Market Dispersion and the Profitability of Hedge Funds*

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Abstract

We examine the impact of market dispersion on the performance of hedge funds. Market dispersion is measured by the cross-sectional volatility of equity returns in a given month. Using hedge fund indices and a panel of monthly returns on individual hedge funds, we find that market dispersion and the performance of hedge funds are positively related. We also find that the cross-sectional dispersion of hedge fund returns is positively related to the level of market dispersion.

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1 Introduction

In this paper, we provide an empirical investigation of the impact of market dispersion on the profitability of hedge funds. In contrast to time series standard deviation, which is a measure of the variation of a given asset return over a period of time, market dispersion measures the diversity of realized asset returns across the market at a given point in time.We use cross-sectional standard deviation of returns as our statistical measure of market dispersion.

The time-series dynamics of market dispersion are of economic importance to hedge funds for at least two reasons. One, market dispersion can be viewed as a measure of the opportunities available to hedge funds for generating active returns. If individual stock returns were all the same in a given time period, market dispersion would be zero, and there would be no opportunity to produce active returns. As market dispersion increases, so does the opportunity to find stocks with higher or lower returns than the market average return. Therefore, market dispersion may serve as a measure of the opportunities for hedge fund managers to add value by selecting outperforming and underperforming securities. There is a long literature in microeconomics, beginning with Stigler (1961), treating the dispersion of goods prices and wage rates as a reflection of imperfect information, and the exploitation of this price dispersion as a measure of informational advantages of better-informed agents, e.g., Salop and Stiglitz (1977), and Burdett and Judd (1983). Hedge fund managers are the prototypical informed agents paying search costs to exploit informational advantages; viewing market dispersion as a measure of their opportunities for gain from superior information is a natural extension of this microeconomics literature to securities markets. (See Garbade and Silber (1976) for a related application of the Stigler model of price dispersion to government bond yields.)

Two, market dispersion can be regarded as a proxy for active risk, because it is a measure of heterogeneity across security returns in the market. Most hedge funds attempt to lower or eliminate market beta risk from their portfolios while taking on active risk through security selection. Hence time variation in market dispersion is a natural measure of the time-varying level of hedge fund risk.

We estimate the cross-sectional volatility of equity returns each month using CRSP data from January of 1994 to December of 2004. Each month we use all the stocks which have a valid return for that month. Consistent with previous studies, such as Campbell, Lettau, Malkiel and Xu (2001), Jones (2001), and Connor, Korajczyk and Linton (2006), the cross-sectional volatility of equity returns varies significantly over the sample period and is serially correlated. We test the hypothesis that cross-sectional volatility affects the profitability of hedge funds using hedge fund indices from Hedge Fund Research, Inc.(HFR). HFR databases classifies hedge funds into several categories according to their investment strategies. To examine incremental explanatory value of cross-sectional volatility to hedge fund returns, we conduct a careful analysis on risk adjustments for hedge fund returns to obtain hedge fund abnormal performance. Many studies have shown that due to the dynamic trading strategies and derivatives used by hedge funds, traditional linear asset pricing models give misleading results on hedge fund performance. We use the seven-factor model of Fung and Hsieh (2004). These factors have been shown to have considerable explanatory power for hedge fund returns.

The results at the hedge fund index level support a positive contemporaneous relationship between cross-sectional volatility and the performance of hedge funds. To test this relationship in more detail, we provide parametric joint (cross-fund) tests using the individual hedge fund return data from the Center for International Securities and Derivatives Markets (CISDM) hedge fund database. Since it is well documented that hedge fund returns exhibit significant serial correlation, we estimate a pooled regression model with panel corrected standard errors (PCSE). Our PCSE specification allows errors to be contemporaneously correlated, heteroskedastic across funds and autocorrelated within each fund's time series. We report the results of several such joint tests. We find a highly statistically significant positive relationship between cross-sectional dispersion of equity returns and hedge fund returns.

We then investigate how the cross-sectional dispersion of hedge fund returns is related through time to market dispersion. Silva, Sapra and Thorley (2001) find that wider dispersion in security returns leads to wider dispersion in mutual fund returns. Consistent with the findings of Silva et alia for mutual funds, we find that the level of hedge fund return dispersion is positively related to the level of market dispersion. By including the Fung and Hsieh factors, we show that market dispersion contains information distinctly different from other hedge fund risk factors. So in addition to its power in explaining hedge fund returns, it has significant explanatory power in explaining their time-varying risk.

The remainder of the paper is organized as follows. Section 2 discusses related literature. Section 3 uses a simple theoretical model to analyze the possible effects of time-varying market dispersion on hedge fund risk and return. Section 4 presents the measures of cross-sectional volatility and links market dispersion to the performance of hedge funds. Section 5 concludes.

2 Related literature

A number of recent papers have studied the risk exposures and returns of hedge funds. Using a variety of hedge fund databases, Ackermann, McEnally, and Ravenscraft (1999), Agarwal and Naik (2000), Edwards and Caglayan (2001), Fung and Hsieh (1997, 2002) and Liang (1999, 2000, 2001) offer comprehensive studies of historical hedge fund performance. Another strand of literature focuses on the characteristic of risk and return in specific hedge fund strategies. For example, Mitchell and Pulvino (2001) study the “risk-arbitrage” strategy; Fung and Hsieh (2001) study the "trend-following" strategy and find that equity-oriented hedge funds have nonlinear, option-like payoffs with respect to the market return. Agarwal and Naik (2004) study a number of equity-oriented strategies. In particular, they include call and put options on the S&P 500 composite index as risk factors.

Some related studies examine the issue whether hedge funds amplify market volatilities and impair stability of financial markets (see, Eichengreen et al., 1998, Fung and Hsieh, 2000), but they do not examine whether hedge funds benefit from volatile financial markets, i.e, whether hedge funds exhibit systematic exposure to market volatility risk. Bondarenko (2004) estimates the value of options contract on market variance from prices of traded options and finds that the return to this contract captures a key determinant of hedge fund performance. Most hedge funds exhibit negative exposure to the variance contract return, implying that they tend to be "short" the risk associated with market volatility. Hence, the performance of hedge funds tends to be worse when markets are volatile. This seems to contradict the conventional wisdom that hedge funds thrive in volatile financial markets. As alternative investment tools a primary benefit to hedge fund investing is the low correlation between returns of hedge funds and of traditional asset classes.[1]

While time series volatility has been extensively studied, little study has been done on cross-sectional volatility. Hwang (2001) compares the properties of cross-sectional volatility with those of time-series market volatility such as squared market returns in the UK and US markets. His empirical results show that cross-sectional market volatility is highly correlated with time-series market volatility and contains more information about the market evolution than squared market returns.

Campbell, Lettau, Malkiel and Xu (2001) decompose the total volatility of each stock into three components, market volatility, industry volatility, and firm specific (idiosyncratic) volatility. They show that average idiosyncractic volatility has strong positive autocorrelation, as well as secular trends. Jones (2001) and Connor, Korajczyk and Linton (2006) get similar findings to Campbell et al, using statistical factor models of equity returns rather than a market-industry factor model.

Since cross-sectional volatility is heavily influenced by idiosyncratic risk, another closely related literature studies the relationship between idiosyncratic risk and stock returns. The asset pricing literature does not have a consensus on the cross-sectional role of idiosyncratic risk in expected returns. According to the traditional CAPM theory, only market risk should be priced in equilibrium, and investors will not be rewarded for taking idiosyncratic risk because it can be diversified away. However, Levy (1978), Merton (1987), and Malkiel and Xu (2002) extend the CAPM. In their models, investors may hold undiversified portfolios for some exogenous reasons, and idiosyncratic risk is priced in equilibrium. For

[1] Patton (2007) proposes generalizing the concept of "market neutrality" to consider the "completeness" of the fund's neutrality to market risks. "Complete neutrality" corresponds to statistical independence of the fund and the market returns. He finds that about one-quarter of funds in the "market neutral" category are not in fact market neutral using this expanded definition.

example, institutional investors may take nonnegligible idiosyncratic risk in order to obtain information-based superior returns. Hence, investors will care about total risk, not just market risk.

Empirical work provides mixed evidence for the role of idiosyncratic risk in asset pricing. On the one hand, Lintner (1965), Tinic and West (1986), Lehmann (1990) and Malkiel and Xu (2002) find there is a positive relation between idiosyncratic volatility and stock returns. On the other hand, Longstaff (1989) finds that a cross-sectional regression coefficient on total variance for size-sorted portfolios has an insignificant negative sign. Ang, Hodrick, Xing and Zhang (2006) find stocks with high idiosyncratic volatility have very low average returns. Hirt and Pandher (2005) find idiosyncratic volatility is negatively priced in risk-adjusted stock returns but its effect is not significant in unadjusted returns.

At the aggregate level of idiosyncratic risk which can be measured by cross-sectional volatility, Goyal and Santa-clara (2003) show that the effects of idiosyncratic risk is diversified away in the equal-weighted portfolio variance measure, even though it makes up almost 85% of the equal-weighted average stock variance. (Their average stock variance can be interpreted as a measure of cross-sectional dispersion of stock returns.) Goyal and Santa-clara find a significant positive relation between average stock variance (largely idiosyncratic) and the return on the market. However, Bali, Cakici,Yan and Zhang (2005) show that this result is driven by small stocks traded on the Nasdaq and it does not hold for the extended sample from 1963:08 to 2001:12 and for the NYSE/AMEX and NYSE stocks.

Market dispersion captured by cross-sectional volatility is also linked to the dispersion of mutual fund returns. Silva, Sapra and Thorley (2001) find that the wide dispersion in security returns has led to wide dispersion in mutual fund returns. This wide dispersion in mutual fund returns has little to do with changes in the informational efficiency of the market or the range of managerial talent. They extend performance benchmarking to incorporate the information embedded in return dispersion by adjusting fund alphas using a period- and asset-class-specific measure of security return dispersion. They argue that an assessment of the performance of money managers should take into account the dispersion of stock returns during the period. They find that the increase in the dispersion of portfolios of money managers in 1999, during the internet bubble, is the result of an increase in the dispersion of the underlying stocks rather than an increase in the diversity of manager talent or a decrease in market efficiency. Similarly, Ankrim and Ding (2002) find that changes in the level of cross-sectional volatility have a significant association with the distribution of active manager returns.

Cross-sectional volatility has also been studied from other perspectives. Christie and Huang (1995) use cross-sectional volatility to capture herd behavior in stock markets. Bessembinder, Chan, and Seguin (1996) use cross-sectional dispersion of stock returns as a proxy for company-specific information flows. Solnik and Roulet (2000) argue that dispersion is a better measure of the benefits of diversification than correlation. They analyze the relationship between correlation, dispersion and the volatility of the market portfolio.

3 Simple comparative static analysis of market dispersion, hedge fund return, and hedge fund risk

Before examining the data, we describe a very simplified model of hedge fund portfolio selection in the presence of security-specific selection ability. We use this simple model to highlight the potential empirical links between hedge fund performance and market dispersion. This simple theoretical model guides the specification of our econometric models and aids the interpretation of our empirical findings.

For the purposes of this simple model we impose a static one period investment environment on the single hedge fund. Let r denote the $n-$vector of security returns available in the market and let r_m denote the market benchmark return. Let $\widetilde{r} = r - 1^n r_m$ denote the vector of active returns to the securities, that is, each asset's return minus the market benchmark return. The hedge fund has total assets of \$1 which it invests in the riskfree security earning return r_0. In addition the fund takes short and long positions in individual stocks; the hedge fund's portfolio weights are given by the $n-$vector w. In order to ensure that its total position in the equity market sums to zero, it takes an offsetting position in the market benchmark of $-w'1^n$. The return to the hedge fund is therefore $r_0 + w'\widetilde{r}$.

We assume that the hedge fund manager has superior information about the returns to securities in the form of an observed $n-$vector of signals s. The conditional returns to securities are tied to the signals in the usual way:

$$\widetilde{r} = s + \eta \tag{1}$$

where $E[\eta|s] = 0^n$. We assume that the vector of conditional returns η has a multivariate normal distribution.

We assume that the hedge fund manager chooses his portfolio w to maximize the expected utility of portfolio return, $r_w = r_0 + w'\widetilde{r}$. We assume that manager's utility function has constant absolute risk aversion with risk aversion parameter λ, that is $E[u(r_w)] = E[-\exp(-\lambda r_w)]$ Taking the expectation of lognormal realized utility, the portfolio optimization problem simplifies to maximizing the risk-aversion-weighted linear combination of expected return and variance:

$$w^* = \arg\max E[r_0 + w'\widetilde{r}] - \frac{1}{2}\lambda w' E[\eta\eta']w. \tag{2}$$

Now we extend this standard model slightly, to allow for comparative static analysis of the effects of changing market dispersion on the performance of the hedge fund. To do this we add parameters a, b, c to the model of active returns (1) with all three parameters set equal to 1. To analyze the effects on hedge fund performance we perturb the parameters away from one. The three scalar parameters a, b, c represent respectively a *balanced change*, *signal-only change*, and *noise-only change* in dispersion. The new version of (1) is:

$$\widetilde{r} = a(bs + c\eta).$$

Note that the nature of the portfolio optimization problem is unchanged by including these three strictly positive parameters. Finding the optimal portfolio w^* (and then the associated expected return and variance) by taking the first derivative of (2) and setting to zero gives:

$$\begin{aligned} w^* &= (\frac{b}{\lambda a c^2})(E[\eta\eta'])^{-1}s \\ E[r_{w^*}] - r_0 &= (\frac{b^2}{\lambda c^2})s'(E[\eta\eta'])^{-1}s \\ Var[r_{w^*}] &= (\frac{b}{\lambda c})^2 s'(E[\eta\eta'])^{-1}s \end{aligned}$$

Taking the derivative of portfolio expected excess return and portfolio variance with respect to a gives:

$$\frac{\partial E[r_{w^*}]}{\partial a} = \frac{\partial Var[r_{w^*}]}{\partial a} = 0.$$

That is, the effect of a balanced change in dispersion on hedge fund return and risk is zero. The reason is easy to see. In this simple set-up, a balanced shift in the hedge fund risk-return opportunity set has no effect on the optimal portfolio's properties, since the fund manager adjusts the active portfolio weights to maintain his optimal risk-return tradeoff. Next consider the comparative statics of a signal-only change in market dispersion:

$$\begin{aligned} \frac{\partial E[r_{w^*}]}{\partial b} &= (\frac{2}{\lambda})s'(E[\eta\eta'])^{-1}s > 0 \\ \frac{\partial Var[r_{w^*}]}{\partial b} &= (\frac{2}{\lambda^2})s'(E[\eta\eta'])^{-1}s > 0 \end{aligned}$$

If market dispersion increases purely due to increased signals to the hedge fund, then both the excess return and variance of the fund will increase; the relative magnitude of their changes depends upon whether the risk aversion coefficient is greater or less than one. Lastly:

$$\begin{aligned} \frac{\partial E[r_{w^*}]}{\partial c} &= -(\frac{2}{\lambda})s'(E[\eta\eta'])^{-1}s < 0 \\ \frac{\partial Var[r_{w^*}]}{\partial c} &= -(\frac{2}{\lambda^2})s'(E[\eta\eta'])^{-1}s > 0. \end{aligned}$$

so that a noise-only increase in market dispersion causes a decrease in the fund's excess return and in its variance, with their relative decrease tied to the manager's risk aversion coefficient.

In this simple model, a balanced change in market dispersion has no effect, a signal-only change has a positive effect on both mean and variance, and a noise-only change has a negative effect on both. Empirically, as discussed below, we find that the signal-related positive relationships seem to dominate the noise-related negative relationships. That is, on a net basis, we find that increased market dispersion increases hedge fund expected returns while also increasing their level of active risk.

A caveat regarding this simple theoretical model is that it relies on *predictable* changes in market dispersion. For some types of options-based hedge fund strategies there can also be a contemporaneous correlation between realized return and *realized* market dispersion, unrelated to predictable changes. For example, if a hedge fund holds a collection of long put-call straddles on individual stocks, then in months when realized market dispersion is high the average payoff on the individual straddles will be positive. The opposite holds for a hedge fund holding a collection of short straddles. In the presence of arbitrary options-related strategies, the predicted sign of the relationship between realized hedge fund return and realized market dispersion is indeterminate. This does not affect the validity of the empirical analysis using total dispersion, but it does potentially affect the proper interpretation of the findings. We also provide some exploratory empirical analysis in which the predictable and unpredictable components of dispersion are included separately.

4 Empirical analysis

In this section, we introduce our dispersion measure and investigate its relation to the performance of hedge funds.

4.1 Data

We analyse hedge funds both at index level and individual fund level. We use the hedge fund indices from the HFR database. We consider seven main fund categories for which data are available from the database inception in 1990. Those include six equity related categories: Convertible Arbitrage, Distressed Securities, Equity Hedge, Equity Market Neutral, Equity

Non-Hedge, Event-Driven; and one aggregate category: Fund of Funds Composite. Table 1 reports summary statistics of monthly returns of HFR indices.

For individual hedge fund returns, we use the CISDM hedge fund database, maintained by the University of Massachusetts in cooperation with Managed Account Reports LLC, with data through August 2004. The CISDM database consists of two sets of files, one for live funds and one for dead funds. Each set consists of a performance file, containing monthly observations of returns, total net assets, and net asset values, and a fund information file, containing fund name, strategy type, management fees, and other supplementary details. We discard funds with less than 48 months of returns.

We single out Equity Hedge, Equity Nonhedge, Market Neutral, Merger Arbitrage, Distressed Securities[2] and Convertible Arbitrage for further scrutiny. Equity hedge funds have grown considerably over time (now representing the single largest strategy according to HFR) and have the highest alpha in Agarwal and Naik (2004). Another large sector of equity-oriented hedge funds is market neutral funds. Market neutral strategies aim at zero exposure to market risk.

Table 2 provides summary statistics on the individual hedge funds data. For each strategy, the table lists the number of funds, and means and standard deviations of basic summary statistics.

For risk adjustment of the hedge fund returns we use seven hedge fund risk factors suggested by Fung and Hsieh (2004). These factors are the S&P 500 return minus the risk free rate, the Wilshire small cap minus large cap return, the change in the constant maturity yield of the 10-year Treasury, the change in the spread of Moody's Baa yield over the 10-year Treasury yield, the bond PTFS, the currency PTFS, and the commodities PTFS, where PTFS denotes a primitive trend-following strategy. The PTFS is defined as a strategy to capture the largest price movement during the time interval. Trend followers generate trade signals based on their observation of the general direction of the market. Fung and Hsieh (2004) lay out the theoretical foundation of the primitive trend-following strategy as lookback straddles, and show empirically that the characteristics of lookback straddle returns

[2] In the CISDM database, event driven style includes merger arbitrage and distressed securities.

resemble those of trend-following fund returns. They then construct PTFS returns by using observable, exchange-traded option prices.

4.2 Measures of time-series and cross-sectional volatility

Cross-sectional dispersion can be captured by a number of different measures, such as range, inter-quartile range and mean absolute deviation. Cross-sectional volatility is an attractive measure of market dispersion, since it takes into account the entire collection of individual security returns. We define equal-weighted cross-sectional volatility as:

$$CSV_t = \sqrt{\frac{1}{n_t}\sum_{i=1}^{n_t}(r_{it} - r_{ew})^2} \tag{3}$$

where r_{it} is the observed stock return on firm i at time t and r_{ew} is the return to the equally-weighted portfolio at time t. This cross-sectional statistic quantifies the average dispersion of individual returns around the realized equally-weighted market average at time t. We compute cross-sectional volatility measure using CRSP data from January of 1994 to December of 2004. Each month, we use all the stocks which have a valid return for that month. In calculating CSV we use the equally-weighted portfolio return as the benchmark return. Since this return equals the cross-sectional average it fits naturally into the definition of cross-sectional volatility.

We also employ the realized time-series volatility of a market index as an alternative, theoretically distinct, volatility measure. We follow French, Schwert and Stambaugh (1987), and compute each month the realized monthly volatility based on daily returns of the S&P 500 market index, with a first-order lagged term to adjust for autocorrelation in the index due to stale prices. That is:

$$MV_t = \sqrt{\sum_{d=1}^{D_t} r_{dt}^2 + 2\sum_{d=1}^{D_t - 1} r_{dt} r_{d+1,t}} \tag{4}$$

where r_{dt} is the reported return to the S&P 500 market index on day d in month t and there are D_t trading days in month t.

Table 3 gives descriptive statistics on the two volatility measures. Both volatility measures show substantial time-variation with strong positive autocorrelation. Figure 1 compares the two time series over the sample period. There was a steady increase in the cross-sectional volatility of monthly returns through the 1990s. During the dot-com bubble period 1999 to 2001, cross-sectional volatility increased sharply and reached its peak. After 2001, cross-sectional volatility declined dramatically, falling below pre-bubble levels in 2004.

Table 4 reports the correlations between the two volatility measures and the Fung-Hsieh risk factors in hedge fund returns. As we can see from the table, cross-sectional volatility and time series market volatility are positively correlated. The Small Cap Minus Large Cap return is also positively correlated with cross-sectional volatility.

4.3 Market dispersion and the performance of hedge funds

We now explore the linkage between cross-sectional volatility and performance of hedge funds. To ensure robust findings, first we need to obtain risk-adjusted hedge fund returns. There is no universally accepted method for hedge fund risk adjustments in the existing literature due to their use of derivatives and dynamic trading strategies. We use as performance benchmarks the seven-factor model developed by Fung and Hsieh (2004). Fung and Hsieh (2004) show that their factor model substantially explains the variation in individual hedge fund returns.

In order to obtain risk-adjusted performance of hedge funds, we regress the net-of-fee monthly excess return (in excess of the risk free rate) of a hedge fund or hedge fund index on the seven factors and an intercept:

$$R_{i,t} = \alpha_i + \beta_i' F_t + \epsilon_{i,t}, \tag{5}$$

where $R_{i,t}$ is the net-of-fee monthly excess return of fund i in month t, β_i is the vector of factor risk exposures of fund i, and F_t is the vector of realizations of the seven factors in month t. The risk-adjusted return of fund i at month t is calculated as:

$$\hat{a}_{i,t} = R_{i,t} - \widehat{\beta}_i' F_t = \hat{\alpha}_i + \hat{\epsilon}_{i,t}, \tag{6}$$

where $\hat{\beta}_i$ is the estimated risk exposure for fund i. Note that the monthly risk-adjusted returns $\hat{a}_{i,t}$ are the sum of the intercept $\hat{\alpha}_i$ and the residual $\hat{\epsilon}_{i,t}$ from the regression and represent the unexplained part of the fund's return.

We begin the empirical analysis using hedge fund index returns. For a given hedge fund index, we take the time series of monthly risk adjusted returns and use it as dependent variable in the following regression:

$$\hat{a}_t = \beta_0 + \beta_1 CSV_t + \beta_2 MV_t + \epsilon_t \tag{7}$$

where $\hat{a}_t$ is risk-adjusted hedge fund return index in month t, CSV_t is cross-sectional volatility in month t, and MV_t is the realized time series volatility of the market index during month t.

Table 5 reports the regression results for each of the eight hedge fund indices. The exposure to cross-sectional volatility is positive and significant for three of the eight fund strategy categories: convertible arbitrage, equity hedge and equity non-hedge funds. All three of these strategies involve long and short positions in individual equities. The sensitivity to time series volatility is negative and insignificant for all fund categories except equity hedge funds.

The hedge fund index results suggest that hedge fund performance for some categories of funds is correlated with market dispersion, but the grouping into fund categories induces a substantial decrease in statistical power. Next we use the entire hedge fund database to make more definitive statements about the statistical significance of the market dispersion effect.

The joint tests involve a panel-data extension of the regression methodology described above. First, we apply (7) to each individual hedge fund return, creating a cross-sectional panel of risk-adjusted returns $\hat{a}_{i,t}$. Then, using all of the data from all individual funds within a given strategy category, we estimate a pooled regression of the form:

$$\hat{a}_{i,t} = c_i + b_1 CSV_t + b_2 MV_t + u_{i,t} \tag{8}$$

with panel corrected standard errors (PCSE), and with the parameters b_1 and b_2 constrained to be the same across funds, but the intercepts c_i allowed to vary across funds. Our PCSE specification allows $u_{i,t}$ to be contemporaneously correlated and heteroskedastic across funds, and autocorrelated within each fund's time series. For notational simplicity we consider the case of a balanced panel in which all n hedge funds have return observations for the full time period. Let X denote the $2xT$ matrix of time-series demeaned values of CSV_t and MV_t, $\widetilde{A}$ the $nT-$vector of individually time-series demeaned values of $\hat{a}_{i,t}$and $b = (b_1, b_2)$ the two regression coefficients (excluding the intercepts). We use the ordinary least coefficient estimates $\widehat{b} = ((X \otimes 1^n)'(X \otimes 1^n))^{-1}(X \otimes 1^n)'\widetilde{A}$. The panel corrected standard errors are the square roots of the diagonals of the covariance matrix:

$$cov(\widehat{b}) = (X'X)^{-1}(X'(\Phi \otimes I_T)X)(X'X)^{-1}$$

where $\Phi = cov(u)$, the unconditional covariance matrix of the $n-$vector of fund-specific residuals in (8). We allow these residuals to have first-order autocorrelation, so that a consistent estimate of their unconditional covariance matrix is given by:

$$\widehat{\Phi} = \frac{1}{T}\sum_{t=1}^{T} \widehat{\mathrm{u}}_t \, \widehat{\mathrm{u}}_t' + \frac{1}{T}\sum_{t=2}^{T} \widehat{\mathrm{u}}_{t-1} \, \widehat{\mathrm{u}}_t' + \frac{1}{T}\sum_{t=2}^{T} \widehat{\mathrm{u}}_t \, \widehat{\mathrm{u}}_{t-1}'.$$

where $\widehat{\mathrm{u}}_t$ denotes the $n-$vector of time t residuals from the ordinary least squares estimation of b. The extension to an unbalanced panel is straightforward although notationally clumsy.

We report the results of joint tests of significance across all funds within each strategy category in Table 6. All six strategy categories have positive estimates for the effect of market dispersion on hedge fund return, and the estimate is highly significant in five of the six; the coefficient is insignificant only for distressed securities.

Consistent with the results of Bondarenko (2004), the point estimates linking realized market volatility and return indicate that market volatility is negatively related to hedge fund performance across all strategies, although the results are only statistically significant for two categories. These results suggest that higher market index volatility is associated with lower hedge fund returns. Many hedge funds seem to use strategies which induce a net short position in market portfolio "vega" risk (in the options literature, vega is defined as return associated with increases in market volatility). Hedge funds may generate a negative exposure to market portfolio vega in several ways. Equity-oriented hedge funds can take short positions in vega through variance swaps (forward contracts on future realized price variance). Some equity-oriented hedge funds take bets on events such as mergers, spin-offs, takeovers, corporate restructuring, and reorganization. These strategies involve the risk of deal failure and may have negative exposure to market portfolio vega because deals are more likely to fail in volatile markets than in normal markets.

4.4 Market dispersion and dispersion of hedge fund returns

Dierick and Garbaravicius (2005) argue that the decreasing dispersion of hedge fund returns could be a broad indication that hedge fund positioning is becoming increasingly similar. Patterns in pairwise correlation coefficients of individual hedge fund return performance within strategies also indicate that hedge fund positioning has resulted in a crowding of trades in some markets, possibly leaving them vulnerable to adverse market dynamics. These concerns are the greatest for convertible arbitrage and credit strategies, as these strategies generally have the highest leverage and therefore significant gross positions. This sub-section examines these issues by analysing the relationship between market dispersion and the dispersion of hedge fund returns.

Within each strategy category we define the cross-sectional volatility of hedge fund returns in the same way as for asset returns:

$$CSVH_t = \sqrt{\frac{1}{n_t}\sum_{i=1}^{n_t}(R_{i,t} - \frac{1}{n_t}\sum_{i=1}^{n_t}R_{i,t})^2}$$

where n_t is the number of fund returns at time t in the database for the given strategy category. Figure 2 graphs the statistic for each of the six strategy categories in CISDM. To investigate the impact of market dispersion on the dispersion in hedge fund returns, we regress cross-sectional dispersion in hedge fund returns on cross-sectional volatility of stock returns.

$$CSVH_t = \gamma_0 + \gamma_1 CSV_t + \gamma_2 STR_t + \gamma_3 SMB_t + \gamma_4 CSVR_{t-1} + \eta_t \tag{9}$$

where $CSVH_t$ is cross-sectional dispersion of hedge fund returns in month t for a given strategy category, CSV_t is cross-sectional volatility of stock returns in month t, STR_t is stock market return in month t, and SMB_t is small minus big portfolio return in month t. To control for serial correlation of $CSVH_t$, we also include one lag of the dependent variable in the regression. Table 7 reports the regression results.

The results indicate that the dispersion in hedge fund returns is positively related to market dispersion. Therefore, the decreasing dispersion of hedge fund returns does not necessarily mean that hedge fund positioning is becoming increasingly similar; it could instead reflect the decline in market dispersion.

4.5 Applying the Hodrick-Prescott Filter

As mentioned in Section 2 above, a weakness of our simple theoretical model is that it relies on predictable dispersion only, ignoring the unpredictable component. If hedge funds engage in options-related strategies, then the unpredictable part of dispersion might be related to hedge fund performance.

For the purposes of exploratory analysis, in this subsection we decompose market dispersion into two additive components, predictable and unpredictable dispersion, using the Hodrick-Prescott filter with smoothing parameter equal to 14400, the recommended value for monthly data (see Hodrick and Prescott (1997)). Figure 3 displays market dispersion and its predictable component; unpredictable dispersion is the difference between them. We repeat the regression tests (7) and (8) with the two components of dispersion, predictable and unpredictable, included as separate explanatory variables. There may be a generated-regressors bias in the two regression coefficients (although not in their sum) so we treat these results as exploratory rather than conclusive. Tables 8 and 9 show the findings. Most of the explanatory power associated with market dispersion comes from the predictable rather than the unpredictable component, although this finding is not uniform across all fund types.

5 Concluding remarks

In this paper, we study the effects of market dispersion on the performance of hedge funds. First, we analyze the time series of cross-sectional dispersion of equity returns, using U.S. stock market data over the 1994-2004 period. We find that market dispersion varies substantially through time with strong positive autocorrelation, and with some evidence for longer-term trends. We show that the time-series fluctuations in market dispersion are positively related to the performance of equity-based hedge funds. We also show that market dispersion may explain part of the hedge fund returns not accounted for by the standard Fung-Hsieh hedge fund risk factors. Market dispersion has a role as an additional risk factor for equity-based hedge funds.

Our findings have important implications for hedge fund portfolio management and performance evaluation. During periods of high cross-sectional volatility, many hedge funds may deliver statistically positive risk-adjusted returns (alpha) if the cross-sectional volatility exposure is not taken into account. However, after correcting for cross-sectional volatility exposure, the performance of some hedge funds may become less impressive, with positive alphas becoming negative or statistically insignificant.

Our paper raises some interesting issues. Cross-sectional volatility can be regarded as a proxy of aggregate idiosyncratic risk. An interesting direction for future research would be to examine the determinants of idiosyncratic risk and how it changes over time. If we could understand the changes in cross-sectional volatility, we will probably have a better understanding of hedge funds' risk exposure.

Table 1 Summary statistics of HFR hedge fund indices

This table reports the means, standard deviations, skewness, kurtosis, first order autocorrelation(ρ_1) and minimum and maximum of returns for HFR hedge fund indices

Hedge fund strategy	Mean	Standard deviation	Skewness	Excess Kurtosis	Minimum	Maximum	ρ_1%
Convertible Arbitrage	0.93	0.93	-0.91	2.59	-3.19	3.33	22.3
Distressed Securities	1.07	1.62	-1.81	9.18	-8.50	5.06	23.8
Equity Hedge	1.52	2.69	0.14	1.14	-7.65	10.88	12.7
Equity Market Neutral	0.86	0.94	-0.02	0.25	-1.67	3.59	-0.3
Equity Non-Hedge	1.36	4.27	-0.51	0.49	-13.34	10.74	16.3
Event Driven	1.17	1.93	-1.40	5.44	-8.90	5.13	27.7
Fund of Funds Composite	0.71	1.74	-0.29	4.43	-7.47	6.85	12.9

Table 2 Summary statistics of CISDM hedge funds

This table presents cross-sectional means and standard deviations of basic summary statistics for funds in the CISDM database over the sample period January 1993 to August 2004. K is the number of funds. L is the average life span of funds (in months). SD denotes standard deviations. $\hat{\rho}_1\%$ and $\hat{\rho}_2\%$ denote first order and second order autocorrelation respectively.

Category	K	L	Mean		SD		Skewness		Kurtosis		$\hat{\rho}_1\%$		$\hat{\rho}_2\%$	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Mkt neutral	121	80	0.96	0.57	3.88	2.98	0.44	1.19	6.57	5.70	13.85	17.72	7.54	15.27
Eq hedge	58	86	0.99	0.84	5.18	2.74	0.01	1.10	6.40	4.85	13.99	16.23	6.88	14.16
Eq nonhedge	20	87	1.24	0.82	8.25	4.69	0.17	0.69	4.86	1.88	6.97	13.16	-0.01	11.30
Distressed	72	89	1.08	0.59	3.82	3.01	-0.14	1.34	7.83	6.36	18.63	16.85	7.81	13.63
Merger arb	106	88	0.89	0.54	3.04	3.72	-0.17	1.14	6.70	5.20	20.67	15.82	11.63	15.57
Conv. arb	106	86	1.02	0.51	2.11	1.71	-0.14	1.38	7.18	5.33	30.93	17.31	12.81	16.87

Table 3
Descriptive statistics of volatility measures

This table presents descriptive statistics on returns and measures of volatility. The sample period is January 1994 to December 2004. The variable CSV is the cross-sectional volatility of stock returns, MV is the time series market volatility. SD is the standard deviation, $\rho_1$and ρ_2 are the first-order and second-order autocorrelation respectively.

	Mean	SD	Skewness	Excess Kurtosis	ρ_1	ρ_2
CSV	0.19	0.05	2.31	6.85	0.29	0.26
MV	0.05	0.02	1.21	0.95	0.67	0.57

Table 4
Pair-wise correlations of the explanatory variables

This table reports pair-wise correlations of the explanatory variables. CSV denotes cross-sectional volatility and MV denotes time-series market volatility. The Fung and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the 10-year Treasury (BD10RET), change in the spread of Moody's Baa minus the 10-year Treasury (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS denotes primitive trend following strategy.

	CSV	MV	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX
CSV	1							
MV	0.30	1						
SNPMRF	0.19	-0.23	1					
SCMLC	0.35	-0.16	-0.09	1				
BD10RET	-0.05	-0.18	0.02	0.07	1			
BAAMTSY	-0.02	0.40	-0.10	-0.27	-0.64	1		
PTFSBD	-0.04	0.27	-0.15	-0.05	-0.10	0.07	1	
PTFSFX	-0.07	0.01	-0.16	0.00	-0.19	0.14	0.15	1
PTFSCOM	-0.14	-0.04	-0.11	-0.01	-0.06	0.06	0.15	0.31

Table 5 Regressions with hedge fund indices

This table reports the results of the regression $a_t = C + \beta_1 CSV_t + \beta_2 MV_t + \epsilon_t$ for the HFR hedge fund indices during the full sample period from January 1994 to December 2004. Where a_t is risk-adjusted hedge fund return index in month t, CSV_t is cross-sectional volatility in month t, MV_t is time series volatility in month t. The t-statistics in parentheses use Newey-West heteroskedasticity and autocorrelation consistent standard errors.

Category	C	CSV	MV	R^2
Convertible arbitrage	0.37	**8.48**	1.00	0.08
	(1.37)	(**3.01**)	(0.14)	
Distressed securities	**1.18**	−0.42	−4.90	0.01
	(**3.23**)	(−0.23)	(−0.62)	
Equity hedge	−0.05	**8.46**	**−13.61**	0.12
	(−0.07)	(**1.96**)	(**−1.86**)	
Equity market neutral	**1.01**	−2.94	−7.19	0.04
	(**4.77**)	(−0.74)	(−1.55)	
Equity non-hedge	0.32	**16.23**	−9.18	0.12
	(1.04)	(**4.03**)	(−1.01)	
Event driven	**1.13**	3.99	−10.53	0.04
	(**4.54**)	(1.14)	(−1.78)	
Fund of funds composite	−0.13	5.14	−7.57	0.05
	(−0.23)	(1.44)	(−0.82)	

Table 6 Pooled regressions with individual hedge funds

This table reports the results of the pooled regression $\hat{a}_{i,t} = b_i + b_1 CSV_t + b_2 MV_t + u_{i,t}$ with panel corrected standard errors (PCSE) where $\hat{a}_{i,t}$ is the estimated risk-adjusted return of fund i in month t. The parameters b_1 and b_2 are constrained to be the same across funds. Our PCSE specification allows $u_{i,t}$ to be contemporaneously correlated and heteroskedastic across funds, and autocorrelated within each fund's time series. Sample period: January 1994 to August 2004.

	CSV	MV
Equity hedge	**12.50** **(4.63)**	**−11.33** **(−2.52)**
Equity non-hedge	**13.48** **(3.02)**	−1.58 (−1.19)
Market neutral	**10.12** **(4.79)**	−1.07 (−0.33)
Merger arbitrage	**3.84** **(1.80)**	**−9.20** **(−2.46)**
Convertible arbitrage	**10.45** **(4.87)**	−0.94 (−0.26)
Distressed securities	1.59 (0.98)	−1.02 (−0.87)

Table 7 Market dispersion and the dispersion in hedge fund returns

This table reports the results of the regression $CSVR_t = \gamma_0 + \gamma_1 CSV_t + \gamma_2 STR_t + \gamma_3 SMB_t + \gamma_4 CSVR_{t-1} + \eta_t$ for four categories of hedge funds during the full sample period from January 1994 to August 2004. Where $CSVR_t$ is cross-sectional dispersion of hedge fund returns in month t, CSV_t is cross-sectional volatility of stock returns in month t, STR_t is stock market return in month t, SMB_t is small minus big portfolio return in month t. The t-statistics in parentheses use Newey-West heteroskedasticity and autocorrelation consistent standard errors.

Category	CSV	STR	SMB	CSVR_{t-1}	R^2
Equity hedge	**0.27**	**−0.14**	−0.05	**0.45**	0.50
	(2.31)	**(−3.73)**	(−0.92)	**(6.58)**	
Equity non-hedge	**0.71**	**−0.14**	0.04	0.08	0.42
	(3.08)	**(−2.86)**	(0.57)	(0.87)	
Market neutral	**0.31**	**−0.06**	−0.03	0.07	0.34
	(3.35)	**(−2.07)**	(−1.01)	(0.87)	
Merger arbitrage	**0.19**	−0.01	−0.07	0.05	0.04
	(1.94)	(−0.14)	(−1.76)	(0.44)	
Convertible arbitrage	**0.16**	−0.03	**−0.06**	**0.26**	0.25
	(4.08)	(−0.97)	**(−2.22)**	**(3.27)**	
Distressed securities	**0.34**	**−0.09**	−0.04	0.12	0.32
	(4.26)	**(−2.05)**	(−1.13)	(1.74)	

Table 8 Results with hedge fund index and two components of market dispersion

This table reports the results of the regression $a_t = C + \beta_1 CSVP_t + \beta_2 CSVU_t + \beta_3 MV_t + \epsilon_t$ for the HFR hedge fund indices during the full sample period from January 1994 to December 2004. Where a_t is risk-adjusted hedge fund return index at month t, $CSVP_t$ is the predictable part of cross-sectional volatility at month t, $CSVU_t$ is the unpredictable part, MV_t is time series volatility at month t. The t-statistics in parentheses use Newey-West heteroskedasticity and autocorrelation consistent standard errors.

Category	C	CSVP	CSVU	MV	R^2
Convertible arbitrage	0.20 (0.59)	**18.02** **(2.51)**	**5.29** **(1.90)**	−3.83 (−0.53)	0.09
Distressed securities	1.10 (3.33)	−3.95 (−0.40)	1.78 (0.60)	−4.71 (−0.49)	0.01
Equity hedge	0.55 (1.06)	**20.33** **(1.96)**	12.15 (1.63)	−12.61 (−1.47)	0.12
Equity market neutral	0.68 (2.75)	**11.58** **(1.90)**	−7.19 (−1.73)	**−13.31** **(−2.94)**	0.09
Equity non-hedge	0.24 (1.45)	4.05 (0.31)	**19.52** **(4.04)**	−4.65 (−0.51)	0.12
Event driven	1.07 (3.26)	6.36 (0.83)	3.01 (0.70)	−11.71 (−1.87)	0.04
Fund of funds composite	0.07 (0.19)	**21.35** **(1.92)**	5.78 (1.13)	−10.82 (−0.99)	0.07

Table 9 Results with pooled regression and two components of market dispersion

This table reports the results of the pooled regression $\hat{a}_{i,t} = b_i + b_1 CSVP_t + b_1 CSVU_t + b_2 MV_t + u_{i,t}$ with panel corrected standard errors (PCSE). Where $\hat{a}_{i,t}$ is the estimated risk-adjusted return of fund i at month t. The parameters b_1 and b_2 are constrained to be the same across funds. Our PCSE specification allows $u_{i,t}$ to be contemporaneously correlated and heteroskedastic across funds, and autocorrelated within each fund's time series. Sample period: January 1994 to August 2004.

	CSVP	CSVU	MV
Equity hedge	**24.38**	4.47	−**14.57**
	(**4.15**)	(1.56)	(−**3.34**)
Equity non-hedge	**13.85**	−0.25	−1.29
	(**3.15**)	(−0.22)	(−0.28)
Market neutral	**18.24**	**8.33**	−2.97
	(**3.62**)	(**3.57**)	(−0.88)
Merger arbitrage	7.03	3.11	−**9.96**
	(1.36)	(1.28)	(−**2.48**)
Convertible arbitrage	**13.73**	**9.79**	−1.64
	(**2.66**)	(**4.06**)	(−0.42)
Distressed securities	1.09	5.48	−5.02
	(0.15)	(1.64)	(−0.91)

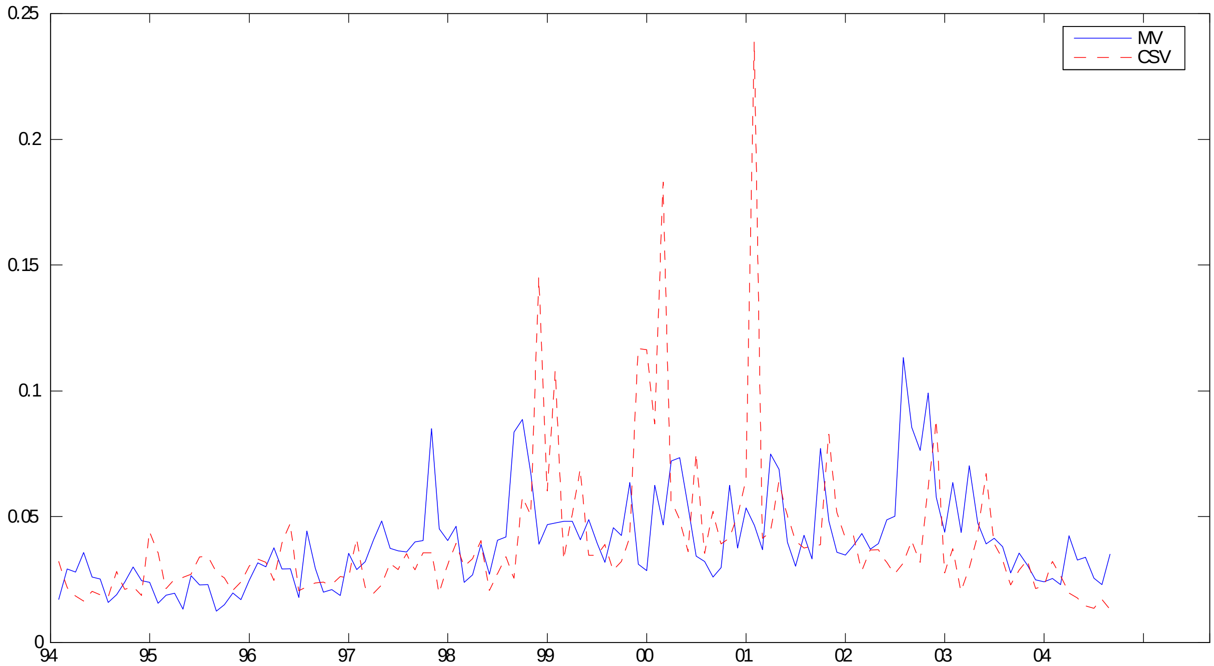

Figure 1 Plot of cross-sectional volatility and time series market volatility(1994-01: 2004-08)

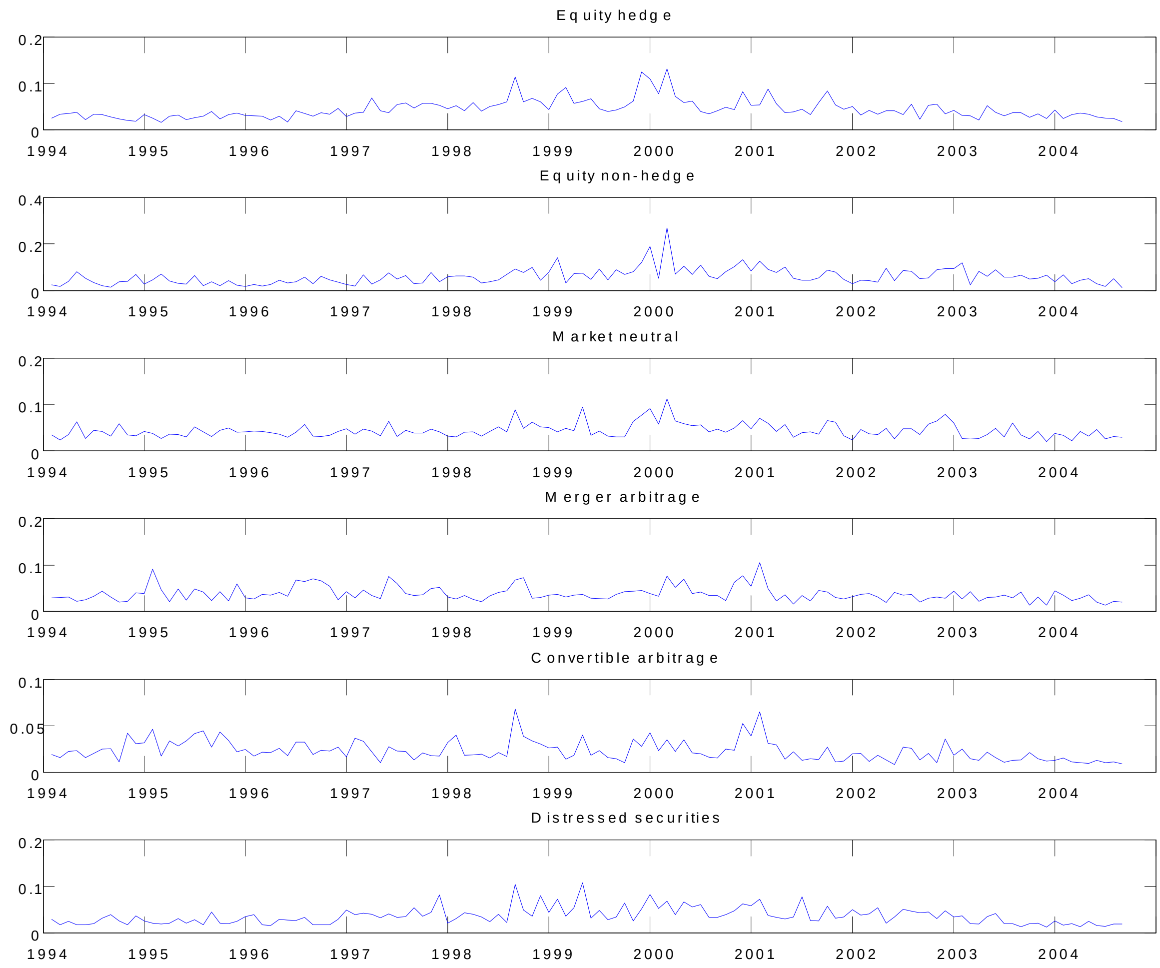

Figure 2: Plot of cross-sectional volatility of hedge fund returns

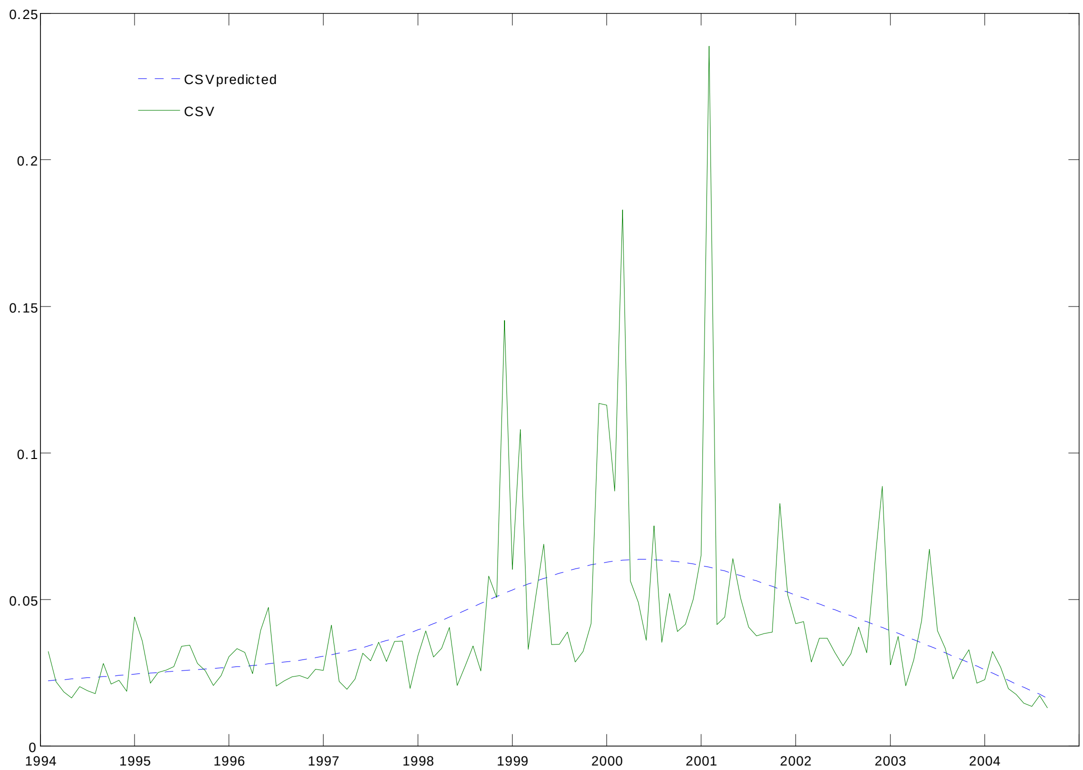

Figure 3: Market dispersion and its predictable component

References

[1] Ackermann, C., R. McEnally and D. Ravenscraft, 1999, The Performance of Hedge Funds: Risk, Return and Incentives, *Journal of Finance*, 54, 833-874.

[2] Agarwal, V. and N.Y. Naik, 2000, Multi-period Performance Persistence Analysis of Hedge Funds, *Journal of Financial and Quantitative Analysis*, 35, 327-342.

[3] Agarwal, V. and N.Y. Naik, 2004, Risk and Portfolio Decisions Involving Hedge Funds, *Review of Financial Studies*, 17, 63-98.

[4] Agarwal, V., N.Y. Naik and N.D. Daniel, 2005, Why is Santa so Kind to Hedge Funds? The December Return Puzzle!, *working paper*.

[5] Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance,* 62, 327-376.

[6] Ankrim, E.M. and Z. Ding, 2002, Cross-Sectional Volatility and Return Dispersion, *Financial Analysts Journal,* 58, 67-72.

[7] Bali, T., N. Cakici, X. Yan and Z. Zhang, 2005, Does Idiosyncratic Risk Really Matter?, *Journal of Finance*, 60, 905-929.

[8] Bessimbinder, H., K.Chan and P.J. Seguin. 1996. An Empirical Examination of Information, Differences of Opinion, and Trading Activity, *Journal of Financial Economics*, 40, 105-134.

[9] Bollerslev, T., R. Chou, and K. Kroner, 1992, ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence , *Journal of Econometrics,* 52, 5-59.

[10] Bondarenko, O., 2004, Market Price of Variance Risk and Performance of Hedge Funds, *working paper*, University of Illinois at Chicago.

[11] Burdett, K., and K.L. Judd, 1983, Equilibrium Price Dispersion, *Econometrica,* 51, 955-969.

[12] Campbell, J.Y., A.W. Lo, and A.C. MacKinlay, 1997, The Econometrics of Financial Markets, Princeton University Press, Princeton, NJ.

[13] Campbell, J.Y., M. Lettau, B. Malkiel, and Y. Xu, 2001, Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk, *Journal of Finance*, 56, 1–43.

[14] Chang, E.C., J.W. Cheng and A. Khorana, 2000, An Examination of Herd Behavior in Equity Markets: An International Perspective, *Journal of Banking and Finance,* 24, 1651-1679.

[15] Christie, W.G. and R.D. Huang, 1995, Following the Pied Piper: Do Individual Returns Herd Around the Market?, *Financial Analysts Journal*, 31-37.

[16] Christie, W.G. and R.D. Huang, 1994, Equity Return Dispersions, *Working paper*, Vanderbilt University.

[17] Connolly, R.A. and C.T. Stivers, 2001, The Conditional Volatility of Individual Firms and Cross-firm Return Information, *Working paper*, University of North Carolina at Chapel Hill,

[18] Dierick, F. and T. Garbaravicius, 2005, Hedge Funds and their Implications for Financial Stability, *Working paper*, European central bank.

[19] Douglas, G.W., 1969, Risk in the Equity Markets: An Empirical Appraisal of Market Efficiency, *Yale Economic Essays*, 9, 3-45.

[20] Edwards, F., and M. Caglayan, 2001, Hedge Fund and Commodity Fund Investments in Bull and Bear Markets, *The Journal of Portfolio Management*, 27, 97-108.

[21] Eichengreen, B. J., D. J. Mathieson, S. Sharma, B. Chadha, L. E. Kodres and A. Jansen, 1998, Hedge Funds and Financial Market Dynamics, *Occasional Paper No. 166*, International Monetary Fund.

[22] French, K.R., G.W. Schwert and R. F. Stambaugh, 1987, Expected Stock Returns and Volatility, *Journal of Financial Economics*, 19, 3-29.

[23] Fu, F., 2005, Idiosyncratic Risk and the Cross-Section of Expected Stock Returns, William E. Simon Graduate School of Business Administration working paper.

[24] Fung, W. and D.A. Hsieh, 1997, Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds, *Review of Financial Studies*, 10, 275-302.

[25] Fung, W. and D.A. Hsieh, 2000, Measuring the Market Impact of Hedge Funds, *Journal of Empirical Finance*, 7, 1-36.

[26] Fung, W. and D.A. Hsieh, 2001, The Risk in Hedge-Fund Strategies: Theory and Evidence from Trend Followers, *Review of Financial Studies*, 14, 313-341.

[27] Fung, W. and D.A. Hsieh, 2002, Asset-based Hedge-fund Style Factors for Hedge Funds, *Financial Analysts Journal,* 58, 16-27.

[28] Garbade, K.D., and W.L. Silber, 1976, Price Dispersion in the Government Securities Market, *Journal of Political Economy,* 84, 721-740.

[29] Ghysels, E., A. Harvey, and E. Renault, 1996, Stochastic Volatility, in G.S. Maddala, ed.Handbook of Statistics, 14, North-Holland, Amsterdam.

[30] Goyal, A., and P. Santa-Clara, 2003, Idiosyncratic Risk Matters!, *Journal of Finance*, 58, 975-1007.

[31] Grinold, R.C. and R.N. Kahn, 2000, Active Portfolio Management. 2nd ed. New York: McGraw-Hill.

[32] Guo, H. and Robert Savickas, 2004, Idiosyncratic Volatility, Stock Market Volatility, and Expected Stock Returns, *Working paper*, George Washington University and the Federal Reserve Bank of St. Louis.

[33] Hirt, G. and G.S. Pandher, 2005, Idiosyncratic Risk & Return Across S&P500 Stocks, *Working paper.*

[34] Hwang, S., 2001, Properties of Cross-sectional Volatility, *Working paper*, City University Business School.

[35] Hodrick, R., and E.C. Prescott, 1997, Postwar U.S. Business Cycles: An Empirical Investigation, *Journal of Money, Credit, and Banking, 29, 1-16.*

[36] Ingersoll, J. E., Jr., 1987, Theory of Financial Decision Making, Rowman and Littlefield, Totowa, NJ.

[37] Lehmann, B.N., 1990, Residual Risk Revisited, *Journal of Econometrics,* 45, 71-97.

[38] Levy, H., 1978, Equilibrium in an Imperfect Market: A Constraint on the Number of Securities in the Portfolio, *American Economic Review,* 68, 643-58.

[39] Liang, B., 1999, On the Performance of Hedge Funds, *Financial Analysts Journal*, 55, 72-85.

[40] Liang, B., 2000, Hedge Funds: The Living and the Dead, *Journal of Financial and Quantitative Analysis*, 35, 309-326.

[41] Liang, B., 2001, Hedge Fund Performance: 1990-1999, *Financial Analysts Journal*, 57, 11-18.

[42] Lintner, J., 1965, Security Prices, Risk and Maximal Gains from Diversification, *Journal of Finance,* 20, 587-615.

[43] Longstaff, F.A., 1989, Temporal Aggregation and the Continuous-time Capital Asset Pricing Model, *Journal of Finance,* 44, 871-887.

[44] Loimgani, P., M. Rush, and W. Tave, 1990, Stock Market Dispersion and Unemployment, *Journal of Monetary Economics*, 25, 367-388.

[45] Malkiel, B. G. and Y. Xu, 2002, Idiosyncratic Risk and Security Returns, *Working paper*, University of Texas at Dallas.

[46] Merton, R., 1987, A Simple Model of Capital Market Equilibrium with Incomplete Information, *Journal of Finance*, 42, 483-510.

[47] Mitchell, M., and T. Pulvino, 2001, Characteristics of Risk in Risk Arbitrage, *Journal of Finance,* 56, 2135-2175.

[48] Patton, A., 2007, Are "Market Neutral" Hedge Funds Really Market Neutral, *Review of Financial Studies,* forthcoming.

[49] Salop, S., and J. Stiglitz, 1977, Bargains and Ripoffs: A Model of Monopolistically Competitive Price Dispersion, *Review of Economic Studies,* 44, 493-510.

[50] Shleifer, A., and Robert W. V., 1997, The Limits of Arbitrage, *Journal of Finance,* 52, 35–55.

[51] Silva, H de, S. Sapra, and S. Thorley, 2001, Return Dispersion and Active Management, *Financial Analysts Journal*, 57, 29-42.

[52] Solnik, B., and J. Roulet, 2000, Dispersion as Cross-Sectional Correlation, *Financial Analysts Journal*, 56, 54–61.

[53] Stigler, G.J., 1961, The Economics of Information, *Journal of Political Economy*, 69, 213-225.

[54] Tinic, Seha M., and R. R. West, 1986, Risk, Return and Equilibrium: A Revisit, *Journal of Political Economy,* 94, 126-147.