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Good News, Bad News, Volatility, and Betas

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ABSTRACT

We investigate the conditional covariances of stock returns using bivariate exponential ARCH (EGARCH) models. These models allow market volatility, portfolio-specific volatility, and beta to respond asymmetrically to positive and negative market and portfolio returns, i.e., "leverage" effects. Using monthly data, we find strong evidence of conditional heteroskedasticity in both market and non-market components of returns, and weaker evidence of time-varying conditional betas. Surprisingly while leverage effects appear strong in the market component of volatility, they are absent in conditional betas and weak and/or inconsistent in nonmarket sources of risk.

MANY RESEARCHERS HAVE DOCUMENTED that stock return volatility tends to rise following good and bad news. This phenomenon, which we call predictive asymmetry of second moments, has been noted both for individual stocks and for market indices.[1] Given this evidence, there is also good reason to expect such an effect to exist in conditional betas as well. We provide a method for estimating time-varying conditional betas based on a bivariate version of the exponential ARCH (EGARCH) model of Nelson (1991), allowing for the possibility that positive and negative returns affect betas differently.

The literature has focused on two classes of explanations for predictive asymmetry of second moments: the first, and most obvious, highlights the role of financial and operating leverage—e.g., if the value of a leveraged firm drops, its equity will, in general, become more leveraged, causing the volatility on equity's rate of return to rise. As Black (1976), Christie (1982), and Schwert (1989) show, however, financial and operating leverage cannot fully account for predictive asymmetry of second moments. A second set of explanations focuses on the role of volatility in determining the market risk

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[1] For example, see Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), Nelson (1989, 1991), Schwert (1989), Ng (1991), Gallant, Rossi and Tauchen (1992), Glosten, Jagannathan, and Runkle (1993), and Engle and Ng (1993). See Bollerslev, Engle, and Nelson (1994) for a complete review of this literature.

premium: if the market risk premium is an increasing function of market volatility, and if increases in market risk premia due to increased volatility are not offset by decreases in riskless rates,[2] then increases in market volatility should lead to drops in the market, contributing to the predictive asymmetry of return variances.[3] If shocks to volatility persist for long periods, then the changes in asset prices due to volatility movements can be large (Poterba and Summers (1986)). Critics of this second explanation have argued that the theoretical link between the market risk premium and market volatility may be weak and that shocks to market volatility are not sufficiently persistent to account for predictive asymmetry of return variances. Whether the link is weak or not depends on whether the market risk premium is constant and how it moves through time. The evidence in Campbell and Shiller (1987) and Harvey (1989) suggests that the link is not weak due to these facts.

There is also good reason to expect asymmetric responses of conditional betas to good and bad news. First, an exogenous shock to the value of a firm's assets that raises (lowers) the firm's financial leverage will raise (lower) the beta of the firm's equity. Thus the unexpected component of stock returns should be negatively correlated with changes in conditional beta.[4] Second, a persistent shock to the riskiness or conditional beta of a firm's equity, *ceteris paribus*, will manifest itself in a change in the price of equity. Again, an unexpected increase (decrease) in the equity beta will be associated with negative (positive) unexpected returns. While the direction of causality differs in these two arguments, in both cases the result is the same: negative correlation between movements in betas and unexpected returns.[5]

Time variation in return volatilities and betas is deeply connected to how asset prices are determined in equilibrium. Better knowledge of the time series properties of conditional second moments of asset returns, whether it be of volatilities or betas, is therefore crucial to advance our understanding of asset pricing. Hence, our model can also be used to advantage in investigations of empirical anomalies in asset payoffs. We focus on one challenge to asset pricing theory in particular: the finding by De Bondt and Thaler (1989) that stocks that have recently experienced sharp price declines ("losers") tend to subsequently outperform stocks that have recently experienced sharp price increases ("winners"). De Bondt and Thaler interpret this as evidence of investor overreaction. Chan (1988) and Ball and Kothari (1989), however, argue that the time series behavior of conditional betas and the market risk premium can explain the performance of winners and losers. Both Chan and Ball and Kothari find evidence that betas of individual stocks rise (fall) in response to

[2] As they sometimes are, for example, in the model of Barsky (1989).

[3] See, among others, Malkiel (1979), Pindyck (1984), Poterba and Summers (1986), French, Schwert, and Stambaugh (1987), and Campbell and Hentschel (1992).

[4] See Hamada (1972).

[5] Note that the second of the arguments for correlation between stock price movements and changes in beta relies crucially on two assumptions: (1) that changes in beta are persistent and (2) that shocks to beta are not also negatively correlated with shocks to the market risk premium.

negative (positive) abnormal returns—i.e., they find predictive asymmetry in conditional betas. Ball and Kothari argue that the asymmetric response of conditional betas to good and bad news is sufficient to account for the relative returns performance of winners versus losers.

We offer an alternative method of estimating time-varying conditional betas. In contrast to other multivariate ARCH models,[6] EGARCH allows for the possibility that good and bad news may affect covariances differently. The bivariate extension we propose is a natural way to capture asymmetries in conditional betas. An alternative approach, which also captures asymmetric effects, is the model of Glosten, Jagannathan, and Runkle (1993). Their model allows a quadratic response of volatility to news, with different responses permitted for good and bad news, but maintains the assertion that the minimum volatility will result when there is no news.

The econometric evidence on whether conditional betas are significantly variable is mixed (see, for example, the discussion and references in Ferson (1989) Section IV). Other methods for estimating time-varying betas include the rolling regression method of Fama and MacBeth (1973), ARCH betas (implicit in Bollerslev, Engle, and Wooldridge (1988), and Ng (1991)), as well as betas conditional on a set of information variables (Shanken (1990) and Ferson and Harvey (1993)).

In this study, we compare the bivariate EGARCH betas to rolling regression betas. To anticipate the empirical results developed below, we (not surprisingly) find very strong evidence of conditional heteroskedasticity in both market and non-market components of returns, and weaker evidence of time-varying conditional betas. What is surprising is that while predictive asymmetry is very strong in both the market component and firm specific component of volatility, it appears to be entirely absent in conditional betas for both industry and decile portfolios.

The structure of the paper is as follows. We present the bivariate EGARCH model in Section I. Section II presents empirical results using monthly equity portfolio data. Section III provides a detailed specification analysis. Section IV concludes.

I. Bivariate EGARCH Model

Let $R_{m,t}$ and $R_{p,t}$ denote the time t excess returns of a market index and a second portfolio respectively. Our strategy is to model the conditional covariance matrix of $R_{m,t}$ and $R_{p,t}$ by splitting it into three pieces: the conditional variance of the market $\sigma^2_{m,t}$, the conditional beta of portfolio p with respect to the market index, $\beta_{p,t}$, and the variance of the nonmarket component of $R_{p,t}$, $\sigma^2_{p,t}$. Specifically, we assume that $R_{m,t}$ and $R_{p,t}$ can be written as

$$R_{m,t} = \mu_{m,t} + \sigma_{m,t} \cdot z_{m,t}, \tag{1}$$

[6] For example, Engle, Ng, and Rothschild (1990) and Bollerslev, Engle, and Wooldridge (1988).

and

$$R_{p,t} = \mu_{p,t} + \beta_{p,t} \cdot R_{m,t} + \sigma_{p,t} \cdot z_{p,t}$$
$$= \mu_{p,t} + \beta_{p,t} \cdot \mu_{m,t} + \beta_{p,t} \cdot \sigma_{m,t} \cdot z_{m,t} + \sigma_{p,t} \cdot z_{p,t}, \tag{2}$$

where $\{z_{m,t}\}_{t=-\infty}^{\infty}$ and $\{z_{p,t}\}_{t=-\infty}^{\infty}$ are contemporaneously uncorrelated, i.i.d. standardized residual processes with zero means and unit variances, and $\mu_{m,t}$, $\mu_{p,t}$ are, respectively, the conditional means of $R_{m,t}$ and $R_{p,t}$. The conditional beta of $R_{p,t}$ with respect to $R_{m,t}$ is given by

$$\beta_{p,t} = \frac{E_{t-1}((R_{p,t} - \mu_{p,t}) \cdot (R_{m,t} - \mu_{m,t}))}{E_{t-1}[(R_{m,t} - \mu_{m,t})^2]}, \tag{3}$$

where $E_{t-1}(\cdot)$ denotes expectation at time $t-1$. $\mu_{m,t}$, $\mu_{p,t}$, $\sigma^2_{m,t}$, $\sigma^2_{p,t}$ and $\beta_{p,t}$ are taken to be measurable with respect to information at time $t-1$.

Equations (1) and (2) split up portfolio returns in a readily interpretable way: $\beta_{m,t} \cdot \sigma_{m,t} \cdot z_{m,t}$ is the market factor in $R_{p,t}$ with conditional variance $\beta^2_{p,t}\sigma^2_{m,t}$, while $\sigma_{p,t} \cdot z_{p,t}$ is the portfolio-specific component of risk, with conditional variance $\sigma^2_{p,t}$. By construction, these two components of returns are uncorrelated.

We assume that the market conditional variance follows a univariate EGARCH process (Nelson (1991)), i.e.,

$$\ln(\sigma^2_{m,t}) = \alpha_{m,t} + \sum_{k=1}^{\infty} \phi_{m,k} g_m(z_{m,t-k}), \qquad \phi_{m,1} \equiv 1 \tag{4}$$

where $\{\alpha_{m,t}\}_{t=-\infty}^{\infty}$ and $\{\phi_{m,k}\}_{k=1}^{\infty}$ are real, nonstochastic, scalar sequences, and where we define the function $g_m(\cdot)$ by

$$g_m(z_{m,t-k}) \equiv \theta_m z_{m,t-k} + \gamma_m(|z_{m,t-k}| - E|z_m|). \tag{5}$$

By construction, $g_m\,(z_{m,t})$ is the innovation in $\ln(\sigma^2_{m,t+1})$. The $\theta_m z_m$ term in (5) allows for leverage effects; recall that the surprise component of returns has the same sign as z_m, so when $\theta_m < 0$, $\ln(\sigma^2_{m,t})$ tends to rise (fall) following market drops (rises). When $\gamma_m > 0$, the $\gamma_m[|z_{m,t-k}| - E|z_m|]$ terms raises (lowers) $\ln(\sigma^2_{m,t})$ when the magnitude of market movements is large (small). Taken together, the $\theta_m z_m$ and $\gamma_m[|z_m| - E|z_m|]$ terms allow the market's conditional variance to respond asymmetrically to positive and negative returns.

For the portfolio-specific conditional variance $\sigma^2_{p,t}$, we modify the univariate EGARCH model:

$$\ln(\sigma^2_{p,t}) = \alpha_{p,t} + \sum_{k=1}^{\infty} \phi_{p,m,k}\, g_{p,m}(z_{m,t-k}) + \sum_{k=1}^{\infty} \phi_{p,k}\, g_p(z_{p,t-k}),$$
$$\phi_{p,m,1} \equiv \phi_{p,1} \equiv 1 \tag{6}$$

where as before, $\{\alpha_{p,t}\}_{t=-\infty}^{\infty}$, $\{\phi_{p,m,k}\}_{k=-\infty}^{\infty}$ and $\{\phi_{p,k}\}_{k=1}^{\infty}$ are nonstochastic, and $g_{p,m}(\cdot)$ and $g_p(\cdot)$ are functions of the form (5), with $\theta_{p,m}$ and $\gamma_{p,m}$ (and θ_p and γ_p) replacing θ_m and γ_m in (5). The intuition for the functional form (6) is similar to that for (4): if $\theta_p < 0$ and $\gamma_p > 0$, then the portfolio-specific conditional variance rises (falls) in response to negative portfolio-specific shocks and portfolio-specific shocks are large (small).

The $g_{p,m}(\cdot)$ function allows contemporaneous correlation between $z_{m,t-1}$ and the innovations in $\ln(\sigma_{p,t}^2)$ and $\ln(\sigma_{m,t}^2)$. This is in line with the work of Black (1976) who found that volatilities of individual stocks tend to change in the same direction. Recall that by (2), the conditional variance of $R_{p,t}$ is $\beta_{p,t}^2\sigma_{m,t}^2 + \sigma_{p,t}^2$. Our model allows two channels through which the volatilities of different portfolios can move together. First, if $\sigma_{m,t}^2$ rises, individual portfolio volatilities with nonzero conditional betas rise because of the $\beta_{p,t}^2 \cdot \sigma_{m,t}^2$ terms. Second, the $g_{p,m}$ terms allow contemporaneous correlation between changes in $\ln(\sigma_{m,t}^2)$ and $\ln(\sigma_{p,t}^2)$—i.e., shocks to the market may feed directly into the non-market component of volatility.

We model the conditional beta, $\beta_{p,t}$, as

$$\beta_{p,t} = \alpha_{\beta,t} + \sum_{k=1}^{\infty} \phi_{\beta,k}(\lambda_{p,m} \cdot z_{m,t-k} \cdot z_{p,t-k} + \lambda_m \cdot z_{m,t-k} + \lambda_p \cdot z_{p,t-k}),$$

$$\phi_{\beta,1} \equiv 1. \quad (7)$$

The $\lambda_m \cdot z_m$ and $\lambda_p \cdot z_p$ terms allow for leverage effects in the conditional betas of the sort envisioned by Chan (1988) and Ball and Kothari (1989): if λ_m is negative, the conditional beta rises in response to negative market returns and drops in response to positive market returns. Similarly, if λ_p is negative, the conditional beta rises in response to negative nonmarket (i.e., idiosyncratic) returns and drops in response to positive nonmarket returns. Since a weighted average of the betas must equal one, however, we would not expect λ_m to be negative for all portfolios. The roles of financial and operating leverage, however, lead us to expect that λ_p should be negative for all portfolios. Since $z_{m,t}$ and $z_{p,t}$ are uncorrelated, the conditional expectation (at time $t - 1$) of $\lambda_{p,m} \cdot z_{m,t} \cdot z_{p,t}$ equals zero because $z_{m,t} \cdot z_{p,t}$ is positive (negative) and $R_{m,t}$ and $R_{p,t}$ moved together more (less) than expected at time $t - 1$. If $\lambda_{p,m} > 0$, the model responds by increasing (decreasing) the conditional covariance by increasing (decreasing) the next period's conditional beta $\beta_{p,t+1}$.

Positive values of $\lambda_{p,m}$, γ_m, and γ_p make the conditional covariance matrix estimates produced by the model robust to model misspecification. To see this, suppose that the current value of $\sigma_{m,t}^2$ is too low—i.e., below the "true" conditional volatility for the market. In estimation we form the standardized residual $\hat{z}_{m,t}$ by:

$$\hat{z}_{m,t} = \frac{R_{m,t} - \hat{\mu}_{m,t}}{\hat{\sigma}_{m,t}}. \quad (8)$$

When $\hat{\sigma}_{m,t} < \sigma_{m,t}$ then $\mathrm{E}_{t-1}|\hat{z}_{m,t}| - \mathrm{E}_{t-1}|z_{m,t}| > 0$ so when $\gamma_p > 0$, $\mathrm{E}_{t-1}g_m(\hat{z}_{m,t}) > 0$. Similarly, when $\hat{\sigma}_{m,t} > \sigma_{m,t}$, $\mathrm{E}_{t-1}g_m(\hat{z}_{m,t}) < 0$. Therefore, $\hat{\sigma}^2_{m,t}$ tends to rise when it is too low, (i.e., below the true $\sigma^2_{m,t}$) and fall when it is too high. $\lambda_{p,m}$ and γ_p, when they are positive, play a similar role. Accordingly, we impose the conditions $\lambda_{p,m} \geq 0$, $\gamma_p \geq 0$, and $\gamma_m \geq 0$ in the empirical implementation reported below. For detailed discussion of this robustness property of ARCH models, see Nelson (1992).[7,8]

Conditions for strict stationarity and ergodicity of the model are easily derived: since the $\beta_{p,t}$, $\ln(\sigma^2_{p,t})$, and the $\ln(\sigma^2_{m,t})$ are linear with i.i.d. errors, the first requirement for strict stationarity is the familiar condition that the moving average coefficients are square summable—i.e., that $\sum_{k=1}^{\infty} \phi^2_{\beta,k} < \infty$, $\sum_{k=1}^{\infty} \phi^2_{p,k} < \infty$, and $\sum_{k=1}^{\infty} \phi^2_{m,k} < \infty$. Second, the intercept terms $\alpha_{\beta,t}$, $\alpha_{p,t}$ and $\alpha_{m,t}$ must be time invariant. Third, we require that $\sum_{k=1}^{\infty} \phi_{\beta,k} \cdot z_{m,t} \cdot z_{p,t} < \infty$ almost surely.[9] The proof of strict stationarity then proceeds along the same lines as the proof in the univariate EGARCH case in Nelson (1991).

There are several limitations to the bivariate EGARCH model. First, while $\ln(\sigma^2_{m,t})$, $\ln(\sigma^2_{p,t})$, and $\beta_{p,t}$ each follow linear processes, they are linked only by their innovations terms, so feedback is not allowed, as it would be if $\ln(\sigma^2_{m,t})$, $\ln(\sigma^2_{p,t})$, and $\beta_{p,t}$ followed, say, a vector ARMA process. Second, although leverage effects enter the model, the way they enter is fairly ad hoc—i.e., it doesn't follow from any economic theory explaining leverage effects. As is true of ARCH models in general, bivariate EGARCH is more a statistical model than an economic model. An interesting future project is to give the bivariate EGARCH more economic content by imbedding it into an explicit model of firm capital structure to directly account for the effects of financial and operating leverage. Third, as is the case with ARCH models in general, asymptotic normality for the MLE estimates is as yet unproven. Fourth, we consider portfolios one at a time, rather than estimating the joint covariance of a whole set of portfolios at once. In the same vein, we also ignore other possible determinants of conditional covariances, such as interest rates (Ferson (1989)) and the list of macroeconomic variables found by Schwert (1989) to influence

[7] The basic intuition underlying Nelson's results is straightforward. Suppose that the data are generated in continuous time by a (heteroskedastic) diffusion process, which the econometrician observes at discrete time intervals of length h. Suppose a conditional covariance is estimated for each point in time using a misspecified bivariate EGARCH model. As $h \downarrow 0$, more and more information is available about the instantaneous covariance of the underlying diffusion (see Merton (1980) or Nelson (1992) for intuition on why this is so). So much information arrives as $h \downarrow 0$, in fact, that even a misspecified bivariate EGARCH can extract the true underlying conditional covariance of the limit diffusion. Many ARCH models have similar continuous time consistency properties.

[8] In allowing market volatility movements to drive the conditional covariance of asset returns, our model is related to the single index model of Schwert and Seguin (1990) in which the conditional covariance of returns on any two assets is linear in market conditional variance. If we take $\beta_{p,t}$ and $\sigma_{p,t}$ to be constant, our model is a special case of Schwert and Seguin equation (1). Schwert and Seguin do not require conditional betas to be constant, but the mechanism they propose for changes in conditional betas is different from ours.

[9] The first condition implies the third if $\mathrm{Var}[z_{m,t} \cdot z_{p,t}] < \infty$.

volatility. There are benefits and costs to doing this: the benefit is parsimony and (relative) ease of computation. The costs are that certain parameter restrictions cannot be used (i.e., the weighted average of the conditional betas equals one, and $\sigma_{m,t}^2$ should not depend on any portfolio p with which it is paired in the bivariate system) and that we lose some information that may help predict volatility (e.g., interest rates).

The asymmetric model of Glosten, Jagannathan, and Runkle (1993) circumvents the above limitations of the EGARCH model. Specifically, the GJR model is linked up more directly with theory. Their inclusion of an exogenous variable in the conditional variance equation permits the incorporation into the model of information that may be relevant for predicting conditional variance.

Despite these limitations, the model has several appealing properties. First, as indicated above, it allows both the size and sign of $R_{m,t}$ and $R_{p,t}$ (as well as their co-movement) to enter the model in a straightforward way. In particular, it allows for leverage effects. Second, it captures, in a natural way, Black's (1976) observation that volatilities on different portfolios tend to move in the same direction. We allow for this both through the $\beta_{p,t}R_{m,t}$ term in $R_{p,t}$, and through the $g_{m,p}$ function. While *allowing* the market to drive all movement in conditional covariances, we do not force it to—portfolio-specific shocks may also affect conditional covariances through the $\lambda_{p,m}$, λ_p, and g_p terms. Third, under some mild regularity conditions, the model has a desirable robustness property: as argued above, when γ_m, γ_p, and $\lambda_{p,m}$ are all positive, the model produces reasonable conditional covariance estimates even if it is misspecified. As we show below, our model produces conditional covariance estimates strikingly similar to (and by some measures better than) the covariance estimates produced by a rolling regression.

II. Empirical Applications

A. Data

For this empirical analysis we use monthly returns from the Center for Research in Security Prices (CRSP) for the period July 1926–December 1990. For the market return, $R_{m,t}$, we use the CRSP equally-weighted market index. For portfolio returns we used two different sets.

For the first set, we created twelve broad-based industry portfolios of New York Stock Exchange (NYSE) stocks according to two-digit SIC codes. The classification of these industries follows exactly from the SIC groupings used by Breeden, Gibbons, and Litzenberger (1989) and Ferson and Harvey (1991a,b). These industry portfolios are equally-weighted. For the second set of portfolios, we used sized based equally-weighted decile portfolios. All portfolios were converted to excess returns using the 1-month T-bill rate from the CRSP tapes.

There are two main reasons why we present the results for the equally-weighted rather than value-weighted portfolios, both related to the fact that value-weighted portfolios give less weight to "losers" than equally-weighted portfolios.[10] First, each of the industry portfolios is a nontrivial component of the total market. When bad news hits an industry, say construction, its portfolio becomes a smaller component of the value-weighted market index. Since it is a smaller component of the market index, the impact of "construction news" on the market index returns may drop, causing the covariance of market returns and the construction portfolio returns to drop. This works in the opposite direction from the leverage effect. Second, there is wide cross-sectional variation in the returns of the stocks making up any given industry portfolio—i.e., even in a "loser" industry, some individual firms will be relative "winners." If the leverage effect holds for conditional betas, then value-weighting the industry portfolios gives more weight to relative "winner" firms than to relative "loser" firms. Again, this works in the opposite direction of the leverage effect—i.e., when bad news hits the portfolio, the leverage effect story says that the portfolio betas should rise. But in computing the portfolio value weights, we give the most weight to the relative winners, whose betas rose the *least*, or even may have fallen. When we use equal weights, we avoid these issues.

Although the bivariate EGARCH model, equations (1) through (7), allows for intercept terms in the mean equations, we de-meaned each series by its unconditional mean. This greatly simplifies the estimation. The rationale is that for monthly stock returns the conditional variance-covariance matrix seems likely to have much larger elements than the outer product of the conditional means. This is clearly true of the *unconditional* means and covariances. Moreover, the unconditional covariance matrix is very large relative to the outer product of the unconditional means. If expected returns are constant and the conditional covariance matrix is the same order of magnitude as the unconditional covariance, using the unconditional means should have a minor effect in estimating the second moment matrix. Researchers have also found that omitting relatively slowly varying components of expected returns, for example riskless interest rates and dividends, has a very minor effect on estimated conditional variances—see, e.g., Schwert (1990) and Nelson (1991).[11]

Although, some researchers, for example Ferson and Harvey (1991a,b), have found evidence that expected returns are highly variable and that a substantial part of the unconditional variance of returns is due to time varying expected returns, we effectively treat all this time variation in expected re-

[10] This was suggested by Philip Dybvig and Christopher Lamoureux. We also conducted estimations using value-weighted industry and decile portfolios. There was, however, no qualitative difference in the results; hence, we present only those results using the equally-weighted portfolios. Furthermore, since the decile portfolios are so highly correlated with each other we only report the results for deciles 1, 5, and 10. *All* of the value-weighted and equally-weighted results are reported in an earlier working paper version of this paper.

[11] Nelson (1992) has shown that when passing to continuous time, misspecification in the conditional means does not affect the estimated conditional covariances. In addition, if the Sharpe-Lintner CAPM holds conditionally each period, then $\mu_{p,t} = 0$ and can be ignored (see Equation 2). Of course, this does not by itself justify ignoring $\mu_{m,t}$.

turns as noise. Using monthly returns data from 1964 to 1986, Ferson and Harvey (1991a, Figure 1) estimate conditional prices of the market beta ranging from -3 to 14 percent per month in January and -4 to 6 percent *per month* during other months of the year. Regressing portfolio returns on their generated expected returns series, yields adjusted R^2s of up to 19.6 percent with an R^2 of about 10 percent for many portfolios (Ferson and Harvey (1991b, Table II)). To the extent that the Ferson-Harvey results accurately represent ex ante expected returns rather than market inefficiency, data mining or sampling error, we potentially overstate the conditional variance of returns by as much as 20 percent in some portfolios.

B. Estimation Procedure

We fit the model using a conditional normal likelihood function. The rationale for assuming conditional normality is predominantly ease of computation. However, as shown by Bollerslev and Wooldridge (1992), quasi-maximum likelihood estimators using conditional normality of the error terms yield consistent and asymptotically normal parameter estimates as long as the conditional means and variances are correctly specified, even when the errors are not conditionally normal. We also note that although the normality assumption directly determines the $E[|z|]$ in Equations (4) and (6), all parameters of our model except α_m and α_p are numerically invariant to the assumption of no unit or explosive autoregressive roots in the variance equations.

We employ Bollerslev and Wooldridge's (1992) robust variance-covariance estimator for computing asymptotic standard errors as well as Wald statistics.[12] Bollerslev and Wooldridge show that, as long as the first two conditional moments are correctly specified, a Wald statistic, W_T, has an asymptotic chi-square distribution under the null hypothesis whether or not the conditional normality assumption holds. Note that the robust Wald statistic has an asymptotic chi-square distribution if the alternative hypothesis has an unrestricted form, e.g., the parameter vector is not equal to zero. In our implementation of the EGARCH model, however, we have imposed the three inequality restrictions: $\lambda_{p,m} \geq 0$, $\gamma_m \geq 0$, and $\gamma_p \geq 0$. Wolak (1989a) shows that the presence of inequality restrictions such as these in either the null or alternative hypothesis changes the asymptotic null distribution of the Wald statistic to a weighted sum of chi-squares. Design of an exact size α test generally requires the numerical solution of a highly nonlinear equation (see Wolak (1989b)). Alternatively, upper and lower bounds on the critical value for a size α test are available from Kodde and Palm (1986). We adopt this simpler approach of Kodde and Palm. Whenever W_T is greater than the appropriate upper bound critical value, $c_u(\alpha)$, one may reject the null hypothesis at the α level of significance; whenever W_T is less than the appropriate lower bound critical value, $c_l(\alpha)$, one is unable to reject the null hypothesis at the

[12] Bollerslev and Wooldridge show how to consistently estimate the sample Hessian matrix using only first derivatives. This involves substituting a consistent estimate of the one step-ahead conditional expectation of the Hessian for its analytic counterpart.

α level of significance. For values of W_T between c_l and c_u, the test is inconclusive.

To implement the model, we reduce the infinite-order moving averages in (4), (6), and (7) to AR(1) processes with constant intercepts:

$$\ln(\sigma_{m,t}^2) = \alpha_m + \delta_m \cdot (\ln(\sigma_{m,t-1}^2) - \alpha_m) + g_m(z_{m,t-1}), \tag{9}$$

$$\ln(\sigma_{p,t}^2) = \alpha_p + \delta_p \cdot (\ln(\sigma_{p,t-1}^2) - \alpha_p) + g_{p,m}(z_{m,t-1}) + g_p(z_{p,t-1}), \tag{10}$$

$$\beta_{p,t} = \alpha_\beta + \delta_\beta \cdot (\beta_{p,t-1} - \alpha_\beta) + \lambda_{p,m} \cdot z_{m,t-1} \cdot z_{p,t-1} + \lambda_m \cdot z_{m,t-1} + \lambda_p \cdot z_{p,t-1}. \tag{11}$$

If $|\delta_\beta| < 1$, then the unconditional expectation of $\beta_{p,t}$ exists and equals α_β. Similarly, α_p and α_m are, respectively, the unconditional means of $\ln(\sigma_{p,t}^2)$ and $\ln(\sigma_{m,t}^2)$ if $|\delta_p| < 1$ and $|\delta_m| < 1$, respectively.

For a given multivariate EGARCH(p,q), the $\{z_{m,t}\}$, $\{z_{p,t}\}$, $\{\sigma_{m,t}^2\}$, $\{\sigma_{m,t}^2\}$, and $\{\beta_{p,t}\}$ sequences can be easily derived recursively given startup values and the data sequences $\{R_{m,t}\}$ and $\{R_{p,t}\}$. To get initial values for these sequences, the variance and the beta series were set to their unconditional expectations. Given parameter values and these initial states we computed the quasi-likelihood function recursively.

C. Results

C. 1. Conditional Betas: Persistence, Variability, and Leverage Effects

The quasi-maximum likelihood parameter estimates and their robust standard errors for the industry portfolios are reported in Table I and the fitted $\beta_{p,t}$ in Figure 1. Looking at the parameter estimates for the $\beta_{p,t}$ equation across the different portfolios, we see that for all of the portfolios, shocks to the $\beta_{p,t}$ processes exhibit strong persistence as indicated by δ_β always being greater than 0.9. To gain intuition about the degree of persistence these autoregressive parameters imply, it is useful to think about the half-life of a shock associated with this parameter, i.e., the number h such that $\delta_\beta^h = ½$. The largest δ_β estimated (ignoring the δ_β greater than 1 for the construction portfolio) was 0.998 for the consumer durables portfolio. This estimate implies a half-life of 29 years. In contrast, the half-life implied by the smallest estimated δ_β, 0.946 for the finance portfolio, is only one year.

The market leverage term from the $\beta_{p,t}$ equation, λ_m, is statistically insignificant at the 5 percent level for all but two industry portfolios, construction and consumer durables, and decile portfolios 1 and 5. The portfolio leverage term from the $\beta_{p,t}$ equation, λ_p, is insignificant for all industry and decile portfolios. The cross term, $\lambda_{p,m}$, is positive and significant for all but four industry portfolios and decile 1. Another way of looking at these results is to consider the decomposition of the time series variation in β into its constituent parts.[13] The most important source of variation in the industry betas is the cross-term, which accounts for at least half of the total variance in almost every case. For the deciles the cross-term accounts for a somewhat smaller portion of beta's total variation, with the other terms accounting equally for the difference. We find these results interesting because, within our bivariate EGARCH model, conditional betas do not exhibit leverage effects in the direction expected given the work of Chan (1988) and Ball and Kothari (1989).

To test the joint hypothesis that both leverage terms and the cross-term are jointly equal to zero, we computed a Wald statistic. We present these results in column one of Table II. This test, while testing the joint significance of $\lambda_{p,m}$, λ_m, and λ_p, equivalently tests for whether the $\beta_{p,t}$ processes are constant across time against the alternative hypothesis that $\lambda_{p,m} \geq 0$ and λ_m, $\lambda_p \neq 0$. Note that all of the test statistics presented in this table are correlated and hence one must draw an overall conclusion from this table with caution. We cannot reject the null hypothesis of constant βs in 3 out of the 12 industry portfolios and all three decile portfolios at a 5 percent critical value. Although this evidence for time-varying betas is somewhat strong, as we show below, this evidence for time-varying betas is weaker than the evidence for time-varying volatility.

C.2. Market Volatility

We present the variance equation parameters for the market equation, $\ln(\sigma^2_{m,t})$, in columns six through nine of Table I for the industry and decile portfolios. As with previous studies, we find evidence of strong persistence in the market's conditional variance as indicated by $\delta_m < 0.95$ regardless of the portfolio with which the market is paired in estimation. The estimated half-lives for shocks to $\sigma^2_{m,t}$ range between 24 and 52 months.

The leverage and magnitude effect results for the market variance equation also confirm previous studies as seen from the $\theta_m < 0$ and $\gamma_m > 0$ with small standard errors. Recall that a negative value of θ_m indicates that volatility tends to rise when return surprises are negative and vice-versa, while a positive value of γ_m implies that $\ln(\sigma^2_{m,t})$ rises when the magnitude of market movements is larger than expected.[14]

Finally, and also as expected, the market variance parameters are virtually invariant to the portfolio with which we pair the market in estimation as seen from the similarity of the parameter estimates in columns six through nine of Table I. Furthermore, we conducted a specification check of the fitted values of the market's volatility from these bivariate models with a standard univariate

[13] It can be shown that the contribution to total variance for a particular shock is $\lambda_i^2/(\lambda_{p,m}^2 + \lambda_m^2 + \lambda_p^2)$, where i is equal to either (p, m), m, or p.

[14] We tested for constant conditional variance in the market by testing the joint hypothesis that θ_m and γ_m are equal to zero against the alternative that $\theta_m \neq 0$ and $\gamma_m \geq 0$. As expected for all 12 industry portfolios and all of the deciles, we overwhelmingly reject the null hypothesis of constant market conditional variances. For sake of brevity we do not present these statistics.

Table I

Bivariate EGARCH(1,0) Maximum Likelihood Parameter Estimates

Bivariate EGARCH estimates using equally-weighted CRSP industry and decile portfolios with the equally-weighted CRSP market return for the time period of July 1926 through December 1990 for a total of 780 observations. The parameters are estimated by maximum likelihood from the following discrete-time system of equations.

$$\beta_{p,t} = \alpha_\beta + \delta_\beta \cdot [\beta_{p,t-1} - \alpha_\beta] + \lambda_{p,m} \cdot z_{m,t-1} \cdot z_{p,t-1} + \lambda_m \cdot z_{m,t-1} + \lambda_p \cdot z_{p,t-1}$$

$$\ln(\sigma^2_{m,t}) = \alpha_m + \delta_m \cdot [\ln(\sigma^2_{m,t-1}) - \alpha_m] + \theta_m z_{m,t-1} + \gamma_m[|z_{m,t-1}| - E|z_m|]$$

$$\ln(\sigma^2_{p,t}) = \alpha_p + \delta_p \cdot [\ln(\sigma^2_{p,t-1}) - \alpha_p] + \theta_p z_{p,t-1} + \gamma_p[|z_{p,t-1}| - E|z_p|] + \theta_{p,m} z_{m,t-1} + \gamma_{p,m}[|z_{m,t-1}| - E|z_m|]$$

β_p is the estimated conditional beta for the industry (or decile) portfolio, $\ln(\sigma^2_m)$ is the log of the conditional variance of the market return and $\ln(\sigma^2_p)$ is the log of the conditional industry (or decile) portfolio return. z_m is the standardized residual for the market portfolio and is calculated as $z_{m,t} = r_{m,t}/\sigma_{m,t}$ where r_m is the demeaned return on the market portfolio. z_p is the standardized residual for the industry (or decile) portfolio and is calculated as $z_{p,t} = (r_{p,t} - \beta_{p,t} \cdot r_{m,t})/\sigma_{p,t}$ where r_p is the demeaned return on the industry (or decile) portfolio. Standard errors are estimated using the robust variance-covariance estimator of Bollerslev and Woolridge (1992) and appear below the coefficient estimates in parentheses.

	Bivariate EGARCH Parameter Estimates														
Portfolio	α_β	δ_β	$\lambda_{p,m}$	λ_m	λ_p	α_m	δ_m	θ_m	γ_m	α_p	δ_p	θ_p	γ_p	$\theta_{p,m}$	$\gamma_{p,m}$
Basic Industries	1.028	0.989	0.012	0.003	−0.001	−5.320	0.979	−0.058	0.182	−7.900	0.991	0.035	0.076	−0.015	0.040
	(0.055)	(0.008)	(0.003)	(0.003)	(0.003)	(0.318)	(0.012)	(0.022)	(0.033)	(0.359)	(0.004)	(0.012)	(0.027)	(0.017)	(0.035)
Capital Goods	1.091	0.960	0.004	0.003	0.001	−5.318	0.981	−0.061	0.169	−8.114	0.994	0.020	0.096	−0.028	0.041
	(0.012)	(0.042)	(0.003)	(0.003)	(0.003)	(0.308)	(0.010)	(0.021)	(0.032)	(0.391)	(0.004)	(0.016)	(0.028)	(0.016)	(0.036)
Construction	1.036	1.007	0.000	−0.007	0.001	−5.335	0.981	−0.074	0.159	−7.204	0.991	−0.038	0.087	−0.019	−0.012
	(0.018)	(0.005)	(0.003)	(0.003)	(0.002)	(0.315)	(0.010)	(0.020)	(0.031)	(0.250)	(0.007)	(0.017)	(0.033)	(0.017)	(0.035)
Consumer Durables	1.196	0.998	0.005	0.004	−0.002	−5.392	0.973	−0.067	0.177	−8.273	0.924	0.047	0.266	−0.028	0.175
	(0.060)	(0.004)	(0.002)	(0.002)	(0.002)	(0.289)	(0.013)	(0.021)	(0.036)	(0.160)	(0.028)	(0.037)	(0.057)	(0.031)	(0.054)

Table I—*continued*

Portfolio	Bivariate EGARCH Parameter Estimates														
	α_β	δ_β	$\lambda_{p,m}$	λ_m	λ_p	α_m	δ_m	θ_m	γ_m	α_p	δ_p	θ_p	γ_p	$\theta_{p,m}$	$\gamma_{p,m}$
Finance/Real Estate	0.909	0.946	0.019	−0.008	0.003	−5.327	0.979	−0.056	0.186	−7.979	0.980	−0.019	0.105	−0.024	0.093
	(0.026)	(0.035)	(0.004)	(0.005)	(0.004)	(0.320)	(0.011)	(0.021)	(0.033)	(0.239)	(0.009)	(0.015)	(0.036)	(0.017)	(0.030)
Food	0.786	0.947	0.010	−0.004	0.001	−5.331	0.981	−0.067	0.159	−8.000	0.972	0.047	0.111	−0.053	0.073
	(0.023)	(0.038)	(0.006)	(0.004)	(0.006)	(0.310)	(0.009)	(0.020)	(0.031)	(0.194)	(0.010)	(0.017)	(0.039)	(0.021)	(0.034)
Leisure	1.015	0.980	0.010	−0.006	0.006	−4.993	0.987	−0.057	0.174	−6.950	0.996	−0.006	0.000	−0.029	0.055
	(0.037)	(0.013)	(0.005)	(0.005)	(0.004)	(0.318)	(0.007)	(0.020)	(0.029)	(0.231)	(0.004)	(0.009)	(0.033)	(0.018)	(0.036)
Petroleum	0.875	0.976	0.010	0.009	−0.004	−5.348	0.980	−0.067	0.173	−6.393	0.981	0.016	0.147	−0.033	0.045
	(0.039)	(0.019)	(0.007)	(0.007)	(0.007)	(0.324)	(0.011)	(0.021)	(0.033)	(0.322)	(0.009)	(0.024)	(0.035)	(0.026)	(0.031)
Services	0.827	0.988	0.028	0.002	0.006	−5.320	0.981	−0.063	0.167	−5.663	1.000	0.026	0.084	−0.035	0.021
	(0.100)	(0.008)	(0.006)	(0.004)	(0.004)	(0.310)	(0.010)	(0.021)	(0.032)	(0.373)	(0.002)	(0.013)	(0.024)	(0.014)	(0.033)
Textiles/Trade	0.984	0.955	0.018	0.006	−0.002	−5.313	0.979	−0.061	0.182	−7.558	0.989	−0.010	0.053	−0.014	0.061
	(0.032)	(0.024)	(0.004)	(0.006)	(0.005)	(0.320)	(0.011)	(0.021)	(0.033)	(0.234)	(0.006)	(0.011)	(0.022)	(0.016)	(0.026)
Transportation	1.120	0.981	0.020	−0.007	0.006	−5.380	0.986	−0.056	0.142	−6.887	0.996	−0.031	0.000	−0.056	0.044
	(0.077)	(0.024)	(0.005)	(0.007)	(0.006)	(0.294)	(0.008)	(0.020)	(0.029)	(0.196)	(0.003)	(0.013)	(0.018)	(0.016)	(0.028)
Utilities	0.588	0.992	0.008	−0.005	0.001	−5.359	0.977	−0.071	0.175	−6.887	0.976	−0.008	0.277	−0.075	0.020
	(0.057)	(0.011)	(0.004)	(0.005)	(0.003)	(0.307)	(0.012)	(0.022)	(0.034)	(0.359)	(0.016)	(0.032)	(0.064)	(0.030)	(0.042)
Decile 1	1.186	0.996	0.006	−0.009	0.003	−5.344	0.980	−0.067	0.153	−6.269	0.998	0.010	0.055	−0.079	0.008
	(0.067)	(0.006)	(0.004)	(0.004)	(0.004)	(0.301)	(0.010)	(0.020)	(0.031)	(0.359)	(0.003)	(0.018)	(0.020)	(0.015)	(0.026)
Decile 5	1.020	0.989	0.004	0.007	0.000	−5.220	0.980	−0.059	0.195	−8.537	0.993	0.009	0.050	−0.045	0.077
	(0.033)	(0.015)	(0.002)	(0.002)	(0.003)	(0.290)	(0.011)	(0.023)	(0.034)	(0.341)	(0.004)	(0.020)	(0.023)	(0.013)	(0.039)
Decile 10	0.685	0.982	0.006	0.003	0.007	−5.364	0.978	−0.070	0.160	−7.847	0.994	0.033	0.000	−0.083	0.003
	(0.029)	(0.009)	(0.003)	(0.004)	(0.004)	(0.292)	(0.011)	(0.020)	(0.032)	(0.145)	(0.004)	(0.008)	(0.020)	(0.016)	(0.013)

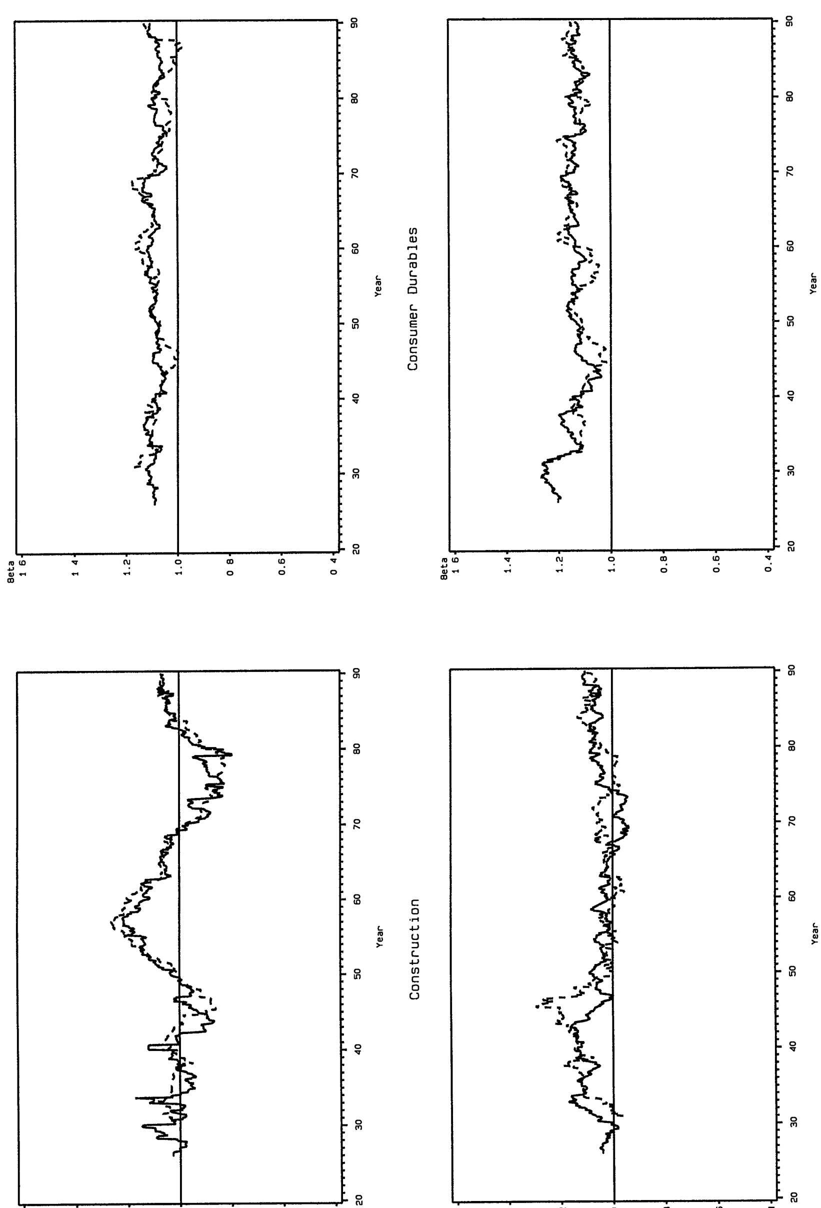

Figure 1. EGARCH(1,0) and Rolling Regression Beta Estimates: 1926–1990. The figures present the estimated conditional betas from the bivariate EGARCH model (solid line) and from rolling regressions (dotted line). All betas are estimated using the CRSP equal-weighted market portfolio. The EGARCH betas are estimated using the whole data sample, July 1926 through December 1990 (780 observations). The rolling regression betas are estimated using overlapping 60-month intervals.

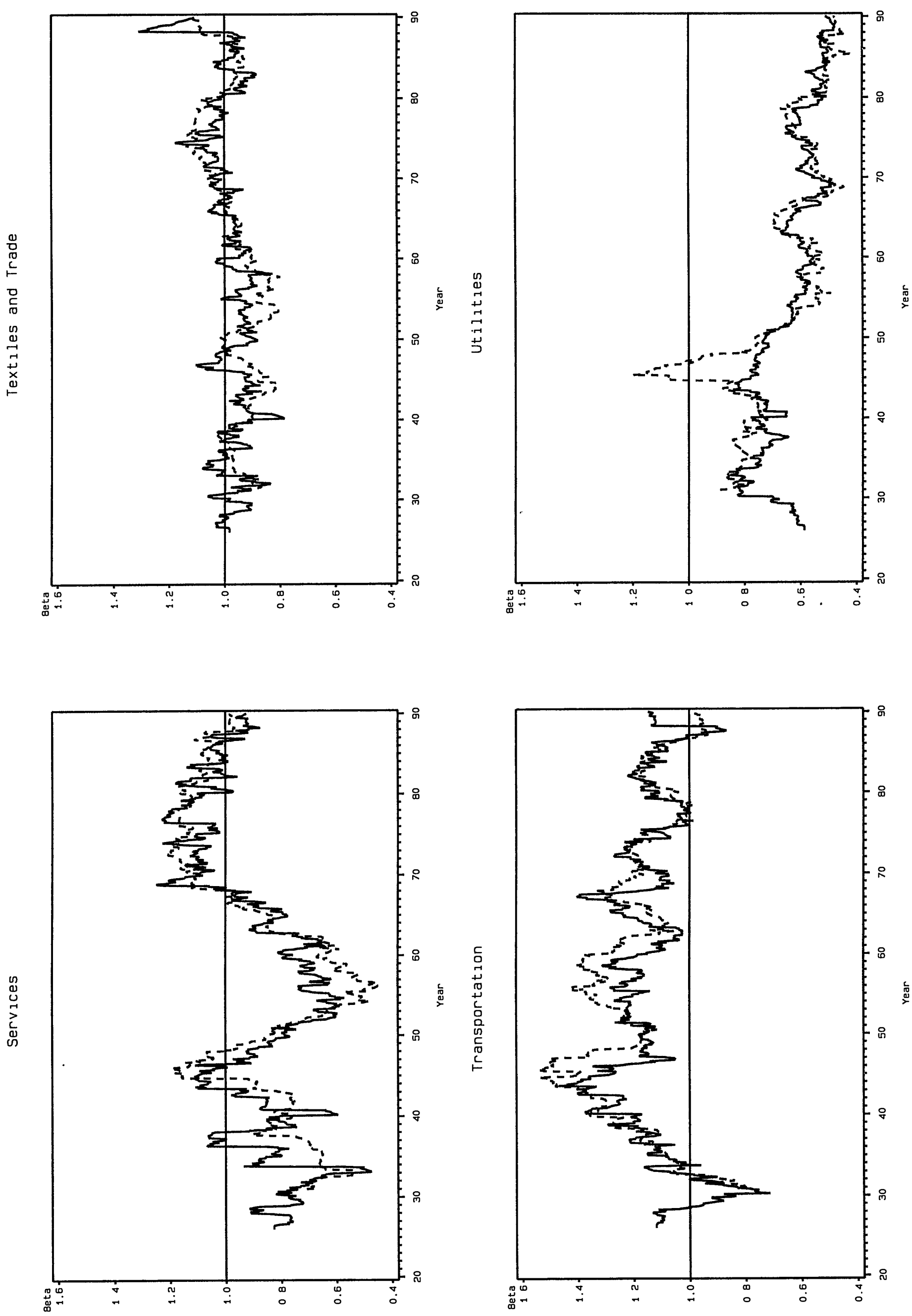

Fig. 1—*continued*

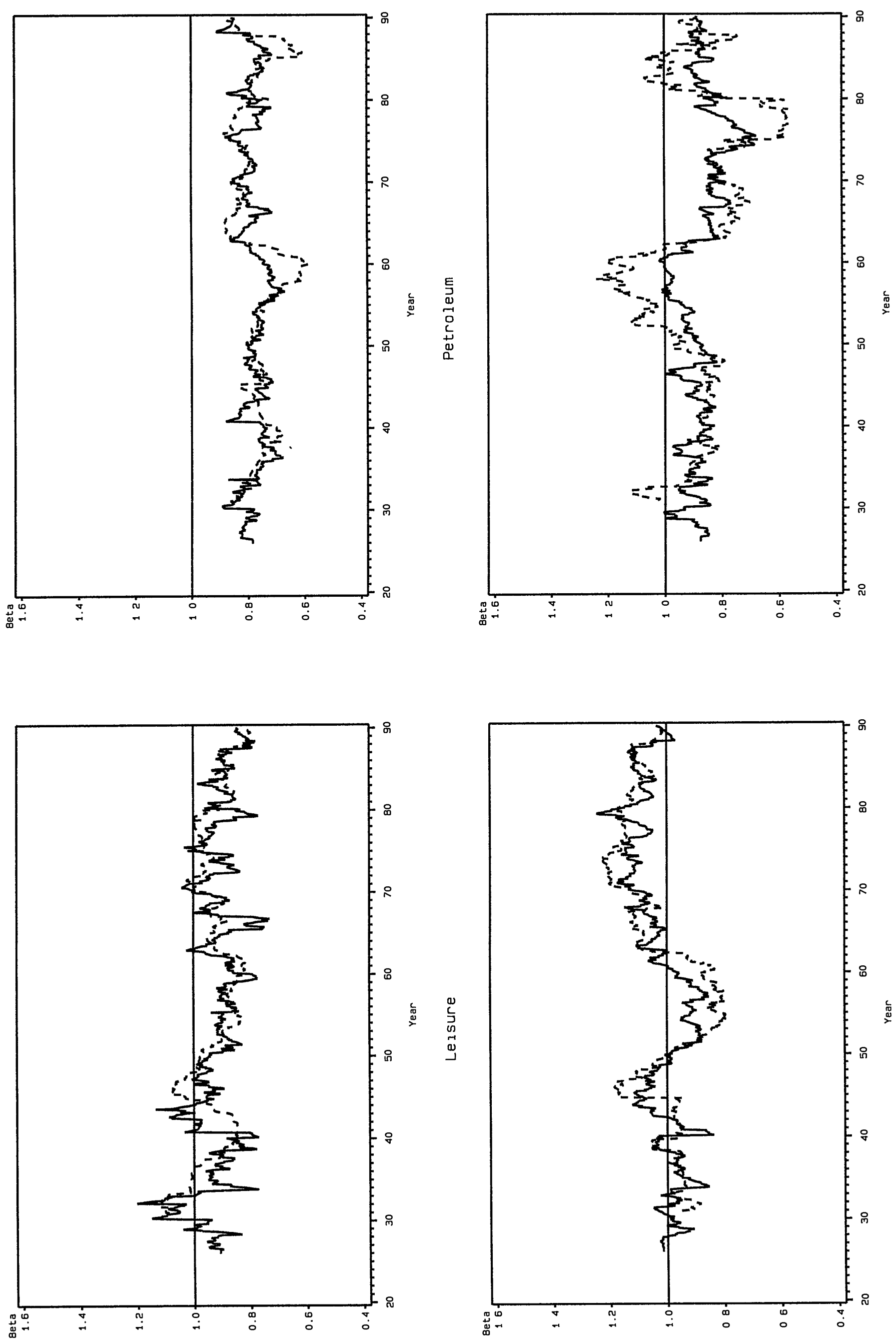

Fig. 1—*continued*

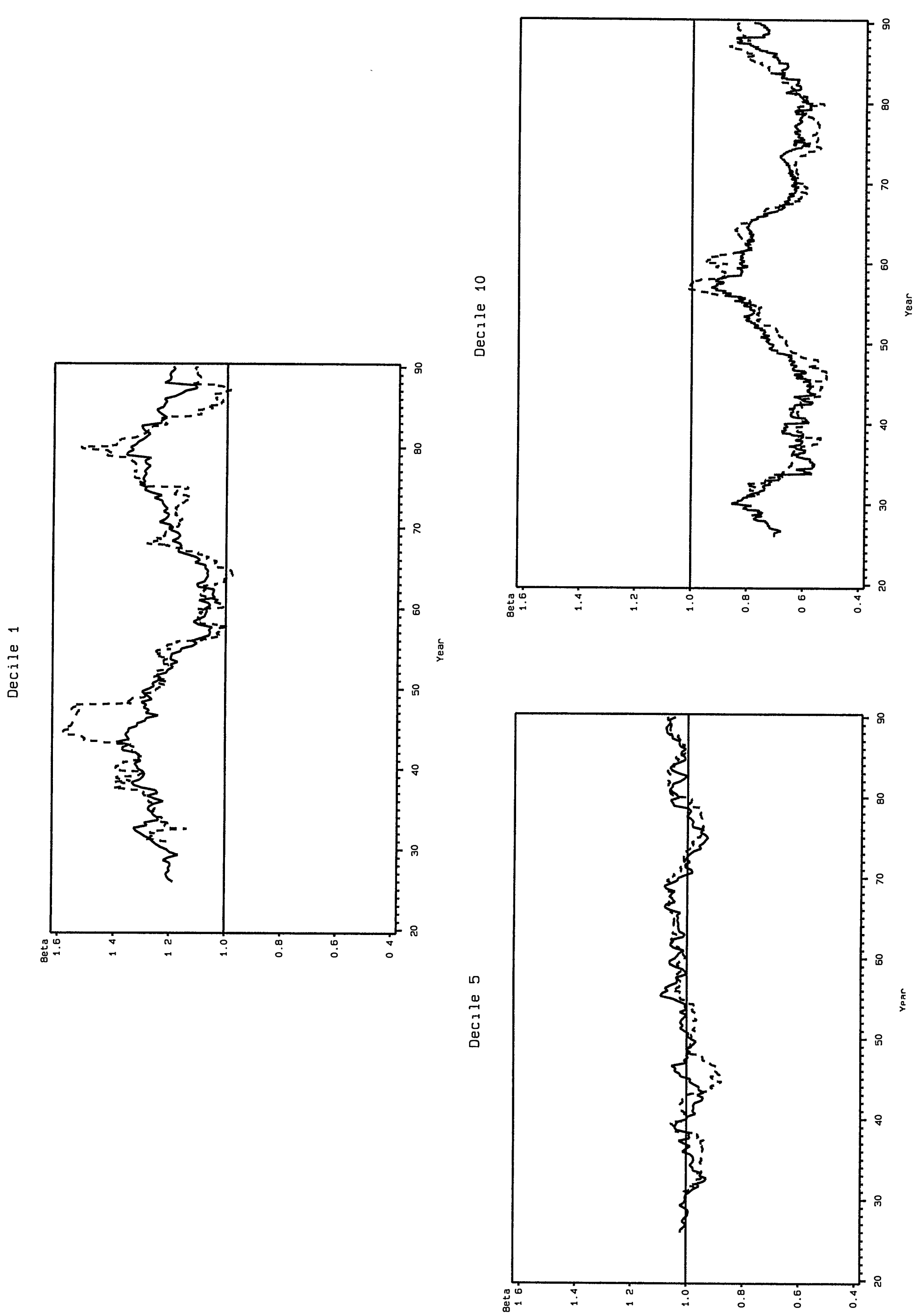

Fig. 1—*continued*

Table II

Bivariate EGARCH(1,0) Wald Statistics

Wald tests of parameter restrictions for the bivariate EGARCH. The EGARCH parameters are estimated using the equally-weighted CRSP industry and decile portfolios with the equally-weighted CRSP market return for the time period July 1926 through December 1990 (780 observations) and are estimated by maximum likelihood from the following discrete-time system of equations.

$$\beta_{p,t} = \alpha_\beta + \delta_\beta \cdot [\beta_{p,t-1} - \alpha_\beta] + \lambda_{p,m} \cdot z_{m,t-1} \cdot z_{p,t-1} + \lambda_m \cdot z_{m,t-1} + \lambda_p \cdot z_{p,t-1}$$

$$\ln(\sigma^2_{m,t}) = \alpha_m + \delta_m \cdot [\ln(\sigma^2_{m,t-1}) - \alpha_m] + \theta_m z_{m,t-1} + \gamma_m[|z_{m,t-1}| - E|z_m|]$$

$$\ln(\sigma^2_{p,t}) = \alpha_p + \delta_p \cdot [\ln(\sigma^2_{p,t-1}) - \alpha_p] + \theta_p z_{p,t-1} + \gamma_p[|z_{p,t-1}| - E|z_p|]$$

$$+ \theta_{p,m} z_{m,t-1} + \gamma_{p,m}[|z_{m,t-1}| - E|z_m|]$$

β_p is the estimated conditional beta for the industry (or decile) portfolio, $\ln(\sigma^2_m)$ is the log of the conditional variance of the market return and $\ln(\sigma^2_m)$ is the log of the conditional industry (or decile) portfolio return. z_m is the standardized residual for the market portfolio and is calculated as $z_{m,t} = r_{m,t}/\sigma_{m,t}$ where r_m is the demeaned return on the market portfolio. z_p is the standardized residual for the industry (or decile) portfolio and is calculated as $z_{p,t} = (r_{p,t} - \beta_{p,t} \cdot r_{m,t})/\sigma_{p,t}$ where r_p is the demeaned return on the industry (or decile) portfolio. These Wald statistics are computed using the robust variance-covariance estimator of Bollerslev and Wooldridge (1992). The c_u and c_l are upper and lower bounds on the critical value as reported in Kodde and Palm (1986). These values take into account the effect of inequality constraints on the distribution of the Wald statistic. If the Wald statistic is greater than c_u the null can be rejected at the 0.05 level. If the Wald statistic is less than c_l, one cannot reject at the 0.05 level. The test is inconclusive if the Wald statistic falls between these bounds.

Critical Values ($\alpha = .05$)	H_0: $\lambda_p = \lambda_m = \lambda_{p,m} = 0$	H_0: $\theta_p = \gamma_p = 0$	H_0: $\theta_{m,p} = \gamma_{m,p} = 0$	H_0: $\theta_p = \gamma_p = \theta_{m,p} = \gamma_{m,p} = 0$
χ^2	7.815	5.991	5.991	9.488
c_u	7.045	5.138	5.138	8.761
c_l	5.138	2.706	5.138	7.045
Portfolio				
Basic Industries	17.61	15.90	5.99	20.41
Capital Goods	3.34	17.75	7.22	21.76
Construction	7.92	11.91	1.04	12.84
Consumer Durables	6.31	22.36	33.91	33.29
Finance/Real Estate	27.71	9.36	28.94	23.88
Food	8.42	15.16	12.43	41.67
Leisure	5.89	0.46	20.96	21.96
Petroleum	3.48	17.33	3.37	20.06
Services	29.99	21.44	5.73	36.42
Textiles/Trade	22.13	6.30	16.77	16.93
Transportation	18.80	5.68	20.73	60.37
Utilities	5.05	20.84	2.08	29.92
Decile 1	8.20	7.79	16.98	44.77
Decile 5	9.79	5.36	44.70	36.11
Decile 10	10.46	19.66	19.30	56.77

EGARCH for the market and found the parameter estimates and the fitted values to be very similar.

C.3. Portfolio-Specific Volatility.

We present the parameter estimates for the $\ln(\sigma_{p,t}^2)$ equation in columns 10 through 15 of Table I for the industry and decile portfolios. As with the market's equation, all of the portfolios show strong persistence as indicated by all of the δ_p's except one being greater than 0.97, with half-lives ranging from 9 months for the consumer durables portfolio to over 14 years for decile 1 (ignoring the unit root in the services portfolio).

The portfolio-specific leverage and magnitude terms, θ_p and γ_p (columns 12 and 13), respectively, differ from their counterparts in the market equation. For 2 out of the 12 industry portfolios, the estimated θ_p is significantly negative and three times significantly positive. One of the decile portfolios, decile 10, has a significantly positive θ_p. Conversely, for both industry and decile portfolios, all but three of the γ_ps are significant at the 5 percent level and all are positive. For the industry portfolios the market-specific leverage and magnitude terms, $\theta_{p,m}$ and $\gamma_{p,m}$, are usually insignificant. The $\theta_{p,m}$s are significant at the 5 percent level for four industry portfolios and the $\gamma_{p,m}$s for four portfolios—in only one case (the food portfolio) are both terms simultaneously significant. For the decile portfolios the $\theta_{p,m}$ is always significantly negative and the $\gamma_{p,m}$ is always insignificant.

To examine the role of leverage and magnitude effects in the above estimations in more detail we estimated three more Wald statistics. The first one, presented in column two of Table II, tests the null hypothesis that all movements in the portfolio-specific conditional variance are caused only by the market return, i.e., $\theta_p = \gamma_p = 0$.[15] Again, note that all of the test statistics presented in this table are correlated, and therefore overall conclusions must be drawn with care. We can reject this null hypothesis at the 5 percent level for all portfolios except the leisure portfolio. The second null hypothesis is that the market return does not enter the $\sigma_{p,t}^2$ equation, i.e., $\theta_{p,m} = \gamma_{p,m} = 0$.[16] We present these results in column three of Table II. We can reject this null hypothesis for all but three of the portfolios: construction, petroleum, and the utilities portfolios.

We also estimated Wald statistics for the null hypothesis of constant portfolio-specific conditional variance, i.e., $\theta_p = \gamma_p = \theta_{p,m} = \gamma_{p,m} = 0$. These results are presented in column four of Table II. As was the case for the market equation, for all portfolios we reject the null hypothesis of homoskedasticity at the 1 percent level. We additionally tested the joint hypothesis of constant conditional variances in both the market and portfolio equations. Again, as expected given the individual results for the two equations, we reject the null hypothesis overwhelmingly in all cases and hence to not present the results.

[15] The alternative hypothesis is $\theta_p \neq 0$ and $\gamma_p \geq 0$.

[16] The alternative hypothesis is $\theta_{p,m} \neq 0$ and $\gamma_{p,m} \neq 0$. Note that this is not equivalent to a null hypothesis that market returns do not enter the conditional variance of $R_{p,t}$.

The insignificance and/or varying signs of the market leverage terms in the portfolio variance equation, (10), and in the beta equation, (11), indicate that, overall, leverage effects affect portfolio variance only through the market variance equation, (9). Although one or the other of the portfolio-specific leverage terms in a majority of the portfolio conditional variance equations are significant for both the industry and decile portfolios, in only one case are they both simultaneously significant. This evidence is not consistent with the financial and operating leverage explanations of the "leverage effect" in conditional variances. It is difficult to understand why leverage effects in portfolio-specific variances are not more evident and consistent across portfolios if these explanations are important. Furthermore, these results suggest that the strong leverage effects in market conditional variances may be better explained by the action of macro forcing variables that have little or no effect on nonsystematic risk. It seems that on an industry or decile portfolio level, the leverage effects are small with respect to portfolio-specific return movements, but when these return shocks are aggregated across portfolios in the market return, there is a market-wide leverage component.

III. Specification Tests

To check the adequacy of the model, we subject it to an array of specification tests, both formal and informal. Our formal specification tests examine the predictions of the model regarding conditional second moments, in particular, the prediction of the model that for each t, $z_{m,t}^2 - 1$, $z_{m,t} \cdot z_{p,t}$, and $z_{p,t}^2 - 1$ have a conditional mean of zero—i.e., are not predictable given past information. We test these restrictions using the regression-based tests developed in Wooldridge (1990). As we see below, the results of these tests are supportive of the model. Our informal specification tests consist of cross-validating our model's performance to a simple and intuitively appealing benchmark, 5-year rolling regressions along the lines of Fama and MacBeth (1973). Again, the model performs well.

A. Conditional Moment Tests

An extensive literature has developed on testing conditional moment restrictions such as these (see, e.g., Newey (1985), Tauchen (1985), White (1987)). In the bivariate EGARCH model, implementing these tests is complicated by both the relative complexity of the model and by the use of quasi-maximum likelihood estimation. However, Wooldridge (1990) has shown how to compute conditional moment tests that are both simple to compute and valid for quasi-maximum likelihood estimators.

To compute the Wooldridge conditional moment tests, we first define an $L \times 1$ vector process ψ_t with conditional expectation zero under the null hypothesis of correct specification. Our model specifies the form of the conditional covariance matrix of $[R_{m,t}, R_{p,t}]$. In particular, correct specification implies that $(R_{m,t}^2 - \sigma_{m,t}^2)$, $(R_{m,t} \cdot R_{p,t} - \beta_{p,t} \cdot \sigma_{m,t}^2)$, and $(R_{p,t}^2 - \beta_{m,t}^2 \cdot \sigma_{m,t}^2 - \sigma_{p,t}^2)$

have conditional means of zero, or, equivalently, that $z_{m,t}^2 - 1$, $z_{m,t} \cdot z_{p,t}$, and $z_{p,t}^2 - 1$ have conditional means of zero. We base our conditional moment tests on the latter set of restrictions, since they correct for conditional heteroskedasticity and thereby increase the power of the specification tests. For our applications, ψ_t will be set equal to either $z_{m,t}^2 - 1$, $z_{m,t} \cdot z_{p,t}$, or $z_{p,t}^2 - 1$ individually, or to a 3×1 vector containing all three.

Next, if p is the number of parameters in the bivariate EGARCH system, define the $L \times p$ process $\Psi_t = \mathrm{E}_t\,[\nabla_{\vartheta}\colon \psi_t]$, where E_t is the time $t-1$ conditional expectation and ∇_{ϑ} denotes differentiation with respect to the system's parameters. Further define Λ_t to be an $L \times q$ matrix of predetermined variables that will be used to try to detect predictability in ψ_t. In the specification tests reported below, each row of Λ_t will consist of a constant, the current 1-month Treasury bill rate r_t, and one lag each of $z_{m,t}^2$, $z_{p,t}^2$, $z_{m,t} \cdot z_{p,t}$, $z_{m,t}$, and $z_{p,t}$. For each portfolio, we compute four conditional moment specification tests; the first test, reported in the first column of Table III, sets ψ_t equal to $z_{m,t}^2 - 1$, and the second and third columns of Table III set ψ_t equal to $z_{m,t} \cdot z_{p,t}$ and $z_{p,t}^2 - 1$, respectively. The specification test reported in the fourth column of Table III sets Λ_t equal to a 3×6 matrix with each row equal to $[1, r_t, z_{m,t-1}^2, z_{p,t-1}^2, z_{m,t-1} \cdot z_{p,t-1}, z_{m,t-1}, z_{p,t-1}]$ and sets $\psi_t \equiv [z_{m,t}^2 - 1, z_{m,t} \cdot z_{p,t}, z_{p,t}^2 - 1]$. All of these tests are distributed asymptotically chi-square with 7 degrees of freedom (i.e., the number of columns in Λ_t).

Our choice of 1 lag is somewhat arbitrary, since theory gives us little guidance on this matter.[17] Adding "too many" variables to the conditioning information set reduces power by adding degrees of freedom to the chi-square test, while including too few reduces power by omitting useful conditioning information. We included the current one month Treasury bill rate since earlier research (e.g., Ferson (1989) and Glosten, Jagannathan, and Runkle (1993)) have found that nominal interest rates have power to forecast stock volatility.

Overall, the models perform well, especially the industry portfolio models. Of the 48 test statistics reported for the industry portfolios, eight reject at the 5 percent level. Three of the rejections find evidence of misspecification in the conditional betas—i.e., of predictability in $z_{m,t} \cdot z_{p,t}$. None of the rejections for the industry portfolios are particularly strong, however, with only one rejection at the 1 percent level. Results are not as favorable for the decile portfolios: of the 12 test statistics calculated, four reject at the 5 percent level and three at the 1 percent level. These results imply that there is evidence that returns on decile portfolios have power to predict market variances. An anomalous aspect of the results we present in Table III is that for some cases, e.g., decile 1, where we reject the null hypothesis for some subset of moment conditions (columns one through three) we fail to reject when we use the complete set of

[17] We repeated the same conditional moment tests using a larger information set: each row of Λ_t consisting of a constant, the current one month treasury bill rate r_t, and six lags each of $z_{m,t}^2$, $z_{p,t}^2$, $z_{m,t} \cdot z_{p,t}$, $z_{m,t}$, and $z_{p,t}$. The results from these six lag tests almost always failed to reject the null hypothesis and hence we do not report the results for sake of brevity.

Table III

Bivariate EGARCH(1,0) Conditional Moment Specification Tests

These are regression-based conditional moment tests computed by the method of Wooldridge (1990). They check for the failure of conditional moment restrictions using a constant, the contemporaneous T-bill rate, and one lag of $[z^2_{m,t}, z^2_{p,t}, z_{m,t} \cdot z_{p,t}, z_{m,t}, z_{p,t}]$. z_m is the standardized residual for the market portfolio and is calculated as $z_{m,t} = r_{m,t} / \sigma_{m,t}$ where r_m is the demeaned return on the market portfolio and σ_m is the conditional standard deviation of the market return calculated from the bivariate EGARCH. z_p is the standardized residual for the industry (or decile) portfolio and is calculated as $z_{p,t} = (r_{p,t} - \beta_{p,t} \cdot r_{m,t})/\sigma_{p,t}$ where r_p is the demeaned return on the industry (or decile) portfolio, β_p is the bivariate EGARCH estimated conditional beta for the industry (or decile) portfolio and σ_p is the conditional standard deviation of the industry (or decile) portfolio return estimated from the bivariate EGARCH. The time series are for the period July 1926 though December 1990 for a total of 780 observations. See Table I for the corresponding parameter estimates. The asymptotic χ^2 (6) statistics are reported above the p-values.

	Moment Restriction			
Portfolio	$E[z_m^2 - 1] = 0$	$E[z_m z_p] = 0$	$E[z_p^2 - 1] = 0$	$E\begin{bmatrix} z_m^2 - 1 \\ z_m z_p \\ z_p^2 - 1 \end{bmatrix} = 0$
Basic Industries	13.55	9.75	15.32	6.88
	(0.060)	(0.203)	(0.032)	(0.441)
Capital Goods	14.73	6.37	9.13	8.93
	(0.040)	(0.497)	(0.244)	(0.258)
Construction	15.00	18.18	3.85	7.55
	(0.036)	(0.011)	(0.797)	(0.374)
Consumer Durables	10.99	12.44	3.77	14.84
	(0.139)	(0.087)	(0.806)	(0.038)
Finance/Real Estate	7.64	4.00	10.51	4.86
	(0.366)	(0.780)	(0.161)	(0.678)
Food	11.93	8.75	6.57	12.02
	(0.103)	(0.271)	(0.475)	(0.100)
Leisure	8.43	1.79	6.40	6.27
	(0.296)	(0.971)	(0.494)	(0.509)
Petroleum	13.51	16.43	9.74	7.88
	(0.061)	(0.021)	(0.204)	(0.343)
Services	8.41	7.36	9.42	6.59
	(0.298)	(0.393)	(0.224)	(0.472)
Textiles/Trade	14.08	4.87	14.60	5.43
	(0.050)	(0.676)	(0.042)	(0.608)
Transportation	13.25	14.83	13.47	13.22
	(0.066)	(0.038)	(0.061)	(0.067)
Utilities	7.88	5.60	4.63	11.48
	(0.343)	(0.587)	(0.705)	(0.119)
Decile 1	16.05	19.74	3.79	2.78
	(0.025)	(0.006)	(0.804)	(0.905)
Decile 5	8.57	9.73	9.64	11.19
	(0.285)	(0.204)	(0.210)	(0.131)
Decile 10	19.98	13.62	12.32	21.29
	(0.006)	(0.058)	(0.090)	(0.003)

moment restrictions (column four). We attribute these reversals to a combination of (i) the relative variance of a particular moment restriction to the other moment restrictions and (ii) large correlations between some of the moment restrictions.

B. Comparison to Rolling Regression

As an informal specification test we compare the EGARCH model to the Fama-MacBeth (1973) or rolling regression approach to estimating betas.[18] The latter method relies on ordinary least squares regressions to obtain betas. The rolling regression model was chosen as a benchmark for comparison because of its simplicity and wide usage. It is also attractive as a benchmark because it allows us to estimate a series of time-varying betas without imposing any particular structure on the way in which conditional covariances change. In contrast, the EGARCH model imposes a considerable degree of structure on the data generating process. The rolling regression approach provides a useful reality check on the EGARCH structure and in this sense we can view the comparisons that follow as informal specification tests. We use these informal specification checks as a means of *cross-validating* our model against a standard benchmark.

To estimate the rolling regression betas we employ a lagged window of 60 months. Thus, we estimate the following model to obtain a beta for date τ:

$$R_{p,t} = \alpha_\tau + \beta_{p,\tau} R_{m,t} + \epsilon_{p,t}, \quad t = \tau - 61, \cdots, \tau - 1. \tag{12}$$

where $\{\epsilon_{p,t}\}$ is a white noise process. This is the conventional way of forming beta estimates; see, for example, Merrill Lynch's beta book (1990). We estimated both the EGARCH and rolling regression models for each portfolio over the entire data set from January 1926 to December 1990. Because the rolling regression method requires 60 months of data, we had 720 observations for comparison.

In Table IV, we gauge the in-sample performance of the two models with four statistics. The first two statistics, mean-square-error (MSE), in columns one and two, and mean-absolute-error (MAE), in columns three and four, indicate how well each model's betas can explain the in-sample variation of portfolio returns. Note that there are alternative metrics we could have employed to cross-validate our model with rolling regressions; however, we selected MSE and MAE again because of their simplicity. Because each model's ability to match in-sample variation of portfolio returns depends on the quality of its beta estimates, these statistics provide evidence of how well each model matches the true underlying covariation of portfolio and market returns.

The mean-square-error and mean-absolute-error of the EGARCH model is consistently lower than the mean-square-error and mean-absolute-error of the

[18] Of course, Fama and MacBeth's motivation when they developed the rolling regression procedure is different from our current motivation. Consequently, some of the details of our implementation will differ.

Table IV

EGARCH(1,0) versus Rolling Regression In-Sample Performance Comparison

In-sample comparison of the fitted conditional means and variances from the bivariate EGARCH and rolling regressions. The statistics used for comparison are:

Statistic	EGARCH	Rolling Regression
MSE	$(1/T)\sum_{t=1}^{T}(R_{pt}-\hat{\beta}_{p,t}R_{m,t})^2$	$(1/T)\sum_{t=1}^{T}(Rpt-\hat{\alpha}_{p,t}-\hat{\beta}_{p,t}R_{m,t})^2$
MAE	$(1/T)\sum_{t=1}^{T}\lvert R_{pt}-\hat{\beta}_{p,t}R_{m,t}\rvert$	$(1/T)\sum_{t=1}^{T}\lvert R_{pt}-\hat{\alpha}_{p,t}-\hat{\beta}_{p,t}R_{m,t}\rvert$
MAE(r_m^2)	$(1/T)\sum_{t=1}^{T}\lvert r_{mt}^2-\hat{\sigma}_{mt}^2\rvert$	$(1/T)\sum_{t=1}^{T}\lvert r_{mt}^2-\sigma_{mt}^2\rvert$
MAE(r_p^2)	$(1/T)\sum_{t=1}^{T}\lvert r_{pt}^2-\hat{\beta}_{p,t}^2\hat{\sigma}_{mt}^2-\hat{\sigma}_{pt}^2\rvert$	$(1/T)\sum_{t=1}^{T}\lvert r_{pt}^2-\hat{\beta}_{p,t}^2\hat{\sigma}_{mt}^2-\hat{\sigma}_{pt}^2\rvert$

R_p is the return on the equally-weighted CRSP industry (or decile) portfolio, R_m is the return on the CRSP equally-weighted market return, β_p is the bivariate EGARCH or rolling regression estimated conditional beta for the industry (or decile) portfolio, α_p is the estimated intercept term from the rolling regressions, r_m is the demeaned return on the market portfolio, r_p is the demeaned return on the industry (or decile) portfolio, σ_m^2 is the conditional variance of the market return calculated from the bivariate EGARCH or the rolling regression, σ_p^2 is the conditional variance of the industry (or decile) portfolio return estimated from the bivariate EGARCH or rolling regression, T is the sample size, 780 observations.

	MSE $\times 10^{-4}$		MAE $\times 10^{-2}$		MAE (r_m^2) $\times 10^{-2}$		MAE (r_p^2) $\times 10^{-2}$	
Portfolio	EGARCH	Rolling Regression	EGARCH	Rolling Regression	EGARCH	Rolling Regression	EGARCH	Rolling Regression
Basic Industries	2.42	2.51	1.11	1.14	5.47	6.22	5.78	6.65
Capital Goods	1.97	2.12	1.01	1.03	5.46	6.22	6.66	7.52
Construction	6.54	6.88	1.83	1.88	5.46	6.22	7.09	8.24
Consumer Durables	2.52	2.69	1.18	1.21	5.29	6.22	7.12	8.07
Finance/Real Estate	2.76	3.19	1.24	1.27	5.46	6.22	5.13	6.07
Food	3.38	3.59	1.33	1.37	5.43	6.22	3.79	4.13
Leisure	6.54	6.93	1.85	1.92	5.90	6.22	6.81	7.01
Petroleum	13.64	14.64	2.72	2.79	5.45	6.22	5.72	6.39
Services	13.72	14.60	2.51	2.56	5.46	6.22	6.00	6.00
Textiles/Trade	4.05	4.31	1.49	1.52	5.49	6.22	5.86	6.33
Transportation	13.51	14.22	2.52	2.64	5.37	6.22	8.45	9.92
Utilities	10.63	11.15	2.23	2.28	5.40	6.22	3.71	4.71
Decile 1	12.36	12.90	2.29	2.36	5.38	6.22	9.87	11.70
Decile 5	1.49	1.64	0.83	0.87	5.65	6.22	5.78	6.14
Decile 10	5.16	5.42	1.60	1.61	5.34	6.22	2.94	3.20

rolling regression model. The differences in MAE between the two models are somewhat smaller than the differences in MSE. Because the MAE statistic puts less weight on large residuals than does the MSE statistic, this indicates that, at least in periods of low market volatility when most residuals are small, the rolling regression model may perform nearer to the EGARCH model. In periods of high market volatility, however, the EGARCH model performs better.

The second set of columns in Table IV indicate how well the two models are able to capture changes in market and portfolio volatility. Columns five and six report the mean-absolute-error of each model in predicting the square of the demeaned *market* return over the whole sample. Columns seven and eight report the same mean-absolute-error comparison for the square of *individual* industry or decile portfolio returns.

The EGARCH model is consistently better than the rolling regression model in matching these second moments of market returns. The improvement in mean-absolute-error is in the range of 5 to 15 percent. The EGARCH model also does consistently better than the rolling regression model in the second moments of the individual industry or decile portfolios. The percentage improvement ranges from 0.5 to 20 percent.

The collection of plots in Figure 1 provide a useful look at how EGARCH and rolling regression betas compare. The solid line in the charts are the betas from the EGARCH model and the dashed line are betas from rolling regressions. The betas from the two models track each other broadly. There are significant differences between portfolios in these plots. Unfortunately, differences across industry portfolios are difficult to reconcile with a casual knowledge about corresponding differences in financial and operating leverage. The EGARCH model generally produces higher frequency movements in beta estimates than does the rolling regression method.[19] Plots of portfolio specific volatilities given by the two models are similar to Figure 1. That is, the EGARCH model produces more variable estimates of conditional volatility which, as indicated by the MAE statistics, produce a better fit to the actual pattern of squared return residuals.

To sum up, the EGARCH model compares quite well to the rolling regression model. It is consistently better than the rolling regression model in explaining in-sample variation of portfolio returns and in fitting second moments of returns. We find these results encouraging and supportive of the thesis that the EGARCH model can build better estimates of beta and volatility than rolling regressions. Furthermore, we conclude that our bivariate EGARCH model is cross-validated with respect to rolling regressions given the MSE and MAE metrics we employ.

IV. Conclusion

The empirical finance literature has amply documented the asymmetric response of volatility to good news and bad news. In this paper, we shed additional light on the issues that surround the evidence for predictive asymmetry of second moments of returns. In particular, it appears that predictive asymmetry occurs mainly at the level of the market—i.e., market volatility tends to rise strongly in response to bad news and fall in response to good news. Surprisingly, however, our evidence indicates that predictive asymmetry is entirely absent (or of the "wrong" sign) in conditional betas and weak in idiosyncratic (e.g., industry-specific) sources of risk for industry portfolios.

[19] Of course, these movements could be picked up by the rolling regressions by choosing a narrower window than 60 months.

Predictive asymmetry *does* show up in the volatility of all portfolios, but it appears most consistently through the market factor rather than through the other terms—i.e., predictive asymmetry appears in portfolio conditional variance $\beta_{p,t}^2\sigma_{m,t}^2 + \sigma_{p,t}^2$ through the $\sigma_{m,t}^2$ term, not through the $\beta_{p,t}^2$ or the $\sigma_{p,t}^2$ terms.

We find this quite surprising, especially given the role of financial and operating leverage in the determination of beta. While it has long been known that leverage per se could not explain all of the leverage effect, the link may be even weaker than had been realized. Our results thus lend indirect support to the explanations of a leverage effect based on macro forcing variables (e.g., Malkiel (1979), French, Schwert, and Stambaugh (1987), Glosten, Jagannathan, and Runkle (1993)) rather than financial structure.

At first glance, our results also appear to contradict the assertions of Chan (1988) and Ball and Kothari (1989) that shifts in conditional betas can explain mean reversion in asset prices. We find evidence for variation in betas at the industry and decile levels, but the variation in betas that we find appears unrelated to the leverage effects postulated by Chan and Ball and Kothari. This offers some support for De Bondt and Thaler's (1989) claim that betas were not responsive enough to account for the differing return performances of "winners" and "losers."

Still, Chan and Ball and Kothari examined individual securities and portfolios of winners and losers, which we have not done. Perhaps because our test design aggregates to the industry and decile level we lose much of the cross-sectional variation in betas and, in particular, miss an asymmetric response of the conditional betas of individual firms to good and bad news. In other words, the predictive asymmetry in betas may take place at the firm rather than the industry and decile level. This suggests that it may be desirable to model conditional covariances at the individual firm level, carefully separating returns into market, industry, and firm-specific components and checking the effects of each on conditional betas, perhaps in the context of a model of financial structure. Still, it is surprising to find virtually *no* evidence that betas rise (fall) in response to bad (good) news at the industry level. Since we have not modelled expected returns, our results say nothing about Chan's (1988) claim that the market risk premium is positively correlated with loser betas. Nevertheless, our results are more supportive of the conclusions of Chopra, Lakonishok, and Ritter (1992), that a leverage effect in betas is not sufficient to explain the market's overreaction to winners and losers, the conclusions of Chan and Ball and Kothari.

It is also possible that an existing leverage effect in betas is obscured by our use of an EGARCH rather than a stochastic volatility model. Stochastic volatility models allow for an independent error term in the conditional variance equation. This inclusion of the error term permits realistic estimation of some standard continuous time problems.[20] Although Nelson (1994) finds that as one approaches a continuous time limit, multivariate ARCH models asymp-

[20] See for example Melino and Turnbull (1990) and the discussion in Jacquier, Polson, and Rossi (1994).

totically approach stochastic volatility models: it is possible that a 1 month interval is not sufficient to approach this limit. Therefore, the recent work of Jacquier, Polson, and Rossi (1995) may be pertinent in interpreting the results of this paper. In particular, Jacquier, Polson, and Rossi find that negative correlations between the mean and variance equation errors for stock returns produce a leverage effect. However, they show that even very high negative correlations could not produce as large asymmetries as those implied by common EGARCH parameter estimates. A full resolution of these issues would require the estimation of stochastic volatility models with time-varying betas.

Our results also indicate that the bivariate EGARCH model may be useful in other contexts which we have not explored. For example, volatility forecasting at the portfolio level can be improved by using information from *both* past portfolio and market returns. Such forecasts may be valuable for option pricing and hedging purposes. The model is also able to generate improved beta forecasts which could be useful in dynamic hedging applications. Finally, while we have focused on a one factor ARCH model, the modeling approach can be extended to allow for additional factors besides the market that drive expected portfolio returns. Such a multi-factor extension of our model is a potential tool for investigating a wide range of practical issues in asset pricing.

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