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BEHAVIORAL FINANCE AND PRICING OF DERIVATIVES: IMPLICATIONS FOR DODD-FRANK ACT

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This study investigates the relevance of noise in the derivative market by examining the responses of returns and time varying risks in six futures and four stock index options markets to a set of investor sentiments. Consistent with previous studies, the estimation results suggest that noise is systematically priced in a wide variety of futures and options markets. Investor sentiments on gold, crude oil, wheat, copper, live cattle and sugar significantly impact the returns and conditional variances in precious metals, energy, oilseed, industrial metals, livestock and soft agricultural futures markets respectively. Similarly returns and volatilities in VIX, VXD, VXN and VXO are significantly affected by sentiments of professional analysts and institutional investors, while there is no such effect of individuals. There seem to be a significant greater response of these derivative markets to bullish than bearish sentiments. Lastly, there are evidences of positive feedback trading by investors and lead-lag relationships among their sentiments. Noise seems to affect risk and return in the derivative market in a similar fashion in which it affects those in stocks. The direct implication of these findings is that traditional measure of time variation in systematic risk in the derivative market omits an important source of risk: noise. It has wider implications for the newly enacted Dodd-Frank financial reform bill on derivative trading. They also have important implications for policies that seek to reduce spillover effects and investors who aim to improve their portfolio performance.

Over the past decade the evidence that psychology and emotions influence financial decisions have become more convincing. Financial economists are now realizing that investors can be irrational and predictable errors by investors can affect valuations. Studies argue that psychological biases, cognitive errors and emotions affect investor decisions. Most of the theoretical and empirical studies on investors' psychology have focused on stock markets and empirical

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evidences on anomalies are well documented.[1] However, behavioral finance has been applied in derivatives pricing to a lesser degree. The current literature on derivatives and investors psychology merely conjectures or provides inconsistent results on whether behavioral factors are relevant in pricing of derivatives. Little empirical work is done to examine the ways in which greed, fear, and irrationality are priced in the options and futures markets. This research attempts to contribute to the literature by empirically investigating whether tenets of behavioral finance are relevant in the pricing of derivatives.

It is beyond the scope of one single study to examine the applicability of all theories and models of one area of research into another. This paper borrows one of the established paradigms from behavioral finance, the role of investor sentiments (also called noise) to examine if it can forecast the future direction of derivative prices. The noise trader models in behavioral finance imply that often investors do not make investment decisions based on a company's fundamentals and are capable of affecting stock prices due to unpredictable changes in their sentiments.[2] In traditional finance only risk premium matters while in behavioral finance both systematic risks and noise are relevant (Hirshleifer, 2001; Baur, Quintero, and Stevens, 1996). After decades of study the sources of risk premiums in financial markets is well understood; while, dynamic psychology based derivative pricing theories are still in the infancy stage.

Evidence which suggests that investor sentiments are a priced factor in futures and options market equilibrium is still in dispute. The existing empirical tests on investor sentiments and derivative pricing is provided by studies such as Wang (2001; 2003; 2004); Han (2008); Chen and Chang (2005); Simon and Wiggins (2001); Sanders, Irwin, and Leuthold (2000; 2003). These studies have found inconsistent results on the significance and causality of relationship between sentiments and derivative pricing. One of the reasons for this could be that the existing tests focus primarily on first moment contemporaneous correlations between investor sentiments and derivative returns while less attention is given to the impact of noise on time

1. The role of investor psychology in stock valuation is well documented by Black (1986), Trueman (1988), DeLong, Shleifer, Summers and Waldman (DSSW) (1990, 1991), Shleifer and Summers (1990), Lakonishok, Shleifer, and Vishny (1991), Campbell and Kyle (1993), Shefrin and Statman (1994), Palomino (1996), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subramanyam (1998); Hong and Stein (1999) and Sias, Starks, and Tinic (2001). Nofsinger (2010) provides an extensive review of theoretical and empirical studies on behavioral finance.

2. Studies related to individual investors sentiments find strong co-movements with stock market returns and volatility (Verma, Baklaci, and Soydemir, 2006, 2008; Verma and Verma 2007; Brown and Cliff 2005; De Bondt 1993) and mixed results regarding its role in short term predictability of stock prices (Brown and Cliff 2004; Fisher and Statman 2000). Similarly, studies examining institutional sentiments find strong co-movements with stock market returns (Verma et al. 2006, 2008; Brown and Cliff 2005) and mixed results regarding its short run implications on stock prices (Brown and Cliff, 2004; Lee, Jiang, and Indro 2002; Clarke and Statman 1998; Solt and Statman 1988). Recent behavioral asset pricing models predict linkages between irrational sentiment and risk to reward ratio (Verma and Soydemir 2009; Yu and Yuan 2005; Basak 2005; Cecchetti, Lam, and Mark 2000; Jouini and Napp 2005; Abel 2002; Girard, Rahman, and Zaher 2003; Garrett, Kamstra, and Kramer 2005; Li and Zhong 2005).

varying risks in futures and options markets. The DSSW (1990) and Sias, Starks, and Tinic (2001) suggest that the impact of noise traders' risk is on both the formation of conditional volatility and expected returns of an asset.[3] Therefore, any tests on the effect of investor sentiments on the mean alone are mispecified and at best incomplete. In case of derivative markets, Sanders, Irwin and Leuthold, (2000; 2003) argue that that investor sentiment does not affect expected returns but could impact its volatilities. However, no analysis is done to investigate the manner in which noise trading may affect expected return through its effect on the market's formation of risk (volatility) in derivative markets as suggested by the DSSW(1990).

Further, the evidence on momentum profitability (Jegadeesh and Titman 1993) and reversals suggest the effect of sentiments on financial markets may be asymmetric (Hong, Lim, and Stein 2000; Hong and Stein 1999). Specifically, a market displays an asymmetric response when returns respond differently to market upturns (bullish) than downturns (bearish) in terms of both speed and magnitude. The economic rationale for this asymmetric response can be explained from the behavioral standpoint of investor psychology. Investors, in general, are more concerned about market downturns than upturns, partly due to their risk-aversion and this tendency gets reflected in market prices, causing different responses to downturns and upturns.[4] Also, due to restrictions on short selling there may be an asymmetric relation between sentiment and valuations. That is, when investors are overoptimistic there is upward pressure on prices that is hard for rational investors to overcome while in the case of pessimism, it is easier for rational investors to trade against the irrational investors. This suggests that prices are not as likely to deviate below intrinsic value as they are above or, magnitude of undervaluation may be different from overvaluation. Given these arguments, it is important to empirically examine whether the relationship between sentiments and derivative pricing are asymmetrical during optimistic and pessimistic periods.

This research is designed to fill a void in the literature related to investor sentiments and derivative pricing by examining the role of behavioral finance in futures and options markets' returns, volatilities and asymmetry. Accordingly, the following three research questions are examined: (i) Is there a role of noise in commodity derivative market returns and risk? (ii) Is there a role of noise in stock derivative market returns and risk? (ii) Are there asymmetrical effects of noise on commodity and stock derivative markets during optimistic and pessimistic periods?

This research makes the following contribution to the literature: first, unlike previous studies which examine the relationship between sentiments and the mean

3. DSSW (1990) show that sentiment can affect expected return of an asset through its effect on the conditional variance of returns. Brown and Cliff (2005) argue that noise trading may impact higher moments of returns such as volatility. Lee, Jiang and Indro (2002) and Verma and Verma (2007) find significant relationship between sentiments and conditional variance in the U.S. stock market.

4. The asymmetric effect of sentiments on the stock market is attributed to the limits to arbitrage (Brown and Cliff, 2004), unidentified risk factors (Fama and French, 1992) and overconfidence (Gervais and Odean, 2001). Empirical tests on asymmetric relationship between sentiments and stock valuation is provided by Lee et al. (2002) and Verma and Verma (2007).

of derivative returns, this research tests the impact of noise on both return and volatilities of futures and options markets; second, unlike previous studies, which examine the symmetrical relationship without segregating between optimism and pessimism, this study examines the existence of asymmetrical impact of bullish and bearish sentiments on derivative markets; third, unlike previous studies which employs bivariate static techniques and treats sentiment of each derivative in isolation this research employs an appropriate multivariate technique to model sentiments of several derivatives of a related assets in one system and examines their relative and spillover effects. Treating sentiments in isolation implicitly ignores potential spillover effects of one type of sentiments on another.

The responses of six commodity futures index returns, volatilities and asymmetry to sentiments on a set of 20 separate commodities are analyzed. The six commodity futures markets identified are: energy, precious metals, industrial metal, agricultural products, grains and livestock. In order to link the relevant sentiments with each futures index, the 20 sentiments are factored into the following six groups: energy (crude oil, heating oil, natural gas, unleaded gasoline), precious metals (gold, silver, platinum), industrial metal (copper), agricultural products (cocoa, coffee, orange, sugar), grain (corn, soybean, soybean oil, wheat) and livestock (live cattle, lean hogs, feeder cattle, pork bellies). Similarly, the returns, volatilities and asymmetry of four stock index options to sentiments of three different categories of investors are analyzed. The four stock index options chosen are: VIX (S&P 500 index options), VXO (S&P 100 index options), VXN (Nasdaq 100 index options) and the VXD (Dow Jones options). The three groups of investors whose sentiments are analyzed are: individual investors, institutional investors, and professional analysts.

This study employs data on weekly basis from the following sources: Datastream; CBOE; CRSP; surveys of American Association of Individual Investors, Investors Intelligence, CONSENSUS Inc., Federal Reserve Bank of St. Louis, and Kenneth French Data Library. The estimation results of a set of multivariate EGARCH models indicate that there is at least one kind of sentiment in each market which significantly affects derivatives' returns and volatilities and also has asymmetric spillover effects. Specifically, investor sentiments on gold, crude oil, wheat, copper, live cattle and sugar are found to significant impact the conditional variance in precious metals, energy, oilseed, industrial metals, livestock and soft agricultural futures markets respectively. There seem to be a significant greater response of these futures markets to bullish than bearish investor sentiments. Similar results are obtained in case of VIX, VXD, VXN and VXO responses to investor sentiments. Both returns and volatilities in these stock index options are significantly affected by sentiments of professional analysts and institutions, while there is no such effect from individuals. There are also evidences of positive feedback trading by investors and lead-lag relationships among their sentiments. Overall, consistent with previous studies, the estimation results suggest that noise is systematically priced in a wide variety of futures and option markets.

These results are consistent with behavioral paradigm that suggests that noise affects an assets return through its impact on its conditional variance. The findings of this study could have important implications for the recently enacted Dodd-Frank's financial-system overhaul which includes measures that would bring more derivatives trading onto regulated exchanges. They also have important implications for policies that seek to reduce spillover effects and investors who aim to improve their portfolio performance.

The remainder of this study is organized as follows. Section I presents the theoretical foundation and reviews the relevant literature on derivative and behavioral finance while Section II presents the model. Section III summarizes data and descriptive statistics. Section IV describes methodology and reports estimation results. Section V presents implications and Section VI concludes.

I. THEORETICAL FOUNDATION

Standard derivative pricing models are based on theories of traditional finance and rest on the assumptions that investors make rational decisions and are unbiased in their predictions about the future. In recent years behavioral finance which incorporates the ideas of non-rational and non-risk neutral investors seems to challenge this notion. In derivative pricing literature, the role of behavioral finance stems from limits to arbitrage (Black 1986; DSSW 1990) and the prospect theory (Kahneman and Tversky 1979). A review of these two theories and empirical work is presented below.

An argument in traditional finance on why noise should not affect market prices lies in the mechanism of arbitrage. It is thought that smart investors look to create profits by trading against irrational traders in order to capture mispricing. Following Black (1986), DSSW (1990) present a model in which noise traders acting as a group can influence stock prices in equilibrium. They argue that arbitrage is limited in a market where informed investors have shorter horizons than noise traders. In their model the deviations in price from fundamental value created by changes in investor sentiments can introduce a systematic risk which is priced , that is, unpredictability in investor sentiments can systematically affect returns.

The theoretical framework describing noise trading in financial markets is provided by studies such as Black (1986), Trueman (1988), DSSW (1990), Shleifer and Summers (1990), Campbell and Kyle (1993), Shefrin and Statman (1994), and Barberis, Shleifer, and Vishny (1998). A trader not trading on information is classified as noise trader. A direct implication of these studies is that a certain groups of investors (noise traders) who often do not make investment decisions based on a company's fundamentals are capable of affecting stock prices by way of unpredictable changes in their sentiments. Noise traders acting in concert on non-fundamental signals can introduce a systematic risk that is priced in the market. Specifically noise trading risk exists because movements in investor sentiment are unpredictable and therefore arbitrageurs betting against mispricing run the risk that such sentiment becomes more extreme and prices move even further away from fundamental value. For this reason, the noise trader risk is measured by unpredictability in investor sentiments.

Several empirical studies have investigated the role of noise trading on stock valuation by using investor sentiments data that indicate the expectations of market participants (see Brown and Cliff 2004; Lee, Jiang and Indro 2002; Verma and Soydemir, 2006; 2008, 2009; Verma and Verma 2007.) In derivative markets the role of noise trading is examined by using investor sentiments data by studies such as Simon and Wiggins (2001) and Sanders et al. (2000, 2003).

Based on DSSW (1990), Brown and Cliff (2004, 2005) explicitly describe the mechanism under which investor sentiments can affect valuations. The environment where sentiments can affect valuations is based on three assumptions. First, some of the investors are biased; second, these biases are persistent in nature, and third, there are limits to arbitrage. Similarly, Shleifer and Summers (1990) present an alternative to the efficient market approach and present a model based on two assumptions: first, some investors are not fully rational and their demand for risky assets is affected by their sentiments; and second, trading by rational investors which are not subject to such sentiments is risky and therefore limited. They find that changes in sentiments are not fully countered by rational arbitrageurs and therefore can affect market prices. Palomino (1996) extends the DSSW (1990) model for an imperfectly competitive market and show that in the presence of risk averse investors, trading with rational speculators based on irrational beliefs may be profitable i.e., noise traders may earn higher returns and obtain higher expected utility than rational investors. It suggests that imperfect competition restricts arbitrage mechanism in two ways: first, quantities traded are smaller as compared to perfectly competitive markets which limit the price stabilizing effect of arbitrageurs; second, irrational behavior can impose higher costs on rational investors than noise traders.

Like in the case of the stock market, valuations in derivative markets can also be affected due to limits to arbitrage. In case of financial futures, the valuation of contracts mainly depends on the relationship between expected prices and spot rate of the underlying asset. This relationship is given by the spot-futures parity theorem (Elton and Gruber 1991). Commodity futures prices are also governed by the same general considerations as financial futures. One difference, however, is that the cost of carrying commodities is greater than the cost of carrying financial assets. Any deviation from this parity relationship would give rise to risk free arbitrage opportunities. Behavioral biases would not matter for derivative pricing if rational arbitrageurs could fully exploit the irrationality of noise traders, and thus trades of profit seeking investors would correct any misalignment in prices. However, behavioral advocates argue that, in practice, several factors limit the ability to profit from mispricing in the derivative market. For example, limits to arbitrage in options market are well documented by Stein (1989), Poteshman (2001), Poteshman and Serbin (2003), and Mahani and Poteshman (2004).

Limits to arbitrage can also be caused due to positive feedback trading in the derivative market. Positive feedback trading or trend chasing is generally considered to be an irrational behavior and associated with noise trading, which has potential to nullify the price stabilizing effect of arbitrage. Kurov (2008) provides evidence on the linkage between investors' attitude and trading behavior at the microstructure level in the futures market. It investigates the response of traders' order flows in S&P500 futures and NASDAQ100 futures indexes and finds that index futures traders use positive feedback trading strategies, that is, buy (sell) index futures contracts after price increases (decreases). It also finds a positive relationship between intensity of such positive feedback trading and individual and institutional investor sentiments. On similar lines, Manaster and Mann (1996) provide a reason as to why irrational behavior can affect trading and thus prices in futures contracts. They argue that index futures markets have a different microstructure as market makers tend to hold relatively small positions and quickly reduce their inventory exposure. Such microstructure characteristics of futures market may affect the propensity of traders to engage in positive feedback trading and limit the arbitrage mechanism of stabilizing prices. However, Antoniou, Koutmos, and Pericli (2005) did not find any evidence of positive feedback trading in index futures, concluding that rational arbitrageurs are able to correct the mispricing by way of arbitrage.

Sanders et al. (2003) examine the lead-lag relationship between returns and sentiments in 28 futures markets. They find that sentiments are increasing function of past returns (positive feedback trading), and noise trader sentiments are useful in predicting futures returns only when sentiments are at extreme level otherwise insignificant. Earlier Sanders et al. (2000) use similar analysis with Market Vane's bullish sentiment index and find consistent results. They argue that sentiment could impact other aspects of price behavior, such as volatility. This argument is consistent with Brown and Cliff (2005), which recognizes that noise trading may impact higher moments of returns, especially volatility. Similar arguments in favor of relationship between sentiments and time varying risk are presented by DSSW (1990) and Sias et al. (2001). These studies find a significant role of noise traders' sentiments in predicting future volatilities in the U.S. stock market. Motivated by these studies, an investigation of linkages between sentiments with conditional volatilities and expected returns in futures and options markets is the primary objective of this research.

Limits to arbitrage and psychological factors can also cause asymmetric behavior of an asset returns to bullish and bearish sentiments (Brown and Cliff 2005). Recent behavioral asset pricing models predict linkages between sentiment and the market price of risk during optimistic and pessimistic periods (Yu and Yuan 2005; Basak 2005; Cecchetti et al. 2000; Jouini and Napp 2005; Abel 2002; Girard et al. 2003; Garrett et al. 2005; Li and Zhong 2005) to be asymmetrical. These studies suggest that irrational investors and rational arbitrageurs hold opposite beliefs: When noise traders are pessimistic, rational arbitrageurs are optimistic. In such a scenario, the compensation for bearing risk should be higher to attract more wealth from rational arbitrageurs, thus adjusting market price of risk upwards. Conversely, when irrational investors are optimistic, market price of risk should be lower to deter rational investors from making investments.

Han (2008) tests the relationship between three types of sentiments and skewness of risk neutral S&P 500 index return and finds results that support the idea that sentiments is an important determinant of index option prices. It also find that index returns have asymmetric response to bullish and bearish sentiments.

Prospect theory describes how people frame and value a decision involving uncertainty. It modifies the analytic description of rational risk averse investors found in standard finance theories. There are four features of prospect theory that appear to be relevant for behavioral finance based derivative pricing models: (i) investors frame their choices in terms of potential gains and losses relative to a specific reference point (either recent highest or purchase price); (ii) investors value the gains/losses according to an S-shaped value function which is concave (convex) for gain (loss); (iii) the value function is asymmetric or steeper for loss than gain; and (iv) investors view each investments separately (also called mental accounting) rather than using a portfolio approach which limits investors' ability to minimize risk and maximize return.

Studies have shown that prospect theory is operative in the options market, and evidence for a concave (convex) value function, as suggested by the prospect theory, is much stronger than standard concave utility function. Actual option prices tend to show systematic and persistent deviation from the prediction of the Black and Scholes (1973) model. Several improvements have been proposed to correct this anomaly. Shefrin and Statman (1993) is one of the earlier behavioral studies to analyze covered call options and find that perceived value and choice from it is consistent with the value function of prospect theory.

Blackburn and Ukhov (2006) investigate the shape of the investors' utility function by examining the index options of Dow Jones and find support for non-concave utility function consistent with the prospect theory. On similar lines, Poteshman and Serbin (2003) analyze call option exercises and argue that a large number of these exercises are irrational in nature, motivated by positive feedback trading and not consistent with generally acceptable market equilibrium models.

Howell and Jagle (1997) argue that behavioral biases affect the subjective valuation as professionals tend to deviate from the Black-Scholes model. Likewise, Miller and Shapira (2004) find that both buyers and sellers price options below its expected values. Verslius, Lehnert, and Woff (2009) design a behavioral model of option pricing by incorporating risk attitude, mental accounting, and probability perceptions. They argue that the result of their behavioral model is better than the traditional Black-Scholes and stochastic volatility model of Heston (1993). Following this, Alemanni, Pena, and Zanotti (2010) find that behavioral version of Black-Scholes is able to better capture option prices than Heston (1993) stochastic volatility model.

Simon and Wiggins (2001) examine the predictive power of three measures of investor sentiments: VIX, put-call ratio, and trading index (TRIN) on 10, 20, and 30 days returns of S&P 500 futures contract. They find a positive relationship between these subsequent returns with the three measures of sentiments. They also find that lagged S&P500 futures contract return is negatively related to VIX and TRIN, a finding consistent with linkage between higher subsequent volatility due to large negative market returns (Nelsen 1991).

Chen and Chang (2005) employed VIX, put-call ratio, and TRIN as sentiment indicators and analyzed their predictive power over S&P 500 futures returns. They employ extended classifier system, one of the artificial intelligence models and find that sentiments are contrarian in nature and can significantly predict the S&P 500 futures returns. Similarly, Brown and Cliff (2004) regress individual and institutional investor sentiments against a set of derivative variables. They find that both VIX and CBOE equity put to call ratio are negatively related to institutional investor sentiments while positively related to individual investor sentiments. They also find that changes in net positions in SPX futures of non-commercial traders and small traders are positively related to institutional investor sentiments.

Wang (2003) uses the COT (Commitment of Traders) report, an indirect measure of sentiments to investigate the forecasting power of actual traders' position over S&P 500 index returns. It finds that both large speculators and large hedgers are useful market timing indicators but provide opposite forecasts. Speculators (hedgers) sentiments are price continuation (contrarian) in nature. It argues that large speculators have superior forecasting ability than hedgers and small traders. Earlier, Wang (2001) did similar analysis with COT data to forecast returns of six major agricultural futures and finds consistent results. Likewise, Wang (2004) investigates the predictive power of COT data on five major currencies — British pound, Canadian dollar, Deutsche mark, Japanese yen, and Swiss franc over their futures returns and find similar results.

In summary, theoretical studies suggest a significant relationship between sentiments and returns which is asymmetric in nature. However, empirical tests on noise and derivative valuation have found inconsistent results on significance and causal relationship between sentiments and options and futures pricing. For example, Sanders, Irwin, and Leuthold (2000, 2003), Antoniou, Koutmos, and Pericli (2005) find insignificant results; Kurov (2008), Han (2008), Simon and Wiggins (2001) suggest significant positive relationships; Chen and Chang (2005) find significant negative relationship; and Brown and Cliff (2004) and Wang (2001, 2003, 2004) find both positive and negative significant relationships.

One of the probable reasons previous studies do not provide any coherent answer is because existing tests focus only on first moment bivariate contemporaneous correlations between sentiments and valuation and ignore conditional volatilities.However, theoretical studies make a strong argument that sentiments can affect derivative valuation through its impact on time varying risk; no empirical test exists. Currently, it is merely conjectured that sentiments might affect both volatilities and returns in options and futures markets. Also, there is little test on how limits to arbitrage and other behavioral factors can cause derivative prices to behave asymmetrically during optimistic and pessimistic periods. This research is positioned to address these voids in the derivative pricing and behavioral finance literature.

II. MODEL

This study follows the approach suggested by DSSW (1990) and Sias et al. (2001) to model the impact of noise on derivative returns, volatility, and asymmetry. Recent empirical studies (Lee et al. 2002; Brown and Cliff 2005) have analyzed similar relationships in case of the stock market. Under this approach sentiments can impact an asset price through the interaction of four effects: (i) price pressure,

(ii) hold more, (iii) Friedman, and (iv) create space. The "price pressure" and "hold more" effects of sentiments directly impact expected returns of an asset. On the other hand, the "Friedman" and "create space" effects of sentiments indirectly impact expected returns through their influence on conditional volatilities of asset returns.

The "price pressure" effect represents the pricing error caused due to noise traders' misperceptions as their bullishness (bearishness) bids up (down) purchase (selling) prices thereby leading to lower expected returns. The "hold more" effect causes the expected returns to be higher (lower) since greater (lower) level of risk is borne by bullish (bearish) irrational investors due to increased (decreased) demand of assets. The "hold more" effect stems from the price pressure effect as irrational traders tend to hold more (less) of those assets whose prices are higher (lower) than their fundamental values. These two effects suggest that sentiments can impact expected returns by moving prices away from intrinsic values and cause a change in the level of market risk. The net impact of these two effects depends on whether noise traders are bullish or bearish. In case of bullishness, when the "hold more" effect is greater (lower) than the "price pressure" effect, expected returns would be higher (lower). However, during bearishness it does not matter which effect is greater since both effects would lead to lower expected returns.

The "Friedman" effect represents the loss which noise trades have to bear due to trade with rational arbitrageurs during the arbitrage mechanism. This is caused by noise traders' misperceptions about the risk of an asset, which makes them buy and sell at wrong time and suffer extreme losses. Like "price pressure," the "Friedman" effect also always leads to lower expected returns. The greater is the irrationality or misperceptions about risk, the larger is loss on noise trading.

The "create space" effect is the heart of the noise trader model. It suggest that assets on which irrational investors are active tend to trade at prices below their intrinsic values and expected to generate higher returns than securities on which noise traders play a less active role. The logic is that noise trading on certain assets increases the price uncertainty, making rational investors to shun those causing prices to fall and expected returns to increase. Noise traders thus create their own space. This variability in returns due to greater create space brings an additional systematic risk that is priced in equilibrium. Noise traders thus gain more by trading on these securities and consequently these assets exhibit greater volatility and mean reversion than the ones which are mainly held by rational investors and trade close to their fundamental values. The greater (lower) the create space than "Friedman" effect; greater (lower) would be the expected returns due to effect of sentiments on conditional volatilities.

The four effects also suggest an asymmetric effect of bullish and bearish sentiments on asset returns. In "price pressure" and "Friedman" effects, it does not matter whether noise traders are bullish or bearish since irrationality causes the expected returns to be always lower. This is in contrast to "hold more" effect where expected returns would be higher or lower depends on bullish or bearish sentiments. Similarly "create space" effect causes an increase in expected returns only when noise traders are bullish while there is no negative effect of bearish sentiments on expected returns. Overall, noise traders can earn higher returns in the presence of "hold more" and "create space" effects only when they are bullish.

In summary, the "price pressure" and "hold more" effects are short-term in nature due to the effect of *directions* of sentiments on the *mean* of excess returns, while the "Friedman" and "create space" capture the long run impact of noise on excess returns due to the effect of *magnitude* of sentiments on the formation of future *volatilities* of returns. In order to examine long term relationship between sentiments and asset valuation, there is a strong case to model both returns and volatilities of futures and options while analyzing the effect of noise on derivative valuation.

This research employs an appropriate multivariate technique to model sentiments of several derivatives of related assets in one system and examines their relative and spillover effects. Treating sentiments in isolation implicitly ignores potential spillover effects of one type of sentiments on another. For example, shocks originating from sentiments of one related asset (say gold) not considered might mistakenly be seen as a disturbance originating from sentiments of other asset (say silver) included in the analysis. Since studies such as Brown and Cliff (2004, 2005) and Verma and Verma, (2007) suggest that risk, returns, and sentiments may act as a system, the multivariate version of Nelson's (1991) Exponential Generalized ARCH (EGARCH) model is employed.

In order to model asymmetric effects of bullish and bearish sentiments on returns and volatilities, the multivariate version of Nelson's EGARCH extended by Koutmos and Booth (1995) is used.[5] This model is estimated separately to investigate the postulated relationships in six commodity futures markets (energy, precious metals, industrial metal, agricultural products, grains and livestock) and four stock index options markets (VIX, VXO, VXN and VXD) with 22 commodities and 3 stock market based investor sentiments, respectively. Table 1 details the list of variables included in each model.

The Vector Autoregressive (VAR) model (Sims 1980) in the mean equation is appropriate when estimating unrestricted reduced-form equations with a uniform set of dependent variables as regressors. The model is also appropriate for analyzing the postulated relationships because it does not impose a priori restrictions on the structure of the system and can be viewed as a flexible approximation to the reduced form of the correctly specified but unknown model of true economic nature.

The mean equation takes the following form:

$$R_{i,t} = \beta_{i,0} + \sum_{i=1,\,j=1}^{K} \beta_{i,j} R_{j,t-m} + \varepsilon_{i,t}; i, j = 1..K; i \neq j \tag{1}$$

5. Nelson's EGARCH model is a univariate one and it only considers the asymmetric impacts of positive and negative innovations of a previous period on current conditional volatility. It does not examine the asymmetric impact of positive and negative innovations of one variable on the volatility of another variable.

Table 1. List of Variables Included in Each Model.

Models		Variables
Model 1: Energy futures market	i	Returns on Reuters-CRB energy sub-index
	ii	Sentiments on crude oil
	iii	Sentiments on heating oil
	iv	Sentiments on natural gas
	v	Sentiments on unleaded gasoline
Model 2: Precious metals futures market	i	Returns on Reuters-CRB precious metals sub-index
	ii	Sentiments on gold
	iii	Sentiments on silver
	iv	Sentiments on platinum
Model 3: Industrial futures market	i	Returns on Reuters-CRB industrial sub-index
	ii	Sentiments on copper
	iii	Sentiments on silver
	iv	Sentiments on platinum
Model 4: Soft agricultural futures market	i	Returns on Reuters-CRB soft agriculture produce sub-index
	ii	Sentiments on cocoa
	iii	Sentiments on coffee
	iv	Sentiments on orange
	v	Sentiments on sugar
Model 5: Grain and oil seed futures market	i	Returns on Reuters-CRB grain and oil seed sub-index
	ii	Sentiments on corn
	iii	Sentiments on soybean
	iv	Sentiments on soybean oil
	v	Sentiments on wheat
Model 6: Livestock futures market	i	Returns on Reuters-CRB livestock seed sub-index
	ii	Sentiments on live cattle
	iii	Sentiments on lean hogs
	iv	Sentiments on feeder cattle
	v	Sentiments on pork bellies
Model 7: Stock index derivative market	i	Returns on VIX
	ii	Returns on VXO
	iii	Returns on VXN
	iv	Returns on VXD
	v	Sentiments of individual investors
	vi	Sentiments on institutional investors
	vii	Sentiments of professional analysts

Here $R_{i,t}$ is the column vector of variables under consideration. $\beta_{i,0}$ is the deterministic component comprised of a constant. $\beta_{i,j}$ is matrix of coefficients, *m* is the lag length and $\varepsilon_{i,t}$ is a vector of random error terms.

This equation is estimated seven times separately to examine the role of noise in the seven derivative markets: energy, precious metals, industrials, soft agricultural, grain and oil seed, livestock, and stock index. In total, these seven models include 25 different types of investor sentiments related to 25 commodities and stock indexes. For example, in Model 1, which examines the role of noise in the energy futures market, sentiments on the following four commodities are used: crude oil, heating oil, natural gas, and unleaded gasoline. Similarly, in Model 2, which investigates the effect of noise in the precious metals futures market, sentiments on the following three commodities are used: gold, silver and platinum.[6]

In the first model, $K = 5$ since there are five variables and thus $i,j = 1,2,3,4,5$. Similarly, in the second model, $K = 4$, or $i,j = 1,2,3,4$ and so on. Here, the parameter $\beta_{ii,j}$ captures the degree of mean spillover effects across sentiments and returns. A significant $\beta_{ii,j}$ coefficient would mean that variable *j* leads variable *i*, or equivalently, that current *j* can be used to predict future *i*. Since the purpose of the paper is not to analyze how market return and volatility are affected by its past innovations, but rather to investigate the spillover effects between sentiments and volatility, the constraint $i \neq j$ is specified.

Following multivariate EGARCH (Koutmos and Booth 1995) the conditional variance equations takes the following form:

$$\sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{K} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-m}^2)\}; i, j = 1...K, i \neq j \tag{2}$$

$$f_j(Z_{j,t-m}) = (\left|Z_{j,t-m}\right| - E\left|Z_{j,t-m}\right| + \delta_j Z_{j,t-m}); j = 1..K \tag{3}$$

where $Z_{j,t-1}$ is the standardized residual at time *t-m* which is defined as $\varepsilon_{j,t-m}/\sigma_{j,t-m,}$ and $E|Z_{j,t-m}|$ is the expected value of $Z_{j,t-m}$. The parameters $\alpha_{i,j}$ captures the volatility spillover among the variables, that is, the effect of innovations from variable *j* to variable *i*.

The asymmetric effect of negative and positive on conditional volatility is measured by the ratio $|-1 + \delta_j|/(1 + \delta_j)$. A negative value of δ_j will lead to a larger value of the ratio indicating that negative innovations will have greater effects on conditional volatility than positive innovations. A significant positive (negative) $\alpha_{i,j}$ coupled with a negative (positive) δ_j implies that negative (positive) innovations in variable *j* have a higher impact on volatility of variable *i* than positive (negative) innovations. This implies that the volatility spillover mechanism is asymmetric.

Following Bollerslev (1990), Koutmos and Booth (1995), and So (2001), a time invariant correlation matrix is assumed while estimating these multivariate EGARCH

6. A description of variables included in each of the seven models is shown in table 1 and their descriptive statistics are shown in Table 2.

models. Under this specification, the covariance is equal to the product of the standard deviations ($\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\,\sigma_{j,j}$ for i, j = 1,2,3; $i \neq j$). This specification reduces the number of parameters and makes the estimation more tractable.

III. DATA AND DESCRIPTIVE STATISTICS

The data for this research are obtained from May 1990 to December 2010 in weekly intervals.[7] A common sample is identified during this period to match all the variables. The description of the data source is as follows:

A. Futures Market Data

This study employs six commodity indices benchmarks to test the effect of noise on futures market. These commodity futures indices attempt to replicate the return available to holding long positions in commodities such as agriculture, metal, energy, or livestock investments (Schneeweis and Spurgin 1997). The futures benchmark therefore serves as an index of the expectations of the commodity market participants towards the future valuation of the underlying assets. Valuations of these indices are based primarily on the following three factors: (i) price return derived from changes in a relative commodity futures contract; (ii) roll return, which is the return associated with rolling over a futures contract prior to its expiration date, and re-investing the entire proceeds in order to keep the portfolio fully invested; and (iii) collateral return, which is the interest earned on any cash value during the investment period.

The commodity futures indices are from the Reuters Commodity Research Bureau Index (CRB). CRB is a leading industry index, and it has served as the most widely recognized measure of global commodities markets and a widely recognized broad measure of overall commodity price trends. Since 2005, the CRB is also known as the Reuters/Jefferies-CRB index. The source for CRB data is the Thomson Financials Datastream database. The details of the CRB component groups (sub-commodity index) used in this study are as follows:

- The benchmark for the energy index is the Reuters-CRB energy sub-index which comprises of crude oil, heating oil, and natural gas, and it accounts for 18% of the overall CRB Index.

- The benchmark for the grains and oilseed index is the Reuters-CRB grains and Oilseeds sub-index which is comprised of corn, soybeans, and wheat, and accounts for 18% of the overall CRB Index.

- The benchmark for industrial materials is the Reuters-CRB industrials sub-index which comprises of copper and cotton, and it accounts for 12% of the overall CRB Index.

- The benchmark for livestock is the Reuters-CRB livestock sub-index

7. The exception is CBOE volatility indices, which started at later dates.

which comprises live cattle and lean hogs and accounts for 12% of the overall CRB Index.

- The benchmark for precious metals is the Reuters-CRB precious metals sub-index which comprises gold, platinum, and silver, and it accounts for 17% of the overall CRB Index.

- The benchmark for soft agriculture produce is the Reuters-CRB soft agriculture produce sub-index which comprises of cocoa, coffee, orange juice, and sugar, and it accounts for 23% of the overall CRB Index.

This paper employs the CRB index returns instead of returns of assets included in each index due to the following two reasons: replacing index with multiple assets comprising each index would substantially increase the number of variables in each multivariate EGARCH models which might make them overparameterized, and for consistency purposes, the CRB index returns is employed in all the models. There would be a substantial increase in the relevant parameters that might lead to loss of generalizability of results if these indexes are replaced with several assets.

B. Options Market Data

This study employs the four options volatility indices from Chicago Board Options Exchange (CBOE) dataset. The CBOE volatility indices are key measures of market expectations of 30 days (near-term) volatility conveyed by different stock index option prices. These indices are based on stock index option prices and incorporate information from the volatility skew by using a wider range of strike prices rather than just at-the-money series. Specifically, the four stock index options chosen are the following: VIX, which tracks the S&P 500 index options; VXO, which tracks the S&P 100 index options; the VXN, which tracks the Nasdaq 100 index options; and the VXD, which tracks the Dow Jones index options.

C. Futures Market Sentiments Data

To measure the expectations of informed investors, this study employs Consensus Bullish sentiment index provided by Consensus Inc. This index gives the attitudes of professional brokerage house analysts and independent advisory services on major financial markets. Consensus Inc. surveys these advisory services on bullishness or bearishness of a particular asset. It compiles a sentiment index for each of these assets by dividing the number of bullish counts to the total number of opinions. This index is compiled on every Friday and released during the early part of the following week. Specifically, this research uses sentiments on 22 different commodities, which can have a bearing on the returns and volatilities in six futures markets chosen for this study. These 22 assets for which sentiments are obtained are (i) for energy futures market (crude oil, heating oil, natural gas, unleaded gasoline); (ii) for precious metals futures market (gold, silver, platinum); (iii) for industrial metal futures market (copper, silver, platinum); (iv) for agricultural products futures market (cocoa, coffee, orange, sugar); (v) for grain futures market (corn, soybean, soybean oil, wheat); and (vi) for livestock futures market (live cattle, lean hogs, feeder cattle, pork bellies).

D. Stock Index Options Sentiments Data

To measure sentiments of market participants on index options, this study employs three different survey data similar to the ones used in the literature on behavioral finance and stock valuation. The three kinds of investors chosen are institutional investors, who participate in the market for a living; individual investors, whose primary line of business is outside the stock market; and professional analysts, who provide advisory services (i.e., informed investors).

The choice of institutional investor sentiment index is survey data of *Investors Intelligence (II)*, an investment service based in Larchmont, New York. *II* compiles and publishes data based on a survey of investment advisory newsletters. To overcome the potential bias problem towards buy recommendation, letters from brokerage houses are excluded. Based on the future market movements, the letters are labeled as bullish, bearish, or correction (hold). For consistency purposes, the sentiment index for the institutional investor is computed as the percentage of bullish responses to the total number of opinions. Since authors of these newsletters are market professionals, the *II* series is interpreted as a proxy for institutional investor sentiments.

The choice of individual investor sentiment index is the survey data of *American Association of Individual Investor (AAII)*. Beginning July 1987, *AAII* conducts a weekly survey asking for the likely direction of the stock market during the next six months (up, down, or the same). The participants are randomly chosen from approximately 100,000 AAII members. Each week, *AAII* compiles the results based on survey answers and labels them as bullish, bearish, or neutral. These results are published as "investor sentiment" in monthly editions of *AAII* Journal. The sentiment index for individual investors is computed as the percentage of bullish investors to total number of opinions. Since this survey is targeted towards individual investors, it is primarily a measure of individual investor sentiments.

The choice of informed investor sentiments is the index provided by Consensus Inc., which gives the attitudes of professional brokerage house analysts and independent advisory services on future stock market movements. Consensus Inc. surveys these advisory services on bullishness or bearishness of stock market. It compiles a sentiment index by dividing the number of bullish counts to the total number of opinions. This index is compiled on every Friday and released during the early part of the following week.

Table 2 reports the descriptive statistics of the above- mentioned 33 variables. In the case of futures and options markets log first differences are used to capture weekly returns while sentiments are at their levels. Overall, the mean returns of commodity futures indices are somewhat higher than those of stock index options (except for VXN). Specifically, precious metals and energy futures have higher mean returns accompanied by higher standard deviation, suggesting that investors are being compensated for bearing additional risk. That these higher statistics are observable in the two futures market may be due to high volatility in crude oil and gold prices during the last few years. The sentiments related to the commodity markets are somewhat in the range of 41%–51%, suggesting that expectations have been almost same for bullishness and bearishness/neutral. The only exception is sentiments related to the natural gas, approximately 20%, indicating that almost 80% of the market participants were either bearish or neutral during the last two decades. Consistent with the volatility in energy and precious metals futures prices, the sentiments related to crude oil, gasoline, heating oil, and gold have higher standard deviation than other expectation indicators. Of the three stock market related sentiments, institutional investors and professional analysts seem to be more bullish than individual investors. The sentiments of institutional investors appear to be more volatile than those of individuals and analysts.

IV. ESTIMATION

In accordance with equations (1, 2, and 3), a set of seven multivariate EGARCH models are estimated. The first model examines the role of noise in the energy market by linking the energy futures market return with sentiments on four energy related assets: crude oil, heating oil, natural gas and unleaded gasoline. Table 3 reports the estimated coefficients of the mean and variance equations. The parameter $\beta_{i,j}$ captures the degree of mean spillover effects across sentiments and returns. Specifically, a significant $\beta_{i,j}$ coefficient would mean that variable *j* leads variable *i*, or equivalently, current *j* can be used to predict future *i*. The significant positive coefficients $\beta_{12,}$ $\beta_{13,}$ $\beta_{14,}$, and β_{15} suggest investor sentiments for the four energy related assets play a significant role in the energy futures market returns. The crude oil sentiments seem to have the maximum impact on energy futures returns. The volatility spillover effects among variables is captured by the parameters $\alpha_{i,j}$, that is, the effect of innovations from variable *j* to variable *i*. A significant and negative α_{12} indicates spillover effects from crude oil sentiments to energy futures market volatility. Unlike the results for energy futures returns, where all four energy related assets have significant effects, in the case of variance only α_{12} is significant and negative. Insignificant volatility spillover effects of heating oil, natural gas and unleaded gasoline sentiments reiterate the dominant effect of crude oil in the energy market.

The possibility of asymmetric impact of investor sentiments on futures market volatilities can be ascertained by examining the coefficients $\alpha_{i,j}$ coupled with δ_j. A significant negative $\alpha_{i,j}$ coupled with a significant positive δ_j would imply that volatility spillover mechanism from j^{th} variable to i^{th} variable is asymmetric or there is greater effect of bullish than bearish sentiments on the conditional variance of returns. In Table 3, a negative and significant $\alpha_{1,2}$ exists with a positive and significant δ_2, suggesting that there is greater response of energy futures volatilities to bullish than bearish crude oil sentiments. Although the parameters δ_3, δ_4, and δ_5 are significant,

Table 2. Descriptive Statistics.

	Mean	Max	Min	S.D.	Skewness	Kurtosis
Panel A: Futures markets returns						
CRB_EGY	0.0016	0.1575	-0.2591	0.0377	-0.7378	7.8725
CRB_IND	0.0007	0.0908	-0.0805	0.0216	-0.0300	4.0453
CRB_GR	0.0009	0.1122	-0.0986	0.0270	0.3317	3.8508
CRB_LIV	0.0004	0.1077	-0.0948	0.0224	0.0693	4.6715
CRB_PR	0.0012	0.0866	-0.1021	0.0233	-0.4611	5.0158
CRB_AG	0.0006	0.0893	-0.0813	0.0256	0.1393	3.4799
Panel B: Stock index options returns						
VIX	0.0003	0.3294	-0.2968	0.0843	0.4315	3.9886
VXD	-0.0001	0.2984	-0.2335	0.0842	0.5125	3.8346
VXN	-0.0018	0.2904	-0.2375	0.0734	0.4074	3.8738
VXO	0.0002	1.2514	-0.5040	0.0936	2.0855	29.5143

Table 2, continued. Descriptive Statistics.

	Mean	Max	Min	S.D.	Skewness	Kurtosis
Panel C: Commodity market sentiments						
Energy:						
S_CRUDE	0.4402	0.9600	0.0000	0.2277	-0.1669	2.3305
S_HEAT	0.4348	0.9400	0.0400	0.2074	0.1116	2.0523
S_NG	0.1940	0.9300	0.0000	0.2496	0.7969	2.1491
S_GASO	0.4116	0.9500	0.0000	0.2329	-0.0517	2.1586
Precious metals:						
S_GLD	0.4804	0.9600	0.0300	0.1898	0.1177	2.2280
S_SLV	0.4709	0.9500	0.0400	0.1783	0.2756	2.6018
S_PLT	0.4909	0.9500	0.0600	0.2034	-0.0838	2.1438
Industrial:						
S_CU	0.4856	0.9600	0.0800	0.1966	0.0236	2.0488
S_SLV	0.4709	0.9500	0.0400	0.1783	0.2756	2.6018
S_PLT	0.4909	0.9500	0.0600	0.2034	-0.0838	2.1438

Table 2, continued. Descriptive Statistics.

	Mean	Max	Min	S.D.	Skewness	Kurtosis
Panel C, continued: Commodity market sentiments						
Agricultural:						
S_COCOA	0.4363	0.9400	0.0400	0.1857	0.3227	2.4439
S_COFFEE	0.4580	0.9600	0.0400	0.1997	0.2195	2.2030
S_OJUICE	0.4238	0.9400	0.0500	0.2091	0.2331	2.1422
S_SUGAR	0.5088	0.9400	0.0500	0.2025	-0.0071	2.1232
Grain and oil seed:						
S_CORN	0.4895	0.9500	0.0500	0.1939	0.1377	2.2009
S_SOY	0.5130	0.9400	0.1200	0.1758	0.0071	2.1301
S_SOYOIL	0.4605	0.9600	0.0500	0.2052	0.1843	2.1291
S_WHEAT	0.4858	0.9200	0.0300	0.1794	0.0410	2.3422
Livestock:						
S_LCATTLE	0.5138	0.8700	0.1200	0.1501	-0.0160	2.2946
S_HOGS	0.4591	0.9300	0.1300	0.1565	0.1400	2.2874
S_FCATTLE	0.4688	0.9500	0.0600	0.1861	0.1650	2.2807
S_PORK	0.4261	0.8900	0.0400	0.1807	0.2334	2.3358

Table 2, continued. Descriptive Statistics.

	Mean	Max	Min	S.D.	Skewness	Kurtosis
Panel D: Stock market sentiments						
AA	0.3984	0.3980	0.6860	0.1280	0.0991	0.1394
II	0.4806	0.4890	0.6290	0.2224	0.0764	-0.6827
CONS	0.4667	0.8600	0.0300	0.1580	-0.0198	2.3193

The variables included in panel A are weekly returns on CRB futures indices related to energy (CRB_EGY), industrial metals (CRB_IND), grains and oil seeds (CRB_GR), livestock (CRB_LIV), precious metals (CRB_PR) and soft agricultural products (CRB_AG) .The variables included in panel B are weekly returns of CBOE volatility index for S&P500 (VIX), Dow Jones (VXD), NASDAQ (VXN) and S&P100 (VXO). The variables included in panel C are % of bullish professional analysts on cocoa (S_COCOA), coffee (S_COFFEE), corn (S_CORN), crude oil (S_CRUDE), copper (S_CU) , feeder cattle (S_FCATTLE), unleaded gasoline (S_GASO), gold (S_GLD), heating oil (S_HEAT), hogs (S_HOGS), live cattle (S_LCATTLE), natural gas (S_NG), orange juice (S_OJUICE), pork (S_PORK), platinum (S_PLT), silver (S_SLV), soybean (S_SOY), soy oil (S_SOYOIL), sugar (S_SUGAR) and wheat (S_WHEAT). The variables included in panel D are % of bullish individual investors (S_AA), institutional investors (S_II) and professional analysts (S_CONS).

Table 3. Multivariate EGARCH Estimation Results for Sentiments and Energy Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	0.0090	0.0106	0.8462
β_{12}	0.0873***	0.0280	3.1144
β_{13}	0.0559***	0.0148	3.7851
β_{14}	0.0470***	0.0133	3.5347
β_{15}	0.0465**	0.0235	1.9796
β_{20}	0.1260***	0.0094	13.4188
β_{21}	0.2025***	0.0558	3.6283
β_{23}	-0.0012	0.0036	-0.3437
β_{24}	0.0092	0.0153	0.6036
β_{25}	0.0064	0.0222	0.2867
β_{30}	0.0403***	0.0075	5.3599
β_{31}	0.0195	0.0182	1.0728
β_{32}	0.0361***	0.0066	5.4629
β_{34}	0.0334***	0.0015	22.6893
β_{35}	0.0187	0.0129	1.4523
β_{40}	0.0025	0.0213	0.1160
β_{41}	-0.0561	0.1119	-0.5009
β_{42}	0.2101***	0.0313	6.7197
β_{43}	0.0207	0.0215	0.9656
β_{45}	0.0428	0.0280	1.5311
β_{50}	0.0959***	0.0086	11.1328
β_{51}	0.2520***	0.0811	3.1090
β_{52}	0.1359**	0.0568	2.3911
β_{53}	0.0199***	0.0058	3.4456
β_{54}	0.2208***	0.0161	13.7025
α_{12}	-0.1797***	0.0625	-2.8752
α_{13}	-0.1493	0.2375	-0.6289
α_{14}	-0.0436	0.0498	-0.8764
α_{15}	-0.0857	0.1939	-0.4417
α_{21}	0.2067	0.1754	1.1783
α_{23}	0.0560	0.1246	0.4497
α_{24}	0.0057	0.0250	-0.2278
α_{25}	0.0846	0.1109	0.7633
α_{31}	-0.1183	0.0966	-1.2246
α_{32}	-0.0685	0.0426	-1.6073
α_{34}	-0.0392**	0.0184	-2.1287
α_{35}	0.3274***	0.0828	3.9557

Table 3, continued. Multivariate EGARCH Estimation Results for Sentiments and Energy Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{41}	0.2324	0.1773	1.3108
α_{42}	-0.1043	0.1036	-1.0071
α_{43}	0.2151	0.2560	0.8401
α_{45}	-0.0313	0.1671	-0.1873
α_{51}	0.2844*	0.1670	1.7025
α_{52}	0.0236	0.0352	0.6711
α_{53}	-0.0287	0.0967	-0.2971
α_{54}	-0.1258***	0.0349	-3.6085
α_{55}	0.5040***	0.1131	4.4545
δ_1	0.3003***	0.0731	4.1090
δ_2	0.7122***	0.0450	15.8273
δ_3	-0.5722***	0.0580	-9.8700
δ_4	1.4381***	0.2580	5.5732
δ_5	-0.3011***	0.0787	-3.8281

The five variables included are: CRB energy futures index returns (i,j=1), investor sentiments on crude oil (i,j=2), heating oil (i,j=3), natural gas (i,j=4) and unleaded gasoline (i,j=5). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters β_{12}, β_{13}, β_{14} and β_{15} captures the effect of sentiments of crude oil, heating oil, natural gas and unleaded gasoline respectively on energy futures market returns. Similarly, α_{12}, α_{13}, α_{14} and α_{15} captures the volatility spillover effects or innovations from sentiments of crude oil, heating oil, natural gas and unleaded gasoline respectively on energy futures market volatilities. The asymmetric effects of these four sentiments on energy futures market volatility is captured by δ_2, δ_3, δ_4 and δ_5. A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on volatility of energy futures market.

they do not imply asymmetric effects of other sentiments on energy futures volatilities since coefficients α_{13}, α_{14}, and α_{15} are statistically insignificant.

Some other significant coefficients also reveal linkages among sentiments of different energy related assets. For example, significant positive parameters β_{32}, β_{42} and β_{52} indicate that sentiments of heating oil, natural gas and unleaded gasoline are formed in part due to investors' perceptions about the future direction of the crude oil prices. However, crude oil sentiments do not seem to be developed in response to expectations about the other three energy related assets (insignificant β_{23}, β_{24} and β_{25}). Similarly, heating oil sentiments seems to be impacted by bullishness/bearishness in natural gas. There is also some evidence of positive feedback trading or trend chasing by investors. Specifically, coefficients β_{21} and β_{51} are positive and significant, suggesting that past futures index returns are an important

Table 4. Multivariate EGARCH Estimation Results for Sentiments and Precious Metals Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	0.0016	0.0207	0.0773
β_{12}	0.0901***	0.0278	3.2410
β_{13}	0.0382	0.0377	1.0133
β_{14}	0.0429	0.0405	1.0593
β_{20}	0.0779***	0.0225	3.4622
β_{21}	1048.0159	584501.4514	0.0018
β_{23}	0.0082	0.1594	0.0514
β_{24}	0.2216	0.2139	1.0360
β_{30}	0.0539	0.0655	0.8229
β_{31}	12440.7844	104018.4407	0.1196
β_{32}	0.3418**	0.1478	2.3126
β_{34}	-0.1498	0.2123	-0.7056
β_{40}	0.0067	0.0778	0.0861
β_{41}	78693.1284	90090.3503	0.8735
β_{42}	0.0782	0.0674	1.1602
β_{43}	0.0451	0.1865	0.2418
α_{12}	-2.5718***	0.8359	-3.0767
α_{13}	-0.5461	0.5169	-1.0565
α_{14}	2.4384	3.7948	0.6426
α_{21}	0.9442	0.9203	1.0260
α_{23}	0.1239	0.5064	0.2447
α_{24}	5.0691	4.6322	1.0943
α_{31}	-0.6950	0.7483	-0.9288
α_{32}	-0.1437	0.6720	-0.2138
α_{34}	-1.5136	2.1564	-0.7019
α_{41}	0.1369	0.5449	0.2512
α_{42}	-0.0431	0.3742	-0.1152
α_{43}	-0.0475	0.5321	-0.0893
δ_1	-0.0413	0.6549	-0.0631
δ_2	0.9875***	0.3561	2.7731
δ_3	-0.3294	0.2544	-1.2948
δ_4	-0.7961***	0.1535	-5.1863

The four variables included are: CRB precious metals futures index returns (i,j=1), investor sentiments on gold (i,j=2), silver (i,j=3), and platinum (i,j=4). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters $\beta_{12,}$ $\beta_{13,}$ and β_{14} captures the effect of sentiments of gold, silver and platinum respectively on precious metal futures market returns. Similarly, $\alpha_{12,}$ $\alpha_{13,}$ and α_{14} captures the volatility spillover effects or innovations from sentiments of gold, silver and platinum respectively on precious metals futures market volatilities. The asymmetric effects of these three sentiments on precious metals futures market volatility is captured by $\delta_{2,}$ $\delta_{3,}$

determinant of sentiments for crude oil and unleaded gasoline.

The second multivariate EGARCH model consists of four variables related to the precious metals asset class. It includes precious metals futures index returns and sentiments for gold, silver and platinum. The estimation results are presented in Table 4. The effect of gold sentiments on precious metals futures returns and volatilities is similar to the impact of crude oil sentiments on the energy futures market. Significant β_{12} and α_{12} indicate that sentiments induced noise trading on gold can affect precious metal futures returns and volatilities respectively. Specifically, the effect of gold sentiments is positive on mean while negative on the conditional variance of CRB futures index returns for precious metals. Moreover, α_{12} coupled with a significant and positive δ_2 suggests the presence of asymmetric response of these volatilities to the bullish and bearish sentiments on gold. The sentiments of other two precious metals (silver and platinum) seem to have an insignificant effect on the returns and volatilities of futures index. Moreover, a significant β_{32} coefficient means that sentiments of silver are significantly driven by traders' expectations about gold.

Table 5 reports the estimation of a five variable multivariate EGARCH model, which includes grain and oil seed futures index returns and sentiments for corn, soybean, soybean oil, and wheat. Three out of four sentiments (corn, soybean and wheat) have significantly positive effect on oil seed futures index returns. Similarly, the conditional variance of futures index returns is significantly affected by soybean and wheat sentiments. Negative and significant coefficients $\alpha_{12,}$ α_{15} mean that optimistic expectations on soybean and wheat prices can negatively affect the volatility in oil and seed futures market. However, since δ_{35} is significant while δ_2 is insignificant, an asymmetric response of futures market volatilities can only be attributed to the sentiments of wheat. The magnitude of coefficients related to wheat in both the mean and variance equations suggest that noise in wheat prices can cause greater effect in this derivative market. There are also evidences of lead-lag relationships among sentiments of the four assets. Significant positive parameters β_{32} and β_{45} suggest that sentiments on soybean and soybean oil are somewhat also caused by expectations about corn and wheat prices respectively. Of the four assets, sentiments on wheat seem to have the most dominant effect on oil and seed derivative market. Also, there is an evidence of positive feedback trading as wheat sentiments are significantly related to past movement in the oil and seed futures index prices.

The fourth model links the sentiments on four soft agricultural produce (cocoa, coffee, orange, and sugar) with Reuters-CRB soft agriculture produce futures index returns. The estimation results are reported in Table 6. Similar to results of other derivative markets in this study, there are significant positive effects of investor sentiments on futures index returns. The coefficients β_{13} and β_{15} are positive and significant suggesting that expectations on coffee and sugar can impact soft agricultural futures market returns. However, in the case of variance, only sentiments on sugar have a significant negative impact. Also, a significant δ_5 suggests that the volatility spillover effect from the sentiments of sugar on futures index market

Table 5. Multivariate EGARCH Estimation Results for Sentiments and Grain and Oilseeds Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	-0.0285***	0.0035	-8.1824
β_{12}	0.0115*	0.0062	1.8580
β_{13}	0.0163***	0.0066	2.4705
β_{14}	0.0036	0.0049	0.7199
β_{15}	0.0217***	0.0061	3.5784
β_{20}	0.0497***	0.0112	4.4238
β_{21}	-0.0471	0.1037	-0.4543
β_{23}	0.0357***	0.0025	14.2971
β_{24}	0.0091	0.0145	0.6302
β_{25}	0.0111	0.0185	0.6028
β_{30}	0.0722***	0.0137	5.2815
β_{31}	-0.0265	0.1101	-0.2406
β_{32}	0.0413*	0.0221	1.8721
β_{34}	-0.0136	0.0117	-1.1565
β_{35}	0.0138	0.0214	0.6455
β_{40}	0.0575***	0.0165	3.4914
β_{41}	0.0297	0.1649	0.1802
β_{42}	0.0220	0.0246	0.8968
β_{43}	0.0190	0.0303	0.6284
β_{45}	0.0445***	0.0044	10.1400
β_{50}	0.0935***	0.0118	7.9165
β_{51}	0.2258**	0.0967	2.3347
β_{52}	-0.0158	0.0186	-0.8474
β_{53}	0.0183	0.0197	0.9269
β_{54}	-0.0185	0.0160	-1.1575
α_{12}	-0.3142***	0.0791	-3.9696
α_{13}	0.1098	0.0888	1.2366
α_{14}	-0.1221	0.0766	-1.5939
α_{15}	-0.4086***	0.0786	-5.2017
α_{21}	-0.0836	0.0697	-1.1988
α_{23}	0.1606***	0.0616	2.6082
α_{24}	0.0532	0.0643	0.8271
α_{25}	-0.2964***	0.0592	-5.0028
α_{31}	-0.1387**	0.0583	-2.3801
α_{32}	-0.0164	0.0497	-0.3308
α_{34}	0.0458***	0.0009	51.7931
α_{35}	-0.0531	0.0502	-1.0578

Table 5, continued. Multivariate EGARCH Estimation Results for Sentiments and Grain and Oilseeds Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{41}	-0.0916***	0.0356	-2.5748
α_{42}	0.1843***	0.0461	3.9974
α_{43}	-0.0443	0.0386	-1.1491
α_{45}	-0.0375	0.0399	-0.9393
α_{51}	-0.0656***	0.0216	-3.0369
α_{52}	0.1059***	0.0269	3.9402
α_{53}	-0.0001	0.0216	-0.0026
α_{54}	0.1601***	0.0299	5.3496
δ_1	-0.1292	0.1567	-0.8248
δ_2	0.0139	0.0979	0.1415
δ_3	-0.2261	0.2072	-1.0913
δ_4	0.2748***	0.1116	2.4628
δ_5	0.3251***	0.0906	3.5891

The five variables included are: CRB grain and oilseeds futures index returns (i,j=1), investor sentiments on corn (i,j=2), soybean (i,j=3), soybean oil (i,j=4) and wheat (i,j=5). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters β_{12}, β_{13}, β_{14} and β_{15} captures the effect of sentiments of corn, soybean, soybean oil and wheat respectively on grain and oil seeds futures market returns. Similarly, α_{12}, α_{13}, α_{14} and α_{15} captures the volatility spillover effects or innovations from sentiments of corn, soybean, soybean oil and wheat respectively on grain and oil seeds futures market volatilities. The asymmetric effects of these four sentiments on grain and oil seeds futures market volatility is captured by δ_2, δ_3, δ_4 and δ_5. A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on volatility of grain and oil seeds futures market.

might be asymmetric in nature. Further, sentiments on sugar are positively related to past returns in the derivative market and also to expectations on oranges prices.

The next volatility model analyzes the role of noise in the industrial metals futures market. Since silver and platinum are utilized as industrial metals; the sentiments on these two metals are also included in this model. The four variables included are industrial metal futures index returns and expectations on copper, silver and platinum. The estimation results are reported in Table 7. The industrial metal futures index is almost identically affected by the sentiments of all the three metals included in the analysis. The coefficients β_{12}, β_{13}, and β_{14} are positive and significant of approximately similar magnitude. However, in the variance equation only α_{12} is significant and negative suggesting that there are volatility spillover effects from sentiments of copper on industrial metal future index market. This coupled with a

Table 6. Multivariate EGARCH Estimation Results for Sentiments and Soft Agriculture Produce and Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	-0.0109	0.0143	-0.7590
β_{12}	0.0350	0.0210	1.6634
β_{13}	0.0650***	0.0166	3.9191
β_{14}	0.0221	0.0141	1.5709
β_{15}	0.0564***	0.0167	3.3733
β_{20}	0.0990***	0.0292	3.3856
β_{21}	0.1513	0.2070	0.7309
β_{23}	0.0474	0.0424	1.1184
β_{24}	0.0589	0.0359	1.6429
β_{25}	0.0471	0.0367	1.2835
β_{30}	0.1433***	0.0399	3.5888
β_{31}	0.4034	0.4454	0.9057
β_{32}	-0.0125	0.0544	-0.2298
β_{34}	-0.0318	0.0508	-0.6248
β_{35}	0.0885	0.0658	1.3453
β_{40}	0.1157***	0.0393	2.9425
β_{41}	-0.0938	0.3593	-0.2611
β_{42}	-0.0062	0.0595	-0.1049
β_{43}	-0.0623	0.0478	-1.3035
β_{45}	0.0169	0.0589	0.2882
β_{50}	0.0903***	0.0185	4.8671
β_{51}	0.1400***	0.0449	3.1156
β_{52}	-0.0352	0.0274	-1.2844
β_{53}	0.0078	0.0076	1.0389
β_{54}	0.0847***	0.0123	6.8954
α_{12}	0.0970	0.0614	1.5802
α_{13}	0.0070	0.0069	1.0150
α_{14}	-0.0179	0.0613	-0.2912
α_{15}	-0.8130**	0.3626	-2.2420
α_{21}	0.3110**	0.1302	2.3881
α_{23}	0.0054***	0.0012	4.5081
α_{24}	0.0781***	0.0535	1.4589
α_{25}	-0.1146	0.1935	-0.5924
α_{31}	-0.3989	0.4694	-0.8497
α_{32}	0.0788	0.1191	0.6615
α_{34}	0.0744*	0.0386	1.9278
α_{35}	0.6119	0.3917	1.5620

Table 6, continued. Multivariate EGARCH Estimation Results for Sentiments and Soft Agriculture Produce and Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{41}	0.0637	0.4435	0.1436
α_{42}	0.2222	0.1948	1.1409
α_{43}	-0.0018	0.0086	-0.2044
α_{45}	0.2940	0.4712	0.6239
α_{51}	0.1515**	0.0722	2.0985
α_{52}	0.0706*	0.0416	1.6975
α_{53}	0.0028	0.0027	1.0412
α_{54}	0.0265**	0.0124	2.1314
δ_1	0.3992*	0.0683	5.8477
δ_2	0.4611	0.6895	0.6687
δ_3	14.1606*	7.6182	1.8588
δ_4	1.3280*	0.7185	1.8484
δ_5	0.8250***	0.0686	12.0230

The five variables included are: CRB soft agriculture produce futures index returns (i,j=1), investor sentiments on cocoa (i,j=2), coffee (i,j=3), orange (i,j=4) and sugar (i,j=5). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters $\beta_{12,}$ $\beta_{13,}$ β_{14} and β_{15} captures the effect of sentiments of cocoa, coffee, orange and sugar respectively on soft agriculture produce futures market returns. Similarly, α_{12}, α_{13}, α_{14} and α_{15} captures the volatility spillover effects or innovations from sentiments of cocoa, coffee, orange and sugar respectively on soft agriculture produce futures market volatilities. The asymmetric effects of these four sentiments on soft agriculture produce futures market volatility is captured by δ_{2}, δ_{3}, δ_{4} and δ_{5}. A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable *j* have a higher impact than positive innovations on volatility of soft agriculture produce futures market.

significant parameter δ_2 indicates that the effect of copper sentiment on the derivative volatility might be asymmetric in nature. Since copper is more widely used industrial metal, it might explain the significant impact of its sentiments on silver and platinum based expectations (significant β_{32}, β_{42}). Unlike results obtained in other derivative markets, there seems to be no evidence of positive feedback trading here.

The role of behavioral finance in the livestock futures market is investigated by jointly modeling sentiments of live cattle, feeder cattle, lean hogs and pork bellies with livestock futures market returns. Table 8 reports the estimation results for this model. Three out of four sentiments are positively and significantly related to livestock futures index returns. The magnitude of feeder cattle based sentiments is the highest followed by those of live cattle and lean hogs while pork bellies expectations seem to have no impact. On the variance side, only coefficient α_{12} is significant, which

Table 7. Multivariate EGARCH Estimation Results for Sentiments and Industrial Metals and Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	0.0136	0.0090	1.5128
β_{12}	0.0488***	0.0079	6.1823
β_{13}	0.0335**	0.0153	2.1911
β_{14}	0.0424***	0.0122	3.4799
β_{20}	0.1730***	0.0312	5.5502
β_{21}	3408.2632	32971.1958	0.1034
β_{23}	-0.0597	0.0923	-0.6473
β_{24}	-0.0656	0.0750	-0.8737
β_{30}	0.0772***	0.0268	2.8875
β_{31}	-15320.1625	74702.4187	-0.2051
β_{32}	-0.0199*	0.0117	-1.7035
β_{34}	-0.0221	0.0637	-0.3472
β_{40}	0.0846***	0.0092	9.2336
β_{41}	5571.9452	5588.5554	0.9970
β_{42}	0.0052*	0.0031	1.6851
β_{43}	0.0120	0.0193	0.6205

means that live cattle based sentiments also impact livestock futures index volatilities negatively. There is also a significant δ_2 indicating asymmetric volatility spillover effects of live cattle on the derivative volatilities. The sentiments of live cattle seem to be driven by the sentiments of other three assets and futures market, suggesting existence of sentiment based noise trading and lead lag relationships among these expectations.

The last multivariate EGARCH model investigates the relevance of noise trading in the stock index options market. Here sentiment of three distinct groups of investors (individual, institutional and professional analysts) and four measures of stock index options (VIX, VXO, VXN, and VXD) are included in the analysis. In order to avoid over parameterization and irrelevant feedback relationships of relatively large number of variables, the model is estimated twice with five variables in each. Specifically, the first model includes changes in VXD, VXN, and three classes of investor sentiments and the second model replaces VXD and VXN with VIX and VXO. The estimation results for these two five variables models are reported in panel A and B respectively of Table 9. In panel A, the coefficients related to the sentiments of professional analysts (β_{14}) and institutional investors (β_{15}) are negative and significant while in panel only β_{14} is negative and significant. The effect of institutional investor sentiments seems to be greater than those of professional analysts. There is a significant negative β_{24} indicating similar effects of professional analysts'

Table 7, continued. Multivariate EGARCH Estimation Results for Sentiments and Industrial Metals and Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{12}	-0.1666***	0.0467	-3.5683
α_{13}	-0.1355	0.1730	-0.7836
α_{14}	-0.1377	0.1173	-1.1740
α_{21}	0.6231	0.9743	0.6395
α_{23}	0.0009	0.2358	0.0040
α_{24}	0.0791	0.3402	0.2325
α_{31}	0.6286	0.7585	0.8287
α_{32}	0.1761	0.1493	1.1794
α_{34}	-0.4798	0.3069	-1.5631
α_{41}	0.5080***	0.1243	4.0883
α_{42}	-0.0137	0.0498	-0.2755
α_{43}	-0.0350	0.0826	-0.4233
δ_1	0.6045***	0.0484	12.4890
δ_2	0.7577*	0.3969	1.9093
δ_3	-0.1368	0.6339	-0.2159
δ_4	-1.7749***	0.1266	-14.0211

The four variables included are: CRB industrial metals futures index returns (i,j=1), investor sentiments on copper (i,j=2), silver (i,j=3), and platinum (i,j=4). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters $\beta_{12,}$ $\beta_{13,}$ and β_{14} captures the effect of sentiments of copper, silver and platinum respectively on industrial metal futures market returns. Similarly, $\alpha_{12,}$ $\alpha_{13,}$ and α_{14} captures the volatility spillover effects or innovations from sentiments of copper, silver and platinum respectively on industrial metals futures market volatilities. The asymmetric effects of these three sentiments on industrial metals futures market volatility is captured by $\delta_{2,}$ $\delta_{3,}$ and $\delta_{4.}$ A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on volatility of industrial metals futures market.

expectations on changes in VXO. However, there are insignificant effects of individual investor sentiments on all the four volatility indices returns. Institutions have a large presence in the derivative market, and that might explain the significant effects of professional analysts and institutional investor sentiments. On the other hand, individuals tend to hold a smaller portion of derivatives in their portfolios, which may cause individual investor sentiments to have insignificant impacts.

The negative effect of investor sentiments in case of options market is in contrast to the results obtained in the six futures markets where sentiments positively affect the mean of returns. A negative relationship between sentiments and changes in volatility measures means that bullishness in the marketplace causes these indices to fall and vice versa. A possible reason for this negative reason could be that

Table 8. Multivariate EGARCH Estimation Results for Sentiments and Livestock Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	0.0102***	0.0020	4.9789
β_{12}	0.0390***	0.0042	9.2355
β_{13}	0.0321***	0.0040	7.9788
β_{14}	0.0795***	0.0040	20.1173
β_{15}	-0.0031	0.0032	-0.9764
β_{20}	0.4367***	0.0155	28.1494
β_{21}	0.0530***	0.0116	4.5699
β_{23}	0.0489***	0.0179	2.7341
β_{24}	0.0486***	0.0165	2.9514
β_{25}	0.0486***	0.0163	2.9844
β_{30}	0.1436***	0.0612	2.3469
β_{31}	0.1849	0.4781	0.3866
β_{32}	0.0763	0.0826	0.9242
β_{34}	0.0039	0.0666	0.0580
β_{35}	0.0467	0.0863	0.5408
β_{40}	0.2000**	0.0911	2.1957
β_{41}	0.3491	0.8155	0.4280
β_{42}	-0.0292	0.1463	-0.1996
β_{43}	0.0011	0.1892	0.0060
β_{45}	-0.0205	0.1435	-0.1432
β_{50}	0.2614***	0.0841	3.1075
β_{51}	0.6024	0.7611	0.7915
β_{52}	-0.0092	0.1403	-0.0655
β_{53}	0.1789	0.1795	0.9967
β_{54}	-0.1535	0.1063	-1.4444
α_{12}	-0.2672**	0.1211	2.2059
α_{13}	-0.0029	0.0297	-0.0985
α_{14}	0.0915	0.2016	0.4537
α_{15}	-0.0294	0.0895	-0.3288
α_{21}	0.0601	0.1534	0.3919
α_{23}	-0.0103	0.0441	-0.2346
α_{24}	-0.0286	0.2041	-0.1399
α_{25}	-0.0192	0.0768	-0.2500
α_{31}	0.0441	0.1639	0.2691
α_{32}	0.1144	0.0954	1.1993
α_{34}	-0.0416	0.1000	-0.4157
α_{35}	-0.0350	0.0584	-0.5993

Table 8, continued. Multivariate EGARCH Estimation Results for Sentiments and Livestock Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{41}	0.1901	0.2707	0.7021
α_{42}	0.0979	0.2309	0.4243
α_{43}	0.0491	0.1906	0.2576
α_{45}	0.0585	0.1647	0.3556
α_{51}	0.2018	0.2152	0.9375
α_{52}	0.0815	0.1457	0.5591
α_{53}	0.0261	0.1075	0.2425
α_{54}	0.0389	0.0416	0.9355
δ_1	0.1070***	0.0310	3.4565
δ_2	0.1069***	0.0463	2.3106
δ_3	3.6350	16.4972	0.2203
δ_4	-0.0799	0.4703	-0.1699
δ_5	1.6898	2.9739	0.5682

The five variables included are: CRB livestock futures index returns (i,j=1), investor sentiments on live cattle (i,j=2), lean hogs (i,j=3), feeder cattle (i,j=4) and pork bellies (i,j=5) . Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters $\beta_{12,}$ $\beta_{13,}$ β_{14} and β_{15} captures the effect of sentiments of live cattle, lean hogs, feeder cattle and pork bellies respectively on livestock futures market returns. Similarly, $\alpha_{12,}$ $\alpha_{13,}$ α_{14} and α_{15} captures the volatility spillover effects or innovations from sentiments of live cattle, lean hogs, feeder cattle and pork bellies respectively on livestock futures market volatilities. The asymmetric effects of these four sentiments on livestock futures market volatility is captured by $\delta_{2,}$ $\delta_{3,}$ $\delta_{4,}$and δ_{5}. A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on volatility of livestock futures market.

CBOE volatility indices are linked with bearishness in the market. Based on Black-Scholes model, these indices compute the markets' expectations of 30-day volatility and are meant to be forward looking measures of market risk. For this reason they are viewed as fear index and thus high VIX measures higher anticipated volatility and are interpreted as bearish. These volatility indices have the tendency to spike during pronounced market weakness or sharp sell offs as investors hedge their equity portfolios by buying stock index puts. For example, the VIX surged to around 80% during the stock market crash in October 1987, compared with a mean level of approximately 20% over the sample period examined in this article (similarly, means of VXO, VXN, and VXD are 21%, 31% and 20%, respectively). Conversely, the VIX typically registers low levels during smoothly upward trending markets because of increased complacency and a lower demand for insurance against market declines. This finding is consistent with Brown and Cliff (2004), which finds that

Table 9. Multivariate EGARCH Estimation Results for Sentiments and Stock Index Options.

Variables	Coefficients	Standard errors	t-Statistics	Coefficients	Standard errors	t-Statistics
	Panel A				Panel B	
β_{10}	0.0102	0.0600	0.1698	0.0395	0.0130	3.0389
β_{12}	0.0508	0.3557	0.1427	0.0721	0.0570	1.2645
β_{13}	-0.0500	0.1043	-0.4797	-0.0202	0.0236	-0.8563
β_{14}	-0.0503***	0.0063	-7.9841	-0.0479***	0.0150	-3.1900
β_{15}	-0.0488***	0.0127	-3.8425	-0.0285	0.0264	-1.0804
β_{20}	0.0940	0.1155	0.8143	0.0724***	0.0072	10.0862
β_{21}	0.0513	0.7026	0.0730	0.0381	0.0248	1.5356
β_{23}	0.0481	0.2298	0.2093	0.0303	0.0210	1.4118
β_{24}	0.0501	0.1581	0.3165	0.0327***	0.0072	4.5798
β_{25}	0.0519	0.3251	0.1595	0.0005	0.0107	0.0468
β_{30}	0.0198	7.4366	0.0027	0.2211***	0.0190	11.6620
β_{31}	0.1025	17.1455	0.0060	0.1461	0.1388	1.0528
β_{32}	0.0112	16.8943	0.0007	0.3054**	0.1450	2.1067
β_{34}	0.0442	9.5755	0.0046	0.01742	0.0253	0.68911
β_{35}	-0.2295	15.3716	-0.0149	-0.01362	0.0488	-0.2790
β_{40}	0.0191	7.8165	0.0024	0.1656***	0.0197	8.4172
β_{41}	0.0481	12.8247	0.0037	0.2567*	0.1369	1.8748
β_{42}	0.0417	12.4044	0.0034	-0.2233	0.1485	-1.5040

Table 9, continued. Multivariate EGARCH Estimation Results for Sentiments and Stock Index Options.

Variables	Coefficients	Standard errors	t-Statistics	Coefficients	Standard errors	t-Statistics
		Panel A			Panel B	
β_{43}	0.0018	9.5195	0.0002	-0.1258***	0.0196	-6.4036
β_{45}	-0.0263	12.1204	-0.0022	-0.0472	0.0457	-1.0332
β_{50}	0.1325	1.8373	0.0721	0.1643***	0.0108	15.2348
β_{51}	-0.0140	1.4883	-0.0094	0.0833	0.0423	1.9671
β_{52}	0.1023	1.5616	0.0655	-0.0841*	0.0478	-1.7602
β_{53}	-0.0920	1.1873	-0.0775	-0.0417***	0.0070	-5.9984
β_{54}	0.0763	0.9362	0.0816	0.0232***	0.0110	2.1089
α_{12}	0.0489	1.3310	0.0367	-0.1053	0.2828	-0.3723
α_{13}	0.0338	5.1610	0.0066	0.0704	0.1077	0.6533
α_{14}	-0.0266	14.3663	-0.0019	0.0754	0.3201	0.2355
α_{15}	-0.0682	0.8707	-0.0783	-0.0608*	0.0346	-1.7572
α_{21}	0.0505	1.2727	0.0397	0.0907	0.0695	1.3049
α_{23}	0.0226	4.1444	0.0055	0.0102	0.0137	0.7488
α_{24}	0.0193	10.4958	0.0018	0.2269	0.1703	1.3325
α_{25}	-0.0852	0.8193	-0.1040	-0.0717***	0.0245	-2.9261
α_{31}	0.0338	6.6495	0.0051	-0.8346***	0.2589	-3.2233
α_{32}	0.0687	7.6947	0.0089	1.0513***	0.2969	3.5406
α_{34}	0.0913	51.5081	0.0018	-0.1673***	0.0556	-3.0118
α_{35}	-0.0060	2.4188	-0.0025	-0.0837**	0.0414	-2.0215
α_{41}	0.0786	5.7654	0.0136	-0.1401	0.4090	-0.3425
α_{42}	0.0078	6.9584	0.0011	0.9608**	0.4470	2.1498
α_{43}	-0.0034	13.5412	-0.0002	0.0382	0.1645	0.2325
α_{45}	-0.2395	1.4161	-0.1692	-0.0827**	0.0410	-2.0183

Table 9, continued. Multivariate EGARCH Estimation Results for Sentiments and Stock Index Options.

Variables	Coefficients	Standard errors	t-Statistics	Coefficients	Standard errors	t-Statistics
		Panel A			Panel B	
α_{51}	0.0313	2.8163	0.0111	-0.1217	0.2428	-0.5014
α_{52}	0.0744	3.0718	0.0242	0.1309	0.2778	0.4712
α_{53}	0.0496	10.7834	0.0046	-0.1465*	0.0828	-1.7689
α_{54}	-0.1077	58.5100	-0.0018	-1.1795**	0.5237	-2.2523
δ_1	0.1011	0.2444	0.4134	0.1060	0.0700	1.5153
δ_2	0.1017	0.4206	0.2417	0.0414	0.0415	0.9975
δ_3	0.4743	178.0140	0.0027	0.6284**	0.2867	2.1918
δ_4	0.8746	1014.7419	0.0009	-0.7083***	0.0687	-10.3075
δ_5	1.4567	12.1890	0.1195	3.1230***	1.1631	2.6850

The five variables included in panel A are: VXD (i,j=1), VXN (i,j=2), individual investor sentiments (i,j=3), professional analysts sentiments (i,j=4) and institutional investor sentiments (i,j=5). The five variables included in panel B are: VIX (i,j=1), VXO (i,j=2), individual investor sentiments (i,j=3), professional analysts sentiments (i,j=4) and institutional investor sentiments (i,j=5). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters $\beta_{13,}$ β_{14} and β_{15}captures the effect of sentiments of individual investors, professional analysts and institutional investors respectively on VXD (panel A) and VIX (panel B) returns. Similarly, parameters $\beta_{23,}$ β_{24} and β_{25} captures the effect of sentiments of individual investors, professional analysts and institutional investors respectively on VXN (panel A) and VXO (panel B) returns. The parameters, $\alpha_{13,}$ $\alpha_{14,}$ and α_{15} captures the volatility spillover effects or innovations from sentiments of individual investors, professional analysts and institutional investors on VXD (panel A) and VIX (panel B) volatilities. Similarly, the parameters, $\alpha_{23,}$ $\alpha_{24,}$ and α_{25} captures the volatility spillover effects or innovations from sentiments of individual investors, professional analysts and institutional investors on VXN (panel A) and VXO (panel B) volatilities. The asymmetric effects of these three sentiments on these options volatilities are captured by $\delta_{3,}$ δ_4 and δ_4 . A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on option volatilities.

VIX is negatively related to institutional investor sentiments.

In the variance equations, only parameter α_{15} in the second model is significant and negative. This suggests that similar to the results of the futures markets, there are significant volatility spillover effects from the institutional investor sentiments on the VIX. However, there are similar insignificant effects on VXN, VXD, and VXO probably due to the fact that VIX is relatively more widely followed indicator than the other there. There is also a significant δ_5 coupled with this α_{15} in panel B, which means that bullishness and bearishness of institutional investor sentiments have dissimilar effects on the VIX changes.

In both these models there are other significant coefficients which lend support to the argument that noise also stems from past market performance or investors engage in positive feedback trading. All three types of investors seem to follow one or more of the volatility indices' past performance while forming their expectations about the future. This indicate that like in the case of stock market, irrespective of their class to a large extent investors are irrational in the derivative market also. Consistent with previous findings, there is also a significant lead-lag relationship among three kinds of investor sentiments. The coefficients β_{43} and β_{53} are negative and significant indicating that both professional analysts and institutions tend to exploit individual investor sentiments as contrarian indicators. This is in contrast to β_{54}, which is positive and significant, suggesting that institutions tend to positively track professional analysts' expectations.[8]

Overall, the significant positive effects of sentiments on mean of six futures market returns is consistent with the *price pressure* and *hold more* effects of sentiments and similar to findings of empirical tests carries in the stock market. The significant negative effects on conditional variance of derivative market returns is in line with the *Friedman* effect and consistent with negative price of time varying risk (Glosten, Jagannathan, and Runkle 1993; DeSantis and Gerard 1997; Verma and Soydemir 2008) and with results obtained in empirical tests on noise and stock market volatilities. The asymmetric effect of bullish and bearish sentiments on derivative volatilities is consistent with the DHS model and other behavioral explanations, which suggest that the effect of bullish and bearish sentiments on asset valuations can be dissimilar in magnitude and pattern (Gervais and Odean 2001; Hong et al. 2000). Significant responses of sentiments of some assets to their

8. DSSW (1990) model suggest that individual investors are more likely to be noise traders than institutional investors. However, whether these two types of noise trading (sentiments) affects stock valuation are investigated by studies such as Nofsinger and Sias (1999), Schmeling (2007), and Verma and Verma (2007). Overall, these studies find that the effect of institutional investor sentiments on stock returns and volatilities are greater than those of individual investors. It is suggested that although both individuals and institutions display significant sentiments, only institutions have enough market power to affect the valuations. These studies also indicate that institutional investors while devising their investment strategies already factor in the sentiments of individual investors. Another reason suggested is that it is much easier for domestic institutional investors to engage in herding behavior than for individual investors, because similar information circulates among funds, allowing them to follow other institutions' decisions more easily. Our findings of greater significant effect of institutional investor sentiments than those of individual investors on stock index options markets are consistent with these empirical studies.

past prices provide support the argument of DeBondt (1993) that sentiments may show extrapolation bias such that increased bullishness can be expected after a market rise and increased bearishness after a market fall. A direct implication of this evidence is "positive feedback trading by investors. This is also consistent with the "bandwagon" effect (Brown and Cliff 2004), which implies that sentiments-induced noise trading is significantly affected by past returns and Clarke and Statman's (1998) argument that institutional investors form their sentiments based on expected continuation (reversals) of short (long) term returns.

V. IMPLICATION

The recently enacted Dodd-Frank financial system overhaul has noble intentions in bringing transparency and accountability to the derivative market. It includes measures that would bring more OTC derivatives trading onto regulated exchanges. This study provides evidence that noise is present in the exchange-traded derivative market where irrational sentiments induced noise trading by institutions and professional investors can systematically affect their valuations. Based on these findings and past literature, it can be argued that shifting OTC derivatives into regulated exchanges might have some unintended consequences due to the introduction of noise. Although it is difficult to identify the exact outcomes and magnitudes of such transition, this study presents a few possible scenarios which might have bearing on the financial system.

Studies have shown that introduction of new kinds of securities in regulated exchanges can attract a new set of uninformed traders. Stein (1987) finds that introduction of futures contracts allows new trader groups to speculate in the derivative market, since due to certain constraints they are restricted to trade in the underlying assets. Stein points out that there is asymmetric information between this new group and existing investors in the spot market on the supply conditions, and as such these new traders bring noise into the derivative market causing mispricing. Gammill and Perold (1989) and Subrahmanyam (1991) argue that uninformed traders avoid trading with informed traders in stock market and when provided opportunities migrate to index-based derivative instruments such as index futures or options. Such migration happens due to the fact that the index is intact from private information advantage and form a convenient trading medium for uninformed traders.

Also, the informational asymmetries that arise due to firm-specific private information are considerably less severe in the index futures and options markets than in the underlying stock market. VanNess, VanNess, and Warr (2005) examine the impact of introduction of Diamond index securities on the underlying Dow Jones stocks and find movement of uninformed investors to these new index securities followed by significant impact of their speculations on the liquidity. Likewise, Jegadeesh and Subrahmanyam (1993) examine the effect of introduction of S&P 500 futures contracts on the spreads of the underlying stocks and find similar results. In international markets, Leemakdej (2002) finds that motivated by greater liquidity and higher informational asymmetry there is migration of uninformed investors from stock market to derivative market in order to speculate in newly introduced warrants.

The situation of moving OTC to regulated exchanges is very similar to the ones described in above mentioned studies. A large part of the derivative market is constituted by OTC derivatives contracts that are traded (and privately negotiated) directly between two parties, without going through an exchange or other intermediary. These contracts are tailor-made to cater to specific requirements of the two involved parties and mainly used for hedging purposes. Shifting these tailor-made OTC derivative contracts — meant for two hedgers to a platform that would allow multiple bids and offers to be made by multiple participants — might attract a new set of investors (mainly noise traders). This might altogether open a new market accessible to a large group of noise traders for assets that were originally designed for hedgers. In all probability this new group of investors might be uninformed or purely profit seeking speculators with no hedging objectives whatsoever. It is well established that uninformed investors tend to be noise traders and primarily deal in speculation and cause pricing misalignment. As such, this move of trading OTC derivatives on regulated exchanges could lead to greater irrational trading activities and cause higher volatility and mispricing and thus potentially refutes the very purpose of the regulation to remove irrational behavior. Alternatively, assuming even if noise traders are not attracted to these new derivatives or their effects are nullified, these tailor-made contracts for two parties designed for over the counter markets might not survive in regulated exchanges in the long run due to lack of liquidity. Noise traders induce necessary liquidity in the market and therefore provide incentives for informed investors to trade (Black 1986; Trueman 1988). As such, nonexistence of noise or any subsequent attempt to artificially remove it from the derivative market might lead to lower returns for rational investors.

Following Black (1986) and Kyle (1985) and more recently Greene and Smart (2009), which links noise with liquidity and the fact that OTC markets have low liquidity, an argument can be made that noise trading is less prevalent in these markets. Studies on OTC markets such as Duffie, Garleanu, and Pedersen (2005) and Lagos, Rocheteacu, and Weill (2009), find that these markets have lower liquidity due to higher opportunity costs, trading frictions of search and bargain, and high transaction costs. Liquidity in OTC markets of mortgage backed securities, collateralized debt obligations, and credit default swaps are provided on a voluntary basis by broker dealers such as large investment banks who match buyers and sellers. Unlike an exchange, an OTC market is more restrictive and has no market maker to provide liquidity. In addition, OTC markets for derivatives related to interest rate swaps and foreign exchanges have lower asymmetric information. Tetlock (2008) shows that markets with greater liquidity are associated with greater price anomalies such as overpricing low probability events and underpricing high probability events while less liquid markets do not exhibit these anomalies. He argues that these results are consistent with the idea that liquidity is a proxy for noise trading, which can impede market efficiency, and mispricing is largely confined to liquid markets and not to illiquid markets. All these findings indicate lower noise trading in

OTC markets compared to an exchange.

Moreover, the Dodd-Frank Act and Volcker rule call for greater capital requirement and lower trading revenues for large institutions. New regulations governing different lines of business, in addition to the substantial increase in the amount of liquid capital banks must hold, might make it too expensive for financial institutions to stay at their current size. It could lead to the end of some Wall Street practices and create new opportunities for speculations. Necessity is the mother of invention. In order to survive and with a motivation to compensate loss in their cash flows, large institutions subjected by new regulations may reinvent their strategies and not only become active speculators in new exchange traded products but also display irrational and risky behavior elsewhere. This may lead to development of riskier innovative instruments that can escape the new regulations. An analogy could be the linkage between Federal Reserve's decision to keep federal funds rate extremely low for an extended time and the origin of subprime mortgage crisis. In a world of very low real returns, individuals and investors tend to seek higher-yielding assets. Investors desiring higher nominal rates might get tempted to seek more speculative, higher-yielding investments. During years preceding the financial crisis, many large investors facing similar choices chose to invest heavily in subprime mortgage-backed securities since they were perceived at the time to offer relatively high risk-adjusted returns. In the current scenario, large financial institutions may end up taking greater risks to compensate for their losses under the new regulation and thus expose the financial system to a greater risk.

An example of ineffectiveness of government regulation on margin in reducing speculation in stock and derivative markets is provided by Kupiec (1989, 1997). Kupiec did not find any evidence that federal regulations can be systematically altered to manage risk in the stock and derivative instruments. On similar lines, Stein (1987) argues that the presence or absence of a futures market does not reduce speculators by altering their leverage constraint. Rather, misinformed speculators who are unable to trade in the spot market can trade in the futures market, and their noise trading may affect the information content of spot market prices. The opening of a futures market allows the imperfectly informed speculators to trade, and their trading distorts the information content of market-clearing spot prices. Stein interprets his model as a formal counter-example to the conjecture that the addition of speculators to an existing market will add to the depth and liquidity of a market and thereby reduce the price effects created by transitory shocks to demand or supply. Even though agents voluntarily trade with the new futures market speculators, they can be made worse off. Stein's results are a specific example of Hart's (1975) general finding that, when markets are incomplete, opening an additional market may make agents worse off if markets remain incomplete.

The implications of this study are consistent with Pirrong (2009), who provides an argument against derivative trading on the exchanges. He argues that exchange facilitates anonymous trade and operates continuous markets and these features would make it impossible for traders to ascertain the motives of their counterparties. It is impossible to design a market in which speculators exist and always trade with hedgers and never with each other. He mentions that some of the biggest speculative failures (such as Barrings, Metallgesellschaft, Hunts) took place primarily on exchanges, and thinking that trading on exchanges will constrain speculation is contrary to centuries of history. Similarly, Wallison (2009) suggests that credit default spreads that trade on OTC market reflect real market judgments on credit quality and effective price discovery. These implications are in line with Kane (1988), which argues that regulatory reformers need to look beyond immediate problems to assess the long run consequences of the policies they wish to install. In the long run, survival patterns of regulation must be economically efficient ones. But even though the invisible hand eventually punishes over and under-regulator alike, in real time the process can produce considerable turmoil. The sequential search for efficiency can take a long time to unfold and can impose substantial plan of financial services firms, their customers and the general taxpayer.

Based on the above arguments, one can argue the ineffectiveness of regulations (such as Dodd-Frank) in removing inherent risk from the financial system and possible introduction of a new set of noise traders. Once financial institutions have adjusted to the new reality, future research with substantial data points is recommended on this subject.

VI. CONCLUSION

This study investigates the relevance of behavioral finance in the derivative market. It employs a set of multivariate EGARCH models to uncover the impact of noise on returns time varying risks in futures and options markets. The response of six futures markets (energy, precious metals, industrial metal, agricultural products, grains, and livestock) to a set of investor sentiments on 20 different commodities is analyzed. Similarly the impact of three distinct categories of investors on stock index options is investigated. Consistent with previous studies, the estimation results suggest that noise is systematically priced in a wide variety of futures and option markets.

There is at least one of a kind sentiment in each derivative market that significantly affects both returns and volatilities and also has an asymmetric spillover effects. Specifically, sentiments on gold, crude oil, wheat, copper, live cattle and sugar are found to significant effects on the mean and conditional variance in their respective futures index markets. There seems to be a significant greater response of futures markets to bullish than bearish sentiments. Similar results are obtained for VIX, VXD, VXN, and VXO responses to investor sentiments. Returns and volatilities in these stock index options are significantly affected by sentiments of professional analysts and institutions, while there is no such effect from individuals.

These results are consistent with a behavioral paradigm which suggests that noise affects an asset’s return through its impact on its conditional variance. Tenets of behavioral finance also apply to futures and options markets. Noise seems to affect risk and return in the derivative market in a similar fashion in which it affects those in stocks. The direct implication of these findings is that traditional measure of time variation in systematic risk in the derivative market omits an important source of risk: noise. The findings of this study could have important implications for policymakers on the recently enacted Dodd-Frank financial system overhaul, which includes measures that would bring more derivatives trading onto regulated exchanges. They also have important implications for investors that seek to reduce spillover effects and investors who aim to improve their portfolio performance.

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