VOLATILITY FORECASTING FOR MUTUAL FUND PORTFOLIOS

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ABSTRACT

The return volatility of portfolios of mutual funds having similar investment objectives is analyzed. Consistent with prior research on individual mutual funds, the presence of significant GARCH effects are found in these portfolios. Further, incorporating macroeconomic variables into the model is significant in explaining some of the conditional volatility of these fund portfolios. However, in out-of-sample forecasts the addition of macroeconomic factors does not provide better volatility forecasts than a simple, single factor GARCH model, though both are superior to a naïve random walk model, indicating that there is benefit to forecasting volatility for aggregate portfolios of mutual funds.

Key Words: forecasting, volatility, GARCH models, mutual funds

JEL Codes: C53

I. INTRODUCTION

According to the Investment Company Institute there are $23 trillion of assets invested in mutual funds world-wide with over 48% of that total accounted for by U.S. mutual funds. Further, as of 2010 more than 50 million households own shares in mutual funds in the U.S. alone.[2] Thus, from an investment standpoint, knowledge about how the returns of distinct classes or portfolios of mutual funds behave over time should be important. In particular, forecasts of asset return volatility are important for the implementation of asset allocation models and for the measurement of fund performance.

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[2] 2010 Mutual Fund Fact Book.

The purpose of this paper is to model and forecast the conditional volatility of aggregate returns on broad classes of mutual funds having similar investment objectives. Prior studies have tested for conditional volatility of individual managed funds (Leonard and Noble, 1981; Fraser and Power, 1992; Sengupta and Zheng, 1997; Copeland and Wang, 2000; Devaney, 2001). That line of research is extended here by analyzing the aggregate returns of actively managed groups of mutual funds with distinctly different risk and return characteristics. Single and multifactor models are used to describe the excess aggregate fund returns, while a GARCH process is used to model the conditional volatility of the residuals. Results show that the multifactor model instruments are significant in explaining excess returns, though they do not provide for an improvement over the single-factor model when forecasting volatility out-of-sample. However, both single-factor model and multifactor model do provide better forecasts when compared to a simple random walk model, indicating that there is a predictable component to the volatility of broad classes of mutual funds.

If the covariance of returns is constant over time, then investors can use past returns and return volatility to determine asset allocations, which they hold constant over their investment horizon. Evidence, however suggests that volatility is time-varying (Hansson and Hordahl, 1998; Ng, 1991). Changes in volatility will alter the efficient frontier for financial assets and mandate that investors periodically adjust their asset allocations. Because volatility is time-varying, investors should benefit from having forecasts of future volatility. The topic of volatility timing for individual stocks (Han, 2002) and market indexes (Fleming, et. al., 2000; Flavin and Wickens, 2003) has received some attention, providing evidence that forecasts of conditional volatility can be used to improve the performance of asset allocation models.[3]

Time-varying volatility is also present in mutual funds. Brown et. al. (1996) has shown that mutual funds change the volatility of their portfolios contingent upon their performance relative to some benchmark, such that outperforming (under-performing) funds lower (raise) their volatility. There is also evidence that mutual fund volatility is time-varying due to the active management decisions of fund management, whereby fund managers alter the risk profile of their portfolio in response to changes in market volatility or market cycles (Busse, 1999). The presence of ARCH and GARCH effects in particular have been found in a variety of managed funds, including UK investment trusts (Fraser and Power, 1992; Copeland and Wang, 2000), real estate investment trusts (Devaney, 2001), closed-end funds (Leonard and Noble, 1981), and individual mutual funds (Sengupta and Zheng, 1997).

Rather than analyze individual mutual funds, the aggregate returns of broad groups of mutual funds with the same investment objective are studied. Practical

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[3] Han (2002) tested two asset allocation models. The first used the unconditional mean plus forecasts of the conditional variance. This model was found to provide better in-sample and out-of-sample performance versus a model using unconditional means and variances. Han's second model used forecasts of the conditional mean and variance. This model was unable to provide any additional improvement. Han's results suggest that dynamic asset allocation models should treat expected returns as constant and forecast only the conditional variance.

investment advice often directs investors to build diversified portfolios by selecting a small number of mutual funds, each with a distinctly different investment objective. This suggests that the asset allocation decision is regarded to have greater importance than the selection of individual investments. Research by Hensel, et. al. (1991) and Ibbotson and Kaplan (2000) and echoes this advice, showing that portfolio returns are more significantly affected by the asset allocation decision than by the selection of individual securities. Consequently, an individual investor might be expected to place a greater emphasis upon the decision of asset weightings. Since funds with similar investment objectives tend to behave in a similar manner, an investor might be interested in determining the risk and return characteristics of each group of funds, and then select randomly a representative fund from each group for inclusion into his portfolio.[4] Consequently, the objective here is to determine if there is time-varying volatility for broad classes of mutual funds and if this conditional volatility can be forecast out-of-sample. In the following section the procedure for building mutual fund portfolios is described. Section three presents details of the empirical model, with results and conclusions in sections four and five.

II. DESCRIPTION OF DATA

A. Mutual Fund Returns

The monthly return volatility is studied for six distinct mutual fund portfolios. Each portfolio is constructed as an equally weighted average of the monthly excess returns of individual mutual funds. Individual mutual fund monthly returns were collected from the Steel Mutual Fund Database only for those funds having continuous returns from January 1968 to December 2000. These funds were then grouped into portfolios based upon their category designation as given in the Steel Database. To derive the monthly excess returns for each of the portfolios the one month Treasury bill rate was subtracted.

The summary statistics for the returns of each of the six mutual fund portfolios are reported in Table 1. It is noteworthy that the mean excess returns (with the exception of the aggressive growth fund portfolio), standard deviations, and range (maximum and minimum mean excess return) provide anecdotal evidence that each of the six groups has distinct risk and return characteristics and that they rank in terms of risk and return, from highest to lowest, in the order presented in Table 1: aggressive growth, growth, growth and income, income, balanced, and bond. The results for the

[4] Sharpe (1992), Brown and Goetzmann (1997), and diBartolomeo and Wiskowski (1997) show that mutual funds often have an effective style that differs from their stated investment objective. They suggest that funds should be grouped according to their effect style rather than their stated style. Because the funds in this paper are grouped according to their stated investment objectives, just as an investor would be expected to do, rather than the effective style of the funds, the resulting volatility forecasts should downward biased. Conversely, grouping funds according to their effective style should lead to improvements in the volatility forecasts relative to those reported in this paper.

first four of these groups are consistent with the results of Ferson and Schadt (1996), who ranked individual funds by their systematic risk. This is important since the interest here is in modeling the volatility of aggregate fund groups rather than individual funds. Because the fund portfolios appear to have statistical properties similar to the underlying fund types that they represent there is greater confidence that the volatility of these fund portfolios can be modeled and forecast. Another key feature of note in Table 1 is the excess kurtosis for all return series. Kurtosis in excess of 3.0 implies fat tails, a feature common to GARCH models which are used in the next section.[5] Since the purpose is to evaluate the out-of-sample forecasting performance of different volatility models, the last 12 months of excess returns is excluded as a "hold-out" sample.

Table 1. Descriptive Statistics

	Aggressive Growth	Growth	Growth & Income	Income	Balanced	Bond
Mean	0.0038	0.0048	0.0046	0.0046	0.0036	0.0014
Median	0.0064	0.0079	0.0072	0.0058	0.0039	0.0021
Maximum	0.1625	0.1569	0.1441	0.1278	0.1008	0.0934
Minimum	-0.2902	-0.2226	-0.2042	-0.1735	-0.1512	-0.0690
Standard Deviation	0.0547	0.0466	0.0405	0.0380	0.0309	0.0190
Skewness	-0.6557	-0.4359	-0.4694	-0.3445	-0.3591	0.3137
Kurtosis	5.3480	4.6081	5.0912	4.6977	4.6976	5.7912

NOTES: Descriptive statistics are computed on the excess monthly returns for the period January 1968 to December 2000.

B. Macroeconomic Variables

Previous studies have shown that publicly available macroeconomic information is useful in explaining security returns and return volatility (Chen et. al., 1986). To the extent that portfolios of mutual funds with consistent investment objectives behave in a similar manner macroeconomic variables should also be beneficial in explaining returns and volatility. The same macroeconomic factors as suggested by Ferson and Schadt

[5] Kurtosis statistics are significant with p-values < 0.01 for all six fund portfolios.

(1996), Chordia and Shivakumar (2002), and Gallagher and Jarnecic (2002) are used. These variables include (1) the yield on one month Treasury bills, (2) a credit risk premium computed as the difference between Baa and Aaa corporate bond yields, (3) a term structure spread computed as the difference between the ten year constant maturity Treasury bond yield less the three month Treasury bill yield, and (4) the market dividend yield computed as the dividend yield on the CRSP value-weighted NYSE index for the previous twelve months, divided by the price of the CRSP value-weighted NYSE index for the current month.[6] The corporate bond yields and the ten year constant maturity Treasury yield are obtained from the St. Louis Federal Reserve Bank's FRED II database. The market risk premium is computed as the monthly return on the CRSP value-weighted return index less the one month Treasury bill yield.[7]

III. EMPIRICAL METHODOLOGY

Factor models are used to describe the excess returns of the mutual fund portfolios, and a GARCH(1,1) is used to model the conditional volatility of the residuals. Two different mean equations are specified in this analysis. The first is a single-factor, CAPM-style model where the excess returns of each fund portfolio are systematically related to the market risk premium. The second uses a multifactor model that treats excess fund portfolio returns as a linear function of the market risk factor and a vector of publicly available macroeconomic variables as specified in the previous section.

The single factor model specifies a linear relationship between the excess returns on each fund portfolio and the excess returns on the market index:

$$(1) \qquad r_{i,t} = b_{i,0} + b_{i,1} r_{m,t} + \varepsilon_{i,t}$$

where $r_{i,t}$ is the excess return on the ith fund group at period t, computed as the fund's excess return over the risk-free rate of interest and $r_{m,t}$ is the market risk premium.

The second formulation of the mean equation is based upon research in which publicly available macroeconomic information has been shown to provide improvement over single-factor models in explaining variation in time-series returns. Contemporaneous macroeconomic factors as suggested by Chen, Roll, and Ross (1986) are used, but included as a linear function of the market excess return (Ferson and Schadt, 1996; Gallagher and Jarnecic, 2002):

$$(2) \qquad r_{i,t} = b_{i,0} + b_{i,1} r_{m,t} + b_{i,2} r_{m,t} z_t + \varepsilon_{i,t}$$

where z_t represents a vector of predetermined factors that have been shown to explain returns.

A common feature of financial time series is that they exhibit volatility clustering. That is, periods of heightened volatility are clustered together as are periods of relative

[6] See Chordia and Shivakumar (2002), p. 988-989 for explanation of these four macroeconomic variables.
[7] Gallagher and Jarnecic (2002) found the return on Australian bond mutual funds to be most significantly impacted by equity returns. Consequently, the same equity market risk premium is used in analyzing both equity and bond fund portfolios in this paper. However, to the extent that the use of a bond index would lead to improved parameter estimates, the forecasts in this paper should be downward biased.

tranquility. When this feature is present, the series may have a non-constant variance and ordinary least squares estimation would be inappropriate. Each model specification was therefore tested for the presence of autoregressive conditional heteroscedasticity (ARCH) using the Lagrange multiplier test (Engle, 1982). It was determined that each return model exhibited ARCH effects. This finding suggests that the variance of the equation is not constant and that the variance changes over time in a way that depends on how large the errors were in the past. The Lagrange multiplier test statistics used to test for the presence of ARCH effects were significant at the 1% level or less.[8]

In order to examine mutual fund returns with time-varying volatility, the mean and variance of the return series is estimated simultaneously via the method of maximum likelihood.

To measure the volatility a GARCH (1,1) model is used.[9] The conditional variance equation for the GARCH(1,1) model is given by:

$$(3) \qquad h_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2$$

where $V(\varepsilon_t \mid \Omega_{t-1}) = h_t^2$ is the conditional variance of ε_t with respect to the information set Ω_{t-1}. The quasi-maximum likelihood covariances and standard errors are computed as described in Bollerslev and Wooldridge (1992). The model is estimated under the assumption that the errors are conditionally normally distributed. Both α and β are non-negative constant parameters and $\alpha+\beta<1$. These restrictions on the parameters prevent negative variances (Bollerslev, 1986).

For the purpose of assessing the performance of these GARCH-class models in forecasting the volatility, a measure of true volatility is constructed to compare with the forecasted volatility from the GARCH (Pagan and Schwert, 1990; Day and Lewis, 1992; Franses and van Dijk, 1996; Gokcan, 2000). Similarly, the unconditional volatility is defined as:

$$(4) \qquad \sigma_t^2 = (r_t - \bar{r})^2$$

where σ^2 is the unconditional volatility, r_t is the actual daily return for day t, and $\bar{r}$ is the expected return for day t. The expected return for January 2000 is measured by calculating the arithmetic average of monthly returns from January 1968 to December 1999; the expected return for February 2000 is measured by calculating the arithmetic average of monthly returns from February 1968 to January 2000. This is repeated for the next 10 months. That is, the GARCH models are estimated using 384 observations and saving the last 12 observations for out-of-sample forecasting comparison. One-period-ahead forecasting errors for the two volatility models are computed using the following equation:

$$(5) \qquad u_{t+1} = \sigma_{t+1}^2 - \hat{h}_{t+1}^2$$

[8] Results of the ARCH LM test are available upon request.

[9] The (1,1) specification was chosen in a manner similar to that which was used to determine the order of the ARMA models. Moreover, Bollerslev, et al. (1992) conclude that the GARCH(1,1) model is preferred in most cases.

where σ^2 is the "true" unconditional volatility and h^2_{t+1} is the forecasted variance generated from the GARCH(1,1) models.

IV. DISCUSSION

The in-sample estimation of the GARCH volatility models is reported in Table 2.

Table 2. In-sample GARCH Parameter Estimates

	Market (β)	p-value (F)	Variance Arch	GARCH	lnL
Single Factor Model					
Aggressive Growth	1.084[a]	---	0.091	0.811[a]	921.6
Growth	1.015[a]	---	0.137	0.605[a]	1219.3
Growth & Income	0.912[a]	---	0.113[a]	0.853[a]	1535.5
Income	0.831[a]	---	0.093[a]	0.901[a]	1367.8
Balanced	0.677[a]	---	0.102[a]	0.889[a]	1366.2
Bond	0.262[a]	---	0.194[a]	0.744[a]	1112.4
Multifactor Model					
Aggressive Growth	1.215[a]	<0.01	0.074[c]	0.867[a]	928.6
Growth	1.08[a]	0.62	0.134	0.626[a]	1220.4
Growth & Income	0.963[a]	<0.01	0.115[a]	0.855[a]	1543.8
Income	0.949[a]	0.09	0.090[a]	0.904[a]	1372.5
Balanced	0.726[a]	0.08	0.098[a]	0.890[a]	1371.0
Bond	0.340[a]	<0.01	0.129[a]	0.812[a]	1125.3

NOTES: Sample period is January, 1968 to December, 1999 using monthly returns. a = significance at the 1% level, b = significance at the 5% level, c = significance at the 10% level.

The parameter estimates for the GARCH models are significant for all fund groups, using both single and multifactor model specifications, indicating the presence of time-varying volatility in each of the mutual fund portfolios. The F-statistic is reported for the vector of public information variables in the multifactor model. The F-statistic is significant for all fund groups with the exception of the growth fund group. The multifactor model also has lower AIC values than those reported for the single factor model. These results suggest that a GARCH model should provide superior volatility forecasts over a naïve random walk model, and that adding the public information variables to the mean equation should increase the forecasting power relative to the single factor model.

Given the findings of Frances and van Dijk (1996) and Gokcan (2000), it is not necessarily the case that the model that performs best in-sample will also be the model that provided the best out-of-sample forecasts of volatility. In order to assess the out-of-sample performance of the models the mean squared error (MSE) is computed. For a sample of size T, the MSE is given by:

$$(6) \qquad MSE = T^{-1} \sum_{t=1}^{T} u_t^2$$

In Table 3 the MSE is reported for the 12 one-step-ahead forecasts generated from the GARCH(1,1) models. The MSE of the out-of-sample forecasts reflects the in-sample standard deviations such that the higher risk aggressive fund group provides for a less accurate forecast out-of-sample than does the lowest risk bond group. However, in all cases the GARCH models outperform the random walk model, producing lower MSE and suggesting that there is benefit to forecasting the conditional volatility of these aggregate fund groups. On the other hand, and contrary to the results from the in-sample tests, use of the public information variables in the multifactor model does not lead to superior out-of-sample performance relative to the simple single factor model. Only in the case of the bond fund portfolio is there any improvement in forecasting by using the more cumbersome multifactor model. Thus, while there is a predictive component to mutual fund return volatility, adding macroeconomic factors to the mean equation does not necessarily improve the forecasts of this volatility.

Table 3. Mean Squared Error Terms

	Random Walk Model	Single Factor Model	Multifactor Model
Aggressive Growth	243208.3	83406.2	85476.8
Balanced	1741.6	1272.1	1280.2
Bond	11.9	11.7	6.1
Growth & Income	7276.8	5347.5	5350.2
Growth	19088.6	10231.4	10233.8
Income	6026.3	4559.9	4562.7

Notes: Forecast period is January 2000 to December 2000 using monthly returns

V. CONCLUSIONS

Unlike prior research that has looked at individual mutual funds, this paper focuses on forecasting return volatility for different fund groups. In particular, GARCH in-sample estimations as well as out-of-sample forecasts for the aggregate excess returns of six distinct portfolios of mutual fund are compared. The findings provide evidence that the GARCH specification produces lower forecasting errors than does the naïve random walk model. This suggests that it is possible to forecast the conditional volatility of broad groups of mutual funds just as prior research has done with individual securities. It is also found that introducing publicly available macroeconomic variables into the mean equation does provide for a better in-sample model compared to the single factor model. However, these additional macroeconomic factors do not increase the out-of-sample forecast power of the model.

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