Macroeconometrics

Developments, Tensions, and Prospects

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Commentary on Chapter 11

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Frank Diebold and Jose Lopez have written an excellent primer on conditional heteroskedasticity (CH) models and their use in applied work. A principal motivation for CH models, as outlined in Diebold and Lopez, is their ability to parsimoniously capture the observed characteristics of many financial time series. By far the most widely used CH model, in part because of the fact that estimators for the model are simple to construct, is the generalized autoregressive conditional heteroskedasticity (GARCH) specification of order $1,1$ with normal innovations (henceforth termed the normal GARCH $(1, 1)$ model). Despite its widespread use, the normal GARCH$(1, 1)$ model does not account for important features in many financial time series. For example, assuming that the GARCH innovations have a normal density generates far fewer outliers than are typically observed in asset prices, while assuming that the order of the GARCH model is $(1, 1)$ fails to account for the variety of dynamic patterns observed in the conditional heteroskedasticity of asset prices.

As Diebold and Lopez note in describing avenues for future research, it is important to consider alternative CH models that do account for such features of asset prices. Two alternatives to a normal GARCH$(1, 1)$ model, which are mentioned by Diebold and Lopez and for which estimators are also simple to construct, are $(1)$ to allow for nonnormal innovations that have a thicker tailed density, thereby accounting for a larger number of outliers and $(2)$ to allow for orders other than $(1, 1)$ by developing powerful test statistics for selection of order in GARCH models, thereby accounting for a wider variety of dynamic patterns. I discuss each of these alternatives in turn, in an effort to bring them within the set of commonly used methods for estimation and testing of CH models.

Unknown Density

Let $y_t$ be a period-$t$ variable (such as an exchange rate) that has conditional mean $x_t \beta$ where $x_t \in \mathbb{R}^k$ and the period-$t$ regressors include a constant. The normal GARCH$(1, 1)$ model for $y_t$ is

$$y_t = x_t \beta + \nu_t,$$

where the period-$t$ conditional variance is

\[ h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \nu_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}, \]

\[ \nu_t > 0. \]
\[ h_t^2 = \omega + \alpha (y_{t-1} - x_{t-1} \beta)^2 + \gamma h_{t-1}^2, \]  

(2)

with period-t innovation \(u_t\), and where \((\beta, \omega, \alpha, \gamma)\) are parameters to be estimated. The sequence \(\{\nu_t\}_{t=1}^T\) is a sequence of independent and identically distributed (iid) normal random variables with mean zero and variance one.\(^1\)

Because the normal GARCH(1, 1) model does not adequately account for outliers in asset prices such as exchange rates, researchers constructing CH models of exchange rates often assume that the density of \(u_t\) has thicker tails than a normal density. For example, Bailie and Bollerslev (1989) use both an exponential-power and a t density to model exchange rates.

Although the use of thicker-tailed parametric innovation densities does account for a larger number of outliers, it also raises the issue of the properties of the estimators if the selected density is misspecified. Virtually all researchers that estimate CH models also use a quasi-maximum likelihood estimator (QMLE). If the assumed density is normal, the QMLE is consistent for the parameters of the conditional variance. If the assumed density is nonnormal, then consistency of the QMLE depends on the specification of the conditional mean. For a nonnormal GARCH(1, 1) model, which is given by (1) and (2) together with the assumption that \(u_t\) has a nonnormal density, Newey and Steigerwald (1994) show that a nonnormal QMLE is not generally consistent.\(^2\)

An alternative estimator that also accounts for a larger number of outliers is a semiparametric estimator. A semiparametric estimator of the parameters in a GARCH(1, 1) model is constructed under the assumption that the innovation density is any member within a class of densities, and uses a nonparametric estimator of the density. Steigerwald (1994) shows that a semiparametric estimator is consistent for general GARCH\((p, q)\) models.

Given that a semiparametric estimator accounts for a larger number of outliers and consistently estimates the parameters of (1) and (2), attention turns to finite sample performance. The finite sample performance of a semiparametric estimator depends on the bandwidth used to construct the nonparametric density estimator. The bandwidth, in turn, depends on the conditional variance parameterization. For the conditional variance parameterization (2), the regularity conditions given in Steigerwald require that the bandwidth used to construct the nonparametric density estimator be smaller than the optimal bandwidth. Such a restriction on choice of bandwidth may lead to a poor estimate of the density, thereby reducing the gains of a semiparametric estimator.

A reparameterization of the conditional variance, which allows the optimal bandwidth to be used to estimate the density, is to let the variance of \(u_t\) be restricted only to be finite and to reparameterize the conditional variance as

\[ h_t^2 = \psi^2 [1 + \alpha (y_{t-1} - x_{t-1} \beta)^2] + \gamma h_{t-1}^2, \]  

(3)

Linton (1993) develops this reparameterization framework in Engle and Gonzalez-Ripoll (1993) and Steigerwald (1993) models.\(^3\)

A guide to the finite sample properties of two conditional variance estimators is found in Engle and Gonzalez-Ripoll (1993). The performance of a semiparametric estimator is measured by the sample size of 2,000. Engle and Gonzalez-Ripoll report that a semiparametric estimator, reported for the parameters in a sample of only fifty observations, performs as well as a fully specified estimator. However, they also note that the parameterization of the semiparametric estimator is much more efficient.

Testing for Order

All discussion in the preceding sections assumed conditional variance. As is noted at the beginning of this section, if the conditional variance is not correctly specified, the time series properties may be incorrect. To test the model against the multivariate alternative, we use the null hypothesis that the conditional variance is specified correctly. The test is to test the null hypothesis against the alternative.

Engle (1982) develops Lagrange multiplier tests for a normal ARCH model and for a general ARCH model. The test is to test the null hypothesis that the conditional variance is specified correctly. The test is to test the null hypothesis against the alternative that the parameter \(p\) of the ARCH model is negative. Therefore, more power is gained. For the univariate testing...
Linton (1993) develops this reparameterization for ARCH models, Drost and Klaasen (1993) and Steigerwald extend the reparameterization to GARCH models.

A guide to the finite sample performance of semiparametric estimators for the two conditional variance parameterizations is provided by the simulations contained in Engle and González-Rivera (1991) and Steigerwald. Both studies compare the performance of a semiparametric estimator with a normal QMLE. For a sample size of 2,000, Engle and González-Rivera report essentially no gain in efficiency for a semiparametric estimator of the parameters in (1) and (2) when the density of \( u_t \) is a \( t \) density with 5 degrees of freedom. Steigerwald, using a different nonparametric estimator, reports more favorable results for a semiparametric estimator of the parameters in (1) and (2), finding some efficiency gains with a sample of only fifty observations when the density for \( u_t \) is a \( t \) density with 5 degrees of freedom. The efficiency gains increase dramatically if (3) replaces (2), indicating that the parameterization of the conditional variance is important for applied work.

**Testing for Order**

All discussion in the preceding section considers a fixed order \((1, 1)\) for the conditional variance. As is noted in the introduction, the \((1, 1)\) order specification fails to account for the variety of dynamic patterns in many time series. In response, I turn to extending the GARCH\((1, 1)\) specification to general order \((p, q)\).

To extend the GARCH\((1, 1)\) specification to GARCH\((p, q)\) requires a test statistic for choosing correct order. To keep the following discussion of test statistics clear, I consider two distinct testing problems. The first problem is to test the null hypothesis that the conditional variance is ARCH\((p)\) against the univariate alternative hypothesis that the conditional variance is ARCH\((p + 1)\). The second problem is to test the null hypothesis that the conditional variance is ARCH\((p)\) against the multivariate alternative hypothesis that the conditional variance is ARCH\((p + k)\), where \( k > 1 \). In particular, the two problems can be viewed as testing the null hypothesis of homoskedasticity against the alternative either of ARCH(1) or ARCH\((p)\).

Engle (1982) develops Lagrange multiplier (LM) test statistics for the univariate testing problem in a normal ARCH model. The test is two sided, the null hypothesis that a specific conditional variance parameter equals zero is tested against the alternative that the parameter is nonzero. Yet to ensure that the conditional variance is always positive, the parameter of the conditional variance must be non-negative. Therefore, more powerful test statistics can be constructed that are one sided. For the univariate testing problem, the signed square-root of the LM test
statistic provides such a one-sided test. For the multivariate testing problem, there is no uniformly best one-sided test because the region over which the power function is evaluated spans more than one dimension. Lee and King (1993) propose a one-sided test statistic, termed an LBS test statistic, for the multivariate testing problem that maximizes the average slope, over all directions, of the power function in a neighborhood of the null hypothesis. They show that their one-sided test can be more powerful in finite samples than a two-sided LM test statistic.

Both the LM test statistic and the LBS test statistic are constructed under the assumption that the innovation density is normal. Fox (1994a) develops semiparametric versions of both test statistics. He finds that incorporating a nonparametric estimator of the density can have important finite sample consequences. Specifically, for samples of 100 observations the semiparametric test statistics achieve size-adjusted power gains of as much as 20 percent over their parametric counterparts. Linton and Steigerwald (1994) extend the semiparametric tests to the reparameterization of the conditional variance in (3) and show that the semiparametric tests are optimal in that they maximize the average slope of the power function in a neighborhood of the null hypothesis for any innovation density in a general class. Fox also finds that testing for correct order is important in estimation, incorrect order specification can lead to substantial bias in the estimators of the conditional variance parameters.

**Empirical Implementation**

To demonstrate the potential importance of semiparametric methods in testing and estimation, I construct a model for the dollar per pound exchange rate. The data are collected at noon on the New York foreign exchange market and span the period January 2, 1985 to September 30, 1993 yielding 2,185 observations. As is commonly done, I model the first difference of the logarithm of the exchange rate rather than the exchange rate itself. The initial model is

\[ y_t = \beta + h_t u_t, \]

where \( y_t \) is the period-\( t \) value of the change in the logarithm of the exchange rate and the conditional variance specification is given by

\[ h_t^2 = e^{\alpha_t[1 + \alpha_t(y_{t-1} - \beta)^2]} + \gamma h_{t-1}^2. \]

Estimates of the parameters are reported in Table 11.1. (Standard errors are reported in parentheses below each estimate.) Although the magnitude of the normal QML and semiparametric estimates differ only slightly, the asymptotic standard errors of the semiparametric estimator are typically about half the size of the asymptotic standard errors for the normal QMLE. In addition, as Fox (1994b) notes, apparently small difference parameters can have important portfolio weights based on it.

Although the GARCH(1, 1) literature, it may not adequately test for incorrect order specification variance is GARCH(1, 1) against variance is GARCH(2, 1). I construct the LM test statistic and the KI semiparametric LM test statistics hypothesis. The parametric King the null hypothesis. Only the test rejects the null hypothesis. It applies a GARCH(1, 1) the power gain estimator and a one-sided alternate.

In summary, recent advances researchers with powerful tools normal GARCH(1,1) model. S available and provide alternative patterns in financial time seri.

**Notes**

1. The variance of \( u_t \) is assumed to be identically.
notes, apparently small differences in the point estimates of the conditional variance parameters can have important economic consequences. He shows that optimal portfolio weights based on the estimated conditional variance process differ markedly for two sets of estimates that differ only slightly, as do those in Table 11.1. The portfolio weights implied by the semiparametric estimators are better, in the sense that the risk associated with a portfolio that provides a fixed expected return is reduced by 8 to 10 percent out-of-sample.

Although the GARCH(1, 1) specification is common in the empirical finance literature, it may not adequately account for the dynamic pattern in the data. To test for incorrect order specification, I test the null hypothesis that the conditional variance is GARCH(1, 1) against the alternative hypothesis that the conditional variance is GARCH(2, 1). I construct both parametric and semiparametric versions of the LM test statistic and the King and Lee test statistic. Both the parametric and semiparametric LM test statistics, which are two-sided tests, fail to reject the null hypothesis. The parametric King and Lee test statistic also fails to clearly reject the null hypothesis. Only the semiparametric King and Lee test statistic clearly rejects the null hypothesis. It appears that if the true dynamic process is richer than a GARCH(1, 1), the power gains available from both a nonparametric density estimator and a one-sided alternative are needed to detect it.

In summary, recent advances in econometric methodology have provided researchers with powerful tools to move beyond the restrictive framework of a normal GARCH(1, 1) model. Semiparametric estimators and test statistics are available and provide alternatives that more flexibly account for the wide variety of patterns in financial time series.

Notes

1. The variance of \( \sigma^2 \) is assumed to equal one because \( \{\alpha, \beta, \gamma\} \) and the scale of \( \sigma^2 \) are not separately identified.
3. To ensure that the likelihood has a unique maximum, which is a necessary condition for consistent estimation, the set of regressors must include the conditional standard deviation.

4. In (3) the parameter \( \sigma \) cannot be separately identified because the variance of \( u_t \) is restricted only to be finite, so only ratios of the parameters (namely \( \sigma^2 \) and \( \sigma \)) are identified.

4. Considering only ARCH processes is not restrictive, as Lee and King (1993) note testing a null hypothesis of homoskedasticity against an alternative hypothesis of ARCH(\( p \)) is equivalent to testing against an alternative of GARCH(\( p, q \)).

References


Introduction

In the field of modeling economic series, the decade of cointegration has seen econometricians like the arrival of new statistical methods, such as those developed by Engle and his colleagues. The results of this research have extended our understanding of the dynamic relationships between economic variables. For example, the use of standard tools, such as the Engle-Granger test, has become more prevalent in empirical research.

The purpose of this section is to review the theoretical foundations of cointegration analysis and to discuss some of the practical challenges associated with its application. We will start by reviewing the basic concepts of cointegration and then proceed to discuss some of the more recent developments in the field.

In the last section, we will illustrate the application of cointegration analysis to a real-world data set. The data set consists of monthly inflation rates for the United States and the United Kingdom. We will use the Engle-Granger two-step procedure to test for cointegration and then estimate the long-run relationship between the two inflation rates. Finally, we will use the estimated cointegrating relationship to construct a forecasting model for the United States inflation rate.