THE TEMPORAL RELATIONSHIP BETWEEN DERIVATIVES TRADING and SPOT MARKET VOLATILITY IN THE U.K.: EMPIRICAL ANALYSIS AND MONTE CARLO EVIDENCE

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This article examines empirically the dynamic relationship between spot market volatility, futures trading, and options trading in the context of a trivariate simultaneous equations model. The empirical analysis provides strong evidence that significant simultaneity, in addition to feedback, characterizes the relationship between the proxy for time-varying spot market volatility and derivative trading. Also, futures trading and options trading are found to affect spot market volatility in opposite directions in the structural model proposed. The

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results, corroborated by Monte Carlo evidence, suggest that the failure to account for any contemporaneous interaction between the variables under consideration, as well as the omission of any of the two derivatives trading activities examined in this study, may generate serious misspecification and ultimately produce misleading estimation results and statistical inference. Jrl Fut Mark 19: 245–270, 1999

INTRODUCTION

Since their introduction almost three decades ago, the considerable expansion of derivatives-trading activity together with widely advertised derivative-related losses has prompted both public concern and a great flurry of academic research on the impact of derivatives trading on the underlying markets. Concern that derivatives may induce an additional source of risk to individual firms, specific markets, and the overall economy has steered regulators toward increased regulation of derivative markets (see Bessembinder & Seguin, 1992), despite the large empirical literature that suggests—mainly on the basis of U.S. data—that, on balance, derivatives trading has a stabilizing influence on underlying markets:

> "The academic research on the effects of derivatives on market volatility is increasingly consistent in its findings, and particularly voluminous after the 1987 crash. The research strongly indicates that derivatives trading either has no effect on, or reduces, volatility in underlying markets" (The Group of Thirty, 1993, p. 24).

The present study contributes to this literature by reexamining empirically the relationship between derivatives trading activity on the Financial Times Stock Exchange (FTSE) 100 index and the volatility of the underlying cash index in the U.K., pointing out a potential misspecification problem that is common to much of the previous empirical literature. In particular, one simple innovation of this article is that it analyzes the impact of both options *and* futures trading on the underlying asset's volatility within the same model. In fact, whereas the relationship between *either* options *or* futures trading and spot market volatility has been extensively analyzed, the impact of options (futures) trading has never been examined—to the best of the authors' knowledge—*in conjunction with* the impact of futures (options) trading on the underlying asset under investigation. This seems a compelling—albeit generally ignored—issue in the U.K., where futures trading and options were introduced at the same time, in 1984. Given that they are derived from the same underlying asset and are likely to be closely linked by both hedging activities and cross-market arbitrage, any empirical study investigating the impact of either options or futures trading alone on spot market volatility may *potentially* suffer from a misspecification problem. Thus this study is in part motivated by the possibility—not accounted for in the empirical literature to date—that the dissimilarities across options and futures markets may extend to their respective roles in price discovery and to their impact on the volatility of the underlying spot market—also implying that different regulatory actions may be required for different derivative markets.

A further important motivation of the present article stems from the circumstance that, in examining the nature of the relationship between derivatives trading and cash market volatility, researchers have often employed vector autoregression (VAR) analysis where no simultaneity is allowed for in the structural relationship between derivatives trading and volatility, mainly focusing on the identification of the direction of causality between the variables in the VAR. As strongly emphasized in a different but related context by Koch (1993), however, if the variables under examination are structurally related, failure to explicitly account for any contemporaneous interactions between them will result in a misspecified model.

The framework employed in this study is very general, as it uses a trivariate simultaneous equation model (SEM) for spot market volatility, futures trading, and options trading that allows for both the simultaneity and causality characterizing the relationship between the variables in question. The empirical results, corroborated by rigorous Monte Carlo evidence, suggest that both the inclusion of futures trading as well as options trading and the allowance for possible simultaneity in the structural model are crucial in determining the estimation results.

DERIVATIVES TRADING AND VOLATILITY

Research on the relationship between derivatives trading and spot market volatility has been especially abundant since the 1987 stock market crash. From a theoretical standpoint, however, the relevant literature is quite sparse to date.[1] Criticisms of derivative markets are largely based on the argument that derivative trading activity, especially by speculators, destabilizes spot prices and increases price volatility. This may occur, for example, because of uninformed speculators who trade in both derivative and spot markets in search of short-term gains, thus increasing uncertainty and reducing the informational role of prices; alternatively, volatil-

[1]Influential relevant theoretical contributions are due to—*among others*—Copeland (1976), Detemple and Selden (1987), Stein (1987), Grossman (1988), and Ross (1989).

ity may be exacerbated by arbitrage-related activities—such as program trading—which are typically expected to generate large short-term price swings (for example, see the references in Chan & Chung, 1993, and Hogan, Kroner, & Sultan, 1997). Arguments of this type often provide the basis to justify regulatory actions as a means to curb speculative positions.

Conversely, proponents of derivatives argue that speculation in derivative markets may be expected to even out price fluctuations. Also, in general, options and futures markets may stimulate additional trading on the basis of marketwide information, simply because firm-specific information asymmetries are relatively lower in options and futures markets; if this leads to an increase in marketwide informed trading, prices may impound information more efficiently, and volatility in the underlying market may decrease, implying that regulation of derivative markets is unnecessary and maybe harmful.

Thus the previous discussion suggests that, theoretically, the impact of derivatives trading on volatility of the underlying market may be stabilizing or destabilizing depending upon the theoretical framework one assumes. Nevertheless, overall, it is probably true to say that few financial economists would rule out the possibility that the structural dynamic relationship between derivatives trading and spot market volatility may potentially be characterized by both simultaneity and (one- or two-way) causality; the validity of this statement, however, has to be addressed empirically using an appropriate econometric model—to that extent, simultaneity and causality between derivatives trading and volatility remain an empirical matter.

The relevant empirical literature to date has differed in terms of the geographical location of the derivatives analyzed, the type of derivative examined, and the estimation methodology employed.[2] Thus far, the preponderance of the relevant literature is based on U.S. data, whereas the literature pertaining to non-U.S. markets is very sparse. However, different market and institutional structures may—to some significant extent—have an impact on the relationship between derivatives trading and asset price volatility. This is backed up, for example, by the contrasting views expressed by the regulatory authorities in the U.S. and the U.K. with regard to the role of derivatives trading activity in the stock market crash of October 1987. Whereas the U.S. Presidential Task Force Report (1988) pays considerable attention to the importance of stock index futures, the view taken by the Bank of England is simply: "the interaction

[2]See Damodaran and Subrahmanyam (1992) for an excellent survey of this literature, based on U.S. evidence.

of the cash and derivative product markets seems to have played a very limited direct role in the crash in London" (Bank of England, 1988, p. 57).

Nevertheless, the empirical literature on the impact of futures trading activity on the volatility of the underlying market provides quite mixed evidence. For example, Harris (1989) and Damodaran (1990) use stocks in the S&P 500 index and find a significant increase in daily return volatility of these stocks relative to non-S&P 500 stocks since the introduction of futures trading in 1982. Blume, MacKinlay, and Terker (1989) also find that S&P 500 stocks were more volatile than non-S&P 500 stocks during the period of the 1987 crash. Similarly, using U.K. data, Antoniou and Holmes (1995) model volatility as a generalized autoregressive conditional heteroskedasticity (generalized ARCH or GARCH) process and find a significant increase in spot market volatility since the introduction of the FTSE 100 index in 1984.

Conversely, Darrat and Rachman (1995) provide evidence that, after controlling for exogenous factors affecting stock market volatility, futures trading activity is not a particularly significant determinant of volatility in the S&P 500 index. Also, Pericli and Koutmos (1997), using an exponential GARCH model, find that the volatility of the S&P 500 index has decreased after the introduction of futures trading. Using U.K. data, Robinson (1993) provides evidence of a stabilizing effect of futures trading activity on the volatility of the FTSE 100 index, in sharp contrast to the results of Antoniou and Holmes (1995).

Whereas the literature on the effects of futures trading on volatility are mixed, studies focusing on the effects of options trading on volatility are relatively more conclusive. Skinner (1989) and Damodaran and Lim (1991a,b)—among others—are examples of event-studies examining the listing effect of options on U.S. equity variance, and provide evidence that the original listing of options on individual stocks had a stabilizing influence on the volatility of stocks. The literature specifically examining the impact of trading index options on the underlying spot market volatility is, however, virtually nonexistent on U.K. data.

Turning to methodological issues, the relevant empirical literature has generally taken two distinct approaches. The majority of authors (for instance, Damodaran & Lim, 1991a; Simpson & Ireland, 1985; Edwards, 1988; Skinner, 1989) have employed the event-study methodology and measured volatility of the underlying asset both pre- and post-listing of derivative contracts. In general, this literature suggests that volatility has significantly decreased post-listing. These findings are not surprising, however, given that derivatives are much more likely to be listed when the variance of the underlying asset is high (notably, see Testler & Higginbotham, 1977).

More recently, other researchers have undertaken a more direct econometric approach to examine the relationship between derivatives trading activity (usually proxied by trading volume) and volatility of the underlying market. For example, Chan and Chung (1993) use seemingly unrelated regressions to examine the relationship between arbitrage spreads, cash and futures price volatility, and trading volume; nevertheless, Chan and Chung fail to account for possible simultaneous interactions between the variables considered, claiming that it may cause ambiguity in interpreting the estimation results. Also, in an elegantly written article, Chatrath, Ramchander, and Song (1995) use a bivariate VAR with options trading volume and spot price volatility, and execute conventional causality tests, providing evidence that there is strongly significant feedback between the two variables; in particular, an increase in cash market volatility seems to cause an increase in the level of options trading, whereas an increase in options trading is followed by a decrease in spot market volatility. Chatrath, Ramchander and Song interpret their results as evidence that options trading reduces cash market volatility.

As first noted by Koch (1993) and discussed extensively later in this article, however, the econometric strategies employed by Chan and Chung (1993) and Chatrath, Ramchander, and Song (1995, 1996) may suffer from a misspecification problem inasmuch as they do not allow for the plausible possibility that the variables under consideration are determined simultaneously. Whereas it would be arrogant to interpret the estimation results of any model as reflecting the true, unknown structural relationship between the variables examined, it is relatively more rigorous to consider a general structural model that allows for both contemporaneous and lagged relationships; of course, the lack of simultaneity in the dynamic relationship examined would show up in the absence of statistical significance of the contemporaneous variables in the model.[3]

Therefore this article examines the relationship between derivatives trading activity and volatility of the underlying market in the context of a simultaneous equations model; the inclusion of both futures *and* options trading activity in the system allows further investigation of the structural dynamic relationship between the two derivatives trading activities ex-

[3]Note, however, that the claim is not that a SEM is always and unconditionally better than a VAR in estimating structural relationships. For example, even when the objective of the analysis is to obtain a structural equations system, the other equations system may sometimes be useful. In particular, if the exogenous shocks are not observable, the SEM may also yield unreliable inferences about the causal relationship between the variables of interest. Hence the choice between a SEM or a VAR depends upon the particular application (see Chan & Chung, 1995).

amined. In fact, as mentioned above, given that futures and options are derived from the same underlying asset, they are likely to be closely linked by both hedging activities and cross-market arbitrage; in turn, this link may create a trading feedback between the two markets. To the best of the authors' knowledge, however, the structural relationship between options and futures trading volumes has yet to be examined, although the importance of the issue is notable: for example, if futures (options) trading leads options (futures) trading and not vice versa, then it may be the case that information flows are affected in futures (options) markets before options (futures) markets; ultimately implications of this type are very important as they provide significant insights into the microstructure of financial markets.

Overall, the estimation methodology proposed in this study is mainly stimulated by the relevant empirical literature that supports the priors that the effects of options trading on spot price volatility should not necessarily be expected to be the same as the effects of futures trading; trading activities in the two derivatives are likely to be closely linked and hence determined in the same model—and the structural relationship between derivatives trading activity and spot market volatility may potentially be characterized by both feedback and simultaneity.

DATA ISSUES

This study employs daily data on options (put and call) and futures written on the FTSE 100 index, as well as price levels of the underlying cash index. Data on options and futures volume and open interest (the net amount of outstanding positions in a particular futures or options contract at the close of trade) are obtained from the London International Financial Futures and Options Exchange's (LIFFE) Market Data Services price history disks. Daily closing, high and low values of the FTSE 100 index are obtained from FTSE International Limited.[4]

Exchange traded index options and futures were first introduced on the then London Traded Options Market (LTOM) simultaneously on 3 May 1984, shortly after the introduction of the underlying index itself in January 1984. Price histories on these instruments are only available from March 1992, when the London International Futures Exchange merged with the LTOM to create the LIFFE. Therefore the time series span from

[4]Given that the index is computed from midspread prices, the impact of infrequent trading of component stocks is minimized. Also, given that in the U.K. the derivative markets cease trading at 16.10 and the underlying index closes at 16.30, FTSE 100 index levels at 16.10 are used in order to avoid noise induced by nonsynchronous market closure.

1 October 1992 to 29 December 1995. Also, because the purpose of the present analysis is to examine the price-volume relationship in a general context rather than to isolate the nature of the relationship around expiration (see Stoll & Whaley, 1987), the closing volume data used in the empirical analysis includes contracts at all expirations.

A particularly important preliminary problem is concerned with the choice of the proxy for spot market volatility, because, in general, estimation results are known to be highly sensitive to the measure of volatility chosen (notably, see Garcia, Leuthold, & Zapata, 1986; Board and Sutcliffe, 1991). Given that all measures of price volatility are "imperfect" in general because they are proxies, this study considers a number of different commonly used measures of price volatility, although it is argued below that only the estimation results obtained when the volatility proxy used is of ARCH-type should be taken seriously.

Intraday volatility is proxied using the adjusted daily price range (ADPR), which is constructed as follows. A daily price range (DPR) is computed as $(P_t^H - P_t^L)$, where P_t^H and P_t^L denote the high and low values of the FTSE 100 index at time t respectively. Whereas DPR has been used extensively in the literature, the use of the adjusted DPR is preferred in order to account for the possibility of overnight price jumps. In particular, DPR is adjusted if the low price today exceeds yesterday's close when prices are increasing, or if today's high price is less than yesterday's close when prices are decreasing; precisely, if $P_t^L > P_{t-1}^C$, the difference $(P_t^L - P_{t-1}^C)$ is added to DPR_t; if $P_t^H < P_{t-1}^C$, then the difference $(P_t^H - P_{t-1}^C)$ is added to DPR_t; otherwise, DPR_t remains the same.[5]

In order to proxy volatility between days, two interday volatility measures commonly employed in similar studies are used, namely the absolute change in daily closing prices (ACDCP), defined as $|P_t^C - P_{t-1}^C|$, and squared returns (SQRET), calculated as R_2^t, where $R_t = \log(P_t^C/P_{t-1}^C)$ denotes returns.

An alternative and increasingly common way to construct a measure of volatility from a time series of asset prices involves modeling the series as some form of ARCH (Engle, 1982) or GARCH (Bollerslev, 1986) process. Many studies suggest that stock return variances are time-varying in nature, heteroskedastic—notably, see Mandelbrot (1963), Fama (1965), Bollerslev, Chou, and Kroner (1992)—implying that inferences about the impact of derivatives trading on volatility of the underlying market may be misleading if the time-dependent nature of volatility is not explicitly taken into account. In fact, it is well known that significant

[5]See Garcia, Lethold, and Zapata (1986) and Board and Sutcliffe (1991) for a discussion of the rationale behind the definitions of the volatility proxies used here.

ARCH effects characterize market volatility both on U.S. and U.K. data and, in particular, a GARCH process has frequently proved to be very satisfactory in modeling volatility—notably, on U.K. data, see Antoniou and Holmes (1995). As discussed later in this article, a GARCH model is selected as the most adequate measure of spot market volatility in the present application. Specifically, log likelihood ratio tests on a GARCH(p,q) model for $p,q \in \{1,2,\ldots,5\}$ are employed in order to find the most parsimonious GARCH representation of the conditional variance of returns; on the basis of the log likelihood ratio tests, a volatility proxy is constructed using the conditional variance of returns, h_t retrieved from the maximum likelihood estimation of a GARCH (1,1) model of the form:[6]

$$R_t = b_0 + b_1 R_{t-1} + e_1, \; e_t|(e_{t-1}, e_{t-2}, \ldots) \sim N(0,h_t) \tag{1}$$

$$h_t = a_0 + a_1 e_{t-1}^2 + a_2 h_{t-1} \tag{2}$$

where eqs. (1) and (2) denote the conditional mean equation and the conditional variance equation respectively; a_1 and a_2 are nonnegative, and e_t is an error term.[7]

The measure for futures (options) trading activity, denoted FTA (OTA), is the daily closing volume of futures (options), standardized by open interest. More formally, following the common practice adopted by the literature (for instance, Garcia, Leuthold, & Zapata, 1986; Chatrath, Ramchander, & Song, 1995, 1996), FTA_t and OTA_t are constructed as follows:

$$FTA_t = \frac{V(FUT)_t}{OI(FUT)_t} \tag{3}$$

$$OTA_t = \frac{V(OPT)_t}{OI(OPT)_t} \tag{4}$$

[6]This finding is perfectly consistent with the evidence reported by Antoniou and Holmes (1995) for similar U.K. data.

[7]Several tests are conducted to confirm that the conditional variance from the GARCH model is an appropriate volatility measure in the present context. In particular, the test for nonlinear dependencies proposed by McLeod and Li (1983), based on the Box-Pierce statistics of the squared residuals from an ARMA model for returns is employed; the McLeod-Li tests—not reported for the sake of maintaining brevity—provide very strong evidence for nonlinear dependence of an ARCH type. In addition, the ARCH tests reported in Tables II through V provide clear evidence that ARCH is present in the residuals from the SEM unless the volatility measure employed explicitly accounts for ARCH. Also, the estimates of the parameters in (1)–(2) are as follows: $b_0 = 0.0564$ (2.2923), $b_1 = 0.0667$ (23.8566), $a_0 = 0.0193$ (2.2392), $a_1 = 0.0453$ (3.2279), and $a_2 = 0.4586$ (11.9509), where figures in parentheses denote t-ratios.

where V(FUT) and OI(FUT) (V(OPT) and OI(OPT)) denote daily closing volume and open interest for futures (options) respectively.[8]

ECONOMETRIC METHODOLOGY

The dynamic relationship between the FTSE 100 volatility and derivatives trading activity is examined in the framework of a SEM for volatility, futures trading and options trading; formally:

$$\sigma_t = \alpha_1 + \sum_{j=1}^{k_1} \beta_{1j}\sigma_{t-j} + \sum_{j=0}^{k_2} \gamma_{1j}\mathrm{FTA}_{t-j} + \sum_{j=0}^{k_3} \delta_{1j}\mathrm{OTA}_{t-j} + \varepsilon_{1t} \quad (5)$$

$$\mathrm{FTA}_t = \alpha_2 + \sum_{j=0}^{k_1} \beta_{2j}\sigma_{t-j} + \sum_{j=1}^{k_2} \gamma_{2j}\mathrm{FTA}_{t-j} + \sum_{j=0}^{k_3} \delta_{2j}\mathrm{OTA}_{t-j} + \varepsilon_{2t} \quad (6)$$

$$\mathrm{OTA}_t = \alpha_3 + \sum_{j=0}^{k_1} \beta_{3j}\sigma_{t-j} + \sum_{j=0}^{k_2} \gamma_{3j}\mathrm{FTA}_{t-j} + \sum_{j=1}^{k_3} \delta_{3j}\mathrm{OTA}_{t-j} + \varepsilon_{3t} \quad (7)$$

where σ_t denotes the spot market volatility measure employed; β_{hj}, γ_{hj}, and δ_{hj} are parameters, k_h is chosen on standard statistical grounds, and ε_{ht} is a white noise error term ($h = 1, 2, 3$).[9]

The main differences between the SEM (5)–(7) and the models typically considered by the previous literature are worth emphasizing. Most of the previous relevant empirical literature considers a structural VAR with only lagged values of the right-hand-side variables in each equation, which is estimated by ordinary least squares (OLS), and executes Granger (1969) causality tests by testing for zero restrictions on subsets of lagged parameters in each equation of the VAR in order to investigate the lead-lag relationship between the variables in question (for instance, see Chatrath, Ramchander, & Song, 1995, 1996). As it is well known and emphasized in this context by Chan and Chung (1993), however, OLS is likely to produce inefficient estimates if the error terms are significantly contemporaneously correlated across equations. Hence Chan and Chung suggest estimating seemingly unrelated regressions (Zellner, 1962), but fail to account for possible simultaneous interactions between the vari-

[8]This definition of FTA and OTA is intended to avoid the need to eliminate transactions occurring at expiration (see Chatrah, Ramchander, & Song, 1995, 1996).

[9]Identification issues are typically an important concern, preliminary to estimation of a SEM. It is obvious that both the order condition and the rank condition are satisfied in the SEM under consideration. However, in the model there are no variables specified as truly exogenous, and one can only distinguish between endogenous variables and lagged endogenous or predetermined variables (see the discussion of Koch, 1993, in footnote 4).

ables under investigation, claiming that allowing for such simultaneity may cause ambiguity in interpreting the results. In an inspiring note, Koch (1993) comments on this omission as follows:

> "The interpretation of the simultaneous equation model is straightforward; the contemporaneous coefficients reflect the simultaneous interaction among the four variables, whereas the lagged coefficients reflect the lagged responses across variables after accounting for their contemporaneous interaction" (Koch, 1993, p. 1195).

Most tellingly, Koch (1993) illustrates that, if the variables under investigation are structurally related both contemporaneously and across time periods, then estimation of a VAR model that ignores the contemporaneous interactions may produce results that differ very significantly from the estimation results using a SEM comprising of *both* contemporaneous and lagged variables (see Zellner & Palm, 1974).

Use of a SEM, as opposed to a VAR that does not allow for simultaneity, seems especially relevant in the present context because it allows an examination of any causal relationship between volatility and derivatives trading activity in a very general fashion using conventional causality tests, while also capturing any possible simultaneous relationship between the variables. A dynamic SEM requires, of course, the instrumental variables (IV) estimator, which provides consistent estimates.

Assuming for simplicity that $k_1 = k_2 = k_3 = m$, the SEM (5)–(7) may be rewritten in matrix form as:

$$\begin{bmatrix} \sigma_t \\ FTA_t \\ OTA_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \beta_1 & \gamma_1 & \delta_1 \\ \beta_2 & \gamma_2 & \delta_2 \\ \beta_3 & \gamma_3 & \delta_3 \end{bmatrix} \begin{bmatrix} \sigma \\ FTA \\ OTA \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \tag{8}$$

where $\beta_h = [\beta_{h0}\, \beta_{h1} \ldots \beta_{hm}]$, $\gamma_h = [\gamma_{h0}\, \gamma_{h1} \ldots \gamma_{hm}]$, $\delta_h = [\delta_{h0}\, \delta_{h1} \ldots \delta_{hm}]$ for $h = 1,2,3$; $\beta_{10} = \gamma_{20} = \delta_{30} = 0$, whereas $x = [x_t\, x_{t-1} \ldots x_{t-m}]$, for $x = \sigma$, FTA, OTA. Given eq. (8), for example, FTA_t does not Granger cause σ_t if the distribution of σ_t conditional on the past of σ_t, FTA_t and OTA_t is the same as that conditional on the past of σ_t and OTA_t. Let H_G be the null hypothesis tested by the Granger causality test; then, for example, the null hypothesis that futures trading activity does not Granger cause volatility can be expressed formally as:

$$H_G\!: \gamma_{11}FTA_{t-1} = \gamma_{12}FTA_{t-2} = \ldots = \gamma_{1m}FTA_{t-m} = 0 \tag{9}$$

that is, under H_G past values of futures trading activity do not have any explanatory power on current volatility. Thus, the test for Granger causality—or, more precisely, noncausality—is based on the F-statistic obtained by estimating eq. (5) in both the constrained (reduced) and the unconstrained (full) form:[10]

$$F = \frac{(RSS_{RF(5)} - RSS_{FF(5)})/m}{RSS_{FF(5)}/(T - 2m - 1)} \tag{10}$$

where $RSS_{RF(5)}$ and $RSS_{FF(5)}$ denote the residual sum of squares (RSS) from the estimated reduced form (RF) and full form (FF) of eq. (5) respectively; T is the number of observations. F follows the χ^2 distribution with degrees of freedom equal to the number of restrictions (m), and corresponds to a Wald test statistic (see Geweke, Meese, & Dent, 1983). The empirical analysis employs this type of causality test, while also providing some Monte Carlo evidence on its performance under various circumstances.

Nevertheless, as discussed by—among others—Davidson and MacKinnon (1993, p. 686), the results of Granger causality tests depend critically on the assumption that all relevant variables are included in the VAR. If a relevant variable is omitted from the VAR considered by the researcher, for example, one may incorrectly conclude that a variable W Granger causes another variable Z, when in fact W has no effect on Z independent of its effect through the omitted variable. This is particularly important in the present context as the previous empirical literature has typically considered bivariate VARs for only one of the two derivatives considered here, where Granger causality tests are likely to give misleading results if, in fact, futures trading, options trading and volatility are determined in the same structural model.

Overall, therefore, whereas it is not possible to claim that the SEM is the true model of determination of the endogenous variables examined, the SEM proposed in this article is likely to provide relatively more reliable Granger causality tests because, if *both* FTA and OTA are found to have explanatory power in each equation of the SEM, all previous studies reporting Granger causality tests from bivariate VARs that only comprised a volatility measure and *either* FTA *or* OTA may potentially be misleading because it is based on a misspecified model.

EMPIRICAL RESULTS

Table I provides some summary statistics of the time series used in the empirical analysis. Interestingly, both the first and the second moment of

[10]Strictly speaking, the tests performed in the empirical analysis below after the estimation of the SEM (5)–(7) are tests of the hypothesis that lagged movements in one series provide statistically significant power for predicting subsequent movements in another series, given the explanatory power of other series in the same regression. Hence, although this is not identical to the original definition of Granger causality, it is very similar and therefore such a term is used in the empirical analysis discussed below.

TABLE I

Summary Statistics (Sample Period: 1 January 1992–29 December 1995)

			Partial Autocorrelation Function (LAGS 1 to 5)					
Series	*Mean*	S.D.	LAG 1	LAG 2	LAG 3	LAG 4	LAG 5	ADF
ADPR	13.861	15.436	0.082	0.074	−0.019	−0.004	0.024	−11.651
ACHDCP	17.515	14.036	−0.025	0.092	0.083	0.032	0.055	−9.781
SQRET	5.290	9.374	0.081	0.077	0.035	0.014	0.016	−11.924
GARCH	0.056	0.031	0.500	0.119	0.059	0.033	0.015	−4.994
FTA	0.227	0.092	0.571	0.173	0.125	0.024	0.081	−7.478
OTA	0.054	0.023	0.289	0.082	0.093	0.001	0.089	−8.442

Notes: Series are denoted as in the text, s.d. denotes the standard deviation of the series considered. The standard deviation for the partial autocorrelation can be approximated by the square root of the reciprocal of the number of observations, T = 821, and is about 0.0349. ADF denotes the augmented Dickey-Fuller test statistic for nonstationarity, with the number of lags chosen such that the residuals are approximately white noise (critical values are given in MacKinnon, 1991).

FTA are considerably larger than the corresponding moments of OTA, suggesting that trading activity in futures is larger on average and more volatile than trading activity in options. The partial autocorrelation functions reported in Table I also suggest that derivatives trading activity is very strongly serially correlated even at relatively high lags, whereas volatility measures tend to be slightly less autocorrelated. In particular, the partial autocorrelation coefficients are found to be statistically significant at the 5% nominal level of significance for up to five lags on FTA and OTA, up to three lags for ACDCP, and up to two lags for ADPR, SQRET, and GARCH. Nevertheless, in estimating the SEMs, given the relatively large number of observations, the authors feel the liberty of employing a symmetric lag structure with five lags for each of the series.[11] Also, the results from executing augmented Dickey-Fuller test statistics for nonstationarity strongly suggest that all of the series in question are realizations of stationary processes.

Tables II through V report the results from the three-stage-least-squares (3SLS) estimation of the SEM (5)–(7), where volatility (σ) is proxied by ADPR, ACDCP, SQRET and GARCH respectively.[12] For each

[11]Particular care was taken in selecting the appropriate lag length of the SEM (5)–(7), given that SEM estimation is known to be quite sensitive to the lag length chosen. Therefore, in addition to investigating the partial autocorrelation functions of the series, the choice of the lag length is also based on the Akaike information criterion, the Schwartz information criterion and the method proposed by Campbell and Perron (1991) generalized to a trivariate system comprising eqs. (5)–(7). A lag structure of five is in fact confirmed—as one may perhaps expect using daily data—by each of the information criteria. Moreover, most of the results presented below are qualitatively unchanged when estimation is executed using an asymmetric lag structure that allows for lower serial correlation in the volatility proxy (full details are available from the authors upon request).

[12]3SLS estimates jointly all parameters in the SEM. More precisely, the first two stages of 3SLS are

TABLE II

Panel A: SEM Estimation Results (Volatility Measure is ADPR)

	Time	σ	*FTA*	*OTA*
Eq. (5)	t		1.418[c]	−2.233
	t-1	0.099[c]	−0.736[c]	1.492[c]
	t-2	0.109[c]	−0.107	0.782[b]
	t-3	−0.010	−0.274[c]	0.369
	t-4	0.027	−0.168[a]	0.745[b]
	t-5	0.013	−0.074	0.546[a]
	R^2 = 0.322	DW = 1.992	LB = 0.578	ARCH = 0.000
Eq. (6)	t	0.269[c]		1.250[c]
	t-1	−0.036[b]	0.489[c]	−0.918[c]
	t-2	−0.050[c]	0.136[c]	−0.544[c]
	t-3	−0.004	0.134[c]	−0.113
	t-4	−0.024	0.061	−0.254[a]
	t-5	−0.000	0.051	−0.148
	R^2 = 0.374	DW = 1.997	LB = 0.839	ARCH = 0.004
Eq. (7)	t	−0.034	0.145[c]	
	t-1	0.007	−0.052[a]	0.288[c]
	t-2	0.001	−0.020	0.093[b]
	t-3	0.002	−0.025[a]	0.084[b]
	t-4	−0.007	−0.032[c]	0.098[b]
	t-5	−0.000	−0.010	−0.076[b]
	R^2 = 0.238	DW = 2.008	LB = 0.837	ARCH = 0.032

Panel B: P-values of Granger causality tests

	σ	*FTA*	*OTA*
Eq. (5)	P = 0.005	P = 0.003	P = 0.004
Eq. (6)	P = 0.004	P = 0.000	P = 0.000
Eq. (7)	P = 0.416	P = 0.051	P = 0.000

Notes: Estimation of the SEM is by three-stage-least-squares. Columns 3, 4 and 5 of Panel A report the estimated coefficients on σ, FTA and OTA respectively ([a], [b] and [c] denote significance at the 10%, 5% and 1% level respectively); R^2 is the coefficient of determination; DW is the Durbin-Watson statistic; LB and ARCH denote the Ljung-Box statistic for serial correlation and the ARCH statistic (Engle, 1982) up to fifth order respectively; for LB and ARCH, which are both distributed as $\chi^2(5)$, only the p-values are reported.

estimated SEM, the coefficient of determination, the Durbin-Watson statistic, the Ljung-Box test statistic for residual serial correlation, and the

those of two stage least squares (2SLS), applied separately to each equation of the system, whereas the third stage is essentially the same as the final stage of feasible generalized least squares estimation of a seemingly unrelated regressions system (see Zellner & Theil, 1962). Identification of the SEM is achieved without any assumption on the variance-covariance matrix, which is estimated from the equation-by-equation 2SLS residuals. Also note that all of the SEMs examined below are also estimated by the authors using the obvious alternative estimator to 3SLS in this context, namely the full information maximum likelihood (FIML) estimator. The results employing the FIML estimator are, however, qualitatively identical to the results from 3SLS estimation, which is not surprising given that 3SLS and FIML estimation are asymptotically equivalent (Hausman, 1975)—both of them being asymptotically efficient—and given the relatively large number of observations used in the present application.

TABLE III

Panel A: SEM Estimation Results (Volatility Measure is ACDCP)

	Time	σ	*FTA*	*OTA*
Eq. (5)	t		0.939[c]	−1.351
	t-1	0.001	−0.424[c]	0.487
	t-2	0.072[b]	−0.018	0.175
	t-3	0.009	−0.062	0.445[a]
	t-4	0.050	−0.012	0.370
	t-5	0.057	0.038	0.092
	R^2 = 0.246	DW = 2.012	LB = 0.287	ARCH = 0.000
Eq. (6)	t	0.235[c]		−2.053[c]
	t-1	−0.024	0.461[c]	−0.909[c]
	t-2	−0.012	0.131[c]	−0.510[c]
	t-3	0.020	0.087[b]	−0.239[a]
	t-4	−0.003	0.047	−0.226[a]
	t-5	−0.029	0.042	−0.069
	R^2 = 0.486	DW = 1.996	LB = 0.983	ARCH = 0.002
Eq. (7)	t	−0.033	−0.211[c]	
	t-1	0.009	−0.085[c]	0.295[c]
	t-2	−0.001	−0.027[a]	0.129[c]
	t-3	−0.012[b]	−0.019	0.102[c]
	t-4	−0.003	−0.024[b]	0.084[b]
	t-5	−0.000	−0.008	0.057
	R^2 = 0.166	DW = 2.004	LB = 0.759	ARCH = 0.027

Panel B: P-values of Granger causality tests

	σ	*FTA*	*OTA*
Eq. (5)	P = 0.133	P = 0.118	P = 0.464
Eq. (6)	P = 0.275	P = 0.000	P = 0.000
Eq. (7)	P = 0.232	P = 0.002	P = 0.000

Notes: See notes to Table II.

ARCH (Engle, 1982) test statistic are reported for each individual equation of the system.

The results obtained using the three measures of volatility that do not account for ARCH (Tables II through IV) show two overriding patterns. First, simultaneous interactions between the variables appear to be important, as confirmed in Panel A of Tables II through IV by the statistically significant coefficients on FTA_t in each equation, and on σ_t and OTA_t in eq. (6).[13] Second, turning to Panel B, the results from executing Granger causality tests show unambiguously that significant feedback exists between options and futures trading activities, presumably as a result of hedging and cross-market arbitrage between the two markets.

[13]This result is not surprising given that daily data is used; unfortunately, however, intraday data on futures and options trading volume are not available from LIFFE.

TABLE IV

Panel A: SEM Estimation Results (Volatility Measure is SQRET)

	Time	σ	*FTA*	*OTA*
Eq. (5)	t		0.004[c]	−0.004
	t-1	−0.018	0.002[b]	0.001
	t-2	0.051	0.003	0.001
	t-3	0.017	−0.001	0.002
	t-4	0.062[a]	−0.002	0.002
	t-5	0.016	−0.001	0.003
	R^2 = 0.411	DW = 2.007	LB = 0.547	ARCH = 0.012
Eq. (6)	t	3.822[b]		−2.053[c]
	t-1	−0.509	0.455[c]	−0.888[c]
	t-2	0.002	0.130[c]	−0.557[c]
	t-3	0.294	0.100[b]	−0.227[a]
	t-4	−0.252	0.050	−0.247[a]
	t-5	−0.056	0.036	−0.122
	R^2 = 0.494	DW = 1.994	LB = 0.472	ARCH = 0.036
Eq. (7)	t	−0.302	−0.186[c]	
	t-1	−0.216[b]	−0.075[c]	0.276[c]
	t-2	−0.109	−0.023[a]	0.131[c]
	t-3	−0.226[b]	−0.019	0.095[b]
	t-4	−0.009	−0.023[b]	0.084[b]
	t-5	−0.174[a]	−0.004	0.077[b]
	R^2 = 0.236	DW = 2.010	LB = 0.598	ARCH = 0.039

Panel B: P-values of Granger Causality Tests

	σ	*FTA*	*OTA*
equation (5)	$P = 0.400$	$P = 0.309$	$P = 0.522$
equation (6)	$P = 0.619$	$P = 0.000$	$P = 0.000$
equation (7)	$P = 0.026$	$P = 0.006$	$P = 0.000$

Notes: See notes to Table II.

Note, however, that whereas residual serial correlation is never significant at conventional nominal levels, the ARCH test statistics suggest that ARCH is *always* present in the residuals from the estimated SEMs unless the time-varying nature of volatility is explicitly accounted for using a GARCH(1,1) model, implying that the assumption of constant variance underlying non-ARCH-type proxies is far too simplistic. These diagnostics confirm, therefore, the priors and earlier empirical findings that spot market volatility is time-varying in nature and displays ARCH; hence only the results in Table V, where volatility is modeled as a GARCH(1,1) process, are considered as statistically reliable and consistent with both the priors and empirical evidence.

Nevertheless, interestingly but not surprisingly, consistent with Garcia, Leuthold, and Zapata (1986) and Board and Sutcliffe (1991), the causal relationships between σ, FTA, and OTA appear to be very sensitive

TABLE V

Panel A: SEM Estimation Results (Volatility Measure is GARCH)

	Time	σ	FTA	OTA
Eq. (5)	t		0.599[c]	−2.306[c]
	t-1	0.514[c]	0.342[c]	−0.441[c]
	t-2	0.175[c]	0.053[b]	−0.462[c]
	t-3	−0.034	0.062[b]	−0.197[b]
	t-4	0.110[a]	0.069[c]	−0.230[c]
	t-5	0.046	0.013	−0.190[b]
	R^2 = 0.679	DW = 2.007	LB = 0.937	ARCH = 0.672
Eq. (6)	t	1.005[c]		−2.772[c]
	t-1	0.542[c]	0.537[c]	−0.797[c]
	t-2	0.185[a]	0.122[c]	−0.699[c]
	t-3	−0.039	0.101[b]	−0.219
	t-4	0.068	0.084[b]	−0.269[b]
	t-5	0.062	0.040	−0.187
	R^2 = 0.613	DW = 2.001	LB = 0.382	ARCH = 0.483
Eq. (7)	t	−0.399[c]	−0.229[c]	
	t-1	−0.208[c]	−0.132[c]	0.187[c]
	t-2	−0.073[b]	−0.020	0.184[c]
	t-3	0.017	−0.024[a]	0.086[b]
	t-4	−0.052	−0.029[b]	0.098[b]
	t-5	−0.018	−0.004	0.084[b]
	R^2 = 0.505	DW = 2.009	LB = 0.598	ARCH = 0.795

Panel B: P-values of Granger Causality Tests

	σ	FTA	OTA
Eq. (5)	P = 0.000	P = 0.000	P = 0.000
Eq. (6)	P = 0.003	P = 0.000	P = 0.000
Eq. (7)	P = 0.000	P = 0.000	P = 0.000

Notes: See notes to Table II.

to the measure of volatility employed. For example, when proxying volatility by either ACDCP or SQRET, no evidence is found of causality between FTA and σ, but when using ADPR there is evidence of feedback. Similarly, there is evidence of unidirectional causality from OTA to σ when volatility is proxied by ADPR—but the direction switches when SQRET is used to measure spot market volatility.

Relatively superior results (reported in Table V) are obtained from the estimation of the SEM (5)–(7) using a GARCH(1,1) model to proxy spot market volatility. As shown in Panel A, the strongly significant estimated contemporaneous coefficients in each equation of the system may be regarded as convincing evidence that *all* the three variables in question are simultaneously determined. Also, the contemporaneous coefficients are generally quite large in magnitude, suggesting that market forces operate rapidly to make the three variables considered interact significantly within a daily interval.

The results from executing Granger causality tests, reported in Panel B, also indicate that significant feedback exists between *all* of the variables examined. Closer examination of the estimated coefficients on lagged values of OTA in eq. (5) suggest that greater options trading on previous days reduces volatility; this is in direct contrast to the significantly positive estimated coefficients on lagged values of FTA in eq. (5) that suggest that increased futures trading generates greater spot market volatility.[14] Also, increases in volatility tend to be followed by increases in futures trading and by decreases in options trading.

Overall, the empirical results provide strong evidence that both feedback and simultaneity characterize the dynamic relationship between derivatives trading activity and volatility of the underlying market, and may also be interpreted as evidence of liquid markets wherein response to information flows is virtually simultaneous within the interval considered.[15] Consequently, the finding of strongly significant simultaneity has important implications for both market participants and regulators.

MONTE CARLO RESULTS

This section provides evidence on the effects of (i) not accounting for possible simultaneity in the relationship between derivatives trading and spot market volatility as well as (ii) the effects of omitting one of the two derivatives trading activities examined in this study on the performance of Granger causality tests. In particular, the focus is on the Wald variant of the Granger causality test described earlier in this article, which is known to be more reliable than the Lagrange multiplier variant (see Geweke, Meese, & Dent, 1983) and is the most commonly used causality test in this literature. Following the aforementioned discussion, the main concern involves the possibility that Granger causality tests may over-reject the null of noncausality, H_G, if a relevant variable is omitted from the estimated model (Davidson & MacKinnon, 1993, p. 686).

Whereas the performance of Granger causality tests in the context of bivariate error-correction models and cointegrated VARs is receiving

[14]These results are consistent with the findings of Chatrath, Ramchander, & Song (1995, 1996) who find, albeit in different underlying markets, that options and futures trading may have opposite effects on underlying markets volatility.

[15]The authors remain agnostic, however, about the precise mechanics producing the opposite sign of the lead-lag relationship between volatility (on the one hand) and the two derivatives trading activities (on the other hand) and consider it as an immediate future avenue for theoretical research in this field.

increasing attention by the econometric literature[16] perhaps the most influential evidence on the performance of Granger causality tests in covariance-stationary VARs is still limited to the study of Geweke, Meese, & Dent (1983). The main findings of Geweke, Meese, & Dent (1983, p. 184–185) for the purposes of this study are that the Wald variant of the Granger causality test rejects the null hypothesis very reliably in the context of stationary and Gaussian time series, although it has a tendency to be 'too large' with its rejection frequency greater than asymptotic distribution theory would lead one to expect. The evidence reported in this section is consistent with the findings of Geweke, Meese, and Dent and also suggests that misspefication due to omission of a relevant variable in the model significantly exacerbates the tendency of the Wald test of causality to be too large.

Thus these issues are investigated by executing a number of Monte Carlo experiments, based on an artificial data generating process (DGP) that is in fact the SEM (5)–(7). In particular, the DGP is calibrated on the basis of the results from estimating the SEM (5)–(7) using a GARCH(1,1) model to proxy spot market volatility, as reported in Table V; the symmetric 3×3 variance-covariance matrix of the true DGP is set equal to the corresponding estimated matrix obtaining between the volatility proxy, futures trading activity and options trading activity. Hence the true DGP allows for both simultaneity and causality between the three variables considered. Samples of 921 observations are generated and the first 100 are discarded, thus yielding samples of exactly the same size as the actual data set; given that the simulated model is stationary, this should reduce the dependence of the results on the initialization. All Monte Carlo results discussed in this section are constructed using 5,000 replications in each experiment, and with identical random numbers across experiments.[17]

First, the percentage of rejections of the null of noncausality HG is calculated when the estimated model is a VAR that does not allow for simultaneity, that is, $\beta_{h0} = \gamma_{h0} = \delta_{h0} = 0$ for h = 1,2,3 in the SEM (5)–(7). The authors consider the possibility of a bivariate VAR comprising volatility and futures trading activity (VAR 1), a bivariate VAR comprising volatility and options trading activity (VAR 2), and a trivariate VAR that includes volatility and both derivatives trading activities considered here (VAR 3). Hence all VARs considered are misspecified in that they do not allow for simultaneity, but VAR 1 and VAR 2 also omit a relevant variable.

[16]For instance, see Luktepohl and Reimers (1992), Toda and Phillips (1993), Toda and Yamamoto (1995), Dolado and Luktepol (1996), Zapata and Rambaldi (1997).
[17]In this section the 5% nominal level of significance is considered, unless otherwise specified.

TABLE VI

Monte Carlo Results: Performance of Granger Causality Tests in Bivariate and Trivariate VARs with No simultaneity

	Eq.	H_G (*for* $j = 1, 2, \ldots, 5$)	π
VAR 1	5	$\beta_{1j} = 0$	100.00
	5	$\gamma_{1j} = 0$	95.65
	6	$\beta_{2j} = 0$	100.00
	6	$\gamma_{2j} = 0$	100.00
VAR 2	5	$\beta_{1j} = 0$	100.00
	5	$\delta_{1j} = 0$	95.40
	7	$\beta_{2j} = 0$	100.00
	7	$\delta_{2j} = 0$	100.00
VAR 3	5	$\beta_{1j} = 0$	100.00
	5	$\gamma_{1j} = 0$	50.75
	5	$\delta_{1j} = 0$	65.80
	6	$\beta_{2j} = 0$	100.00
	6	$\gamma_{2j} = 0$	100.00
	6	$\delta_{2j} = 0$	95.75
	7	$\beta_{3j} = 0$	100.00
	7	$\gamma_{3j} = 0$	66.80
	7	$\delta_{3j} = 0$	100.00

Notes: The true data generating process is the SEM (5)–(7), calibrated on the estimation results reported in Table V as described in text; all results are obtained using 5,000 replications. The percentage of rejections (π) of the null hypothesis of noncausality H_G, tested using a Wald test statistic, are calculated considering the 5% nominal level of significance, and are based on estimated VAR models which do not allow for simultaneity—that is, $\beta_{h0} = \gamma_{h0} = \delta_{h0} = 0$ for $h = 1, 2, 3$ in (5)–(7). Precisely, VAR 1 (VAR 2) is bivariate and comprises artificial volatility and artificial futures (options) trading activity with a symmetric lag length, $m = 5$; VAR 3 is trivariate and comprises artificial time series for volatility, futures trading activity and options trading activity.

The results, reported in Table VI, indicate very clearly that, whereas Granger causality tests reject the null very reliably, in the bivariate VARs the omission of a derivative trading activity variable induces a much larger percentage of rejections relative to the trivariate VAR 3. Also, this effect appears to be particularly strong in the volatility equation, eq. (5), where the percentage of rejections equals 50.75% and 65.80% for futures trading activity and options trading activity respectively in VAR 2, whereas it is equal to 95.65 for futures trading activity in VAR 1 and to 95.40 for options trading activity in VAR 3.[18]

Thus the same experiments are repeated estimating three types of SEMs; namely: bivariate SEMs including volatility and futures trading activity (SEM 1) or options trading activity (SEM 2), in addition to SEM 3 that is identical to the model given by eqs. (5)–(7) and hence to the true DGP. The results of the simulations, reported in Table VII, suggest

[18]Note that estimation of the VAR using ordinary-least-squares rather than instrumental variables does not seem to affect the results significantly in these simulations.

that, if the true DGP is the SEM (5)–(7), the power of the Wald test increases significantly when using a SEM relative to a VAR that does not allow for simultaneous interactions between the variables. In addition, the tendency to over-reject in misspecified bivariate models that omit one of the two derivatives trading activity examined remains also using a SEM, although the difference between the percentage of rejections for SEMs 1–2 and SEM 3 is not very significant because in all cases the power of the test is very high, as one would expect when executing these tests on stationary time series and with over 800 data points (Geweke, Meese, & Dent, 1983).[19] Table VII reports the percentage of rejections of the null hypothesis that each of the contemporaneous variables is not statistically significantly different from zero using a t-ratio; for each SEM examined, the simulation results suggest that the t-ratio rejects the false null hypothesis very reliably.[20]

Overall, the evidence reported in this section suggests that, if the true model characterizing the relationship between futures and options trading and spot market volatility is a trivariate SEM, failure to account for simultaneity reduces the power of Granger causality tests; however, misspecification due to the omission of one of the two derivatives trading activities considered tends to bias the Wald test upward, leading to over-rejection of the null of noncausality. These results clearly indicate that the performance of causality tests is significantly dependent upon the assumption that all relevant variables have been included in the structural VAR. Therefore, given the impossibility of knowing with certainty the true structural relationship between the variables examined, it may generally be more rigorous to consider a general structural model that allows for both contemporaneous and lagged relationships and then execute deletion tests on the contemporaneous variables in addition to causality tests on the subsets of the lagged variables.[21] Finally, the simulations also suggest that, in a correctly specified model (SEM 3), Granger causality tests

[19]A further interesting set of experiments executed involves arbitrarily imposing unidirectional causality in the true DGP and evaluating the performance of the causality tests in the case when the null of noncausality is true; whereas in the correctly specified model (SEM 3), the percentage of rejections is found to be close to the 5% nominal level of significance, in misspecified models that omit one of the two derivatives trading activities the causality tests reject in a much large number of cases (up to 50%) than expected. In other words, one may easily find bidirectional causality as an effect of misspecification, if in the true model causality is unidirectional.

[20]The authors also execute some simulations assuming that the true DGP is a VAR allowing for feedback but not for simultaneity between the three variables examined, and estimate SEMs 1, 2, and 3; the results suggest that the percentange of rejections of the t-ratio is very close to the nominal level of significance, indicating therefore that statistically significant simultaneity is not found by chance.

[21]The authors also estimate trivariate VAR models with no simultaneity between the three endogenous variables corresponding to the SEMs estimated and discussed earlier in this article. Interest-

TABLE VII

Monte Carlo Results: Performance of Granger Causality Tests and *t*-tests in Bivariate and Trivariate SEMs

	Eq.	H_G	*t*-tests on	π
SEM 1	5	$\beta_{1j} = 0$	—	100.00
	5	$\gamma_{1j} = 0$	—	100.00
	5	—	$\gamma_{10} = 0$	100.00
	6	$\beta_{2j} = 0$	—	100.00
	6	$\gamma_{2j} = 0$	—	100.00
	6	—	$\beta_{20} = 0$	100.00
SEM 2	5	$\beta_{1j} = 0$	—	100.00
	5	$\delta_{1j} = 0$	—	100.00
	5	—	$\delta_{10} = 0$	100.00
	7	$\beta_{2j} = 0$	—	100.00
	7	$\delta_{2j} = 0$	—	100.00
	7	—	$\beta_{20} = 0$	100.00
SEM 3	5	$\beta_{1j} = 0$	—	100.00
	5	$\gamma_{1j} = 0$	—	100.00
	5	$\delta_{1j} = 0$	—	98.95
	5	—	$\gamma_{10} = 0$	100.00
	5	—	$\delta_{10} = 0$	99.00
	6	$\beta_{2j} = 0$	—	100.00
	6	$\gamma_{2j} = 0$	—	100.00
	6	$\delta_{2j} = 0$	—	100.00
	6	—	$\beta_{20} = 0$	100.00
	6	—	$\delta_{20} = 0$	100.00
	7	$\beta_{3j} = 0$	—	89.65
	7	$\gamma_{3j} = 0$	—	100.00
	7	$\delta_{3j} = 0$	—	100.00
	7	—	$\beta_{30} = 0$	99.10
	7	—	$\gamma_{30} = 0$	100.00

Notes: See notes to Table VI; the Granger causality tests and the *t*-tests are based on the following estimated SEMs: SEM 1 (SEM 2) is bivariate and comprises artificial volatility and artificial futures (options) trading activity with a symmetric lag length, m = 5; SEM 3 is trivariate and comprises artificial time series for volatility, futures trading activity and options trading activity.

ingly, the results from executing Granger causality test statistics often lead to nonrejection of the null hypothesis of noncausality. In particular, the volatility proxy is found not to Granger cause FTA for any of the proxies considered—hence also in the case of the most appropriate proxy, GARCH. Estimation of bivariate VAR models with volatility and either FTA or OTA indicates, however, always bidirectional causality. In addition, the authors estimate VAR models with dummies for days of the week without allowing for simultaneity between the endogenous variables—but the estimation results and the outcome of the Granger causality tests are unchanged, therefore suggesting that seasonal dummies do not appear to be a substitute for simultaneity. Overall, therefore, estimation of these VAR models—misspecified for the omission of the simultaneity between the variables in question and, in the case of bivariate models, also for the omission of a relevant variable—provides results (not reported to conserve space but available from the authors upon request) that are consistent with the findings suggested by the Monte Carlo simulations.

are very powerful, with percentage of rejections comparable to those found by Geweke, Meese, & Dent (1983).[22]

CONCLUSIONS

This article reexamines empirically the dynamic relationship between derivatives trading activity and spot market volatility using daily data for the U.K. The results of the empirical analysis provide strong evidence that spot market volatility is time-varying and well characterized by a GARCH process; futures trading, options trading, and volatility of the underlying asset are determined in a system of equations that allows for both simultaneity and feedback, as one would expect if speculation, hedging and cross-market arbitrage operate efficiently.

These findings imply that much of the previous empirical literature investigating the lead-lag relationship between derivatives trading and spot market volatility in the context of structural VARs that omit any of the two derivatives trading activities examined in this study or fail to account for simultaneous interactions between the variables should be interpreted with caution because they are based on misspecified models. In fact, the Monte Carlo evidence presented in this article suggests that, if the true structural model is a simultaneous equations model, failure to account for simultaneity reduces the power of Granger causality tests, whereas omission of a relevant variable in the model tends to bias causality tests toward rejection of the null of noncausality, overall generating potentially misleading results.

Finally, although the empirical results may be regarded as quite satisfactory, the core of the article remains methodological; it is hoped that further insights may be gained by experimenting with alternative nonlinear processes for modeling spot market volatility in the simultaneous equations model that has been proposed, and perhaps considering nonparametric methods requiring less restrictive assumptions relative to the present estimation methodology; more importantly, it would be interesting to replicate this study on the basis of higher-frequency data, unfortunately not available for the U.K. to date.

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