THE RETURN-IMPLIED VOLATILITY RELATION FOR COMMODITY ETFS

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Keywords: VIX, return-volatility relation, implied volatility

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ABSTRACT

We examine the return-implied volatility relation by employing "commodity" option VIXs for the euro, gold, and oil. This relation is substantially weaker than for stock indexes. We propose several potential reasons for these unusually weak results. Also, gold possesses an unusual positive contemporaneous return coefficient, which is consistent with a demand volatility skew rather than the typical investment skew. Moreover, the euro and gold are not asymmetric. We relate the results to trading strategies, algorithmic trading, and behavioral theories. An important conclusion of the study is that important differences exist regarding implied volatility for certain types of assets that have not yet been explained in the literature; namely, the results in this paper concerning commodity ETFs vs. stock indexes, plus previous research on stock indexes vs. individual stocks, and the pricing of stock index options vs. individual stock options.

1. INTRODUCTION

The stock market return-volatility relation is one of the most interesting issues in finance. Whereas a long standing tenet of finance is the positive expected return-volatility (CAPM) relation for the stock market, in reality the actual empirical return vs. implied (and often actual) volatility relation is negative.[1] Moreover, empirical evidence shows that a negative return (positive volatility) shock has a greater effect relative to a positive return (negative volatility) shock; thus, the relation is asymmetric.

Three theories exist that explain the stock market asymmetric negative return-volatility relation. Black (1976) and Christie (1982) develop the leverage hypothesis, stating that a declining stock price (a negative return) causes firms with a high debt-to-equity leverage to become riskier, creating a higher volatility for their stock prices. The second theory, labeled the time-varying risk premium or volatility feedback hypothesis, states that a change in conditional volatility causes an opposite change in the stock price (see Poterba and Summers (1986), French, Schwert, and Stambaugh (1987), and Campbell and Hentschel (1992)). Finally, the newest approach uses the behavioral concepts of representativeness, affect, and the extrapolation bias to explain why a negative asymmetric return-volatility relation can exist, even for short intraday periods (see Hibbert, Daigler, and Dupoyet (2008)).

The newly available implied volatility VIX values for the commodity ETF options for the euro, gold, and oil allow us to examine several important features of these markets and their associated return-volatility relations and to extend the return-volatility analysis to assets outside

[1] Bollerslev and Zhou (2006) investigate the linkage between the theoretical concept of the positive *expected* excess return-volatility relation and the empirical evidence of the negative *contemporaneous* return-volatility relation using the simple one-factor affine Heston model. They also show that the return-implied volatility relation is stronger than employing realized volatility. More recently, Li (2010) studies the return-volatility relation for the S&P500 index in terms of a model specification problem. The results show a robust negative excess return-jump volatility relation and a robust negative *expected* excess return-unexpected diffusion volatility relation.

the stock market.[2] Importantly, the use of the CBOE implied volatility index (VIX) methodology for examining the return-volatility relation eliminates statistical issues, namely the sampling errors and model specification errors, as well as demonstrating the perception of risk by option traders in financial markets.

This paper adds to the literature in several ways. First and foremost, we examine the return-volatility relation by using commodity ETF data instead of the typical stock data. Such data provides the opportunity to determine if instruments with different characteristics could possess different return-volatility relations, which could arise from different supply and demand characteristics at different parts of the implied volatility curve. Second, we extend limited previous research on the behavioral explanation of the return-volatility relation to examine the use of implied volatilities in the relation. Finally, we extend the limited analysis of the new VIX implied volatility stock data to commodity instruments to determine the results for volatility quintile groupings and 30-minute intraday time intervals.

Our results show that the linkage between the commodity ETF price changes and their associated bid-ask option implied volatility changes (via the changes in the associated VIXs) is very weak, as evidenced by the much lower R-squared values for the commodity return vs. implied volatility regressions relative to the comparable stock index results. In other words, the low R-squares show that the option implied volatilities from changes in the option bid-ask price changes are not revised at the same time as the underlying ETF price changes. We discuss potential reasons for why commodity markets behave differently than stock markets in this regard.[3] Second, we find a *positive* return-volatility relation for gold, whereas the typical negative daily return-volatility relation exists for the euro, oil, and the stock markets. Furthermore, whereas we would also expect the return-volatility relation for oil to be positive because instruments with a dominance of large positive jumps in price should be positive, empirically the relation for oil is negative. Third, the quintile rankings do *not* show an asymmetric component for commodities. However, the daily results are robust, since the intraday coincident return coefficients for all commodities are even more significant than the daily coefficients. Fourth, we conclude that behavioral models can explain the return-volatility results for commodities better than the traditional leverage and volatility feedback hypotheses, especially since these non-behavioral hypotheses are not directly associated with commodities nor are they associated with the shorter-term daily and intraday periods or the use of option implied volatilities.

The next section of this paper examines the literature and associated theories concerning the return-volatility relation, and then proceeds to examine empirically the return-implied volatility relation for the commodity ETFs and stock indexes in terms of daily, quintile, and intraday data.

2. ISSUES AND THE LITERATURE

2.1 The Stock Market and the Traditional Theories of the Return-Volatility Relation

Evidence for the negative and asymmetric return-volatility relation for stocks and stock

[2] We use the term “commodity” for the euro, gold, and oil ETFs throughout this paper for explanatory convenience and to distinguish them from the stock index return-volatility relation.

[3] Although the time period of analysis includes the 2008-2009 financial crisis period, the commodities did not have the same extreme volatility changes as did the stock market. Even so, the stock index results had much higher R-squares and consistency results across volatility rankings than did the commodity ETFs. Previous studies, such as by Hibbert et al. (2008), that did not include this unusual period of volatilities had qualitatively similar high R-squares and contemporaneous return results for stock indexes.

market indexes is explained by three distinct theories. The two traditional theories of the leverage and time-varying risk premiums are discussed in this section, and the behavioral theory is examined in the next section. Black (1976) and Christie (1982) present the leverage hypothesis, which documents the return-volatility relation for individual U.S. stocks in terms of negative returns causing a higher debt leverage for the associated firms because of the lower stock prices, which in turn makes the companies riskier (and therefore the stock prices become more volatile). French et al. (1987) and Campbell and Hentschel (1992) explain the time-varying risk premium theory (or volatility feedback hypothesis) in terms of a change in the conditional volatility causing a change in the stock market price.[4] Thus, when volatility is priced, a positive volatility shock causes a higher future required rate of return, causing current prices to decline (creating a negative return), and vice-versa for a negative volatility shock. However, the conceptual basis of the volatility feedback hypothesis flows through cash flows and dividends, making it difficult to interpret in terms of commodities. Comparatively, the asymmetric return-volatility relation explained by the leverage hypothesis runs from price to volatility, whereas the relation as explained by the volatility feedback hypothesis runs from volatility to price.

Previous studies (for example, Glosten, Jagannathan, and Runkle (1993), Engle and Ng (1993), Fleming, Ostdiek, and Whaley (1995), Bekaert and Wu (2000), and Hibbert et al. (2008)) document the negative and asymmetric return-volatility relation for the S&P500 and Nasdaq markets. Some of these studies employ implied volatility generated from the options market as a measure of implied future volatility rather than realized volatility, although the two classic theories are not directly related to implied volatility.[5]

Bollerslev and Zhou (2006) and Ederington and Guan (2010) show that the strength of the asymmetric relation depends on the volatility measure used, in particular whether realized or implied volatility is employed.[6] More specifically, the asymmetric negative relation is generally more pronounced when using option implied volatilities (see Bates (2000), Poteshman (2001), Wu and Xiao (2002), Eraker (2004), and Denis et al. (2006)), and when using a market index rather than individual stocks (see Kim and Kon (1994), Tauchen et al. (1996), Bekaert and Wu (2000), Anderson et al. (2001), and Denis et al. (2006)). However, these studies use the old VIX, which only employs near-the-money options rather than the new VIX that uses the entire range of strike prices.[7]

[4] The volatility feedback hypothesis can be explained in terms of a changing market risk premium for the overall stock market and implied volatility. In particular, one can interpret implied volatility as a good proxy for the expected volatility of the underlying asset. Assuming the "market price of risk" is constant, the market risk premium should positively co-move with the stock index implied volatility. Consequently, changes in the market risk premiums (due to changes in the expected volatilities) should be negatively related to the stock returns. This interpretation is consistent with the volatility feedback hypothesis. However, there is no a priori reason for commodity ETFs or individual stock returns to have the same relation, as they are not similarly related to the market risk premium. Therefore, it is logical to assume these non-stock-market instruments could possess a weaker return-volatility relation or different associations for the independent variables.

[5] A well-known methodology for testing the leverage and volatility feedback hypotheses is based on (G)ARCH-type models (see table 1, page 3 of Bekaert and Wu (2000)), which generally assume an equal impact of positive and negative volatility innovations. Bekaert and Wu provide an excellent literature review on the asymmetric return-volatility relation in terms of the leverage and volatility feedback hypotheses.

[6] Becker, Clements, and McClelland (2009) find that historical jump activity is incorporated into the VIX and future jump activity can be explained by the VIX. This behavior of the VIX shows how it differs from realized volatility.

[7] Avramov, Chordia, and Goyal (2006) consider trading strategies to explain the asymmetric return-volatility relation for individual stocks. They propose that the *type* of selling activity is the origin of the asymmetric relation. In particular, trades by informed and/or rational investors stabilize prices and therefore reduce volatility, whereas trades by uninformed and/or irrational investors destabilize prices and therefore create higher volatility. Thus, if

In addition, over the past five years algorithmic trading has increased liquidity substantially in the stock market (Hendershott et al. (2011)), with such activities being associated with both market making and arbitrage programs of these algorithmic traders. Moreover, such liquidity from electronic market making activity has spread to the stock options market (Mishra et al. (2012)). Such algorithmic arbitrage affects the co-movement between the underlying stock market indexes and the associated options instruments via the activity of the algorithmic traders attempting to profit from pricing discrepancies.

2.2 Behavioral Theories for the Return-Volatility Relation

This section provides a discussion for the behavioral concepts of the return-implied volatility relation. Low (2004) and Hibbert et al. (2008) provide behavioral explanations for this asymmetric relation. Low suggests that the return-implied volatility relation is both non-linear (a downward-sloping reclining S-curve) and asymmetric, which he relates to the behavior of risk aversion. In general, the behavioral concepts associate a substantial downward movement in asset prices with the fear of risk, and a substantial upward trend in prices with exuberance. Hibbert et al. propose that the behavioral theories explain the return-volatility relation better than either the leverage effect or volatility feedback hypotheses. The behavioral approach is most relevant when implied volatility is the volatility measure, since both the return and implied volatility variables reflect current price changes in active markets. Moreover, the leverage and volatility feedback theories were developed specifically for realized volatility and for stocks.

Several behavioral concepts are related to the return-volatility relation, namely representativeness, affect, and the extrapolation bias. A behavioral representative investor is one who holds erroneous beliefs, for example a belief of a declining market based solely on recent price movements. Such a belief would cause a representative investor to purchase out-of-the-money put options in order to protect his/her portfolio value against a further decline in prices, regardless of the prices of the puts, causing the demand for puts to create a higher VIX value. More generally, investors commonly view negative returns as representing high risk, i.e. a negative risk-return relation. Related to representativeness is the behavioral theory of affect, when a trader makes an emotional association with the trading decision such that a “good affect” or “bad affect” label is determined by the success of the trade. Future decisions refer back to such previous emotional labels to aid in decision making. Such “heuristic rules” are based on intuition and instinct and are common among less experienced traders. Thus, when a trader *believes* the market is affected by fear due to the current or potential market volatility, then they will buy put options for portfolio protection, regardless of the current situation. Subsequently, the VIX increases, creating a negative return-volatility relation. The concept of the extrapolation bias causes a trader to view a past set of events as a proxy for a future forecast; such “trend following” from extrapolating from past events affects the supply and demand for options, and thereby affects the implied volatility. In particular, when traders see a decline in prices and therefore expect a further decline, then they will bid up put prices for protection.

3. CONCEPTS, DATA, METHODOLOGY, AND HYPOTHESES

Examination of the return vs. implied volatility relation for commodity ETFs is now possible due to the creation of VIX option indexes for the euro currency (EVZ), gold (GVZ), and oil (OVX) ETFs. An important part of investigating the strength, slope, and asymmetry of this

selling is dominated by contrarians and informed traders then future volatility is reduced following a positive return, whereas selling by herding investors and uninformed traders increases future volatility following a negative return.

relation for commodities is the potential different supply and demand characteristics for these types of instruments. As supply and demand changes across strike prices, so does the shape of the implied volatility curve, i.e. the so-called "volatility skew," which is then transmitted to the return-volatility relation. In fact, the conceptual discussion offered by Poon and Granger (2003), as well as anecdotal evidence from traders, supports different volatility skew shapes for different types of products. Moreover, examining ranked volatility quintile regressions allows us to investigate the asymmetry for the return-volatility relation previously found for stock indexes.

3.1 Trading Strategies Affecting the Implied Volatility Curve[8]

Conceptually, the simple movement of underlying asset prices will cause option prices to change via the delta and gamma relation.[9] However, the overall VIX was developed to abstract from the effect of these simple asset price changes. On the other hand, if traders believe volatility will change, then option prices will change more (or less) than warranted by the asset price change, causing a change in the value of the VIX. In fact, Bollen and Whaley (2004) show that the order flow for options markets creates supply and demand pressures on the prices of options, which subsequently changes option prices more than expected from the option's delta, thereby affecting the implied volatility of the option and the shape of the IVF. Specifically, they find that net put buying dominates the IVF for S&P 500 index options, whereas net call buying dominates individual stock IVFs. The shapes of commodity IVF curves have not been examined empirically. Moreover, the fact that put option prices are affected by price pressure in addition to the delta effect suggests that behavioral reasons help determine the movements of option prices (the VIXs). Theoretically, the asymmetric negative return-*implied* volatility relation for the stock market is not based on a rational expectations model as its foundation to explain why this relation exists. Rather, we explain the relation in terms of behavioral effects. Our explanation is supported by Shefrin (2005), who discusses the behavioral approach to option pricing in some detail. He examines various issues regarding equilibrium pricing, showing how the equilibrium approach can be invalid from a behavioral perspective. In particular, he shows how the bullish or bearish attitudes of investors affect prices vs. the equilibrium option pricing function, and even how the Black-Scholes (1973) call (put) price differs from the equilibrium call (put) price. Consequently, our discussion relies on behavioral finance as a foundation to explain ETF-ETF option relations.

As Bollen and Whaley (2004) show, the IVF is directly related to the supply and demand of option traders. Correspondingly, the supply and demand is related to the desired positions of option traders, which is affected by their predictions of future market movements and their needs for price protection. Here we summarize how different trader positions determine the shape of the IVF or "volatility skew." Changes in option trader attitudes toward their positions affect changes in option prices (and therefore changes in the VIX), which subsequently affect the assets return vs. implied volatility relation.[10]

Three potential implied volatility skews exist. The first is the "investment volatility skew," which is a downward sloping curve from left to right, with the lower strikes on the left. The

[8] We thank Shelly Natenberg for the implied volatility function (IVF) trader designations and explanations.

[9] Poon and Granger (2003) document and discuss that the existence of different implied volatility function shapes is related to the distributional assumption of the option pricing model, the role of stochastic volatility, the affects of market microstructure and measurement errors, and the risk preferences of traders.

[10] These strategies are best measured by the new VIX, which employs the entire range of strike prices, rather than the old VIX used by most research since the latter is restricted to near-the-money options.

higher the strike price, the smaller the implied volatility. Under this scenario an investor buys out-of-the-money put options and/or sells covered calls as a protective portfolio value strategy against market downturns. The higher demand for the deeper out-of-the-money put options increases the put prices, which consequently increases the implied volatility for these puts. Similarly, when an investor sells an out-of-the-money covered call, (s)he receives the call option price, decreasing the associated out-of-the-money call prices, thereby decreasing the associated higher strike call implied volatilities. The “demand volatility skew” is upward sloping, with higher strike prices having higher implied volatilities. In a demand market, short sellers of the asset protect themselves from an increase in the price of the underlying asset by purchasing out-of-the-money protective calls or selling out-of-the-money covered puts. The put option prices with the lower strike prices become cheaper, causing a lower implied volatility for lower strikes, whereas those who buy higher strike call options cause an increase in option prices, and thus a higher implied volatility.[11] Lastly, the "balanced (or symmetric) volatility skew" is present when hedging and/or speculative activity exists both for an increase and a decrease in the asset price.

3.2 Sources and Data Descriptions

The daily and 30-minute intraday ETF, stock index, and VIX data are obtained from TradeStation. The data period begins August 4, 2008 and ends March 31, 2012, which covers the recent credit crisis, financial market crisis, and the subsequent rebound in the equity markets, as well as major movements in the euro, gold, and oil and the European credit crisis. Because of the date limitation imposed by the recent launch of the commodity implied volatility indexes, we start our analysis on August 4, 2008, which yields a total of 919 daily and 11,962 intraday observations. The 30-minute interval provides a time interval with substantial liquidity for the commodity ETFs in this paper.[12]

The CBOE recently introduced VIX-type indexes on three non-stock (“commodity”) assets that trade as ETFs. In addition to examining the relation between implied volatility and commodity ETF returns, we also examine the relation for the U.S. stock indexes and their associated VIX values for comparison purposes. The symbols for the different series are as follows:

Types	ETF	Stock Index	Volatility Index	ETF Options Started Trading
Eurocurrency	FXE	-	EVZ	January 10, 2008
Gold	GLD	-	GVZ	June 3, 2008
Oil	USO	-	OVX	May 9, 2007
S&P 500	-	SPX	VIX	-
Dow Jones	-	DJ	VXD	-
Nasdaq	-	NDX	VXN	-

[11] The demand skew is relevant for markets where an upward jump or increase in the asset price is detrimental to hedgers buying the underlying asset, or beneficial to speculators who believe the asset price will increase.

[12] Intraday volatility often possesses a U-shaped pattern. Our results examine the intraday behavior of the VIX and changes in the VIX. After the first time interval no significant pattern exists across the day for the commodity ETF VIXs. Therefore, there is no evidence to support including an intraday pattern in examining a bias in the results. In any case, to the extent any pattern existed then this would only affect the lagged VIX changes in the regression, which are essentially control variables, and consequently this would not substantially affect the coefficients we interpret.

3.3 Methodology and Regression Equations

The variables and regression equations in this paper follow Hibbert et al. (2008), where the regression models are designed to explain the return-implied volatility relation in terms of the behavioral concepts of representativeness, affect, and the extrapolation bias, as explained earlier. Use of the same models as Hibbert et al. allows a direct comparison of the relative importance of the differing independent variables for commodities versus stock indexes. Moreover, model M2 is used by Fleming et al. (1995) and models M3 and M4 are employed by Low (2004). The regression equations for the four different models are as follows:

$$M1 \quad \Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \alpha_2 R_{i,t-1} + \alpha_3 R_{i,t-2} + \alpha_4 R_{i,t-3} + \alpha_7 \Delta Vol_{i,t-1} + \alpha_8 \Delta Vol_{i,t-2} + \alpha_9 \Delta Vol_{i,t-3} + \alpha_{13} \Delta 5min_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$M2 \quad \Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \alpha_2 R_{i,t-1} + \alpha_3 R_{i,t-2} + \alpha_5 R_{i,t+1} + \alpha_6 R_{i,t+2} + \alpha_{14} |R_{i,t}| + \varepsilon_{i,t} \tag{2}$$

$$M3 \quad \%\Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \varepsilon_{i,t} \tag{3}$$

$$M4 \quad \%\Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \alpha_{15} R_{i,t}^2 + \varepsilon_{i,t} \tag{4}$$

where $\Delta Vol_{i,t}$ is the change in the volatility index and i refers to the euro currency (EVZ), gold (GVZ), oil (OVX), the S&P500 (VIX), the Dow Jones (VXD), and the Nasdaq (VXN), respectively; R_t is the return for the underlying index or ETF; $R_{t-1}, R_{t-2}, R_{t-3}, R_{t+1}$, and R_{t+2} are the one-, two-, and three-day lagged returns and the one- and two-day lead returns for the index or ETF, respectively; $\Delta 5min_t$ is the change from day $t-1$ to day t in the daily volatility calculated using five-minute intervals. Using the five-minute measure of intraday realized volatility allows us to investigate the contribution of realized volatility to the daily changes in implied volatility in relation to the other variables in the equation.[13] Also note that equation (2) employs $|R|$ to examine the asymmetry in the return-volatility relation. The significance of the negative (positive) absolute return coefficient (irrespective of the direction of the underlying asset's movement) is associated with a decrease (increase) in the implied volatility. When both the contemporaneous return and the absolute current return appear in equation (2), then the sum of the coefficients of these two variables measures the asymmetry of the association between the changes in implied volatilities and the corresponding returns in the underlying assets.[14] In other words, net positive returns are measured as the sum of the contemporaneous and absolute return coefficients $(\alpha_1 + \alpha_{14})$, whereas net negative returns are measured as the difference of the coefficients $(\alpha_1 - \alpha_{14})$.[15]

[13] The (negative) volatility risk premium is the difference between the realized volatility for an entire period (say 30 days) and the implied volatility forecasted for that time period. Typically this difference is negative and significant for the S&P500 index options. However, this difference only slowly dissipates over the time to expiration of the option. Consequently, the relative effect on daily or intraday price changes between the options and underlying assets due to this volatility risk premium would be negligible and statistically insignificant. It would also show up in the intercept of a regression and therefore not affect the R-squared value. The discussion of the coefficients in terms of the behavioral biases is undertaken in conjunction with the results.

[14] See Fleming, Ostdiek, and Whaley (1995) for further discussion.

[15] An alternative methodology is to employ quantile regression, as given by Badshah (2012). The advantage of quantile regression is that it uses the absolute value approach, which reduces the effect of outliers, as well as not assuming a given distribution of the error term. In particular, the quantile approach provides additional information for the asymmetry return-volatility issue. We employ the traditional OLS methodology in order to compare our results to past literature, which only employs OLS. Moreover, the OLS procedure is conservative when lower R-squares are present, as in our paper, since quantile regression generally provides lower R-squares than OLS, which

The ETF-VIX option relation measured by the regression models used here is dependent on the ETF price changes being related to the supply and demand effects for the out-of-the-money option price changes that determine the VIX indexes. The foundations of the option pricing theory developed by Black and Scholes (1973) relate dynamic delta hedging between the underlying asset and the associated options as a no-arbitrage model. Moreover, such delta hedging (theoretically) would not affect the value of the VIX if prices conform to their delta relation. However, option prices can deviate from their theoretical value, causing arbitrage activity that is typically undertaken by algorithmic traders in recent years. Such option mispricings are reflected in their implied volatilities, and therefore in their VIX values. In addition, the direction of the VIX changes can be affected by dominant option strategies employed by traders (as outlined previously). To the extent (1) an arbitrage opportunity exists due to option mispricing, (2) the series of option prices are affected by supply and demand via the trading strategies explained above, and/or (3) there is a lack of market makers using delta hedging, then the fit of the regression line will provide information on the common co-movement of the ETF and option series price changes based on these factors. If the strength of the co-movement is weak, then either limited arbitrage activity exists, option prices are not consistently affected by typical option strategies, or market makers do not employ dynamic delta hedging between the ETFs and their options (in particular, market makers could set the option bid-ask spread sufficiently wide so that the spread does not change when the underlying ETF price changes).[16]

3.4 Hypotheses

Our initial interest is to test the degree of market co-movement between the underlying ETF price changes and their associated VIX (implied volatility) changes using the R^2 values from the regression equations (see Pukthuanthong and Roll (2009) and Berger, Pukthuanthong, and Yang (2011) for further discussion regarding the use of R-squares for common market movement). We then examine the regression coefficients to interpret the associations determined by the empirical results. The availability of commodity ETFs and stock market indexes with their associated VIX values allow us to examine the following hypotheses in relation to the regression results. These hypotheses are relevant for both stock market ETFs/indexes and commodity ETFs, allowing us to compare the results across different types of contracts. Our hypotheses are as follows:

Hypothesis I. The daily and intraday degree of market co-movement between the commodity ETF price changes and their options VIX changes is equivalent to the strength of market co-movement between the stock market indexes and their options VIX changes.

Hypothesis II. The commodity ETF price changes co-movement with the extreme changes in their VIX values is equivalent to the extreme changes co-movement for stock market index VIX values.

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is already a key result of our paper. In any case, the use of quantile regression would be an interesting extension to this paper.

[16] Grower and Thomas (2012) examine several weighting schemes for VIX-type indexes to reduce the effect of less liquid options, especially deeper-out-of-the-money strikes in order to improve the informativeness of the volatility index. They find that the spread-adjusted index performs best in reducing the illiquidity effect of such options.

We also examine the data in terms of the behavioral explanations of the return-implied volatility relation, as originally examined for the stock market by Hibbert et al. (2008).[17] Our analysis extends previous studies of the stock market's return-volatility relation by focusing on the commodity market's return-volatility relation. The coefficients of the independent variables in the regression equations are examined for this analysis. The role of the implied volatility skew and individual trading strategy factors on the return-implied volatility relation for different underlying assets such as stock index versus commodity ETFs motivates us to test the following hypotheses:

Hypothesis III. The contemporaneous return is the most significant variable associated with the changes in implied volatility.

Hypothesis IV. Lagged returns and/or the changes in past implied volatilities are significant variables to determine the changes in the current implied volatility.

Hypothesis V. A change in the contemporaneous realized intraday volatility is a significant variable in explaining the change in implied volatility.

Finally, we employ equation (1) to study the impact of creating volatility quintiles to examine the effect of the size of volatility changes on the asymmetric return-implied volatility relation. As with the above hypotheses, these are selected from studies on the stock market. The related hypotheses are:

Hypothesis VI. Asymmetry exists for the return-implied volatility relation.

Hypothesis VII. The significance of the contemporaneous return variable is dominated by the extreme changes in the volatility index.

4. RESULTS

4.1 Summary Statistics

Panels A, B, and C of Table 1 present the summaries of the basic statistics for each stock index, each commodity ETF, and each VIX-type volatility index for the daily observations over the entire sample period. The stock market results in Panel A yield average positive returns, whereas the euro and oil results in Panel B provide average negative returns. Panel C shows that all of the stock volatility indexes possess the same basic statistical properties; for example the average of the volatility indexes and their standard deviations range from 24.976 to 28.569 and 10.984 to 12.012, respectively, implying that the volatility of volatilities among stock indexes are relatively similar. The average of the level of the commodity volatility indexes is significantly wider than that of the stock volatility indexes, i.e. with values of 14.480 for the euro, 25.523 for gold, and 43.883 for oil; this shows that gold and oil typically possess a higher VIX volatility than the stock markets do.

Table 2 presents the summary statistics for the 30-minute interval data on the stock indexes, commodity ETFs, and their associated volatility indexes. Generally, the summary statistics for the intraday data are qualitatively similar to the daily results.[18]

[17] Behaviorists claim that the notions of representativeness, affect, and the extrapolation bias better capture the asymmetric return-volatility relation than the historical explanations of the leverage effect and the volatility feedback hypotheses, especially for intraday results.

[18] The oil ETF excess kurtosis for the daily (10.584) and intraday (10.529) data is leptokurtic, which differs from the other commodity ETFs. Table 2 omits the four statistical moments for the levels of the indexes and ETFs, since the

4.2 Analysis of Market Co-movement

We examine the degree of market co-movement between the changes in the ETF/index prices and the associated changes in the VIX by employing the R-squared values from the return-volatility regressions. This approach is similar to using R-square to measure hedging effectiveness for futures markets.

Table 3 summarizes the R-squared values for all of the regressions used in this study. All of the daily and intraday *stock index* results yield high R-squared values, showing the strong linkage between the returns in the stock market and the implied volatility movements of the associated options instruments. The M1 model provides the strongest association between each market and its associated implied volatilities for all stock index results. In fact, these R-squared values are superior to Hibbert et al.'s (2008) findings by an increase in the R-squared of 6%.[19] However, the strength of the market co-movement between the stock markets price changes and the implied volatilities changes typically is reduced by 1% to 9% relative to the daily results when intraday data is employed.

The market co-movement R^2 values for the commodity ETFs are dramatically smaller than the stock index results; moreover, model M1 is not the best model for all situations. The best fit for the daily regressions is model M4 for the euro, with a 14.10% R-squared value, model M2 for gold with a 18.97% R-squared value, and model M1 for oil with a 22.25% R-squared value; each of these is much smaller than the comparable R-squared values for the stock indexes. Thus, Hypothesis I regarding the equivalence of market co-movement across different types of assets is *not* supported by these results.[20] Moreover, the intraday market co-movement results are often noticeably weaker than the daily results. Also note that the commodity ETFs possess larger R-squares for the extreme levels of volatility changes than they do for the smaller volatility change quintiles. However, the strength of this co-movement is still substantially less than that of the stock index-option co-movement at the extreme quintiles. Therefore, Hypothesis II, regarding the equivalence of market co-movement at the extreme quintiles of volatility changes, is also *not* supported. Interestingly, the R-squared values for the largest negative volatility changes in quintile 1 for the euro and oil are statistically significantly larger than the largest positive volatility changes in quintile 5, showing that these markets are more strongly related when volatility is decreasing than when it is increasing.[21]

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values of these moments are equivalent to those found in Table 1 to the first decimal place. A potential explanation for oil's high excess kurtosis value is that the oil ETF invests in near-term crude oil futures, whereas the other commodity ETFs invest in the relevant spot markets. A near-term futures contract generally possesses a greater price sensitivity to new information and supply and demand changes than does the spot market. Also, the standard deviation of the daily and intraday euro currency ETF is low relative to the other commodity ETFs due to the lower trade activity of the euro and the lower volatility of this spot market.

[19] Our results provide larger R-squares than those in Hibbert et al. (2008) because we include the more volatile 2008-2009 financial crisis period, since large dependent variable changes will increase R-squared values when variables are correlated. Also note that the Nasdaq results are substantially higher than those found by Giot (2005).

[20] The inclusion of non-coincident variables can increase the R–squared value (see Kim, Moshirian, and Wu (2005), Table 3). In fact, when one compares model M2 to the other model results in Table 3, we find that model M3 logically does have lower R-squares. However, the conclusions of this study are not affected. Moreover, the inclusion of lead and lagged variables provides insights to the factors affecting changes in volatility, and when these changes occur. In fact, when Kim et al. investigate stock market integration among markets in the European Monetary Union (Section 4, Page 2492), they find that many lagged variables are important for stock market results, supporting our use of lagged variables.

[21] The euro's R-square for quintile 5 (5.78%) is much lower than for the other commodities. One possibility for this result is the fewer numbers of jumps for the euro in this quintile compared to the gold and oil ETFs.

The disparate results for the stock indexes versus the commodity ETFs raises the question of what causes these instruments to create such significant differences in their index/ETF-implied volatility co-movements. Several possibilities exist. First is the possible differences in option mispricing and related arbitrage activity; option mispricing can affect changes in implied volatility, whereas one strategy of algorithmic traders is to search for and to eliminate arbitrage opportunities. Therefore, differences in the degree of algorithmic arbitrage trading may exist between the stock and commodity options markets. A second possibility is that less frequent revision in the option bid-ask spreads occurs for commodity ETF options when the underlying ETF price changes, i.e. the ETF options do not respond to changes in the ETF prices, causing a lack in the return-implied volatility relation because market makers do not use delta hedging in these markets or they set the option bid-ask spreads wider than for stock index options. This reason is supported by Grover and Thomas (2012), who show that illiquid options make volatility indexes less informative. A third possibility is that changes in the VIX values for ETF options are biased in some ways, for example due to a fewer number of strike prices. A fourth potential reason is that the ETF option market does not include traders who employ the investment volatility skew and/or demand volatility skew strategies that affect the supply and demand of options and thereby change the options implied volatility.

The importance of the weak co-movement results for the commodity ETFs cannot be understated. Andersen et al. (2001) and Denis et al. (2006) show significantly differences for stock index vs. individual stock results. Moreover, Bollen and Whaley (2004) find substantially different supply and demand effects on option prices and implied volatilities for stock index options and individual stocks. Combined with our results shows that different types of assets provide different relations regarding return and implied volatility. As of yet, no one has found the common link to explain these differences. However, determining which of the above reasons explain the differences identified above is beyond the scope of this paper, as well as not possible given the dataset employed here. However, a solution from future research would be a significant step forward in fully understanding the behavior of implied volatility in relation to return.[22]

4.3 The Daily Return-Volatility Relation for Commodities

Table 4 presents the results of the daily regression models for our three commodity ETFs, namely the euro currency, gold, and oil. The most interesting result in Table 4 is the *positive* coefficient for the contemporaneous return variable for gold for model M1.[23] Thus, an increase in gold price *increases* risk, unlike stock indexes and the other two commodity ETFs. This pattern is consistent with the demand volatility skew discussed earlier, i.e. speculators buy calls in anticipation of an increase in gold prices in the future, and short hedgers buy more out-of-the-money protective calls and sell out-of-the-money covered puts to offset such price increases. The other two commodities possess negative significant coefficients for the contemporaneous return

[22] Theoretically, the leverage and volatility feedback hypothesis do not explain the commodity results, as these theories are based on stock market relations. As discussed earlier, one would not expect commodities (or individual stocks) to be related to the market risk premium associated with the volatility feedback hypothesis.

[23] All other models possess an *insignificant* contemporaneous return variable for gold. In general, one can argue that the volatility for gold "differs in functionality" from the stock market, making the relation different from the negative relation found in the stock market studies. In particular, gold often is thought of as a safe-haven from inflation, currency, and stock market volatility, i.e. its volatility relates to its hedging function. Consequently, gold's implied volatility could be positively related to its return since gold would rise in value at the same time its volatility increases, causing a positive relation to implied volatility. Thus, the return-implied volatility relation for gold could have a different underlying functionality relation than the stock market.

variable, i.e. implied volatility moves in the opposite direction of ETF returns.[24] This relation is equivalent to stock markets where generating put protection to avoid asset losses creates an investment volatility skew. The negative contemporaneous return is significant for the euro and oil for the daily data for all models. Overall, unlike for stock indexes, the contemporaneous return variable is not always the most significant variable, with some measure of realized or lagged volatility dominating for the euro and gold. The results also show that Hypothesis IV (lagged returns and the changes in past implied volatilities are significant variables for the return-volatility relation) and Hypothesis V (the realized intraday volatility is an important factor for the return-volatility relation) are valid for the commodity ETFs.

In conclusion, Hypothesis III (the contemporaneous return is the most significant determinant of the return-volatility relation) is valid only for oil across all of the models, and gold has a *positive* relation to implied volatility. Importantly, the use of implied volatility and trader supply and demand strategies associated with different parts of the option strike range suggest that behavioral concepts are relevant to explain the return-implied volatility relation. In fact, the results from Bollen and Whaley (2004) support the mispricing of options and therefore the influence of behavioral factors affecting the change in VIX values Our results show that the behavioral concepts of representativeness and affect (as given as explanations to help explain a strong contemporaneous association between negative returns and volatility in Hibbert et al. (2008)), can be supported for commodity ETFs.

4.4 Asymmetry for the Return-Volatility Relation for Commodities

This section explores the asymmetry of the return-implied volatility relation. The absolute return variable included in model M2 allows us to examine the asymmetric effect in the return-volatility relation. The impact on the changes in implied volatility when the return is positive is equal to the sum of the contemporaneous return and absolute return coefficients ($\alpha_1 + \alpha_{14}$), whereas the impact when the return is negative is equal to the difference between these two coefficients ($\alpha_1 - \alpha_{14}$).[25]

Table 5 shows the quintile regressions that allow us to examine the effect of returns and lagged/realized volatilities on the ranked negative to positive changes in implied volatility. In terms of the statistical significance of the estimated parameters, these results differ from the asymmetric results in Table 4. Specifically, the contemporaneous return coefficients are insignificant for all of the euro quintiles and two of the five quintiles for the gold and oil ETFs. In fact, the contemporaneous return variables for the extreme quintile regression rankings are *insignificant* for five of the six cases; thus, no statistically valid asymmetry in returns exists for

[24] One explanation for the demand skew for gold could be its tendency to jump *upward* in price, unlike stock markets that more often jump downward in price. The demand skew is the pattern of the implied volatility skew that consistent with such upward jumps. A more fundamentally related reason for the different relation for gold could be its often stated "safe-haven" characteristic to financial turmoil. For example, gold tends to possess a positive response to negative macroeconomic news (see Baur and Lucey (2010) and Baur and McDermott (2010)).

[25] For example, the results for model M2 for the oil ETF in Table 4 shows that a positive return of one unit impacts the change in implied volatility equal to -38.516 + 29.618 = -8.898, meaning that an increased return in the oil ETF price is associated with a corresponding decrease in the associated ETF's options implied volatility. When the return is negative then the impact on the implied volatility change is equal to -38.516 - 29.618 = -68.134, meaning that the downward price change in the oil ETF is associated with a much larger increase in the options' implied volatility. The size difference in these two computed coefficients (-8.898 vs. -68.134) is interpreted as the asymmetric effect, in this case a negative return has a greater effect than a positive return for the return-volatility relation. Note that the gold ETF possesses a positive asymmetric return-volatility relation, i.e. a positive (negative) return creates a combined coefficient of 74.626 (-63.932), showing that the asymmetry is slightly positive.

the commodities in terms of the quintile results; therefore, Hypothesis VI is *not* supported statistically. Contrasting the results of commodities to stock indexes (not shown here for space considerations), the relation is strong for stock indexes at the extreme levels, especially for the largest positive volatility changes (quintile 5), showing the asymmetric relation for the contemporaneous return variable.

The lack of a strong relation across the quintiles, as well as the weak contemporaneous return significance for the quintiles, provides further evidence of substantial differences between the commodity ETF and stock index return-implied volatility relations. As explained previously, differences in these markets could exist for a number of reasons, such as a lack of arbitrage, a lack of sufficient market making, wide and less responsive bid-ask spreads, and/or a lack of implied volatility strategies employed by market participants.

4.5 The Return-Volatility Relation for Stock Market Indexes

This section briefly compares the stock market index results to the commodity results presented in a previous section. The empirical results for the stock market indexes are not presented here due to space considerations and since they are not the focus of this paper.[26]

As expected, the contemporaneous return for the stock indexes is the most important determinant of implied volatility change, supporting Hypothesis III. Behavioral theories of representativeness and affect explain the relation well, since behavioral concepts show that investors associate negative returns with higher volatility. However, most of the lagged return variables and the changes in the past implied volatilities are not significant factors, showing that Hypothesis IV is *not* strongly supported by these results.[27] In addition, the contemporaneous intraday volatility measure is strongly significant for all models (Hypothesis V is supported), showing that the return-volatility relation is not a simple one. The intraday volatility evidence supports the behavioral explanation of the return-volatility relation by showing that high realized volatility induces an increase in future volatility, which would increase the current implied volatility.

As with previous research on the stock market, the R^2 values are large for the extreme quintiles and much smaller for the other quintiles. For these quintile results the asymmetry for the return-volatility relation exists, supporting Hypothesis VI. For the middle ranked groups, quintiles 2 to 4, the contemporaneous return is much less significant than for the extreme ranked groups of quintiles 1 and 5, which is consistent with Hypothesis VII.

[26] The stock market index results are available upon request.

[27] If the lagged VIX variables affect the current VIX value then a trend in the option time value exists. Such a trend is consistent with the extrapolation bias (see Hibbert et al. (2008)). However, the insignificance of the past changes in implied volatility in the results shows that no significant trend in the option time values exists over time, causing the extrapolation bias to be an inconsistent explanation for the return-volatility relation. Overall, combining our findings of weak or insignificant lagged return variables, the effect of changes in the past implied volatilities, and a strong effect from the contemporaneous realized intraday volatility, the behavioral theory of the extrapolation bias hypothesis does not explain the asymmetric return-volatility relation well for the stock market index. This finding contrasts with Hibbert et al., who support this theory. In addition, note that the R-squared values for models M1 and M2 are almost equivalent.

5. ROBUSTNESS CHECK: INTRADAY EVIDENCE FOR COMMODITIES

The use of 30-minute data allows us to investigate the behavior of markets on an intraday basis. Moreover, the use of 30-minute data solves the mismatching of closing times between options and ETF markets.[28] The R-squared values in Table 3 for commodities are lower for the intraday than for the daily results for all but only one case (Model M1 for the euro), although none of the R-squared values are considered to be high. The intraday regression coefficient results in Table 6 differ in terms of significance from the daily results in places, although the signs of the coefficients remain consistent. Thus, the same investment/demand volatility skews apply. However, the contemporaneous return coefficients do possess much larger *t*-statistic values for the intraday data relative to the daily data, with part of this effect due to the larger sample size.

Examining the other variables, the changes in the *past* implied volatilities for the intraday data become more important variables in determining the change in the current implied volatility for the euro and gold ETFs, both in terms of the number of significant variables and the degree of significance. For oil, all of the lagged returns also are significant. These results support a behavioral explanation (using the concepts of representativeness, affect, and the extrapolation bias) of the return-volatility relation, as given in Hypotheses III and IV.[29] Overall, for the intraday data the behavioral concepts of the return-volatility relation provide a better explanation than the leverage and volatility feedback hypotheses, especially since these non-behavioral theories were developed for stocks and realized volatility and are not as well suited for intraday data.[30]

6. SUMMARY AND CONCLUSIONS

In this paper we examine various aspects of the return-implied volatility relation using commodity ETF data for the euro currency, gold, and oil and their associated options. First, we determine to what extent the price changes of the ETFs vs. the associated VIX implied volatilities for the options form co-moving variables. Second, we analyze the similarities and differences of the return-implied volatility relation for these instruments. Finally, we examine the effect of the change in volatility (via five ranked volatility quintiles) on the return-implied volatility relation and test the robustness of the daily results by examining 30-minute time intervals. We associate our results to behavioral theories more than the classical theories of the return-volatility relation.

Our results show that the market co-movement between the price changes of the commodity ETFs and their option VIX changes is substantially weaker than the corresponding results for stock indexes. Second, we find that the contemporaneous return coefficient for the return-volatility relation for the gold ETF is significantly positive, unlike the other assets; we also find

[28] Five and fifteen minute intervals are also examined, with similar results; however, we employed the 30-minute intervals due to significantly greater liquidity, especially early in the life of the ETFs. Longer intervals than 30 minutes are not appropriate as an adequate high frequency robustness check of the relation.

[29] The significance of the contemporaneous return (Hypothesis III) implies that traders associate negative returns with higher volatilities, consistent with the representativeness and affect theories. The behavioral theory of extrapolation bias is consistent with the significance of lagged returns and/or changes in past implied volatilities (Hypothesis IV), such that traders would expect volatility changes to maintain a trend as option time values change.

[30] Neither the leverage effect nor the volatility feedback hypotheses explains the negative return-volatility relation at a high frequency level, since the volatility feedback hypothesis includes a long-term time-varying risk premium variable that should not exist in high frequency data. Moreover, the leverage theory is not applicable for non-stock or high frequency data, since it is based on the *long-term* debt-to-equity ratio of the firm.

that the asymmetry found for this return-implied volatility relation for stock indexes does not exist for the commodities in our study. Third, we determine that the return coefficient for commodities is more significant for the intraday data than for the daily data. Finally, behavioral theories provide a weak explanation for the return-volatility relation for commodities, although behavioral theories still are better than the leverage or volatility feedback hypotheses.

Several specific factors could affect our results: market makers may not employ delta hedging, a lack of investment/demand volatility skew strategies could exist among commodity ETF option traders, wide bid-ask spreads may change infrequently relative to the underlying price changes, or the new VIX formulation may not precisely measure the implied volatility changes. In fact, in general, we do not know whether commodity options provide the same quality of knowledge regarding future volatility as does stock market options. Thus, the specific reason(s) for the substantially different results between the commodity ETFs, stock indexes, and individual stocks requires future research with microstructure and realized volatility datasets. Once the reason(s) for the differing results across different types of assets are determined, then a more definitive broad theory of the return-volatility relation can be developed. Consequently, further research and explanations, if not a new theory, are needed to explain why the return-implied volatility relation differs across different types of financial instruments.

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Table 1 Summary statistics for the daily data

Panel A: Stock Market Indexes

	Mean	Std. Dev.	Skew-ness	Excess Kurtosis	R_t (%) * 10^2 Mean	R_t (%) Std. Dev.	$\|R_t\|$ (%) Mean	$\|R_t\|$ (%) Std. Dev.	R_t^2 (%) Mean	R_t^2 (%) Std. Dev.	$\Delta 5Min_t$ (%) * 10^3 Mean	$\Delta 5Min_t$ (%) Std. Dev.
S&P 500	1125.487	165.732	-0.492	-0.626	1.303	1.821	1.182	1.385	0.033	0.095	-0.384	0.440
DJIA	10580.263	1524.512	-0.405	-0.694	1.711	1.646	1.068	1.253	0.027	0.080	-0.561	0.440
Nasdaq	1904.502	413.345	-0.252	-0.865	4.588	1.822	1.209	1.364	0.033	0.097	-0.384	0.450

Panel B: ETFs

	Mean	Std. Dev.	Skew-ness	Excess Kurtosis	R_t (%) * 10^2 Mean	R_t (%) Std. Dev.	$\|R_t\|$ (%) Mean	$\|R_t\|$ (%) Std. Dev.	R_t^2 (%) Mean	R_t^2 (%) Std. Dev.	$\Delta 5Min_t$ (%) * 10^3 Mean	$\Delta 5Min_t$ (%) Std. Dev.	Average Volume
Euro	136.501	7.004	0.006	-0.674	-1.750	0.812	0.622	0.523	0.007	0.012	-0.028	0.154	1,155,739
Gold	120.847	29.700	0.257	-1.094	6.610	1.457	1.030	1.033	0.021	0.059	-0.507	0.405	16,136,020
Oil	39.544	12.135	3.198	10.584	-9.877	2.600	1.890	1.788	0.068	0.135	-2.061	0.563	14,146,993

Panel C: VIX Volatility Indexes

VIX for	Mean	Std. Dev.	Skew-ness	Excess Kurtosis	Max	Min
S&P500	27.779	12.012	1.628	2.685	80.860	14.260
DJIA	24.976	10.984	1.663	2.853	74.600	12.760
Nasdaq	28.569	11.635	1.725	3.136	80.640	15.850
Euro	14.480	3.837	1.427	1.866	30.660	9.190
Gold	25.523	9.354	1.572	2.081	64.520	14.720
Oil	43.883	15.609	1.549	1.787	100.410	25.420

The sample period is from August 4, 2008 to March 31, 2012, totaling 919 observations. R_t is the return for the underlying stock index or the commodity ETF. $\Delta 5min_t$ is the change in the five-minute volatility. $|R_t|$ and R_t^2 are the absolute return and return squared for the underlying stock index or the commodity ETF, respectively.

Table 2 Summary statistics for the intraday data

Panel A: Stock Market Indexes

	R_t (%) * 10^2 Mean	R_t (%) Std. Dev.	$\|R_t\|$ (%) Mean	$\|R_t\|$ (%) Std. Dev.	R_t^2 (%) Mean	R_t^2 (%) Std. Dev.
S&P 500	0.098	0.448	0.259	0.366	0.002	0.009
DJIA	0.132	0.418	0.239	0.343	0.002	0.008
Nasdaq	0.349	0.460	0.275	0.368	0.002	0.009

Panel B: ETFs

	R_t (%) * 10^2 Mean	R_t (%) Std. Dev.	$\|R_t\|$ (%) Mean	$\|R_t\|$ (%) Std. Dev.	R_t^2 (%) Mean	R_t^2 (%) Std. Dev.
Euro	-0.135	0.217	0.121	0.180	0.000	0.002
Gold	0.497	0.388	0.217	0.321	0.002	0.007
Oil	-0.784	0.708	0.419	0.570	0.005	0.020

Panel C: VIX Volatility Indexes

VIX for	Mean	Std. Dev.	Skew-ness	Excess Kurtosis	Max	Min
S&P500	27.821	12.014	1.633	2.675	81.370	14.140
DJIA	25.126	11.094	1.669	2.830	75.080	12.450
Nasdaq	28.695	11.714	1.751	3.264	84.270	15.520
Euro	14.497	3.843	1.447	1.914	30.680	9.150
Gold	25.534	9.390	1.565	2.066	71.110	14.650
Oil	43.804	15.496	1.566	1.881	101.370	25.110

The sample period is from August 4, 2008 to March 31, 2012, totaling 11,962 observations. Values every 30 minutes are employed, starting 30 minutes after each market opens. R_t is the return for the underlying index or the commodity ETF. $|R_t|$ and R_t^2 are the absolute return and return squared for the underlying stock index or the commodity ETF, respectively.

Table 3 Underlying vs. implied volatility co-movement: Summary of the R-squares for the regression models

R^2(%)	Commodity ETFs Underlying			Stock Indexes Underlying		
	Euro	Gold	Oil	S&P 500	DJIA	Nasdaq
Daily Results						
M1	10.50	17.74	22.25	72.96	71.96	67.22
M2	12.68	18.97	19.46	72.17	70.82	66.55
M3	5.98	0.08	16.07	59.53	57.32	54.93
M4	14.10	11.41	20.97	60.65	58.04	56.02
Intraday Results						
M1	11.23	3.90	16.72	69.28	63.46	62.60
M2	5.72	3.01	15.18	69.20	63.29	62.34
M3	4.68	0.01	14.76	58.09	51.65	54.08
M4	7.22	2.91	16.26	58.78	52.62	54.88
Quintile (M1 Model) Results						
1st	16.83	20.74	32.81	59.20	65.33	54.91
2nd	2.48	5.14	6.41	10.26	5.26	6.07
3rd	4.79	6.29	4.97	10.88	12.08	5.38
4th	5.85	3.69	6.63	11.32	16.75	8.57
5th	5.78	16.20	12.57	62.70	53.79	57.59

This table shows the summary of the R-squares values for the return-implied volatility regressions, which are used to measure market co-movement between their underlying assets (stock market indexes and commodity ETFs) and their corresponding implied volatility indexes (VIXs). For the quintile regressions we employ model M1, since it performs the best for all stock market regressions and for most commodity market regressions, and because it includes more relevant variables capturing the return-implied volatility relation.

Table 4 Daily regression results for the commodity volatility indexes

Euro	R^2(%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	R_{t+1}	R_{t+2}	ΔEVZ_{t-1}	ΔEVZ_{t-2}	ΔEVZ_{t-3}	$\Delta 5Min_t$	$\|R_t\|$	R_t^2
M1	10.50	-0.003	-22.231*	-6.291***	9.732*	0.053			-0.138*	-0.053	-0.115*	72.151*		
		(-0.11)	(-6.64)	(-1.84)	(2.84)	(0.02)			(-4.23)	(-1.63)	(-3.54)	(4.10)		
M2	12.68	-0.267*	-21.994*	-4.320	11.048*		6.508**	-0.456					42.612*	
		(-6.42)	(-6.67)	(-1.31)	(3.35)		(1.96)	(-0.14)					(8.33)	
M3	5.98	0.001	-1.570*											
		(0.64)	(-7.64)											
M4	14.10	-0.007*	-1.588*											125.210*
		(-3.94)	(-8.08)											(9.31)

Gold	R^2(%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	R_{t+1}	R_{t+2}	ΔGVZ_{t-1}	ΔGVZ_{t-2}	ΔGVZ_{t-3}	$\Delta 5Min_t$	$\|R_t\|$	R_t^2
M1	17.74	-0.024	11.525*	9.248**	-5.781	6.522***			0.006	-0.200*	0.020	143.863*		
		(-0.44)	(3.08)	(2.48)	(-1.56)	(1.75)			(0.20)	(-6.51)	(0.63)	(10.41)		
M2	18.97	-0.734*	5.347	17.752*	-7.940**		-3.620	6.983***					69.279*	
		(-9.72)	(1.46)	(4.86)	(-2.17)		(-0.99)	(1.90)					(13.43)	
M3	0.08	0.001	0.119											
		(0.65)	(0.85)											
M4	11.41	-0.006*	0.091											35.475*
		(-3.02)	(0.69)											(10.82)

Oil	R^2(%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	R_{t+1}	R_{t+2}	ΔOVX_{t-1}	ΔOVX_{t-2}	ΔOVX_{t-3}	$\Delta 5Min_t$	$\|R_t\|$	R_t^2
M1	22.25	-0.081	-38.991*	-14.730*	-3.629	1.686			-0.281*	-0.060***	-0.016	37.768*		
		(-1.00)	(-12.33)	(-4.30)	(-1.05)	(0.49)			(-8.48)	(-1.74)	(-0.49)	(2.57)		
M2	19.46	-0.612*	-38.516*	-3.319	1.002		6.519**	2.710					29.618*	
		(-5.07)	(-11.99)	(-1.04)	(0.32)		(2.05)	(0.85)					(6.33)	
M3	16.07	0.000	-0.831*											
		(0.03)	(-13.25)											
M4	20.97	-0.006*	-0.743*											5.494*
		(-3.36)	(-11.98)											(5.03)

This table gives the results of the four regression models using daily data provided in the text (M1 to M4). The *t*-statistics are shown in parentheses and *, **, and *** are significant at the 1%, 5%, and 10% levels, respectively.

$M1 \quad \Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \alpha_2 R_{i,t-1} + \alpha_3 R_{i,t-2} + \alpha_4 R_{i,t-3} + \alpha_7 \Delta Vol_{i,t-1} + \alpha_8 \Delta Vol_{i,t-2} + \alpha_9 \Delta Vol_{i,t-3} + \alpha_{13} \Delta 5min_{i,t} + \varepsilon_{i,t}$

$M2 \quad \Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \alpha_2 R_{i,t-1} + \alpha_3 R_{i,t-2} + \alpha_5 R_{i,t+1} + \alpha_6 R_{i,t+2} + \alpha_{14} |R_{i,t}| + \varepsilon_{i,t}$

$M3 \quad \%\Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \varepsilon_{i,t}$

$M4 \quad \%\Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \alpha_{15} R_{i,t}^2 + \varepsilon_{i,t}$

Table 5 Quintile regressions for daily changes in the commodity volatility indexes

Panel A: Euro Currency

Quintile	R^2(%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	ΔEVZ_{t-1}	ΔEVZ_{t-2}	ΔEVZ_{t-3}	$\Delta 5Min_t$
1	16.83	-0.918*	5.456	-17.884**	4.649	0.695	-0.219*	-0.130**	-0.219*	-19.945
		(-14.60)	(0.73)	(-2.45)	(0.76)	(0.11)	(-4.36)	(-2.26)	(-3.21)	(-0.52)
2	2.48	-0.275*	-0.791	-0.612	-0.233	0.372	0.014	0.010	0.007	0.815
		(-41.89)	(-0.72)	(-0.66)	(-0.26)	(0.37)	(1.24)	(0.96)	(0.89)	(0.18)
3	4.79	-0.034*	-0.711	-1.116	-0.672	-0.062	-0.003	-0.001	-0.019**	-4.929
		(-7.32)	(-0.94)	(-1.64)	(-1.07)	(-0.10)	(0.35)	(-0.14)	(-2.01)	(-1.24)
4	5.85	0.215*	-1.522	0.790	1.351	-0.486	0.016	0.010	0.023**	1.545
		(28.76)	(-1.36)	(0.76)	(1.17)	(-0.46)	(1.07)	(0.69)	(2.14)	(0.32)
5	5.78	1.129*	1.974	-13.188***	5.679	-0.085	0.005	0.163*	-0.022	-25.171
		(15.45)	(0.32)	(-1.89)	(0.72)	(-0.01)	(0.08)	(2.61)	(-0.35)	(-0.69)

Panel B: Gold

Quintile	R^2(%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	ΔGVZ_{t-1}	ΔGVZ_{t-2}	ΔGVZ_{t-3}	$\Delta 5Min_t$
1	20.74	-1.840*	1.529	10.728***	-1.487	-4.765	-0.033	-0.190*	-0.027	33.175
		(-18.49)	(0.19)	(1.84)	(-0.32)	(-0.88)	(-0.75)	(-5.04)	(-0.64)	(1.35)
2	5.14	-0.651*	2.578**	1.312	0.012	1.342	-0.001	0.004	-0.005	0.907
		(-55.51)	(2.03)	(1.40)	(0.02)	(1.49)	(-0.10)	(0.43)	(-0.57)	(0.20)
3	6.29	-0.132*	1.929***	0.210	-1.717	-0.403	0.017***	0.008	0.002	8.393***
		(12.01)	(1.72)	(0.21)	(-1.56)	(-0.43)	(1.75)	(0.98)	(0.25)	(1.74)
4	3.69	0.442*	2.330***	0.724	-1.739	-0.386	-0.003	0.004	-0.009	5.904
		(28.73)	(1.79)	(0.60)	(-1.26)	(-0.32)	(-0.25)	(0.29)	(-0.83)	(1.16)
5	16.20	1.924*	5.947	4.830	-15.582	11.965	0.044	-0.245*	0.101	117.364*
		(12.21)	(0.95)	(0.51)	(-1.55)	(1.36)	(0.60)	(-3.37)	(1.51)	(4.56)

Panel C: Oil

Quintile	R^2(%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	ΔOVX_{t-1}	ΔOVX_{t-2}	ΔOVX_{t-3}	$\Delta 5Min_t$
1	32.81	-2.632*	-6.011	-17.204*	-9.962	1.566	-0.429*	-0.142	-0.060	-26.185
		(-13.45)	(-0.86)	(-2.82)	(-1.63)	(0.25)	(-9.04)	(-2.73)	(-1.04)	(-0.84)
2	6.41	-0.908*	-0.885	0.098	0.553	0.126	-0.000	0.001	-0.018**	6.036
		(-48.77)	(-0.85)	(0.10)	(0.60)	(-0.15)	(0.00)	(0.10)	(-2.19)	(1.54)
3	4.97	-0.187*	-2.036*	0.141	0.023	0.030	0.014	0.001	-0.002	2.486***
		(-13.83)	(-2.83)	(0.20)	(0.03)	(0.05)	(1.42)	(0.13)	(-0.45)	(0.88)
4	6.63	0.536*	-1.806***	-0.720	-0.469	-2.113**	0.008	0.002	-0.008	-2.223
		(27.51)	(-1.94)	(-0.87)	(-0.55)	(-2.24)	(0.76)	(0.19)	(-0.72)	(-0.54)
5	12.57	2.855*	-26.843*	-14.266	-16.089***	-0.851	-0.155***	-0.170***	-0.081	-25.301
		(10.87)	(-3.93)	(-1.58)	(-1.73)	(-0.09)	(-1.83)	(-1.76)	(-0.86)	(-0.74)

This table provides regression results for model M1, as described in the text and previous tables, for quintiles of change in the volatility index. Quintile 1 includes the largest negative volatility changes, whereas quintile 5 includes the largest positive volatility changes. The *t*-statistics are shown in parentheses and *, **, and *** are significant at the 1%, 5%, and 10% levels, respectively.

Table 6 Regression results for the intraday (30-minute) changes in the commodity volatility indexes

Euro	R^2(%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	R_{t+1}	R_{t+2}	ΔEVZ_{t-1}	ΔEVZ_{t-2}	ΔEVZ_{t-3}	$\|R_t\|$	R_t^2
M1	11.23	-0.019*	-23.405*	-12.330*	-0.365	-0.674			-0.247*	-0.043*	-0.023**	15.612*	
		(-7.07)	(-22.29)	(-11.52)	(-0.34)	(-0.63)			(-27.18)	(-4.63)	(-2.49)	(12.33)	
M2	5.72	-0.020*	-23.981*	-6.360*	2.148**		2.195**	-0.630				16.154*	
		(-7.05)	(-22.16)	(-5.89)	(1.99)		(2.03)	(-0.58)				(12.38)	
M3	4.68	0.000	-1.568*										
		(0.74)	(-24.24)										
M4	7.22	-0.000**	-1.430*										115.256*
		(-3.09)	(-22.24)										(18.09)

Gold	R^2(%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	R_{t+1}	R_{t+2}	ΔGVZ_{t-1}	ΔGVZ_{t-2}	ΔGVZ_{t-3}	$\|R_t\|$	R_t^2
M1	3.90	-0.044*	2.272**	-0.946	-0.060	0.053			0.082*	0.043*	-0.009	19.947*	
		(-10.58)	(2.56)	(-1.07)	(-0.07)	(0.06)			(9.10)	(4.78)	(-0.98)	(18.58)	
M2	3.01	-0.045*	2.360*	-0.797	0.025		0.783	1.261				20.501*	
		(-10.87)	(2.65)	(-0.89)	(0.03)		(0.88)	(1.42)				(19.04)	
M3	0.01	0.000	0.029										
		(0.45)	(0.91)										
M4	2.91	-0.000*	0.072**										30.868*
		(-3.36)	(2.33)										(18.90)

Oil	R^2(%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	R_{t+1}	R_{t+2}	ΔOVX_{t-1}	ΔOVX_{t-2}	ΔOVX_{t-3}	$\|R_t\|$	R_t^2
M1	16.72	-0.060*	-36.733*	-9.736*	-2.000**	-1.726***			-0.133*	-0.021**	-0.027*	12.915*	
		(-8.02)	(-42.99)	(-10.63)	(-2.17)	(-1.88)			(-14.66)	(-2.28)	(-2.93)	(12.18)	
M2	15.18	-0.058*	-36.820*	-4.658*	-0.604		0.724	-0.633				12.592*	
		(-7.65)	(-42.71)	(-5.44)	(-0.70)		(0.85)	(-0.74)				(11.77)	
M3	14.76	-0.000	-0.780*										
		(-0.01)	(-45.51)										
M4	16.26	-0.000*	-0.739*										8.845*
		(-3.56)	(-42.90)										(14.64)

This table gives the results of the four regression models using 30-minute interval data provided in the text (M1 to M4). The *t*-statistics are shown in parentheses and *, **, and *** are significant at the 1%, 5%, and 10% levels, respectively.

$M1\ \ \Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \alpha_2 R_{i,t-1} + \alpha_3 R_{i,t-2} + \alpha_4 R_{i,t-3} + \alpha_7\, \Delta Vol_{i,t-1} + \alpha_8\, \Delta Vol_{i,t-2} + \alpha_9\, \Delta Vol_{i,t-3} + \alpha_{13}\, |R_t| + \varepsilon_{i,t}$

$M2\ \ \Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \alpha_2 R_{i,t-1} + \alpha_3 R_{i,t-2} + \alpha_5 R_{i,t+1} + \alpha_6 R_{i,t+2} + \alpha_{14}|R_{i,t}| + \varepsilon_{i,t}$

$M3\ \ \%\Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \varepsilon_{i,t}$

$M4\ \ \%\Delta Vol_{i,t} = \alpha_0 + \alpha_1 R_{i,t} + \alpha_{15} R_{i,t}^2 + \varepsilon_{i,t}$