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Successfully Riding the Correlation Rollercoaster

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Correlated markets dominated the investment landscape in 2011 and into 2012 — a situation that seems likely to persist. For investors, understanding the benefits and pitfalls of investing in different correlation environments is essential. Here we examine some strategies suited to a high correlation environment, and offer a series of "do's and don'ts" for investors as they ride the correlation rollercoaster.

Successfully Riding the Correlation Rollercoaster

Scott Hamilton, Sebastian Ceria, PhD, and Melissa Brown, CFA

The headlines said it all:

Stock Correlation Still Easing, *The Wall Street Journal*, February 17, 2011

When the Markets Move as One, *The New York Times*, April 3, 2011

Stock Correlation Reaches Record As Traders Fear Grim Economy,
Huffington Post Business, August 24, 2011

Correlation of US stocks highest since 1987 crash, *Financial Times,* September 8, 2011

High Stock Correlations Could Be Here to Stay, *The Wall Street Journal,* January 4, 2012

Say Goodbye to Stock Correlation, *The Wall Street Journal,* March 14, 2012

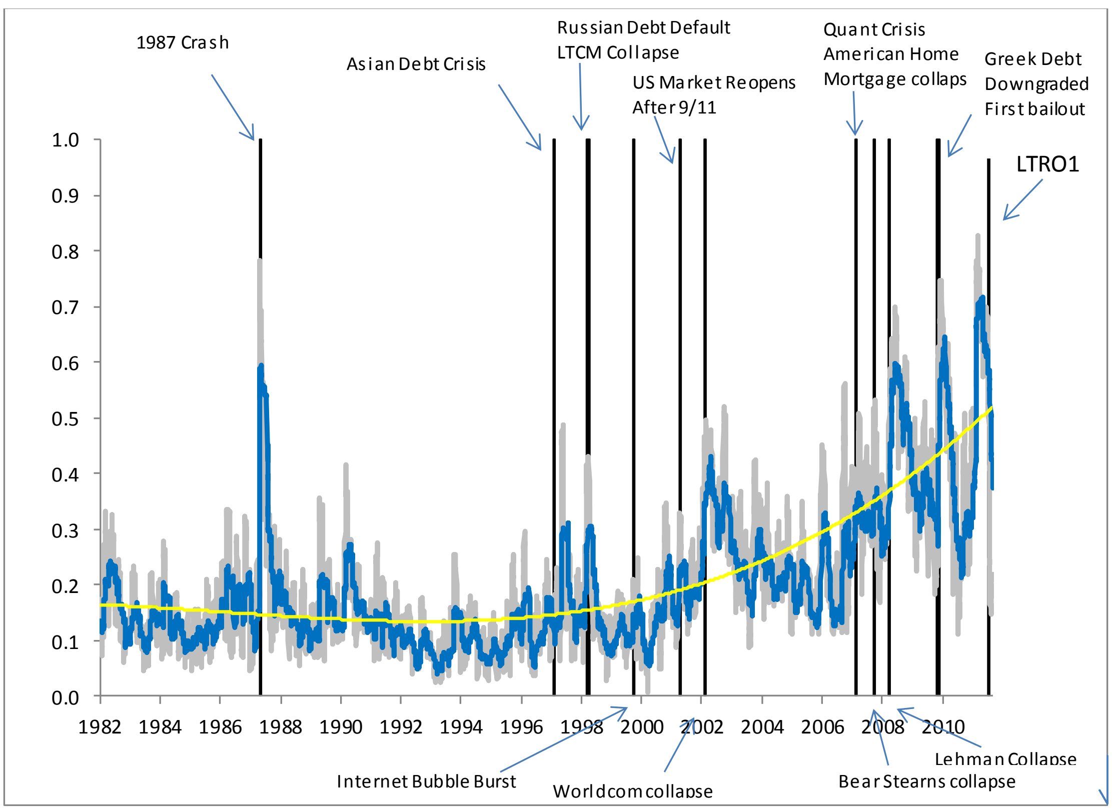
Correlations within and across markets were front-and-center news in 2011 and into 2012. Correlations have continued to fluctuate widely this year, and macro themes are likely to continue to dominate the investment landscape for some time to come. When macro issues—from the European debt crisis to the 2011 tsunami in Japan—cloud the picture for companies' future prospects, their stocks tend to move down together and, by definition, correlations increase. In particular, correlations within many markets have exhibited a strong upward secular trend, with significant cyclical fluctuations.

Investing in a high correlation environment can be substantially different from investing when correlations are low. In this paper we attempt to help investors understand the benefits and pitfalls of investing in different correlation environments, and to develop a series of "do's and don'ts" to help guide investors as they ride the correlation rollercoaster.

Figure 1 depicts the median forward 20 and 60-day realized correlations for stocks in the Russell 1000, with vertical bars on the days of some notable events. Correlation peaks tend to coincide with these events, but median correlations remain high for some time after the event. Just as we observe clustering in volatility levels the same seems to be true for correlations. What is deemed to be a crisis in retrospect does not always lead to such a dramatic level of correlations, but the impact on correlations can persist. Immediately after the collapse of Lehman Brothers on September 15, 2008, the median 60-day forward correlation was about 0.32. That median steadily climbed over the next few months, reaching a peak of about 0.6 in mid-December 2008, and it subsequently took over a year for it to drop to its pre-Lehman level.

Thus, after a major shock to the market, we can expect correlations to remain high long enough that it is useful to think about investment strategies to use in such environments. In addition, the recent trend in correlations seems to be following an upward secular path, with quite a bit of cyclical variation around that path. Our study below discusses some of the implications of investing in a high correlation environment, and suggests some possible strategies an investor might use to mitigate some of the issues.

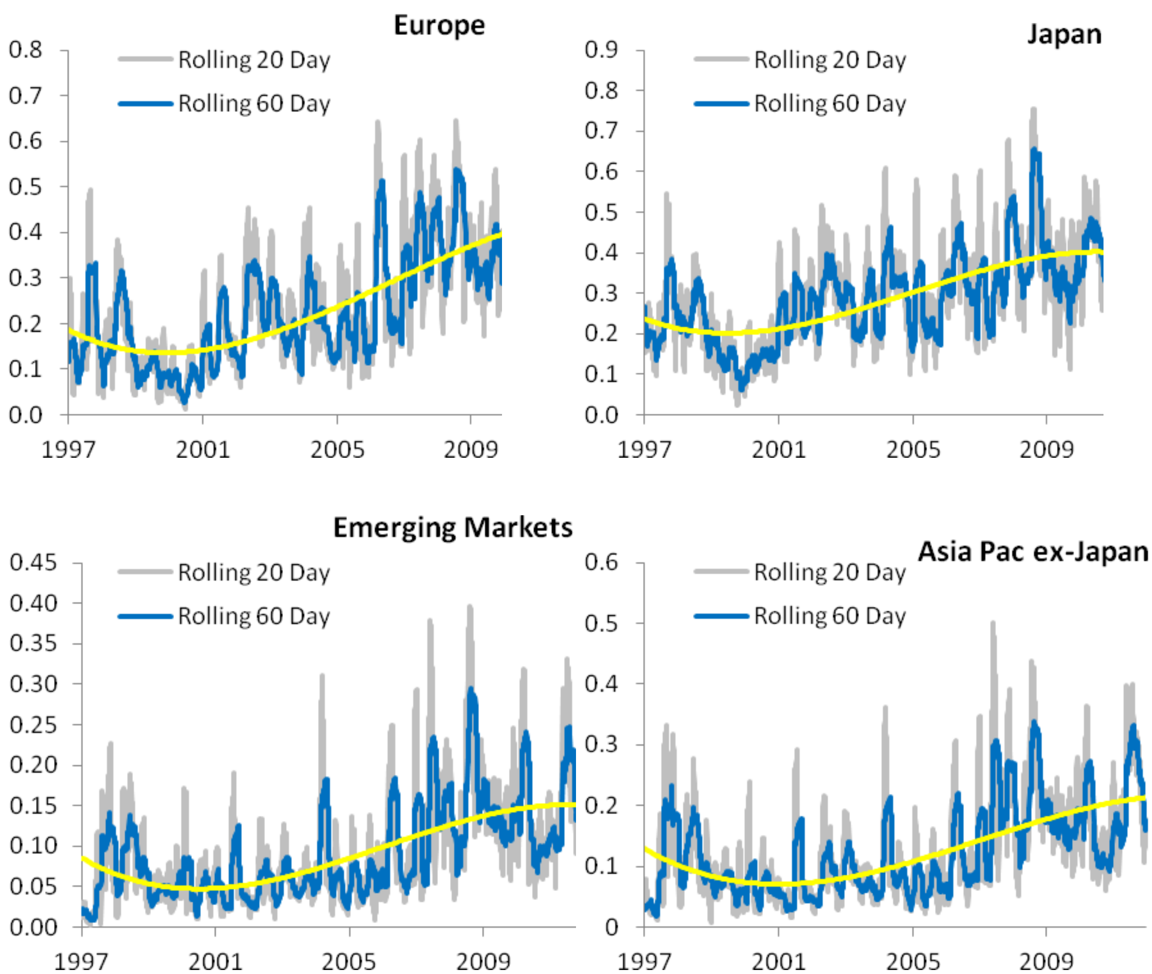
Figure 1. Major events tend to be associated with spikes in correlations



Source: Frank Russell, Axioma, Inc.

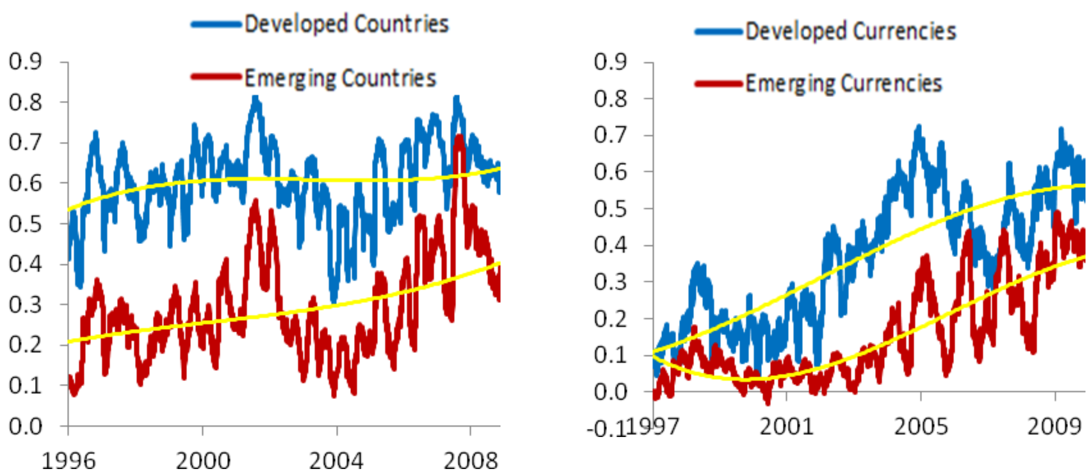
Within-market correlations across the world tend to follow a similar pattern—spikes followed by elevated correlations for a period of time, as well as a secular uptrend in the median correlation for most markets (Figure 2). The secular correlation increase is evident across currencies as well, but more so in emerging countries than in developed countries, and from a lower base (Figure 3).

Figure 2. Correlations have been trending up worldwide



Source: FTSE, Axioma, Inc.

Figure 3. Correlations within emerging market countries and currencies are rising more than in developed countries, but from a lower base



Source: Axioma, Inc.

We have developed six guidelines to help investors navigate the correlation rollercoaster.

Our Six Guidelines:

DON'T **expect the impact of correlation to be the same for every investment strategy**

DO **use risk models to understand the impact of correlation**

DO **understand the relationship between correlation and dispersion**

DON'T **expect your information coefficient (IC) to remain stable as correlation changes**

DO **use correlation information to your advantage**

DON'T **assume there is nothing you can do about high correlations**

DON'T expect correlation to impact all strategies in the same way

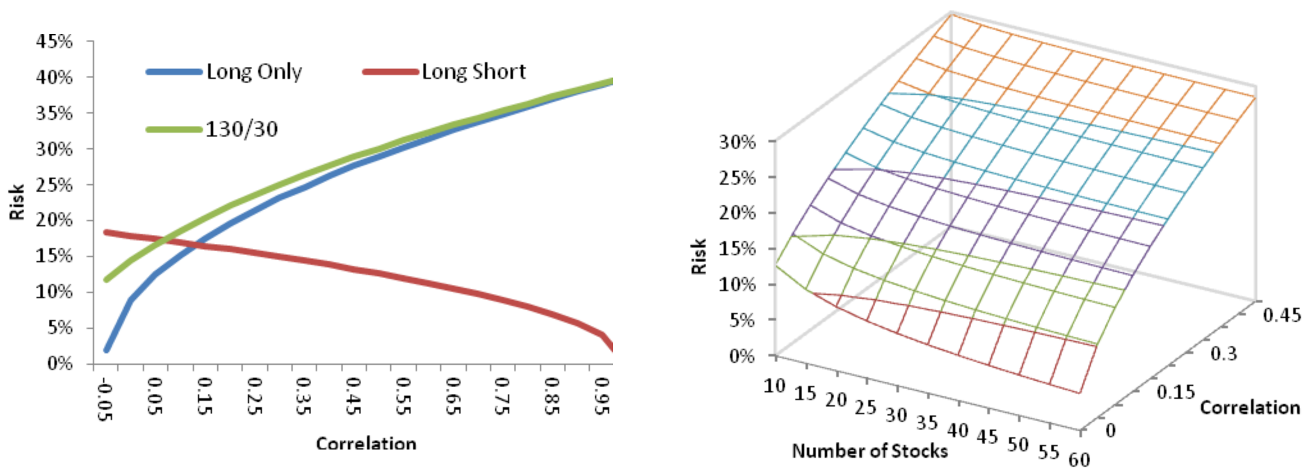
High correlations can theoretically benefit some strategies while hurting others. Below, we state some "rules of thumb" regarding correlation and risk. These won't always be observed in practice, but all other things being equal…

- Total risk of long only portfolios tends to increase as correlations increase[1]
- Total risk of 100% long-short (dollar neutral) portfolios tends to decrease as correlations increase
  - As correlations increase the short positions become a better hedge for the long positions
- Total risk of 130/30 portfolios tends to increase as correlations increase
  - The decrease in the long-short portion of the portfolio is dominated by the increase in the long only portion
- Active risk tends to decrease as correlations increase
  - Active positions around a benchmark form a long-short portfolio
- The diversification benefit of adding more stocks decreases as correlations increase
- Increased correlation leads to a higher proportion of factor risk (and a lower proportion of stock-specific risk)

We illustrate some of these behaviors on simple theoretical portfolios in Figure 4. The surface chart on the right illustrates the fact that as correlations increase there is less potential risk reduction from adding more securities to the portfolio.

[1] It helps to keep the risk equation in mind when figuring out the intuition of these rules of thumb: in a 2-stock portfolio, $Var(P) = w_1^2 Var(R_1) + w^2 Var(R_2) + 2 w_1 w_2 \sigma_1 \sigma_1 \boldsymbol{\rho_{12}}$

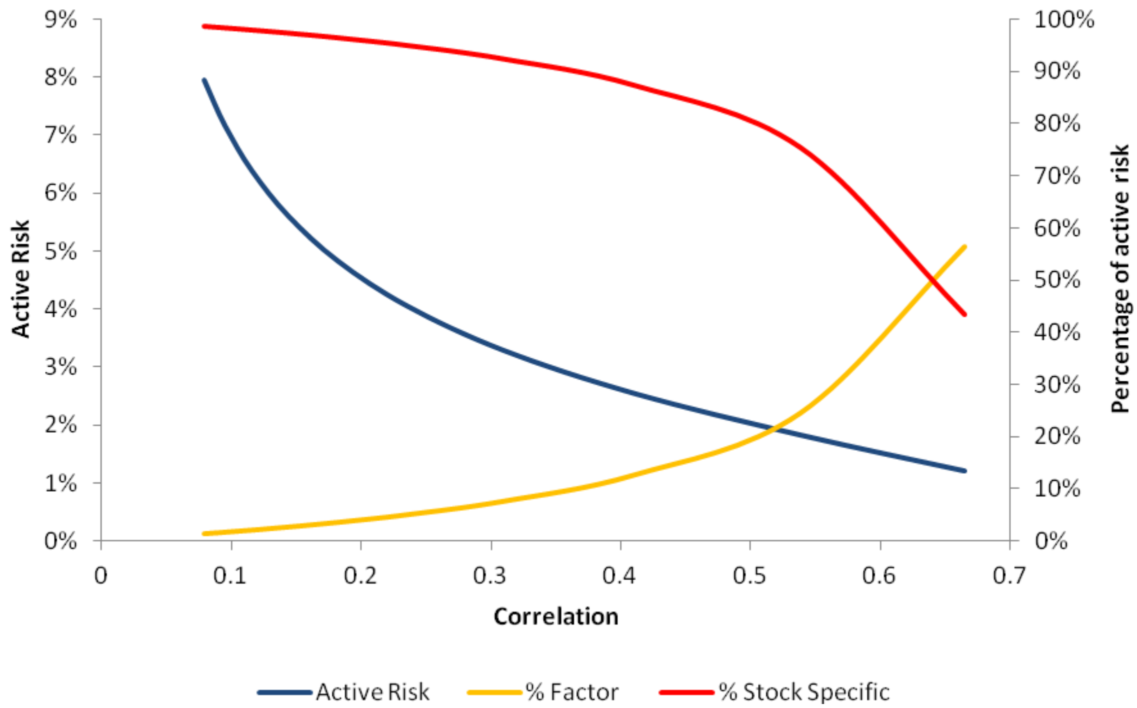
Figure 4. Illustrations of the impact of correlation on total risk and diversification



Source: Axioma, Inc.

In Figure 5. we explore the correlation impact on active risk. Here we use a hypothetical, simple two-factor covariance matrix and a 10-stock long-short portfolio. We vary the asset-level correlation to determine the impact on risk. Using this simplified example, which can be extended to the more general case, we observe that tracking error falls as correlation increases. At the same time, stock-specific risk declines while factor risk increases. *Thus, rising correlations can lead to a double-whammy—lower active risk combined with a decreasing proportion of stock-specific risk—that results in less alpha for strategies based on stock selection.*

Figure 5. The potential consequence of correlation on active portfolios



Source: Axioma, Inc.

DO use risk models to understand the impact of correlation

Risk models allow users to clearly see the impact of correlation on risk. The change in predicted risk, *all other things equal*, is proportionally related to the change in correlation. We would generally expect changes in volatility to dominate changes in correlation (as the variances are more significant than the covariances) however there are several potential contributors to a change in forecast risk, which we discuss below.

So, how is a change in correlation reflected in changes in risk model forecasts? In Table 1 we break down the change in forecast risk for each of the past five years for the Russell 1000 into its component parts. To understand what is driving the change in risk of a benchmark (or any portfolio) we can look at the contribution to change from each of the underlying components: portfolio composition and weights, portfolio stock characteristics, stock-specific volatility, factor volatility and factor correlations[2]. Asset-level correlations are not expressed directly in the factor model so to see the impact of changes in stock correlations, in the bottom panel we also show the decomposition of the full asset covariance matrix.

[2] The components of a risk forecast are the portfolio holdings, its factor exposures, the covariance matrix, and stock-specific risk. In order to decompose the change in risk of a benchmark or portfolio, we employ the following methodology: We first look at the impact of the change in holdings, so we use last period's risk model with the current portfolio to calculate a risk forecast. The difference is attributable solely to the change in holdings. Next, to evaluate the change in stocks' characteristics, we update the factor exposures and again use last period's risk model, but with current holdings and exposures. Third, we look at the impact of specific risk changes by using current specific risk estimates but the prior period's covariance matrix. We calculate the impact of changes in correlation by using last period's correlations with all the other data as of the current period. Finally, the residual is the impact of the change in factor volatility. While the ordering described above will affect the results, we find that the results do not change substantially when we change the order. Intuitively, we believe that the biggest impact will come from change in factor volatility, and our results bear out our intuition.

Table 1. Changes in correlation are but one component of overall risk changes

Factor level change in risk	**2007**	**2008**	**2009**	**2010**	**2011**
Risk at start	9.1%	14.7%	38.3%	23.7%	16.8%
Portfolio composition	0.4%	-0.8%	1.5%	0.6%	-0.5%
Stock characteristics	0.2%	0.8%	-1.6%	-0.3%	0.0%
Stock specific volatility	0.0%	0.2%	-0.1%	0.0%	0.0%
Factor volatility	3.8%	20.8%	-14.5%	-7.2%	7.9%
Factor correlations	1.2%	2.6%	0.1%	0.1%	0.2%
Total change	5.7%	23.6%	-14.6%	-6.9%	7.6%
Risk at end	14.7%	38.3%	23.7%	16.8%	24.4%
Asset level change in risk					
Avg. initial volatility	24.2%	33.5%	72.6%	39.0%	28.6%
Avg. final volatility	33.5%	72.6%	39.0%	28.6%	39.5%
Avg. initial correlation	19.4%	23.6%	41.8%	47.3%	41.7%
Avg. final correlation	23.8%	41.0%	47.3%	41.7%	52.5%
Risk at start	9.1%	14.7%	38.3%	23.7%	16.8%
Portfolio composition	0.4%	-0.8%	1.5%	0.6%	-0.5%
Stock volatility	3.7%	20.4%	-18.7%	-6.6%	6.4%
Stock correlations	**1.6%**	**4.0%**	**2.6%**	**-0.9%**	**1.6%**
Total change	5.7%	23.6%	-14.6%	-6.9%	7.6%
Risk at end	14.7%	38.3%	23.7%	16.8%	24.4%

Source: Frank Russell, Axioma, Inc.

You may be wondering how a change in asset-level correlations is captured by the factor model, given that all the correlations in the model are dictated purely by factor relationships. By construction, factor models reduce the dimensionality of underlying set of asset returns. One of the key reasons for doing this is that asset level relationships are often spurious whereas factor relationships tend to be more stable. However, the general level of asset correlations remains reflected in the model in the relative proportion of factor risk to stock-specific risk.

Remember that the asset level covariance matrix is defined as follows

$$\Sigma_{asset} = \mathrm{E}.\Sigma_{factor}.\mathrm{E}^T + \Delta$$

where:

E = matrix of asset exposures to factors

Σ_{factor} = factor covariance matrix

Δ = stock specific variance diagonal matrix (with zeros on the off diagonals)

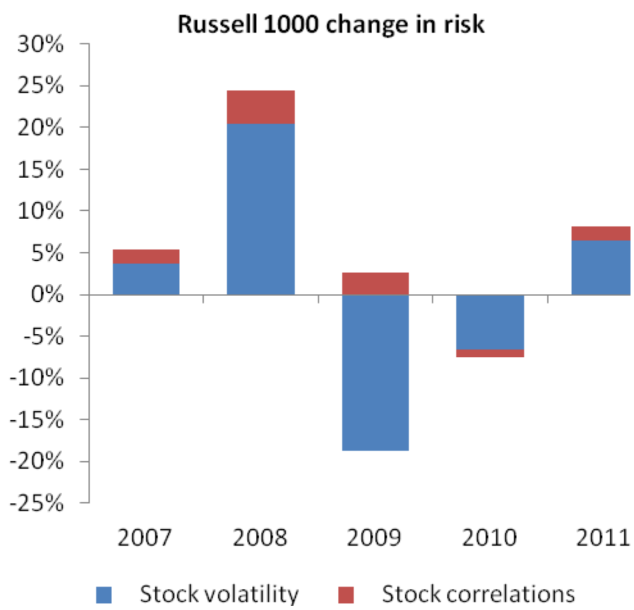
The correlation between two assets "a" and "b" is therefore defined as

$$cor(a,b) = \frac{e_a^T.\Sigma_{factor}.e_b}{\sqrt{(\Sigma_{aa} + \Delta_{aa})*(\Sigma_{bb} + \Delta_{bb})}}$$

In the case where there is no stock-specific risk then the implied asset correlations will directly reflect the exposure weighted factor correlations. However, as stock specific risk is added, the implied correlations between assets shrinks. When stock-specific risk is large relative to factor risk, then the implied asset correlations approach zero.

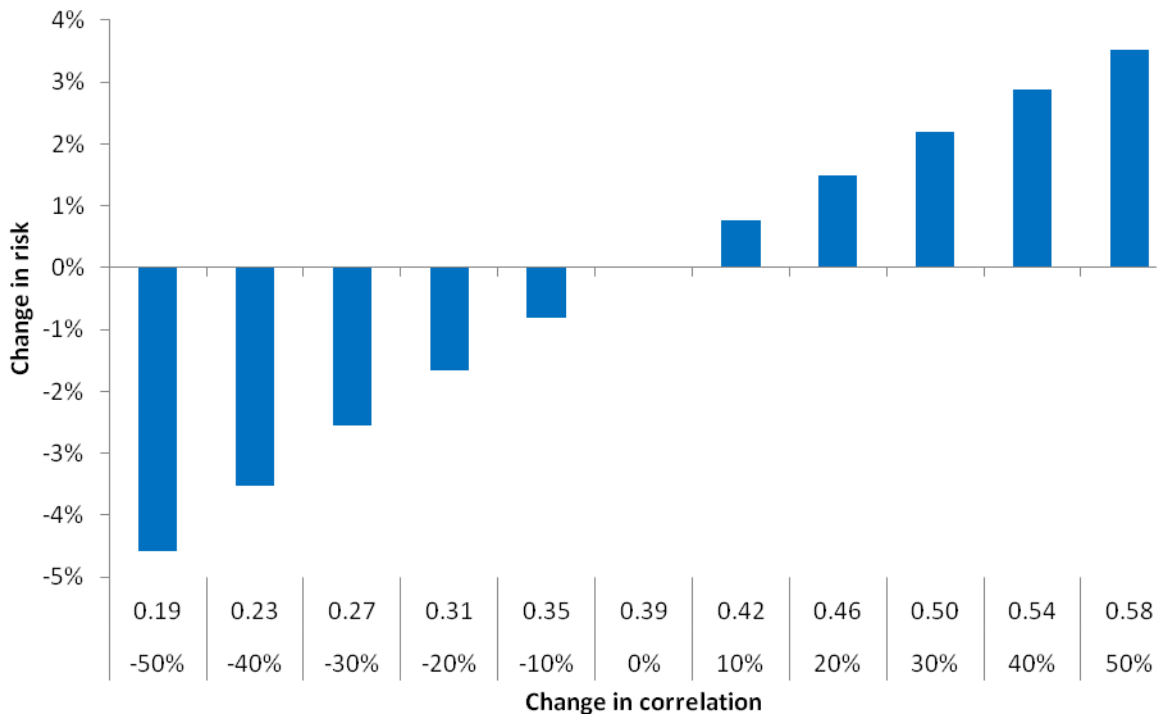
From the full-covariance-matrix decomposition we see that changes in asset-level correlations contribute a relatively small, but still significant portion of the change in risk, roughly 15%-to-30% in most of the past five years (Figure 6). We also note that they can amplify the effect of changes in volatility (as in 2007, 2008, 2010 and 2011) or they can offset it (as in 2009), a further indication that it is important to understand the impact of correlation on changes in risk, and to use a risk model to enhance that understanding. Finally, to isolate the impact of correlation on risk, we simulated the change in risk for the Russell 1000, holding all components constant except correlations (Figure 7).

Figure 6. Correlation can enhance or offset changes in volatility



Source: Frank Russell, Axioma, Inc.

Figure 7. Holding all other variables constant, correlation can have a large impact on risk



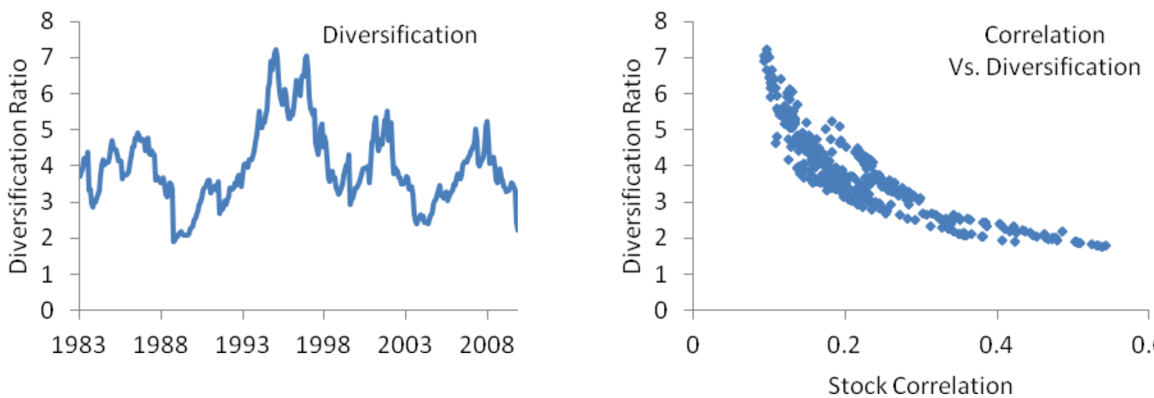
Source: Frank Russell, Axioma, Inc.

In what other ways are asset-level correlations reflected in portfolio characteristics? Below we look at three different measures that are strongly interrelated with correlation.

- The "diversification ratio" of a portfolio is defined as the ratio of the weighted average total risk forecasts for a portfolio divided by the total risk forecast for the portfolio (Sénéchal 2010). If all correlations were one, the numerator and denominator would be the same, the diversification ratio would be one, and there would be no diversification benefit. The higher the ratio, the more correlations are helping the investor achieve diversification. The left chart in Figure 8 shows the diversification ratio of the Russell 1000 from 1982 through 2011. Clearly, this ratio can be extremely variable. The chart on the right shows the relationship between median correlation and the diversification ratio. Here we note that even a median correlation of 0.5

means there is relatively little diversification benefit. A risk model will help the investor understand and react to this impact of high correlations—or benefit when the correlation is lower.

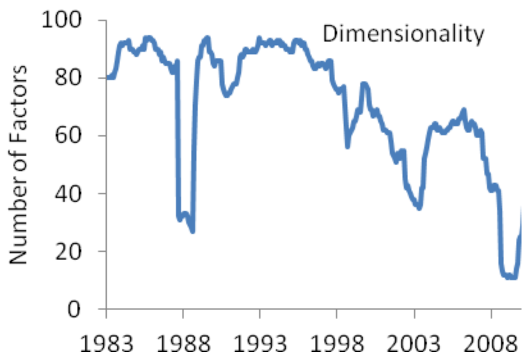
Figure 8. The higher the correlation, the lower the diversification ratio

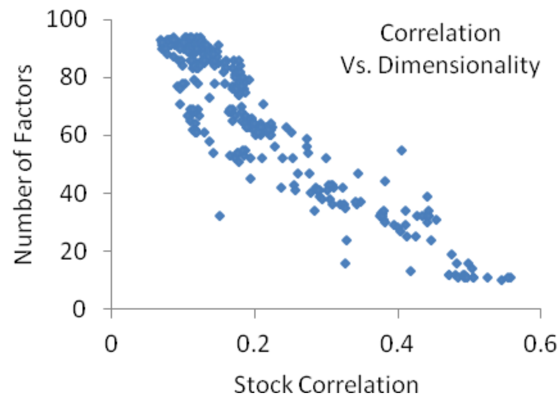


Source: Frank Russell, Axioma, Inc.

- Another way to look at the relationship between correlation and risk is through dimensionality, which we define as the number of factors in a statistical model needed to explain 50% of the risk. The left chart in Figure 9 plots dimensionality through time and the right is a scatter plot of correlation versus dimensionality. We observe that dimensionality has trended down since 1995, and the higher the median correlation the lower the dimensionality. This relationship again suggests it is more difficult to achieve diversification when correlation is high, as there are relatively fewer (but increasingly significant) drivers of risk.

Figure 9. Higher correlation is closely associated with lower dimensionality





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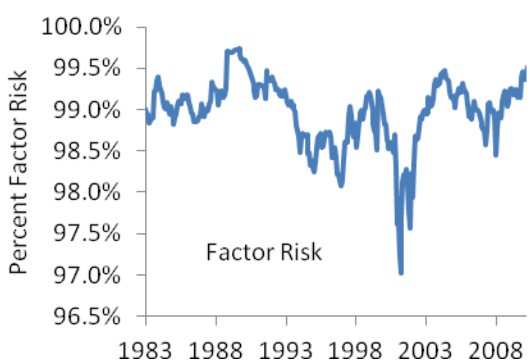
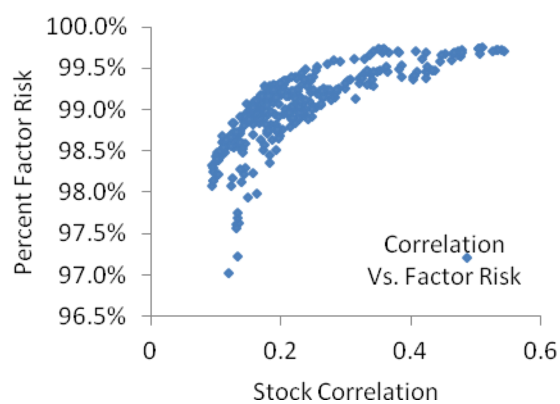
Source: Frank Russell, Axioma, Inc.

- As we have already mentioned, a third way of thinking about correlation is the proportion of factor risk versus stock-specific risk. In Figure 10 we see that as median correlation goes up, factors account for more of the portfolio's risk relative to specific risk, meaning a good stock picker's prowess would have had less impact on the portfolio. When viewed on a total risk basis (as in the charts below) the factor risk will always be the dominant component; this relationship holds for active risk, as well.

Figure 10. The higher the correlation the higher the proportion of risk coming from factors





Source: Frank Russell, Axioma, Inc.

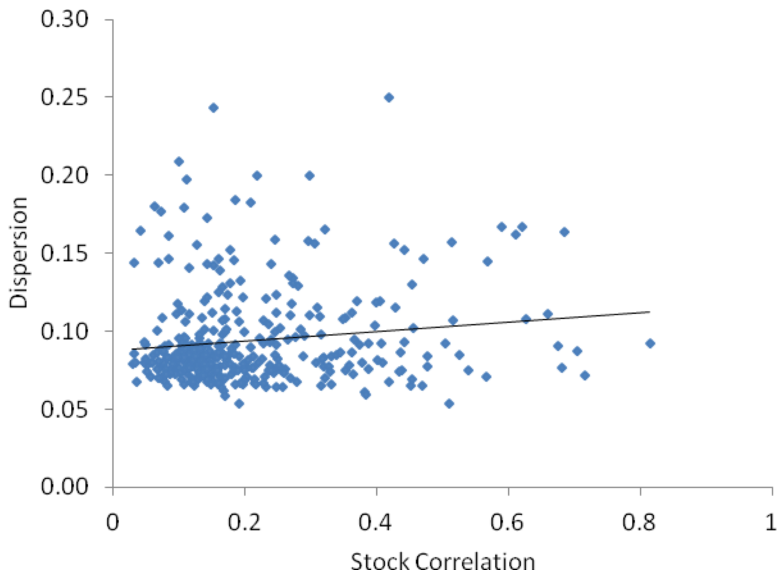
DO understand the relationship between correlation and dispersion

One of the key points of our study is that high correlation does not necessarily mean low dispersion—and dispersion, not correlation, drives the opportunity set for stock pickers.

Dispersion is the cross-sectional volatility of stocks, and is a key driver of the magnitude of active performance: **the higher the dispersion, the greater the payoff to differentiating between the winners and losers**. Conventional wisdom states that when correlations go up dispersion goes down, which in turn makes it more difficult for active managers to outperform. The link between correlation and dispersion has been discussed in the literature. For example, Solnik and Roulet (2000) show, with some simplifying assumptions, that correlation between markets is a function of the ratio of the dispersion around the average and the volatility of the average. Lillo et al (2001) demonstrate in the case of a simple factor model that the average correlation is a function of the ratio of stock-specific volatility to market volatility. And Tan and Greyserman (2004) examine the mathematical relationship between covariance and dispersion. They demonstrate that dispersion is proportional to the average covariance of stocks over the period. In other words, dispersion captures both volatility and correlation, which we will expand upon below.

Despite conventional wisdom, empirical observation seems to suggest that dispersion actually went up as correlation increased (Figure 11). Perhaps stock picking does not become irrelevant as correlation increases, as some observers might believe. Of course, if increased correlation did reduce dispersion it would be detrimental to performance.

Figure 11. Dispersion appears to increase as correlations increase



Source: Frank Russell, Axioma, Inc.

Why do we observe the apparently counterintuitive relationship between correlation and dispersion?

From a mathematical perspective, correlation actually measures *fluctuation around a trend* and does not necessarily indicate that stocks are moving in the same direction if the path of the trend is different. Take the following examples of daily stock returns (Table 2):

Table 2. High correlation does not necessarily mean stocks are moving together

	Daily Returns			
	Stock A	Stock B	Stock C	Stock D
Day 1	1	-3	-2	2
Day 2	3	-1	1	3
Day 3	1	-3	0	3
Day 4	3	-1	0	2
Day 5	2	-3	13	1
5-Day Return	10.4%	-10.5%	11.8%	11.5%
Correlation A & B	0.91			
Correlation C & D	-0.71			
Correlation A & C	0.12			
Correlation B & D	0.33			

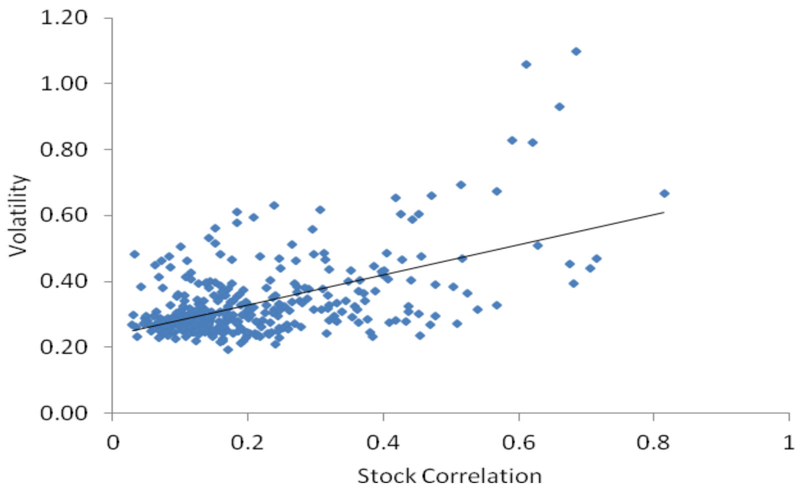
Source: Axioma, Inc.

A and B have a very high correlation, but their returns are in the opposite direction. C and D have a very negative correlation, but very similar returns. A and C have five-day returns that are in the same direction, but a low correlation, and B and D's correlation is moderate, but positive, whereas their returns are in opposite directions. So, stocks can be highly correlated even though they are moving in different directions, or have a low correlation with similar returns.

To understand the relationship between correlation and dispersion we need to consider the contribution of volatility. Although we cannot ascertain causality, there is a strong, positive relationship between correlation and volatility (Figure 12)[3]. Increased time series volatility will likely result in higher cross-sectional volatility.

[3] We believe it is most likely that another set of confounding variables, such as debt crises in one or more countries, is driving both increased correlation and increased volatility.

Figure 12 . Higher correlation is associated with higher volatility



Source: Frank Russell

Because dispersion is a function of both correlation and volatility (which in turn have some dependency) we need to condition the data on volatility to get a clear picture of the impact of correlation. To do this, we divided monthly periods since 1982 into a four by four matrix—four correlation quartiles and four volatility quartiles and calculated average dispersion for each of the 16 states.

It now becomes clear that there is a relationship between correlation and dispersion. Although it was relatively rare for the market to experience high correlation and low volatility (Table 3), when it did, average dispersion—the necessary ingredient for a good stock picker to add value—was notably much lower than average (Table 4). Conversely, it is commonly the case that dispersion is above average in times of very high correlation when volatility is also very high.

Table 3. It was rare to experience very high correlation and low volatility…

	Correlation Quartile			
Volatility Quartile	Low	Mid	High	Very High
Low	28	28	29	5
Mid	36	27	14	13
High	15	21	33	21
Very High	11	14	14	51

Source: Frank Russell, Axioma, Inc.

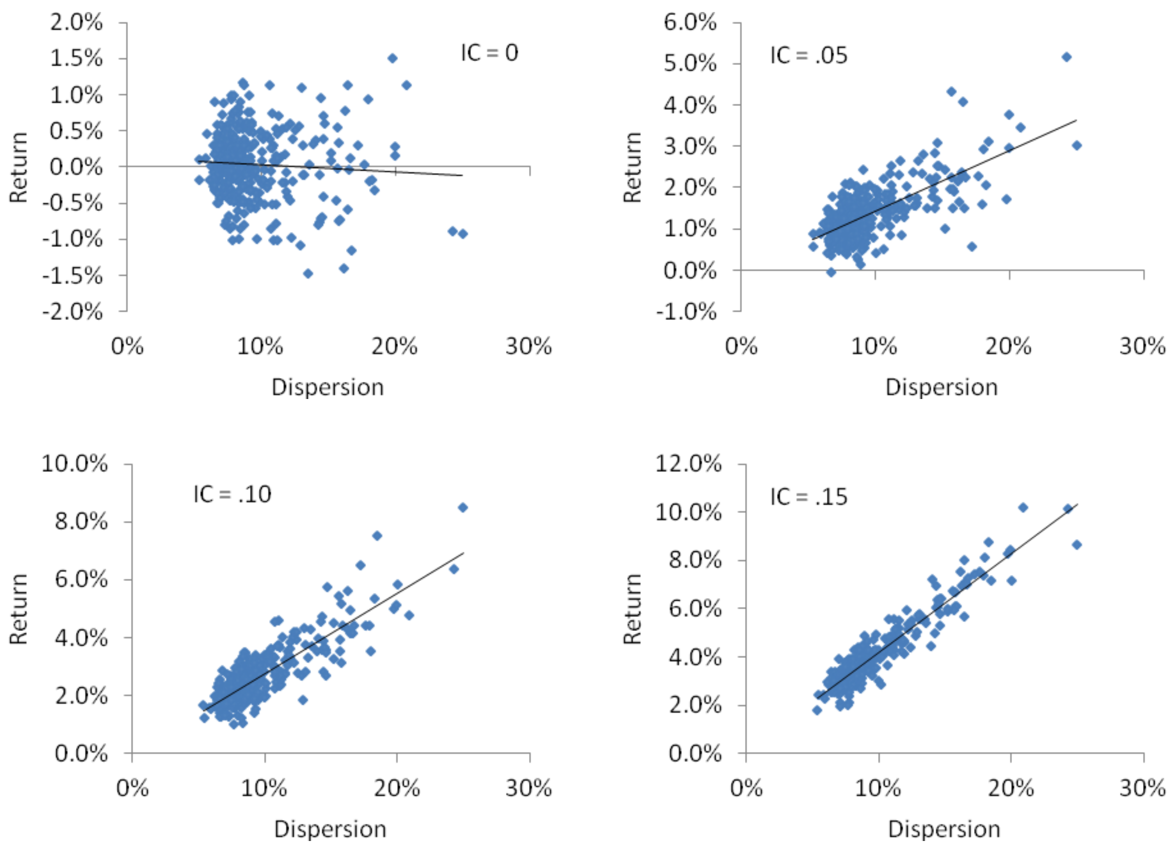
Table 4. …but that scenario meant much lower total return dispersion

	Correlation Quartile			
Volatility Quartile	Low	Mid	High	Very High
Low	7.5%	7.3%	7.0%	6.4%
Mid	8.4%	8.0%	7.9%	7.1%
High	9.3%	8.9%	9.4%	8.6%
Very High	16.5%	14.0%	14.3%	12.1%

Source: Frank Russell, Axioma, Inc.

Active managers should be aware of the impact dispersion can have on their ability to add value. To illustrate this we simulated different alpha strategies on the Russell 1000 universe with pre defined information coefficients (IC). In Figure 13 we plot the relationship between strategy return and dispersion for different levels of IC. As the IC increases, the noise decreases, and returns are increasingly leveraged to dispersion. Thus, the impact of dispersion becomes increasingly important as the strategy's ability to forecast returns increases. *The better you are at stock picking, the more attention you should pay to correlation and dispersion!*

Figure 13. The higher the IC, the more it is impacted by dispersion

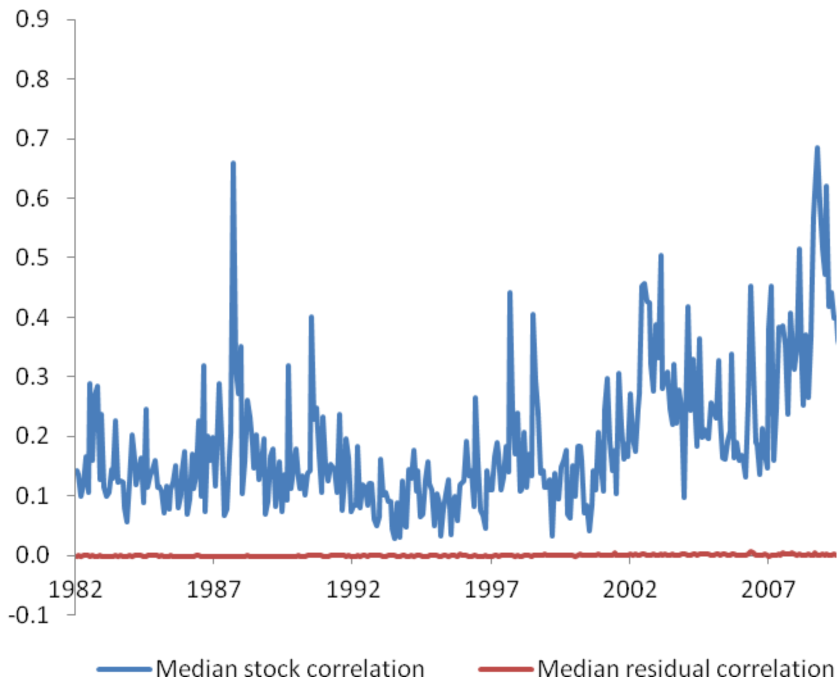


Source: Frank Russell, Axioma, Inc.

Most discussions of correlation look at correlations of realized *total* returns. Active managers, of course, are more concerned with *excess* returns. In Figure 14 we show the computed median residual correlation (residual returns from our medium-horizon fundamental risk model). This illustrates clearly that residual return correlations are not impacted by asset level correlations.[4]

[4] Of course correlations of residual returns from a well-constructed risk model *should* be zero.

Figure 14. Residual correlations are not impacted by total return correlations



Source: Axioma, Inc.

Some observers have suggested that, because of the lack of correlations amongst excess returns, benchmark-relative (or, more specifically, factor-neutral) investors are not impacted by correlations at the asset level. However, because the proportion of factor risk increases as correlations rise, residual dispersion can also decrease with increasing asset correlation. Just as we see with total returns, there is a clear relationship between correlation and residual return dispersion, once volatility is taken into account (Table 5). Although the worst-case scenario (low correlation and low volatility) is quite rare it is not correct to assume that just because one is benchmarked on active performance that one's strategy will be immune to asset-level correlations.

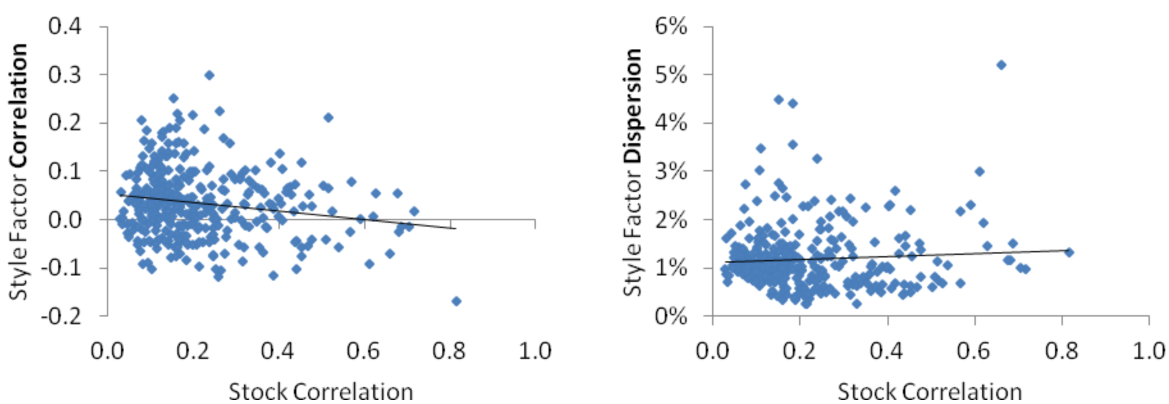
Table 5. *Residual* dispersion was also lowest when volatility was low but correlations were high

	Correlation Quartile			
Volatility Quartile	Low	Mid	High	Very High
Low	6.8%	6.4%	6.7%	6.2%
Mid	7.9%	7.3%	7.2%	6.7%
High	8.6%	8.2%	8.3%	7.8%
Very High	13.3%	12.3%	12.1%	10.0%

Source: Frank Russell, Axioma, Inc.

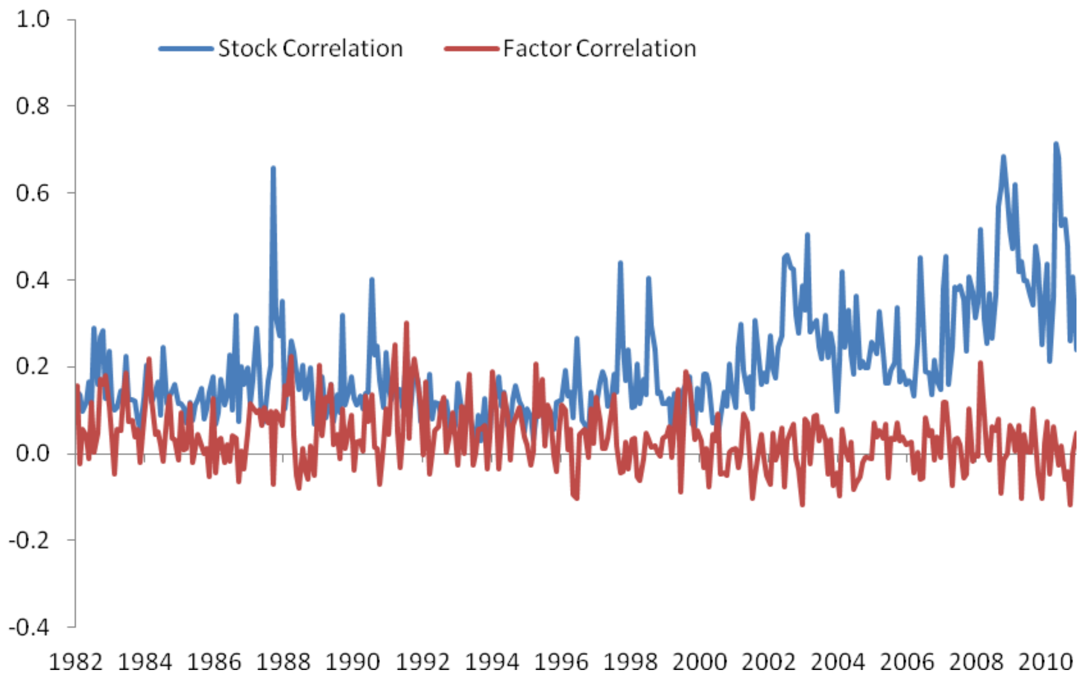
At the factor level, we show in Figure 15 that residual style factor correlations and dispersion do not appear to be related to underlying asset level correlations. In addition, there is little evidence of long-term trends in style-factor correlations like we see with asset correlations (Figure 16).

Figure 15. Style factor correlations and dispersion have little relationship to stock correlations



Source: Axioma, Inc.

Figure 16. Factor correlations are not related to stock correlations



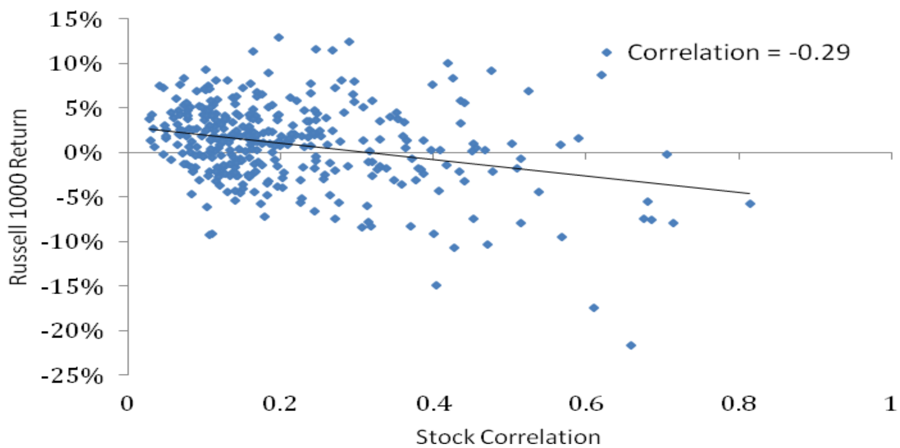
Source: Axioma, Inc.

DON'T expect IC to remain stable as correlation changes

Market behavior is affected by, or affects, changes in correlation. There is a strong negative relationship between market returns and correlation, as shown in Figure 17 and 18.

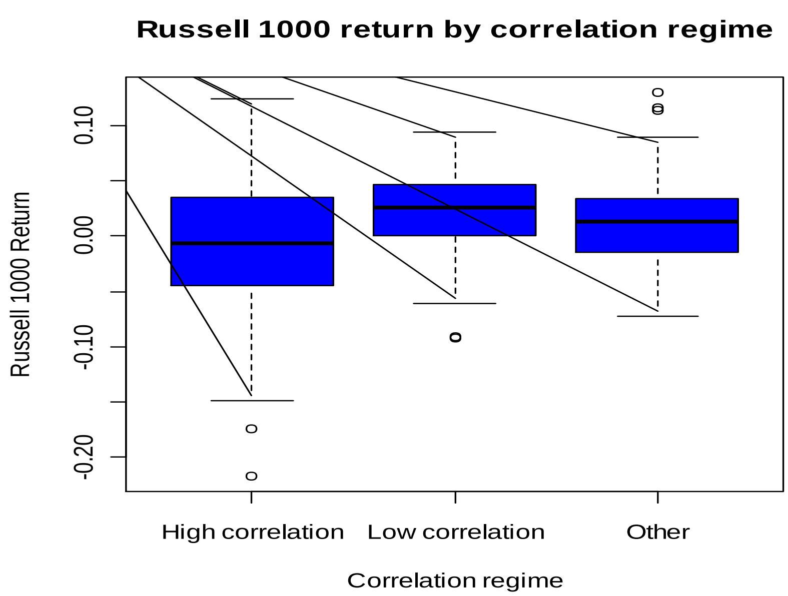
In addition, we see different performance—in many cases statistically significant differences—of our risk factors in high versus low correlation environments. In particular, in the US Leverage, Liquidity and Momentum had significantly different average performance, which held true in most markets on which we have run this analysis (Table 6). Similarly, data on hedge funds suggests that many different types of funds have done substantially better in low correlation regimes than in high correlation ones (Table 7).

Figure 17. Higher correlation is associated with lower returns



Source: Frank Russell, Axioma, Inc.

Figure 18. Returns were lower, on average, and more disperse in high correlation environments



Source: Frank Russell, Axioma, Inc.

Table 6. Difference in return by regime is significant for many style factors…

	Average Monthly Return		
Axioma Style Factor	**High correlation**	**Low correlation**	**Significance of difference**
Value	0.13%	0.27%	*
Growth	0.37%	0.48%	
Leverage	-0.48%	-0.04%	***
Liquidity	0.16%	0.70%	***
Market Sensitivity	0.06%	-0.06%	
Medium-Term Momentum	0.22%	0.66%	**
Short-Term Momentum	-1.57%	-2.26%	***
Size	0.00%	-0.30%	
Volatility	-1.21%	-1.13%	
Exchange Rate Sensitivity	0.01%	0.02%	

* 90% confidence, ** 95% confidence, ***99% confidence
Based on data from 1982 – 2011. Source: Axioma, Inc.

Table 7. …and for most hedge fund categories

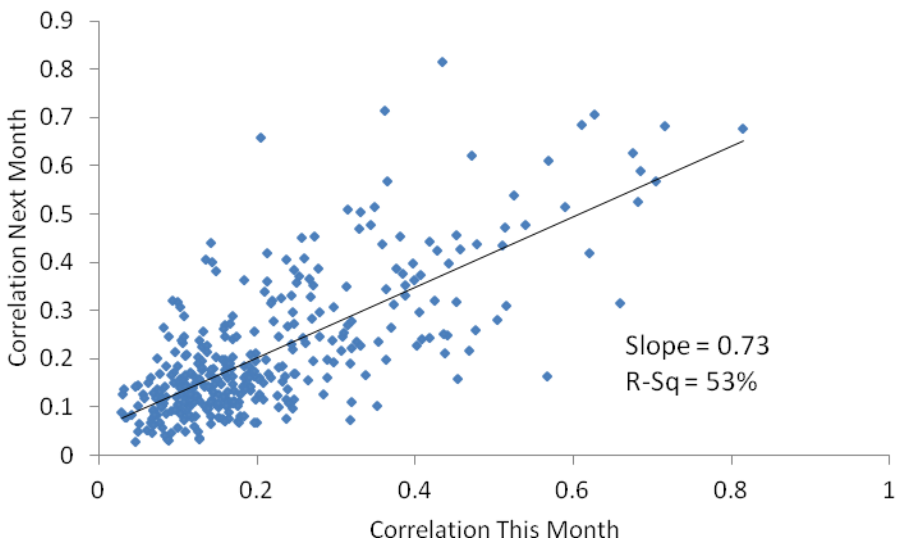
	Average Monthly Return		
	High Correlation	**Low Correlation**	**Significance of difference**
Barclay Hedge Fund Index	-0.48%	1.98%	***
Convertible Arbitrage	0.22%	1.30%	**
Distressed Sec	-0.72%	1.57%	***
Equity Long Short	-0.48%	2.32%	***
Event Driven	-0.32%	1.90%	***
Fixed Income Arbitrage	-0.42%	1.00%	***
Fund of fund	-0.68%	1.64%	***
Merger Arbitrage	0.13%	1.30%	***
Multi Strategy	0.00%	1.59%	***
Long Bias	-1.05%	2.26%	***
Short Bias	0.71%	-0.42%	
Market Neutral	0.42%	0.55%	
Global Macro	0.82%	0.94%	

* 90% confidence, ** 95% confidence, ***99% confidence
Based on data from 1996 – 2011. Source: BarclayHedge Alternative Investment Fund database, Axioma Inc.

DO use correlation information to your advantage

We have demonstrated that average performance across a number of dimensions can differ widely in different correlation regimes. This suggests that investment strategies that are able to anticipate and react to the correlation regime might be able to take advantage of this differential performance. Of course, one key question must be answered - is it possible to forecast the upcoming correlation? The presence of serial correlation in the median monthly correlations suggests that correlations tend to cluster and that a recent period's median asset correlation is a good estimate of the next period's correlation (Figure 19). It is important to note that these correlations are calculated using non-overlapping windows of data.

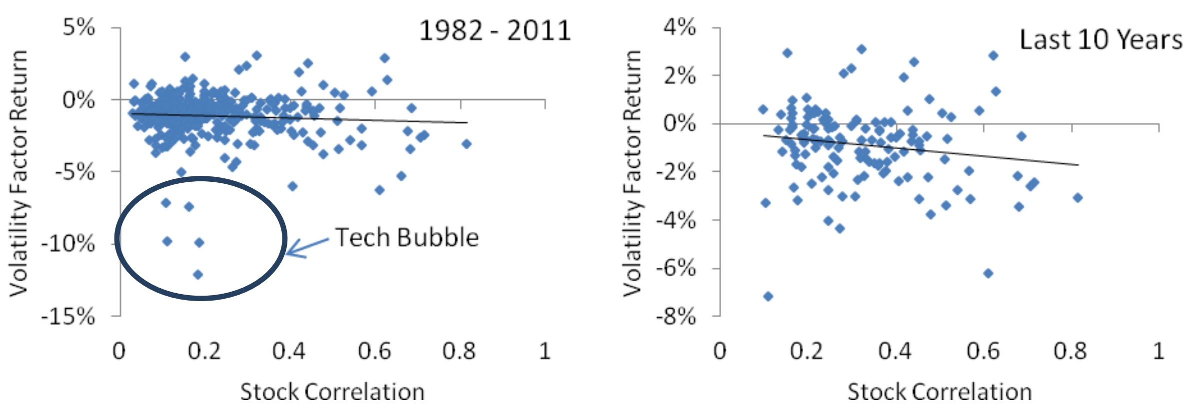
Figure 19. The serial relationship in correlations has been strongly positive



Source: Axioma, Inc.

As demonstrated in Table 6, in the US, Momentum, Leverage and Liquidity have struggled in high correlation environments. An investor might want to impose tighter constraints (or even take on negative exposures) on these factors in a high correlation environment. An investor might want to rein in a positive exposure to leverage, eliminate lower liquidity stocks from the portfolio and avoid buying more, and/or lower the portfolio's target tracking error. In addition, although the longer-term results do not suggest that volatility has a strong relationship with correlation, over the past 10 years that (negative) relationship has strengthened and low volatility has acted as a correlation "hedge." Earlier results may have been strongly affected by the tech bubble (Figure 20) and the negative relationship between correlation and volatility holds true in many other markets we have studied. Therefore, a tilt toward lower volatility when correlations are high may be worthwhile.

Figure 20. After the tech bubble volatility fared better in a low correlation environment

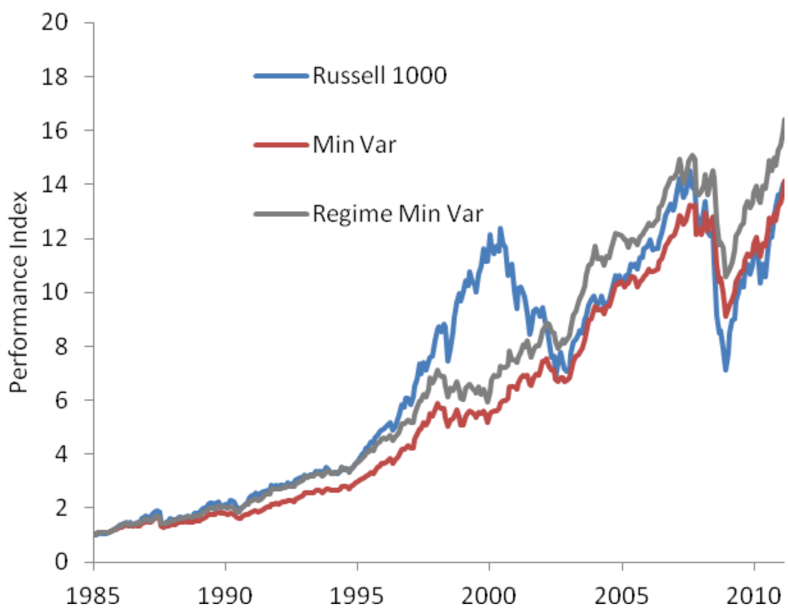


Source: Axioma, Inc.

To explore the ability to exploit correlation information, we backtest a minimum variance strategy that switches state depending on the forecast correlation regime. Correlation forecasts are formed by ranking the most recent period's correlation against all the available correlation history (starting in 1985 with a three-year window of data). If the recent correlation is in the top quartile, we forecast high correlation for the coming period. If the recent correlation is in the bottom quartile, we forecast low correlation; otherwise we forecast neutral correlation.

When the correlation forecast is high, we tilt the minimum variance strategy toward low risk stocks (at the expense of diversification). If the correlation forecast is low, we increase the beta of the portfolio (since we expect market returns to be better when correlations are low). Finally, when the correlation forecast is neutral we stick with the standard minimum variance strategy. Using this simple regime-switching strategy monthly from 1985 through 2011 our test results showed better returns than a standard minimum variance strategy (Figure 21), with only slightly increased risk. Both strategies produced substantially better Sharpe ratios than the Russell 1000, on which they were based (Table 8).

Figure 21. A regime-switching strategy beat a standard minimum variance strategy, and both beat the index…



Source: Frank Russell, Axioma, Inc.

Table 8. …and the regime-switching Sharpe Ratio was higher

	Annual Return	Annual Risk	Sharpe Ratio
Russell 1000	10.2%	15.8%	0.65
Min Variance	10.4%	9.9%	1.05
Regime Min Variance	11.2%	10.2%	1.09

Source: Frank Russell, Axioma, Inc.

Last, but not least...

DON'T assume there is nothing you can do about high correlations

The correlation rollercoaster seems unlikely to subside any time soon. And although the secular uptrend has a hard stop, however improbable, at 1.0, as market crises ebb and flow we will continue to see a good deal of cyclical fluctuation. As global markets become more and more interconnected, correlations on average are likely to stay high.

Therefore, it is critical for an asset manager to understand the impact of correlations and act appropriately when correlations increase. Effective use of risk models is key to a portfolio manager's success when riding the correlation rollercoaster. Benefits from using Axioma's risk models include:

- Daily model updates, which allow a portfolio manager to react quickly to changes in correlation and other aspects of risk. The use of daily forecasts is key, since market events that drive volatility and correlation higher do not neatly happen at the end of the month. An investor using a monthly risk model could miss out on one of the main benefits of using a risk model if the model cannot react quickly.
- Multiple views of risk (Fundamental, Statistical, Short-Horizon, Medium-Horizon) allow a manager to look at risk from several vantage points. When risk is changing rapidly, short-horizon models may pick up those changes more quickly, whereas investors may prefer medium-horizon models in steadier markets. Fundamental factors describe risk consistently, but sometimes a new factor, picked up by the statistical models, can have a big impact.

- Axioma's optimizer allows users to easily use and change constraints, and Risk Analysis clearly highlights exposures, even for those users who choose not to optimize.
- Axioma's Alpha Alignment Factor allows users to identify when there are factors unique to their process that are affecting portfolio risk.
- Finally, the high quality of Axioma's model suite allows users to rest assured they have achieved true diversification.

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