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Can Fundamental Factors Explain Asymmetric Correlations in Stock Market Returns?

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Honors Thesis
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Can Fundamental Factors Explain Asymmetric Correlation in Stock Market Returns?

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Submitted December 8th, 2008

Abstract

Asymmetric Correlation is an empirical observation that correlations between security returns are significantly higher during market downturns compared to upturns. Previous literature has focused on examining this asymmetry by way of a rigorous statistical analysis. However, the sources of this phenomenon had not been explored yet.

In this paper, I propose a simple hypothesis: asymmetric correlations can be explained in terms of the securities' underlying fundamental factors. Using the recently proposed Dynamic Conditional Correlations (DCC) class of GARCH models, I estimate the covariance of the fundamental factors and model securities' returns.

I find that fundamental factors can only partially explain the asymmetric correlation. In my final model, I show that despite taking fundamental factors into account, the correlations still exhibit asymmetry. Therefore behavioral factors also play a significant role in causing this phenomenon. Modeling behavioral causes will be the next important step towards understanding asymmetric correlation.

Acknowledgements

First and foremost, I would like to thank my advisor, mentor and friend Professor Liang Ding for all the hard work he has put into this project. His guidance made this all possible. I would also like to thank Professor Vittorio Addona for his assistance in creating computer codes, as well as my peer Colin Hottman for his help during the summer. I am very grateful to Professor Pete Ferderer for his support throughout the year. Last but not least, I would like to thank Aaron Albertson without whom I would not have been able to collect the vast literature I delved into during the course of the year.

1. Introduction

Studying correlations across security and portfolio returns is critical to portfolio management. In classical frameworks such as the Capital Asset Pricing Model, the correlations between portfolio and market returns are assumed to be constant. However, studies of Bollerslev, Engle and Wooldridge (1988), Longin and Solnik (1995), Tse (2000), and Engle and Sheppard (2001), show that correlations between assets are not always constant over time. Furthermore, Longin and Solnik (2001), Ang and Chen (2002), and Hong, Tu and Zhou (2007), among others, have shown that correlations between security prices increase during market downturns compared to upturns. This phenomenon is often referred to as asymmetric correlation.

The implications of asymmetric correlation are twofold. One is that while hedging relies crucially on the correlations between the assets that are hedged and the financial instruments that are used to hedge, the presence of asymmetric correlations can cause problems in its effectiveness. Another is that although standard investment theory advises portfolio diversification, the value of this advice might be debatable if all stocks tend to fall with the market. To design more efficient hedging strategies, it is necessary to predict the asymmetric correlations, while understanding what causes such asymmetries becomes imperative in obtaining reliable estimations of these asymmetries.

In the current literature, there are several studies related to this issue (see Longin and Solnik (2001), Ang and Chen (2002), and Hong, Tu and Zhou (2007)). Although they show that asymmetries exist through rigorous statistical analysis, they have not explained *why* they exist in the first place. This study makes the initial attempt to explain the causes of the phenomenon.

In the related field of comovement, a study of how security prices move together, the first major attempt to explain how this arises modeled price movements on the fundamental factors.[1] I follow this approach and propose that fundamental factors can explain asymmetric correlation. Alternatively, several behavioral factors have been proposed to explain comovement. These include herding, leverage effects, volatility feedback, etc.[2] In this study I also examine whether alternative explanations are needed, although no specific cause is modeled.

To test this hypothesis, a two factor model that uses a common factor and an individual factor is applied to explain portfolio returns. The univariate GARCH procedure is employed to estimate the variance of the common factor and the recently proposed Dynamic Conditional Correlations (DCC) GARCH model is utilized to estimate the covariances between the individual factors. The results show that the variance of the common factor and some of the covariances between the individual factors are asymmetric. However, when the variance and the covariances are substituted back into the two factor model equation, the coefficients still exhibit asymmetries. These results indicate that while fundamental factors can at least partially explain why asymmetric correlation arises, alternative explanations are also needed.

The remainder of this paper is organized as follows. Section 2 provides a brief survey of the previous literature. I review both the asymmetric correlation literature and the

[1] See Pindyck and Rotemberg (1993) and Karolyi and Stulz (1996) – cited with further details in Section 2.
[2] See Bekaert and Wu (2000) and Barberis, Shleifer and Wurgler (2004)

comovement literature. Section 3 explains the methodology. Using a simple framework, the two disparate strands of literature are connected. Section 4 details the data I. Section 5 presents the results and discusses their implications. Section 6 concludes.

2. A Brief Survey of Literature

2.1 Literature on Asymmetric Correlation

Asymmetric correlation is an empirical observation that correlations between security prices are higher during downturns. The literature is quite recent and small. Longin and Solnik (2001) is the first paper that addressed asymmetric correlation directly. Their work is followed by Ang and Chen (2002) and Hong, Tu and Zhou (2007). A common theme to their papers is the development of a formal statistical method to test for the existence of asymmetric correlation.

Longin and Solnik (2001) focus on correlations between returns in either the negative or the positive tail of the multivariate return distribution. Empirically, they use equity index returns for five countries, and conclude that the null hypothesis of multivariate normality is rejected for the negative tail but not for the positive.

Ang and Chen (2002) develops the so-called *H* statistic that quantifies the degree of asymmetry in correlations across downside and upside markets relative to a particular model or distribution.[3] Whereas authors such as Bekaert and Wu (2000) or Kroner and

[3] The statistic *H* is given by

$$H = [\sum_{i=1}^{N} w(\vartheta_i) * (\check{\rho}(\vartheta_i, \phi) - \bar{\rho}(\vartheta_i))^2]^{\frac{1}{2}}$$

The details of this equation are too long to note here, and are not relevant to this study. The author would like to refer the readers to the original paper.

Ng (1998) document the covariance asymmetry of domestic stock portfolios using asymmetric multivariate GARCH models, the H statistic looks at the tails of the distribution. Their approach is an improvement over that of Longin and Solnik (2001) in two ways. First, they estimate a single statistic to quantify asymmetry. Whereas Longin and Solnik (2001) had to look at different thresholds of extremity, Ang and Chen (2002) give weights to various thresholds using the Newey-West kernel, arriving at a single quantity which is easier to understand. Second, they allow for different models and distributions, not just the multivariate normal, and hence is a more flexible approach. They report empirical evidence that many of their characteristic-mimicking portfolios[4] are asymmetrically correlated with the market.

Hong, Tu and Zhou (2007) improve on Ang and Chen (2002) by deriving a nonparametric, model-free statistic J, where the correlation does not have to be compared to any model or distribution at all.[5] They confirm the existence of asymmetric correlation on size-sorted portfolios.

In sum, empirical evidence shows that asymmetric correlations do exist. However, there is no direct study in the literature that explains the causes of the asymmetries. I refer to the literature on comovement as the two phenomena, asymmetric correlation and comovement, are intimately related, and because it is more extensive.

[4] Portfolios based on Industry, Size, Value, Leverage, Momentum and Beta are constructed. These attributes "characterize" various aspects of the market. See Fama and French (1993), Jegadeesh and Titman (1993).

[5] The improved statistic J is given by the following:

$$J_\rho = T(\hat{\rho}^+ - \hat{\rho}^-)'\hat{\Omega}^{-1}(\hat{\rho}^+ - \hat{\rho}^-)$$

The details of this equation are too long to note here, and are not relevant to this study. The author would like to refer the readers to the original paper.

2.2 Literature on Comovement

There are two main types of comovement literature. One focuses on econometrically modeling the phenomenon rather than giving intuitive explanations of comovement. The other, in contrast attempts to explain the phenomenon with economic intuition by using the statistical methods that were developed.

The premise of the comovement literature is that covariances between security prices vary with time. To model these time-varying covariances, a class of models called Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MV-GARCH) models has been utilized. Time-varying volatility has been successfully captured by the ARCH model proposed by Engle (1982), and the generalization of ARCH that led to the GARCH class of models (Bollerslev, 1986). For a survey of the application of ARCH and GARCH models to the literature on volatility modelling, see Bollerslev, Chou and Kroner (1992). Naturally, time-varying covariances have been modelled through their multivariate variation, MV-GARCH.

A major work in the first category of comovement literature is Kroner and Ng (1998). They survey four models of MV-GARCH, namely the VECH, BEKK, factor ARCH (FARCH) and the constant correlation (CCORR) models, and examine their properties. The most relevant part of their paper is where they examine the asymmetric variations to these models. In empirically modeling the comovement between large-firm and small-firm portfolios, they define two regime-switch variables: one where the large-firm portfolio is producing negative returns and another where small-firm portfolio is producing negative returns. They find that the sign of the large-firm return shocks is more important than the sign of the small-firm return shocks.

MV-GARCH models have not been as successful as GARCH models because of two problems. One is the fact that most MV-GARCH models require huge computational power, or otherwise, the assumptions are too restrictive. The other problem is that the conditional covariances attained through the models have been quite unreliable. The Dynamic Conditional Correlations (DCC) model, developed by Engle (2001), attempts to tackle these problems.

Engle and Sheppard (2002) explore the theoretical and empirical properties of DCC. A major improvement is that DCC framework models returns from each asset separately using univariate-GARCH. The transformed residuals are then taken from this first stage, and a conditional correlation estimator is estimated. This reduces the computational power needed because now it is not necessary to model asset returns simultaneously. Engle and Sheppard find that DCC demonstrates very strong performance in modeling conditional covariance of up to 100 assets using S&P 500 Sector Indices and Dow Jones Industrial Average stocks.

I now turn to the second category of literature; one that builds structural models to explain comovement. Earlier works focused on explaining comovement through economic fundamentals; while more recent works have examined alternative explanations.

An example of the attempts to explain comovement through economic fundamentals can be found in Pindyck and Rotemberg (1993). The implication of this hypothesis is that the prices of stocks of companies whose earnings are uncorrelated should move together only in response to changes in macroeconomic conditions. They create groups of companies whose earnings are uncorrelated among each other, estimate a latent variable factor model that accounts for unobserved expectations of future macroeconomic variables, and test whether the errors of this model are uncorrelated across companies. They reject the hypothesis that comovement is justified by economic fundamentals.

Karolyi and Stulz (1996) introduce MV-GARCH in exploring fundamental factors that affect cross-country stock return correlations. They use data of American Depository Receipts of Japanese corporations, and U.S. stock portfolios, and model them against information variables such as the return on the Yen/Dollar exchange rate, the U.S. Treasury bill futures or the Nikkei and Standard and Poor's 500 index returns. They conclude that correlations between the two portfolios vary with some information variables. They then use a constant conditional correlation GARCH (1, 1) model to understand how shocks to the information variables affect comovement over time, and investigate the impact of shocks on the correlations. They show that correlations and covariances are high when markets move a lot.

Alternative explanations have been more behavioral based. The work of Barberis, Shleifer and Wurgler (2004) is a case in point. In examining why common factors that cause comovement arise in the first place, they propose three alternative hypotheses to the traditional fundamentals-based theory, which are classified in the broad "friction-based" and "sentiment-based" theories of comovement. One is the category view, which dictates that investors simplify their portfolio decisions by grouping assets into categories, thereby inducing common factors in the returns of assets that happen to be in the same category, even though these assets' cash flows may be uncorrelated. Another is the habitat view; many investors only trade a subset of all available securities,[6] and when their risk aversion, sentiment, or liquidity needs change, they alter their exposure to the securities in their habitat, thereby inducing a common factor in the returns of these securities. The third is the information diffusion view, which predicts that due to some market friction, information is incorporated more quickly into the prices of some stocks than others. A common factor arises in the returns of stocks that incorporate information at similar rates. By using additions to the S&P 500, they reject the fundamentals-based theory of comovement, and support the alternative friction- or sentiment-based view.

These non-fundamentals based views could easily be incorporated into the asymmetric correlations literature. People tend to react stronger to negative news, which would in turn cause higher correlation when the market is experiencing a downturn. Wu (2001) examines the determinants of asymmetric volatility along this line. He introduces two hypotheses; leverage effects and volatility feedback effects. Leverage effect occurs when a drop in the value of the stock increases its volatility. This is because drop in the value of the stock increases financial leverage, which makes the stock riskier. Volatility feedback effect occurs when an anticipated increase in volatility decreases stock price. This comes from the assumption that volatility is priced; an anticipated increase in volatility increases the required return on equity, which in turn leads to a stock price decline. Wu finds that both are important determinants of asymmetric volatility. Through both these behavioral causes, asymmetric correlation could conceivably arise.

[6] The fact that investors only invest in a subset of all securities is an observed phenomenon. This could be explained in terms of transaction costs, international trading restrictions, or lack of information.

Some more recent works include Wong and Vlaar (2003), and Baele, Bekaert and Inghelbrecht (2007). Wong and Vlaar (2003) examine the time-varying correlations of asset returns using the Dynamic Conditional Correlation (DCC) models, recently proposed by Engle (2002). They report that correlations vary considerably over time, and that conditional correlations exhibit asymmetry. I also use the DCC model, but improve it to incorporate regime-switches.[7] Baele, Bekaert and Inghelbrecht (2007) study the economic sources of stock-bond return comovement and its time variation using a dynamic factor model. They conduct a regime-switching analysis of stock and bond returns.

2.3 Summary

Previous literature on asymmetric correlation focuses on statistically showing the existence of asymmetric correlations but does not shed light onto the question of *why* this phenomenon exists in the first place. This paper attempts to fill this gap.

The most natural place to look to find sensible, feasible hypotheses is the comovement literature. The literature can be divided into a category that focuses on developing new econometric methods to model comovement – particularly the MV-GARCH models – and another that proposes explanations on why comovement occurs. The first explanation was that fundamental factors cause comovement; hence I adopt the hypothesis and focus on this explanation in this paper. Also, of the several MV-GARCH models that have been

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[7] I used the codes originally created by Kevin Sheppard, presently of Oxford University, obtained from his website:
http://www.kevinsheppard.com/wiki/UCSD_GARCH
The codes were improved to incorporate regime-switches by Liang Ding of Macalester College.

developed thus far, DCC offers several advantages over others. This specification is therefore used in this study.

3. Methodology

3.1 Overall Framework

In order to test the hypothesis, a model where correlation across portfolios is related back to the fundamental factors is needed. Following Karolyi and Stulz (1996), the below model is considered. Let $R_{m,t}$ and $R_{p,t}$ denote market and portfolio returns minus the risk-free rate (excess returns) at time t respectively. The correlation between these two returns is given by the equation:

$$\rho_{mp,t} = \frac{Cov(R_{m,t}\,, R_{p,t})}{\sqrt{Var(R_{m,t})}\sqrt{Var(R_{p,t})}} \tag{1}$$

Consider the following. Let $r_{m,t}$ and $r_{p,t}$ denote the standardized returns, i.e.

$$r_{m,t} = \frac{R_{m,t} - \overline{R_{m,t}}}{\overline{\sigma_{m,t}}} \tag{2}$$

where $\overline{R_{m,t}}$ is the unconditional mean of the excess market returns, and $\overline{\sigma_{m,t}}$ is the unconditional standard deviation. The same procedure is applied to portfolio returns. Then, the following equation is constructed:

$$r_{p,t} = \alpha + \beta\, r_{m,t} + \varepsilon_t \tag{3}$$

In this equation, β is given by:

$$\beta = \frac{Cov(r_{m,t}, r_{p,t})}{Var(r_{m,t})}$$

$$= E(r_{m,t} * r_{p,t})$$

$$= E(\frac{R_{m,t} - \overline{R_{m,t}}}{\overline{\sigma_{m,t}}} * \frac{R_{p,t} - \overline{R_{p,t}}}{\overline{\sigma_{p,t}}})$$

$$= \frac{Cov(R_{m,t}, R_{p,t})}{\sqrt{Var(R_{m,t})}\sqrt{Var(R_{p,t})}}$$

$$= \rho_{mp,t} \tag{4}$$

Hence, the estimated coefficient for the standardized portfolio return in equation (3) is the correlation coefficient between the two returns.

Now, model the returns as follows:

$$r_{p,t} = \delta_{p1}F_{c,t} + \delta_{p2}F_{p,t} + \varepsilon_{p,t} \tag{5}$$

$$r_{m,t} = \delta_{m1}F_{c,t} + \delta_{m2}F_{m,t} + \varepsilon_{m,t} \tag{6}$$

where $F_{c,t}$ represents a common factor, and $F_{m,t}$, $F_{p,t}$ represent individual factors. Many variables could be used in this analysis. For the common factor, I considered historical inflation rate, expected inflation, the cost of production, oil prices, monetary base and the interest rate.[8] Preliminary results suggested interest rate, measured by the 3-Month Treasury Bills yield, has the most explanatory power empirically (highest R-square value in estimating equations (5) and (6)); hence it is subsequently used as the common factor.

[8] The factors were measured as follows. Historical Inflation Rate: Change in log CPI; Inflation Expectation: The difference between 1-Year Treasury Bond Yield and 3-Month Treasury Bills Yield; Cost of Production: Producer Price Index. The data are taken from Federal Reserve Economic Database (FRED), available at: http://research.stlouisfed.org/fred2/
I focused on one variable early on due to computational power and time constraints.

For the individual factor, earnings per share is used. This is the most widely used variable to explain firms' fundamentals in previous literature.

Now, β becomes:

$$\beta = \frac{Cov(r_{m,t}, r_{p,t})}{Var(r_{m,t})}$$

$$= \frac{Cov(\delta_{m1}F_{c,t} + \delta_{m2}F_{m,t} + \varepsilon_{m,t}\, , \delta_{p1}F_{c,t} + \delta_{p2}F_{p,t} + \varepsilon_{p,t}}{Var(\delta_{m1}F_{c,t} + \delta_{m2}F_{m,t} + \varepsilon_{m,t})}$$

$$= \delta_{m1}\delta_{p1}Var(F_{c,t}) + \delta_{m2}\delta_{p2}Cov(F_{m,t}\, , F_{p,t}) \quad (7)$$

Hence, equation (3) could be rewritten as:

$$r_{p,t} = \alpha + (\delta_{m1}\delta_{p1}Var(F_{c,t}) + \delta_{m2}\delta_{p2}Cov(F_{m,t}\, , F_{p,t}))\, r_{m,t} + \varepsilon_t \quad (8)$$

$$r_{p,t} = \alpha + \beta_1 Var(F_{c,t})\, r_{m,t} + \beta_2 Cov(F_{m,t}\, , F_{p,t}) r_{m,t} + \varepsilon_t \quad (9)$$

Now, take a regime-switch dummy s_t to indicate market downturns, i.e. $s_t = 1$ if market is experiencing a downturn, and $s_t = 0$ otherwise. This regime-switch dummy is interacted with the variables in equation (9) to get the final regression model:

$$\begin{aligned} r_{p,t} = \alpha + d_3\, s_t + (\beta_1 + d_1\, s_t) Var(F_{c,t})\, r_{m,t} \\ + (\beta_2 + d_2\, s_t) Cov(F_{m,t}\, , F_{p,t})\, r_{m,t} + \varepsilon_t \end{aligned} \quad (10)$$

The implications of equation (10) are the following. First of all, if fundamental factors can explain the asymmetric correlations, then the variance and the covariance terms ($Var(F_{c,t})$ and $Cov(F_{m,t}\, , F_{p,t})$) should be higher in magnitude during downturns. Further, if they can completely explain the phenomenon, then the dummy coefficients d_1 and d_2 should not be significant. The presence of significant dummy coefficients would indicate that fundamental factors are not completely explaining asymmetric correlations; therefore other explanations need to be tested.

In order to estimate equation (10), variance of the common factor and the covariance between the individual factors need to be estimated. Also, whether the variance and the covariances are indeed higher during market downturns need to be tested. Following the previous literature on comovement, the univariate GARCH model is applied to estimate the time-varying variance of the common factor, and a multivariate GARCH model (DCC) is employed to estimate the time-varying covariance of the individual factors.

3.2 Estimation of Variance and Covariance

3.2.1 Univariate GARCH

Previous literature has shown that variance of security returns is time-varying. The univariate GARCH procedure is the often used method in estimating this conditional variance. Previous literature has also shown that the simple GARCH (1, 1) model is both parsimonious and accurate.[9] The simple univariate GARCH (1, 1) model is expanded to include a regime-switch dummy s_t, as according to equation (10), asymmetry in correlation should be caused by the asymmetry in the variance of the common factor:

$$F_{c,t} = E\left[F_{c,t} \middle| I_{t-1}\right] + \varepsilon_t$$

$$h_t = \omega + d\, s_t + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{11}$$

[9] For example, see Hansen and Lunde (2005)

where h_t denotes the variance of F_{ct}at time t, s_t is the regime-switch dummy and ε is the innovation. Here, assume that the innovation ε_t is normally, independently and identically distributed ($n.i.d$) conditional on the information available at time $t-1$.

$$\varepsilon_t = z_t h_t^{1/2}$$

$$z_t \sim \mathcal{N}(0,1)$$

$$\varepsilon_t | I_{t-1} \sim \mathcal{N}(0, h_t)$$

I_t denotes all the information that was available at time t. In this study, a standard ARMA(1, 1) filter is utilized for this procedure.

The assumption of normality gives rise to the log-likelihood function for our univariate GARCH (1, 1) model:

$$L(\theta) = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln(h_t) - \frac{1}{2}\sum_{t=1}^{T}\frac{\varepsilon_t^2}{h_t} \tag{12}$$

where θ denotes the vector of the parameters to be estimated, i.e. $\theta = (\omega, d, \alpha, \beta)$.

The term h_t estimated through this procedure is then substituted as $Var(F_{c,t})$ into equation (10). If the coefficient d of the regime-switch dummy s_t is significant in equation (11), then it implies that there is a systematic difference in the magnitude of the conditional variance in common factors. I expect this coefficient to be positive.

3.2.2 Multivariate GARCH

Following previous literature an MV-GARCH model is used to estimate the time-varying covariance. Many specifications of this procedure have been proposed; for surveys see Kroner and Ng (1998), Silvennoinen and Terasvirta (2008). In this analysis, the Dynamic

Conditional Correlations (DCC) model proposed by Engle (2002) is utilized. According to Wong and Vlaar (2003), there are several advantages that this particular model offers. First of all, it estimates correlation coefficients of the standardized residuals and thus accounts for heteroskedasticity directly. Second of all, the models are flexible, since they allow the volatility of different assets to follow different GARCH models. Hence, additional explanatory variables could be included in the mean equation to ensure that the model is well specified. Third of all, the number of parameters to be estimated grows linearly in the number of assets, and therefore the model is relatively parsimonious. In other models, the number of parameters to be estimated grows polynomially in the number of assets. And finally, the parameters are estimated in a two-step procedure, such that the number of parameters to be estimated simultaneously is relatively small. Therefore, the computational power needed for the estimation is relatively small compared to other models. As per equations (10) and (11), a dummy variable is included to account for the systematic switch.

The DCC model is based on the assumption that returns from k assets are conditionally multivariate normal, where the expectation is assumed to be zero and covariance matrix is H_t:

$$r_t | I_{t-1} \sim \mathcal{N}(0, H_t) \tag{13}$$

$$H_t \equiv D_{H_t}^{1/2} R_t D_{H_t}^{1/2} \tag{14}$$

where R_t is the time-varying correlation matrix, all available information up to $t-1$ is contained in $I_{t-1}$and r_t is a vector of excess returns. Each of the diagonal elements of D_{H_t}, denoted as $h_{i,t}$, can be represented by the univariate GARCH model as in equation (11).

For this model, the returns are replaced with individual factors $F_{m,t}$ and $F_{p,t}$. In other words, r_t is now a $2 \times T$vector containing elements $F_{m,t}$ and $F_{p,t}$. This time, the ARMA-X(1, 1) filter is applied to estimate equation (13), i.e. it is assumed that individual factors of up to time $t-1$ is known and accounted for (ARMA), as well as the common factor (X).

The estimates of $h_{i,t}$ obtained from this first step are then used to calculate the standardized residuals z_t. Every r_t for $t = 1, \dots, T$ is divided element-wise by the vector h_t that contains elements $h_{i,t}$ to obtain z_t, i.e. $z_t = r_t / h_t$ for $t = 1, \dots, T$. This z_t will be used in the second step to model the correlation of the original returns, r_t. The DCC model with dummy is given by:

$$Q_t = d\, s_t + (1 - a - b)\bar{Q} + a z_{t-1} z_{t-1}' + b Q_{t-1} \tag{15}$$

and

$$R_t = D_{Q_t}^{-1/2}\, Q_t D_{Q_t}^{-1/2} \tag{16}$$

where $Q_t$is the conditional and $\bar{Q}$ is the unconditional correlation matrices, a, b are scalars and s_t again is the regime-switch dummy. In the estimation procedure $\bar{Q}$ is replaced by the sample analogue $T^{-1} \sum_{t=1}^{T} z_t z_t'$. For R_t to be positive definite the only condition that needs to be satisfied is that Q_t is positive definite, since the elements of the matrix R_t are of the form $\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}$, where $q_{ij,t}$, $q_{ii,t}$ and $q_{jj,t}$ are the elements of Q_t corresponding to the indices. For more details on the conditions see Engle and Sheppard (2001).

The sufficient conditions for H_t to be positive definite are the usual GARCH restrictions, i.e. $\omega, \alpha, \beta > 0$ for the univariate GARCH (1, 1) model. Also, this univariate GARCH process needs to be stationary, i.e. $1 - \alpha - \beta > 0$, for the unconditional covariance matrix of the standardized residuals to exist. Finally, the DCC correlation parameters in (15) have to satisfy $a, b > 0$ and $a + b \leq 1$. If these conditions are satisfied, the H_t will be positive definite for all t. Under the normality assumption, the log likelihood function for the estimation of (15) is given by:

$$
\begin{aligned}
L &= -\frac{1}{2}\sum_{t=1}^{T}(k\ln(2\pi) + \ln|H_t| + r_t' H_t^{-1} r_t) \\
&= -\frac{1}{2}\sum_{t=1}^{T}(k\ln(2\pi) + \ln|D_{H_t}^{1/2} R_t D_{H_t}^{1/2}| + r_t' D_{H_t}^{-1/2} R_t^{-1} D_{H_t}^{-1/2} r_t) \\
&= -\frac{1}{2}\sum_{t=1}^{T}(k\ln(2\pi) + \ln|D_{H_t}| + \ln|R_t| + z_t' R_t^{-1} z_t) \\
&= -\frac{1}{2}\sum_{t=1}^{T}(k\ln(2\pi) + \ln|D_{H_t}| + \ln|R_t| + r_t' D_{H_t}^{-1/2} D_{H_t}^{-1/2} r_t - z_t' z_t + z_t' R_t^{-1} z_t)
\end{aligned}
$$

The term H_t estimated through this procedure is then substituted as $Cov(F_{m,t}, F_{p,t})$ in equation (10). If the coefficient d of the regime-switch dummy s_t is significant in equation (15), then it implies that there is a systematic difference in the magnitude of the covariance between individual factors. I expect this coefficient to be positive as well.

3.3 Definition of Regime-Switching Dummy Variables

Ang and Chen (2002) and Hong, Tu and Zhou (2007) provide the following definition. First, excess returns for the market and portfolios are standardized using unconditional mean and variance. Then, they consider the periods in which both the market return and the return of a particular portfolio exceed certain number of standard deviations away from zero.

Their definition is useful for a model-free statistical approach to assessing asymmetries, but it cannot be applied in this analysis. Rather, I follow Kroner and Ng (1998), and define market downturn as those months where the market portfolio is producing negative returns.

3.4 Procedure

I will now summarize this section by outlying the entire procedure. First, returns and earnings data (individual factor) of the market and individual portfolios, as well as the common factor, are standardized. The fundamental factors are standardized as well so as to ensure that the coefficients in the final regression (equation (10)) are comparable across common factors.

The standardized fundamental factors are filtered using an ARMA (1, 1) model, to take information at time $t - 1$ into account. The Univariate GARCH with dummy model is applied to the innovations estimated through the ARMA (1, 1) model, as in equation (11). By applying ARMA (1, 1) before plugging the data into the Univariate GARCH, I ensure that the data follows a Gaussian process. The conditional variance vector h_t is now estimated, to be used in the final regression.

Next, the standardized individual factors are filtered using the ARMA-X (1, 1) model. The common factor is used for the explanatory series X, to guarantee that the individual factors are orthogonal to the common factors (equation (7)). This procedure is superior to conducting a regression between common factor and individual factor, taking the residuals, and then applying ARMA, because now it is a simultaneous process. The innovations are taken out from this and DCC MV-GARCH with dummy model is applied as per equation (15). The covariance matrix H_t is now estimated, to be used in the final regression.

Finally, portfolio returns are regressed against market returns, using the variance vector and covariance vector (stacked from the covariance matrix), where each term is interacted with the regime-switch dummy (Equation (10)).

4. Data

The price and earnings data are from The Center for Research in Security Prices (CRSP) and Standard & Poor's COMPUSTAT. I follow Ang and Chen (2002), as they have conducted the most comprehensive study on asymmetric correlations, using a wide variety of firm and distributional characteristics. Monthly data from July 1st, 1963 to December 31st, 1998 are used to construct three sets of portfolios based on various firm and distributional characteristics. The data on 3-Month Treasury Bills, which are used to proxy the risk-free rate as well as the common factor, are from the Federal Reserve Economic Data (FRED), available from the Federal Reserve Bank of St. Louis website.[10]

The first set of portfolios is sorted by industry, the second set of portfolios is sorted by size, and the final set of portfolios is sorted by value. I focus on these portfolios because industries have varying exposure to economic factors, and the Fama and French (1993) model which uses size and value to sort portfolios has been very popular in the literature.

I use the standard industry classification (SIC) codes to partition the companies into 13 industries, namely, miscellaneous, petroleum, finance, durables, basic industry,

[10] http://research.stlouisfed.org/fred2/

food/tobacco, construction, capital goods, transportation, utilities, textile/trade, service and leisure. The returns and earnings data are then weighted according to the firms' market capitalizations.

The size-sorted portfolios are made as follows. At the beginning of every month, breakpoints on market capitalization for the stocks are determined using the quintile breakpoints of stocks listed on the NYSE[11]. Then, as in the industry portfolio, value-weighted returns and earnings are computed.

The third set of portfolios is the value-based portfolio. At the beginning of every month, the stocks are once again sorted based on quintile breakpoints of stocks listed on the NYSE, this time according to their book-to-market ratios.

For more details on the methodology, refer to Ang and Chen (2002).

5. Empirical Results

5.1 Discussion of Expected Results

We look at the significance of dummy variables on equations (10), (11), and (15). If the dummy on equation (11) were significant, this would indicate that the conditional variance of the common factors is significantly higher when market is experiencing a downturn. If the dummy on equation (15) were significant, this would indicate that the conditional covariance between individual factors is significantly higher when the market is experiencing a downturn.

[11] The breakpoint data can be obtained from Kenneth French's website at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

If either of the two is significant, it would mean that we could explain the asymmetry in the correlation at least partially.

Suppose that the dummies on equations (11) and (15) are not significant, and the dummy on equation (10) is significant. This would mean that there are no systematic differences in the variance of the common factor or the covariance of the individual factors, yet asymmetric correlation exists. This would indicate that asymmetric correlation is caused entirely due to non-fundamental (perhaps behavioral) factors.

Another scenario is one in which all the dummies are significant. This would mean that there are both systematic differences, and also behavioral causes. Finally, if none of the dummies are significant, this means that according to our model, asymmetric correlation does not exist.

5.2 Empirical Results

Table 1 reports the results of the univariate GARCH with dummy, which estimates the time-varying variance of the common factor. The coefficient on the regime-switch dummy is significant and positive. This means that variance is higher during market downturns, as expected. This is consistent with the asymmetric volatility literature such as Bekaert and Wu (2000).

Table 2 reports the results of the DCC MV-GARCH with dummy, which estimates the time-varying covariance between the individual factors. The results here are mixed. Among the industry portfolios, Finance, Basic Industry and Textile/Trade portfolios exhibit asymmetric covariance. While the reported figures for many of the dummy coefficients are 0.000002, this simply indicates that our program could not find a meaningful numerical departure from zero.[12] Among the size-sorted portfolios, only the SIZE-2 portfolio exhibits asymmetry. Therefore, we see that size does not determine asymmetries between the fundamental factors of the portfolio and the market. Finally, among the value-sorted portfolios, VAL-4 and VAL-5 portfolios exhibit asymmetry. Furthermore, the coefficient on the regime-switch dummy is getting larger and thus more significant as book-to-market ratio rises. This is consistent with Ang and Chen (2002)'s finding that "value stocks are more asymmetric than growth stocks." The results here indicate that the covariances between the fundamental factors are more asymmetric for value stocks than for growth stocks, and that is why we can see the pattern that Ang and Chen (2002) observed.

Table 3 reports the results of the final regression, as per equation (10). Among the industry portfolios, Petroleum, Finance, Service and Leisure portfolios show significant coefficients on the regime-switch dummy for both the variance of the common factor (Var) term and the covariance between the individual factors (Cov) term. This means that behavioral factors also account for the asymmetric correlation, as explained in Section 5.1. Construction, Capital Goods, Transportation, Utilities and Textile/Trade portfolio has a significant Var term and insignificant Cov term. This is an intuitive result: behaviorally, people react to news on common factors but not as much to news on individual factors. While the negative signs on the Cov term for transportation and utilities portfolios are worrying, they are comfortably insignificant. The coefficients on the regime-switch dummies in the Miscellaneous and Basic Industry portfolio are both

[12] The program gives 0.000002 as the result when it cannot generate a convergent result.

Table 1. Univariate GARCH – Common Factor: 3 Month Treasury Bills Rate

$$h_t = \omega + d\, s_t + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

	Coefficient (Standard Error)
ω	0.000083 (0.000000)***
d	**0.000125 (0.000000)*****
α	0.733193 (0.002829)***
β	0.266805 (0.002376)***

* 10% level of significance, ** 5% level of significance, *** 1% level of significance

Table 2. Multivariate GARCH

$$Q_t = d\, s_t + (1 - a - b)\bar{Q} + a z_{t-1} z_{t-1}' + b Q_{t-1}$$

Industry Portfolios

Portfolio	Miscellaneous	Petroleum	Finance	Durables	Basic Industry	Food/Tobacco	Construction
d	**0.000002 (0.000197)**	**0.000002 (0.032547)**	**0.000002 (0.000000)*****	**0.000002 (0.004274)**	**0.014761 (0.004571)*****	**0.000002 (-0.000020)**	**0.000002 (0.000693)**
a	0.000002 (0.000064)	0.313074 (0.111359)***	0.000002 (0.000064)	0.000002 (0.000345)	0.038534 (0.008936)***	0.160801 (0.011960)***	0.096196 (0.017340)***
b	0.261047 (0.076146)***	0.222363 (0.802377)	0.000029 (-0.000001)***	0.232798 (0.081329)***	0.000002 (0.461338)	0.042878 (0.002099)***	0.899657 (0.026656)***

Portfolio	Capital Goods	Transportation	Utilities	Textile/Trade	Service	Leisure
d	**0.000002 (0.000087)**	**0.000002 (0.000028)**	**0.000002 (0.000301)**	**0.045386 (0.016460)*****	**0.000002 (0.000012)**	**0.034014 (0.030736)**
a	0.106394 (0.003804)***	0.428977 (0.014416)***	0.723608 (0.017216)***	0.000002 (0.026786)	0.000002 (0.000045)	0.115164 (0.139635)
b	0.655579 (0.017866)***	0.177913 (0.015077)***	0.043728 (0.006185)***	0.745356 (0.251788)***	0.950578 (0.084974)***	0.850820 (0.307114)***

( ): Standard Error

* 10% level of significance, ** 5% level of significance, *** 1% level of significance

Table 2. Multivariate GARCH – cont'd

$$Q_t = d\, s_t + (1 - a - b)\bar{Q} + a z_{t-1} z_{t-1}' + b Q_{t-1}$$

Size-Sorted Portfolios

Portfolio	SIZE – 1: Smallest	SIZE – 2	SIZE – 3	SIZE – 4	SIZE – 5: Largest
d	0.000002 (0.000196)	0.171501 (0.004388)***	0.000002 (0.000905)	0.000002 (0.000222)	0.000002 (0.000004)
a	0.049795 (0.000778)***	0.049968 (0.009895)***	0.495531 (0.060628)***	0.313520 (0.018210)***	0.127763 (0.008217)***
b	0.948289 (0.001641)***	0.000002 (0.113303)	0.043409 (0.001273)***	0.327876 (0.063568)***	0.760338 (0.038959)***

Value-Sorted Portfolios

Portfolio	VAL – 1: Growth	VAL – 2	VAL – 3	VAL – 4	VAL – 5: Value
d	0.000002 (0.001021)	0.000002 (0.002021)	0.000002 (0.000158)	0.000505 (0.000026)***	0.064382 (0.004171)***
a	0.055539 (0.007136)***	0.000002 (0.000850)	0.041387 (0.000164)***	0.076789 (0.001262)***	0.050457 (0.002954)***
b	0.128488 (0.016880)***	0.000002 (0.019489)	0.958609 (0.000356)***	0.922703 (0.001252)***	0.809426 (0.025658)***

( ): Standard Error

* 10% level of significance, ** 5% level of significance, *** 1% level of significance

Table 3. Final Regression

$$r_{pt} = \alpha + d_3\, s_t + (\beta_1 + d_1\, s_t) Var(F_{ct})\, r_{mt} + (\beta_2 + d_2\, s_t) Cov(F_{mt}, F_{pt})\, r_{mt} + \varepsilon_t$$

Industry Portfolios

Portfolio	Miscellaneous	Petroleum	Finance	Durables	Basic Industry	Food/Tobacco	Construction
R-Squared	0.4816	0.2997	0.4436	0.3836	0.0280	0.4142	0.2950
N	426	426	426	426	426	426	426
β_1	-0.178810 (-0.314)	-0.053864 (-0.026)	1.065853 (0.583)	-0.209239 (-0.336)	-6.128510 (-2.536)**	-0.231681 (-0.379)	1.389064 (0.674)
d_1	**-9.799551 (-1.279)**	**28.776335 (4.379)*****	**25.854496 (4.424)*****	**-11.322968 (-1.355)**	**8.404671 (1.088)**	**-13.840834 (-1.700)***	**28.319072 (4.304)*****
β_2	7.819801 (2.102)**	1.669779 (0.864)	0.240077 (1.010)	23.626904 (0.707)	4.728503 (1.251)	7.380223 (0.307)	-0.170698 (-0.236)
d_2	**4.937258 (0.839)**	**6.939725 (2.336)****	**0.823912 (2.235)****	**100.202384 (1.981)****	**5.392258 (0.779)**	**75.167921 (2.363)****	**-0.279486 (-0.278)**
α	0.617622 (11.604)***	0.454648 (7.672)***	0.588125 (11.129)***	0.568434 (9.646)***	0.063020 (0.933)	0.601427 (11.375)***	0.481819 (8.314)***
d_3	-1.258080 (-16.157)***	-0.821529 (-9.534)***	-1.128766 (-14.739)***	-1.114712 (-13.039)	-0.110800 (-1.114)	-1.169544 (-14.704)***	-0.909243 (-10.705)***

Portfolio	Capital Goods	Transportation	Utilities	Textile/Trade	Service	Leisure
R-Squared	0.4823	0.4671	0.3139	0.4370	0.5108	0.3908
N	426	426	426	426	426	426
β_1	1.957506 (0.846)	1.863206 (1.041)	-0.283459 (-0.131)	0.448572 (0.244)	-0.707614 (-0.410)	-0.725714 (-0.376)
d_1	**24.388408 (4.163)*****	**19.156423 (3.348)*****	**35.487374 (5.431)*****	**12.426908 (2.104)****	**32.034568 (5.845)*****	**11.544040 (1.869)***
β_2	-5.436408 (-1.010)	-0.029093 (-0.010)	1.008929 (0.220)	38.279153 (2.255)**	22.964023 (3.324)***	4.999803 (1.725)*
d_2	**5.457026 (0.768)**	**-2.342263 (-0.260)**	**-2.522942 (-0.460)**	**17.538391 (0.828)**	**7.217508 (0.687)**	**11.153952 (2.518)****
α	0.658824 (13.036)***	0.638922 (12.696)***	0.494185 (8.709)***	0.552780 (9.809)***	0.573126 (11.014)***	0.551935 (10.188)***
d_3	-1.270203 (-17.293)	-1.266383 (-17.039)***	-0.914176 (-10.946)***	-1.073097 (-13.243)***	-1.119292 (-15.110)***	-1.037831 (-12.895)***

( ): t-statistics

* 10% level of significance, ** 5% level of significance, *** 1% level of significance

Table 3. Final Regression

$$r_{pt} = \alpha + d_3\, s_t + (\beta_1 + d_1\, s_t) Var(F_{ct})\, r_{mt} + (\beta_2 + d_2\, s_t) Cov(F_{mt}, F_{pt})\, r_{mt} + \varepsilon_t$$

Size- and Value-Sorted Portfolios

Portfolio	SIZE – 1: Smallest	SIZE – 2	SIZE – 3	SIZE – 4	SIZE – 5: Largest
R-Squared	0.2328	0.3565	0.3633	0.6006	0.6451
N	426	426	426	426	426
β_1	1.719143 (0.795)	0.077282 (0.039)	0.216755 (0.110)	-2.430472 (-1.253)	-0.110385 (-0.076)
d_1	**9.648280 (1.400)**	**21.003585 (3.342)*** **	**23.420172 (3.736)*** **	**24.961554 (4.882)*** **	**30.401727 (6.5144)*** **
β_2	37.481230 (7.957)***	-1.681324 (-0.745)	-0.605533 (-0.120)	17.005922 (3.080)***	0.607778 (3.068)***
d_2	**-30.658403 (-3.681)*** **	**0.339839 (0.146)**	**-2.034580 (-0.328)**	**16.136848 (2.214)** **	**0.041293 (0.147)**
α	0.214863 (3.496)***	0.542536 (9.567)***	0.563223 (10.159)***	0.634223 (13.544)***	0.711653 (16.935)***
d_3	-0.518063 (-5.793)***	-1.056917 (-12.869)***	-1.092657 (-13.509)***	-1.209566 (-18.004)***	-1.395967 (-22.887)***

Portfolio	VAL – 1: Growth	VAL – 2	VAL – 3	VAL – 4	VAL – 5: Value
R-Squared	0.5449	0.5615	0.5351	0.4923	0.2571
N	426	426	426	426	426
β_1	-0.705976 (-0.424)	5.496677 (3.384)***	-0.162704 (-0.097)	0.287453 (0.163)	2.945312 (1.303)
d_1	**28.488486 (5.388)*** **	**18.878003 (3.638)*** **	**29.812971 (5.581)*** **	**25.425119 (4.480)*** **	**4.788689 (0.617)**
β_2	11.447235 (3.229)***	16.717140 (2.321)**	0.182632 (0.975)	4.287286 (1.252)	-34.288091 (-4.193)***
d_2	**4.685038 (0.934)**	**24.099333 (2.169)** **	**0.410820 (1.599)**	**0.039536 (0.010)**	**51.071745 (4.425)*** **
α	0.587589 (11.1973)***	0.609324 (12.277)***	0.663230 (13.858)***	0.636673 (12.808)***	0.511219 (8.346)***
d_3	-1.155455 (-15.732)***	-1.198162 (-16.958)***	-1.273264 (-18.284)***	-1.230774 (-16.903)***	-0.889815 (-9.791)***

( ): t-statistics

* 10% level of significance, ** 5% level of significance, *** 1% level of significance

insignificant. This could indicate that fundamental factors can explain the asymmetry. For Miscellaneous portfolio, this makes sense as it is simply an amalgamation of all the companies that do not fit into a particular portfolio. But for the Basic Industry portfolio, the extremely low R-square value suggests that my model is not capturing the correlation dynamics. Durables and Food/Tobacco industry portfolios exhibit negative regime-switch coefficient for the Var term and a large positive regime-switch coefficient for the Cov term. This could be because the covariance between these portfolios and the market are small and varying. The coefficient on the Cov term therefore became very large, and yet at the same time the significance is mild. This led to a situation in which the effect of Var term is not captured properly.

For the size-sorted portfolios, SIZE-2, SIZE-3 and SIZE-5 portfolios report significant coefficient for the Var term, while Cov term is not significant. Again, this is an intuitive result. SIZE-4 shows significant coefficients for both the Var term and the Cov term. SIZE-1 is an anomaly, reporting a negative coefficient for the Cov term while the Var term is insignificant. In sum, when fundamental factors are taken into account, the findings of Ang and Chen (2002) that asymmetry increases when size decreases cannot be seen. Behavioral factors need to be modeled for further analysis.

And finally, as for the value-sorted portfolios, VAL-1, VAL-3 and VAL-4 portfolios report significant Var coefficients and insignificant Cov coefficients. VAL-2 shows significant coefficients for both, while VAL-5 shows significant Cov term and insignificant Var term. A pattern was detected for MV-GARCH, but a pattern cannot be detected in this final regression. This means that the pattern observed by Ang and Chen

(2002) arises because of fundamental factors. However, the results also show that there are non-fundamental factors in shaping asymmetric correlation also. The model, unfortunately, cannot indicate *which* behavioral factors matter; neither does it indicate *how* the behavioral factors play a role.

6. Conclusion

This paper provides some evidence that asymmetric correlation can be modeled on fundamental factors. The univariate GARCH with dummy finds significant increase in the variance of the common factor during market downturns. This result is consistent with the previous findings that volatility increases during market downturns.

The Dynamic Conditional Correlations Multivariate GARCH with dummy finds significant increase in covariance of the individual factors for some portfolios, and no increase for others.

However, the results from the final equation indicate that fundamental factors cannot completely explain the phenomenon, and therefore other factors such as behavioral factors or liquidity also play significant roles in shaping asymmetric correlation.

To my knowledge, this is the first study to explain the phenomenon. However, it opens up to new questions. What is the mechanism with which people react asymmetrically to news? Why are fundamental factors asymmetrically correlated? Previous literature sheds light to the next direction. Some explanations for comovement, which could well be applied here, include leverage effect and volatility feedback effect (Bekaert and Wu,

2000) and frictions- or sentiment-based movements (Barberis, Shleifer and Wurgler, 2004), although modeling for these explanations goes beyond the scope of this study.

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