MARKET INFORMATION AND THE FEEDBACK EFFECT OF THE CBOE S&P500 VARIANCE FUTURES ON THE UNDERLYING ASSET

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ABSTRACT

The present study delves into the issue of whether the newly cultivated platform of derivatives volatility trading has altered the behavior of the underlying asset. The empirical evidence presented supports market realities and opens avenues for future research. The onset of variance futures trading has lowered the cash market volatility, and significantly reduced the impact of shocks to volatility. The latter are of considerably lower magnitude and time-persistence in the post-futures phase. The volatility process is characterized by long-memory effects regardless of the period under examination and the estimator employed. Some preliminary evidence also supports the mean reverting nature of volatility. The latter needs to be further established in forthcoming versions of this paper. Market data do not support the impact of leverage effects on conditional volatility. Finally, the correlation between the equity index level and return volatility remains low further confirming the role of these instruments to facilitate portfolio diversification.

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Key Words: S&P 500 Variance futures; Information arrival; Conditional volatility; TGARCH modeling; Cash volatility market

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I. INTRODUCTION

Increased market volatility and the role of derivatives trading have received considerable attention from academics and practitioners in the U.S. and across the world. The particular phenomenon is important for regulators, financial institutions, hedgers, speculators, as well as government agencies and policy makers. The debate remains still alive on the impact of derivatives activity on spot markets volatility, the existence of any speculative effects, and finally whether derivatives destabilize spot markets or not. In many cases the state had to interfere to alleviate the strain on the spot market and to avoid possible negative externalities. Active measures taken include strict trading supervision, temporary trading proscriptions - until the crisis is judged to have passed, and/or indefinite interdict on the grounds that derivatives trading destabilizes the underlying cash market.

In 1936, the U.S. Congress prohibited all sales of options on certain agricultural commodities listed in the Commodity Exchange Act. The ban was lifted in 1982 under the Futures Trading Act, which permitted agricultural options trading under the regulation of the Commodity Futures Trading Commission (CFTC). In 1958, the U.S. Congress passed a bill to outlaw the Chicago onion-futures market on the basis of disrupting the underlying asset values. Moreover, the CFTC suspended, for two days, the wheat futures trading after the U.S. grain embargo of the Soviet Union in January 1980, following the Soviet invasion of Afghanistan. Finally, during the Gulf Crisis of 1990-91, some observers proposed shutting down these markets for a "cooling-off period" (U.S. Senate, 1991).

Nonetheless, the existence of derivatives cannot be as damaging as it appears in the aforesaid examples. Theoretical work both supports and refutes the argument that derivatives permeate excess volatility in the underlying cash market. Friedman (1953) notes that, in the long-run, market players who are willing to take risks would contribute to the smoothing of prices. The latter is countered by Baumol's (1957) trend-following strategies; while Peck (1976) asserts that production and storage decisions, made on the basis of commodity futures prices, help to alleviate commotions in the spot market. According to Seiders (1981), a necessary condition for the level of disruption in the underlying cash market is the speculators' forecasting accuracy. Based on a limited sample, Powers (1970) and Stoll & Whaley (1988) conclude that futures increase the routes and the speed with which information is disseminated. Cox (1976) derives a relation between information, expected prices and spot price volatility, and defines information content as knowledge regarding random disturbances having an impact on demand in the real economy. Due to the lack of modeling conditional variances (Engle & Ng, 1993) at that time, Cox does not show how information is a function of the information flow per se.

Over the last decade(s) financial engineering has exacerbated the growth of derivatives instruments, and altered their impact on price insurance (risk reduction), asset allocation and price discovery[1]. Thus new instruments arise and old ones cease to exist[2]. The purpose of this paper is to examine the impact of the CBOE S&P 500 Three-Month Variance Futures (VT) on the underlying volatility of the equity index. The VT contract[3] was listed in 2004, and is a brand new instrument aiming to hedge the variability in the stock market. Although a number of studies have concentrated on commodities and financial derivatives; this is the first study, at least to our knowledge, that concentrates on variance futures and its effect on the underlying asset. Thus the present analysis offers a fresh perspective on the issue. Volatility itself has become an asset class (Gangahar, 2006) and a group of volatility derivatives – both exchange-traded and over the counter – is now being widely available. The current research is motivated primarily by the lack of similar studies, and the increased number of traders working on the basis of volatilities rather than prices. In addition to that, two more points are worth noting. First, hedging variability in equity markets with options (instead of volatility futures), as it was the case until recently, is not ideal as options hedge against price risk, but delta-hedging is inaccurate. Second, the CBOE VT contract is based on realized variance which is more tangible than the implied volatility derived through theoretical models and numerical methods.

The remaining of the paper is structured as follows. Section II presents a brief discussion on the volatility debate. Sections III and IV form the main body of the paper where the data, methodology and empirical results are discussed. Finally, Section V summarizes our findings, draws some conclusions and points out avenues for future research.

[1] There is ample literature on the price discovery hypothesis. See Staikouras (2004) for recent evidence on this issue and the time variation of risk premia.

[2] According to the Commodity Futures Trading Commission (CFTC), since the Commodity Futures Modernization Act (CFMA) in 2000, over 450 new products have emerged, compared to less than 200 in the previous years. The CFMA, as adopted, is a significant step forward for U.S. financial markets. This important new law creates a flexible structure for regulation of futures trading, codifies an agreement between the CFTC and the SEC to repeal the 18-year old ban on trading single stock futures and provides legal certainty for the over-the-counter derivatives markets.

[3] For a complete description of the particular contract see http://cfe.cboe.com/Products/Spec_VT.aspx

II. A BRIEF REVIEW OF THE DEBATE

The relationship between cash and derivatives markets[4] usually sparks discussions evolving around the term 'financial stability'. The latter is usually translated into volatility, an inevitable experience mirroring market expectations and information arrival. In fact, fundamentally justified volatility is not a bad thing, and it can form the basis for efficient price discovery. The particular issue is a vivid example of scholarly debate, with the views divided as to how much spot price volatility is induced by derivatives trading. The issue becomes even more complicated when derivatives trading is split into hedging, based on its core existence, and speculative orientated mechanisms.

Market analysts may pin down the origins of volatility to either uninformed trading or collective irrationality – possibly resulting from herding behavior. Such approach reinforces the view that speculation can lead to unjustified price variability (Baumol, 1957). Since speculators do not have enough information to or cannot predict peaks and troughs in advance, their retrospect trading activities can only accelerate downward and upward movements or even increase the amplitude and frequency of fluctuations. It can be argued that there will always be a large uninformed group that lose money, while informed and knowledgeable speculators earn profits – indicating that speculation would be unprofitable in the aggregate (Kaldor, 1939).

On the other hand, the advent of derivatives instruments is due to their fundamental role of reducing price risk. Futures markets should be able to facilitate provisions such as portfolio immunization, centralized trading, clearing and enhancing information, competitive price discovery, and improved market efficiency. News is not only assessed by futures traders, but also by cash market participants, since such information will be distributed in the market by members of the futures exchanges, brokerage houses and dealers. The aforesaid will amply assist the decision making, based on more information, while prices will reflect fundamental economic conditions. Thus, under this framework, the existence of futures trading should reduce cash market volatility and increase financial stability.

Although each argument is theoretically justified, the debate is not empirically established yet. Research has been conducted in various segments of financial markets such as interest rates, equities, foreign exchange and commodities, with each study using different definitions of volatility, methodologies, and time periods. A strand in the literature

[4] To keep the task manageable, this section aims to briefly overview some empirical findings with no intention to lessen the importance of any studies excluded. A number of other studies are available from the authors upon request.

has documented no apparent change in the variability of the underlying asset upon the introduction of derivatives trading. Using the hedge ratio between weekly spot prices of GNMA and long-term T-bonds, Froewiss (1978) shows that there is no apparent change in that ratio in the pre- and post-futures period. He concludes that the spot market has become more informationally efficient. In the same market, Simpson & Ireland (1982) find analogous results by either using daily or weekly data. They employ a multivariate model aiming to eliminate any time dependency in their sample. The above results are further corroborated by Corgel & Gay (1984) who illustrate, via intervention analysis[5], that futures have improved cash market efficiency. Later, Moriarty & Tosini (1985) reexamine the findings of Figlewski (1981) by extending the sample period[6]. Based on the same methodological framework, they conclude (contrary to Figlewski) that GNMA futures trading has no effect on the spot market volatility. However, they do point out that differences in results could be contingent on the sub-periods analyzed. Extending their previous work, Simpson & Ireland (1982) notice a reduction in spot T-bill yield volatility, but this was short-lived as the volume of futures trading started rising and the market became more mature. Elsewhere, Bessembinder & Seguin (1992) argue that active futures markets lead to stability by enhancing the depth and liquidity of the cash market.

On the other hand, scholars have identified a significant change in the nature of volatility as a result of futures trading. Based on GNMA data, Figlewski (1981) detects an increase in monthly price volatility transmitted from the futures arena. A possible explanation of that increase could be the existence of a not well-informed group of futures traders. In a similar vein, Aggarwal (1988) finds an increased volatility trend in the stock index futures market between 1981 and 1987. She does acknowledge, however, that such increase is common for other markets, during that period, which do not have futures contracts. The cash price movements at the expirations of futures contracts, show a mild and temporary swing in spot prices, which is reversed on the following day (Stoll & Whaley, 1990). Examining the variance homogeneity, Brorsen (1991) shows that stock index futures have increased market efficiency (reduced autocorrelations) as well as the variance of the cash stock index (S&P 500) market. The latter is evident in daily price changes, while for weekly and monthly prices changes the variance remains the same. Examining the period around the 1987 crash, Koutmos & Tucker (1996) adeptly show that innovations originating

[5] The interested reader is referred to Box & Tiao (1975).

[6] It is worth noting that their period (1975-1983) is characterized by the Fed's shift in monetary policy (October 6, 1979) and financial deregulation in the years following 1979. The Fed directed the trading desk to focus on monetary aggregates, letting the federal funds rate move more freely, which resulted in high interest rate volatility. Figlewski's (1981) sample period goes until 1979.

in the futures markets increase volatility in the stock market in an asymmetric fashion *i.e.* bad news increases future volatility more than good news. The picture looks different when Edwards (1988a,b) demonstrates, over an 18 year period, either a decrease in volatility for the S&P500, 90-day T-bill and 90-day Eurodollar markets, or no significant change for the Value Line Index. Their study excluded the volatile interest rate phase of 1979-82. Using a conditional volatility approach and 25 years of daily data, Staikouras (2006) finds a decrease in the UK short-term interest rates variability since the onset of futures trading in 1982.

At the same time published evidence unveils that stock market volatility may not be related to the futures trading per se. For instance, one could argue that focusing in the U.S. market during the 1980s, empirical findings could be affected by the bull market (1985-87), the growth of foreign ownership of U.S. equities, the budget and trade deficit, the growth in index funds, and/or the fall of the dollar. Black (1982) goes further to separate the notion of causation from correlation. Based on causality tests, Bhattacharya, Ramjee & Ramjee (1986) provide some evidence of casual influence running from futures to spot GNMA markets, but no direct findings are reported to support the stabilization or destabilization hypothesis. No evidence of speculative destabilization both in the futures and spot T-bill markets is also reported by Dale & Workman (1981). The stock cash market volatility inflation could be due to the use of hedging strategies by fund managers in the spot market (Grossman, 1988), where sudden orders of large volumes will cause unusual movements; or it could be attributed to other index-related phenomena according to Harris (1989). Harris rightly argues that foreign ownership may be concentrated on the S&P 500, where information is widely available, and overreaction might be a problem. He also discusses the booming of index-funds which replicate a number of these equity indices. Further research by Becketti & Roberts (1990) unveils that neither the level of futures trading nor the existence of the derivatives contributes to the equity spot market volatility. Pericli & Koutmos (1997) find that past errors (innovations) have been reduced, but the persistence has risen. During that period, however, the incremental impact of derivatives trading, flexible exchange-rate regime and liberalization of brokerage commission rates cannot be assessed independently.

Overall, the empirical and theoretical work so far provides conflicting and unconvincing signals as to what drives the spot market volatility across different markets. Most of the work has concentrated in the US financial and commodities markets and thus more global verification seems necessary. A common ground for opinion convergence may never be achieved, and essentially the debate still remains in the battlefield of empirical research.

III. DATA AND METHODOLOGY

New York has the largest equity market in the world, and it seems natural to collect data from the S&P family of indices. The S&P 500 index is considered as a supreme gauge of the U.S. stock market. The index covers over 80% of the U.S. equities and thus it is ideal in capturing wide market conditions. Unlike the general belief that the index consists of the largest firms by market capitalization or by revenues; it is actually the case that its constituents are based on widely held common stocks, chosen by the S&P Index Committee[7] for market size, liquidity as well as sector representation.

The S&P 500 futures started trading in April 21, 1982 on the Chicago Mercantile Exchange (CME). The volatility contract[8], that this paper is particularly interested in, is represented by the S&P 500 three-month variance futures (ticker VT), which was introduced in May 18, 2004. Its quotation is based on the realized return variance of the S&P 500 Composite Stock Price Index multiplied by 10,000. The contract aims to offer a platform for hedging volatility risk, as well as to provide convenience and ease of execution to the over-the-counter traders. The sample consists of daily data starting from January 3, 2000 until November 30, 2006. Daily data are chosen on the basis of providing more degrees of freedom and closely tracking changes in the volatility of the underlying asset. Moreover, the three-month volatility is constructed by excluding non-trading days, public holidays, and any other market interruptions. Panel A in the Appendix illustrates the return of the S&P 500 and its three-month volatility over the period examined. The return is multiplied by 2.5 for improved illustration.

The focus of the current research is on the volatility of the S&P 500 and whether this has been affected by the induction of futures trading. The methodology employed aims to capture any changes in the spot market volatility. Because of the approach's well established nature and the extensive material available on these estimators, a brief description will suffice for the purpose of the present study. Conditional heteroscedastic processes, as originally proposed by Engle (1982) and Bollerslev (1986, 1987), are the ideal tool for this purpose. Such framework makes it possible to simultaneously model the conditional mean and variance of a series, and hence capture most of the variation in stock

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[7] Standard and Poor's economists and index analysts form the S&P Index Committee who is responsible in maintaining the indices provided by the firm. Since September 19, 2006, a small number (ten) of non-U.S. firms are included in the index, and technically it makes the index less U.S. based. However, since more weight is attributed to larger firms, it tends to reflect the price movement of those companies.

[8] The interested reader is referred to the website of CBOE http://cfe.cboe.com/Products/Spec_VT.aspx. The authors are grateful to Bloomberg for generously providing a wide range of their volatility calculations for this particular market.

returns. To make this operational, let the general representation of the regression equation be

$$y_t = \boldsymbol{x}'\boldsymbol{\beta} + \varepsilon_t \qquad E(\varepsilon_t) = E(v_t\sqrt{h_t}) = 0, \qquad E(\varepsilon_t^2 \mid \Omega_{t-1}) = h_t$$

$$h_t = \mu + \theta(L)\,\varepsilon_t^2 + \delta(L)\,h_t + \gamma Z$$

$\boldsymbol{x}'$ denotes a vector of predetermined exogenous variables, which could include lagged values of y; $\boldsymbol{\beta}$ denotes the vector of estimated parameters; v_t is an *i.i.d* sequence with zero mean and unit variance; Ω is the information set at a certain period; $\theta(L)$ and $\delta(L)$ are lag polynomials of order p and q respectively and L is the backward shift operator; Z denotes other stochastic exogenous variables; non-negativity of h_t requires the identification condition that $\mu > 0$ and $(\theta, \delta) \geq 0$.

Financial time series data are influenced by time dependent information flows which result in pronounced temporal volatility clustering. The above formulation captures satisfactory such a phenomenon, and when correctly structured produces very interesting and reliable results. When conditional heteroscedasticity is present, but not correctly modeled, the parameters from an OLS regression will be unbiased. However, the non-linear ML estimator will produce greater efficiency gains (Engle, 1982). A nice survey covering the family of conditional volatility models is provided by Bollerslev, Chou & Kroner (1992). The increased importance of volatility in global markets, along with the recent futures trading on volatility provide a fertile and unexplored terrain and this is what the paper turns to next.

IV. EMPIRICAL RESULTS

This section looks at the empirical (ir)regularities, which are related to the triangular relation among information, spot market volatility, and futures trading activity. The two series of main interest employed in this study are the realized volatility of the S&P 500 over a three-month trading period –as the endogenous variable (*VL*); and the return on the world index – as the exogenous variable (*Rwi*). The latter aims to capture any market wide movements and other global macro-economic effects. The study also divides the sample in three time frames so that the examination can focus in the overall period, as well as in the pre- and post-futures phases. This time segmentation would be followed throughout the econometric analysis in order to provide insight into the effect of the CBOE S&P 500 three-month Variance Futures trading on the underlying asset's volatility. Table 1 provides the descriptive statistics of the series involved in the empirical analysis.

Table 1
Descriptive Statistics

	Whole Period [a]		*Pre-Futures*		*Post-Futures*	
	VL	*Rwi*	*VL*	*Rwi*	*VL*	*Rwi*
Mean	-5.6E-05	3.0E-07	-3.5E-05	-0.00032	-9.2E-05	0.00056
Median	-3.0E-06	0.00032	-5.0E-07	0.00017	-8.0E-06	0.00073
Max.	0.03081	0.04604	0.03081	0.04604	0.00871	0.02072
Min.	-0.03435	-0.04984	-0.03435	-0.04984	-0.00881	-0.02042
Std. Dev.	0.00376	0.00915	0.00445	0.01060	0.00205	0.00573
Skewness	0.27145	-0.07586	0.24628	-0.01159	-0.00341	-0.01507
Kurtosis	20.4157	5.64150	16.1912	4.73462	6.53043	3.57208
Q (36) [b]	276.02		199.54		79.08	
Q^x (36) [c]	63.60		31.19 *		50.43 *	

VL = the change of the S&P 500 three-month volatility; *Rwi* = the return on the world index.
a Total Nobs. is 1,718 – for the pre-future is 1,099 and for the post-futures is 619.
b Q = Ljung-Box test for serial correlation for up to 36 lags.
c Q^x test for nonlinearity. Q test critical value at 1% level of significance: X^2 (36) = 58.62
* These values indicate no ARCH effects. See discussion in the main text.

The data might not exhibit skewness, but they do suffer from excess kurtosis relative to the normal distribution. The Ljung-Box test, for serial correlation up to 36 lags, is significant, at the 1% tolerance level, indicating that the volatility is highly forecastable. In the view of the existing evidence that excess kurtosis is due to a possible time-varying volatility [Akigary, Booth, Hatem & Mustafa (1991), Fujihara & Mougoue (1997)], a test for nonlinearity is conducted based on the McLeod & Li (1983) approach. The test is used to gauge the existence of conditional heteroscedasticity in the change of the S&P 500 three-month volatility. The particular method is based on the autocorrelation coefficients and the Q^x-statistic for the squared data. The value reported in table 1, for the whole period, is statistically significant indicating that the series exhibits some form of conditional heteroscedasticity. For the other two periods the test shows no ARCH effects, but this does not preclude the existence of GARCH effects as it is later unveiled via the estimation process. The non-constant nature of volatility is also confirmed in the illustartion under Panel B in the Appendix, where a recursive estimation[9] of the variance is provided. Such estimation sheds light as to whether the variance of a series remains constant (the classical assumption) or varies over time. The latter is the cornerstone of all conditional volatility

[9] The calculation is based on the squared difference between the variable (X) and its unconditional mean. The mathematical expression is as follows: *sum* $(X_s - \bar{X})_s{}^2 \times t^{-1}$ for s = 1……t.

estimators. The recursive estimation reveals an unstable series prior to the onset of futures trading, but during the second period the series declines vividly and levels out.

An analysis of the difference in means of the volatility variable (*VL*) between the pre- and post-futures era shows a z-value of 0.3648 which is significantly lower than any critical value and thus accepting the equality of the means. Turning to the standard deviation of the same series a visual inspection confirms that the difference between the two regimes is noticeable. The *F*-statistic based on the variance equality of the two samples shows a value of 4.718 which is well above the critical value (1.126) and thus rejecting the null hypothesis. However, this is only a preliminary test to confirm the potential change of the underlying asset's return variability. The analysis so far has laid the infrastructure for the formal estimation using conditional heteroscedasticity estimators. In the mean equation of the GARCH model the return on the world index[10] is employed as the exogenous variable aiming to control for wide market factors. In the conditional variance equation a time dummy is constructed to capture the possible effect of the onset of futures trading (18/5/04) on the CBOE. Using a likelihood ratio test and after experimentation with up to five lags for each parameter p and q, the GARCH (1,1) representation is found to be the most appropriate structure. The results of this estimation process are presented in Table 2.

Table 2
GARCH estimation for the S&P 500 three-month volatility

$VL_t = c + \beta_1 Rwi_t + \varepsilon_t$

$h_t = \mu + \theta\, \varepsilon_{t-1}^2 + \delta h_{t-1} + k\, df_t$

	Whole Period		*Pre-Futures*		*Post-Futures*	
	Coefficient	*z-value*	*Coefficient*	*z-value*	*Coefficient*	*z-value*
c	-3.4E-05	-0.76	-7.1E-05	-0.58	-6.5E-05	-1.01
β_1	0.0063	1.17	0.0089	1.23	0.0063	0.63
μ	2.5E-06	2.44	3.3E-06	7.12	1.3E-06	1.25
θ	0.0942	2.50	0.4621	5.98	0.0661	1.54
δ	0.8147	18.22	0.5403	13.63	0.6395	2.56
k	-1.4E-06	-2.21	–	–	–	–

VL is the daily change in the three-month volatility of the S&P 500; *Rwi* is the return on the world index; *df* is the dummy variable signifying the onset of futures trading.

The residual kurtosis exhibits values of 11.82 (whole period), 18.34 (pre-future) and 6.31 (post-futures), which are afar from the ones indicated by normal distribution. Under

[10] The Morgan Stanley world index measures the total return attributable to the largest capitalized companies on the world's major stock exchanges. The index is compiled and reported monthly in local and common currencies, and has more than $800 billion in assets indexed to it.

the null hypothesis of conditional normality, the test statistic for the sample kurtosis has an asymptotic normal distribution with mean 3. In light of this evidence the models are estimated based on a conditional student-*t* density function[11]. The log likelihood function, under the assumption that the residuals follow a conditional student-*t* density, is given below

$$Log(L) = \sum_{t=1}^{n}\left\{\log\left(\Gamma\left(\frac{df+1}{2}\right)\right) - \log\left(\Gamma\left(\frac{df}{2}\right)\right) - 0.5\times\left[\log\left((df-2)h_t\right) - (df+1)\times\log\left(1+\frac{u_t^2}{h_t(df-2)}\right)\right]\right\}$$

where n is the sample size, df is the degrees of freedom (>2), and $\Gamma(\cdot)$ is the gamma function. Under the conditional t distribution, the additional parameter $1/df$ is estimated. The log likelihood function for the conditional t distribution converges to the log likelihood function of the conditional normal GARCH model as $1/df \rightarrow 0$.

Looking under the whole-period column, the futures dummy coefficient (k) exhibits a negative value, which is also statistically significant, clearly indicating the reduction of volatility in the post-futures period. Both the autoregressive (δ) and moving average (θ) coefficients in the conditional variance equation are highly significant as well. The ARCH effect is significantly smaller than the GARCH effect, which implies that the volatility series is characterized by long memory. That is, higher order lagged errors ($> \varepsilon_{t-1}^2$) have a bigger influence on current volatility. For instance, 1% change in the "recent news" coefficient (θ) will increase volatility by 0.09%, while a similar change in the "old news" coefficient[12] will result in a 0.81% rise in volatility. Ideally one would expect that the current ARCH term should have a higher impact on volatility, while older innovations to be of minor importance. In other words, the most recent news should have been of more importance than yesterday's information.

Looking at the mean equation, the analysis has also employed exogenous dummy variables related to certain events, which could possibly have an effect on the volatility of the underlying asset[13]. None of these dummy variables is found to be statistically significant. Interestingly, the broad market index comes out with an insignificant coefficient too. This is in line with the wide market perception that volatility contracts should be used to increase portfolio diversification instead of other products such as precious metals,

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[11] The estimated coefficients are obtained by using the Berndt, Hall, Hall & Hausman (1974) algorithm.

[12] Note that the conditional lagged volatility can be also expressed as $h_{t-1} = \mu + \theta\, \varepsilon_{t-2}^2 + \delta\, h_{t-2}$ which in turn is a function of past news through the "news" coefficient theta (θ) or even much older news through delta (δ).

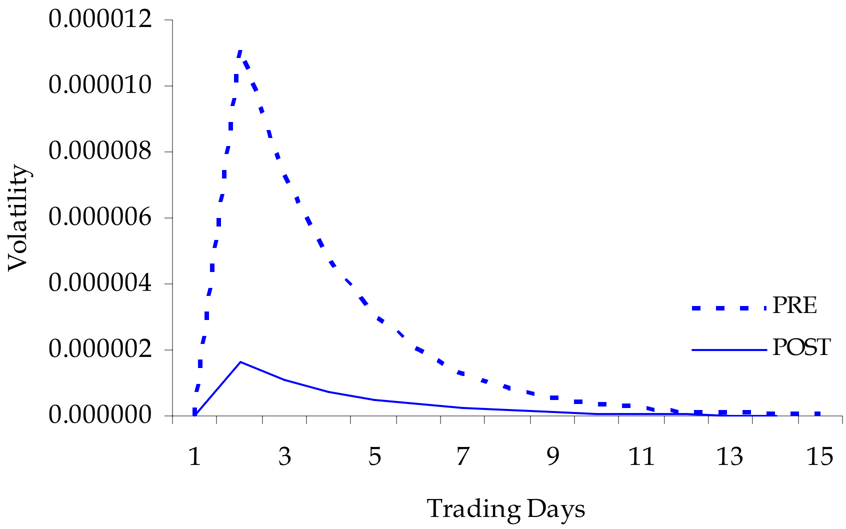
[13] The events tried in the current study are: the Gujarat earthquake on January 26, 2001; the New York terror attacks on September 11, 2001 (no prices until 9/14); the Asian tsunami on December 26, 2004 (Sunday); the Hurricane Katrina on August 29, 2005; and the South Asia earthquake on October 8, 2005.

commodities, property etc. The low-correlated nature of volatility with the equity market is the most appealing feature of these derivative contracts. Market realities can support a negative/low correlation between volatility and stock/index levels. That is, volatility is higher during bearish markets compared to bullish trends, and tends to stay high during a downward market trend. Thus, in a portfolio framework, the leading feature of the volatility futures contracts is their contribution to lower risk significantly. Looking at Panel C in the Appendix, one could see the negative correlation[14] between the index level and the volatility of returns.

When the whole period is split into the pre- and post-futures intervals the results are very interesting. The wide market index continues to have a zero impact on volatility, while long memory effects seem to dictate the conditional variance in either phase. Looking at the pre-future period, the sum of the ARCH (δ) and GARCH (θ) coefficients is approximately equal to unity. That is, an integrated GARCH (IGARCH) emerges, which automatically implies the existence of a non-stationary volatility process. The latter is translated into having shocks in the market that persist for a much longer period than expected. This comes in contrast to the post-futures phase where the GARCH estimator is stationary ($\theta+\delta \approx 0.71 < 1$). In this case, shocks in the market will disappear much quicker when compared with the earlier non-stationary period. Such an impact is put into test by introducing shocks on the conditional volatility of our data series. Figure 1 presents the shock's impact on the volatility measure.

[14] Please note that since this is a roll-over estimation over a three-month period, to match the futures contract's maturity/calculation, a gap will appear (values are constrained to zero) when the futures contract is launched. In the graph the gap is depicted as a "moving average (MA)" overlapping period. This comes as a result of aiming to avoid correlation figures calculated by using values from both the pre- and post futures regime. That is, the first correlation value after the onset of futures trading is based on estimates of volatility and equity index that solely reflect their values during that period *i.e.* the three-month volatility/index are not "contaminated" with their values from the pre-futures period.

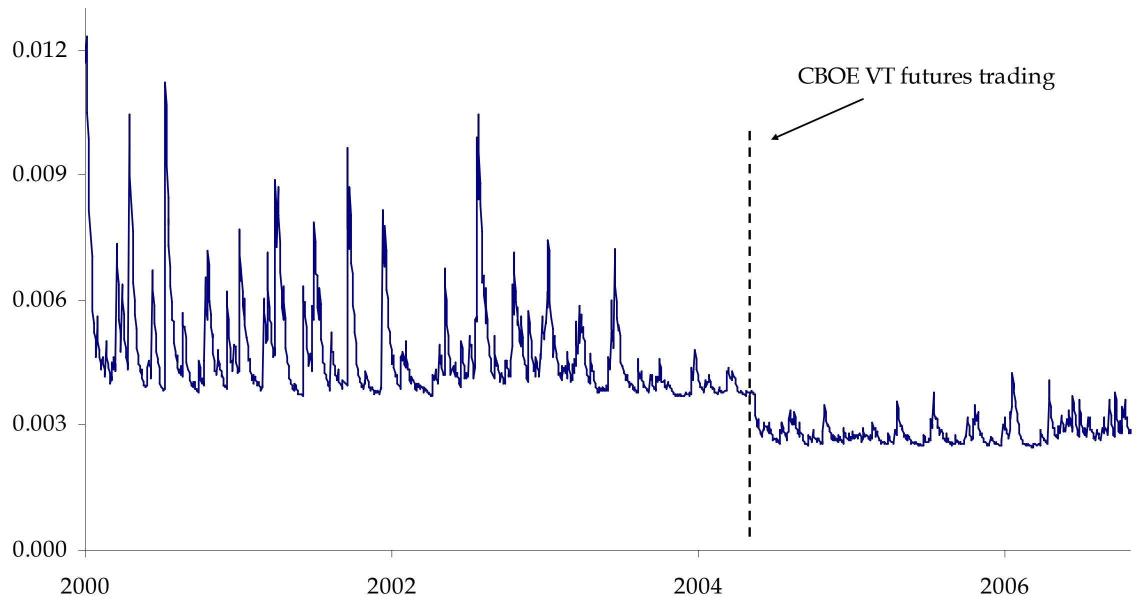
Figure 1 A unit size shock on volatility.



The above graph illustrates the result of a unit size shock over a 15-day trading period. It is clearly visible that a shock in the pre-futures period increases volatility by a much bigger scale than in the aftermath of futures trading. It also takes twice the time, before the onset of futures market, for the volatility to settle down after the unit size shock is introduced. One should also bear in mind that a) futures trading attracts additional traders into the market due to their appealing characteristics of hedging, speculating and low transaction costs; and b) the participants in that market trade and communicate their information more effectively, since futures trading is more centralized. Thus it can be reasonably argued that volatility futures trading has made the market more liquid, enhanced the information flow in the spot and derivatives markets and thus reduced not only the level of volatility, but the severity of the shock's impact on volatility. Interestingly, the improvement of information flow or more accurately the "rapid" absorption of information by the volatility market is verified by looking at the pre- and post futures estimation results. The recent news coefficient is not only reduced between the two periods, from 0.46 to 0.067, but it also becomes insignificantly different from zero when futures trading on volatility takes place.

The analysis further estimates the GARCH(1,1) model, with the futures dummy in the conditional variance equation, and extracts the conditional volatility from that estimation. Figure 2, illustrates and further confirms the change in the volatility since the onset of futures trading. The graph is based on the estimation of the GARCH estimator for the whole sample period and clearly show the high picks in the pre-futures period. The drop in the level of volatility is attributed to the significant negative dummy variable in the conditional variance equation. Nevertheless, one should be very broad minded when such issues are examined as it is difficult to possibly attribute excessive volatility levels just to the activities of "irrational" or probably uninformed futures speculators who hope for short-term profits. Market realities are much more complicated than it appears to be in our quantitative analysis.

Figure 2 Conditional volatility for the whole sample period.



One of the contributions of the conditional volatility estimators is the fact that they provide the link between volatility and information. Actually, in 1976, Cox argued that futures trading has an impact on price expectations by altering the flow of information into the market. Cox put forward the link between information, expected prices and spot price volatility. He defined information content as knowledge regarding random disturbances having an impact on demand in the real economy. However, the limitation of his approach, at that time, was that although futures may increase the flow of information, he did not show how volatility is a function of the information flow per se. Thus the other issue worth exploring is whether leverage has an impact on volatility. The leverage effect measures the impact of negative or positive innovations, on conditional volatility, by allowing either the slope of the two sides of the news impact curve to differ or the centre of the news impact curve to locate at a certain point.

As pointed out by Engle and Ng (1993), failure to model the leverage effect leads to misspecification of the volatility process. For example, linear ARCH models tend to underpredict volatility associated with negative innovations. Thus their usage in the past may have led to erroneous inferences regarding the role of derivatives on stock market volatility. Table 3 presents the results of a threshold GARCH model (TGARCH) which is designed for this particular purpose. These estimators were introduced independently by Glosten, Jaganathan & Runkle (1993) and Zakoïan (1994). The conditional variance equation is amended to incorporate an extra term which, in the current study, represents the negative innovations captured by the gamma (γ) coefficient. There is no reason, however, why one cannot test for a model where the leverage effect stems from a positive rather than negative innovation *i.e.* $d_t = 1$ if $\varepsilon_t > 0$ and *zero* otherwise.

Table 3
Threshold GARCH estimation for the S&P 500 three-month volatility

$$VL_t = c + \beta_1 Rwi_t + \varepsilon_t$$
$$h_t = \mu + \theta \varepsilon^2_{t-1} + \delta h_{t-1} + \gamma \varepsilon^2_{t-1} d_{t-1} + k\, df_t$$

	Whole Period		*Pre-Futures*		*Post-Futures*	
	Coefficient	*z-value*	*Coefficient*	*z-value*	*Coefficient*	*z-value*
c	-3.3E-05	-0.73	-6.9E-05	-0.56	-0.0001	-1.27
β_1	0.0061	1.13	0.0092	1.26	0.0149	1.43
μ	2.4E-06	2.43	3.2E-06	7.40	9.8E-07	2.75
θ	0.0898	2.24	0.4609	5.49	0.0830	2.22
δ	0.8150	19.04	0.5412	14.49	0.6026	5.23
γ	0.0274	0.79	0.0438	1.38	0.0920	1.70
k	-1.3E-06	-2.19	–	–	–	–

VL is the daily change in the three-month volatility of the S&P 500; *Rwi* is the return on the world index; *df* is the dummy variable signifying the onset of futures trading; $d_t = 1$ if $\varepsilon_t < 0$ and *zero* otherwise, and γ measures the impact of leverage on the conditional volatility.

The above modeling structure differs from the standard equity TGARCH model in the sense that the endogenous variable in the mean equation is volatility rather than equity returns. Thus good news in this case would be represented by negative innovations ($\varepsilon_{t-1} < 0$) and the opposite applies for bad news[15]. In the present model the impact of good news is measured by the sum of the coefficients $\theta + \gamma$, while the bad news has an impact of theta (θ). For gamma (γ) values which are statistically different from zero the news impact is asymmetric. The empirical findings suggest that the market data do not discern between negative and positive innovations and their associated effect on conditional volatility. A

[15] In the equity return TGARCH structure good and bad news are represented by positive ($\varepsilon_{t-1} > 0$) and negative ($\varepsilon_{t-1} < 0$) innovations respectively.

twofold explanation can be provided for the insignificant leverage effect: a) that market participants are concerned with the level of volatility rather than what triggered it, and b) news arrival might not be that important as they are now able to hedge their volatility exposure in the derivatives market. Regarding the appearance of the conditional volatility, using a TGARCH model, this remains the same as in the graph (see Fig. 2) already taken from the estimator without the leverage term. By using either a standard GARCH or a TGARCH framework, examination of mean reversion is currently under investigation. Preliminary results disclose a significant coefficient for the two-period lagged dependent variable. These results have both economic and practical intuition. Based on market experience, when volatility reaches high levels, then it is not expected to perpetuate on these level, and likewise when volatility is too low. Finally, and in a similar vein with the previous results, the pre-futures period is characterized by an IGARCH process, which is subsequently "corrected" in the next period.

V. CONCLUDING REMARKS

Given the argument that cash and futures markets are linked by arbitrage operations, then one would expect that participants in the forward looking futures market would convey information to the underlying cash market. Drawing upon this argument, the present study examines whether the onset of futures trading has conveyed enough information to alter spot market volatility. Using conditional volatility estimators a number of interesting findings have emerged.

More specifically, the introduction of variance futures has altered the level of volatility in the underlying asset – as measure by the three-month rolling volatility of index returns. Futures trading have conveyed confidence in the market by reducing equity return volatility as well as exposure to such a risk. The latter is inherent in the primary role of the particular futures contract. Unexpected shocks in the markets are no longer able to affect volatility in any significant way during the post-futures period. These shocks are easily absorbed and quickly disappear from the market, as a result of "risk neutrality", since participants have hedged their exposure to market fluctuations. All the GARCH processes employed seem to be dominated by long-memory effects as past conditional volatility has an important role to play on this particular sample. The three-month volatility measure exhibits a mean reversion pattern confirming a wide market belief; while its low/negative correlation with the wide market index level substantiates its role to lower portfolio risk.

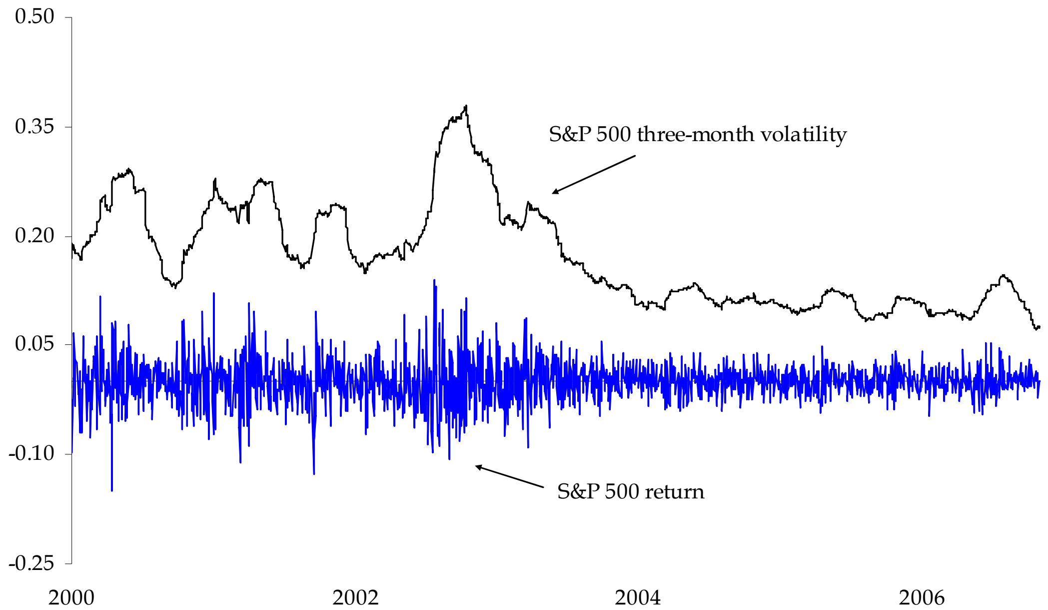
When the leverage effect is taken into account, market data do not seem to assign any particular statistical importance to either negative or positive innovations to volatility.

Thinking for a way forward, one could argue that the presented estimation framework, along with the associated results, sheds light on the information signal per se, but remains silent as to the optimum amount of information required[16], as well as the dispersion and quality of information flow. It is also a fact that the portion of implied (realized) volatility decreases (increases) as time elapses towards the maturity of any derivatives contract. Thus one may wish to examine the relationship between implied and realized volatility on a short- and long-term framework. Although the US economy is one of the dominant markets, empirical evidence from other economies has to corroborate/refute the present empirical findings before any final conclusions are drawn. Given the increasing interest in trading volatility, risk arbitrage, portfolio hedging, risk management of financial institutions and overall market stability such contributions seem worth of an actual application.

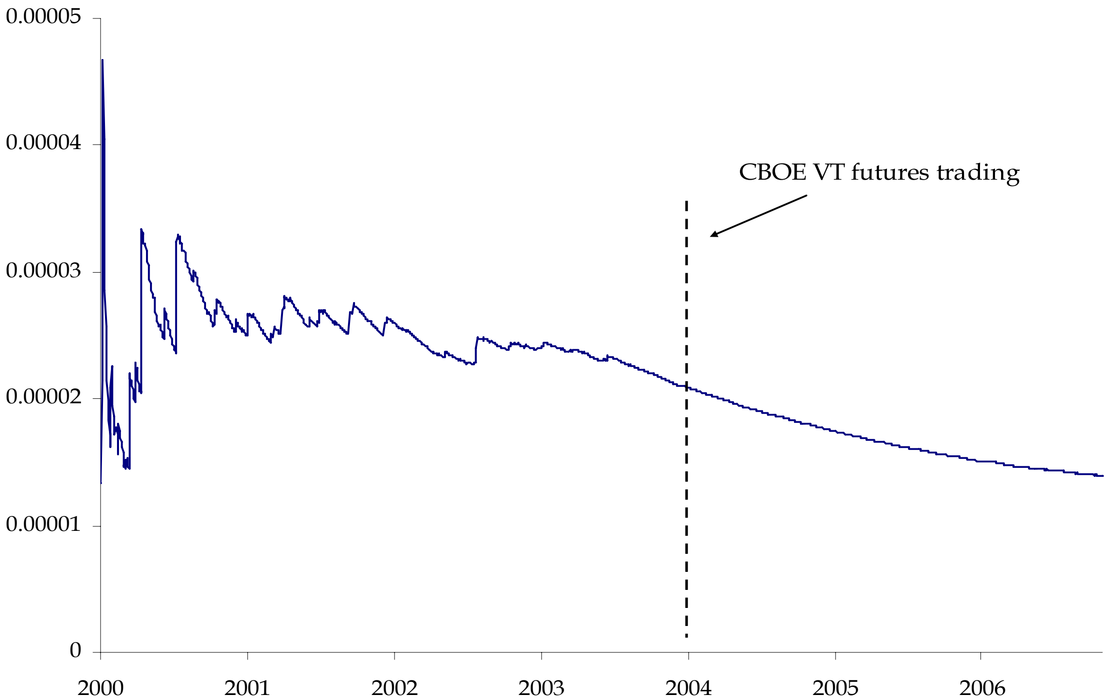
[16] Note that market forces alone are insufficient to cause all material information to be disclosed. Information is material if it has an impact on securities prices when it becomes publicly available for the first time. If it has no impact on price, it is largely irrelevant, although it may cause portfolio adjustments that leave prices unchanged.

Appendix Graphical Illustrations on the Time Series Employed

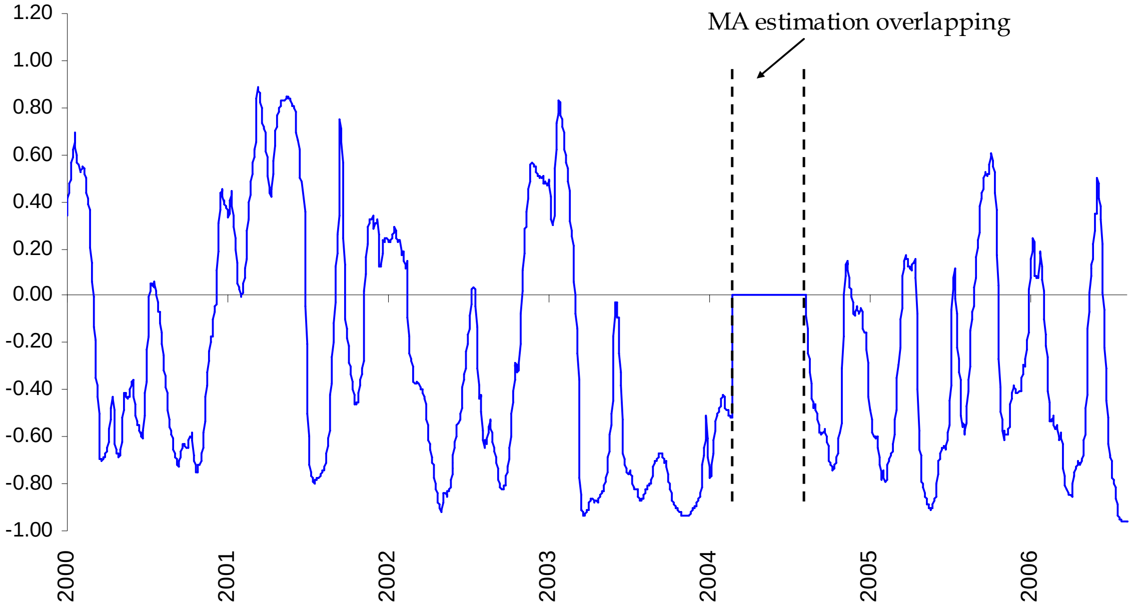
Panel A. Volatility and return of the S&P 500.



Panel B. Recursive estimation of the S&P 500 three-month volatility.



Panel C. Three-month correlation between S&P 500 level and volatility.



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