
Simple estimate: 60 months of Daily Returns	12	0	29	12	0	29
Simple estimate: 30 months of Daily Returns with Correction	6	0	35	5	0	36
Simple estimate: 60 months of Daily Returns with Correction	9	0	32	10	0	31
Structural Model: Based on Monthly Returns	2	2	37	1	2	38

Dates: 19980501 to 20010801	Over	Under	In	Active Over	Active Under	Active In
Simple estimate: 30 months of Monthly Returns	0	10	31	0	25	16
Simple estimate: 60 months of Monthly Returns	0	17	24	0	36	5
Parkinson estimate: 30 months of Intra-month Hi/Lows	0	7	34	0	4	37
Parkinson estimate: 60 months of Intra-month Hi/Lows	0	16	25	0	15	26
Combined Simple and Parkinson Estimates: 30 months	2	2	37	0	1	40
Combined Simple and Parkinson Estimates: 60 months	0	6	35	0	7	34
Simple estimate: 30 months of Daily Returns	1	4	36	0	13	28
Simple estimate: 60 months of Daily Returns	0	8	33	0	25	16
Simple estimate: 30 months of Daily Returns with Correction	0	6	35	0	19	22
Simple estimate: 60 months of Daily Returns with Correction	0	10	31	0	26	15
Structural Model: Based on Monthly Returns	3	4	34	0	11	30

Dates: 20010901 to 20041201	Over	Under	In	Active Over	Active Under	Active In
Simple estimate: 30 months of Monthly Returns	21	0	20	19	0	22
Simple estimate: 60 months of Monthly Returns	23	0	18	26	0	15
Parkinson estimate: 30 months of Intra-month Hi/Lows	12	0	29	19	0	22
Parkinson estimate: 60 months of Intra-month Hi/Lows	21	0	20	28	0	13
Combined Simple and Parkinson Estimates: 30 months	27	0	14	30	0	11
Combined Simple and Parkinson Estimates: 60 months	31	0	10	36	0	5
Simple estimate: 30 months of Daily Returns	23	0	18	28	0	13
Simple estimate: 60 months of Daily Returns	32	0	9	35	0	6
Simple estimate: 30 months of Daily Returns with Correction	22	0	19	23	0	18
Simple estimate: 60 months of Daily Returns with Correction	28	0	13	35	0	6
Structural Model: Based on Monthly Returns	3	3	35	6	0	35

For the random portfolios over the complete 10-year period, the historical monthly estimate, and the structural model had average bias statistics close to 1, both in specific and active specific risk. The Parkinson method also had a bias statistic close to 1, but this was achieved through a calibration, described above, to make up for deficiencies in the original method. The calibration optimized the 10-year performance in-sample. All three models had few significant over- or under-predictions. However, the daily returns-based historical models and the hybrid models experienced some problems with over-forecasting. As we will see below, over-forecasting by the daily returns-based models can be attributed to their lack of responsiveness, i.e. to their lingering memories of high-risk periods in periods of lowered risk. Over-forecasting by the hybrid model is expected, since the hybrid model always selects the larger of two candidate forecasts. The degree of over-forecasting is a measure of the fluctuating error in one or both of the candidates.

The relative model performances in the style portfolios were generally similar to those in the random portfolios. Especially among the style portfolios, it is clear that adjusting the daily returns-based models for serial correlations improves forecast quality.

In order to examine the forecasting behavior of the models more closely, the 10-year period is broken down into three 3.3-year sub-periods. The second of the three sub-periods includes the culmination and collapse of the internet-bubble, while the final interval reveals falling risk levels.

During the first period, January 1995 - April 1998, the structural, monthly historical, and 60-month Parkinson models perform well (non-active and active cases). Most of the models have a similar number of portfolios within the 95% no-bias confidence interval. Risk levels are very low in the mid-1990s, and many models show a small but definite tendency to over-predict.

In the second sub-period, May 1998-August 2001, risk levels rise rapidly and under-prediction becomes an issue for many of the models. The exceptions are the 30-month hybrid and the structural models. The hybrid model tends to produce risk forecasts above the prevailing levels, so it is unsurprising that it performs best when risk levels rise sharply. In contrast, the structural model performs well because it is able to recognize and respond to rapidly changing overall specific risk levels. The other models do less well because they use long data windows and process information asset-by-asset, thus failing to take advantage of the possibilities offered by cross-asset information pooling.

During the last period, September 2001–December 2004, specific risk levels decline abruptly and all models over-forecast. The structural model clearly weathers this period better than the other forecasting techniques, since its construction allows it to respond promptly to rapid change.

Table 3 contains a summary of the results from the 4 periods. The structural model is the only model that performs well across all the periods.

Conclusions

The decade examined in this study was characterized by changes in risk levels so large and violent that they might be termed regime shifts. Confronted with such a changeable environment, forecasting models need to adapt quickly and surely. A forecasting technique that looks for emerging trends across the universe of model assets can identify new behavior and adjust far more quickly than a technique that is confined to individual asset time-series. This consideration underlies the consistent success of the structural approach.

Table 3

Period	Over Prediction	Under Prediction	Unbiased
19950101–20041201	Historical Daily uncorrected (30 & 60 month) Historical Daily corrected (30 & 60 month) Hybrid (30 & 60 month) Historical Monthly (30 & 60 month)		Structural, Historical Monthly (30 & 60 month) Parkinson (60 month)
19950101–19980401	Historical Daily uncorrected (30 & 60 month) Historical Daily corrected (30 & 60 month) Parkinson (30 month) Hybrid (30 & 60 month)Structural		
19980501–20010801		Historical Daily uncorrected (30 & 60 month) Historical Daily corrected (30 & 60 month) Historical Monthly (30 & 60 month) Parkinson (30 & 60 month) Hybrid (60 month)	Structural Hybrid (30 month)
20010901– 20041201	Historical Daily uncorrected (30 & 60 month) Historical Daily corrected (30 & 60 month) Historical Monthly (30 & 60 month) Parkinson (30 & 60 month) Hybrid (30 & 60 month)Structural		

In periods of rapidly changing risk, shorter historical time windows improve the responsiveness of Parkinson forecasts and of daily returns-based historical methods. The daily historical models likely suffered from the large windows utilized in forming the estimates. A much shorter window of daily returns, perhaps 6 months, is likely to produce better forecasts. It will be interesting to compare more reactive daily returns-based forecasts (corrected for serial correlations) with monthly returns-based structural models.

As we observed earlier, heuristically derived coefficients that relate the ratios of monthly high and low prices to risk levels in the Parkinson model differed, both across assets and over time, from the theoretical value. This failure in the technique stems from failures in the underlying model for price motions, the most serious of which is probably its neglect of serial correlations. An attempt was made at an "ad hoc" correction by selecting a coefficient that yielded the best average bias statistic for the random portfolios over the 10-year window. Even with this in-sample adjustment the approach suffered during several of the sub-periods. We conclude that the Parkinson method is interesting, but is too flawed to compete successfully against either daily returns-based historical or structural forecasting methods.

A remaining question is whether applying daily data to the structural technique might further improve it. Certainly the historical technique seemed to benefit from the higher data density, and the key idea behind the Parkinson technique is to gain some information about intramonth return dynamics by observing monthly high and low prices. The question is an open one; it is quite possible that serial dependence among daily returns will inhibit their effective exploitation. In any case, it is already clear that monthly data already can support very responsive specific risk forecasts in the structural model.

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05

Barra Event & Industry Conference

September, October,
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MSCI Barra

Barra Calendar of Events

SEPTEMBER

14 **Aegis Portfolio Management Workshop**
Frankfurt, Germany

14 **Cosmos Global Risk Manager Workshop**
London, UK

21-22 **The 3rd Annual Art of Indexing Forum**
Washington, D.C.

21 **Aegis Portfolio Management Workshop**
New York, NY

22 **Credit 2005-Counterparty Credit Risk**
Venice, Italy

OCTOBER

12 **Aegis Portfolio Management Workshop**
London, UK

19 **Aegis Portfolio Management Workshop**
Boston, Massachusetts

25 **Aegis Portfolio Management Workshop**
Toronto, Canada

NOVEMBER

15–16 **The 7th Annual Masters of Investment Management Conference**
Singapore, Hong Kong

15–16 **TotalRisk User Summit**
San Francisco, CA

16 **Cosmos Global Risk Manager Workshop**
London, UK

16 **Aegis Portfolio Management Workshop**
Chicago, Illinois

DECEMBER

4–7 **The 10th Annual Super Bowl of Indexing**
Scottsdale, AZ

7 **Aegis Portfolio Management Workshop**
New York, NY

14 **Aegis Portfolio Management Workshop**
London, UK

Barra Speaking Engagements

September 22
Credit 2005-Counterparty Credit Risk

Venice, Italy
MSCI Barra speaker: Lisa Goldberg
Topic: A Top Down Approach to Multi-Name Credit

Industry Conferences

The 3rd Annual Art of Indexing Forum

September 21-22 / Washington, D.C.

Sponsored by: SRI

MSCI Barra Speaker: Mark Sladkus

Location: JW Marriott Hotel Pennsylvania Ave.

The 7th Annual Masters of Investment Management Conference

November 15– 16 | Singapore, Hong Kong

Sponsored By: IMN

MSCI Barra Speaker: Khalid Ghayur

Location: Shangri-La Hotel | Singapore, Hong Kong

The 10th Annual Super Bowl of Indexing

December 4–7 | Scottsdale, AZ

Sponsored By: IMN

Location: Seaport Hotel & World Trade Center | Boston, Massachusetts

Barra Client Education

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September 14 | Frankfurt, Germany

September 21 | New York, NY

October 12 | / London, UK

October 19 | / Boston, Massachusetts

October 25/ Toronto, Canada

November 16/ Chicago, Illinois

December 14 | London, UK

December 14 | London, UK

Cosmos Global Risk Manager Workshop

September 14 | London, UK

November 16 | /London, UK

December 07 | New York, NY

December 14 | London, UK

TotalRisk User Summit

November 15–16 | San Francisco, CA

Location: Hotel Nikko San Francisco

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