Examining the Effects of Cross-Sectional Volatility on the Risk and Return of Equity Market Neutral Strategies

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23 MAR 2011

1. Introduction

The body of literature examining the impact of time-series volatility on the risk and return of investment portfolios stems at least as far back as the Capital Asset Pricing Model in the early 1960s. In particular, the standard deviation of historical returns (realized time-series volatility) and the predicted value of same (implied or forecasted time-series volatility) have become some of the primary estimators of risk in an investment portfolio.

However, in 2001, researchers began to examine the portfolio implications of cross-sectional volatility, or the dispersion of individual asset returns within a market of securities at a particular moment in time (hereafter referred to as "CSV"). In particular, Ankrim & Ding (2001) and deSilva *et al* (2001) put forth the notion of CSV as an alternative measure of risk for actively managed asset portfolios. In this application, CSV is defined as the standard deviation of the individual returns of the assets in a benchmark relative to the overall return of the benchmark:

$$\sigma_{cs} = \sqrt{\sum_i w_i (r_i - R)^2} \qquad (1)$$

where

$\sigma_{cs} = Cross - sectional\ volatility$
$w_i = Benchmark\ weight\ of\ asset\ i$
$r_i = Total\ return\ of\ asset\ i$
$R = Return\ of\ the\ benchmark$

Several important papers have identified two potential areas of utility for CSV: (1) as a measurement of the opportunity set available to active managers to outperform a particular benchmark and (2) as a measure of the risk of active management relative to a particular benchmark.[1]

From the above, we note that the main body of existing work has been focused on benchmark investing, which seems to emphasize CSV as a measure of "collective idiosyncratic" attributes as opposed to systemic attributes. This makes sense since the notion of CSV seems to rest more soundly on idiosyncratic risk and return rather than systemic. If this is the case, then it stands to reason that CSV may be of particular importance to the risk and return of equity market neutral portfolios since these strategies seek to maximize idiosyncratic factors and minimize systemic factors. With this in mind, we will seek to examine and, where possible, quantify the effect of equity market CSV on equity market neutral strategies (hereafter referred to as EMN). The remainder of this paper will be in seven sections: a review of the theoretical underpinning behind our efforts, a description of the data set and methodology, a description of our base factor model, an empirical examination of the CSV effect on EMN return, an analysis of our return results in light of the heterogeneity of EMN managers, an empirical examination of the CSV effect on EMN risk and a conclusion.

2. A review of the theoretical underpinnings of the effects of CSV on equity market neutral funds

The notion of CSV as a measure of the potential for an active manager to outperform (or underperform) a benchmark stems from the observation that, if all stocks in a benchmark were perfectly correlated, there would be no opportunity for a fully-invested active manager to outperform that benchmark. As a corollary, the greater the CSV within a particular benchmark, the greater the potential gains from active management.

Gorman *et al* (2010) builds on deSilva *et al* (2009) to derive the expected Alpha of a portfolio relative to a benchmark as a function of the size of the opportunity to outperform the benchmark, as measured by the CSV, and the skill of the manager at exploiting that opportunity set, as measured by the Information Coefficient.

$$E(r_a) = IC \cdot \sigma_{cs} \cdot z \qquad (2)$$

where

$E(r_a) = Expected\ return\ of\ portfolio\ r\ over\ a\ specific\ benchmark\ (expected\ Alpha)$[2]
$IC_a = The\ Information\ Coefficient\ of\ the\ active\ manager$
$\sigma_{cs} = Cross - Sectional\ volatility\ of\ the\ benchmark$
$z = A\ Normally\ Distributed\ factor\ between\ 0\ and\ 1$

If we tie equation (2) back in to the CAPM, we find that the return of a portfolio can be described in terms of passive and active components:[3]

$$E(r_P) = \underbrace{\beta\left(E(R_B) - R_{rf}\right) + R_{rf}}_{\text{Passive}} + \underbrace{(IC \cdot \sigma_{cs} \cdot z)}_{\text{Active}} \qquad (3)$$

where

$E(r_P) = Expected\ return\ of\ the\ portfolio$
$\beta\left(E(R_B) - R_{rf}\right) + R_{rf} = Passive\ component\ of\ return$
$(IC \cdot \sigma_{cs} \cdot z) = Active\ component\ of\ return$
$\beta = Beta\ coefficient\ for\ the\ portfolio\ relative\ to\ the\ benchmark$
$E(R_B) = Expected\ return\ of\ the\ benchmark$
$R_{rf} = The\ risk\ free\ rate$
$IC = The\ Information\ Coefficient\ of\ the\ active\ manager$
$\sigma_{cs} = Cross - Sectional\ volatility\ of\ the\ benchmark$
$z = A\ Normally\ Distributed\ factor\ between\ 0\ and\ 1$

The presence and positioning of the Beta coefficient in Equation (3) helps to illustrate the relative importance of the active return component for market neutral funds and, by extension, the importance of the CSV in this regard. To the extent that one assumes that a market neutral strategy has a Beta coefficient of zero, then the expected return of the portfolio simply becomes the risk free rate plus the CSV multiplied by the IC and z factor. In this sense, equity market neutral strategies have a much greater potential to benefit from CSV than other strategies that rely on directional benchmark returns, at least on a relative basis.

It is important to note that an increase in CSV will result in an increase in expected Alpha *only* if the manager's Information Coefficient is positive. Put more simply, as CSV increases, expected Alpha can either increase *or* decrease substantially, depending on the skill of the manager. Therefore, it may be difficult to draw a definitive conclusion about the effect of CSV on the performance of equity market neutral as a strategy, unless we are able to obtain definitive ex-ante estimates of the average manager IC.

If we assume that we cannot say with certainty that the future IC of EMN managers will be positive, we can generalize that the risk of underperforming (or outperforming) a benchmark increases as CSV increases. This suggests that the "risk" in an actively managed portfolio is positively correlated with CSV. In this respect, Gorman *et al* (2010) formalize the contribution of CSV to the risk of a portfolio as:

$$\sigma_P^2 = \beta\left(\rho\sigma^2 + \frac{\sigma_{cs}^2}{N}\right) + \left(\sigma_{cs}^2 \cdot \left[\frac{1}{n} - \frac{1}{N}\right]\right) \quad (4)$$

where

$\sigma_P^2 = Total\ Portfolio\ Risk$
$\beta\left(\rho\sigma^2 + \frac{\sigma_{cs}^2}{N}\right) = Systemic\ Risk$
$\left(\sigma_{cs}^2 \cdot \left[\frac{1}{n} - \frac{1}{N}\right]\right) = Idiosyncratic\ Risk$[4]
$\beta = Portfolio\ Beta$
$\rho = Average\ stock\ correlation$
$\sigma = Average\ stock\ volatility$
$\sigma_{cs} = Cross - Sectional\ volatility$
$N = Total\ number\ of\ stocks\ in\ market$
$n = Number\ of\ stocks\ in\ portfolio$

Gorman (2010) makes the point that CSV contributes to both systemic and idiosyncratic risk. However, as the number of stocks in a market increases (N) the contribution of CSV to the systemic risk of that market decreases. In practice, for any realistic value of N, the contribution of CSV to systemic risk is negligible. Similarly, as the number of active positions in a portfolio increases (n), idiosyncratic risk decreases due to diversification. For a well-diversified portfolio, the idiosyncratic risk contribution from CSV can be quickly overwhelmed by the systemic risk factor. Gorman (2010) points out that these conclusions agree with Modern Portfolio Theory, which states that you can diversify away idiosyncratic risk, but you cannot diversify away systemic risk.

However, we can again note that the systemic risk contribution to the portfolio is scaled by the Beta of the portfolio. In the case of an equity market neutral portfolio, we could theoretically assume a Beta of zero, which would make portfolio risk a direct function of CSV and the number of positions in the portfolio, assuming that there are no other systemic contributions to return.[5] This implies that CSV has enhanced implications for the risk of EMN portfolios relative to other types of strategies that have a non-zero exposure to the equity market.

In the following sections, we will seek to test empirically the theoretical implications of Equations 3 & 4 above.

3. Data and Methodology

We start by establishing a comparative equity index. We selected the S&P 500. An argument could be made for a broader index, with a relatively strong argument to be made for a more globally-inclusive index. We acknowledge that we may be introducing bias into our study, particularly to the extent that the cross-sectional volatility of the average investible universe for HFRI equity market neutral managers does not perfectly correlate with the cross-sectional volatility of the S&P 500. However, we felt that the S&P 500 struck an attractive balance between applicability to our study and manageability and accessibility of data points, particularly in light of the likelihood that no publically published index will match the average investible target universe exactly.

We then calculated a weighted, monthly CSV index as per Equation (1) using S&P 500 constituent weights. For each month, we eliminated any stock that did not have a full price record for the month. Our decision to use a cap-weighted CSV index instead of an equal-weighted index was heavily influenced by Bouchey, Fjelstad & Vadlamudi (2010), who showed that cap-weighted (specifically, free-float weighted) indexes more fully explain manager dispersion than equal-weighted indexes.

We then selected the Hedge Fund Research Monthly Equity Market Neutral Index as our operative data set (hereafter referred to as HFRI). We selected the HFRI data for three reasons: (1) it is a widely-accepted and publically available proxy for hedge fund returns, (2) they have a sub-index that specifically tracks equity market neutral managers, and (3) they make available the individual performance of the constituent managers. We targeted our study to the 2004-2010 time period since 2004 was the first year that there were over 50 managers in the HFRI EMN index. Since we anticipated calculating the CSV of equity market neutral manager returns, we wanted to make sure we had a sufficient number of managers to achieve a representative calculation. Despite the somewhat arbitrary time period, we note that it does cover the tumultuous 2008 period and it dove-tails nicely with the Conner & Li (2010) study, which was from 1994-2004.

We then calculated an Equity Market Neutral Dispersion Index (EMN CSV) as per Equation (1). However, we chose to equal-weight rather than asset-weight the EMN index ($w_i = 1/N$). Our decision to use an equal-weighted index was driven by two practicalities of our data set: (1) the HFRI index is itself equal-weighted and (2) we did not feel that the individual assets under management figures were verifiable since they were self-reported.

4. Developing a factor exposure model

In order to isolate the true effect of CSV on risk and return, we need to first build a factor model to adjust for identifiable non-CSV sources of return. [Cites] The path we took to our factor model is summarized in Tables 1 and 2.

As an initial approach to developing our factor model, we started with the 7-factor model prescribed by Fung & Hsieh (2004), which has been shown to explain a substantial portion of returns for consolidated hedge fund indexes. However, Fung & Hsieh themselves point out that the factors they developed were created to explain the returns of a generalized and diversified hedge fund index. They suggest that other factors may be found to be more suitable for individual strategies. In fact, Fung & Hsieh take what appears to be an a-la-carte approach to factor building, identifying two factors as "Equity ABS factors" targeted at equity-based funds, two factors as "Bond ABS Factors" targeted at fixed-income based funds, and three factors as "Trend Following Factors" targeted at commodity and macro-based funds. We therefore sought to modify the Fung & Hsieh factors to provide a better theoretical and empirical fit with the specifics of the equity market neutral strategy.

The first step in this modification process was to eliminate the three trend following ABS factors. They did not have a theoretical basis for inclusion nor did they contribute to the predictive power of the model.

Secondly, we substituted a simple risk-free rate proxy for the Fung & Hsieh bond ABS factors (change in 10-year Treasury and the change in Moody's Baa credit spread). We found that the change in 1-month Treasury Bills improved the predictive power of the model slightly and had a stronger theoretical underpinning since it is directly linked to Equation (3). Changing the bond factors increased the Adjusted R^2 of the regression from 0.1282 to 0.1545, a mild improvement (although still a fairly low level). In addition, it increased the F-statistic for the regression from 4.05 to 6.055, both of which are significant at the 5% level.

Lastly, Hasanhodzic & Lo (2007) and Racicot & Théoret (2009), amongst others, have suggested that the CBOE Volatility Index (VIX) can have significant explanatory power for hedge fund returns. We find that adding the VIX further increases adjusted R^2 from 0.1545 to a more respectable 0.2645 (F increased from 6.055 to 8.462). We felt this improvement warranted inclusion, particularly given the support it has in the literature.

We therefore arrived at a base factor model that included the VIX, the change in the 1 month TBill, the S&P 500 return and the return of small cap stocks less the return of large cap stocks.

$$r_{emn} = C + \beta_1 X_{VIX} + \beta_2 X_{TB} + \beta_3 X_{SP} + \beta_4 X_{SC} + \epsilon \qquad (5)$$

5. Return analysis: the contribution of Cross-Sectional Volatility

To analyze the effects of Cross-Sectional Volatility on the risk and return of equity market neutral funds, we introduced the CSV factor into our base model and examine the resulting fit to the empirical data. Table 3 shows the results of our regression analysis, which conformed to Equation (6) below.

$$r_{emn} = C + \beta_1 X_{CS} + \beta_2 X_{VX} + \beta_3 X_{TB} + \beta_4 X_{SP} + \beta_5 X_{SC} + \epsilon \qquad (6)$$

As we may have anticipated from Equation (3), our base factor model, even as adapted to equity market neutral, does not hold much predictive power for the return of the aggregate index. Although the regression tests as significant at the 5% level, the adjusted R^2 is only 0.2645, suggesting that only a little over 26% of the equity market neutral index return is sensitive to aggregate changes in the VIX, Treasury Bills and equity markets. Many practitioners may consider this to be too low an R^2 to be of practical, stand-alone use.

However, adding our CSV factor actually *lowers* the predictive value of our model from this already low level. When we add our CSV factor, we find that the adjusted R^2 drops from 0.2645 to 0.2593. Although the model as a whole tests as significant at the 5% level, the specific regression coefficient for the CSV factor has a t-stat of 0.5218, which is well below the level needed to test as significant (Table 3 again).

Given the ambiguous theoretical impact on performance as predicted in Equation (3) and the results of our regression analysis on empirical data, we have to conclude that CSV is not a significant factor in predicting or explaining the return of the aggregate equity market neutral index as calculated by HFRI, at least in so much as we have modeled it here and for this time period.

7. Return analysis: heterogeneity of equity market neutral universe

There have been several studies that have commented on the heterogeneity of funds clustered into hedge fund indexes (for example, Martin (2000) and Miceli & Suinno (2003, 2004)). In practice, we observe that there are different methods that managers may employ to achieve equity market neutral returns. It would therefore stand to reason that the HFRI Equity Market Neutral Index may be heterogeneous, potentially to the point where it may not be possible to draw an effective single conclusion from the aggregate data. Conner & Li (2010) control for heterogeneity by adjusting each individual fund manager's return by the equity ABS factors as prescribed by Fung & Hsieh (2004). This creates a pooled set of returns that are comparable across all funds in the index, regardless of style or sub-style.

We have opted to take a different approach. Following Das (2003), we use a K-means clustering algorithm to sort the individual equity market neutral manager returns into one of three sub-indexes based on correlation of return. Our sorting algorithm was designed to group funds into sub-indexes that maximized the correlation of managers within a sub-index while minimizing the inter-sub-index correlation of managers. Table 4 shows the results of our cluster analysis. We identified three distinct sub-indexes, which we have labeled Styles A, B and C. Although not as statistically precise as the Conner & Li method, we feel that the sub-index approach might be of more use to asset allocators (investors), since asset allocators tend to think in terms of taxonomies and such groupings can help visualize the workings of a particular asset class.

We ran the same regressions on these style indexes as we did on the aggregate equity market neutral index and report the results in Table 5. We find that the regression results of the individual sub-indexes confirm the results of the aggregate index with respect to the impact of CSV on EMN returns. Although there was a slight increase in the adjusted R^2 for Style A, there was a decrease for Styles B and C. Importantly, the CSV factor did not test as statistically significant for any of the styles. As a result, we determined that our original conclusion survives the heterogeneity effect and verifies that CSV is not a significant return factor for equity market neutral management.

In the interest of pointing out areas for future study, we did uncover some potentially counterintuitive conclusions regarding the style indexes and the heterogeneity of the equity market neutral strategy which bear mentioning. Most notably, one of the style indexes (Style A) appears to generate a large portion of return by taking directional bets on the broad equity index. The Fung & Hsieh equity factors both test as significant at the 5% level and explain 65% of the return for the style, compared to a more intuitive 2% and 9% for Styles B and C, respectively. This finding is confirmed by our single-factor regressions on Table 5, which suggest that the return of the S&P 500 alone might explain 62% of the returns from Style A. Style C also tests as statistically significant for the S&P 500 factor, although the R^2 is much lower, suggesting that it is only a minor factor. Only Style B has an S&P 500 exposure that can be described as both statistically insignificant and de minimis.

It may be tempting to declare that the Style B funds are practicing equity market neutral in its purest form while Style A and Style C funds are exhibiting some style drift towards net market exposure. This may be particularly tempting since the only return factor that tests as statistically significant in the Style B model is the change in Treasury Bills, which seems to conform to the theoretical exposure in Equation (3). However, such an investigation is beyond the scope of this paper. What we feel is both clear from this analysis and pertinent to this paper is that there are distinct enough styles within the equity market neutral sector to warrant at least a cursory sub-index investigation before any definitive statistical conclusions about the asset class can be drawn.

6. Dispersion analysis

Having built our exposure model, including CSV, and vetted it against the aggregate equity market neutral index and style-indexes, we now turn our attention to analyzing the impact of equity CSV (CSV_{SPX}) on the dispersion of equity market neutral manager returns (CSV_{EMN}).

Several studies, including Gorman (2004) and Conner & Li (2010), have linked equity market dispersion to the dispersion of returns of active managers. Equation (4) might predict that the impact of CSV on manager dispersion in the equity market neutral universe might be particularly acute. We note that, unlike the equation for EMN return, the equation for EMN risk does not require an assumption about the aggregate IC of the managers. In theory, this should lead to a more stable estimate, if not more reliable.

As we can see from the regression results in Table 6, CSV does appear to play a significant role in the dispersion of manager returns. Our base model with CSV explains 63% of the manager dispersion, representing significantly more predictive power than the same model had on predicting aggregate returns. In addition, the CSV-specific contribution to the explanatory power of the model is much more pronounced than in our return-based regressions and tests as significant for the aggregate index as well as 2 of the 3 Style Indexes. The CSV factor did not test as significant for Style C, but its significance in Styles A and B as well as for the aggregate index drive us to conclude that CSV is indeed a significant factor for determining the dispersion of EMN managers as a whole. This is particularly so when you consider that Style C contains the fewest number of managers.

As a quick and casual test of the utility of CSV, we performed an exercise to tie CSV back into the more popular time-series method of risk analysis: historical standard deviation of returns. Table 7 shows the results of a regression analysis we conducted to determine the explanatory power of our CSV model on the 12-month standard deviation of EMN returns. We do not consider this a definitive study for several reasons, not the least of which is that we only have monthly data points for the EMN index, which makes for an uncomfortably small N value for our standard deviation calculation, and the necessity of transforming our CSV data into a moving average, which may serve to blur causality.

Having said that, our casual regressions do seem to suggest that our model does explain a substantial portion of the realized volatility of the EMN index and our style indexes. All of the regressions tested as statistically significant with adjusted R^2 values all over 0.80. Statistical significance at the factor level was spotty, which may be attributable to our small N value as mentioned above [run study]. However, as a casual effort, we feel this serves as a provocative risk management point and a potential item for further research.

7. Conclusion

Our studies indicate that equity CSV does not show a lot of promise for investors looking to predict returns from equity market neutral strategies. However, we find that equity CSV is a highly impactful factor in describing the risk of equity market neutral portfolios.

From the standpoint of EMN managers, developing robust ex-ante CSV estimates allows for robust predictions of future portfolio risk. Such predictions can lead to higher risk-adjusted returns if a manager is able to actively decrease portfolio risk in advance of an increase in equity CSV and actively increase risk in advance of a decrease in equity CSV. In theory, this would allow for a more constant risk profile and potentially higher aggregate returns.

From the standpoint of investors, evaluating the risk of EMN managers in light of equity CSV may help to better isolate and evaluate the effects of a manager's active decision making process. This can lead to a more comparable measure of manager skill, at least in so much as it relates to risk management.

And finally, we point out that our study is by far complete and there are several additional aspects of CSV that we feel warrant further exploration. Notably, a reliable model for developing ex-ante estimates of CSV, and by extension future equity market neutral risk, would be of particular use to managers. In addition, our study leaves open questions surrounding the heterogeneity of the equity market neutral asset class, which may warrant reconciliation. But perhaps most importantly, we feel that the notion of using CSV as a portfolio tool is new enough that there must certainly be extensive gains to be made from its study, at least in relation to older and more accepted risk management metrics.

TABLE 1
REGRESSION FACTORS AS IMPLEMENTED

This table shows the original asset-based return factors as described by Fung & Hsieh (2004), our adjustments to those factors and our rationale.

Fung & Hsieh (2004)	As Implemented	Rationale
S&P 500	S&P 500	N/A
Wilshire 1750 - Wilshire 750	Russell 3000 - Russell 1000	Data access
Change in 10 yr Treasuries	Change in 1 month TBill	Improves R^2/ higher theoretical support
Change in Moody's Baa spread to 10 year Treasury	Not implemented	Low aggregate significance/no theoretical basis
Bond Trend Following Index	Not implemented	Low aggregate significance/no theoretical basis
FX Trend Following Index	Not implemented	Low aggregate significance/no theoretical basis
Commodity Trend Following Index	Not implemented	Low aggregate significance/no theoretical basis
N/A	CBOE Implied Volatility Index	Improves R^2/ supported by literature

Study Factor:

N/A	S&P 500 Dispersion Index	As per Conner & Li (2010)

TABLE 2
BASE FACTOR MODEL REGRESSION

Regression results for the period January 2004 to December 2010 inclusive (monthly data).

$$r_{emn} = C + \beta_1 X_{VIX} + \beta_2 X_{TB} + \beta_3 X_{SP} + \beta_4 X_{SC} + \epsilon$$

r_{EMN}= Return of HFRI Equity Market Neutral Index
X_{VX}= CBOE Volatility Index
X_{TB}= Change in 1-month Treasury Bill
X_{SP}= Total Return for S&P 500
X_{SC}= Total Return Russell 3000 – Total Return Russell 1000

Figures presented are the associated coefficients. The numbers in parentheses are the t-statistics as adjusted by the Newey-West consistent standard errors for heteroskedasticity and autocorrelation. Figures in bold test significant at the 5% level or better (non-bold figures are italicized for enhanced recognition in some print mediums).

Return	Adj R^2	VIX	TBill	TBond	Baa-T	SPX	SC-LC
HFRI EMN	**0.1282**			*0.6409*	*0.1316*	**0.0564**	*-0.0051*
	F: 4.05			*(1.9222)*	*(0.6328)*	**(3.1701)**	*(-0.1249)*
HFRI EMN	**0.1545**		*-0.1976*			**0.0530**	*0.0178*
	F: 6.055		*(-1.9112)*			**(3.6552)**	*(0.4636)*
HFRI EMN	**0.2645**	**-0.0278**	*-0.2057*			*0.0248*	*0.0173*
	F: 8.462	**(-4.4541)**	*(-1.9353)*			*(1.8064)*	*(0.4962)*

TABLE 3
RETURN-BASED REGRESSION RESULTS

Regression results for the period January 2004 to December 2010 inclusive (monthly data).

$$r_s = C + \beta_1 X_{CS} + \beta_2 X_{VX} + \beta_3 X_{TB} + \beta_4 X_{SP} + \beta_5 X_{SC} + \epsilon$$

r_s= Return of Style Index s
X_{CS}= S&P 500 Cross-Sectional Volatility
X_{VX}= CBOE Volatility Index
X_{TB}= Change in 1-month Treasury Bill
X_{SP}= Total Return for S&P 500
X_{SC}= Total Return Russell 3000 – Total Return Russell 1000

Figures presented are the associated coefficients. The numbers in parentheses are the t-statistics as adjusted by the Newey-West consistent standard errors for heteroskedasticity and autocorrelation. Figures in bold test significant at the 5% level or better (non-bold figures are italicized for enhanced recognition in some print mediums).

Return	Adj R^2	CSV	VIX	TBill	SPX	SC-LC
HFRI EMN	**0.2645**		**-0.0278** **(-4.4541)**	*-0.2057* *(-1.9353)*	*0.0248* *(1.8064)*	*0.0173* *(0.4962)*
HFRI EMN	**0.2593**	*0.0314* *(0.5218)*	**-0.0344** **(-2.2876)**	**-0.2176** **(-2.1115)**	*0.0246* *(1.8860)*	*0.0123* *(0.3964)*

TABLE 4
RESULTS OF K-MEANS CLUSTER ANALYSIS

The following table shows the result of our K-means clustering algorithm. Our algorithm was designed to maximize the intra-cluster correlation while minimizing the inter-cluster correlation. Correlations represent average individual pairwise correlation.

Style	Average Intra-Style Correlation	Average Inter-Style Correlation	Average Number of Managers	Minimum Number of Managers	Ave Monthly Monthly Return
Style A	0.3769	(0.0049)	28	13	0.63%
Style B	0.5673	0.1904	34	21	0.40%
Style C	0.4087	0.0208	23	13	0.37%

TABLE 5
RETURN-BASED REGRESSION RESULTS

Regression results for the period January 2004 to December 2010 inclusive (monthly data).

$$r_s = C + \beta_1 X_{CS} + \beta_2 X_{VX} + \beta_3 X_{TB} + \beta_4 X_{SP} + \beta_5 X_{SC} + \epsilon$$

r_s = Return of Style Index s
X_{CS} = S&P 500 Cross-Sectional Volatility
X_{VX} = CBOE Volatility Index
X_{TB} = Change in 1-month Treasury Bill
X_{SP} = Total Return for S&P 500
X_{SC} = Total Return Russell 3000 – Total Return Russell 1000

Figures presented are the associated coefficients. The numbers in parentheses are the t-statistics as adjusted by the Newey-West consistent standard errors for heteroskedasticity and autocorrelation. Figures in bold test significant at the 5% level or better (non-bold figures are italicized for enhanced recognition in some print mediums).

Return	Adj R^2	CSV	VIX	TBill	SPX	SC-LC
Style A	**0.6426**		*-0.0062* *(-0.6574)*	*0.0396* *(0.3698)*	**0.1485** **(6.5888)**	**0.0697** **(2.9007)**
Style B	**0.1384**		**-0.0377** **(-3.3373)**	**-0.3249** **(-2.0174)**	*0.0100* *(0.4791)*	*-0.0060* *(-0.0926)*
Style C	**0.3096**		**-0.0442** **(-4.0076)**	**-0.3393** **(-3.1562)**	**-0.1199** **(-4.2019)**	*-0.0193* *(-0.4476)*
Style A	**0.6614**	*0.0949* *(1.4388)*	**-0.0262** **(-2.1468)**	*0.0037* *(0.0324)*	**0.1480** **(7.9254)**	**0.0545** **(2.5703)**
Style B	**0.1298**	*-0.0380* *(0.7321)*	*-0.0297* *(-1.1388)*	**-0.3105** **(-2.1304)**	*0.0102* *(0.4970)*	*0.0001* *(0.0026)*
Style C	**0.3057**	*-0.0471* *(0.7389)*	**-0.0541** **(-4.0927)**	**-0.3571** **(-3.0733)**	**-0.1201** **(-4.4087)**	*-0.0268* *(-0.6457)*
Style A	**0.6215**				**0.1697** **(11.5197)**	
Style B	**0.0258**				*0.0514* *(1.6557)*	
Style C	**0.0933**				**-0.0747** **(-5.5728)**	

TABLE 6
DISPERSION-BASED REGRESSION RESULTS

Regression results for the period January 2004 to December 2010 inclusive (monthly data).

$$CSV_s = C + \beta_1 X_{CS} + \beta_2 X_{VX} + \beta_3 X_{TB} + \beta_4 X_{SP} + \beta_5 X_{SC} + \epsilon$$

CSV_s= Manager Dispersion of HFRI Equity Market Neutral Index or Style Index s, as appropriate
X_{CS}= S&P 500 Cross-Sectional Volatility
X_{VX}= CBOE Volatility Index
X_{TB}= Change in 1-month Treasury Bill
X_{SP}= Total Return for S&P 500
X_{SC}= Total Return Russell 3000 – Total Return Russell 1000

Figures presented are the associated coefficients. The numbers in parentheses are the t-statistics as adjusted by the Newey-West consistent standard errors for heteroskedasticity and autocorrelation. Figures in bold test significant at the 5% level or better (non-bold figures are italicized for enhanced recognition in some print mediums).

Dispersion	Adj R^2	CSV	VIX	TBill	SPX	SC-LC
HFRI EMN	**0.6333**	**0.1369** **(2.5434)**	**0.0322** **(2.4046)**	**0.1920** **(3.3255)**	*0.0201* *(1.1078)*	*0.1369* *(2.5434)*
Style A	**0.7385**	**0.1039** **(2.8194)**	**0.0398** **(5.0352)**	**0.4466** **(13.2297)**	*0.0085* *(0.6577)*	*0.1039* *(2.8194)*
Style B	**0.5280**	**0.2401** **(3.4851)**	*0.0092* *(0.4478)*	**0.1361** **(2.4725)**	**-0.0596** **(-2.9212)**	*0.2401* *(3.4851)*
Style C	**0.3859**	*0.2676* *(1.6796)*	**0.0892** **(2.2149)**	*-0.1568* *(-0.7662)*	*0.0949* *(1.3849)*	*0.2676* *(1.6796)*

TABLE 7
DISPERSION-BASED REGRESSION RESULTS

Regression results for the period January 2005 to December 2010 inclusive (monthly data).

$$\sigma_s = C + \beta_1 \bar{X}_{CS} + \beta_2 \bar{X}_{VX} + \beta_3 X_{TB} + \beta_4 X_{SP} + \beta_5 X_{SC} + \epsilon$$

σ_s= 12 month historical standard deviation of returns for HFRI Index or Style Index s, as appropriate
$\bar{X}_{CS}$= 12 month average S&P 500 Cross-Sectional Volatility
$\bar{X}_{VX}$= 12 month average CBOE Volatility Index
X_{TB}= 12 month change in 1-month Treasury Bill yield
X_{SP}= 12 month Total Return for S&P 500
X_{SC}= 12 month Total Return Russell 3000 – 12 month Total Return Russell 1000

Figures presented are the associated coefficients. The numbers in parentheses are the t-statistics as adjusted by the Newey-West consistent standard errors for heteroskedasticity and autocorrelation. Figures in bold test significant at the 5% level or better (non-bold figures are italicized for enhanced recognition in some print mediums).

Standard Deviation	Adj R^2	CSV	VIX	TBill	SPX	SC-LC
HFRI EMN	**0.8016**	*0.0288* *(0.6298)*	*-0.0014* *(-0.1553)*	*0.3361* *(1.3660)*	**-0.0958** **(-4.0531)**	*-0.0059* *(-0.0843)*
Style A	**0.9101**	*0.0005* *(0.0047)*	*0.0439* *(1.8868)*	**0.4783** **(3.3882)**	*0.0508* *(1.7395)*	*0.0032* *(0.0343)*
Style B	**0.8631**	**0.1552** **(2.2572)**	**-0.0284** **(-2.0591)**	*0.7154* *(1.4305)*	**-0.2085** **(-5.2705)**	*-0.1302* *(-1.2733)*
Style C	**0.8748**	*0.1360* *(0.2471)*	*0.0076* *(0.0665)*	*0.1561* *(0.2095)*	*0.0235* *(0.1573)*	*-0.0146* *(-0.0288)*

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[1] Ankrim & Ding (2001), deSilva *et al* (2001), Lillo *et al* (2001), diBartolomeo (2006), Yu & Sharaiha (2007), Connor & Li (2009), Gorman *et al* (2010), Bouchey *et al* (2010), among others.

[2] In this paper, we have taken the liberty of explicitly re-casting the return as the return in excess of the benchmark (Alpha).

[3] Derivation of formula hp

[4] Gorman (2010) assumes that all securities in the portfolio are equal-weighted, which is typically not the case in practice. However, we feel that such an assumption is suitable for illustration purposes.

[5] As we show later in this paper, there are other possible systemic factors to equity market neutral returns, most notably, the change in risk free rates.