CROSS-MARKET CORRELATIONS AND TRANSMISSION OF INFORMATION

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We investigate characteristics of cross-market correlations using daily data from U.S. stock, bond, money, and currency futures markets using a new multivariate GARCH model that permits direct hypothesis testing on conditional correlations. We find evidence that arrival of information in a market affects subsequent cross-market conditional correlations in the sample period following the stock market crash of 1987, but there is little evidence of such a relationship in the precrash period. In the postcrash period, we also find evidence that the prime rate of interest affects daily correlations between futures returns. Furthermore, we find that conditional correlations between currency futures and other markets decline steeply a few months before the crash and revert to normal dynamics after the crash. © 2002 Wiley Periodicals, Inc. Jrl Fut Mark 22:1059–1082, 2002

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INTRODUCTION

In this article we examine characteristics of cross-market correlations using daily data from four major financial markets in the United States—the stock, bond, money, and currency futures markets—to shed light on how information is transmitted across markets. We develop a new multivariate GARCH model that directly parameterizes the conditional correlation process, thus enabling direct hypothesis tests on its determinants. We examine whether arrival of information in a market affects subsequent conditional correlations (in the Granger-causal sense) between its return and the return from other markets. We also test whether exogenous covariates are significant determinants of cross-market conditional correlations. Finally, we examine the time path of the correlations in the months surrounding the stock market crash of 1987, and check for possible anomalous behavior during that period.

There are a number of reasons for studying cross-market correlations between U.S. financial markets, and especially futures markets. First, cross-market correlations are important because they affect the volatilities of portfolios and, therefore, have implications for asset allocation. Second, cross-market correlations are important for the pricing of derivative securities, especially exotic options, whose payoffs depend on more than one underlying asset price (see Muthuswamy et al., 2001, and additional references therein for details). Third, prices of specific futures contracts capture overall market dynamics very well, so results obtained in this study can be generalized to spot and other related markets. Finally, the links between U.S. futures markets have implications for regulatory policy in futures and spot markets.

There is growing empirical evidence on the contemporaneous relation between international stock return volatilities and cross-market correlation. Bennett and Kelleher (1988) show that higher daily volatility within a month is associated with a larger cross-country correlation. King and Wadhwani (1990) find support for this hypothesis using hourly stock returns from markets in London, New York, and Tokyo from July 1987 to February 1988. King, Sentana and Wadhwani (1994) study 16 national stock markets using monthly data for the period January 1970 through October 1988. They find a positive contemporaneous relation between volatility and correlation. These studies examine contemporaneous relationships, whereas we examine sequential transmission, that is, we examine whether information at time $t - 1$ is transmitted to cross-market conditional correlations at time t.

Longin and Solnik (1995) and Dumas, Harvey and Ruiz (1999) show that variables affecting economic activity including interest rates are significant determinants of monthly cross-market correlations. Both studies test the effects of these covariates indirectly, i.e., the multivariate GARCH models estimated in these studies do not allow direct tests on the determinants of conditional correlations. Campbell (1987) and Glosten, Jagannathan and Runkle (1993) find that nominal interest rates are significant determinants of volatility in a GARCH framework. Our econometric model allows for direct testing of the impact of covariates on conditional volatility and correlation. Although measures of economic activity at a daily frequency are very limited, we consider two interest rate proxies for changes in economic activity—the prime rate, and the commercial paper rate. Moreover, given the well-known weekend and holiday effects, according to which the variance of returns tends to be higher on days following market closures (see, e.g., Hamao et al., 1990; Hsieh, 1989), we examine the effects of these variables on conditional correlations and volatility.

Although there are a number of studies of cross-market linkages among international stock markets and among foreign exchange markets, there is little published work for asset markets in the United States. Fleming, Kirby, and Ostdiek (1998) is a notable exception. Using GMM estimation techniques, they find strong evidence of contemporaneous correlation between volatilities in pairs of markets. Moreover, they find that correlations between volatilities have become stronger since the 1987 stock market crash.

The empirical evidence in studies of international stock markets and currencies suggest that greater volatility is associated with greater correlation. However, there is no a priori theoretical reason to believe this must be true. We present a theoretical framework that dilineates the conditions under which information arrival in a market leads to either an increase or decrease in cross-market correlations. We demonstrate the possibility of sequential transmission of information to conditional correlations, not simply contemporaneous associations between information and correlations. We show that if the information is common and moves prices of both assets in the same direction, then information arrival increases cross-market correlation. If common information moves prices in opposite directions, or if the information is specific to one market, cross-market correlation declines.

For the empirical analysis we develop a new multivariate GARCH model that allows us to test hypotheses on the nature of time-varying correlations. A multivariate GARCH framework is desirable given the evidence of time variation in conditional volatility (see Bollerslev et al., 1992, for a survey), and time variation in the conditional covariances

(Klaassen, 1999; Longin & Solnik, 1995; Muthuswamy et al., 2001). But existing parameterizations of multivariate GARCH models either directly parameterize the conditional covariance, which make testing hypotheses on the conditional correlation inconvenient, or specify constant correlations.

In the next section we present a framework that formally demonstrates the relationship between volatility and correlation. In the Economics Model section we describe the shortcomings of previous multivariate GARCH specifications in greater detail and introduce a multivariate Logistic Exponential GARCH (LEGARCH) model that overcomes the objections. In the Data section we describe the data and present some characteristics of market returns. Empirical results based on the LEGARCH model are presented in the Results section, then we conclude.

VOLATILITY AND CONDITIONAL CORRELATION

King et al. (1994) use intertemporal asset pricing theory to derive the relationship between returns and factors associated with information, thus generating a contemporaneous relationship between cross-market correlations and information. We extend this framework to show how cross-market correlation at time t is affected by information at time $t - 1$. Specifically, we derive the conditions under which correlation at t is positively or negatively related to information at $t - 1$. To demonstrate this, we consider two types of information, common and market-specific.

Consider a model with two common information factors and one market-specific factor. Then returns in market i are determined by

$$r_{it} = \mu_{it} + \beta_{i1} f_{1t} + \beta_{i2} f_{2t} + v_{it} \tag{2.1}$$

where f_{1t} and f_{2t} are common unobservable and stochastically independent factors, β_{i1} and β_{i2} denote the sensitivities of market i's return to the associated factor, and v_{it} is a market-specific unobservable factor. μ_{it} includes other observable factors. Suppose that $\beta_{i1} > 0$ and $\beta_{i2} > 0$. Similarly, let returns in market j be determined by

$$r_{jt} = \mu_{jt} + \beta_{j1} f_{1t} - \beta_{j2} f_{2t} + v_{jt} \tag{2.2}$$

with $\beta_{j1} > 0$ and $\beta_{j2} > 0$. The negative sign before β_{j2} implies that, while the factor f_{1t} increases returns in both markets, f_{2t} increases returns in market i and decreases returns in market j.

Let $V_t(f_{1t}) = \lambda_{1t}$, $V_t(f_{2t}) = \lambda_{2t}$, $V_t(v_{it}) = \omega_{it}$ and $V_t(v_{jt}) = \omega_{jt}$ denote the conditional variances of the common and specific factors (based on information up to t). Furthermore, let

$$\begin{aligned} \lambda_{1t} &= \rho_1 \lambda_{1t-1} + \zeta_{1t} \\ \lambda_{2t} &= \rho_2 \lambda_{2t-1} + \zeta_{2t} \\ \omega_{it} &= \delta_i \omega_{it-1} + u_{it} \\ \omega_{jt} &= \delta_j \omega_{jt-1} + u_{jt} \end{aligned} \tag{2.3}$$

where $0 < \rho_1, \rho_2, \delta_i, \delta_j < 1$ and ζ_{1t}, ζ_{2t}, u_{it} and u_{jt} are independently distributed random variables with zero means.[1] That is, the conditional variances of the common and market-specific factors are positively autocorrelated.[2] Then, conditional on information up to $(t-1)$, the conditional variances of returns are

$$\begin{aligned} V_{t-1}(r_{it}) &= \beta_{i1}^2 \rho_1 \lambda_{1t-1} + \beta_{i2}^2 \rho_2 \lambda_{2t-1} + \delta_i \omega_{it-1} \\ V_{t-1}(r_{jt}) &= \beta_{j1}^2 \rho_1 \lambda_{1t-1} + \beta_{j2}^2 \rho_2 \lambda_{2t-1} + \delta_j \omega_{jt-1} \end{aligned} \tag{2.4}$$

and the conditional correlation between markets i and j is

$$\mathrm{Corr}_{t-1}(r_{it}, r_{jt}) = \frac{\beta_{i1}\beta_{j1}\rho_1\lambda_{1t-1} - \beta_{i2}\beta_{j2}\rho_2\lambda_{2t-1}}{[V_{t-1}(r_{it})V_{t-1}(r_{jt})]^{1/2}} \tag{2.5}$$

Differentiating the conditional correlation equation, one can show that it is an increasing function of λ_{1t-1}, and a decreasing function of λ_{2t-1}, ω_{it-1} and ω_{jt-1}. Hence, an increase in the volatility of the common factor that affects both markets in the same direction will increase the correlation between the markets while an increase in the volatility of the common factor that affects both markets but in opposite directions will decrease the correlation. Furthermore, because the volatility of market-specific factors affects conditional variances but not the conditional covariance, an increase in the volatility of a specific factor will decrease the conditional correlation.

ECONOMETRIC MODELS

The GARCH framework has been successful in modeling second moments of asset prices, in part because its features are consistent with the observed time variation in conditional volatility and conditional

[1]Strictly speaking, ζ_{1t}, ζ_{2t}, u_{it}, u_{jt} should be positive random variables to ensure the positivity of the conditional variance of returns. The assumption of zero means is not substantive; it simply makes the algebraic notation less messy.

[2]This does not necessarily imply that information releases are positively autocorrelated.

covariances. Because existing parameterizations of multivariate GARCH model are inadequate for reasons detailed below, we develop a new GARCH model that allows us to test hypotheses on the nature of time-varying correlations.

In the multivariate GARCH model, the M-element residual vector ε_t is specified as follows:

$$\boldsymbol{\varepsilon}_t \,|\, \Omega_{t-1} \sim D(0, \mathbf{H}_t) \tag{3.1}$$

where $\mathbf{H}_t : (M \times M)$ is the time-varying conditional covariance matrix, and D is some distribution. Several specifications of $\mathbf{H}_t$ have been discussed in the econometric literature. One popular model is the diagonal vech form of Bollerslev, Engle, and Wooldridge (1988), in which the components of $\mathbf{H}_t$ in a GARCH(p,q) process are given by

$$h_{ij,t} = c_{ij} + \sum_{k=1}^{q} a_{ij,k}\varepsilon_{i,t-k}\varepsilon_{j,t-k} + \sum_{k=1}^{p} g_{ij,k}h_{ij,t-k}, \quad i, j = 1, 2, \ldots M, \quad i \neq j \tag{3.2}$$

This form is parsimonious because each element of the covariance matrix is a function of only its past history. This variant does not guarantee positive definiteness of $\mathbf{H}_t$ for all realizations of $\boldsymbol{\varepsilon}_t$. In the Engle and Kroner (1995) generalized positive definite form, the conditional covariance matrix is specified as:

$$\mathbf{H}_t = \mathbf{C}^* + \sum_{k=1}^{K}\sum_{i=1}^{q} \mathbf{A}'_{ik}\varepsilon_{t-i}\varepsilon'_{t-i}\mathbf{A}_{ik} + \sum_{k=1}^{K}\sum_{i=1}^{p} \mathbf{G}'_{ik}\mathbf{H}_{t-i}\mathbf{G}_{ik} \tag{3.3}$$

The choice of K determines the generality of the process. If $K = 1$, one obtains the positive definite GARCH formulation that has been utilized in a number of applications. But neither the diagonal vech nor the positive definite forms are appropriate for our study because neither permits convenient tests on the conditional correlation process. Kroner and Ng (1998) extend this class of models to allow for nonsymmetric effects of volatility on variances and covariances. Although they show the advantages of their specification over (3.2) and (3.3), their model also does not permit direct tests on the properties of conditional correlations.

In factor GARCH models such as described in Ng, Engle, and Rothschild (1992), the asset returns are assumed to be driven by a small set of common factors. Klaassen (1999) develops a model in which the number of factors is equal to the number of assets. Although factor

GARCH models have a number of attractive features including the existence of time-varying conditional correlations, they do not allow direct testing of restrictions on the conditional correlations. In fact, they place a priori restrictions on the conditional correlations.

Braun, Nelson and Sunier (1995) use a bivariate version of the EGARCH model to estimate a CAPM relationship between asset (portfolio) and market returns with a time-varying conditional beta. Because of their specifications of the time-varying conditional beta and conditional variances, their model implies a time-varying conditional correlation. However, their model is inadequate because it is impossible to test specific hypotheses on the correlation without imposing severe restrictions on the variances and/or the conditional beta.

To test hypotheses on the conditional correlation between a pair of assets, it is preferable to specify a GARCH process with a parametric form for the conditional correlation instead of the conditional covariance. The multivariate constant correlation GARCH model (Bollerslev, 1990) is such a specification in which the conditional correlation is a constant.

The Logistic Exponential GARCH Model

We model conditional variances using the Exponential GARCH specification of Nelson (1991). Let $\eta_{i,t} = h_{ii,t}^{-1/2}\varepsilon_{i,t}$ denote the standardized disturbances. Then the conditional variance function of the multivariate LEGARCH(p, q) process is given by

$$\log(h_{ii,t}) = c_{ii} + \sum_{k=1}^{q} a_{ii,k}|\eta_{i,t-k}| + \sum_{k=1}^{p} g_{ii,k}\log(h_{ii,t-k}), \quad i = 1, 2, \ldots, M \tag{3.4}$$

In the EGARCH process, the logarithm of variance is driven by past values of absolute standardized shocks. Nelson (1991) proves that this formulation guarantees stationarity of conditional volatility under general conditions.

The conditional covariance function $h_{ij,t} = \rho_{ij,t}\sqrt{h_{ii,t}h_{jj,t}}$, $i \neq j$ is the product of the conditional correlation $\rho_{ij,t}$ and the relevant conditional standard deviations. Our objective is to specify an appropriate functional form for $\rho_{ij,t}$. Because the conditional correlation must be in $(-1, 1)$ to be properly defined, it is preferable to begin with an index function $\xi_{ij,t} \in (-\infty, \infty)$. Since the index function can take any values on the real line, it may be specified freely without any constraints on the parameters. We specify $\xi_{ij,t}$ as a linear "ARMA" process in past values of the crossproducts of the standardized errors, $\eta_{i,t-k}\eta_{j,t-k}$ and past values of the index function, $\xi_{ij,t-k}$, i.e.,

$$\xi_{ij,t} = c_{ij} + \sum_{k=1}^{q} a_{ij,k}\eta_{i,t-k}\eta_{j,t-k} + \sum_{k=1}^{p} g_{ij,k}\xi_{ij,t-k} \tag{3.5}$$

The crossproduct $\eta_{i,t-k}\eta_{j,t-k}$ is a natural choice for the random variable in the ARMA process because $E_t(\eta_{i,t-k}\eta_{j,t-k}) = \rho_{ij,t-k}$.[3] This follows in the tradition of using lagged squared errors as the random variable in the ARMA process for the GARCH framework where $E_t(\varepsilon_{t-k}^2) = h_{t-k}$.

The conditional correlation $\rho_{ij,t}$ is specified as a logistic transformation of the index function,

$$\rho_{ij,t} = 2\left(\frac{1}{1 + \exp(-\xi_{ij,t})}\right) - 1, \quad i, j = 1, 2, \ldots, M; \quad i \neq j \tag{3.6}$$

The transformation of the conditional correlation to the index function is symmetric and monotonic and implies that $\rho_{ij,t} \in (-1, 1)$ for all values of $\xi_{ij,t} \in (-\infty, \infty)$.[4]

In the bivariate version of this model, the conditional correlation thus specified is globally positive definite. In the general multivariate case $\rho_{ij,t} \in (-1, 1)$ is a necessary but not sufficient condition for positive definiteness. In this case, global positive definiteness cannot be guaranteed, but in-sample positive definiteness can be ensured during estimation.[5]

The vector of errors is assumed to follow a multivariate normal distribution so the conditional log likelihood for each observation is given by

$$l_t(\boldsymbol{\theta}) = -\frac{M}{2}\log(2\pi) - \frac{1}{2}\log|\mathbf{H}_t(\boldsymbol{\theta})| - \frac{1}{2}\varepsilon_t'(\boldsymbol{\theta})\mathbf{H}_t^{-1}(\boldsymbol{\theta})\varepsilon_t(\boldsymbol{\theta}) \tag{3.7}$$

[3]Monotonic transformations of $\eta_{i,t-k}\eta_{j,t-k}$ were considered in preliminary analysis but none dominated the untransformed versions in terms of overall model fit.

[4]Note that, although the logistic function imposes a particular functional relationship between the correlation and underlying index, it is sufficiently flexible so as not to be unduly restrictive. In principle, any other statistical distribution function could be used in place of the logistic to achieve the same transformation.

[5]At each step of the maximization algorithm, positive definiteness is checked by examining the eigenvalues of the conditional covariance matrix. If the covariance matrix is not positive definite, the estimated parameters are not in a valid parameter space. Valid parameters are obtained by imposing appropriate bounds. These are usually achieved by either penalizing the likelihood function when the parameters are in an invalid space, or by reducing the step size in the estimation algorithm when invalid space is encountered.

where $\boldsymbol{\theta}$ is the vector of all parameters. The log likelihood to be maximized is

$$l(\boldsymbol{\theta}) = \sum_{t=1}^{T} l_t(\boldsymbol{\theta}) \tag{3.8}$$

The use of a normal distribution can be justified asymptotically by quasi-maximum likelihood (QML) theory even when the true distribution of errors is skewed, leptokurtic or otherwise non-normal. Under suitable regularity conditions, QML parameter estimates are consistent and asymptotically normal (Gouriéroux et al., 1984). Upon convergence, the estimator of the covariance matrix of $\hat{\boldsymbol{\theta}}$, the QML estimate of $\boldsymbol{\theta}$, is given by

$$V(\hat{\boldsymbol{\theta}}) = \mathcal{H}^{-1}(\hat{\boldsymbol{\theta}})[\mathcal{G}'(\hat{\boldsymbol{\theta}})\mathcal{G}(\hat{\boldsymbol{\theta}})]\mathcal{H}^{-1}(\hat{\boldsymbol{\theta}}) \tag{3.9}$$

where $\mathcal{G}(\hat{\boldsymbol{\theta}})$ is the gradient matrix and $\mathcal{H}(\hat{\boldsymbol{\theta}})$ is the Hessian (Bollerslev and Wooldridge, 1992).

The LEGARCH model is estimated using the Broyden, Fletcher, Goldfarb, and Shanno algorithm with numerical derivatives. Both $\mathcal{G}(\hat{\boldsymbol{\theta}})$ and $\mathcal{H}(\hat{\boldsymbol{\theta}})$ are computed numerically.

Our empirical analysis uses the bivariate form of the model. We study pairs of markets, rather than one system with all four markets, because the conditional correlation process is naturally defined for pairs of markets and to avoid the parameter proliferation inherent in the multivariate system.

Modeling Determinants of Conditional Correlations

Consider a vector z_t of potential determinants of the conditional correlation. These are incorporated into the conditional correlation by augmenting (3.5) to

$$\xi_{ij,t} = c_{ij} + z_t'\beta_{ij} + \sum_{k=1}^{q} a_{ij,k}\eta_{i,t-k}\eta_{j,t-k} + \sum_{k=1}^{p} g_{ij,k}\xi_{ij,t-k} \tag{3.10}$$

Because the covariates z_t are also likely to affect volatility, we augment (3.4) to

$$\log(h_{ii,t}) = c_{ii} + z_t'\beta_{ii} + \sum_{k=1}^{q} a_{ii,k}|\eta_{i,t-k}| + \sum_{k=1}^{p} g_{ii,k}\log(h_{ii,t-k}), \quad i = 1, 2, \ldots, M \tag{3.11}$$

An important objective of this article is to examine whether the arrival of new information in market i ($i = 1, 2, \ldots M$) at time $t - 1$ significantly affects the correlation $\rho_{ij,t}$, between markets i and j ($i, j = 1, 2, \ldots, M$; $i \neq j$) at time t. New information is measured by the squared pricing shock, $\varepsilon^2_{i,t-1}$, in period $t - 1$. The specification of the index function given in equation (3.10) is further extended to

$$\xi_{ij,t} = c_{ij} + z_t'\beta_{ij} + \sum_{k=1}^{q} a_{ij,k}\eta_{i,t-k}\eta_{j,t-k} + \sum_{k=1}^{p} g_{ij,k}\xi_{ij,t-k} + d_i\varepsilon^2_{i,t-1} + d_j\varepsilon^2_{j,t-1} \quad (3.12)$$

in which the correlation between a pair of markets i and j is affected by lagged information arrival in markets i and j. Tests of the null hypothesis of no effect of information arrival on subsequent conditional correlation are tests of the restrictions $d_i = 0$ and $d_j = 0$.

Note that this model does not distinguish between common and market-specific information, i.e., $\varepsilon_{i,t-1}$ and $\varepsilon_{j,t-1}$ each measure aggregate information. Therefore, $d_i \neq 0$ or $d_j \neq 0$ conclusively establishes the existence of a relationship between information at $t - 1$ and correlation at t, but cannot distinguish between common and specific information. However, we cannot rule out the possibility that $d_i = 0$ or $d_j = 0$ simply because common and specific information (as defined in the theoretical framework) have equal and opposite effects on cross-market correlations.

THE DATA

The dataset covers over eleven years (January 3, 1983 through July 31, 1994) of daily closing prices for four futures contracts obtained from the CRB-Bridge InfoTech database. As proxies for the stock, bond, money, and currency markets, we use the S&P 500 futures contract traded on the Chicago Mercantile Exchange (CME), the Treasury bond futures contract traded on the Chicago Board of Trade (CBOT), the 3-month Treasury bill futures contract traded on the International Monetary Market (IMM), and the Deutsche Mark futures contracts traded in U.S. Dollar terms on the IMM, respectively. Each of these futures markets represents the largest in its class, and each was among the futures contracts with the largest trading volume in 1991 and 1992.[6] The S&P 500

[6]In preliminary analysis, we estimated models using some alternative proxies: the NYSE Composite futures contract traded on the New York Financial Exchange, the 10-year Treasury note contract traded on the CBOT and the Swiss Franc contract traded on the IMM. In each case, the correlations of these asset-returns with the related asset is over 0.9 and results based on these variables are qualitatively similar.

futures contract represents the youngest market beginning operations in 1982. The other contracts have been traded since the 1970s.

We define daily returns as logarithmic differences of close prices (multiplied by 100) for the nearest-to-maturity contract. To generate a continuous series of returns, we switch to a new contract when the nearby stock and currency contracts enter their final week. For bond and money markets, we switch to a new contract when the nearby contracts enter the final month. On the day of the switch, returns are computed using the current and previous day prices of the new contract. The full period consists of $T = 2895$ observations.

There is growing evidence that the dynamics of market returns and relationships across asset markets changed substantially following the stock market crash of 1987. Program trading curbs were adopted in the stock market in 1988, index futures volume and open interest declined after the crash (Bessembinder et al., 1996), correlations between volatilities in the stock, bond, and money markets became stronger (Fleming et al., 1998), and the correlations between major U.S. dollar exchange rates declined (Klaassen, 1999). Given this evidence, and the desire to ensure that our results are robust to the highly unusual features of returns during and around the crash, the date of the crash is a natural breakpoint in the data. Therefore, we present results based on separate models estimated using the pre- and postcrash sample periods. We divide the sample into two subperiods, a precrash period from January 3, 1983 through September 30, 1987 ($T = 1194$), and a postcrash period from November 2, 1987 through July 31, 1994 ($T = 1679$), for separate analyses. The ending date of the precrash period and the beginning date of the postcrash period are chosen, following Fleming, et al. (1998), to eliminate the possibility of results appearing simply due to the existence of influential observations surrounding the crash of 1987.

Table I presents summary statistics of the market returns in all three samples. In this, and all subsequent tables, we have highlighted significance at the 10 and 5% levels. However, given the large sample size, it is possible that more complex models may be spuriously favored (Lindley's paradox). Therefore, the reader may wish to consider even higher levels of significance.[7] The average daily return is positive in each market with stock futures showing the largest average return followed by bond futures. Bond and money market volatilities are substantially lower in the postcrash period. Although each market displays evidence of significant excess kurtosis, stock and money markets have substantially higher

[7]We thank the editor for pointing this out to us.

TABLE I
Summary Statistics of Daily Asset Returns

Market	*Mean*	*Var.*	*S*	*K*	$\rho(1)$	$Q(20)$	$Q^2(20)$
Full period: Jan. 3, 1983–Jul. 31, 1994 (T = 2895)							
Stock	0.027	1.502	−6.526	216.496	−0.021	12.895	245.961*
Bond	0.018	0.494	0.007	1.836	0.040	24.292	616.737*
Money	0.003	0.008	1.083	26.152	0.104*	21.616	83.363*
Currency	0.011	0.561	0.156	2.033	0.012	19.386	225.881*
Precrash period: Jan. 3, 1983–Sep. 30, 1987 (T = 1194)							
Stock	0.054	0.907	−0.149	2.101	−0.027	21.805	51.489*
Bond	0.011	0.664	−0.162	0.675	0.037	23.885	210.404*
Money	0.004	0.010	−0.613	5.940	0.076*	21.416	33.486*
Currency	0.005	0.579	0.463	2.428	−0.019	24.622	164.869*
Postcrash period: Nov. 2, 1987–Jul. 31, 1994 (T = 1679)							
Stock	0.022	0.894	−1.031	11.076	−0.057	24.132	113.719*
Bond	0.019	0.345	0.019	1.847	0.015	20.299	71.354*
Money	0.001	0.005	0.249	4.839	0.092*	24.576	261.474*
Currency	0.011	0.546	−0.069	1.746	0.034	18.733	80.082*

Notes. Returns are measured in percents per day.
S is the skewness statistic, K is the excess kurtosis statistic, and $\rho(1)$ is the first-order autocorrelation coefficient. $Q(20)$ is a heteroskedasticity consistent Ljung-Box statistic for autocorrelation up to 20 lags. $Q^2(20)$ is a test for ARCH up to 20 lags. Both statistics are asymptotically distributed as $\chi^2(20)$.
*Indicates that the $\rho(1)$, $Q(20)$, and $Q^2(20)$ statistics are significant at the 5% level.

kurtosis in the postcrash period. The heteroskedasticity consistent tests for serial correlation up to 20 lags show no evidence of serial correlation. The first-order autocorrelation coefficients are small in each case in the pre- and postcrash samples, but the statistic is significant for the money market contract. For consistency with the other data series, we report results based on models with no adjustments for this potential autocorrelation. However, in preliminary analysis we estimated models in which Treasury Bill returns were initially filtered to eliminate the serial correlation. The results reported below are robust to these choices of specification. Finally, there is substantial evidence of ARCH effects in each period for each market.

Changes in the prime rate of interest and the commercial paper rate, holiday and weekend dummies, and a dummy variable for the date of the contract rollover are considered as additional potential determinants of the conditional correlation. The prime rate and the commercial paper rate are highly correlated so we do not consider them simultaneously as covariates in the bivariate GARCH models. Moreover, bivariate GARCH models estimated using the prime rate give qualitatively similar

TABLE II
Summary Statistics of Covariates

Variable	*Mean*	*Std. Dev.*
	Full period: Jan. 3, 1983–Jul. 31, 1994	
Δ Prime rate	−0.016	0.644
Δ Prime rate|change	−0.888	4.771
Holiday	0.026	0.158
Weekend	0.205	0.404
	Precrash: Jan. 3, 1983–Sep. 30, 1987	
Δ Prime rate	−0.023	0.616
Δ Prime rate|change	−1.052	4.118
Holiday	0.026	0.159
Weekend	0.205	0.404
	Postcrash: Nov. 2, 1987–Jul. 31, 1994	
Δ Prime rate	−0.012	0.651
Δ Prime rate|change	−0.901	5.483
Holiday	0.026	0.158
Weekend	0.205	0.404

Notes. Δ Prime rate denotes the daily percentage change in the prime rate. Holiday and weekend are dummy variables that equal 1 if the date follows a holiday and weekend, respectively, and are 0 otherwise.
Δ Prime rate|change denotes the percentage change in the prime rate conditional on a change. The prime rate changed 52 times over the full period. It changed 26 times in the precrash and 24 times in the postcrash periods.

results as models estimated with the commercial paper rate. Therefore, we report only results involving the prime rate of interest for brevity.[8] The dummy variable for the rollover date was not significant in either variance or correlation equations in preliminary analysis. So, they were dropped from the final set of models reported here. Summary statistics for changes in the prime rate of interest, holiday, and weekend dummies are reported in Table II. Note that the prime rate only changed 52 times in the full sample period. Therefore, we have also reported summary statistics conditional on a move.

Table III reports the correlations of cross-market returns in the full and divided samples. The correlations are generally small but statistically significant. Stock–bond and bond–money have the largest correlation coefficients. All the correlations are smaller in the postcrash period than in the precrash period, with substantial changes in the stock–money, currency–stock, and currency–money pairs between the two periods.

[8]Results of models that include the commercial paper rate are available upon request.

TABLE III
Sample Cross-Market Correlations

Markets	*Full Period*	*Precrash*	*Postcrash*
Stock–bond	0.346*	0.431*	0.408*
Stock–money	0.121*	0.291*	0.109*
Bond–money	0.659*	0.705*	0.608*
Currency–stock	−0.036	0.052	−0.057*
Currency–bond	0.047*	0.087*	0.031
Currency–money	0.102*	0.175*	0.083*

Notes. *Indicates that the correlation is significantly different from zero at the 5% level.

RESULTS FROM LEGARCH MODELS

Following much of the literature using daily returns to measure volatility, we simply specify the mean equation as a constant plus error, i.e., $R_t = \mu + \varepsilon_t$. Univariate EGARCH models estimation suggested that the EGARCH(1,1) specification adequately explained the conditional variance process for each market. Although we have no a priori evidence regarding the number of lags in the correlation function, we begin with a LEGARCH(1,1) model for each pair of markets and check for model adequacy post estimation.

Parameter estimates and residual diagnostics of the bivariate model given by equations (3.11)–(3.12) for each period separately are reported in Tables IV and V.[9] We find that serial correlation in the conditional variances and correlations of the residuals are successfully eliminated, as is evident from the values of the $Q(20)$ statistics. In general, most of the ARCH and GARCH parameters are statistically significant. There are some notable differences between the parameter estimates, especially of c_{12} and g_{12}, in the pre- and postcrash sample periods.

The parameters of the variance equations are consistent with the stylized facts of GARCH models, i.e., the ARCH parameters (a_{11}, a_{22}) are small while the GARCH parameters (g_{11}, g_{22}) are large, suggesting a high degree of persistence in the conditional variance. Much like the parameters obtained from estimation of conditional variances, the ARCH parameter (a_{12}) in the conditional correlation equation is positive and small but generally significant. The GARCH parameter (g_{12}) is similarly

[9]Note that because we are estimating bivariate systems of equations, the variance parameters for a particular series in one pair will not be the same as the variance parameters for the same series in another pair, although one would expect them to be similar in a well-specified model. This is indeed what we find.

TABLE IV

Parameter Estimates and Specification Tests of LEGARCH(1,1) Models: Jan. 3, 1983–Sep. 30, 1987

	Stock(1)–Bond(2)			*Stock(1)–Money(2)*			*Bond(1)–Money(2)*		
	h_{11}	ρ_{12}	h_{22}	h_{11}	ρ_{12}	h_{22}	h_{11}	ρ_{12}	h_{22}
Δ Prime$_{t-1}$	−0.016	0.026	0.002	−0.011	0.007	0.035	0.037**	−0.015	0.048
	(0.020)	(0.058)	(0.025)	(0.019)	(0.052)	(0.032)	(0.021)	(0.073)	(0.037)
Holiday	0.223**	0.170	0.403*	0.241*	0.156	0.551*	0.315*	−0.137	0.459*
	(0.126)	(0.263)	(0.159)	(0.126)	(0.271)	(0.178)	(0.108)	(0.342)	(0.158)
Weekend	0.096	−0.035	0.019	0.100	−0.038	−0.090	−0.045	−0.480*	−0.161
	(0.164)	(0.193)	(0.141)	(0.164)	(0.174)	(0.191)	(0.135)	(0.219)	(0.175)
g	0.987*	0.659*	0.975*	0.990*	0.722*	0.989*	0.989*	0.779*	0.984*
	(0.011)	(0.252)	(0.015)	(0.009)	(0.470)	(0.008)	(0.008)	(0.106)	(0.013)
a	0.063*	0.078	0.107*	0.062*	0.011	0.122*	0.086*	0.068	0.129*
	(0.026)	(0.064)	(0.025)	(0.022)	(0.040)	(0.026)	(0.023)	(0.061)	(0.036)
d_1		−0.024			−0.005			−0.108**	
		(0.026)			(0.024)			(0.060)	
d_2		−0.028			0.001			0.047	
		(0.045)			(1.607)			(2.347)	
$Q(20)$	20.037	19.436	28.572**	19.930	12.714	12.644	27.895	23.322	11.493
	Currency(1)–Stock(2)			*Currency(1)–Bond(2)*			*Currency(1)–Money(2)*		
	h_{11}	ρ_{12}	h_{22}	h_{11}	ρ_{12}	h_{22}	h_{11}	ρ_{12}	h_{22}
Δ Prime$_{t-1}$	−0.007	−0.025	−0.014	−0.008	0.002	0.011	−0.002	0.007	0.030
	(0.023)	(0.027)	(0.021)	(0.047)	(0.082)	(0.045)	(0.023)	(0.021)	(0.032)
Holiday	0.367*	0.363*	0.245*	0.333*	0.027	0.371*	0.321*	0.050	0.519*
	(0.132)	(0.176)	(0.141)	(0.138)	(1.399)	(0.142)	(0.133)	(0.158)	(0.177)
Weekend	0.236	−0.388**	0.117	0.244	−0.336	−0.005	0.234	−0.134	0.060
	(0.155)	(0.183)	(0.163)	(0.205)	(0.326)	(0.194)	(0.156)	(0.228)	(0.194)
g	0.984*	0.960*	0.989*	0.985*	0.987*	0.981*	0.985*	0.983*	0.986*
	(0.010)	(0.018)	(0.010)	(0.016)	(0.126)	(0.014)	(0.010)	(0.011)	(0.009)
a	0.151*	0.029*	0.067*	0.142*	0.028	0.101*	0.142*	0.033**	0.122*
	(0.038)	(0.014)	(0.026)	(0.044)	(0.221)	(0.024)	(0.039)	(0.018)	(0.026)
d_1		0.001			−0.001			−0.000	
		(0.010)			(0.006)			(0.005)	
d_2		−0.016*			−0.004			0.001	
		(0.007)			(0.006)			(0.326)	
$Q(20)$	17.526	3.585	19.764	17.267	14.984	28.031	17.488	0.387	14.186

Notes. The model estimated is based on Equations (3.11), (3.6), and (3.12) with the log likelihood formed by Equations (3.7) and (3.8).

The subscripts 1 and 2 refer to the first and second markets in the labeled pair, respectively.

$Q(20)$ denotes the test for autocorrelation up to 20 lags. The statistic is reported for squared standardized residuals and the crossproduct of standardized residuals to test for the adequacy of the GARCH equations for variance and correlation. In each case, the statistic is asymptotically distributed as $\chi^2(20)$.

*Indicates that the statistic is significant at the 5% level.

**Indicates that the statistic is significant at the 10% level.

TABLE V

Parameter Estimates and Specification Tests of LEGARCH(1,1) Models: Nov. 2, 1987–Jul. 31, 1994

	Stock(1)–Bond(2)			*Stock(1)–Money(2)*			*Bond(1)–Money(2)*		
	h_{11}	ρ_{12}	h_{22}	h_{11}	ρ_{12}	h_{22}	h_{11}	ρ_{12}	h_{22}
Δ Prime$_{t-1}$	−0.014	0.049*	0.048*	−0.018	0.125*	0.035	0.049	0.050	0.046
	(0.016)	(0.019)	(0.020)	(0.016)	(0.051)	(0.026)	(0.032)	(0.042)	(0.030)
Holiday	0.136	−0.042	0.247*	0.113	−0.119	0.176	0.299*	0.250	0.178
	(0.121)	(0.120)	(0.117)	(0.128)	(0.207)	(0.145)	(0.139)	(0.173)	(0.206)
Weekend	−0.485*	−0.052	−0.643*	−0.480**	−0.043	−0.646*	−0.645*	−0.282	−0.626*
	(0.241)	(0.199)	(0.146)	(0.256)	(0.161)	(0.204)	(0.140)	(0.273)	(0.242)
g	0.992*	0.974*	0.970*	0.991*	0.765*	0.991*	0.967*	0.970*	0.990*
	(0.004)	(0.010)	(0.012)	(0.005)	(0.061)	(0.004)	(0.015)	(0.014)	(0.011)
a	0.068*	0.012	0.064*	0.077*	0.060	0.070*	0.125*	0.043*	0.077*
	(0.020)	(0.011)	(0.019)	(0.027)	(0.038)	(0.018)	(0.034)	(0.020)	(0.035)
d_1		−0.006**			0.012			0.005	
		(0.003)			(0.009)			(0.016)	
d_2		0.045			−0.375			0.012	
		(0.029)			(3.237)			(0.758)	
$Q(20)$	29.703**	49.421*	16.077	25.101	11.526	13.473	18.767	14.674	13.740

	Currency(1)–Stock(2)			*Currency(1)–Bond(2)*			*Currency(1)–Money(2)*		
	h_{11}	ρ_{12}	h_{22}	h_{11}	ρ_{12}	h_{22}	h_{11}	ρ_{12}	h_{22}
Δ Prime$_{t-1}$	−0.032	0.081	−0.011	−0.030	0.013	0.048*	−0.034	−0.110**	0.050**
	(0.020)	(0.057)	(0.017)	(0.021)	(0.022)	(0.021)	(0.021)	(0.067)	(0.030)
Holiday	0.252**	−0.390	0.134	0.258**	0.172	0.256*	0.267*	0.133	0.186
	(0.133)	(0.269)	(0.129)	(0.134)	(0.110)	(0.120)	(0.134)	(0.150)	(0.164)
Weekend	−0.043	0.124	−0.501**	−0.028	−0.413*	−0.647*	−0.020	−0.432*	−0.565*
	(0.127)	(0.146)	(0.256)	(0.126)	(0.161)	(0.145)	(0.129)	(0.151)	(0.202)
g	0.972*	0.520*	0.990*	0.970*	0.965*	0.968*	0.967*	0.925*	0.990*
	(0.009)	(0.130)	(0.005)	(0.010)	(0.012)	(0.014)	(0.011)	(0.062)	(0.006)
a	0.094*	0.087*	0.079*	0.098*	0.032**	0.069*	0.097*	0.017	0.076*
	(0.020)	(0.028)	(0.029)	(0.022)	(0.018)	(0.024)	(0.022)	(0.023)	(0.026)
d_1		0.103*			0.027*			−0.002	
		(0.051)			(0.011)			(0.017)	
d_2		0.026*			−0.043*			−0.000	
		(0.008)			(0.021)			(1.228)	
$Q(20)$	20.427	3.836	24.608	20.421	17.427	15.988	20.841	16.889	14.045

Note. See notes to Table IV.

large and close to one. Thus, time-varying correlations display a high degree of persistence as well, implying strong similarities between the well known dynamics of conditional variances and those of conditional correlations.

Determinants of Conditional Correlations

We report the analysis of three covariates as additional determinants of conditional correlations. These are dummy variables for holidays and weekends, and the change in the prime rate of interest (measured at $t - 1$). As noted earlier, we also considered the commercial paper rate and a dummy variable for the contract rollover date in preliminary analysis. Models that use the commercial rate deliver very similar results compared to those which use the prime rate. The dummy variable for the contract rollover date was generally not significant. Therefore, both are dropped in the final analysis.

The prime rate is not a statistically significant determinant of the conditional correlation in the precrash period. In the postcrash period, the prime rate is a significant determinant of the stock–bond, stock–money and currency–money correlations. Holiday and weekend dummies are generally not significant in the correlation equations, but the magnitudes of these coefficients are sometimes large. In some cases, the large coefficients have noticeable (but not statistically important) effects in estimated correlations. These are discussed in the following section. There is greater evidence that these covariates, especially the holiday and weekend dummies, affect conditional variances in these markets.

The results displayed in Table IV show that there is little evidence that information shocks significantly affect subsequent conditional correlations in the precrash period. Specifically, there is weak evidence that information arrival in the bond market is transmitted to the correlation between it and the money market, and stronger evidence that information arrival in the stock market is transmitted to its correlation with the currency market. In the cases we do not find evidence of significant transmission, it is possible that the effects of common and market-specific information change correlations in equal and opposite directions. When significant effects are detected, however, these results can be interpreted as demonstrating the preponderance of one type of information over the other.

The results reported in Table V show greater evidence that information is transmitted to conditional correlations via pricing shocks in the postcrash period. Equation (3.12) allows for the possibility of one-way and two-way Granger-causal transmission from pricing shocks in a market to the conditional correlation between it and another market. In a one-way transmission, information in only one of the two markets is influential in determining the subsequent cross-market correlation. Two pairs of markets show evidence of two-way transmission in the postcrash period, while one pair shows evidence of one-way transmission. Pricing shocks or information arrival in the currency and stock markets are most influential in determining subsequent conditional correlations. We also find evidence of both positive and negative relationships, consistent with our theoretical framework.

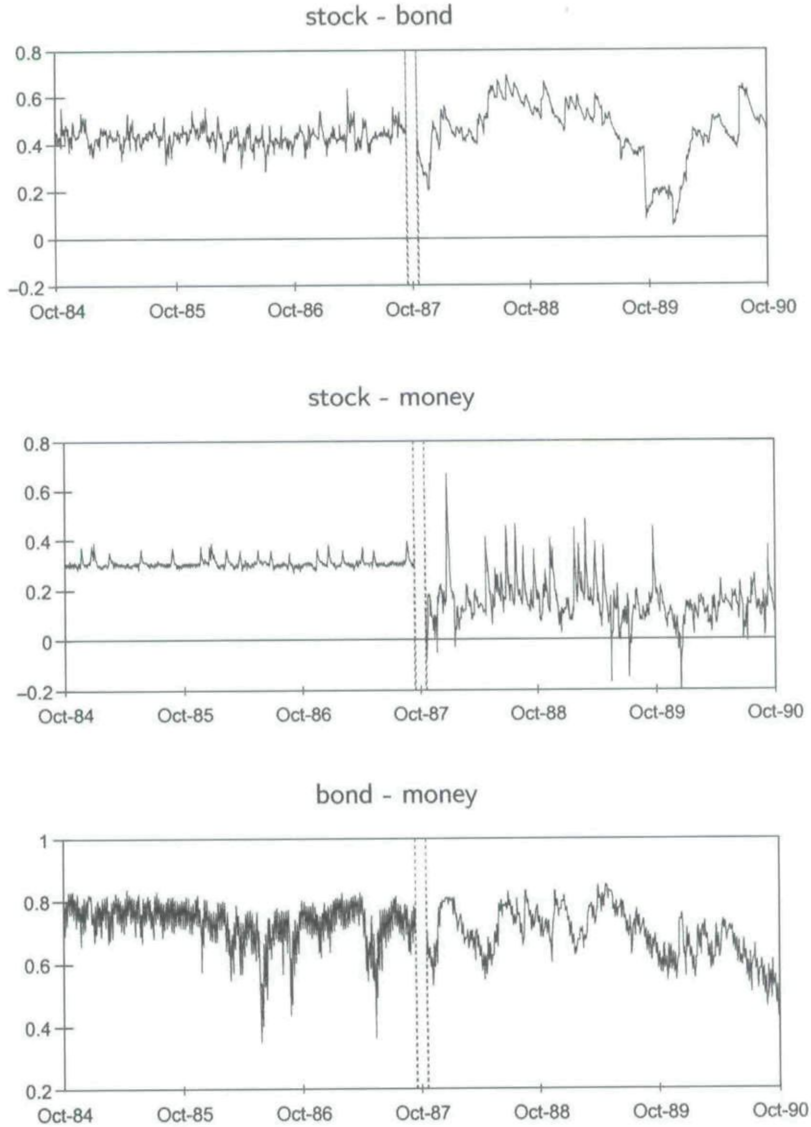
Dynamics of Conditional Correlations

Estimated conditional correlations from the LEGARCH(1,1) model for each pair of markets are displayed in Figure 1. Each figure plots the conditional correlations for the last 3 years in the precrash period and the first 3 years in the postcrash period.[10] The dashed vertical lines demarcate the end of the precrash and beginning of the postcrash sample periods. In almost every case there is considerable short-term variation driven by pricing shocks and changes in values of the covariates, although precisely which matter for a particular pair are difficult to determine from the figures. On closer examination of the estimated correlations, we find that weekend effects are the source of the short term fluctuations most noticeable for bond–money and currency–stock in the precrash period, for currency–money in the postcrash period, and for currency–bond in both periods. The short-term movement represents a sharp drop in the cross-market correlation after each weekend. This is followed by a gradual increase in correlation to "normal" levels as the week progresses. Although the prime rate is significant for three pairs of markets in the postcrash period, the magnitudes of its effect on correlations are not large enough to be separately noticeable.

Perhaps the most dramatic difference between the pre- and postcrash correlations is for the stock–money pair. In the precrash period, the conditional correlation varies very little, while the correlation not only varies more but also has a number of spikes in the postcrash period. We find that two features of the parameter estimates reported in

[10]We chose 3-year windows for visual clarity. Graphs for the entire pre- and postcrash sample periods provide no additional insights.

Tables IV and V are the source of the differences. First, the estimate of d_2 in the postcrash period is much larger compared to its estimate in the precrash period. Unfortunately, the standard error of the estimate in the postcrash period is also very large, so we cannot rule out the possibility that the observed differences in pre- and postcrash correlations are



Note. The dashed vertical lines demarcate the end of the precrash and the beginning of the postcrash periods of data.

FIGURE 1
Estimated conditional correlations.

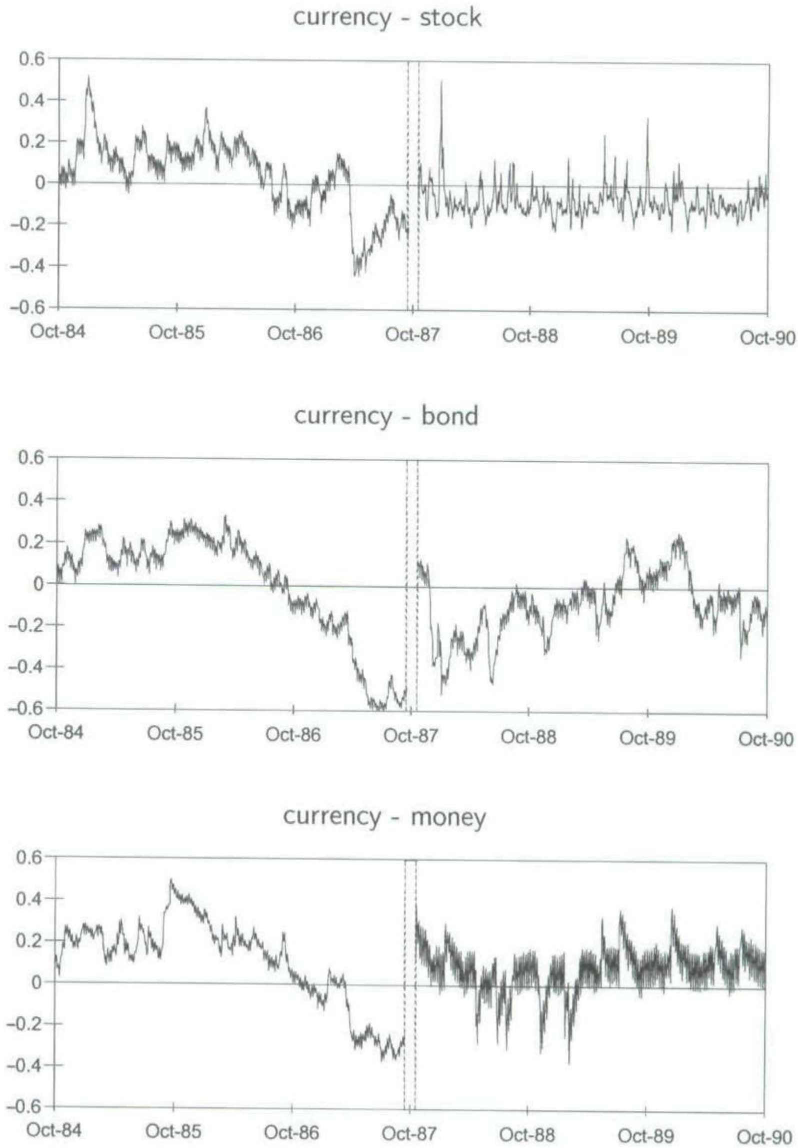


FIGURE 1 (*Continued*)

within estimation error.[11] Second, the ARCH parameter a is much larger in the postcrash period. This also contributes to the observed increased variability of conditional correlation, and is more likely to be indicative of a substantive difference.

In many cases, the cross-market correlations display trends over a few months. Trends are most noticeable in all three markets involving currencies in the precrash period and for the stock–bond, bond–money,

[11]We are thankful to an anonymous referee for pointing this out.

and currency–bond correlations in the postcrash period. These are all associated with GARCH parameters g being close to 1. Note that, as in the standard GARCH variance case, and for linear ARMA models, larger autoregressive parameters are associated with greater persistence of shocks. When the autoregressive parameters are close to 1, the series typically show drifts of the kind associated with unit roots. In these cases, the range of estimated conditional correlations is sufficiently large so that it may be worthwhile for portfolio managers to adjust asset allocations on the basis of changing correlations.[12] In the currency–money, stock–money, and bond–money pairs, structural differences in the dynamics of conditional correlations in the pre- and postcrash sample periods are quite noticeable. These features lend additional support to the claim of a structural change between the two sample periods.

The graphs show that the conditional correlations of the currency–stock and currency–bond and currency–money markets decline rapidly from February 1987 until the latter half of July, 1987. Following the crash, they appear to have reverted quickly back to more "normal" levels, such as those prevalent immediately prior to the steep decline. Because the currency market is involved in each of the pairs of markets that displays such a feature, movements in the foreign exchange market may have caused these deviations from the norm. One can point to a potential impediment to market forces in the currency market in the months before the crash. Between January 1986 and January, 1987, the U.S. dollar had declined by almost 24%. In an attempt to arrest this decline, officials from the G-7 nations forged a deal at a meeting in Paris on February 22, 1987, to support the tumbling U.S. dollar via central bank intervention. Through that year, there was "$100 billion of net official dollar purchases by the monetary authorities of 14 major countries, including the United States" (p. 21, Board of Governors of the Federal Reserve System, 1988). In fact, the steep decline in conditional correlations begins shortly after February 22, 1987. Because exchange rate movements naturally reflect divergences in economic conditions in different countries, attempts to suppress such movements could alter the relationships between it and other financial markets.

The steep decline in correlation, which began in the end of February 1987, ends sometime in the latter half of July, 1987. This feature of an apparent return to normalcy in July or August of 1987 is consistent with the results of Bates (1991). He examines prices of S&P futures options and finds that there was pronounced evidence of downside risk prior to

[12]A formal investigation of this possibility is beyond the scope of this article.

the crash, especially during June–August 1987, implying crash fears. But these fears subsided as the market peaked in August 1987, and the market subsequently displayed no features consistent with downside risk. This feature of the correlation between currency and other markets in early 1987 provides possible evidence of the effects of intervention in a market on its relationships with other markets.

CONCLUSION

In this article we develop a new multivariate GARCH model that directly parameterizes the conditional correlation process, thus enabling direct hypothesis tests on its determinants. Using daily futures prices from four U.S. markets, we examine whether volatility in a market affects subsequent cross-market correlations. We also examine whether exogenous covariates are significant determinants of conditional correlations. Finally, we analyze the time path of the correlations in the months surrounding the stock market crash of 1987 to check for possible anomalous behavior during that period.

There is weak evidence in some markets that shocks to returns affect conditional correlations before the crash. On the other hand, there is considerable evidence of transmission of information to cross-market correlations in the postcrash period. We find evidence of both positive and negative relations. The existence of information transmission to correlations has potential regulatory implications. It suggests that policies directed at influencing behavior in one market may have complex effects on its relation with other markets. Generally, the covariates considered in our study are insignificant determinants of cross-market correlations, but there is evidence that the prime rate of interest is a significant determinant in the postcrash period. Shortly after the G-7 agreement in early 1987 to stabilize the U.S. dollar, the results also show a steep decline in correlations between currency and other markets for a few months. The steep decline in correlations provide evidence of a possible unintended effect of intervention in a market on its relationships with other markets.

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