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ON THE ROLE OF FUTURES TRADING IN SPOT MARKET FLUCTUATIONS: PERPETRATOR OF VOLATILITY OR VICTIM OF REGRET?

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Abstract

We examine the role of index futures trading in spot market volatility. We use the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) approach to measure volatility, analyze causality and feedback relations between volatilities in the spot and futures markets, and test various hypotheses in the context of a multivariate model that incorporates other macrostate variables. Our empirical results suggest index futures trading may not be blamed for the observed volatility in the spot market. Rather, we find stronger and more consistent support for the alternative posture that volatility in the futures market is an outgrowth of a turbulent cash market. We use the regret (cognitive dissonance) theory to explain our results.

JEL Classifications: G13, G18

I. Introduction

The introduction of stock index futures in April 1982 has significantly altered the risk management schemes of institutional investors. These investors frequently use various index futures-based strategies such as index arbitrage, portfolio

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insurance, and tactical asset-allocation programs that affect the price-adjustment dynamics between index futures and the underlying spot index. It is sometimes argued that the execution of these strategies increases volatility in the spot price of the underlying index.

Whether futures trading affects stock market volatility has received considerable attention in recent years, particularly following the stock market crash of 1987 and the mini-crash of 1989 (e.g., Kawaller, Koch, and Koch 1990). Derivative securities, in general, and index futures and options, in particular, have been blamed for excess volatility in the spot market. The underlying belief is that derivatives encourage speculation and futures destabilize the spot market. The detrimental economic and financial consequences of perceived increased market volatility have prompted many analysts and policy makers to call for limiting futures activities, and some proposals have recommended the abolition of these markets.

Our study strengthens the evidence that futures market volatility does not induce cash market volatility. In fact, we find evidence that the volatile cash market is partly responsible for volatility in the futures market. In the words of some researchers in the field (Gordon, Moriarty, and Tosini 1987; Herbst and Maberly 1987), our empirical results imply that "the dogs wag the tails," not the other way around.

Herbst and Maberly (1987) point out that some index-constituent stocks may react to news with longer delays than others, resulting in slower price formation of the index, whereas the single index futures price is immediately determined by the underlying demand and supply. Herbst, McCormack, and West (1987) attribute this difference in the speed of adjustment to the composition and trading mechanism of the two markets. The spot index itself is not a traded asset, but its component securities are. The effect of information on the spot index reflects the sum of the changes in each of hundreds of (slow and fast moving) component securities. This broad base of the spot index tends to slow down its reaction to information. A futures index, on the other hand, attempts to reach an equilibrium value on each trade much more quickly. Furthermore, specialists on the New York Stock Exchange and the American Stock Exchange may be able to stabilize cash price movements and therefore slow down the news-adjustment process of index prices. Futures exchanges, however, have no specialists, and prices there react to news with minimal delay. Focusing on these response differentials to explain price relations across the two markets requires the use of intraday price data. We, however, take another path and offer new behavioral insights to explain why the dog may wag the tail. We use monthly rather than intraday data so that our inferences will unlikely be distorted by time differentials in the markets' reaction to economic news.

There is little agreement among researchers as to the effect futures contracts have on the underlying spot market. Despite the public outcry concerning increased volatility in stock prices allegedly due to the introduction of derivatives, the empirical evidence regarding this issue is far from conclusive. Many researchers report results supporting the common perception that futures trading has provoked volatility in the spot market, perhaps through encouraging excessive, and largely irrational, speculative activities. For example, Antoniou and Holmes (1995) report that volatility in the cash market increased after the introduction of futures trading. They argue that the apparent volatility increase is the result of futures trading expanding the channels through which information flows into the market. Herbst and Maberly (1992) suggest that one of the main functions of futures market is to act as a conduit for transmitting economic news to uninformed investors. Maberly, Allen, and Gilbert (1989) present evidence showing that volatility in the cash market has either increased, decreased, or remained relatively unchanged since the introduction of index futures, depending on the choice of pre- and post-futures periods in the analysis.

Several other studies categorically deny any increase in spot market volatility resulting from the introduction of index futures trading. They conclude futures activities attract more informed traders to the cash market, making it more liquid and, if anything, less volatile (Pericli and Koutmos 1997).

Some researchers focus on the Granger causal relation between the spot and futures markets. In particular, Herbst, McCormack, and West (1987) examine the lead-lag relation between the S&P 500 futures, Value Line futures, and their respective spot indexes. They find that index futures prices tend to lead the underlying indexes for the Value Line and S&P 500. Results reported by Kawaller, Koch, and Koch (1987) suggest that futures price movements consistently lead index movements by about forty-five minutes, whereas movements in the index rarely affect futures beyond one minute. Finnerty and Park (1987) investigate the relation between changes in Major Market Index futures prices and subsequent changes in the Major Market Index. Their results indicate the presence of a significant link between futures prices and subsequent index prices. Gordon, Moriarty, and Tosini (1987) and Herbst and Maberly (1987) point out that the significant correlation reported by Finnerty and Park (1987) does not necessarily imply causality. In particular, Gordon, Moriarty, and Tosini argue that the observed correlation could instead be the outcome of bidirectional rather than unidirectional causality.

Our study adds to the existing literature in three ways. First, most previous studies focus on relations between returns of cash prices and their futures counterparts. Yet, a more direct issue involves the causal linkage between the volatilities of these returns. We examine volatility using a class of stochastic processes known as exponential generalized autoregressive conditional heteroskedasticity (EGARCH). This approach seems econometrically superior to several alternative methods for measuring volatility in asset returns. Moreover, this volatility measure avoids the potential biases associated with different reporting and recording procedures of futures and cash price data. Second, as Gordon, Moriarty, and Tosini (1987) and Herbst and Maberly (1987) warn, significant correlations reported in the literature are insufficient grounds for establishing the direction of causality between volatilities in the two markets. Consequently, we focus on causality and feedback relations between volatilities in cash and futures markets.

Finally, futures prices adjust to information more quickly than do cash prices (Herbst and Maberly 1987). Hence, findings of futures prices leading (or lagging) cash prices in bivariate models (like those in Finnerty and Park 1987) could be due to the failure to control for fundamental economic news. In their examination of the Japanese experience, Chang, Cheng, and Pinegar (1999) report that temporal relations between the spot and futures markets can be seriously distorted if other relevant factors are ignored in the process. Thus, excessive volatility in the cash market may be erroneously attributed to futures trading when the culprit is, for example, a volatile economic environment. To overcome this potential problem, we go beyond the simple bivariate model and examine the implications of futures trading for cash market volatility in the context of a multivariate system that incorporates the potential effects of several other economic variables. As we discuss afterward, the finance literature suggests several macrostate variables are important forces behind fluctuations in asset prices.

II. Data and Related Issues

Our sample is monthly and spans November 1987 through November 1997 (121 monthly observations). We compile month-end daily closing prices and compute returns as natural logarithms of monthly price relatives. Recent evidence in Pericli and Koutmos (1997) shows that the pre- and post-1987 stock market crash periods are different in terms of the basic stochastic properties of U.S. stock returns. To avoid contaminating the empirical results with significant structural breaks, we confine our attention to the post-crash period. There are several reasons for using monthly observations. First, monthly data may mitigate possible distortionary effects from nontrading, nonsynchronous trading, and the bid-ask spread bias associated with daily or weekly stock return data.

A second reason for using monthly price observations regards the reporting structure of futures and cash data. As Herbst and Maberly (1987) point out, the time lapse between an actual trade and the recorded time of the trade is minimal for index futures, but considerably longer for the spot index.[1] These different time patterns can distort causality results between futures and cash indexes in studies that relate current changes in intraday spot index to preceding intraday changes in index futures (e.g., Finnerty and Park 1987). This bias, however, should be trivial in our case because we derive causality results from prices measured in months rather than in minutes. Moreover, with intraday data, it is difficult to distinguish between

[1] We are indebted to Anthony F. Herbst for alerting us to this important data issue.

Herbst, McCormack, and West's (1987) interpretation based on different speeds of adjustment to market information and our interpretation based on investors' quasi-rational, regret-aversion behavior. Such a distinction is possible in the context of monthly data. We separately estimate the EGARCH measures of volatility in the spot and futures markets using their respective monthly returns. EGARCH is a weighted moving average of past volatility and return regression residuals. The averaging process of EGARCH further dampens the effect of reporting and recording time differences in monthly data. Last, we use monthly (rather than daily) observations because necessary data on most macrostate variables are available only monthly.

We obtain data on S&P 500 index spot prices from the Center for Research in Security Prices (CRSP) database of the University of Chicago and obtain the S&P 500 index futures prices from Futures Industry Institute. The futures contract of the most immediate maturity is generally the most heavily traded until the beginning of the delivery month, when market interest shifts over to the contract with the next most immediate maturity. Thus, our price data are for the most immediate contract, except during the delivery month, when the next most immediate contract is used. Moreover, by eliminating price observations for the most immediate contract in the delivery month, the effect of any abnormal price variability that may occur during the delivery month is removed.

According to the present value model, fluctuations in asset prices are largely attributable to movements in underlying fundamental values (expected future cash flows and discount rates). Research also reveals that many macrostate variables (e.g., real economic activity, inflation, and policy actions) affect market fundamentals and hence asset prices (Darrat and Brocato 1994). Volatile asset prices reflect changing market expectations about future economic fundamentals. Therefore, we incorporate the volatility of several macrostate variables to avoid possible misspecification. In particular, we include the volatilities of the following variables: the inflation rate, the industrial production index, the term structure of interest rates (measured by the difference between the ten-year government bond rate and the three-month T-bill rate), risk premium (as measured by the difference between the yield on ten-year government bonds and the yield on Baa-rated corporate bonds), monetary base (representing monetary policy), and the cyclically adjusted federal budget deficit (representing fiscal policy).[2] Monthly data on these macrostate variables come from the Basic Economics Database of the Quantitative Micro Software (S&P/DRI).

[2]Cyclically adjusted, in contrast to actual, federal budget deficits better account for business cycles and can thus more genuinely reflect fiscal policy moves. However, monthly data on cyclically adjusted deficits are unavailable, and we follow the procedure outlined in Darrat and Brocato (1994) to extract the necessary data from the corresponding actual figures.

TABLE 1. Descriptive Summary Statistics of S&P 500 Index Spot and Futures Returns Monthly Data: November 1987–November 1997.

	Spot Returns			Futures Returns		
	Full Period	First-Half Subperiod	Second-Half Subperiod	Full Period	First-Half Subperiod	Second-Half Subperiod
Mean	0.479	0.383	0.576	0.468	0.363	0.576
Std. dev.	1.562	1.769	1.327	1.576	1.800	1.316
Max.	4.594	4.594	3.268	4.622	4.622	3.131
Min.	−4.302	−4.302	−2.570	−4.819	−4.819	−2.574
Skewness	−0.323	−0.215	−0.398	−0.541**	−0.483	−0.444
Kurtosis	0.491	0.441	−0.192	1.063**	1.014	−0.198
Augmented Dickey-Fuller	−6.668**	−5.072**	−3.996**	−6.715**	−4.999**	−3.953**
Weighted symmetric	−6.794**	−5.229**	−4.171**	−6.817**	−5.174**	−4.129**
Ljung-Box-Q (12)	8.035	5.865	13.170	7.537	5.084	14.900

Note: The figures for the mean, standard deviation, maximum, and minimum are all in percentages. The full period is split at midpoint to create two equally sized subperiods.

**Significant at the 5% level.

Table 1 reports some statistical properties of the S&P 500 index and futures returns. We measure index and futures returns by the logarithmic first differences of the corresponding end-of-month prices. As the table shows, the means and standard deviations of both spot and futures market returns show considerable variation over time. Returns in both markets have similar means (of about 0.50% per month) and similar standard deviations (of about 1.50% per month). However, the nature of their distributions is dissimilar, as reflected in markedly different degrees of skewness and kurtosis. According to the augmented Dickey-Fuller (ADF) and weighted symmetric (WS) tests, returns of both spot and futures indexes are stationary in levels. Only futures returns possess significant skewness, implying a "fat-tail" distribution. Both the spot and futures returns pass the Ljung-Box autocorrelation test that may be taken as initial evidence of market efficiency in at least the weak sense. The general instability and asymmetry of the distributions of the two markets' returns suggest that models that account for conditional variances should measure their volatilities.

III. Measuring Volatility Using the EGARCH Approach

A typical behavioral characteristic of asset returns is volatility clustering where one period of high volatility is followed by more of the same and then successive periods of low volatility (Bollerslev 1986). Given this common characteristic, the literature shows a growing interest in GARCH-based models that parameterize time-varying conditional variances and covariances of stochastic processes.

The EGARCH approach is superior to the more common GARCH method for several reasons. Compared with a GARCH approach, the EGARCH does not impose nonnegativity constraints on the parameters of the conditional variance. Thus, EGARCH is a more general process that encompasses the random oscillatory behavior of asset return volatility. Unlike GARCH, the EGARCH model also explicitly accounts for asymmetry in asset return volatility, thereby avoiding possible misspecification in the volatility process. In addition, the EGARCH model allows for a general probability density function (i.e., generalized error distribution, GED), which nests the common normal distribution along with several other possible densities.

EGARCH expresses the conditional variance of a given variable as a nonlinear function of its own past values and the past values of standardized innovations. That is,

$$R_t = \sum_{i=1}^{k} \alpha_i R_{t-i} + \sum_{j=1}^{12} \eta_j D_{jt} + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \exp\left\{ \sum_{j=1}^{12} \delta_j D_{jt} + \sum_{i=1}^{p} \phi_i \ln\left(\sigma_{t-i}^2\right) \right.$$
$$\left. + \sum_{i-1}^{q} \varphi_{\mathrm{i}} \left[\gamma \left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - E\left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right) \right) + \theta \left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right) \right] \right\}, \tag{2}$$

where R_t denotes asset returns, D_{jt} are dummy variables to allow for different monthly mean returns and variances, and ε_t are the innovations distributed as a GED with zero mean and conditional variance (σ_t^2). The coefficients α, η, δ, ϕ, φ, γ, and θ are the estimated parameters. Equation (1) represents dynamic changes in the first moment (mean) of returns, and equation (2) describes time variation in the conditional second moments (variance). We estimate equations (1) and (2) jointly and take the predicted values of σ^2 from equation (2) as our measure of conditional variance (volatility). The EGARCH method allows the conditional variance to respond asymmetrically to positive and negative changes in stock returns. The term

$$\left[\gamma \left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - E\left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right) \right) \right]$$

represents the size effect, whereas

$$\left[\theta \left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right) \right]$$

represents the sign effect.

Estimating this model requires the adoption of some density function for the error vector (ε_t), and the most commonly used density function is the normal variant. However, the normal density function may not be appropriate here for it fails to reflect the "fat-tail" that is a common feature of stock return distributions. We employ the GED to accommodate the fat-tail and peakedness in stock returns.

To ensure flexibility, we allow for up to twelve autoregressive monthly lags ($n = 12$) in the mean equation (1). We determine the number of lagged variance terms (p) and the number of squared residuals (q) in equation (2) using several criteria. In particular, the chosen specification must be free from any significant autocorrelation in the residuals. Squared standardized residuals should also be unpredictable on the basis of observed variables.[3] Results (available on request) suggest no significant misspecification in the estimated models for the spot and futures returns. Our modeling efforts produce an EGARCH model that, according to the criteria just discussed, appears to be adequate for measuring volatility in spot and futures returns.

IV. Empirical Results

We use the EGARCH approach to measure both the volatility of spot returns and the volatility of futures returns. To avoid biases of bivariate models, we use a multivariate framework that includes the volatilities of six other macrostate variables.[4] We adopt a similar method to estimate these six additional volatilities as well, extracting the volatilities from their respective stationary processes.

Our objective is to investigate the direction of Granger causality (lead-lag relation) between volatilities in the spot and futures markets in the context of a multivariate model. As typically perceived, volatilities across the two markets are indeed related. The estimate of the correlation coefficient between the EGARCH-based volatilities of the spot and futures markets is 0.26, which is statistically significant at better than the 5% level ($t = 2.76$). Yet, significant correlations between the volatilities of the two market returns are insufficient to establish whether futures trading incites volatility in the spot market, or vice versa. Causality is better examined by testing the following two-equation system:

$$\mathrm{VSR}_t = \beta_0 + \beta_1^{n1}(L)\mathrm{VSR}_t + \beta_2^{n2}(L)\mathrm{VFR}_t + \beta_3^{n3}(L)\mathrm{VZ}_t + \mu_t, \tag{3}$$

$$\mathrm{VFR}_t = \Psi_0 + \Psi_1^{m1}(L)\mathrm{VFR}_t + \Psi_2^{m2}(L)\mathrm{VSR}_t, + \Psi_3^{m3}(L)\mathrm{VZ}_t + \varepsilon_t \tag{4}$$

[3]We use four sign and size bias tests. These are (a) the sign bias t-test, (b) the negative size bias t-test, (c) the positive size bias t-test, and (d) the joint F-test for the previous three effects.

[4]Pericli and Koutmos (1997) also use the EGARCH approach to examine the role of futures trading in stock market volatility. However, their results are based on restrictive bivariate models and ignore reverse causality from the spot to futures markets.

where VSR indicates the volatility of spot returns, VFR indicates the volatility of futures returns, VZ is a vector of six other macrostate variables (representing the volatilities of inflation, industrial production, the term structure, the risk premium, base money, and cyclically adjusted budget deficits), L is the lag operator, β_i and Ψ_i are distributed polynomials in L, the n's and m's are the lag lengths for the various explanatory variables, and μ and ε are Gaussian error terms.

Three comments are in order. First, before estimating the model, we should check the stationarity of the volatility variables. The presence of nonstationarity (or unit roots) in one or more variables may result in spurious regressions and incorrect statistical inferences. We use the ADF and the WS tests to examine the stationarity properties of the eight volatility variables in the model. The results suggest all eight volatility variables are stationary in levels, and as such, all cannot be cointegrated. Hence, there is no reliable equilibrium relation binding the volatility of these eight variables together in the long run. We may thus infer that the various volatilities can only be related in the short run, a possibility that we investigate using the two-equation system.

An important step relates to determining the lag structure of each variable in the two-equation model (i.e., lengths of n_i and m_i). Given the sensitivity of distributed-lag models to the lags used, we search within twelve monthly lags for the proper lag profile using Akaike's final prediction error (FPE) in conjunction with the specific-gravity criterion. Equations (3) and (4) may be estimated individually by ordinary least squares (OLS). However, when the error terms across the two equations are correlated, statistical efficiency may be enhanced by pooling the two equations together and estimating them as a system by Zellner's seemingly unrelated regression (SUR) method.

To test the direction of Granger causality between volatilities in the spot and futures returns, we calculate the likelihood ratio (LR) statistics derived from SUR system estimations.[5] Table 2, Panel A, displays these LR test results for the spot market (equation (3)), and Panel B displays the results for the futures market (equation (4)). The results unambiguously suggest, contrary to the common perception, that activities in the futures market are not responsible for increased volatility in the spot market. More specifically, the null hypothesis that VFR does not Granger-cause VSR cannot be rejected even at the 10% level of significance (see test 5 in Panel A).

The results reject (at better than the 5% level) the alternative hypothesis that volatility in spot returns does not propagate volatility in futures returns (see test 3 in Panel B). This novel finding implies that the futures market is itself a victim of

[5]To conserve space, details of the coefficient estimates and related summary statistics are not reported here but they are available on request. The estimated equations show a good fit and pass a battery of statistical tests indicating no evidence of significant autocorrelation, heteroskedasticity, or structural instability.

TABLE 2. Likelihood Ratio Tests (SUR System Estimations).

Null Hypotheses	LR Statistics	d.f.
Panel A. Dependent Variable: Volatility of Spot Returns (VSR)		
Volatility of industrial production does not Granger-cause VSR	17.20**	6
Volatility of budget deficit does not Granger-cause VSR	1.36	1
Volatility of the risk premium does not Granger-cause VSR	66.01**	12
Volatility of money growth does not Granger-cause VSR	3.82	2
Volatility of futures returns does not Granger-cause VSR	12.94	11
Volatility of the term structure does not Granger-cause VSR	5.66*	2
Volatility of inflation does not Granger cause VSR	1.03	1
Panel B. Dependent Variable: Volatility of Futures Returns (VFR)		
Volatility of industrial production does not Granger-cause VFR	32.93**	6
Volatility of inflation does not Granger-cause VFR	8.70**	2
Volatility of spot returns does not Granger-cause VFR	21.80**	12
Volatility of budget deficit does not Granger-cause VFR	8.83**	2
Volatility of the term structure does not Granger-cause VFR	3.36	2
Volatility of the risk premium does not Granger-cause VFR	0.001	1
Volatility of money growth does not Granger-cause VFR	13.25	9

Notes: Degrees of freedoms (d.f.) correspond to the number of lags selected by final prediction error. The variables are ranked for inclusion in the two equations according to the specific-gravity criterion.

**Significant at the 5% level.
*Significant at the 10% level.

an erratic stock market. As we discuss later, cognitive dissonance (or regret) theory may provide a rationale for this finding. In their attempt to avoid the feeling of regret, investors tend to hedge volatile returns in the spot market through increased involvement in futures trading. These empirical results are consistent with the recent evidence reported by de Roon, Nijman, and Veld (2000) that hedging activities go beyond own-market to incorporate cross-market hedging as well.

Given this new finding on the spot and futures markets interrelation, we perform additional tests to ensure that we are not misled by the statistics previously discussed. In particular, one might argue that the use of a multivariate model is objectionable because the inclusion of extraneous variables might have clouded the relation between return volatilities in the two markets. That is, the causal effect of futures trading on spot market volatility might simply be masked (or absorbed) when we control for the effects of other volatilities in the model. Of course, excluding potentially important variables is a more serious statistical problem than including unimportant variables. Nonetheless, it is useful to see whether omitting the volatilities of the six macrostate factors materially alters our conclusions. We reinvestigate the lead-lag relation between volatilities in the spot and futures markets in the context of bivariate models. The results continue to suggest that futures activities do not induce volatility in the spot market, and that it is the latter that incites a more volatile futures market.[6] In addition, we estimate equations (3) and (4) by the SUR approach to gain statistical efficiency. To determine to what extent the results are sensitive to this estimation technique, we perform our tests using OLS. The results (available on request) continue to support the central conclusion of our article.

Testing dynamic relations among time series may require evidence that goes beyond statistical significance of group coefficients. Another procedure is to test the ability of one variable, say, spot return volatility, to account for the forecast error variance of futures returns at various monthly horizons, and vice versa. Results from these variance decompositions (VDCs) offer additional evidence supportive of the central conclusion that volatility in the spot market drives volatility in the futures market rather than the opposite. For example, based on a twelve-month forecast horizon in a bivariate setting with six lags, innovations in futures return volatility explain only a small and insignificant portion of the forecast error variance of spot return volatility (1.30%, $t = 0.37$). In contrast, over a similar twelve-month forecast horizon, innovations in spot return volatility explain a much larger and statistically significant proportion of the forecast error variance of futures returns (9.03%, $t = 2.04$). Using other lag specifications and different monthly forecast horizons does not alter the conclusions. A similar picture emerges when we expand the bivariate models by incorporating volatilities of other macrostate variables. Specifically, although innovations in futures return volatility still account for an insignificant percentage of the forecast error variance in spot return volatility over a twelve-month forecast horizon (0.09%, $t = 0.07$), the reverse continues to yield a larger and significant proportion of forecast error variance (9.42%, $t = 2.01$). Again, these inferences from the expanded systems prove insensitive to the lag length and the duration of the forecast horizons.

Besides volatility in spot returns, volatilities in three macrostate variables significantly influence the behavior of the futures market: volatility in industrial production, volatility in inflation, and volatility in the government budgetary process. Thus, the futures market is an important hedging device to absorb uncertainty in major macrostate variables. As to determinants of spot market volatility, our results are consistent with those of Chen, Roll, and Ross (1986) and suggest that volatilities in industrial production, risk premium, and term structure all have significant effects on volatility in spot returns.[7]

The empirical results suggest that index futures trading may not be blamed for the observed volatility in the spotmarket. We find stronger and more consistent

[6]For the effect of futures on spot volatility, the calculated LR is highly insignificant (6.59, with 12 degrees of freedom). For the reverse effect, the LR is significant at better than the 10% level (19.13, with 12 degrees of freedom).

[7]Volatility in money growth is not without weight either because its effect on volatility in both markets almost achieved statistical significance (p-value $\approx$ 12%) as seen in test 4 of Panel A and test 7 of Panel B.

support for the alternative posture that volatility in the futures market is itself an outgrowth of a turbulent cash market. Recent developments in behavioral finance seem consistent with perverse causality from spot to futures markets' volatility. For example, the regret theory postulates that investors may take certain admittedly "irrational" actions simply to mitigate or avoid the pain of regret. Shefrin (2000) postulates that regret may go beyond the pain of loss to feeling responsible for it. As such, regret is an important factor shaping decisions. It is this pain of regret, the theory contends, that induces investors to sell winning stocks too soon and hold losing ones too long. A related concept is the cognitive dissonance theory, which maintains that people generally try to reduce cognitive dissonance in a way that would not normally be considered fully rational. For example, money flows more rapidly into mutual funds that are performing well than it flows out of funds that are performing poorly. Investors behave in this fashion because, after losing, they become unwilling to confront the fact that trading the stocks was a bad decision.

These behavioral patterns may be used to justify why a volatile spot market is capable of provoking volatility in the futures market. As the spot market itself becomes more volatile, investors increasingly try to reduce cognitive dissonance and avoid possible regrets of making wrong investment decisions. This psychology encourages investors to engage in more hedging activities, not only to minimize perceived risk, but also to avoid future pain of regret. Of course, one popular way to hedge is futures trading which, in turn, induces further swings in futures prices. Under this scenario, the observed positive correlation between volatilities in the spot and futures markets is more consistent with causality running from the former to the latter.

V. Conclusions

Recurrent turbulence in the stock market, especially since 1987, has intensified research into possible causes of market volatility. Many analysts ascribe part of the volatility in the cash market to the advent, and in fact the explosive growth, of index futures trading. Theory alone, however, is unable to resolve the debate because arguments for and against this popular view have equal theoretical appeal. The empirical literature does not fare much better, and the evidence is still mixed.

In the present article we contribute to the debate by proposing a behavioral finance interpretation of the empirical results. We argue that, in an excessively volatile cash market, the fear of regret sways quasi-rational investors to engage in more hedging activities in the futures market. As a result, index futures returns may experience some "irrational exuberance" behavior. We also adopt a different, and perhaps superior, approach to measuring return volatility, namely, the EGARCH method. We further argue that although futures activities could incite volatility in the spot market (as commonly perceived), another theoretical possibility is that an unstable spot market itself could provoke volatility in the index futures market. By using monthly (rather than intraday) data, our results could not be ascribed to differences between futures and cash markets in their time responses to economic news. The effect of these time differentials is not likely to persist over monthly horizons, but the effects of regret-aversion behavior may. Additionally, we avoid potential biases of the common bivariate models by examining multivariate models that incorporate the volatilities of other theoretically relevant macrostate variables.

We find that index futures trading may not be blamed for increased volatility in the spot market. On the contrary, our results support the alternative hypothesis that volatility in the futures market is itself an outgrowth of a turbulent spot market. These inferences prove robust to several model specifications, and results obtained from variance decompositions concur. Our findings are consistent with the regret (cognitive dissonance) theory and with the evidence reported in Darrat and Rahman (1995) and Pericli and Koutmos (1997).

Consequently, proposed regulations to restrict activities in the futures markets appear unwarranted, and perhaps even counterproductive, because these regulations might impose heavy and disruptive costs on market participants. As argued elsewhere (Darrat and Rahman 1995), the common notion that futures activities are responsible for increased volatility in the spot market may have diverted attention away from other, more plausible sources of instability in the stock market, including investor psychology, the capital market globalization, trading technology, and market microstructures. Understanding the true culprit(s) behind volatility in the spot market is important, not only for promoting overall confidence in capital markets, but also for mitigating volatility in the futures market.

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