Volatility and Correlation Modeling for Sector Allocation in International Equity Markets

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Abstract

Reliable estimates of volatility and correlation are crucial in asset allocation and risk management. This paper investigates Static, RiskMetrics, and Dynamic Conditional Correlation (DCC) models for estimating volatility and correlation by testing them in an asset allocation context. Optimal allocation weights for one year found using estimates from each model are carried to the subsequent year and the realized Sharpe ratio is computed to assess portfolio performance. We also study cumulative risk-adjusted returns over the entire sample period. Our findings indicate that DCC does not consistently have an advantage over the other two models, although it is optimal in certain scenarios.

JEL Classification: C32; C51; G11; G15

Keywords: Equities, Emerging Markets, Asset Allocation, Dynamic Correlation, Volatility

1 Introduction

Estimating volatility and correlation plays a vital role in portfolio construction and risk management. Academics and market practitioners have used a range of static and dynamic models for estimation purposes, and new models (or extensions of existing models) continue to be explored for improved accuracy. Dynamic models have become popular through the work of Bollerslev (1986) and Engle (2002a). In this thesis, we estimate volatility and correlation using a range of models, for portfolios of both U.S. and Emerging Markets equities. We then assess these models in an asset allocation context by utilizing the estimates out-of-sample within a constrained portfolio optimization framework. This allows us to measure the effectiveness of the three models in a practical application.

There exist various methods to model volatility and correlation, and differences between these methods can have significant impact on portfolio management. Volatilities and correlations are complex functions of returns and estimating them is a challenging exercise. Engle and Patton (2001) argue that a good volatility model should have the ability to forecast, exhibit persistence, and display mean-reversion, among other characteristics. They show that the widely-used GARCH (Generalized Autoregressive Conditional Heteroskedasticity) class of volatility models developed by Bollerslev (1986) and others adequately captures these features.

Different models propose different weightings on past information for volatility and correlation estimation. For example, a rolling historical model has a fixed termination point in the past where data prior to that point is deemed uninformative. Other models use declining weights without a fixed termination point. A distinction is also made between conditional and unconditional models. An unconditional perspective is adopted by popular approaches (Andersen et. al. 2007) such as rolling historical (Officer 1973) and extreme-value theory (Taylor, 1987; Wiggins 1992; Longin and Solnik 2001). These models have mostly given way to more dynamic conditional models (Campbell et. al. 2001), as increasing evidence shows that international covariance and correlation matrices are unstable over time (Longin and Solnik 1995). Due to this dynamic nature of volatilities and correlations, simple unconditional risk measures can lead to poor forecasting performance (Solnik et. al. 1996).

Various dynamic models have been proposed in recent years. The RiskMetrics exponential smoother, first established at J.P. Morgan (JP Morgan / Reuters 1996), and the Dynamic Conditional Correlation (DCC) developed by Engle (2002a) are two of the most prominent among the dynamic models. RiskMetrics involves a smoothing parameter that determines the weighting of previous periods for both volatility and correlation estimates. DCC incorporates a volatility estimation step by using, for example, the GARCH model (Bollerslev 1986). In contrast to the predetermined parameter in the RiskMetrics model, DCC parameters are determined empirically, allowing for greater flexibility.

Much current research has been done to examine and compare the effectiveness of RiskMetrics and variations of DCC/GARCH models. Andersen et. al. (2007) comment on the lack of mean-reversion in RiskMetrics compared to GARCH. This can lead to an exaggeration of the variation in volatility relative to the true variation. In other words, on tranquil days RiskMetrics underestimates risk and on volatile days it overestimates risk. In addition to evaluating the different properties between these models, researchers have also assessed them in an asset allocation context. For example, Billio et. al. (2005) apply three variations of conditional correlation models to optimize portfolios consisting of Italian equities. They use correlation estimates from these models to construct constrained and unconstrained portfolios and measure model performance through assessing the mean and variance of one-step-ahead portfolio returns.

In this paper, we employ a similar approach to model comparison. We select three existing methods for volatility and correlation estimation: the traditional Static approach that simply takes the sample standard deviation and correlations, the RiskMetrics exponential smoother widely used by practitioners, and the more recently developed DCC model. To compare the performance of these models in an asset allocation context, we set up two portfolio optimization algorithms with target returns and volatility constraints. The first optimization replicates a mutual fund-style long-only strategy with annual rebalancing. The second mimics a hedge fund investing style with short-selling permitted up to a leverage limit. For each of the Static, RiskMetrics, and DCC models, we estimate volatilities and correlations for a given year, and then use these estimates as inputs into the optimization for the subsequent year. We then measure the implied portfolio return and variance in that subsequent year, and evaluate these measures across the three models.

Through the aforementioned methodology, we investigate the implications of the three models on the two types of fund strategies that best represent the majority of investment capital. Mutual funds have become increasingly popular in the past two decades, with over $24.7 trillion invested worldwide as of 2010 (Investment Company Institute 2011). Hedge funds, while more exclusive, are nevertheless believed to hold significant assets under management, with estimates ranging from $1.64 trillion to $2.46 trillion (Forbes 2012). While mutual funds traditionally employ long-only strategies, there has been a growing trend of long-short mutual funds, such as Fidelity's 130/30 Large Cap Fund and J.P. Morgan's Multi-Cap Market Neutral Fund. In this paper, however, we characterize mutual funds as funds that use the traditional long-only strategy and refer to hedge funds when testing the long-short strategy approach.

Many of these funds attempt to maximize their risk-adjusted returns through diversification, either geographically or by industry sector. Since our dataset includes sector returns in both the Emerging Markets and the U.S., we focus on sector diversification. Recent research highlights the increasing appeal of sector versus country diversification, especially in the Emerging Markets (Lazard Investment Research 2011). Furthermore, much research has been done on the differences between the U.S. and Emerging Markets. For example, Bekaert and Harvey (2002) present several distinguishing characteristics of Emerging Markets equities, including higher average returns, more predictable returns, and higher volatility. Bodie et. al. (2009) further confirm that the Emerging Markets exhibit higher returns and volatility over the period of 1999-2008. To illustrate the difference between developed and developing markets, we optimize portfolios comprised of industry sectors for the Russell 3000 index (henceforth "US") and industry sectors for the Emerging Markets equities ("EM") according to the methodology outlined above. The industry sector "groupings" are average weekly returns of all equities in a given sector for the US and EM from 1996 to 2009.

In summary, we explore the differences in volatility, correlation, and portfolio outcomes suggested by the three volatility and correlation models for both long-only and long-short portfolios in EM and US. Our findings indicate that DCC tends to perform better in the US than in EM, for asset allocation purposes. However, it does not show a consistent advantage over the Static and RiskMetrics methods in any of these markets.

The rest of the paper is organized as follows. Section 2 introduces the dataset used in our study. Section 3 discusses our methodology, including details of the models as well as the process of portfolio optimization. Section 4 presents our findings on volatility and correlation estimates along with comparison of the three models through Sharpe ratio analysis. Finally, Section 5 concludes the paper.

2 Data

We obtain weekly equity returns for both US Russell 3000 index equities and Emerging Markets equities, acquired from Russell Investments (Egger 2010)[1]. Our data comprises of weekly returns on 9 US sectors and 9 EM sectors, as well as weekly equal-weighted returns on the overall US Russell index and the overall EM Russell index from July 1996 to June 2009 [2].

Returns in the US index are reported by industry sector as designated by Russell. The nine sectors are: Technology, Healthcare, Discretionary, Consumer Staples, Energy, Materials & Processing, Producer Durables, Financial Services, and Utilities. Returns in each sector are calculated as the average weekly return across all equities in that sector. The number of equities in each sector ranges from 90 to 751, with the count per sector varying slightly over the sample period.

Returns in the EM index are also reported by sector, using the average weekly return across all equities in each of the same nine sectors as for the US. In EM, the number of equities in each sector varies from 25 to 859, with equity count in each sector varying somewhat over time.

Figures 1 and 2 show the time series of cumulative returns by sector for EM and US respectively. The sectors in EM show similar patterns of a dip in 1997-98 (the so-called Asian Contagion period), a rally through early 2000 (especially in the tech sector), and a drop-off

[1] Clean sector level weekly data is provided by Professor Daniel Egger from the Center of Quantitative Modeling at Duke University.

[2] EM data consists of 15 countries/clusters. Countries in the overall EM index that contain fewer than 15 equities at any time during the sample period are grouped into three regional clusters: Asia, South America, and EMEA (Europe, Middle East, and Africa). For a complete list of countries and cluster components, see Appendix A.

following the dot-com bust, followed by a slow but steady improvement (with a sharp rally in energy) until the credit crisis from late 2007. Returns in US show a somewhat different pattern in the early years of the sample, with only a slight dip around the time of the Asian Contagion, but similar sector-by-sector performances as the EM countries during the internet boom-bust period and the remainder of the decade.

Figure 1: EM Cumulative Returns by Sector

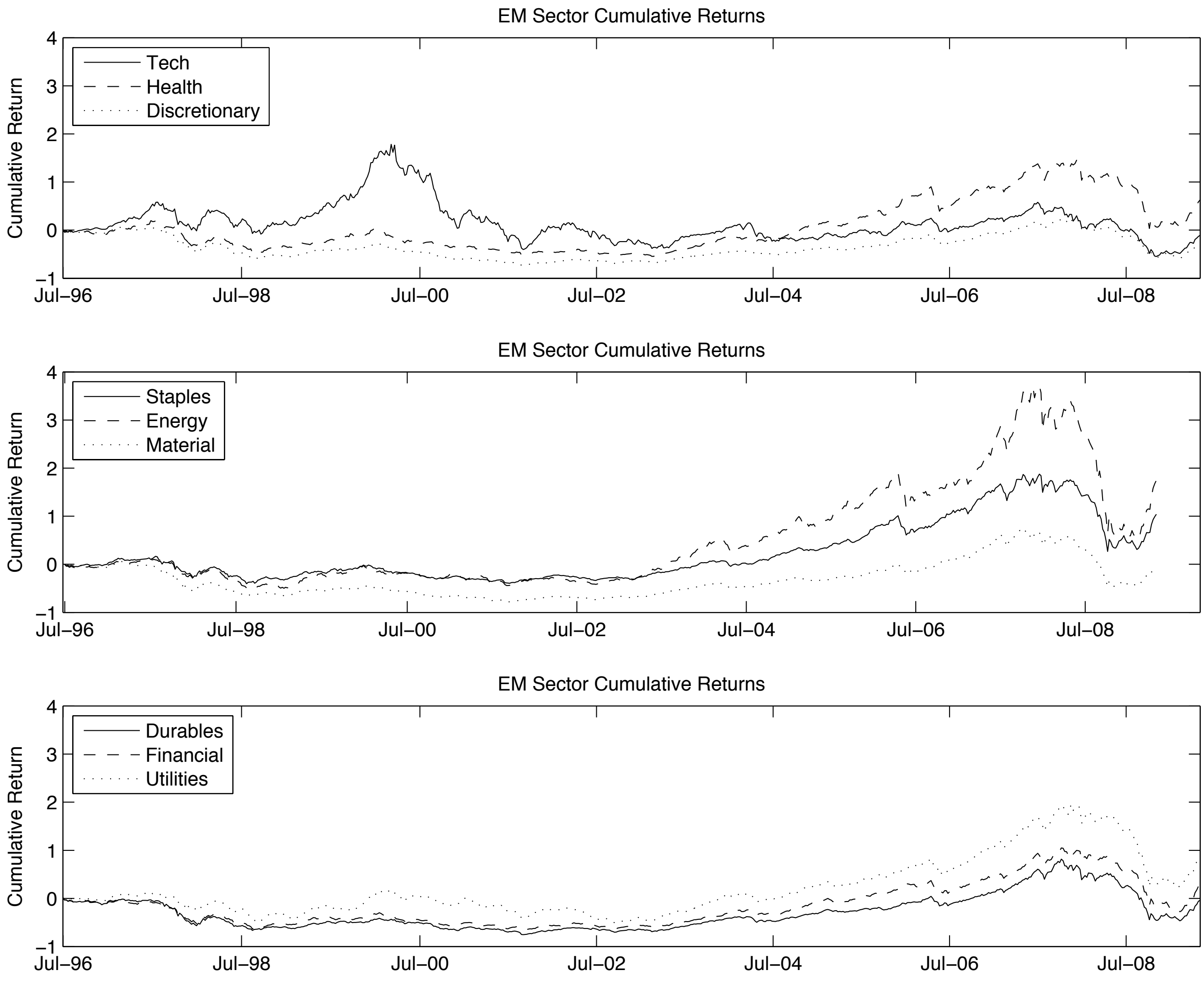
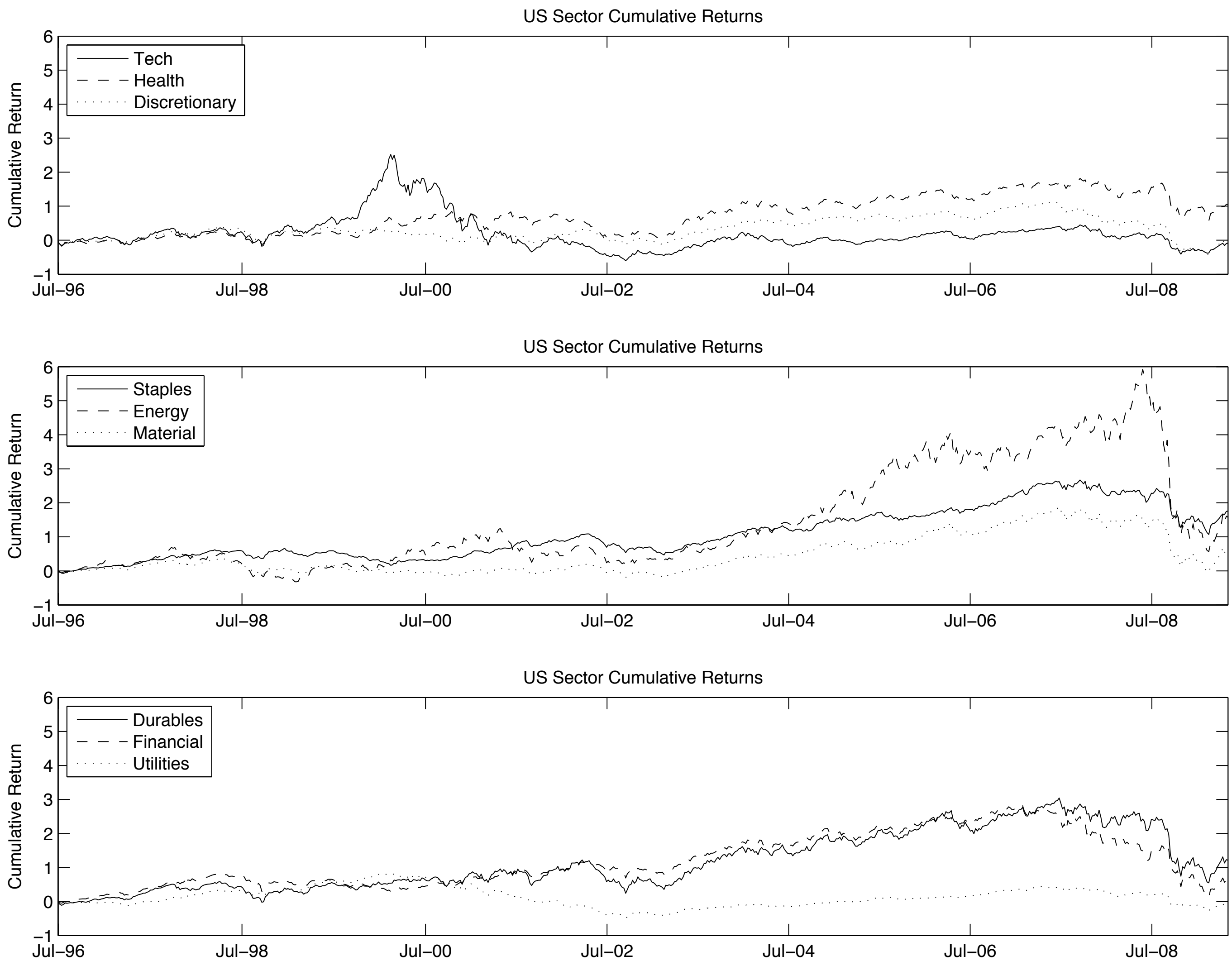


Figure 2: US Cumulative Returns by Sector



3 Methodology

We estimate volatility of the sectors and correlations between sectors using three models: Static, RiskMetrics and Dynamic Conditional Correlation (DCC). In the Static model, we simply calculate sample standard deviations of sector returns and correlations between sectors. In the RiskMetrics model and the DCC model, we compute conditional volatility and correlation that account not only for returns, but also past volatility. Section 3.1 specifies models for the conditional mean and Section 3.2 specifies models for the conditional volatility and correlation. Finally, Section 3.3 presents the application to portfolio management.

3.1 Models for the Mean

3.1.1 Mean for RiskMetrics

To implement the RiskMetrics model, we first de-mean the return series by subtracting the sample mean of that series from each observation:

$$y_{i,t} = X_{i,t} - \frac{1}{T}\sum_{t=1}^{T} X_{i,t} \tag{1}$$

where $y_{i,t}$ is the de-meaned return for sector i in week t. $X_{i,t}$ is our weekly return data for sector i in week t, and $T = 673$, the total number of weeks in the sample.

3.1.2 Mean for DCC: ARMA Process

In order to obtain the zero-mean series to be used for the DCC model, we first estimate the mean return by an autoregressive moving average (ARMA) model. An ARMA process captures the return series' dependance on its own previous value plus a combination of current and previous values of a white-noise error term. We use an ARMA(1,1) model as such:

$$X_{i,t} = \zeta + \psi X_{i,t-1} + \theta y_{i,t-1} + y_{i,t} \tag{2}$$

y_i is the de-meaned series for a specific sector i that we take into the estimation of covariance and correlation.

3.2 Models for Volatility and Correlation

3.2.1 RiskMetrics Exponential Smoother

RiskMetrics uses the exponential smoother to estimate covariance at time t based on information up to time $t-1$. There is a single parameter, λ, that determines the computation of the covariance.

With the de-meaned series from Section 3.1.1, we find the conditional covariance between two sectors i and j as follows:

$$\sigma_{i,j,t} = \lambda\sigma_{i,j,t-1} + (1-\lambda)y_{i,t}y_{j,t} \tag{3}$$

where $\lambda = 0.94$ (J.P. Morgan/Reuters 1996).

The conditional correlation is then found in equation 4 by rescaling the covariance.

$$\rho_{i,j,t} = \frac{\sigma_{i,j,t}}{\sigma_{i,t}\sigma_{j,t}} \tag{4}$$

While RiskMetrics is fairly simple to implement, it can lack flexibility due to having only one fixed parameter compared to a more dynamic model (Engle 2002a).

3.2.2 Dynamic Conditional Correlation

The DCC model proposed by Engle (2002a) parameterizes conditional correlations directly and estimation is carried out in two steps. The first step involves the estimation of conditional volatility. We use Bollerslev's GARCH(1,1), which allows the conditional variance of the current period to be a function of both lagged conditional variance and past residuals:

$$\sigma_{i,t}^2 = \omega + \beta\sigma_{i,t-1}^2 + \alpha y_{i,t-1}^2 \tag{5}$$

The GARCH parameters ω, β and α are estimated using Maximum Likelihood Estimation (MLE)[3].

In the second step of DCC, we estimate conditional correlation. First, the standardized residuals or volatility-adjusted returns s_i are calculated from GARCH volatilities:

$$s_{i,t} = \frac{y_{i,t}}{\sigma_{i,t}} \tag{6}$$

These standardized residuals are used as inputs in estimating quasi-correlations $q_{i,j,t}$ between series i and j in the DCC model:

$$q_{i,j,t} = \mu_{i,j} + \eta s_{i,t-1}s_{j,t-1} + \phi q_{i,j,t-1} \tag{7}$$

where

$$\mu_{i,j} = (1 - \eta - \phi)\bar{R}, \quad \bar{R} = \frac{1}{T}\sum_{t=1}^{T} s_{i,t}s_{j,t} \tag{8}$$

These quasi-correlations are then rescaled to be between -1 and 1:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{q_{i,i,t}q_{j,j,t}} \tag{9}$$

Thus, $\rho_{i,j,t}$ is the conditional correlation at time t between the two series i and j.

[3]Both GARCH and DCC are estimated in MatLab using the MFE and UCSD_GARCH toolboxes developed by Professor Kevin Sheppard at Oxford University.

3.3 Application to Portfolio Management

3.3.1 Portfolio Optimization

Our goal is to evaluate the performance of the three volatility and correlation models in the context of a constrained portfolio optimization. We assume that a portfolio manager wishes to estimate an optimal allocation among the EM sectors (or similarly for the US sectors), with maximum possible expected return subject to a portfolio volatility constraint. We use the volatility and correlation estimates derived in the previous section as inputs into each year's asset allocation model, along with expected returns from the CAPM model. We then apply the optimal allocation outputs as fixed weights for the subsequent year, and calculate the portfolios' realized returns and volatilities for that year based on these allocations.

We carry out this exercise for each of the 10 estimation years from 1998-2007, for four hypothetical portfolios: long-only funds allocating across EM sectors or US sectors; and leveraged funds allocating across EM sectors or US sectors. In addition to the nine sectors, we add a riskless asset with an assumed 0% return to the portfolios. This option to invest in cash gives managers more flexibility to allocate money into other sectors. In the case where we aim to replicate portfolios of a hedge fund, we use a maximum leverage ratio of 3x, which prevents the fund from shorting more than three times its total assets. While funds with different strategies tend to have different ranges of leverage ratios, in many cases 3x levered is an appropriate maximum (Barbarino 2009).

We begin by approximating expected returns for sector i in a given estimation year l using the Capital Asset Pricing Model (CAPM):

$$E(r_{i,l}) = 7\%\beta_{i,q} \tag{10}$$

where we assume a 0% risk-free rate and 7% long-run market risk premium for both EM and US. The values of beta are estimated using returns from the start of the sample period to the end of the estimation year. For a given estimation year l, beta is calculated as

$$\beta_{i,q} = \frac{\sigma_{im,q}}{\sigma^2_{m,q}}, \quad q = 1, ..., \text{last week in year } l \tag{11}$$

where σ^2_m is the variance of the market (i.e., the overall US Russell index and the overall EM Russell index) and σ_{im} is the covariance between sector i and the relevant market index.

Next, we incorporate the estimated volatility and correlation values from the three models into our optimization. For the Static model, we take the sample volatilities and correlations of the entire estimation year. For RiskMetrics and DCC, we compute conditional volatilities and correlations from the beginning of the sample period to the end of the estimation year. We then take these values from the last week in the estimation year as inputs in the portfolio optimization. For example, in the estimation year of 2000, we include return data from July 1996 to the last week of 2000 in RiskMetrics and DCC. The volatility and correlation estimates from this last week of 2000 are the values used in the optimization algorithm.

We constrain the target portfolio volatility to be less than or equal to 20% based on historical equity index levels, and find the optimal asset allocation to maximize returns in both the long-only and long-short cases. For a given estimation year l, we solve for the optimal weights of the assets, $w^*_{i,l}$, by maximizing portfolio returns (equation (12)) subject to volatility (equation (13)) and leverage constraints as discussed above.

$$E(r_{p,l}) = \sum_i w_{i,l} E(r_{i,l}), \quad i = 1, ..., 10 \tag{12}$$

$$\sigma^2_{p,l} = \sum_i \sum_j w_{i,l} w_{j,l} \sigma_{i,l} \sigma_{j,l} \rho_{i,j,l}, \quad i, j = 1, ..., 10 \tag{13}$$

3.3.2 Testing Optimal Portfolio Weights

We apply the optimal weights associated with each of the three methods (Static, RiskMetrics, DCC) in the following year $l+1$ to calculate the realized return of portfolios over a one-year horizon. We denote $w^*_{i,l}$ as the optimal weights from equations (12) and (13) and $C_{i,l+1}$ as the annual return for sector i in year $l+1$. We then obtain the return ($R_{p,l+1}$) implied by the optimized portfolio by taking the sum product of the weights from year l with the annual returns in year $l+1$, as shown in equation (14) below:

$$R_{p,l+1} = \sum_i w^*_{i,l} C_{i,l+1} \tag{14}$$

To obtain the annual volatility implied by the optimal portfolio weights in year $l+1$, we start by calculating the weekly volatility by taking the sample standard deviation of the weekly portfolio returns in that year.

$$\tilde{\sigma}^2_{p,l+1} = \frac{\sum_n (H_n - \bar{H}_n)^2}{n-1}, \quad H_n = \sum_i w^*_{i,l} X_{i,n} \tag{15}$$

In equation (15), H_n is the weekly portfolio return, X_i is our weekly return data as defined in equation (1), and n represents the weeks in year $l+1$.

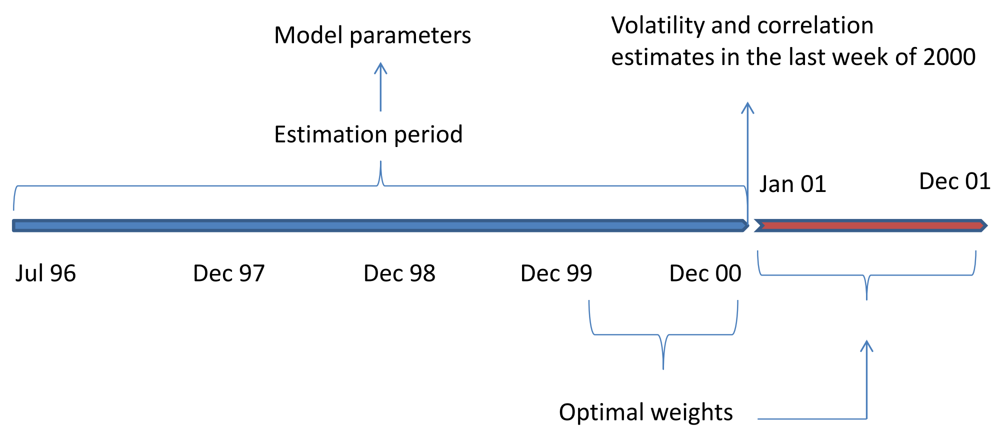
Finally, we annualize weekly volatility and calculate Sharpe ratios (π_{l+1}) to compare portfolio performance under the volatility and correlation estimates from the three models:

$$\pi_{l+1} = \frac{R_{p,l+1}}{\sqrt{52\, \tilde{\sigma}^2_{p,l+1}}} \tag{16}$$

In addition to using the Sharpe ratio to compare the three models on a yearly basis, we also employ it to assess results over a ten-year cumulative horizon.

To reiterate our methods, we present an example in a timeline form. Figure 3 below illustrates the process for an estimation period through 2000 and an application for 2001.

Figure 3: Sample Timeline for RiskMetrics and DCC - Estimation Period Through 2000



4 Results

For the sake of brevity, we select two years to report our results. 2000 and 2003 are the two estimation years chosen and the weights found from these two years are applied to 2001 and 2004. We select these two years as representative of bear and bull market years, as 2000 yielded significant negative returns due to the bursting of the Internet bubble and 2003 produced significant positive returns as economic growth spiked. The ARMA, GARCH, and DCC parameters for these years are reported in Appendix B.

4.1 Volatility and Correlation Findings

4.1.1 Emerging Market Results

Tables 1 and 2 show the sector volatilities estimated using the three methods for 2000 and 2003. Estimates from the three methods differ but not significantly. In 2000, volatility in the Technology sector is significantly higher than that in any other sector, due to the aforementioned Internet boom and eventual bust. Staples has the lowest volatility as it is a fairly conservative and consistent industry. Technology again ranks among the most volatile sectors in 2003 but to a much lesser extent than three years prior. Staples posts the lowest volatility once again.

The volatility estimates for the Technology sector in both years serve well to highlight the differences between the three models used. In 2000, the GARCH estimate for Technology volatility is higher than that from the other two methods while in 2003 it is lower. Since GARCH responds more flexibly to changes in volatility, this result is reasonable; the Technology sector was extremely volatile towards the end of 2000 and less so at the end of 2003. Although GARCH does not necessarily assign greater weight to the most recent period's volatility compared to RiskMetrics, it captures better the variation in volatility due to more degrees of freedom given by the parameters.

Table 1: 2000 EM Sector Volatilities

	Static	RiskMetrics	GARCH(1,1)
Technology	33.90%	39.92%	41.56%
Health	17.63%	17.47%	18.87%
Discretionary	16.58%	19.12%	18.95%
Staples	11.71%	11.61%	11.58%
Energy	15.74%	15.70%	16.23%
Materials	16.68%	17.24%	16.47%
Durables	20.23%	22.85%	23.14%
Financial	16.53%	16.06%	15.68%
Utilities	22.33%	19.11%	19.11%

Table 2: 2003 EM Sector Volatilities

	Static	RiskMetrics	GARCH(1,1)
Technology	25.98%	19.40%	17.41%
Health	15.87%	17.32%	18.04%
Discretionary	15.71%	14.74%	15.73%
Staples	10.46%	10.46%	11.80%
Energy	15.07%	17.84%	17.68%
Materials	16.06%	15.10%	15.43%
Durables	18.36%	16.62%	17.61%
Financial	15.45%	14.44%	15.92%
Utilities	16.52%	16.04%	16.71%

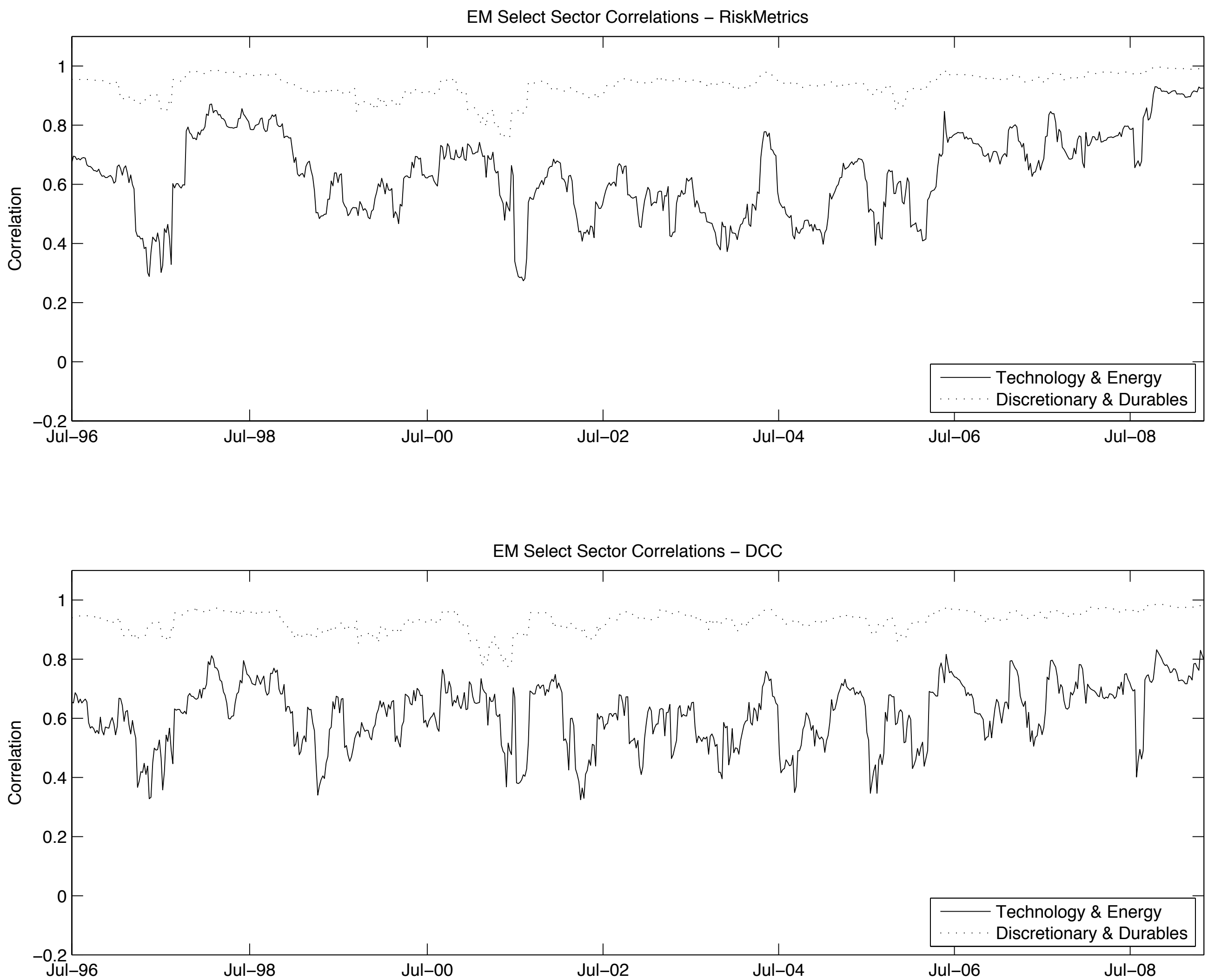
The sector correlations for 2000 and 2003 calculated by our three methods are given in Appendix C. Below, we summarize the evolution of correlations over the entire sample period. Table 3 presents sample correlations between all sectors calculated using the Static method. Technology appears to have the lowest level of correlations with other sectors with numbers ranging from 0.67 to 0.84. Almost all other sector correlations are above 0.8, the highest being that of Materials and Discretionary at 0.96.

Table 3: EM Static Sector Correlations - 10 year horizon

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.6793	0.8109	0.7161	0.6736	0.7669	0.8443	0.7739	0.6797
Health		0.8539	0.8359	0.8052	0.8236	0.8195	0.8276	0.7358
Disc.			0.9350	0.8649	0.9570	0.9558	0.9435	0.8143
Staples				0.8855	0.9390	0.9009	0.9141	0.8335
Energy					0.8846	0.8471	0.8680	0.8572
Materials						0.9548	0.9369	0.8138
Durables							0.9308	0.7888
Financial								0.8410

For RiskMetrics and DCC estimated correlations, we show two pairs of sectors over the entire time period in Figure 4. Technology & Energy and Discretionary & Durables are chosen to show examples of volatile and stable correlations, respectively. The first pair fluctuates regularly between 0.2 and 0.9 while the second pair holds steady around 0.9 and higher the entire time. Both methods show the same peaks and troughs for each sector pair, though sometimes to different extents.

Figure 4: EM Select Sector Correlations



4.1.2 US Results

Tables 4 and 5 show the sector volatilities in US estimated using the three methods for 2000 and 2003, respectively. In both years, Technology has the highest volatility and Staples has the lowest volatility, a pattern that is similar to what is observed in EM. In 2000, GARCH almost always gives higher volatility estimates than the other two methods while in 2003, GARCH almost always provides the lowest volatility estimates among the three.

Comparing EM and US results shows that sector volatilities are often higher in the U.S, contrary to the widespread belief that EM is more volatile. This finding, however, is consistent with our data structure where the EM sectors inherently carry geographic diversification. In both EM and US, sector volatilities are lower in 2003 than in 2000; this is expected due to higher volatilities in bear markets.

Table 4: 2000 US Sector Volatilities

	Static	RiskMetrics	GARCH(1,1)
Technology	50.24%	58.88%	75.36%
Health	27.72%	28.96%	35.15%
Discretionary	22.60%	27.84%	38.11%
Staples	12.81%	11.15%	11.82%
Energy	31.31%	32.52%	40.86%
Materials	18.58%	22.06%	26.52%
Durables	22.60%	27.33%	36.70%
Financial	15.43%	16.87%	21.54%
Utilities	20.24%	25.46%	30.56%

Table 5: 2003 US Sector Volatilities

	Static	RiskMetrics	GARCH(1,1)
Technology	30.41%	29.78%	29.47%
Health	21.34%	19.67%	18.49%
Discretionary	19.51%	18.79%	17.92%
Staples	12.62%	11.09%	10.92%
Energy	18.15%	17.35%	19.67%
Materials	18.68%	17.65%	16.38%
Durables	23.21%	21.28%	18.81%
Financial	13.78%	13.10%	12.09%
Utilities	16.85%	15.27%	13.94%

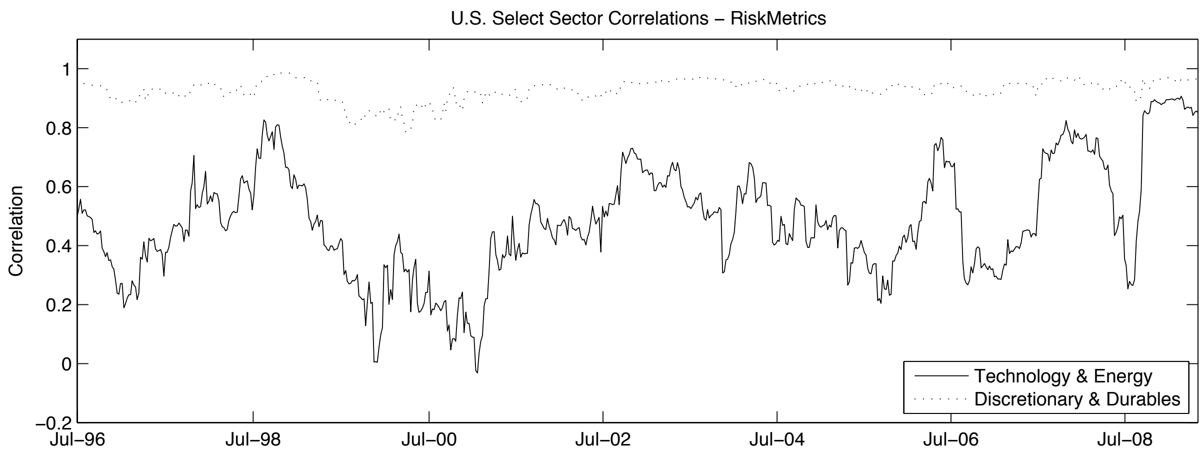
Table 6 shows the sample correlations across sectors for the entire period. Energy, which is one of the most volatile sectors, has the lowest level of correlations with other sectors with values ranging from 0.50 to 0.73. Its correlation with the Technology sector at 0.50 is the lowest correlation among all pairs. Discretionary has the highest level of correlations with other sectors. The highest correlation among all the pairs is between Discretionary and Durables at 0.93. These values are consistent with our choice of selected pairs in the correlation plots. Figure 5 shows the time-series correlations estimated by RiskMetrics and DCC for the two selected pairs.

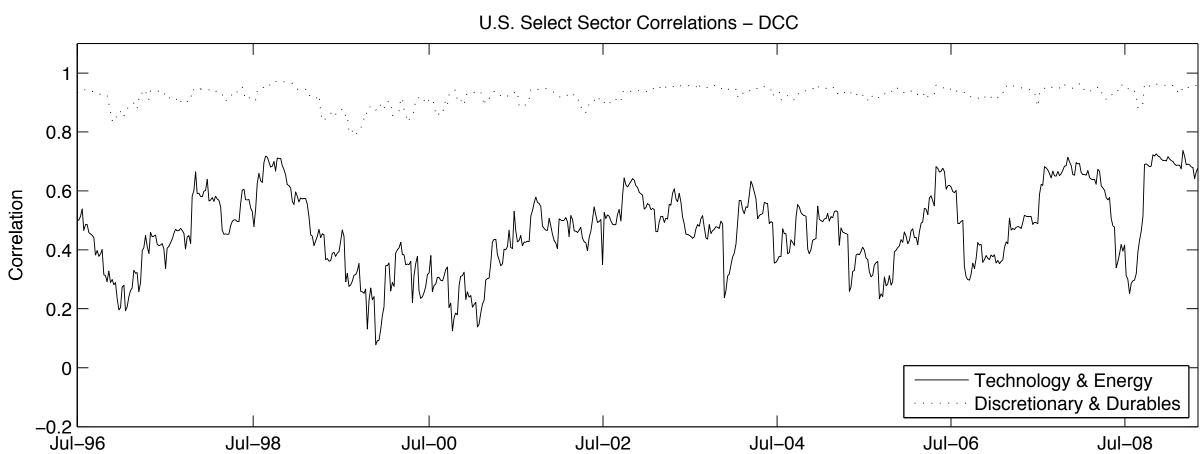
From the Static correlation tables, it can be seen that US sectors have greater co-movements than EM sectors. Looking at the RiskMetrics and DCC correlation plots, differences between Discretionary & Durables in US and EM are minimal because correlation is consistently very high. In Technology & Energy, however, the trends differ. There is a large drop in correlation around 2000 in the U.S. that is not present in EM, perhaps due to the Internet bubble having a greater impact in US.

Table 6: US Static Sector Correlations - 10 year horizon

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.8095	0.8122	0.5711	0.5002	0.6875	0.8440	0.6607	0.7866
Health		0.8001	0.7212	0.5432	0.7325	0.8174	0.7427	0.7699
Disc.			0.8189	0.6076	0.9009	0.9344	0.8892	0.7866
Staples				0.5778	0.8379	0.8172	0.8323	0.7052
Energy					0.7334	0.6495	0.5770	0.5961
Materials						0.9178	0.8656	0.7526
Durables							0.8632	0.8102
Financial								0.7395

Figure 5: US Select Sector Correlations





4.2 Allocation and Sharpe Ratio Comparison

4.2.1 Emerging Market Results

The volatilities and correlations in 2000 and 2003 are used to determine the sector weightings in 2001 and 2004. These weights are presented in Tables 7 and 8 for both long-only portfolios and long-short portfolios. The long-only scenario usually results in allocating capital to three sectors or fewer. In 2004, both RiskMetrics and DCC assign weight only to the Technology sector. This is due to those two methods predicting volatilities for that sector to be under the limit of 20%, while returns are very high. The long-short case appears to distribute capital more evenly across all sectors. The three methods disagree somewhat, as there are sectors such as Discretionary and Materials where one method indicates a long position while another recommends a short position.

Table 7: 2001 EM Sector Weights

	Long-Only			**Long-Short**		
	Static	RiskMetrics	DCC	Static	RiskMetrics	DCC
Technology	0.0000	0.0000	0.0000	(0.3503)	(0.5225)	(1.0142)
Health	0.0000	0.0000	0.0000	(0.3058)	(0.1074)	(0.2037)
Discretionary	0.0000	0.0000	0.0000	1.1102	(1.0381)	(0.6973)
Staples	0.0000	0.0000	0.0000	0.7220	0.6650	0.3611
Energy	0.0000	0.0000	0.0000	0.5213	0.8657	0.4241
Materials	0.0400	0.0704	0.1764	(0.1988)	0.6960	(0.4527)
Durables	0.9600	0.6566	0.6486	0.1828	0.9559	2.3203
Financial	0.0000	0.2730	0.1750	0.4999	0.3046	0.2673
Utilities	0.0000	0.0000	0.0000	(0.5716)	(0.0743)	0.6273
Cash	0.0000	0.0000	0.0000	(0.6096)	(0.7448)	(0.6321)

Table 8: 2004 EM Sector Weights

	Long-Only			**Long-Short**		
	Static	RiskMetrics	DCC	Static	RiskMetrics	DCC
Technology	0.3076	1.0000	1.0000	(0.3057)	0.2866	1.1017
Health	0.0000	0.0000	0.0000	(0.5221)	(0.5285)	(0.1787)
Discretionary	0.0000	0.0000	0.0000	1.1903	0.7555	(0.1122)
Staples	0.0000	0.0000	0.0000	0.1695	0.0652	(0.4808)
Energy	0.0000	0.0000	0.0000	0.0504	(0.2902)	(0.0536)
Materials	0.0000	0.0000	0.0000	0.3910	0.5144	1.2627
Durables	0.6572	0.0000	0.0000	(0.3389)	(0.3954)	(0.6737)
Financial	0.0352	0.0000	0.0000	0.5968	0.5389	0.1054
Utilities	0.0000	0.0000	0.0000	0.2572	0.4320	0.1968
Cash	0.0000	0.0000	0.0000	(0.4885)	(0.3784)	(0.1676)

We use the Sharpe ratio to compare the three models both on a yearly basis and over a ten-year cumulative horizon. This ratio is commonly used by practitioners to measure risk-adjusted performance of portfolios. For positive Sharpe ratios, we simply select the model that yields the largest ratio. For negative Sharpe ratios, however, we examine the returns and volatilities case by case and determine whether one methodology has the least negative risk-adjusted return. If this clear distinction does not exist, we designate the methodology with the smallest loss as optimal due to the reasoning that in bear markets money managers are more focused on minimizing losses (Schultz 2002).

Looking at the cumulative results for the long-short portfolio in Table 9, RiskMetrics yields the highest Sharpe ratio, 0.24, followed closely by Static and finally DCC. DCC performs poorly cumulatively, posting lower returns and higher volatility than the other two methods, leading to a Sharpe ratio of 0.03. On an individual year basis, Static has the most years with the best Sharpe ratio. RiskMetrics and DCC are tied with two years each.

In the long-only scenario in Table 10, Static does the best job cumulatively with a Sharpe ratio of 0.10 and is the only one to yield a positive return. DCC edges out RiskMetrics slightly by having a smaller negative return with the same volatility. In the individual years, Static has the highest count of the best Sharpe ratios.

Despite being the most flexible, DCC does not appear to have an advantage in portfolio allocation in the Emerging Markets. This is true especially in the case where shorting is allowed and when looking at the cumulative results. Static actually appears to be the best method; even when it is not the optimal choice it performs reasonably well.

Table 9: EM Long-Short

Year	**Static** Return	**Static** Volatility	**Static** Sharpe Ratio	**Riskmetrics** Return	**Riskmetrics** Volatility	**Riskmetrics** Sharpe Ratio	**DCC** Return	**DCC** Volatility	**DCC** Sharpe Ratio
1999	35.16%	13.56%	2.59	34.69%	18.28%	1.90	84.59%	42.82%	1.98
2000	-49.13%	24.08%	(2.04)	-49.46%	27.23%	(1.82)	-75.73%	42.35%	(1.79)
2001	-7.66%	30.89%	(0.25)	-1.85%	30.36%	(0.06)	3.00%	34.68%	0.09
2002	14.34%	13.17%	1.09	20.46%	14.25%	1.44	23.39%	15.52%	1.51
2003	152.96%	23.35%	6.55	141.21%	24.41%	5.79	136.92%	22.72%	6.03
2004	9.73%	22.72%	0.43	10.56%	25.70%	0.41	-17.31%	33.25%	(0.52)
2005	41.78%	14.40%	2.90	32.81%	17.30%	1.90	27.34%	21.68%	1.26
2006	65.94%	32.25%	2.04	76.02%	31.35%	2.43	58.73%	25.06%	2.34
2007	50.50%	26.88%	1.88	47.57%	29.47%	1.61	39.26%	29.43%	1.33
2008	-58.54%	35.86%	(1.63)	-50.94%	23.80%	(2.14)	-62.21%	48.88%	(1.27)
Cumulative	11.45%	60.53%	0.19	13.77%	56.79%	0.24	1.73%	64.42%	0.03

Table 10: EM Long-Only

Year	**Static** Return	**Static** Volatility	**Static** Sharpe Ratio	**Riskmetrics** Return	**Riskmetrics** Volatility	**Riskmetrics** Sharpe Ratio	**DCC** Return	**DCC** Volatility	**DCC** Sharpe Ratio
1999	28.66%	12.13%	2.36	27.77%	14.68%	1.89	35.30%	18.34%	1.93
2000	-38.77%	20.23%	(1.92)	-38.77%	20.23%	(1.92)	-38.77%	20.23%	(1.92)
2001	-3.24%	26.61%	(0.12)	-4.10%	24.70%	(0.17)	-5.12%	24.57%	(0.21)
2002	8.45%	14.10%	0.60	6.08%	13.22%	0.46	9.08%	14.65%	0.62
2003	70.00%	18.58%	3.77	71.05%	18.39%	3.86	67.73%	19.01%	3.56
2004	9.36%	19.45%	0.48	-15.65%	26.43%	(0.59)	-15.65%	26.43%	(0.59)
2005	28.79%	13.82%	2.08	32.69%	17.86%	1.83	33.75%	19.11%	1.77
2006	9.48%	19.80%	0.48	9.80%	19.73%	0.50	11.64%	19.36%	0.60
2007	4.06%	24.00%	0.17	4.06%	24.00%	0.17	4.06%	24.00%	0.17
2008	-54.96%	39.46%	(1.39)	-53.89%	37.38%	(1.44)	-53.06%	37.32%	(1.42)
Cumulative	0.16%	34.91%	0.10	-2.17%	35.83%	(0.06)	-1.22%	35.83%	(0.03)

4.2.2 US Results

Tables 11 and 12 present the optimal allocations in 2001 and 2004 for the U.S. market. In the long-only portfolios, capital is usually allocated to a few sectors that have relatively high returns and low correlations with other sectors, such as Technology and Energy. When shorting is allowed, weight assignments are more diversified across different sectors including cash. For example in 2001, cash is borrowed under all three models while in 2004, cash carries positive weight under all three models. Similar to what we observe in EM, the three methods do not always agree in the weights assigned in a certain year nor are they consistent in determining the sign of those weights.

Table 11: 2001 US Sector Weights

	Long-Only			**Short**		
	Static	RiskMetrics	DCC	Static	RiskMetrics	DCC
Technology	0.1025	0.0939	0.0388	0.2186	0.4394	0.3609
Health	0.1087	0.1744	0.2386	0.0537	(0.0764)	0.2069
Discretionary	0.0000	0.0000	0.0000	0.0874	(0.0439)	(0.6818)
Staples	0.0000	0.0720	0.3493	0.6543	1.4412	2.7405
Energy	0.1360	0.1512	0.0514	0.1812	0.1197	(0.3669)
Materials	0.0000	0.0000	0.0000	(0.1619)	(0.3321)	(0.1970)
Durables	0.3685	0.0443	0.0000	0.0400	(0.4001)	0.1066
Financial	0.2844	0.4641	0.3219	0.6802	1.1839	0.5851
Utilities	0.0000	0.0000	0.0000	(0.4013)	(0.6504)	(0.5170)
Cash	0.0000	0.0000	0.0000	(0.3522)	(0.6813)	(1.2372)

Table 12: 2004 US Sector Weights

	Long-Only			**Short**		
	Static	RiskMetrics	DCC	Static	RiskMetrics	DCC
Technology	0.4996	0.5192	0.4520	0.5727	0.5230	(0.1049)
Health	0.0000	0.0000	0.2062	0.0771	0.3624	0.5075
Discretionary	0.0000	0.0000	0.0000	1.2427	0.6046	0.4240
Staples	0.0000	0.0000	0.0000	(1.1229)	(1.7094)	(2.1621)
Energy	0.4581	0.4808	0.3418	0.5673	0.8311	0.3894
Materials	0.0000	0.0000	0.0000	(0.3624)	(0.7001)	(0.3734)
Durables	0.0000	0.0000	0.0000	(0.7315)	(0.2452)	0.7239
Financial	0.0000	0.0000	0.0000	0.2135	0.9878	0.4882
Utilities	0.0000	0.0000	0.0000	0.0686	(0.2319)	0.6213
Cash	0.0423	0.0000	0.0000	0.4748	0.5778	0.4862

In the long-short portfolio shown by Table 13, DCC does the best in five years out of the ten years we examine, while Static has the highest ratio in three years and RiskMetrics in two years. However, Static outperforms the other two models in the cumulative result with a Sharpe ratio of 0.29. DCC does the worst with a ratio of only 0.14.

In the long-only portfolio shown by Table 14, DCC again gives the best Sharpe ratios in half of the individual years. RiskMetrics and Static are tied with two years each. However, RiskMetrics does the best cumulatively with a Sharpe ratio of 0.19, slightly better than the 0.17 and 0.15 given by DCC and Static respectively.

In the U.S. market, DCC clearly does the best job in individual years for both long-short and long-only portfolios, although it does not have an obvious advantage when we cumulate portfolio returns. Static and RiskMetrics perform fairly equally in individual years as well as cumulatively.

4.3 Comparing EM and US Results

Comparing the EM and US cumulative results, we find that US portfolios consistently produce higher Sharpe ratios. We also find that DCC is a better choice in the U.S. for the yearly results. The Sharpe ratios over the ten-year horizon in both EM and US in all scenarios are remarkably low compared to a benchmark Sharpe ratio of 0.35 for an equity index portfolio (with an assumed 7% return and 20% volatility to stay consistent with our choice of return and volatility targets above). This finding is surprising because funds with an annual rebalancing strategy are expected to outperform the market[4].

In addition, long-short portfolios do not guarantee superior returns compared to their long-only counterparts. For example in 2004 in the U.S., the largest return in the long-short case is only 0.82%, while the smallest return in the long-only case is 7.61%. While we might normally expect larger returns for long-short portfolios, in this case we are not using the actual volatility and correlation but rather estimates from the previous year.

[4]Rebalancing semi-annually was also carried out; results are not materially different.

Table 13: US Long-Short

	Static			**Riskmetrics**			**DCC**		
Year	Return	Volatility	Sharpe Ratio	Return	Volatility	Sharpe Ratio	Return	Volatility	Sharpe Ratio
1999	41.20%	21.69%	1.90	51.01%	24.59%	2.07	-11.55%	32.78%	(0.35)
2000	46.62%	26.91%	1.73	25.18%	26.29%	0.96	14.97%	41.79%	0.36
2001	34.43%	21.97%	1.57	59.31%	19.82%	2.99	99.45%	24.26%	4.10
2002	1.91%	28.10%	0.07	-10.12%	28.28%	(0.36)	-28.25%	42.17%	(0.67)
2003	68.55%	18.76%	3.65	69.59%	18.75%	3.71	85.17%	21.57%	3.95
2004	-0.64%	20.60%	(0.03)	0.45%	24.78%	0.02	0.82%	24.83%	0.03
2005	-3.76%	18.87%	(0.20)	4.82%	17.47%	0.28	0.80%	15.23%	0.05
2006	-3.72%	30.22%	(0.12)	-16.78%	32.58%	(0.52)	-22.35%	26.77%	(0.84)
2007	2.37%	17.53%	0.13	0.62%	18.30%	0.03	19.01%	19.97%	0.95
2008	-45.02%	47.43%	(0.95)	-42.79%	44.25%	(0.97)	-27.78%	31.05%	(0.89)
Cumulative	9.50%	33.01%	0.29	8.76%	36.27%	0.24	6.22%	45.01%	0.14

Table 14: US Long-Only

	Static			**Riskmetrics**			**DCC**		
Year	Return	Volatility	Sharpe Ratio	Return	Volatility	Sharpe Ratio	Return	Volatility	Sharpe Ratio
1999	18.29%	14.32%	1.28	29.24%	13.15%	2.22	32.68%	20.17%	1.62
2000	-0.50%	30.81%	(0.02)	-2.68%	28.15%	(0.10)	-8.47%	29.88%	(0.28)
2001	5.60%	25.14%	0.22	6.60%	20.57%	0.32	16.32%	17.02%	0.96
2002	-7.37%	21.42%	(0.34)	-11.38%	21.92%	(0.52)	-25.59%	24.96%	(1.03)
2003	52.83%	17.07%	3.09	53.01%	16.85%	3.15	63.39%	19.41%	3.27
2004	9.80%	21.51%	0.46	10.35%	22.43%	0.46	7.61%	21.18%	0.36
2005	7.32%	12.58%	0.58	9.98%	13.11%	0.76	10.23%	12.85%	0.80
2006	11.19%	18.35%	0.61	11.19%	18.35%	0.61	11.19%	18.35%	0.61
2007	1.83%	18.15%	0.10	1.83%	18.15%	0.10	1.83%	18.15%	0.10
2008	-39.88%	39.04%	(1.02)	-37.68%	35.89%	(1.05)	-31.03%	27.49%	(1.13)
Cumulative	3.50%	22.93%	0.15	4.53%	23.81%	0.19	4.75%	27.33%	0.17

5 Conclusion

Our objective in this paper is to examine the performance of various volatility and correlation models in an asset allocation context using sector equity data from both the U.S. and Emerging Markets. We first construct long-only and long-short portfolios with volatility and correlation estimates from three models (Static, RiskMetric and GARCH/DCC). We then calculate the Sharpe ratios for one-year-ahead portfolios using the optimal sector weights from the previous year.

For the long-only portfolios, we find that all three methods allocate capital to only a few sectors that have relatively high returns. In most cases, these chosen sectors are consistent under the three methods. The long-short portfolios utilize every sector under all three models, although the exact positions differ by model. On a yearly basis, DCC estimates result in portfolios with higher realized adjusted returns compared to the other two models in the U.S., but not in EM. However, DCC does not necessarily perform better on a cumulative basis in either US or EM when we consider portfolio returns over a ten-year horizon. In fact, the Static model performs sufficiently well on the cumulative basis. We also find that US portfolios have higher cumulative Sharpe ratios than the EM portfolios under all three models.

These discrepancies between model performance in US and EM could be due to the underlying volatility and correlation estimation mechanisms as well as different sector equity behaviors in those markets. For example, GARCH tends to respond more flexibly to variations in sector volatilities than RiskMetrics does. In addition, sector volatility estimates are often higher in the U.S. than in EM under all three models. Correlations estimated by the two time-varying models (RiskMetrics and DCC) display similar patterns. The Technology sector is shown to have the lowest correlations with other sectors, while Discretionary tends to have high correlations with the other sectors. Comparing the correlation levels in US and EM, we observe that US exhibits stronger co-movements between sectors.

In our analysis, we carry out annual rebalancing for our portfolios. One possible direction for further research is to rebalance on a more frequent basis (i.e., monthly or weekly). This may help distinguish the difference in estimate values from the models. Since our EM data comprises of many individual countries/clusters, it would also be of interest to perform the same exercise comparing portfolios that diversify geographically rather than by sectors.

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A Complete List of Countries and Clusters

Countries	**EMEA Cluster**	**S. America Cluster**	**Asia Cluster**
Brazil	Morocco	Colombia	Philippines
Chile	Oman	Argentina	Vietnam
China	Mauritius	Venezuela	Laos
Indonesia	Pakistan	Peru	
India	Qatar	Panama	
Korea	Poland		
Mexico	Portugal		
Malaysia	Romania		
Thailand	Russia		
Turkey	Slovenia		
Taiwan	Slovakia		
South Africa	Tunisia		
	Ukraine		
	Latvia		
	Libya		
	Greece		
	Egypt		
	Czech Republic		
	Cyprus		
	Botswana		
	Bahrain		
	Bulgaria		
	Croatia		
	Hungary		
	Kazakhstan		
	Kuwait		
	Jordan		
	United Arab Emirates		
	Israel		

B Select ARMA, GARCH and DCC Parameters

Table 15: 2000 EM Sector ARMA Parameters

	ζ	ψ	θ
Technology	0.0001	0.9056	(0.8167)
Health	(0.0026)	(0.9614)	0.9463
Discretionary	(0.0043)	(0.1978)	0.1749
Staples	(0.0014)	(0.2545)	0.2309
Energy	(0.0001)	0.8426	(0.7525)
Materials	(0.0007)	0.8451	(0.7471)
Durables	(0.0049)	(0.2100)	0.1808
Financial	(0.0054)	(0.7748)	0.8290
Utilities	(0.0000)	0.7659	(0.6438)

Table 16: 2003 EM Sector ARMA Parameters

	ζ	ψ	θ
Technology	0.0003	0.7623	(0.6728)
Health	0.0000	0.8712	(0.7976)
Discretionary	(0.0001)	0.8599	(0.7731)
Staples	0.0001	0.8371	(0.7558)
Energy	0.0003	0.8384	(0.7209)
Materials	(0.0001)	0.8586	(0.7355)
Durables	(0.0001)	0.8441	(0.7511)
Financial	(0.0001)	0.8149	(0.7136)
Utilities	0.0002	0.7705	(0.6216)

Table 17: 2000 Russell Sector ARMA Parameters

	ζ	ψ	θ
Technology	0.0017	0.4898	(0.3939)
Health	0.0018	0.4480	(0.3430)
Discretionary	0.0005	(0.0643)	0.2777
Staples	0.0006	0.6674	(0.5552)
Energy	0.0042	(0.1767)	0.2890
Materials	0.0002	0.3097	(0.1012)
Durables	0.0024	0.1866	(0.0662)
Financial	0.0030	(0.2115)	0.3966
Utilities	0.0019	(0.1439)	0.2962

Table 18: 2003 Russell Sector ARMA Parameters

	ζ	ψ	θ
Technology	0.0011	0.5443	(0.4517)
Health	0.0012	0.5743	(0.5082)
Discretionary	0.0009	0.4837	(0.3899)
Staples	0.0007	0.6699	(0.5380)
Energy	0.0046	(0.7957)	0.8773
Materials	0.0005	0.6325	(0.5367)
Durables	0.0012	0.6108	(0.5769)
Financial	0.0018	0.3820	(0.3818)
Utilities	0.0001	0.6023	(0.5260)

Table 19: 2000 EM Sector GARCH Parameters

	ω	α	β
Technology	0.0000	0.1883	0.8117
Health	0.0000	0.0521	0.9200
Discretionary	0.0001	0.2669	0.6962
Staples	0.0000	0.2206	0.7433
Energy	0.0000	0.1465	0.8485
Materials	0.0001	0.2233	0.7281
Durables	0.0001	0.1982	0.7586
Financial	0.0000	0.1624	0.8090
Utilities	0.0000	0.1288	0.8610

Table 20: 2003 EM Sector GARCH Parameters

	ω	α	β
Technology	0.0000	0.1739	0.8261
Health	0.0000	0.0421	0.9265
Discretionary	0.0000	0.1086	0.8520
Staples	0.0000	0.1446	0.8083
Energy	0.0000	0.1067	0.8763
Materials	0.0001	0.1306	0.8073
Durables	0.0001	0.1264	0.8246
Financial	0.0000	0.0949	0.8553
Utilities	0.0000	0.0847	0.8939

Table 21: 2000 Russell Sector GARCH Parameters

	ω	α	β
Technology	0.0001	0.1780	0.7920
Health	0.0001	0.2019	0.6877
Discretionary	0.0000	0.1847	0.7683
Staples	0.0000	0.0777	0.8394
Energy	0.0001	0.1536	0.8224
Materials	0.0000	0.1215	0.8522
Durables	0.0001	0.1870	0.7393
Financial	0.0001	0.1811	0.6955
Utilities	0.0000	0.1150	0.8748

Table 22: 2003 Russell Sector GARCH Parameters

	ω	α	β
Technology	0.0001	0.1380	0.8321
Health	0.0001	0.1688	0.7628
Discretionary	0.0000	0.1544	0.8148
Staples	0.0000	0.0884	0.8223
Energy	0.0001	0.1548	0.8135
Materials	0.0000	0.1059	0.8654
Durables	0.0000	0.1453	0.8192
Financial	0.0001	0.1905	0.6813
Utilities	0.0000	0.1273	0.8630

Table 23: 2000 EM Sector DCC Parameters

	Health	Discretionary	Staples	Energy	Materials	Durables	Financial	Utilities
Technology	$\eta = 0.0310$	0.0506	0.0418	0.0725	0.0846	0.1078	0.0717	0.0267
	$\phi = 0.6643$	0.8915	0.9187	0.8833	0.8676	0.8617	0.8885	0.9120
Health		0.1741	0.1324	0.0271	0.1283	0.0318	0.0382	0.0306
		0.0793	0.3129	0.9211	0.3536	0.9370	0.9234	0.9335
Discretionary			0.0587	0.0415	0.0795	0.0390	0.0530	0.0423
			0.9137	0.9234	0.6716	0.9024	0.9148	0.9201
Staples				0.0410	0.0884	0.0318	0.0898	0.0568
				0.9271	0.5155	0.9400	0.8089	0.8892
Energy					0.0491	0.0617	0.0399	0.1456
					0.9191	0.8962	0.9084	0.7495
Materials						0.0434	0.1151	0.0304
						0.9287	0.6653	0.9281
Durables							0.0588	0.0565
							0.8978	0.9024
Financial								0.0552
								0.8817

Table 24: 2003 EM Sector DCC Parameters

	Health	Discretionary	Staples	Energy	Materials	Durables	Financial	Utilities
Technology	$\eta = 0.0389$	0.0440	0.0373	0.0368	0.0653	0.0731	0.0588	0.0241
	$\phi = 0.8258$	0.9333	0.9304	0.9155	0.9110	0.8775	0.9097	0.9175
Health		0.1134	0.1384	0.0467	0.1188	0.0253	0.0380	0.0408
		0.4736	0.1566	0.8812	0.4872	0.9387	0.9171	0.9219
Discretionary			0.0633	0.0434	0.0716	0.0634	0.0726	0.0262
			0.9064	0.9282	0.8833	0.8828	0.8799	0.9578
Staples				0.0396	0.1081	0.0752	0.1080	0.0453
				0.9350	0.7092	0.8299	0.7699	0.9238
Energy					0.0262	0.0443	0.0311	0.0756
					0.9445	0.9321	0.9324	0.8736
Materials						0.0858	0.0762	0.0146
						0.8865	0.8094	0.9540
Durables							0.0737	0.0355
							0.8815	0.9380
Financial								0.0257
								0.9531

Table 25: 2000 Russell Sector DCC Parameters

	Health	Discretionary	Staples	Energy	Materials	Durables	Financial	Utilities
Technology	$\eta = 0.0511$	0.0587	0.0562	0.0395	0.0605	0.0470	0.0544	0.0682
	$\phi = 0.9409$	0.9409	0.9312	0.9362	0.9284	0.9361	0.9255	0.8132
Health		0.0661	0.0749	0.0708	0.0733	0.0534	0.0616	0.0957
		0.9249	0.9114	0.8677	0.9123	0.9247	0.9179	0.8330
Discretionary			0.0415	0.0560	0.0632	0.0600	0.1021	0.0533
			0.9449	0.9065	0.9172	0.8640	0.6186	0.7761
Staples				0.1892	0.0337	0.0429	0.0274	0.0700
				0.0263	0.9358	0.9458	0.9552	0.9087
Energy					0.0219	0.0504	0.0358	0.0299
					0.9385	0.8912	0.9090	0.9308
Materials						0.1741	0.0886	0.0801
						0.6339	0.4319	0.8164
Durables							0.0236	0.0207
							0.9505	0.8962
Financial								0.0394
								0.9392

Table 26: 2003 Russell Sector DCC Parameters

	Health	Discretionary	Staples	Energy	Materials	Durables	Financial	Utilities
Technology	$\eta = 0.0454$	0.0693	0.0571	0.0318	0.0765	0.0659	0.0592	0.1094
	$\phi = 0.9496$	0.9195	0.9340	0.9433	0.9105	0.9194	0.9255	0.8201
Health		0.0657	0.0581	0.0486	0.0808	0.0578	0.0587	0.0564
		0.9284	0.9336	0.9124	0.8998	0.9218	0.9225	0.9228
Discretionary			0.0431	0.0462	0.0691	0.0681	0.0547	0.0611
			0.9469	0.9200	0.9034	0.9020	0.9055	0.8716
Staples				0.1915	0.0373	0.0423	0.0370	0.0778
				0.0000	0.9560	0.9529	0.9504	0.9129
Energy					0.0298	0.0288	0.0425	0.0322
					0.9087	0.9281	0.9109	0.9466
Materials						0.0519	0.1249	0.0687
						0.9262	0.6393	0.9016
Durables							0.0316	0.0579
							0.9629	0.9077
Financial								0.0407
								0.9542

C Select Sector Correlations

Table 27: 2000 EM Sector Correlations - Static

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.5036	0.8164	0.5698	0.6115	0.7139	0.8697	0.6828	0.6602
Health		0.7159	0.6755	0.7081	0.6664	0.5758	0.6682	0.5485
Disc.			0.8668	0.7920	0.9353	0.9090	0.8804	0.7866
Staples				0.7576	0.9138	0.7383	0.8529	0.7740
Energy					0.6857	0.6785	0.7505	0.7861
Materials						0.8607	0.8839	0.7271
Durables							0.8488	0.6787
Financial								0.7755

Table 28: 2000 EM Sector Correlations - RiskMetrics

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.6965	0.8451	0.5984	0.6857	0.7511	0.9183	0.7326	0.5767
Health		0.8278	0.7424	0.7762	0.7854	0.7210	0.7583	0.6115
Disc.			0.8587	0.8302	0.9479	0.9122	0.8761	0.6601
Staples				0.7301	0.9072	0.7223	0.8710	0.7176
Energy					0.7378	0.7150	0.7451	0.7547
Materials						0.8573	0.9043	0.6521
Durables							0.8614	0.5663
Financial								0.7042

Table 29: 2000 EM Sector Correlations - DCC

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.6375	0.8020	0.6253	0.6388	0.6835	0.9236	0.7119	0.6023
Health		0.7676	0.6859	0.6959	0.6838	0.7122	0.7319	0.6270
Disc.			0.8490	0.7870	0.9037	0.9234	0.8679	0.6731
Staples				0.7245	0.8911	0.7794	0.8588	0.7300
Energy					0.7280	0.7051	0.7631	0.6592
Materials						0.8600	0.8712	0.6810
Durables							0.8496	0.5734
Financial								0.7250

Table 30: 2003 EM Sector Correlations - Static

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.5530	0.8293	0.6791	0.4674	0.8401	0.8907	0.7863	0.5380
Health		0.7846	0.7313	0.6354	0.7239	0.7134	0.7431	0.5496
Disc.			0.8677	0.6547	0.9030	0.9377	0.8712	0.6118
Staples				0.7101	0.8326	0.8040	0.8586	0.7301
Energy					0.6677	0.6374	0.7132	0.7081
Materials						0.9417	0.8918	0.6506
Durables							0.8776	0.6452
Financial								0.6644

Table 31: 2003 EM Sector Correlations - RiskMetrics

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.4895	0.7945	0.6111	0.3978	0.7143	0.8225	0.7339	0.4192
Health		0.7681	0.7532	0.7631	0.8168	0.7019	0.7594	0.6802
Disc.			0.8686	0.7060	0.9172	0.9386	0.8947	0.6350
Staples				0.7377	0.8711	0.7811	0.8889	0.7641
Energy					0.8092	0.6828	0.7749	0.7951
Materials						0.9122	0.9122	0.7643
Durables							0.8835	0.6218
Financial								0.7420

Table 32: 2003 EM Sector Correlations - DCC

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.5576	0.7980	0.6549	0.4801	0.6944	0.8283	0.7255	0.5228
Health		0.7322	0.6998	0.6773	0.6963	0.6797	0.7159	0.6133
Disc.			0.8738	0.7125	0.9225	0.9242	0.9041	0.6390
Staples				0.7156	0.9049	0.7955	0.8965	0.7355
Energy					0.7673	0.6865	0.7622	0.8120
Materials						0.8890	0.9172	0.7167
Durables							0.8775	0.6150
Financial								0.7349

Table 33: 2000 US Sector Correlations - Static

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.7692	0.7693	-0.1094	0.2579	0.3201	0.7129	0.4504	0.7902
Health		0.6547	0.1477	0.2758	0.3625	0.6276	0.4928	0.6295
Discr.			0.3508	0.2881	0.7486	0.9188	0.7740	0.8249
Staples				0.1537	0.6254	0.4247	0.5485	0.1495
Energy					0.3719	0.3471	0.2404	0.3081
Materials						0.7974	0.8119	0.5560
Durables							0.7648	0.7623
Financial								0.5992

Table 34: 2000 US Sector Correlations - RiskMetrics

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.7892	0.8661	0.1306	0.1747	0.5048	0.7680	0.5210	0.8405
Health		0.7920	0.2938	0.2915	0.5733	0.7113	0.6705	0.7078
Disc.			0.4669	0.3188	0.7851	0.9115	0.7384	0.8710
Staples				0.4225	0.6121	0.5413	0.5089	0.3656
Energy					0.5632	0.4331	0.4708	0.3166
Materials						0.8504	0.8480	0.6680
Durables							0.8073	0.7942
Financial								0.6440

Table 35: 2000 US Sector Correlations - DCC

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.7951	0.8560	0.1935	0.2124	0.4904	0.7923	0.5844	0.8023
Health		0.8007	0.3721	0.3288	0.5777	0.7295	0.7048	0.7669
Disc.			0.5089	0.3445	0.7432	0.9259	0.7725	0.8396
Staples				0.7609	0.6882	0.5420	0.5999	0.4917
Energy					0.5677	0.4632	0.5046	0.3465
Materials						0.8141	0.8946	0.6158
Durables							0.7873	0.7456
Financial								0.6580

Table 36: 2003 US Sector Correlations - Static

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.8180	0.9137	0.7820	0.3962	0.8175	0.9254	0.8725	0.8467
Health		0.8473	0.8168	0.4751	0.8288	0.8253	0.8339	0.8207
Disc.			0.8929	0.4108	0.9118	0.9654	0.9395	0.8641
Staples				0.4538	0.9063	0.8868	0.8727	0.8654
Energy					0.5367	0.4261	0.4748	0.4497
Materials						0.9257	0.9049	0.8243
Durables							0.9381	0.8590
Financial								0.8591

Table 37: 2003 US Sector Correlations - RiskMetrics

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.8383	0.9315	0.8002	0.3541	0.7905	0.9312	0.8593	0.8547
Health		0.8497	0.8201	0.3995	0.7977	0.8337	0.8366	0.8146
Disc.			0.9065	0.4226	0.8844	0.9591	0.9400	0.8765
Staples				0.5156	0.8986	0.8916	0.9171	0.8601
Energy					0.6096	0.4559	0.4895	0.5400
Materials						0.9110	0.9026	0.8253
Durables							0.9337	0.8721
Financial								0.8599

Table 38: 2003 US Sector Correlations - DCC

	Health	Disc.	Staples	Energy	Materials	Durables	Financial	Utilities
Tech	0.8366	0.9197	0.7602	0.3423	0.7378	0.9130	0.8210	0.8105
Health		0.8511	0.7980	0.3221	0.7510	0.8277	0.8203	0.7758
Disc.			0.8775	0.3838	0.8566	0.9410	0.9029	0.8384
Staples				0.4595	0.8771	0.8750	0.8735	0.8311
Energy					0.5845	0.4823	0.4265	0.4640
Materials						0.8938	0.8324	0.7762
Durables							0.9131	0.8213
Financial								0.8410