# THREE ESSAYS ON LEVERAGE, INFORMATIVE TRADING, AND OPTION-IMPLIED PREDICTABILITY

by

ADAM HARPER

Presented to the Faculty of the Finance Department at

The University of Texas at Arlington in Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

The University of Texas at Arlington

May 2017

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ABSTRACT

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The University of Texas at Arlington, 2017

Supervising Professor: Salil Sarkar

This study will take a three-prong approach to examine the role high-leveraged option trades have in determining the informational content of options market trading. First, I closely observe the structure of the volatility spread ahead of firm-level corporate earnings events to strengthen the well documented lead-lag relationship between the option and stock markets. I find that volatility spreads driven by deep, out-of-the-money options exceed the predictability of equivalent volatility spreads that are more uniform in distribution. I then explore the differential behavioral responses of leveraged trades and earnings, such the role of the disposition effect and overconfidence. I find that while options traders do suffer from the disposition effect, they also experience profit loss due to the disposition of equity traders to hold losers following negative news releases. This occurs despite signals released by options market trading suggesting poor news may be ahead on the horizon.

Next, I conduct simulations of the return deviations for both positive and negative Leveraged Exchange Traded Funds (LETFs). I find that the compounding deviations for negative LETFs tend to be larger than those of their positive counterparts, but both tend to deteriorate during times of higher volatility. By consequence this implies, and I show, that compounding deviations are also higher for more volatile indices and lower for less volatile ones. Finally, I examine options markets of LETFs and the predictability of compounding errors over multi-day horizons through simulations of LETFs from 1996 to

2015. I find that option implied volatility in the S&P 500 does predict the performance of hypothesized returns of positive LETFs.

# ACKNOWLEDGMENTS

I would like to thank the members of my dissertation committee, Sanjiv Sabherwal, Karan Bhanot, David Rakowski, and J. David Diltz for their input and suggestions regarding this dissertation. A special thank you goes to Salil Sarkar, the committee chairman, for his many hours of advice, counsel, and encouragement. His dedication to my project served as a motivational force that I intend to emulate in my future endeavors. And thank you to my fellow candidates, Trang T. Thai, Yiling Zhang, and Jinsuk Yang for their friendship and encouragement over the years. A special thanks belong to Samar Ashour, whose gentle nature and unyielding kindness never failed to lift my spirits. Finally, I'd like to thank my brother, Nate, for his support, patience, and love during the leaner years.

To my Family

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# Chapter 1

## Introduction

Options contracts have been an increasingly popular venue for all types of investors. This is despite the theoretical implications that options are redundant assets whose payoffs can be replicated, and past research has unearthed compelling evidence of a lead-lag relationship between the option and stock markets. Several studies have linked this relationship to informed trading in the options markets.[1] Informed traders, however they obtain their information, will be inclined to seek the additional leverage of options markets, and the additional risk of options markets will be less concerning to a trader who is rightly informed.[2] Informed traders may be persuaded by their knowledge to seek leverage in alternative assets, such as leveraged Exchange Traded Funds (LETF), when available. But such leverage is also attractive to overconfident investors, or even those who are misinformed. This dissertation will attempt to examine how informed (and misinformed) traders seek leverage, their role in price discovery, and their ability to generate abnormal equity returns and how it relates to market efficiency. Additionally,

[1] E.g. Hayunga and Lung (2014)
[2] Easley (1998)

I will examine the predictability of LETF performance against their stated multiples, and the relationship of compounding effects and how they differ between positive and negative ETFs. Finally, I include a representative model measuring the difference in return deviation between positive LETFs and negative LETFs with the same multiple and underlying index.

This dissertation will consist of three separate essays. In the first essay, I examine the role of highly leveraged option trades in determining the informational content in options markets ahead of firm-level corporate earnings events. I find that lead-lag relationship between options and equities found in the option-implied volatility spread is driven by interest in out-of-the-money (OTM) option pairs during these periods. Specifically, when the implied volatility spread of an option chain with a given expiration date is (is not) driven by OTM pairs, the predictive relationship between the volatility spread and future equity returns is enhanced (reduced). This finding is extended with the creation of long and short portfolios and funds to examine if uninformed traders can nevertheless profit from informed traders' knowledge. Additionally, I examine if the theory put forth by Odean (1998b) of overconfident informed traders improving price discovery can strengthen the evidence of informed trading, while overconfident price-takers, i.e., uninformed, worsen it. If this is true, we'd expect to see price discovery following leveraged trading in the options market that proved to be prescient to be more efficient that those following leveraged trading that proved to be incorrect in its prediction. Additionally, I create a strategic timing fund which employs the procedure of purchasing equities ahead of earnings announcements based upon information parsed from the volatility spread, and find that the fund generates positive abnormal returns that generate a consistent, steady accumulation of value. This fund, operating from June 2001 to December 2014 outperforms the S&P 500 by a significant amount using a mean- variance criteria as a yardstick. The fund's consistency is evident even during the tumultuous period of the 2007-2009 financial crisis.

The second essay conducts simulations of LETF returns for both positive and negative LETFs and documents the difference in compounding deviations between the two types. In this chapter, I also create portfolios which take long positions in both types to find statistical differences and potentially positive returns over longer-term holding periods.  A simulation of LETF compounded returns following at-the-money volatility spreads show that performance ratios, or actual returns divided by targeted-multiple returns, can be directionally predicted by examining the informational content of options on the S&P 500. I then conduct empirical tests on 18 major market indexes and their associated leveraged ETFs. Preliminary results show that this predictability in the simulation is evident in the empirical results after the creation of LETFs.

The third chapter examines the predictive power of option-implied information in LETFs and finds some relationship between option-implied information and the future returns and performance of LETFs, both positive and negative. In this, I find evidence of a lead-lag relationship between LETF funds and their own options. Consistent with the research on equity options, large positive (negative) deviations in put-call parity have weekly returns which outperform (underperform) the other LETF securities. Furthermore, the separate effects of put and call option-implied volatilities are examined. High daily and weekly changes in call (put) implied volatilities are followed by subsequent returns which outperform (underperform) the benchmark ETF.

The results of this study provide evidence of informed trading occurring in both equity options and LETF options, as well as LETF products themselves. Since both options and LETFs provide attractive environments for informed traders, the two avenues are, in a sense, in competition with each other for informed traders. This suggests a tradeoff exists between LETF products and both their own options and the options their underlying indices. Informed and misinformed traders have the choice of multiple avenues of leverage. Although this goes beyond the scope of this study, a potential extension exists in examining these tradeoffs and providing empirical evidence that such a relationship exists. Such factors that we could consider as relevant would include the liquidity of the options market, as well as the expenditure of options contracts, as measured by implied volatility

# Chapter 2

The role of leverage and informed trading amid corporate earnings events

## *2.1 Abstract*

This chapter examines the role of high-leveraged option trades in determining the informational content of options markets. I find that the predictive power of the market price inherent within the option-implied volatility spread is driven by interest in out-of-the-money pairs ahead of corporate earnings events. Specifically, when the implied volatility spread of an option chain with a given expiration date is (is not) driven by out-of-the-money pairs, the predictive relationship between the volatility spread and future equity returns is enhanced (reduced). Furthermore, I show that volatility spreads of ex-post facto incorrect options trading activity ahead of earnings announcements are slow to return to ordinary levels, indicating overconfidence in such trades, and a disposition to hold losers. Finally, this study suggests that the disposition effect in equity markets diminishes market efficiency following poor earnings news, and this delays and decays the returns of ex-post facto correct put holders.

### *2.2 Informed Trading and Equity Options*

Recent research has uncovered rich evidence of informed trading in the options market. Cremers and Weinbaum (2010) find that deviations from put-call parity in equity options lead future returns on underlying stocks. Johnson and So, 2012, find information embedded in stock volume ratios, and Pan and Poteshman, 2006 provide evidence of the predictive power of put/call price ratios. Some studies have found that this lead-lag relationship is strongest ahead of corporate events, such as earnings announcements (Roll et al. 2010), mergers and acquisitions (Jayaraman et al. 2001), and analyst revisions (Hayunga and Lung 2014). This is inherently reasonable as periods ahead of firm-level events, specifically planned events such as earnings, are marked by a high degree of information asymmetry. Such environments can offer high rewards at high risks, but for rightly informed traders, such risks are severely diminished.

The prevailing theory behind the empirical results of predictive information embedded in options is that informed traders will prefer to trade in levered markets (Easley et al. 1998), where their private knowledge can be utilized optimally to provide maximum returns. According to the studies provided above, the market supply and demand of options can leave fingerprints in the market-priced implied volatility, giving a sense of investor sentiment in direction and uncertainty, which can be used to unearth predictive relationships on the underlying stock return. Thus, some of the favored metrics to capture informed trading have been the implied volatility spread between put and call options (IV spread) and the implied volatility skew between at-the-money call options and out-of-the-money put options (IV skew). These two variables have been shown to have the strongest and most durable relationship ahead of planned and unplanned firm-level events, with their associated high degree of information asymmetry.[3]

As earnings announcements approach, informed and overconfident traders move into options for the added leverage. Their added demand fuels the prices of options upward, increasing the implied

[3]See Cremers and Weinbaum (2010), Hayunga and Lung (2014), DeMiguel et al. (2013)

volatility. With the assumption that uninformed options traders will proportion themselves between calls and puts relative to market sentiment, informed traders will put additional upward pressure on the prices and implied volatilities of the option type in which they've invested, thus tilting the difference between call and put implied volatilities and providing us a measure of informed trading.

More leverage within the options markets can come from buying deep out-of-the-money (OTM) options. Investors can achieve more "bang for the buck" from these options if prices move in their favor. For an investment in a deep OTM option to pay off, a large move is necessary, and in the correct direction. OTM options typically have a low delta, so that small changes in the price of the stock have little effect on the price of the option, particularly if the underlying equity moves leaves the option even deeper out of the money. Thus, not only would informed investors prefer the larger bang for the buck offered by OTM options, but traders in OTM options are more likely to be informed. Thus, they are more willing to take on the higher probability of zero payoffs from OTM options, because their private information suggests that the market-implied probability of a zero payoff is higher than reality. OTM options, therefore, mimic the payoffs of other leveraged situations, such as high financial or high operating leverage; the payoffs from both positive and negative moves in the underlying is amplified.

Investors with private information will prefer to make leveraged trades to capitalize on this advantage. However, as the leverage of an option increases, its liquidity typically declines, indicated by larger bid-ask spreads. At-the-money (ATM) options typically enjoy tighter bid-ask spreads and more open interest than the highly levered OTM options. It stands to reason, however, that if an investor has private information that is deemed to be exceptionally reliable, then the loss of liquidity, similar to the perceived risk of the trade, will not dissuade him from taking on additional leverage. This especially holds true for options markets. An investor who has a strong conviction that the price of an underlying stock will decrease (increase) following an earnings miss (rise) will not be concerned with the lack of liquidity in OTM put (call) options, since he will expect that option to be ATM or ITM following the price decline (increase), and the illiquidity of OTM options will no longer be a concern. Indeed, our results conform to the Bali and Hovakimian (2009) assertion that the volatility spread is a proxy for jump risk. The addition of our leverage indicator variable enhances the reliability of this proxy, as it represents informed traders' sentiment in the underlying equity, and anticipates a jump.

It is also the case that the IV spread metric used to measure informational content may be driven by the implied volatility imbalance of a particular pair. Examination of an option chain with a given expiration shows that the volatility spread different from zero may arise from a single OTM pair, or conversely, a single ATM or ITM pair. If the IV spread is determined by informed traders, then it stands to reason that the more strongly traders believe in the reliability of their private information, the more likely they are to select OTM options in order to benefit from the increased leverage. Thus, we would expect that IV spreads driven by OTM pairs are likely to have stronger predictive power than IV spreads driven by ATM pairs or those that are not driven by any singular pair. Table 1 demonstrates this feature. The table gives relevant option information for STX on August 1, 2016.[4] The option pairs listed have 19 days until expiration. The IV spread is measured at -0.1581, a large negative. Column *Cvol-Pvol* measures weighted, but unsummed, volatility spread contributions from each pair. At first glance, we can see the overall persistence of the volatility spread. Each pair weighs the spread down the volatility spread, indicating higher prices for put options, driven at least in part by higher demand. It is apparent, however, that the bulk of the negative volatility spread is being driven by OTM puts; more than 50% by a single pair.

In light of the above, this chapter will study this relationship in several ways. First, I will examine the relationship between IV spread and future stock returns for split samples. In doing this, I will run models using dummy variables which will indicate when the IV spread is driven by a particular pair. The hypothesis is that if informed traders that are more certain of their private information prefer leverage, then IV spreads driven by highly levered OTM pairs ahead of firm events should be more likely

[4] Data provided by TD Ameritrade's *Thinkorswim* platform

to predict subsequent earnings beat or misses or analyst upgrades or downgrades. Thus, we would expect a leveraged indicator to have a positive coefficient. The next step is to ensure that the directional moves correspond with IV spreads. Leveraged-driven spreads that are negative indicate higher trading activity on OTM puts, whereas leveraged-driven positive spreads indicate high trading activity in OTM calls. To my knowledge, no study has attempted examining the volatility spread to detect the prevalence of levered bets within an IV spread and the predictive ability of these trades.

## *2.3 Methodology and Metrics*

We attempt to take this further by examining the nature of a stock's daily volatility spread. It stands to reason that informed traders, relatively secure in the reliability of their knowledge, would prefer to trade in option pairs that offered larger returns per dollar invested; a greater "bang for the buck." These pairs would typically be out-of-the-money put and call options. If nonpublic information were held by an influential few, we'd expect to see higher open interest in OTM pairs, and thus, a greater impact of OTM pairs on the volatility spread. For example, if informed traders had reason to believe a firm's earnings would miss estimates, and future guidance would be lowered, they would reasonably assume the market would react by selling the underlying stock, sending its price down. By trading ahead of the news release in OTM options, the informed trader would position himself to optimize investment returns. Ahead of earnings, this could be examined through high negative IV spreads on option pairs well below the spot price.

Following Cremers and Weinbaum (2010), I construct the volatility spread metric. The volatility spread of an option is the sum of the weighted difference in the implied volatilities of call and put options for a given pair. For each day *t*, and for every stock *i*, the volatility spread is calculated as

The average difference in implied volatility among pairs of put and call options with the same expiration and strike price, weighted by the total open interest among all pairs.

Many studies have used the volatility spread as a predictive metric for underlying equity return, and it has been shown to be a durable predictive variable. I split the volatility spread into quintiles, the lowest quintile containing the lowest volatility spreads (highly negative), and the highest quintile containing the highest volatility spreads (high positive). According to Bali and Hovakimian (2009), the highly negative (positive) spreads would indicate substantial jump-risk to the downside (upside).

If informed traders are operating ahead of earnings, and a significant move in earnings is realized, then we'd expect that volatility spread to be driven by pairs that are OTM for the higher demanded pair. For example. If the volatility spread is calculated at 0.20 for the day, and one pair, above the spot price, is contributing 0.10 to the volatility spread, then we can safely assume there is high pricing in OTM call options, and the volatility spread is largely driven by this single pair (50% of total). Therefore I could conclude that informed traders believe the stock will increase in price after the positive earnings announcement. I thus create an indicator variable, *lev_dum* equal to 1 for each trading day if the following conditions are satisfied. First, the volatility spread must be in the largest quintile. Second, if in the largest quintile, at least 25% of the volatility spread must be realized in a pair with a call delta less than 0.375; i.e., an OTM pair. If in the smallest quintile, and at least 25% of the volatility spread must be realized in a pair with a put delta greater than -0.375. For this characteristic, I create a second indicator variable, *neg_lev* equal to one and zero otherwise.

Because of the nature of the trade, higher returns for greater risk, the indicator variable is referred to as the leverage indicator if the volatility spread is positive and the negative leverage indicator if the volatility spread is negative. This allows us to separate the effects of the leverage indicator (which should predict high returns) and the negative indicator (which should predict low returns). I then use the daily leverage dummy variable to create another variable, *lev_pre*, which is the average sum of the value of the leverage dummy variable and the negative leverage dummy variable for the nine-day pre-earnings period. The volatility spread can itself be very volatile, and so can the spread of an individual pair. It is not unusual for *lev_dum* to be equal to 1 on one day, then be equal to 0 the next, then return back to 1. Much more rare, however, is the indicator variable moving from 1 to -1 or vice-versa during the course of the pre- earnings period. The *lev_pre* variable can range from -1 to +1, with higher values indicating more persistent trading in OTM call options and lower values indicating more persistent trading in OTM put options. This way, fleeting moments of high interest in leveraged trades are not weighted as heavily as more persistent trading activity.

A problem may arise due to the fact that some equity options have more trading pairs than others. An option of a given expiration date may have more than 30 option pairs. This, assuming a uniform distribution of demand among all pairs, would make such a high percentage (as 25%) statistically improbable. It is common knowledge among options markets, however, that such a uniform distribution does not reflect reality. Interest in pairs has a tendency to coalesce around particular pairs. I suspect two reasons for this pattern. First, traders have a preference for numbers that would be characterized as "round" numbers, e.g., numbers that end with a zero or a five. Such numbers are seen as natural barriers - resistance and support levels for underlying prices. For options of lower priced underlying stocks, however, such grouping can occur anyway due to a preference for options with more open interest and trading volume. High liquidity will keep bid-ask spreads low. I therefore also amend the leverage indicator variable to be formed based upon the weighted total of OTM options' contribution to the volatility spread.

## *2.4Empirical Results*

We calculate excess returns, *xret*, as the three-day return from the day before, the day of, and the day after earnings announcements. I then split the variable into 5 quintiles and examine averages for the relevant variables. Table 2 provides the results. We observe that *iv_spread*, *iv_pre, lev_pre*, and *lev_dum* increase with higher quintiles of *xret*. Meanwhile, *neg_lev* decreases with *xret*. The results indicate that higher excess returns about earnings announcements observed higher levels of pre-earnings volatility spread, and were more likely to exhibit levered trading. This provides base evidence that both *iv_spread* and leveraged trading may have predictive power over earnings returns. In Panel B, I provide average 10-day returns, *fret10,* along with *xret,* after splitting two ways. First into high and low *iv_spread* quintiles and then with leverage and without. The results displayed show higher 10-day returns and higher *xret* when the volatility spread is high.  Additionally, both returns get an extra boost when the leverage indicator variable is equal to one. Conversely, when the volatility spread is low, returns for leveraged indicator decline, indicating predictive interest in options that imply a downside move in the underlying. The results are consistent with our assertion that OTM options have explanatory power over future returns

Table 3 provides daily regressions of earnings period excess returns on various explanatory variables. In column one, we observe the predictive power of *iv_spread* is positive and significant. However, the addition of our leverage indicator variables reduces this predictive power to insignificant levels. The t-statistic for the volatility spread declines from 2.22 to 1.55 with the inclusion of *lev_dum*. Additionally, I include interaction terms, such as *iv_lev* which is formed by taking the product of the volatility spread and the leverage indicator variable. This inclusion is not significant but does alter the results of the previous column. In column 4, I include the negative leverage dummy variable, which also serves to diminish the role of the volatility spread, although the effect is not a strong.

Table 4 provides the results of Fama MacBeth regressions using the full sample. The dependent variable is the 3-day excess returns around the earnings announcement date.  Independent variables are the pre-earnings volatility spread, *iv_pre*, the base volatility spread, *iv_base*, the pre-earnings leverage, *lev_pre*, the leverage dummy variable, *lev_dum*, and the negative leverage dummy variable, *neg_lev*. The results show that the pre-earnings volatility spread has a significant and positive relationship with the earnings period excess returns, while the coefficient on the base volatility spread is not significant. With the introduction of *lev_pre* in column 4, the effect of *iv_pre* is diminished; t-statistics dropping from 2.39

to 1.22. Meanwhile, the significance of *lev_pre* is stronger than 1%. Columns 5, 6, and 7 include the *lev_dum* and *neg_lev* variables, which also serve to diminish the predictive power of the pre-earnings volatility spread.

Panel B shows the results when fixed effect regressions are run instead of Fama MacBeth. Again it is observed that the predictive power of the pre-earning volatility spread is drastically reduced with the inclusion of the leverage variables, but the coefficients on *iv_pre* remain significant. It is also noted that the positive leverage dummy variable appears to be stronger than the negative leverage variable in both magnitude and significance, and in its ability to diminish the significance of *iv_pre*.

Panel C presents the full-period regressions on ranked variables following the example of Jin et al. (2012). I rank the pre-earnings and base volatility spreads along with *iv_pre* into five quintiles, then assign a new ranked variable equal to 0.5 if the variable is in the highest quintile and equal to -0.5 if in the lowest quintile, and finally equal to zero otherwise.

We then examine several subsamples to ensure the robustness of the results. I first split the sample into equal halves and run Fama-MacBeth regressions for the sub-periods from 2001-2007 and 2008-2014 with the same variables. For robustness, the ranked tests of Jin et al. (2012) are also provided. Panel A of table 5 displays the results for the early period. None of the relevant variables appear to have significant predictive power in this period, even results for the ranked tests are only weakly significant at best. For the later sub-period in Panels B and B-ranked, results remain strong, despite the small sample size.

Initial tests for a structural break in the regressions give an indication that a break may exist in the $33^{rd}$ quarter of the sample; the first quarter of 2009. This quarter corresponds with the bottom of market, indicating the predictive power may itself be market dependent. I conduct tests to ensure that the result is not driven entirely by this period. Table 6 provides the results, and I include tests for ranked tests for robustness. In Panel A, I extend the sample in Table 5 to include the 5 additional quarters up to the first quarter of 2009. The results show significance with *iv_pre* and *lev_pre* with the inclusion of these time periods, and removing them from the second half of the sample also removes the significance of the relevant variables. This brings up the possibility that our results only exist because of conditions that existed in the market during the year of 2008 and the first quarter of 2009. In Panel C of Table 6, I remove only these 5 periods from the full sample. While the results on *lev_pre* and *iv_pre* weaken, they are nevertheless significant. Thus we can conclude that the overall relationship does hold in the long run, but augmented strength of the results arises from the sub-period in question.

## *2.5Overconfidence and the Disposition Effect*

A well-known strategic refrain for investors is "cut your losses and let your profits run." One basis for this idea, spelled out by Constantinides (1984), is that tax incentives give this strategy a natural advantage. Losses that are recognized before the end of the year can offset gains, reducing the tax burden. Additionally, tax advantages on capital gains begin following investment horizons greater than one year. A more commonsensical grounding for the mantra is that trades resulting in losses were based on poor or misinterpreted information while resulting gains were based on good information.

However, investors often employ the opposite of this strategy, holding losers in hopes for a reversal and cutting winners in fear of losing unrecognized gains. They do this despite the obvious tax disadvantages and often despite new information which may contradict their previously held beliefs. Kahneman and Tversky (1979) suggest that investors may not have "made peace" with their losses and are therefore more likely to engage in risky behavior, such as refusing to act on new information.

Behavioral finance suggests that prospect theory can explain the irrational behavior of market participants. An investor may have a preconceived notion of a security's future price, thus making expected return a fluid measure which can be reduced following an increase in the price early in the investment horizon.  If the investor believed while opening her position, that a stock price would return

10% over the course of a year, this expectation may be reduced if the stock increased by 5% in the first month. In an efficient market, such an increase would not matter to the stock's expected gain of 10% per year. But she may believe that the stock can only gain another 4.76% in the next 11 months, thus the Sharpe ratio for the investment declines. Additionally, the positive gain on the stock has placed the investor on the concave portion of the utility curve for investment returns. Thus her risk aversion has increased, and she now has a lower certainty equivalent relative to expected returns.[5]

Conversely, an investor with a losing position will be placed on the convex portion of the utility curve increasing his risk appetite. Additionally, he may feel that his expected future returns are now higher. That same 10% expectation for a year may increase to 15.8% expected return for the following 11 months, if he's irrational. With the risk premium now negative, and expectations of future returns potentially even higher, he'll willingly seek out risk in an effort to recoup his losses. These trading tendencies that describe how investors are reluctant to sell losers and eager to sell winners in spite of the disadvantages have come to be known as the disposition effect.

With respect to the disposition effect and overconfidence, I examine if the theory put forth by Odean (1998b) of overconfident informed traders improving price discovery can strengthen the evidence of informed trading, while overconfident price-takers, i.e., uninformed, worsen it. If this is true, we'd expect to see price discovery following leveraged trading in the options market that proved to be prescient to be more efficient that those following leveraged trading that proved to be incorrect in its prediction.

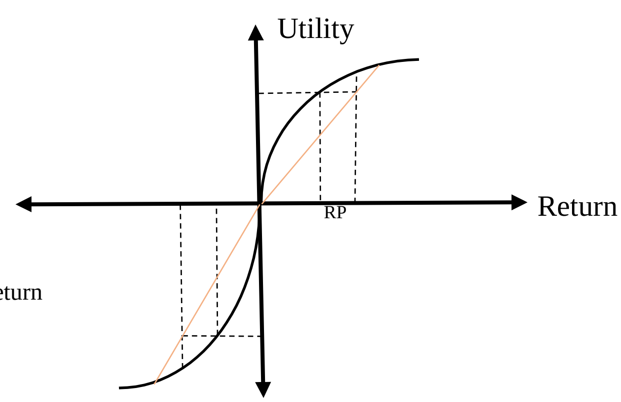



Figure 1: Utility function of return

[5] Kahneman and Teversky (1979)

Table 8 considers the volatility spreads following announcement dates for returns with a positive *lev_pre* variable, indicating high volatility spreads generated by interest in OTM call options. I split the *xret* variable into quintiles and display in each row along with the difference in volatility spreads between the 1st and 5th quintiles in the shaded row. For each column, I examine the volatility spread $t^{th}$ days following earnings announcement, as well as the pre-earnings volatility spread in the first column and the post-earning drift of the volatility spread in the shaded column.

Table 8 displays two important features. First, it shows that volatility spreads, which average around -0.90[6], return to normal levels quickly when leveraged trades display prescience; that is when earnings-period excess returns are high. Meanwhile, volatility spreads following low excess returns around earnings remain high and are slow to return to normal levels. Second, the post-earnings drift of ex-post facto "wrong" trades is much larger, indicating a drawn out process in price discovery. Volatility spreads for the loser trades remain high for days, indicating a persistent expectation that future returns will be high, despite recent losses and potentially conflicting news out of the earnings report.

Table 9 repeats the process of Table 8, but for stocks with negative *lev_pre* values. The mirror-image tells the same story. Pre-earnings volatility spreads are lower than average but relatively equal to each other across *xret* quintiles. Despite some initial overshooting for winner investments (i.e. lower excess returns), volatility spreads are faster to return to around normal levels.

There may be some question as to whether the changes in volatility spreads are due to the underlying returns themselves. Implied volatilities themselves are typically high in the days ahead of earnings, as uncertainty and information asymmetry increases. Following earnings announcements, implied volatilities tend to fall. But volatility spreads are based on the difference between call and put volatilities, both of which decline after earnings. Thus, for equal rates of post-earnings declines in implied volatilities, we shouldn't expect spreads to change one way or the other. Regardless, I test this by

[6] Volatility spreads are multiplied by 100 for aesthetic purposes

including Table 10, which replicates the two previous tables for samples where the *lev_pre* variable is equal to zero, indicating no leveraged trading activity. If indeed these discrepancies are caused by movements in the underlying themselves, then dispersions in spreads should exist across *xret* quintiles following earnings. Indeed, we do see this immediately after; volatility spreads for high returns decrease while spreads for low return increase, perhaps due to the underlying return, and perhaps indicating some market expectation of reversal for the underlying asset. Nevertheless, such deviations between rows 5 and 1 are quickly reduced, unlike those in Tables 8 and 9, which persist more strongly during the 7-day period. Thus, while initial changes in volatility spreads may be due to underlying returns, such returns have no bearing on the persistence of such spreads. Tables 8, 9, and 10 provide support to Odean (1998b) assertion that overconfident insiders improve price efficiency while overconfident "price-takers" worsen it. Table 10 has no overconfident traders, thus deviations in volatility spreads are quickly reduced, Tables 8 and 9 are full of overconfident traders (both justifiably and unjustifiably), thus traders who are proven wrong hold their losers longer, accepting greater risk in the hope of recovering losses.

One question unanswered by this study is the result of the options trades themselves. Options traders face unique hurdles around an underlying firm's earnings report. The most significant is the well-known decline in implied volatility following an earnings release. As the earnings date approaches, the demand for options typically increases, pushing up the price and the implied volatility alike. This uptick in demand comes from both informed and overconfident traders. The base function of the implied volatility metric is to measure market expectations in future volatility and measure can be skewed between calls and puts depending upon the relative supply and demand of the two. Following earnings, the supply of options increases, as traders seek to close their positions. This pushes the implied volatility and the price of the option down. Additionally, rational and irrational options traders face the hurdle of irrational equity traders following an earnings release. Disposition and cognitive dissonance can delay the price discovery process and prevent equity prices from reaching market equilibrium.[7] Thus, options

[7] See Shefrin and Statman (1985), Frazzini (2006),

traders may face an accelerating time decay, as those seeking leverage will also prefer shorter term options. Indeed, studies have shown that options traders typically do not profit in this manner and may even use stock options as lottery tickets and typically overpay.[8] The higher implied volatilities of OTM options serve to support this claim.

However, it may be possible that equity traders can use information pulled from options traders to generate positive abnormal returns. If equity markets are only efficient in the semi-strong form, as the lead-lag relationship between options and stocks suggests, then we would expect an equity trader to be able to generate positive alpha. To consider the long-run profitability of the leverage indicator metric, I create five strategic-timing funds based upon the different levels of the *lev_pre* variable. Fund 1 will buy stock(s) when the value of *lev_pre* is less than -0.3, Fund 2 between 0 and -0.3, Fund 3 equal to zero, Fund 4 between 0 and +0.3, and Fund 5 consists of stocks with a *lev_pre* greater than +0.3. Each fund begins with $1, opens trading on June 1, 2001, and closes trading on December 31, 2014. On day $t - 2$, stocks are sorted into their prescribed funds and equal-weighted positions are purchased, which are closed on day $t + 1$. The funds invest only 10% of their asset value into a new portfolio on a given day, as they may be required to create 2 additional portfolios before closing and recognizing payoffs from the first investment. Asset values are calculated as *available funds + investments made* (not the current value of the investment in play). Thus, at a $1 asset value, a $0.10 investment is made today, another $0.10 investment may be made tomorrow, and another potential $0.10 investment is made on the third day. At the end of the third day, the first position created is closed and the asset value of the fund is recalculated; process continues until the close of the fund. Some days there are no investments to be made, many days there is only one stock that satisfies the criteria, and on some days there are multiple stocks (the highest count for Fund 5 is 12 stocks in one day). Meanwhile, Fund 3 can have up to 100 different stocks in a portfolio on a given day.

[8] See Boyer and Vorkink (2014), Erkar and Ready (2015)

Figure 2 provides the time-plot of asset value for the 5 funds. Fund 5 (in black) achieves substantial growth over the 13.5 year period, increasing to a value greater of $4.61 at the fund's closing. The cumulated annual growth rate (CAGR) is equal to almost exactly 12%, compared with 3.8% for the S&P 500. Furthermore, the daily returns of the fund value indicate far superior mean-variance metrics. Fund 5's annualized Sharpe ratio is 1.55 compared with 0.30 for the S&P 500 over the same period. The asset values of the various funds decrease monotonically with the strategy used. Fund 5 is valued at more than Fund 4, which is valued at more than Fund 3 and so on. Fund 1 is the only fund which closes with an asset value of less than $1, closing at $0.74. This aligns with my previous observation that the effect of the leverage indicator is greater for call options. However, a closer examination of the returns following earnings reveals decreased efficiency in equity prices during and following earnings are preventing the fund from losing even more value.

Table 11 displays daily and cumulated Fama-French 3-Factor alphas pre- and post-earnings for different levels of the pre-earnings leverage metric. The variable, *lev_pre*, measures the average value of the leverage indicator variable during the 9-day period between $t - 10$ and $t - 2$, inclusive. Then the sample is split into five subsamples, indicated to the left of the table. Betas for market, size, and value premiums for individual equities are calculated using the past 150 trading days of premium information provided by Kenneth French's website, and alphas are assumed to have the same distribution. The data sample runs from June 2001 to December 2014.

In Panel A, I give the individual daily alphas from $t - 1$ to $t + 6$ for equally weighted portfolios created at the end of day $t - 2$. The portfolios are named Portfolio 1, *lev*_pre values below -0.3, through Portfolio 5 which have *lev*_pre values above +0.3. Portfolio 3 has a *lev_pre* value equal to zero. Interestingly, for Portfolios 4 and 5, all alphas are realized either the day before earnings or the day of earnings. Post earnings, there is no further significance. For Portfolios 1 and 2, the opposite holds true. Individual daily alphas only reach a negative significance following earnings, up to 5 days after earnings in the case of Fund 1. In Panel B, I display the cumulative abnormal returns (CARs), for the 8-day earnings and post-earnings period. CARs are fully depleted for call-driven trades by the post-earnings period. Meanwhile, despite the gradual depletion of equity prices following put-drive trades, Fund 1 in Panel B never achieves significant CAR levels, despite the gradual increase in magnitude. The insignificant alphas during the earnings period are too much to overcome.

We can now see that the failure of Fund 1 to generate more negative returns (or more positive, if shorted) may be due to the behavioral inefficiencies of equity traders. While never achieving complete strong-form efficiency, equity prices are more strongly efficient when earnings news is positive and options investors have correctly predicted it be so. When earnings news is negative, the disposition effect and cognitive dissonance amongst equity traders prevents the full realization of true values in equity prices, and thus options prices as well, bringing forth my next assertion that equity prices are less efficient, even when informed and overconfident traders are correct following negative news. Additionally, the delayed realization of "put-driven" alphas diminishes the returns of put holders. Equity traders are better off not taking a position on put-driven stocks until after earnings, once the news is released and is poor.

Fund 6 is created in this response, which delays the opening of positions until day *t+1* and holds the investments until the end of day *t+5*. Additionally, a short position is taken in each portfolio of stocks on a given day, to account for the expectations of negative returns signaled by *lev_pre*. Despite the statistical significance, from the fund created, there appears to be little economic significance. Fund 6 closes at approximately $1.25 for a CAGR of 1.67%. Similarly, as long-short portfolio that attempts to combine the strategies of Funds 5 and 6 fails to exceed the end value of Fund 5. This long-short fund closes at $2.52.

This brings up other relevant questions. One question that comes to mind is just how efficient are ex-post facto call driven stocks during the pre-earnings period. If the options market of a stock enters the pre-earnings period at day *t-10* with leveraged trading, is it possible that equity traders recognize this signal and begin purchasing stocks ahead of earnings, driving the price up before the earnings period? For example, if the leveraged indicator variable was equal to one on days *t-10*, *t-9*, and *t-8*, stock investors may then buy up the underlying in response to this signal. Two things would occur from this scenario. First, call prices would increase and strike prices which triggered the leveraged indicator variable may no longer be out of the money. In this case, the leverage dummy variable would revert to zero. Second, we can expect implied volatilities on OTM call options to fall as they closer to the money. Similarly, we'd anticipate that ITM put options will also be closer to the money and therefore their implied volatilities should fall. But given what we understand about the disposition effect, the call implied volatilities will have the additional weight of increased option supply as call holders seek to close their positions in disproportion to put holders. If this is true, then on average we can anticipate that call implied volatilities will decrease more, and a previously high positive volatility spread will declines. In both scenarios, the end result is a leverage indicator variable that moves from 1 to 0 on day *t-7*.

Therefore, a more efficient market would enhance the results given in this study, and may possibly even help explain them. To borrow an analogy from a simple physics example, the pre-earnings and earnings period can be viewed as a rubber band, with informed trading representing the potential energy created by pulling one end of the rubber band back, and the returns representing the kinetic energy resulting from the stretched end being released. Each day during the pre-earnings period that has a leverage indicator variable equal to 1 represents an increase in the length of the rubber band and an increase in the potential energy stored within. If the indicator returns to zero, the tension is relaxed and the potential energy reduced. If the full nine days of the pre-earnings period witnesses the leveraged indicator variable, then we can expect a lot of potential energy stored, ready to be released when the earnings period begins. The short, the persistence of the leverage indicator variable is related to the efficiency of the underlying stocks. We'd expect stocks that are followed more closely to lean more toward strong-form efficiency, thus reducing the *lev_pre* variable and the tension on the analogous rubber band.

## 2.6Conclusion

This paper provides evidence that the volatility spread does have predictive properties ahead of earnings period returns, but that this predictive power is driven by informed trading in out-of-the-money options. Options traders with private knowledge trade in OTM options, which drives the volatility spread away from its averages and leads future returns. Volatility spreads that are not driven by OTM options have, by comparison, fewer informative properties and less predictive power over future returns. The implications of these results are clear for investors seeking abnormal returns on equity investments. Furthermore, this paper shines additional light on the role of overconfidence and the disposition effect following earnings announcements. I provide evidence that overconfident options traders are slow to respond to earnings news that doesn't correspond with their pre-earnings beliefs. Volatility spreads for ex-post facto incorrect trades maintain at abnormal levels following earnings, indicating a lack of supply as traders hold their positions. For put holders, there may be some benefit, as I show a large disposition effect among equity traders following poor earnings news that is diffused slowly, while ex-post facto correct call holders realize their gains much more quickly. This also demonstrates the nuanced nature of market efficiency following earnings. The lead- lag relationship between options and stocks holds, indicating market prices are less than strong-form efficient for these stocks. However, stock prices do in fact lead their own earnings news when options traders correctly hold call options, indicating market prices are more than semi-strong-form efficient.

Behavioral characteristics such as disposition effect and cognitive dissonance among equity traders, however, slow the response to negative news, even when put holders are correct in their trades. Post-earnings alphas on such stocks exist well after the announcement date, indicating markets failing to achieve even weak-form efficiency on such stocks. Finally, a strategic timing fund based upon option-implied information and the leverage indicator is created, showing consistent, steady returns even during tumultuous markets.

## 2.7Tables and Figures

**Table 1:** Option chain for STX, August 2016

| | Calls | | | Puts | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Imp Vol | Open.Int | Delta | Imp Vol | Open.Int | Delta | Tot OpInt | Cvol-Pvol | %Spr |
| | 44.99% | 1877 | 0.88 | 59.93% | 846 | -0.19 | 1361.5 | -0.01579 | 10% |
| | 46.02% | 170 | 0.83 | 59.64% | 84 | -0.23 | 127 | -0.00134 | 1% |
| | 44.88% | 2198 | 0.79 | 58.76% | 594 | -0.26 | 1396 | -0.01504 | 10% |
| | 45.61% | 244 | 0.74 | 59.85% | 285 | -0.31 | 264.5 | -0.00292 | 2% |
| | 44.35% | 12524 | 0.68 | 60.00% | 532 | -0.35 | 6528 | -0.07931 | 50% |
| | 45.04% | 566 | 0.62 | 58.99% | 180 | -0.39 | 373 | -0.00404 | 3% |
| | 44.26% | 1652 | 0.56 | 59.80% | 135 | -0.44 | 892.5 | -0.01078 | 7% |
| ITM | 44.65% | 130 | 0.5 | 58.79% | 156 | -0.49 | 143 | -0.00157 | 1% |
| | 42.86% | 1174 | 0.44 | 59.94% | 64 | -0.53 | 619 | -0.00773 | 5% |
| | 42.89% | 152 | 0.38 | 59.47% | 83 | -0.57 | 117.5 | -0.00142 | 1% |
| | 42.85% | 1518 | 0.33 | 62.90% | 9 | -0.6 | 762.5 | -0.01188 | 8% |
| | 42.80% | 103 | 0.27 | 62.54% | 3 | -0.64 | 53 | -0.00081 | 1% |
| | 42.23% | 352 | 0.22 | 65.16% | 12 | -0.67 | 182 | -0.00429 | 3% |
| | 42.47% | 90 | 0.15 | 68.95% | 29 | -0.72 | 59.5 | -0.00118 | 1% |
| | | | | | | | **IV_Spread** | **-0.15811** | |

**Table 2:** Summary statistics split by excess returns for the earnings period. Averages are presented for the full sample and for each quintile of *xret*

| xret | iv_pre | lev_pre | lev_dum | neg_lev |
|---|---|---|---|---|
| 0.0040 | -0.0092 | 0.0049 | 0.0413 | 0.1220 |
| **Quintile** | | | | |
| 1 | -0.0111 | -0.0033 | 0.0167 | 0.3219 |
| 2 | -0.0100 | -0.0004 | 0.0313 | 0.2838 |
| 3 | -0.0090 | 0.0008 | 0.0209 | 0.2870 |
| 4 | -0.0078 | 0.0138 | 0.0747 | 0.2594 |
| 5 | -0.0086 | 0.0144 | 0.0678 | 0.2959 |

**Table 3:** Fama MacBeth regressions on daily observations. The sample includes all earning announcements with data available from 2001 to 2014. The dependent variable is excess returns during earnings announcement period, defined as the three-day period beginning the day before and ending the day after the announcement day. Panel B presents the results of fixed-effect regressions.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret |
| iv_spread | 0.0111*** | 0.00556 | 0.00534 | 0.00640* | 0.00465 |
| | (2.222) | (1.549) | (1.449) | (1.752) | (1.197) |
| lev_dum | | 0.00452*** | 0.00432*** | | |
| | | (5.570) | (2.973) | | |
| iv_lev | | | 0.00439 | | |
| | | | (0.268) | | |
| neg_lev | | | | -0.00334*** | -0.00226* |
| | | | | (-2.943) | (-1.925) |
| iv_neg | | | | | 0.0155 |
| | | | | | (1.343) |
| Constant | 0.00452*** | 0.00405*** | 0.00405*** | 0.00477*** | 0.00476*** |
| | (19.84) | (16.67) | (16.64) | (20.17) | (20.15) |
| Observations | 121,764 | 121,764 | 121,764 | 121,764 | 121,764 |
| R-squared | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 4:** Coefficients of Fama-MacBeth regressions based on 56 quarterly regressions. The sample includes all earning announcements with data available from 2001 to 2014. The dependent variable is excess returns during earnings announcement period, defined as the three-day period beginning the day before and ending the day after the announcement day. Panel B presents the results of fixed-effect regressions See appendix for variable definitions. Panel C displays the results of using variable that are ranked in the example of Jin et al. (2012). To form ranked variables, relevant variables are sorted into quintiles, then assigned a value equal to 0.5 if in the highest quintile, -0.5 if in the lowest, and 0 otherwise.

**Panel A**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| iv_pre | 0.0434** | | 0.0535** | 0.0302 | 0.0381* | 0.0393* | 0.0359 |
| | (2.390) | | (2.409) | (1.222) | (1.719) | (1.791) | (1.632) |
| iv_base | | 0.0115 | -0.0169 | -0.0173 | -0.0172 | -0.0166 | -0.0162 |
| | | (0.650) | (-0.837) | (-0.867) | (-0.862) | (-0.825) | (-0.804) |
| lev_pre | | | | 0.00904*** | | | |
| | | | | (2.675) | | | |
| lev_dum | | | | | 0.00247** | | 0.00241* |
| | | | | | (2.654) | | (1.686) |
| neg_lev | | | | | | -0.00306* | 0.000499 |
| | | | | | | (-1.999) | (0.203) |
| Constant | 0.00450*** | 0.00399*** | 0.00429*** | 0.00379*** | 0.00376*** | 0.00509*** | 0.00377*** |
| | (2.561) | (2.098) | (2.294) | (2.887) | (2.795) | (2.782) | (2.716) |
| Observations | 34,018 | 31,374 | 31,374 | 31,374 | 31,374 | 31,374 | 31,374 |
| R-squared | 0.004 | 0.002 | 0.006 | 0.010 | 0.010 | 0.009 | 0.012 |
| Number of groups | 56 | 56 | 56 | 56 | 56 | 56 | 56 |

**Panel B**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| iv_pre | 0.0363*** | | 0.0397*** | 0.0212 | 0.0260* | 0.0328** | 0.0262* |
| | (2.462) | | (2.838) | (1.354) | (1.776) | (2.266) | (1.791) |
| iv_base | | 0.0126 | -0.00677 | -0.00414 | -0.00492 | -0.00608 | -0.00461 |
| | | (0.947) | (-0.455) | (-0.277) | (-0.330) | (-0.408) | (-0.309) |
| lev_pre | | | | 0.00565*** | | | |
| | | | | (2.610) | | | |
| lev_dum | | | | | 0.00197*** | | 0.00332*** |
| | | | | | (2.183) | | (2.935) |
| neg_lev | | | | | | -0.00204* | 0.00282 |
| | | | | | | (-1.880) | (1.426) |
| Constant | 0.00273*** | 0.00263*** | 0.00284*** | 0.00266*** | 0.00266*** | 0.00342*** | 0.00175* |
| | (2.272) | (2.268) | (2.552) | (2.317) | (2.337) | (2.989) | (1.700) |
| Observations | 34,018 | 31,374 | 31,374 | 31,374 | 31,374 | 31,374 | 31,374 |
| Number of id | 1,539 | 1,484 | 1,484 | 1,484 | 1,484 | 1,484 | 1,484 |

**Panel C**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| rspread_pre | 0.00727*** | | 0.00739*** | 0.00497** | 0.00560*** | 0.00605*** | 0.00546*** |
| | (2.643) | | (2.655) | (2.563) | (2.807) | (2.887) | (2.740) |
| rspread_base | | 0.00104 | -0.000539 | -0.000763 | -0.000841 | -0.000765 | -0.000815 |
| | | (0.715) | (-0.373) | (-0.524) | (-0.573) | (-0.524) | (-0.555) |
| rlev_pre | | | | 0.00515** | | | |
| | | | | (2.301) | | | |
| lev_dum | | | | | 0.00203** | | 0.00191 |
| | | | | | (2.286) | | (1.481) |
| neg_lev | | | | | | -0.00266* | 0.000104 |
| | | | | | | (-1.780) | (0.0466) |
| Constant | 0.00416*** | 0.00415*** | 0.00416*** | 0.00467*** | 0.00386*** | 0.00491*** | 0.00392*** |
| | (2.205) | (2.200) | (2.207) | (2.656) | (2.903) | (2.727) | (2.857) |
| Observations | 34,018 | 34,018 | 34,018 | 34,018 | 34,018 | 34,018 | 34,018 |
| R-squared | 0.003 | 0.002 | 0.005 | 0.008 | 0.008 | 0.008 | 0.010 |
| Number of groups | 56 | 56 | 56 | 56 | 56 | 56 | 56 |

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 5:** Coefficients of Fama-MacBeth regressions based on two subsamples. The dependent variable is excess returns during earnings announcement period, defined as the three-day period beginning the day before and ending the day after the announcement day. Panel A presents the results for the sub period from 2001-2007. Panel B presents the results for the sub period from 2008-2014 See appendix for variable definitions.

**Panel A**

| VARIABLES | (1) xret | (2) xret | (3) xret | (4) xret | (5) xret | (6) xret | (7) xret |
|---|---|---|---|---|---|---|---|
| iv_pre | 0.0412 | | 0.0495 | 0.0430 | 0.0417 | 0.0382 | 0.0396 |
| | (1.426) | | (1.700) | (1.311) | (1.376) | (1.303) | (1.321) |
| iv_base | | 0.0222 | 0.00522 | -0.000341 | 0.00355 | 0.00458 | 0.00301 |
| | | (0.986) | (0.234) | (-0.0142) | (0.154) | (0.200) | (0.133) |
| lev_pre | | | | 0.00481 | | | |
| | | | | (0.951) | | | |
| lev_dum | | | | | 0.00143 | | 0.000697 |
| | | | | | (0.998) | | (0.347) |
| neg_lev | | | | | | -0.00238 | -0.00117 |
| | | | | | | (-1.120) | (-0.425) |
| Constant | 0.00449** | 0.00437** | 0.00463** | 0.00424** | 0.00435** | 0.00528*** | 0.00477** |
| | (2.720) | (2.430) | (2.516) | (2.258) | (2.284) | (2.791) | (2.647) |
| Observations | 15,358 | 14,160 | 14,160 | 14,160 | 14,160 | 14,160 | 14,160 |
| R-squared | 0.005 | 0.002 | 0.006 | 0.010 | 0.011 | 0.010 | 0.013 |
| Number of groups | 28 | 28 | 28 | 28 | 28 | 28 | 28 |

**Panel B**

| VARIABLES | (1) xret | (2) xret | (3) xret | (4) xret | (5) xret | (6) xret | (7) xret |
|---|---|---|---|---|---|---|---|
| iv_pre | 0.0456* | | 0.0576 | 0.0174 | 0.0344 | 0.0382 | 0.0322 |
| | (2.024) | | (1.688) | (0.465) | (1.049) | (1.303) | (0.984) |
| iv_base | | 0.000860 | -0.0390 | -0.0343 | -0.0380 | 0.00458 | -0.0353 |
| | | (0.0311) | (-1.161) | (-1.069) | (-1.164) | (0.200) | (-1.064) |
| lev_pre | | | | 0.0133*** | | | |
| | | | | (2.996) | | | |
| lev_dum | | | | | 0.00352*** | | 0.00412* |
| | | | | | (2.964) | | (2.043) |
| neg_lev | | | | | | -0.00238 | 0.00217 |
| | | | | | | (-1.120) | (0.528) |
| Constant | 0.00450** | 0.00362* | 0.00395** | 0.00335* | 0.00318 | 0.00528*** | 0.00277 |
| | (2.318) | (1.927) | (2.107) | (1.790) | (1.644) | (2.791) | (1.301) |
| Observations | 18,660 | 17,214 | 17,214 | 17,214 | 17,214 | 14,160 | 17,214 |
| R-squared | 0.003 | 0.002 | 0.006 | 0.009 | 0.009 | 0.010 | 0.011 |
| Number of groups | 28 | 28 | 28 | 28 | 28 | 28 | 28 |

t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table 5 ranked:** Coefficients of Fama-MacBeth regressions of ranked variables based on two subsamples. The dependent variable is excess returns during earnings announcement period, defined as the three-day period beginning the day before and ending the day after the announcement day. Panel A presents the results for the sub period from 2001-2007. Panel B presents the results for the sub period from 2008-2014 See appendix for variable definitions. To form ranked variables, relevant variables are sorted into quintiles, then assigned a value equal to 0.5 if in the highest quintile, -0.5 if in the lowest, and 0 otherwise.

**Panel A**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| rspread_pre | 0.00509* | | 0.00502* | 0.00261 | 0.00379 | 0.00406 | 0.00377 |
| | (1.959) | | (1.901) | (0.966) | (1.422) | (1.459) | (1.396) |
| rspread_base | | 0.00129 | 0.000354 | 0.000198 | 0.000208 | 0.000278 | 0.000142 |
| | | (0.659) | (0.180) | (0.0965) | (0.0995) | (0.136) | (0.0686) |
| rlev_pre | | | | 0.00429 | | | |
| | | | | (1.217) | | | |
| lev_dum | | | | | 0.00102 | | 0.000663 |
| | | | | | (0.733) | | (0.360) |
| neg_lev | | | | | | -0.00139 | -0.000322 |
| | | | | | | (-0.630) | (-0.111) |
| Constant | 0.00432** | 0.00433** | 0.00432** | 0.00481*** | 0.00407** | 0.00475** | 0.00424** |
| | (2.510) | (2.520) | (2.512) | (2.782) | (2.282) | (2.646) | (2.362) |
| Observations | 15,358 | 15,358 | 15,358 | 15,358 | 15,358 | 15,358 | 15,358 |
| R-squared | 0.004 | 0.002 | 0.005 | 0.009 | 0.009 | 0.009 | 0.011 |
| Number of groups | 28 | 28 | 28 | 28 | 28 | 28 | 28 |

**Panel B**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| rspread_pre | 0.00944*** | | 0.00977*** | 0.00733** | 0.00742** | 0.00803** | 0.00715** |
| | (2.130) | | (2.205) | (2.657) | (2.489) | (2.561) | (2.426) |
| rspread_base | | 0.000783 | -0.00143 | -0.00172 | -0.00189 | -0.00181 | -0.00177 |
| | | (0.360) | (-0.670) | (-0.828) | (-0.909) | (-0.865) | (-0.842) |
| rlev_pre | | | | 0.00602** | | | |
| | | | | (2.134) | | | |
| lev_dum | | | | | 0.00304*** | | 0.00315* |
| | | | | | (2.781) | | (1.746) |
| neg_lev | | | | | | -0.00392* | 0.000529 |
| | | | | | | (-1.946) | (0.155) |
| Constant | 0.00400* | 0.00398* | 0.00400* | 0.00454** | 0.00365* | 0.00506** | 0.00360* |
| | (2.026) | (2.012) | (2.027) | (2.369) | (1.821) | (2.584) | (1.709) |
| Observations | 18,660 | 18,660 | 18,660 | 18,660 | 18,660 | 18,660 | 18,660 |
| R-squared | 0.003 | 0.002 | 0.005 | 0.008 | 0.008 | 0.008 | 0.010 |
| Number of groups | 28 | 28 | 28 | 28 | 28 | 28 | 28 |

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 6:** Coefficients of Fama-MacBeth regressions based on 56 quarterly regressions. The sample includes all earning announcements with data available from 2001 to 2014. The dependent variable is excess returns during earnings announcement period, defined as the three-day period beginning the day before and ending the day after the announcement day. Panel B presents the results of fixed-effect regressions See appendix for variable definitions. Panel C displays the results of using variable that are ranked in the example of Jin et al. (2012). To form ranked variables, relevant variables are sorted into quintiles, then assigned a value equal to 0.5 if in the highest quintile, -0.5 if in the lowest, and 0 otherwise.

| **Panel A** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| iv_pre | 0.0504* | | 0.0782*** | 0.0652** | 0.0647** | 0.0647** | 0.0627** |
| | (2.005) | | (2.751) | (2.152) | (2.281) | (2.301) | (2.228) |
| iv_base | | 0.0224 | -0.0217 | -0.0241 | -0.0223 | -0.0208 | -0.0209 |
| | | (1.118) | (-0.848) | (-0.958) | (-0.887) | (-0.824) | (-0.839) |
| lev_pre | | | | 0.00680 | | | |
| | | | | (1.451) | | | |
| lev_dum | | | | | 0.00235* | | 0.00206 |
| | | | | | (1.734) | | (0.994) |
| neg_lev | | | | | | -0.00267 | 0.000551 |
| | | | | | | (-1.222) | (0.153) |
| Constant | 0.00470*** | 0.00420** | 0.00460*** | 0.00395** | 0.00379** | 0.00530*** | 0.00391** |
| | (2.234) | (2.675) | (2.863) | (2.382) | (2.201) | (2.204) | (2.133) |
| Observations | 18,423 | 17,013 | 17,013 | 17,013 | 17,013 | 17,013 | 17,013 |
| R-squared | 0.005 | 0.002 | 0.006 | 0.010 | 0.011 | 0.010 | 0.013 |
| Number of groups | 33 | 33 | 33 | 33 | 33 | 33 | 33 |

| **Panel B** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| iv_pre | 0.0334 | | 0.0182 | -0.0199 | -0.000206 | 0.00275 | -0.00262 |
| | (1.280) | | (0.520) | (-0.496) | (-0.00598) | (0.0802) | (-0.0765) |
| iv_base | | -0.00413 | -0.00999 | -0.00762 | -0.00993 | -0.0105 | -0.00933 |
| | | (-0.128) | (-0.300) | (-0.230) | (-0.298) | (-0.314) | (-0.274) |
| lev_pre | | | | 0.0123** | | | |
| | | | | (2.559) | | | |
| lev_dum | | | | | 0.00265** | | 0.00291 |
| | | | | | (2.202) | | (1.566) |
| neg_lev | | | | | | -0.00363* | 0.000425 |
| | | | | | | (-1.749) | (0.134) |
| Constant | 0.00421* | 0.00370 | 0.00385* | 0.00356 | 0.00373 | 0.00480** | 0.00357 |
| | (1.829) | (1.659) | (1.734) | (1.634) | (1.692) | (2.079) | (1.645) |
| Observations | 15,595 | 14,361 | 14,361 | 14,361 | 14,361 | 14,361 | 14,361 |
| R-squared | 0.003 | 0.003 | 0.006 | 0.009 | 0.009 | 0.009 | 0.011 |
| Number of groups | 23 | 23 | 23 | 23 | 23 | 23 | 23 |

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| iv_pre | 0.0377* | | 0.0354 | 0.0146 | 0.0228 | 0.0222 | 0.0206 |
| | (1.926) | | (1.583) | (0.570) | (1.003) | (1.000) | (0.912) |
| iv_base | | 0.0103 | -0.00164 | -0.00363 | -0.00253 | -0.00224 | -0.00256 |
| | | (0.542) | (-0.0853) | (-0.184) | (-0.130) | (-0.115) | (-0.130) |
| lev_pre | | | | 0.00818** | | | |
| | | | | (2.319) | | | |
| lev_dum | | | | | 0.00198** | | 0.00170 |
| | | | | | (2.085) | | (1.229) |
| neg_lev | | | | | | -0.00294* | -0.000452 |
| | | | | | | (-1.984) | (-0.219) |
| Constant | 0.00437*** | 0.00406*** | 0.00428*** | 0.00394*** | 0.00407*** | 0.00506*** | 0.00423*** |
| | (2.200) | (2.914) | (2.037) | (2.788) | (2.849) | (2.478) | (2.064) |
| Observations | 30,953 | 28,521 | 28,521 | 28,521 | 28,521 | 28,521 | 28,521 |
| R-squared | 0.004 | 0.003 | 0.006 | 0.010 | 0.010 | 0.009 | 0.012 |
| Number of groups | 51 | 51 | 51 | 51 | 51 | 51 | 51 |

t-statistic in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Table 6 ranked:** Coefficients of Fama-MacBeth regressions based on 56 quarterly regressions. The sample includes all earning announcements with data available from 2001 to 2014. The dependent variable is excess returns during earnings announcement period, defined as the three-day period beginning the day before and ending the day after the announcement day. Panel B presents the results of fixed-effect regressions See appendix for variable definitions. Panel C displays the results of using variable that are ranked in the example of Jin et al. (2012). To form ranked variables, relevant variables are sorted into quintiles, then assigned a value equal to 0.5 if in the highest quintile, -0.5 if in the lowest, and 0 otherwise.

**Panel A**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| rspread_pre | 0.00826*** | | 0.00802** | 0.00516* | 0.00624** | 0.00686** | 0.00620** |
| | (2.742) | | (2.646) | (1.779) | (2.059) | (2.120) | (2.040) |
| rspread_base | | 0.00273 | 0.000952 | 0.000791 | 0.000731 | 0.000862 | 0.000786 |
| | | (1.455) | (0.530) | (0.424) | (0.386) | (0.465) | (0.418) |
| rlev_pre | | | | 0.00546* | | | |
| | | | | (1.707) | | | |
| lev_dum | | | | | 0.00168 | | 0.00158 |
| | | | | | (1.342) | | (0.899) |
| neg_lev | | | | | | -0.00185 | 0.000575 |
| | | | | | | (-0.864) | (0.181) |
| Constant | 0.00429*** | 0.00428*** | 0.00429*** | 0.00493*** | 0.00375** | 0.00478*** | 0.00374** |
| | (2.832) | (2.826) | (2.833) | (2.263) | (2.345) | (2.024) | (2.159) |
| Observations | 18,423 | 18,423 | 18,423 | 18,423 | 18,423 | 18,423 | 18,423 |
| R-squared | 0.004 | 0.002 | 0.006 | 0.009 | 0.009 | 0.009 | 0.011 |
| Number of groups | 33 | 33 | 33 | 33 | 33 | 33 | 33 |

**Panel B**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| rspread_pre | 0.00585** | | 0.00649** | 0.00470* | 0.00469** | 0.00487** | 0.00440* |
| | (2.577) | | (2.728) | (2.037) | (2.093) | (2.241) | (2.005) |
| rspread_base | | -0.00139 | -0.00268 | -0.00299 | -0.00310 | -0.00310 | -0.00311 |
| | | (-0.621) | (-1.130) | (-1.309) | (-1.351) | (-1.341) | (-1.343) |
| rlev_pre | | | | 0.00470 | | | |
| | | | | (1.559) | | | |
| lev_dum | | | | | 0.00253* | | 0.00238 |
| | | | | | (2.064) | | (1.248) |
| neg_lev | | | | | | -0.00381* | -0.000572 |
| | | | | | | (-1.938) | (-0.191) |
| Constant | 0.00398 | 0.00398 | 0.00398 | 0.00430* | 0.00401* | 0.00509** | 0.00418* |
| | (1.701) | (1.700) | (1.703) | (1.892) | (1.725) | (2.203) | (1.835) |
| Observations | 15,595 | 15,595 | 15,595 | 15,595 | 15,595 | 15,595 | 15,595 |
| R-squared | 0.002 | 0.002 | 0.004 | 0.007 | 0.007 | 0.007 | 0.009 |
| Number of groups | 23 | 23 | 23 | 23 | 23 | 23 | 23 |

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | xret | xret | xret | xret | xret | xret | xret |
| rspread_pre | 0.00543*** | | 0.00568*** | 0.00355* | 0.00420** | 0.00443** | 0.00405** |
| | (2.122) | | (2.176) | (1.973) | (2.380) | (2.461) | (2.296) |
| rspread_base | | 8.19e-05 | -0.00101 | -0.00124 | -0.00128 | -0.00124 | -0.00133 |
| | | (0.0556) | (-0.666) | (-0.811) | (-0.829) | (-0.809) | (-0.857) |
| rlev_pre | | | | 0.00447* | | | |
| | | | | (1.910) | | | |
| lev_dum | | | | | 0.00170* | | 0.00144 |
| | | | | | (1.808) | | (1.089) |
| neg_lev | | | | | | -0.00248 | -0.000435 |
| | | | | | | (-1.656) | (-0.210) |
| Constant | 0.00417*** | 0.00417*** | 0.00417*** | 0.00458*** | 0.00404*** | 0.00490*** | 0.00421*** |
| | (2.972) | (2.978) | (2.975) | (2.312) | (2.847) | (2.454) | (2.990) |
| Observations | 30,953 | 30,953 | 30,953 | 30,953 | 30,953 | 30,953 | 30,953 |
| R-squared | 0.003 | 0.002 | 0.005 | 0.008 | 0.008 | 0.008 | 0.010 |
| Number of groups | 51 | 51 | 51 | 51 | 51 | 51 | 51 |

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 7:** Coefficients on Fama MacBeth regressions split by market volatility terciles. The sample includes all earning announcements with data available from 2001 to 2014. The dependent variable is excess returns during earnings announcement period, defined as the three-day period beginning the day before and ending the day after the announcement day. The independent variables are three ranked pre-earnings volatility spread and the ranked pre-earnings leverage To form ranked variables, relevant variables are sorted into quintiles, then assigned a value equal to 0.5 if in the highest quintile, -0.5 if in the lowest, and 0 otherwise.

| mktvol | rspread | t_rspread | rlev | t_rlev |
|---|---|---|---|---|
| 1 | 0.0042 | 1.496 | | |
| 2 | 0.0080 | 2.713 | | |
| 3 | 0.0096 | 2.198 | | |
| 1 | 0.0043 | 1.506 | -0.0003 | -0.089 |
| 2 | 0.0054 | 1.579 | 0.0053 | 1.582 |
| 3 | 0.0049 | 1.273 | 0.0100 | 2.146 |

**Table 8:** Daily volatility spreads on stocks in the days following announcement for stocks with a positive *lev_pre* variable prior to announcement. The values are split into quintiles based on the 3-day excess return of stock and the SueScore of the stock, provided by Compustat.

| | Days After Announcement | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **xret** | Pre | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 7-1 |
| 1 | 0.6969 | 0.8075 | 0.2327 | 0.1685 | 0.2058 | 0.0846 | -0.0407 | -0.2134 | -1.021 |
| 2 | 0.5697 | 0.5546 | -0.0905 | -0.5051 | 0.1075 | -0.0162 | -0.3307 | -0.2033 | -0.7579 |
| 3 | 0.5136 | -0.2575 | -0.2175 | -0.2844 | -0.2355 | -0.4651 | -0.5937 | -0.3929 | -0.1354 |
| 4 | 0.5825 | -0.7439 | -0.2409 | -0.2289 | -0.2277 | -0.4609 | -0.6248 | -0.5981 | 0.1459 |
| 5 | 0.6599 | -1.284 | -0.7497 | -0.5877 | -0.5160 | -0.7612 | -0.7410 | -0.8202 | 0.4642 |
| 5-1 | -0.0370 | -2.092 | -0.9824 | -0.7561 | -0.7218 | -0.8457 | -0.7003 | -0.6068 | 1.485 |
| **suescore** | Pre | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 7-1 |
| 1 | 0.9492 | -0.0456 | 0.3060 | 0.0583 | 0.1958 | 0.0579 | -0.3105 | -0.1844 | -0.139 |
| 2 | 0.4610 | -0.1828 | -0.1765 | -0.3295 | 0.0830 | -0.1486 | -0.3625 | -0.2686 | -0.0858 |
| 3 | 0.5330 | -0.4578 | -0.6367 | -0.4372 | -0.3065 | -0.3830 | -0.6189 | -0.6579 | -0.2001 |
| 4 | 0.6122 | -0.2526 | -0.3055 | -0.4524 | -0.2367 | -0.6236 | -0.6691 | -0.8170 | -0.5644 |
| 5 | 0.5048 | -0.253 | -0.2879 | -0.3828 | -0.4960 | -0.4890 | -0.4424 | -0.4018 | -0.1490 |
| 5-1 | -0.4444 | -0.207 | -0.5939 | -0.4411 | -0.6917 | -0.5469 | -0.1318 | -0.2174 | -0.010 |

**Table 9:** Daily volatility spreads on stocks in the days following announcement for stocks with a negative *lev_pre* variable prior to announcement. The values are split into quintiles based on the 3-day excess return of stock and the SueScore of the stock, provided by Compustat.

| | Days After Announcement | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **xret** | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 7-1 |
| 1 | -3.1606 | 0.1474 | -1.1889 | -1.2418 | -0.9699 | -1.1129 | -1.0067 | -1.0701 | -1.217 |
| 2 | -2.7237 | -0.8550 | -1.4811 | -1.5637 | -1.3945 | -1.7512 | -1.3602 | -1.6113 | -0.7564 |
| 3 | -2.4700 | -1.6536 | -1.4047 | -1.5391 | -1.2624 | -1.8493 | -1.4426 | -1.5308 | 0.1228 |
| 4 | -2.6253 | -2.1820 | -1.3670 | -1.5698 | -1.5598 | -1.3334 | -1.4624 | -1.4963 | 0.6857 |
| 5 | -2.6953 | -2.498 | -1.6960 | -1.5264 | -1.9666 | -1.6254 | -1.8394 | -1.5949 | 0.9036 |
| 5-1 | 0.4653 | -2.646 | -0.5072 | -0.2846 | -0.9967 | -0.5125 | -0.8327 | -0.5249 | 2.121 |
| **suescore** | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 7-1 |
| 1 | -3.1564 | -1.4729 | -1.5931 | -1.5953 | -1.3442 | -1.9198 | -1.6412 | -1.4194 | 0.054 |
| 2 | -2.8034 | -1.1180 | -1.3462 | -1.7104 | -1.3473 | -1.3777 | -1.3096 | -1.5597 | -0.4417 |
| 3 | -2.7435 | -1.4383 | -1.4292 | -1.4530 | -1.3899 | -1.4929 | -1.5920 | -1.4622 | -0.0239 |
| 4 | -2.6006 | -1.4648 | -1.4059 | -1.2865 | -1.3795 | -1.3767 | -0.9759 | -1.3938 | 0.0711 |
| 5 | -2.4678 | -1.213 | -1.0974 | -1.2159 | -1.4854 | -1.5045 | -1.5495 | -1.5092 | -0.2958 |
| 5-1 | 0.6887 | 0.259 | 0.4957 | 0.3794 | -0.1412 | 0.4153 | 0.0917 | -0.0899 | -0.349 |

**Table 10:** Daily volatility spreads on stocks in the days following announcement for stocks with a *lev_pre* variable equal to zero prior to announcement. The values are split into quintiles based on the 3-day excess return of stock and the SueScore of the stock, provided by Compustat.

| | Days After Announcement | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **xret** | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 7-1 |
| 1 | -1.0755 | -0.1711 | -0.8170 | -0.8592 | -0.5537 | -0.5226 | -0.8620 | -0.6174 | -0.446 |
| 2 | -0.8915 | -0.5516 | -0.5556 | -0.6181 | -0.7371 | -0.8325 | -0.6240 | -0.9269 | -0.3753 |
| 3 | -0.8169 | -0.6753 | -0.7086 | -0.5804 | -0.4661 | -0.9099 | -0.8340 | -0.5777 | 0.0976 |
| 4 | -0.8014 | -0.9540 | -0.8832 | -0.7047 | -0.7956 | -0.9184 | -0.8421 | -0.8996 | 0.0544 |
| 5 | -0.8954 | -1.589 | -1.1341 | -1.0332 | -0.9495 | -0.9996 | -1.1224 | -1.2525 | 0.3368 |
| 5-1 | 0.1801 | -1.418 | -0.3172 | -0.1740 | -0.3957 | -0.4769 | -0.2604 | -0.6351 | 0.783 |
| **suescore** | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 7-1 |
| 1 | -1.1207 | -0.8003 | -0.9609 | -0.9169 | -0.6513 | -0.9029 | -0.9124 | -0.7916 | 0.009 |
| 2 | -0.9321 | -0.9250 | -0.6854 | -0.6951 | -0.6858 | -0.7352 | -0.9258 | -1.0613 | -0.1362 |
| 3 | -0.7771 | -0.6147 | -0.7741 | -0.6286 | -0.6516 | -0.7068 | -0.6353 | -0.8115 | -0.1968 |
| 4 | -0.7547 | -0.7220 | -0.7294 | -0.7620 | -0.7769 | -0.6594 | -0.8325 | -0.7108 | 0.0112 |
| 5 | -0.7005 | -0.914 | -0.9261 | -0.6138 | -0.6637 | -0.9697 | -0.8706 | -0.8398 | 0.0745 |
| 5-1 | 0.4202 | -0.114 | 0.0348 | 0.3031 | -0.0124 | -0.0668 | 0.0418 | -0.0482 | 0.066 |

**Table 11:** Individual (Panel A) and cumulative (Panel B) Fama-French 3-Factor abnormal return during the earnings and post-earning periods for equal-weighted portfolios based the pre-earnings value of the *lev_pre* variable. Test statistics displayed in parentheses below. The data sample runs from June 2001 to December 2014.

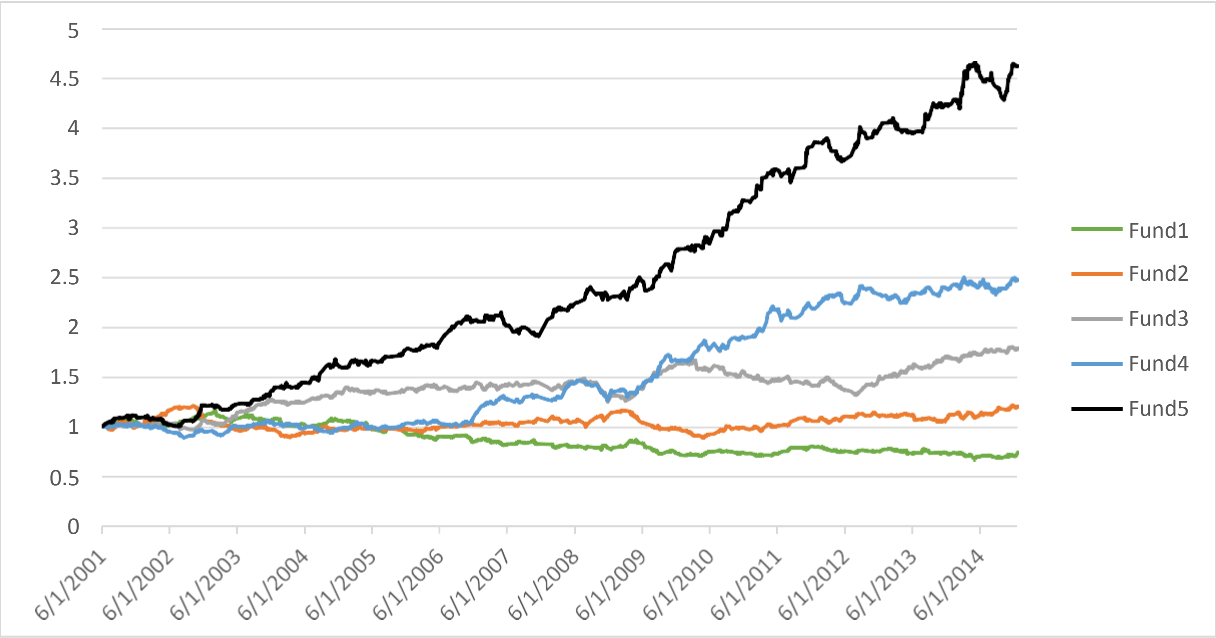
**Panel A**

| | Days After Earnings Announcement | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ***lev_pre*** | **-1** | **0** | **1** | **2** | **3** | **4** | **5** | **6** |
| **≤ -0.3** | -0.05 | -0.07 | 0.11 | -0.12 | -0.11 | 0.00 | -0.14 | -0.07 |
| | -(0.858) | -(0.724) | (0.938) | -(1.945) | -(1.902) | -(0.039) | -(2.494) | -(1.452) |
| **-0.3 - 0.0** | -0.07 | 0.05 | -0.08 | -0.11 | -0.07 | -0.08 | 0.01 | -0.06 |
| | -(1.784) | (0.750) | -(1.010) | -(2.697) | -(1.868) | -(2.165) | (0.333) | -(1.551) |
| **= 0** | 0.06 | 0.10 | 0.13 | -0.01 | 0.02 | 0.05 | 0.03 | 0.04 |
| | (2.270) | (2.275) | (2.477) | -(0.386) | (0.822) | (1.871) | (1.023) | (1.461) |
| **0.0 - 0.3** | 0.04 | 0.24 | 0.06 | -0.08 | -0.04 | 0.02 | -0.01 | -0.04 |
| | (1.054) | (3.868) | (0.892) | -(1.993) | -(0.995) | (0.400) | -(0.158) | -(1.072) |
| **≥ 0.3** | 0.22 | 0.41 | 0.01 | -0.09 | 0.05 | -0.10 | 0.00 | -0.06 |
| | (3.302) | (4.262) | (0.090) | -(1.391) | (0.767) | -(1.554) | (0.016) | -(0.867) |

**Panel B**

| ***lev_pre*** | **-1** | **0** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|---|---|
| **≤ -0.3** | -0.05 | -0.11 | 0.00 | -0.14 | -0.27 | -0.28 | -0.43 | -0.50 |
| | -(0.858) | -(0.716) | -(0.013) | -(0.360) | -(0.545) | -(0.473) | -(0.609) | -(0.617) |
| **-0.3 - 0.0** | -0.07 | -0.02 | -0.10 | -0.21 | -0.29 | -0.39 | -0.39 | -0.45 |
| | -(1.784) | -(0.211) | -(0.471) | -(0.784) | -(0.852) | -(0.952) | -(0.790) | -(0.798) |
| **= 0** | 0.06 | 0.16 | 0.28 | 0.26 | 0.29 | 0.32 | 0.34 | 0.38 |
| | (2.270) | (2.081) | (2.079) | (1.455) | (1.258) | (1.131) | (1.027) | (0.970) |
| **0.0 - 0.3** | 0.04 | 0.28 | 0.34 | 0.26 | 0.23 | 0.23 | 0.22 | 0.18 |
| | (1.054) | (2.546) | (1.711) | (0.976) | (0.668) | (0.537) | (0.431) | (0.298) |
| **≥ 0.3** | 0.22 | 0.63 | 0.65 | 0.55 | 0.59 | 0.47 | 0.46 | 0.41 |
| | (3.302) | (3.551) | (1.968) | (1.246) | (1.048) | (0.670) | (0.552) | (0.417) |

**Figure 2:** Progression of value from various funds employing strategic-timing strategies. Each fund purchases equal-weighted portfolios at the end of day *t-2* and closes the position on day *t+1*. Fund 1 buys and sells stocks that have a *lev_pre* variable less than -0.3. The remaining funds are as follows: Fund 2, between 0 and -0.3; Fund 3, equal to zero; Fund 4 between 0 and +0.3; Fund 5 greater than +0.3.



## 3.1 Abstract

This study simulates return deviations for both positive and negative Leveraged Exchange-Traded Funds (LETFs) with daily rebalancing over various holding periods. I document that while both compounding deviations for both positive and negative LETFs have a decreasing relationship with the volatility of the underlying index, the distribution of compounding deviations for negative LETFs has a much larger range and standard deviation. This implication of this is that portfolios that combine multi-day long positions in both types of LETFs, called "combined portfolios" with the same multiple and the same underlying index will typically close with non-zero returns that also have a negative relationship with the underlying volatility. I document this to be the case. Finally, I find that significant economic gains are possible by employing a strategy which takes a long combined portfolio position that utilizes a typically low-volatility underlying index and a short combined portfolio position that utilizes a typically high-volatility underlying index. However, such gains are unsteady and only appear to provide significant results when high multiples are used or during unique periods. Such strategies can also prove very damaging to asset value, when underlying correlations are low, or when traditional volatility roles are reversed.

## 3.2 Literature on Leverage Exchange Traded Funds

Leveraged Exchange Traded Funds (LETFs) are products that deliver a multiple of the daily returns of a specified underlying index or fund using a mix of swaps, futures, and other financial derivatives. Introduced in June of 2006 by ProShares, LETFs, and their negatively leveraged counterparts, initially found substantial popularity, but shortly after, the financial crisis of 2008 and 2009 triggered large deviations from naïve expected multiples, which led to media criticisms, lawsuits, and warnings from regulatory bodies that LETFs were unsuitable for long-term investors.

Loviscek, Tang, and Xu (2014) debunk this sentiment by simulating the would-be returns of LETFs with the Dow Jones Industrial Average (DJIA) and the S&P 500 as the underlying indices. They find that, contrary to the warnings, hypothetical investors in a (3X) LETF with the DJIA as the underlying index from 1896 to 2010 would have earned nine times the unleveraged return of the DJIA, and three times its own, stated, leverage multiple. Such results run contrary to the sentiment that LETFs are unsuitable for long-term investors.

LETFs are like equity options in that they provide an ideal environment that informed investors find an attractive environment in the form of their provided leverage. Investors who obtain an informational advantage about overall market trends or future macroeconomic policy decisions would see LETFs as a simple method in which to achieve optimal returns. LETFs are, much like options themselves, theoretically redundant assets. Given the assumptions of complete markets, informational symmetry, and the absence of trading restrictions, LETFs are easily replicable. But in reality, such assumptions do not hold. Furthermore, institutions who market and sell LETFs are likely to have better trading arrangements and more favorable pricing than individual investors. This can be largely attributed to economies of scale. LETFs trade in complex derivatives on a daily basis in order to achieve targeted multiples. Such large-scale orders on a consistent basis would be attractive to suppliers of the necessary derivative products, thus inducing them to compete more aggressively through lower prices for buyers in bulk.

The novelty of LETFs in the early years may have led to popularity, then confusion and criticisms of the industry and research remain in its infancy. But unique characteristics of LETFs have been acknowledged by researchers may serve to soften the critics. First, it is now well-established that LETFs, which promise a multiple on *daily* underlying returns, do not typically return the targeted multiple of the underlying ETF for longer investment horizons. This is due to the compounding effect. When LETFs are held for longer than one day, discrepancies will occur. Lu and Wang (2009) demonstrate this process. A first-day return of 10% and a second-day return of 9.09% results in a two-day return of 20% for an underlying ETF or index (UETF). An LETF with a multiple of (2X) will experience daily returns of 20% and 18.18%; each value exactly twice the UETF's return. But the two-day return is 41.82% - a multiple of approximately 2.1. Meanwhile, a corresponding inverse or negative LETF with a stated multiple of (-2X) will experience a two-day return of -34.5%, a multiple of -1.72; again, greater than the targeted multiple. Thus, the result of two fairly even up moves results in a realized multiple that exceeds the target. Lu and Wang (2009) continue to demonstrate an increased compounding effect in sideways markets.

Thus, Avellandeda and Zhang (2009) suggest the use of geometric returns would be more appropriate, due to the daily rebalancing. Furthermore, they show that LETFs typically underperform their benchmark multiples. They also point out that holders of LETFs are exposed to excessive levels of volatility. As volatility increases, the number of daily transactions required for rebalancing increases, resulting in increased underperformance. In addition to deriving a formula for the return of an LETF as a function of its expense ratio, the interest rate, and the realized return and variance of the UETF, Avellandeda and Zhang (2009) also show that targeted multiples can be achieved using a dynamic hedging strategy. An investor in LETF holds a time-decay due to the effects of being long convexity (or gamma) and short variance. In short, both positive and negative LETFs will underperform targeted multiples unless the returns overcome break-even levels which are dependent upon the realized volatility.

In claiming that LETFs typically underperform their targeted multiples, Avellandeda and Zhang (2009) look at a very small sample size, only reaching back as far as 2006, when LETFs were first introduced. Loviscek et al. (2014) demonstrate that this is not the case. LETFs in fact, have been hypothetically more likely to over-perform their targeted multiples. Furthermore, in extending their analysis, they determine that while Monte Carlo simulations of returns that assume a normal distribution do not provide beneficial compounding effects to LETF investors, the highly leptokurtic distribution of daily real-world returns, together with a positive mean, does benefit the compounding effect in a positive direction over longer horizons. Thus, the literature suggests that compounding deviations are positive when returns are steady, non-volatile, and leptokurtic, but negative when highly volatile and exhibiting lower levels of kurtosis.

## 3.3 Literature on Option-Implied Information and Predictability

The predictive power of options markets has been attributed to informational asymmetry regarding the underlying asset, but asymmetric information has two potential sources. First, traders can become more informed by receiving non-public information, or be tipped of public information ahead of time; insider trading. Many studies consider the options market's predictability of individual stocks, and their ability to anticipate the effects of planned and unplanned firm-specific events, such as mergers, earnings surprises, and analyst revisions. It can be persuasively argued that such predictability results from this type of informational advantage. Second, traders can gain an informational advantage by anticipating events with more precision and skill than the general populace, that is, by having superior analytical skills. Because ETFs and LETFs contain multiple equities within them, it is less likely that the movements of individual stocks brought upon by firm-specific events will dominate the movement of the entire fund.  Thus, any predictive power inherent in the information implied by ETF and LETF options, it can be argued, is derived from the superior skills LETF option traders have analyzing and anticipating new information.

Recent studies have found predictive power in information implied through the prices of equity options. Much of the evidence links future abnormal stock returns to the implied volatility reflected in options prices. Cremers and Weinbaum (2010) find that deviations from put-call parity predict future equity movements. Along with Xing, Zhang, and Zhao (2010), this study examined the joint effects of put and call implied volatilities. An et al. (2014) examine the separate effects, finding that increasing implied volatility levels measured in call (put) prices are followed by outperformance (underperformance) in the underlying asset returns. Furthermore, as DeMiguel et al. (2013) show, using option-implied information, specifically implied volatility, can improve portfolio performance.

Other studies have examined the predictive power of alternative assets created through option-implied measures. Evidence of a negative relation between the returns of an implied skewness-asset and risk-neutral skewness, according to Bali and Murray (2013), suggest that investors prefer asset returns that are positively skewed, and are willing to accept a lower return for higher skewness. Goyal and Saretto (2009) form volatility assets and find a positive link between the returns of these securities and the spread between historical and implied volatilities.

The story behind the relationship between contemporary option-implied information and future asset returns is a story of information asymmetry. Informed traders seek the increased leverage of the options market in order to maximize returns and the additional demand created by their volume bids options prices up to abnormally high levels relative to the variance of their underlying assets. High call prices lead to high stock returns and high put prices lead to low stock returns. The sequential trade model developed by Easley et al. (1998) expounds this view, suggesting that if informed trading exists in the options market, then such predictive power should exist. Their research helps confirm the view regarding option markets as a leading indicator of equity market returns. For example, Cremers and Weinbaum

(2010) find evidence that deviations in put-call parity are more likely to occur in environments where information asymmetry is high.

These studies have effectively demonstrated the predictive power of options and produced some evidence that environments of high informational asymmetry add to this predictive power. Moving forward, the nature of the informational asymmetry has also been examined. The degree of private knowledge that arises from insider information can be considered by examining option-implied measure's predictability of significant, informational, firm-level events that alter public perception of the firm's value. For example, Jayaraman et al. (2001) find spikes in options volume ahead of mergers, suggesting that options markets are more conducive to price discovery. Cao et al. (2005), along with several other papers, confirm this view, having found that option-implied volatilities tend to spike before mergers, acquisitions, and takeovers. Similarly, Jin et al. (2012) find predictability ahead of earnings surprises, and Hayunga and Lung (2014) report evidence that option-implied information trading activity increases just ahead of analyst revisions, and in the correct direction. These findings suggest private information accumulated by traders, potentially through tips from managers, analysts, and insiders privy to these firm-specific events.

Intuition suggests that informed traders can achieve stronger results by trading in leveraged markets. The literature supporting this view has grown substantially since Black (1975) made the suggestion that options markets would provide the ideal leverage and truncated payoffs to the downside to attract informed traders. The subsequent studies confirm this view. However, most that seek to examine the activities of informed traders find that the information asymmetry implied by option-price predictability is derived through traders who have access to non-public information.

The linkage between option markets ahead of firm-specific events appears to dominate the predictable aspect of option-implied information. If firm-specific events lead to asymmetric information due to tipping and subsequently leads to the predictability of options markets, then we might not expect such predictability to exist in options of mutual funds, ETFs, or ETFs that are leveraged in either a positive or a negative direction (LETFs). In such securities multiple firms are present, and thus they are unlikely to be dominated by the movements of a single company. Put another way, if the information implied by the options of ETFs or LETFs has predictive power ahead of the movements of the underlying securities, this would be more indicative of activities performed by traders with superior skills analyzing public information, rather than traders who hold non-public information, or who obtain public information ahead of the general population.

If high levels of realized volatility are associated with the relative underperformance in LETFs, does the option-implied volatility of LETFs have any predictive power regarding the relative performance of an LETF? On the one hand, if option-implied volatility (IV) is a sound predictor of future realized volatility, then high IVs may suggest a future underperformance, at least for longer investment horizons. On the other hand, in equity-options literature, high IVs are associated with abnormal future returns; positive for high call-IVs and negative for high put-IVs. Such large returns (positive or negative) will offset the loss associated with increased volatilities and reduce underperformance or even generate over-performance. One focus of this study will be to examine the relationship between high put and call IVs and future performance of LETFs relative to the targeted multiples.

## 3.4 Methodology and Results

Building on the previous literature, notably Loviscek et al. (2014), I construct a framework to examine the response of compounding deviations to market characteristics. I extend upon Loviscek et al. (2014) by including inverse LETFs as well as a portfolio combining both positive and negative LETFs of the same multiple. I first use the S&P 500 index (SPX) from Jan 4, 1960, until March 13, 2017. For robustness, I include (DJIA), and 16 other popular market indices that have liquid LETF and options markets. For each index, I simulate the return of a daily compounding LETF by using actual historical returns for the underlying index to calculate the targeted return of the LETF for the specified multiple. For example, if SPX returns 5%, the (2X) LETF on SPX is calculated as 10%. Meanwhile, the (-2X)

LETF on SPX is calculated as -10%. I then calculate the cumulative target return for each LETF over holding periods from 5 trading days to 30, in intervals of 5 days. The naïve expected return is simply calculated as the product multiple multiplied by the return of the underlying index over the entire holding period. Thus the compounding deviation can be calculated as the difference between the cumulative return of the LETF and the naïve expected return. In the example given earlier, with the two-day underlying return of 20% and the two-day (2X) LETF return of 41.82%, the compounding deviation would be calculated as 182 basis points.

Loviscek et al. (2014) show that the compounding deviations of LETFs have a negative relationship with the volatility in the holding period. Higher volatility worsens the compounding effect, leading to the negative compounding deviations of "underperforming" LETFs. But they do not discuss the effect on negatively leveraged ETFs. Table 1 examines these products and displays the calculated compounding deviation of positive and negative LETF deviations from the naïve expected return for various holding periods. The sample is split into deciles based on the calculated standard deviation of underlying returns during the *t*-day holding period.

Naturally, compounding deviations are zero for hypothetical (1X) LETF returns, which is always equal to the cumulative returns of the underlying index. However, compounding deviations do occur for negative LETFs, even when the targeted multiple is equal to one. This can be demonstrated by considering an investment portfolio; a \$100 investment in the underlying index, and an equal investment in the inverse or (-1X) LETF of the underlying index. Following a 5% return on day one, an index investment of \$100 will be equal to \$105, while and equal \$100 investment in the (-1X) LETF will now be worth \$95. Note that the return on the portfolio is zero; i.e., it is still worth \$200. On day two, the dollar return on the (-1X) LETF can no longer match the dollar return on the underlying index, since the values of the two investments are no longer equal. At this point, not only with the compounding deviations of the (-1X) LETF no longer be equal to zero but the return on the investment portfolio will not be equal to zero either. The effect of the second-day return will be stronger on the underlying index since it is worth more than the (-1X) LETF.  Thus, if the second-day return is positive, the investment on the underlying index will return more than the investment on the (-1X) LETF will lose, leading to a positive return on the portfolio. If the second-day return is negative, then the underlying index will lose more than the (-1X) investment will gain, leading to a negative return in the portfolio.

In Panel A of Table 1, we see that the compounding deviation from (-1X) LETFs increase with volatility, although the relationship is not purely monotonic. In fact, for all holding periods, compounding deviations hold relatively steady until we move into the more extreme deciles, above 6 or 7, after which, a dramatic decrease is a witness for higher levels of volatility. In the last column, I display the difference in compounding deviations between the 1st volatility decile and the 10th. The difference is negative for all holding periods, indicating worsening compounding effects in highly volatile markets. In Panels B and C, I consider the compounding deviations for (2X) and (3X) LETFs, respectively, and their negative counterparts. Now compounding deviations are non-zero for positively levered ETFs, but the results otherwise mimic those of Panel A. Compounding deviations maintain their overall negative relationship with volatility, and Panels B and C confirm that this relationship holds true for LETFs with positive and negative multiples. In the third section of each panel, I provide the sum total of compounding deviations from the positive and negative LETF. This total should provide the expected return of the portfolio investment example described above.

Table 2 provides robustness by considering the combined effects of 18 different popular market indices and demonstrates that this relationship is independent of the index used.[9] In fact, the relationship between volatility and compounding deviations is shown to be more monotonic using multiple indices, and the difference between the two extreme deciles is even greater. These results confirm with Loviscek et al. (2014) that increased volatility deteriorates the compounding effect for positively leveraged ETFs and demonstrates that volatility has a similar effect on the compounding deviations for inverse LETFs and therefore, a portfolio combining the two investments would also

[9] See list of indices used in Appendix

Nevertheless, the non-monotonous regression of compounding deviations in Table 1 suggests another factor at work. Indeed, Loviscek et al. (2014) point out that the magnitude of the trend also plays a role in determining compounding deviations. The stronger the underlying trend, whether positive or negative, the stronger the compounding deviations. Compounding deviations have a positive relationship with the trend of the underlying index.

Thus, a portfolio position that takes long positions in both a positive and negative LETF with the same absolute multiple will typically have a non-zero return which has a negative relationship with the volatility of the underlying index's returns. I demonstrate this in another fashion in Tables 3 and 4. Table 3 displays the mean returns of the S&P 500 along with the hypothetical returns for (1X), (2X), and (3X) daily compounding LETFs. Each panel in Table 3 has cumulative *t*-day returns for both negative and positive LETFs, along with the cumulative returns of the portfolio described above for each of the volatility deciles. While compounding effects for positive and negative LETFs have the same relationship with volatility, their returns have opposite relationships. Positive LETFs see their returns decrease with volatility, while negative LETFs have returns that increase with volatility. Since volatility is often accompanied by downward moves, this is not surprising. The combined LETF portfolio's returns have a negative relationship, indicating the effect on volatility is stronger for positive LETFs than it is for negative LETFs. Table 4 shows these relationships holding for other market indices. These results are due to the similar negative relationship to the volatility of the compounding deviations of both types. While volatility increases the returns of negative LETFs, it simultaneously holds them back in the form of negative compounding deviations. Thus, the returns of the combined portfolio are negative with high volatility.

This brings forth an interesting question. If volatility decreases the returns on the combined portfolio, will this effect be significantly stronger if the underlying market index is itself more volatile? If so, will a long combined position on a low-volatility underlying index and a short combined position on a high-volatility index garner consistent positive returns?

To answer this question, I calculate the full-sample standard deviations for each of the major indices used and construct a correlation matrix, provided below. I attempt to isolate the differential volatility of two indices by finding pairs that are highly correlated yet have large differences between their respective standard deviations. Table 5 provides the standard deviation for several indices and Table 6 displays a correlation matrix for the combined portfolio of selected indices. We can observe, for example, that NDX and DJX have combined portfolio returns that are highly correlated at 0.894, yet the standard deviations are noticeably different at 68 basis points. The strategy then begins with a fund with $1 in assets that takes a long combined position in the industry-heavy, low-volatility DJX and a short combined portfolio position in the tech-heavy, high-volatility NDX. The long-short position is then rebalanced every 10 trading days. The investment strategy opens in January of 2000 and closes in February of 2017.

Figure 1 displays the progression of the value of the asset fund. The blue line represents a (1X) leverage, the red line is for (2X) portfolios, and the green line is for (3X) leverage on the combined portfolio. While the return on the (1X) strategy is under 20% gain and insubstantial, the (2X) strategy doubles the value of the asset while the (3X) strategy increases the fund value to more than $4. By contrast, the return on a dollar invested in the S&P 500 on the same date is 63.1%. The Dow Jones returned 83.9%, the NASDAQ returned 42.3%. As the progression on the (3X) strategy indicates, most of these returns were realized early during the Dotcom bubble at the beginning of the sample. This era saw high volatility and sharp declines in tech companies and the NASDAQ, which former of which played well for the strategy. By January of 2003, the fund was worth $3.19. In the 14 years following, the fund would only increase to $4.23; a 32.6% increase. Although not occurring in this sample, would expect that the bursting of a hypothetical industrial bubble would have deleterious effects on the fund's asset value, particularly if it were accompanied by a stable tech industry. In this sample, there is a reason to believe that the strategy may be safer. Despite the higher return of the strategy, the standard deviations of returns, at 0.0199, is significantly less than the standard deviation of 10-day returns on DJX, which is 0.0330. Thus, annualized Sharpe ratios for the strategy was 0.9078. For DJX, it was 0.2945.

However, the strategy implemented on certain pairs indicate major potential risks, and Figure 2 provides a potent example of such risks. Figure 2 implements the same strategy with IEI, iShares Barclay's 3-7 year Treasury Bond ETF, as the long end of the strategy, and GDX, the Market Vector's Gold Miner's ETF as the short end of the trade. GDX is characterized by a very high volatility while IEI is very low. The two pairs are lack correlation with each other, with a value -0.0383. As such, the value of the fund is decimated early during the financial crisis, dropping from $1.05 in July of 2008 to $0.32 in November of the same year. During this period the decline in the portfolio does not appear to be driven by the disparate volatilities of the two. The volatility on GDX was extraordinarily high during this period, but the trend was strongly downward; GDX more than halved during the 4 month period. Meanwhile, IEI trended upward, gaining more than 8% during the same period. In this case, the compounding deviations for IEI, the long end of the strategy, were flat, averaging -3 basis points. The 10-day compounding deviations for the short leg of the strategy, by contrast, averaged 599 basis points. Thus, despite the higher volatility, the sharp negative trend of the period characterized by an average daily drop of 136 basis points overwhelmed the effects of the increased volatility, leading to high positive compounding deviations in the short leg of the strategy and asset decline in fund implementing the strategy.

## 3.4 Conclusion

Like their positively leveraged counterparts, negative LETFs also feature compounding deviations that have a negative relationship with volatility. However, this relationship is significantly stronger for negative LETFs. The resulting implications are that combined portfolios that take long positions in both types of LETFs with the same multiple and underlying index also feature a negative relationship with volatility. Additionally, an underlying market index with a historically low volatility, such as the Dow Jones or the S&P 500 can be paired in a long-short position of combined portfolios with more volatile market indices, such as the NASDAQ.

An extension of this study would be to unearth the predictive factors of volatility in an attempt to predict compounding deviations. One such could theoretically be fear. Fear and volatility have a rich relationship in the literature, and how fear might predict compounding deviations of LETFs would be of great interest to practitioners and market makers.

## 3.5 Table and Figures

**Table 1**: Hypothetical compounding deviations for (1X), (2X), and (3X) daily compounding LETFs with the S&P 500 as the underlying index. LETFs with positive multiples are shown separately from those with negative multiples and the added effects are shown in the third panel. The data sample is from Jan, 1960 to March, 2017. Panel A displays (1X) and (-1X) LETFs. Panel B displays (1X) and (-1X) LETFs. Panel C displays (1X) and (-1X) LETFs.

**(1X) Leverage: Panel A**

**Volatility Deciles**

| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Pos LETF** | **5** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | **10** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | **15** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | **20** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | **25** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | **30** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| **Neg LETF** | **5** | 0.006 | 0.006 | 0.007 | 0.008 | 0.007 | 0.006 | 0.006 | 0.005 | -0.003 | -0.056 | -0.063 |
| | **10** | 0.015 | 0.015 | 0.021 | 0.014 | 0.009 | 0.008 | 0.008 | -0.003 | -0.009 | -0.143 | -0.158 |
| | **15** | 0.025 | 0.027 | 0.027 | 0.017 | 0.009 | 0.013 | 0.013 | -0.004 | -0.015 | -0.230 | -0.256 |
| | **20** | 0.035 | 0.042 | 0.029 | 0.016 | 0.025 | 0.020 | -0.006 | 0.006 | -0.021 | -0.303 | -0.338 |
| | **25** | 0.046 | 0.054 | 0.024 | 0.018 | 0.049 | 0.020 | -0.014 | 0.009 | -0.009 | -0.398 | -0.444 |
| | **30** | 0.060 | 0.066 | 0.026 | 0.014 | 0.044 | 0.027 | -0.013 | -0.016 | 0.015 | -0.478 | -0.538 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| **Pos + Neg** | **5** | 0.006 | 0.006 | 0.007 | 0.008 | 0.007 | 0.006 | 0.006 | 0.005 | -0.003 | -0.056 | -0.063 |
| | **10** | 0.015 | 0.015 | 0.021 | 0.014 | 0.009 | 0.008 | 0.008 | -0.003 | -0.009 | -0.143 | -0.158 |
| | **15** | 0.025 | 0.027 | 0.027 | 0.017 | 0.009 | 0.013 | 0.013 | -0.004 | -0.015 | -0.230 | -0.256 |
| | **20** | 0.035 | 0.042 | 0.029 | 0.016 | 0.025 | 0.020 | -0.006 | 0.006 | -0.021 | -0.303 | -0.338 |
| | **25** | 0.046 | 0.054 | 0.024 | 0.018 | 0.049 | 0.020 | -0.014 | 0.009 | -0.009 | -0.398 | -0.444 |
| | **30** | 0.060 | 0.066 | 0.026 | 0.014 | 0.044 | 0.027 | -0.013 | -0.016 | 0.015 | -0.478 | -0.538 |

**(2X) Leverage: Panel B**

**Volatility Deciles**

| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Pos LETF** | **5** | 0.006 | 0.006 | 0.007 | 0.008 | 0.007 | 0.006 | 0.006 | 0.005 | -0.002 | -0.054 | -0.061 |
| | **10** | 0.015 | 0.015 | 0.021 | 0.014 | 0.009 | 0.008 | 0.008 | -0.003 | -0.009 | -0.128 | -0.143 |
| | **15** | 0.026 | 0.028 | 0.027 | 0.017 | 0.009 | 0.013 | 0.013 | -0.004 | -0.015 | -0.197 | -0.223 |
| | **20** | 0.036 | 0.042 | 0.029 | 0.016 | 0.026 | 0.021 | -0.006 | 0.006 | -0.023 | -0.240 | -0.275 |
| | **25** | 0.047 | 0.054 | 0.024 | 0.018 | 0.049 | 0.021 | -0.016 | 0.008 | -0.011 | -0.303 | -0.349 |
| | **30** | 0.061 | 0.067 | 0.027 | 0.014 | 0.044 | 0.027 | -0.016 | -0.018 | 0.014 | -0.349 | -0.410 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| **Neg LETF** | **5** | 0.019 | 0.019 | 0.022 | 0.024 | 0.023 | 0.018 | 0.017 | 0.014 | -0.008 | -0.171 | -0.191 |
| | **10** | 0.044 | 0.046 | 0.063 | 0.041 | 0.026 | 0.024 | 0.023 | -0.010 | -0.027 | -0.444 | -0.488 |
| | **15** | 0.075 | 0.082 | 0.083 | 0.050 | 0.026 | 0.038 | 0.040 | -0.012 | -0.045 | -0.725 | -0.801 |
| | **20** | 0.105 | 0.127 | 0.087 | 0.048 | 0.074 | 0.059 | -0.017 | 0.019 | -0.063 | -0.973 | -1.078 |
| | **25** | 0.136 | 0.161 | 0.071 | 0.055 | 0.146 | 0.058 | -0.041 | 0.028 | -0.025 | -1.290 | -1.426 |
| | **30** | 0.179 | 0.197 | 0.079 | 0.041 | 0.132 | 0.081 | -0.037 | -0.045 | 0.045 | -1.561 | -1.740 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| **Pos + Neg** | **5** | 0.026 | 0.026 | 0.029 | 0.032 | 0.030 | 0.024 | 0.022 | 0.019 | -0.010 | -0.226 | -0.251 |
| | **10** | 0.059 | 0.062 | 0.083 | 0.055 | 0.034 | 0.032 | 0.031 | -0.013 | -0.036 | -0.572 | -0.631 |
| | **15** | 0.101 | 0.110 | 0.110 | 0.067 | 0.035 | 0.051 | 0.053 | -0.016 | -0.060 | -0.922 | -1.023 |

| Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 20 | 0.140 | 0.169 | 0.115 | 0.064 | 0.100 | 0.080 | -0.024 | 0.025 | -0.085 | -1.213 | -1.353 |
| 25 | 0.183 | 0.215 | 0.095 | 0.073 | 0.195 | 0.078 | -0.057 | 0.035 | -0.036 | -1.592 | -1.775 |
| 30 | 0.240 | 0.264 | 0.106 | 0.055 | 0.176 | 0.108 | -0.053 | -0.063 | 0.059 | -1.911 | -2.151 |

**(3X) Leverage: Panel C**

**Volatility Deciles**

| | Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pos LETF | 5 | 0.019 | 0.019 | 0.022 | 0.024 | 0.022 | 0.018 | 0.017 | 0.015 | -0.007 | -0.161 | -0.180 |
| | 10 | 0.045 | 0.046 | 0.062 | 0.041 | 0.026 | 0.024 | 0.024 | -0.010 | -0.026 | -0.371 | -0.416 |
| | 15 | 0.077 | 0.083 | 0.081 | 0.051 | 0.026 | 0.039 | 0.040 | -0.014 | -0.045 | -0.560 | -0.637 |
| | 20 | 0.108 | 0.127 | 0.086 | 0.047 | 0.077 | 0.063 | -0.019 | 0.017 | -0.069 | -0.660 | -0.767 |
| | 25 | 0.141 | 0.162 | 0.072 | 0.056 | 0.148 | 0.063 | -0.050 | 0.022 | -0.035 | -0.819 | -0.959 |
| | 30 | 0.185 | 0.201 | 0.080 | 0.043 | 0.133 | 0.080 | -0.052 | -0.057 | 0.041 | -0.933 | -1.118 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Neg LETF | 5 | 0.039 | 0.038 | 0.044 | 0.047 | 0.045 | 0.035 | 0.034 | 0.029 | -0.015 | -0.346 | -0.385 |
| | 10 | 0.088 | 0.093 | 0.125 | 0.082 | 0.052 | 0.048 | 0.046 | -0.019 | -0.054 | -0.918 | -1.006 |
| | 15 | 0.150 | 0.164 | 0.167 | 0.101 | 0.052 | 0.075 | 0.079 | -0.023 | -0.090 | -1.519 | -1.669 |
| | 20 | 0.208 | 0.254 | 0.173 | 0.097 | 0.148 | 0.117 | -0.034 | 0.039 | -0.123 | -2.070 | -2.278 |
| | 25 | 0.270 | 0.322 | 0.141 | 0.109 | 0.291 | 0.113 | -0.079 | 0.057 | -0.046 | -2.758 | -3.028 |
| | 30 | 0.355 | 0.394 | 0.157 | 0.081 | 0.264 | 0.162 | -0.067 | -0.085 | 0.089 | -3.364 | -3.719 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Pos + Neg | 5 | 0.058 | 0.057 | 0.066 | 0.071 | 0.067 | 0.053 | 0.051 | 0.043 | -0.023 | -0.507 | -0.565 |
| | 10 | 0.133 | 0.139 | 0.188 | 0.123 | 0.078 | 0.071 | 0.070 | -0.030 | -0.080 | -1.289 | -1.422 |
| | 15 | 0.227 | 0.247 | 0.247 | 0.152 | 0.078 | 0.114 | 0.120 | -0.037 | -0.135 | -2.078 | -2.306 |
| | 20 | 0.316 | 0.381 | 0.260 | 0.144 | 0.225 | 0.180 | -0.054 | 0.056 | -0.192 | -2.730 | -3.046 |
| | 25 | 0.411 | 0.484 | 0.213 | 0.165 | 0.440 | 0.176 | -0.129 | 0.079 | -0.081 | -3.576 | -3.987 |
| | 30 | 0.540 | 0.595 | 0.238 | 0.124 | 0.397 | 0.242 | -0.120 | -0.141 | 0.130 | -4.297 | -4.837 |

**Table 2** Hypothetical compounding deviations for (1X), (2X), and (3X) daily compounding LETFs using 18 popular market indices as the underlying indices. LETFs with positive multiples are shown separately from those with negative multiples and the added effects are shown in the third panel. The data sample is from Jan, 2000 to March, 2017. Panel A displays (1X) and (-1X) LETFs. Panel B displays (2X) and (-2X) LETFs. Panel C displays (3X) and (-3X) LETFs.

**(1X) Leverage: Panel A**

**Volatility Deciles**

| | Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pos LETF | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Neg LETF | 5 | 0.012 | 0.011 | 0.009 | 0.010 | 0.005 | 0.004 | -0.001 | -0.009 | -0.018 | -0.179 | -0.191 |
| | 10 | 0.025 | 0.017 | 0.011 | 0.011 | -0.002 | -0.011 | -0.030 | -0.031 | -0.080 | -0.421 | -0.446 |
| | 15 | 0.037 | 0.022 | 0.020 | 0.003 | -0.010 | -0.026 | -0.055 | -0.080 | -0.153 | -0.608 | -0.645 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 20 | 0.053 | 0.039 | 0.022 | 0.003 | -0.022 | -0.049 | -0.073 | -0.128 | -0.204 | -0.805 | -0.858 |
| | 25 | 0.064 | 0.056 | 0.029 | 0.004 | -0.027 | -0.079 | -0.116 | -0.125 | -0.290 | -1.013 | -1.077 |
| | 30 | 0.078 | 0.064 | 0.030 | 0.006 | -0.028 | -0.083 | -0.146 | -0.170 | -0.359 | -1.178 | -1.256 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| **Pos + Neg** | 5 | 0.012 | 0.011 | 0.009 | 0.010 | 0.005 | 0.004 | -0.001 | -0.009 | -0.018 | -0.179 | -0.191 |
| | 10 | 0.025 | 0.017 | 0.011 | 0.011 | -0.002 | -0.011 | -0.030 | -0.031 | -0.080 | -0.421 | -0.446 |
| | 15 | 0.037 | 0.022 | 0.020 | 0.003 | -0.010 | -0.026 | -0.055 | -0.080 | -0.153 | -0.608 | -0.645 |
| | 20 | 0.053 | 0.039 | 0.022 | 0.003 | -0.022 | -0.049 | -0.073 | -0.128 | -0.204 | -0.805 | -0.858 |
| | 25 | 0.064 | 0.056 | 0.029 | 0.004 | -0.027 | -0.079 | -0.116 | -0.125 | -0.290 | -1.013 | -1.077 |
| | 30 | 0.078 | 0.064 | 0.030 | 0.006 | -0.028 | -0.083 | -0.146 | -0.170 | -0.359 | -1.178 | -1.256 |

**(2X) Leverage: Panel B**

**Volatility Deciles**

| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Pos LETF** | 5 | 0.012 | 0.011 | 0.009 | 0.010 | 0.004 | 0.004 | -0.001 | -0.009 | -0.018 | -0.176 | -0.187 |
| | 10 | 0.025 | 0.017 | 0.011 | 0.011 | -0.003 | -0.011 | -0.031 | -0.032 | -0.082 | -0.386 | -0.412 |
| | 15 | 0.038 | 0.022 | 0.019 | 0.003 | -0.011 | -0.028 | -0.055 | -0.080 | -0.149 | -0.525 | -0.563 |
| | 20 | 0.054 | 0.038 | 0.022 | 0.000 | -0.024 | -0.050 | -0.074 | -0.129 | -0.195 | -0.645 | -0.698 |
| | 25 | 0.065 | 0.056 | 0.028 | 0.001 | -0.032 | -0.081 | -0.118 | -0.123 | -0.275 | -0.747 | -0.811 |
| | 30 | 0.078 | 0.064 | 0.026 | 0.003 | -0.035 | -0.089 | -0.152 | -0.165 | -0.340 | -0.790 | -0.868 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| **Neg LETF** | 5 | 0.035 | 0.032 | 0.027 | 0.030 | 0.014 | 0.011 | -0.003 | -0.027 | -0.052 | -0.542 | -0.576 |
| | 10 | 0.074 | 0.050 | 0.033 | 0.035 | -0.007 | -0.032 | -0.090 | -0.092 | -0.239 | -1.305 | -1.379 |
| | 15 | 0.110 | 0.066 | 0.060 | 0.010 | -0.027 | -0.078 | -0.165 | -0.241 | -0.464 | -1.929 | -2.039 |
| | 20 | 0.157 | 0.116 | 0.068 | 0.010 | -0.063 | -0.147 | -0.220 | -0.385 | -0.624 | -2.598 | -2.754 |
| | 25 | 0.190 | 0.168 | 0.089 | 0.015 | -0.076 | -0.234 | -0.348 | -0.378 | -0.887 | -3.317 | -3.507 |
| | 30 | 0.232 | 0.193 | 0.093 | 0.022 | -0.078 | -0.244 | -0.432 | -0.516 | -1.099 | -3.945 | -4.176 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| **Pos + Neg** | 5 | 0.046 | 0.043 | 0.036 | 0.039 | 0.018 | 0.015 | -0.004 | -0.036 | -0.071 | -0.718 | -0.764 |
| | 10 | 0.100 | 0.067 | 0.043 | 0.046 | -0.010 | -0.043 | -0.121 | -0.124 | -0.320 | -1.691 | -1.791 |
| | 15 | 0.148 | 0.088 | 0.079 | 0.013 | -0.038 | -0.106 | -0.220 | -0.322 | -0.613 | -2.453 | -2.602 |
| | 20 | 0.211 | 0.154 | 0.089 | 0.010 | -0.088 | -0.197 | -0.294 | -0.515 | -0.820 | -3.242 | -3.453 |
| | 25 | 0.255 | 0.224 | 0.117 | 0.016 | -0.108 | -0.315 | -0.466 | -0.501 | -1.162 | -4.064 | -4.319 |
| | 30 | 0.310 | 0.257 | 0.118 | 0.024 | -0.113 | -0.333 | -0.584 | -0.681 | -1.439 | -4.734 | -5.044 |

**(3X) Leverage: Panel C**

**Volatility Deciles**

| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Pos LETF** | 5 | 0.035 | 0.033 | 0.027 | 0.029 | 0.013 | 0.011 | -0.002 | -0.027 | -0.056 | -0.524 | -0.559 |
| | 10 | 0.077 | 0.051 | 0.032 | 0.032 | -0.010 | -0.034 | -0.093 | -0.096 | -0.247 | -1.131 | -1.207 |
| | 15 | 0.116 | 0.066 | 0.056 | 0.007 | -0.034 | -0.085 | -0.164 | -0.242 | -0.446 | -1.508 | -1.624 |
| | 20 | 0.162 | 0.115 | 0.065 | -0.002 | -0.076 | -0.151 | -0.221 | -0.389 | -0.580 | -1.805 | -1.967 |
| | 25 | 0.195 | 0.168 | 0.083 | -0.002 | -0.102 | -0.248 | -0.357 | -0.369 | -0.811 | -2.031 | -2.227 |
| | 30 | 0.235 | 0.190 | 0.072 | 0.004 | -0.115 | -0.274 | -0.464 | -0.491 | -1.003 | -2.094 | -2.328 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Neg LETF | 5 | 0.069 | 0.063 | 0.053 | 0.059 | 0.027 | 0.022 | -0.006 | -0.054 | -0.102 | -1.092 | -1.161 |
| | 10 | 0.148 | 0.100 | 0.065 | 0.070 | -0.013 | -0.063 | -0.180 | -0.183 | -0.475 | -2.707 | -2.855 |
| | 15 | 0.218 | 0.132 | 0.121 | 0.022 | -0.053 | -0.156 | -0.331 | -0.483 | -0.939 | -4.089 | -4.308 |
| | 20 | 0.311 | 0.232 | 0.136 | 0.023 | -0.123 | -0.294 | -0.441 | -0.771 | -1.275 | -5.562 | -5.874 |
| | 25 | 0.378 | 0.336 | 0.180 | 0.035 | -0.143 | -0.464 | -0.692 | -0.766 | -1.810 | -7.137 | -7.515 |
| | 30 | 0.462 | 0.388 | 0.193 | 0.047 | -0.145 | -0.480 | -0.855 | -1.050 | -2.245 | -8.583 | -9.045 |
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Pos + Neg | 5 | 0.104 | 0.096 | 0.080 | 0.088 | 0.040 | 0.033 | -0.008 | -0.081 | -0.159 | -1.616 | -1.720 |
| | 10 | 0.224 | 0.152 | 0.097 | 0.103 | -0.022 | -0.096 | -0.272 | -0.279 | -0.721 | -3.838 | -4.062 |
| | 15 | 0.334 | 0.198 | 0.177 | 0.029 | -0.087 | -0.240 | -0.495 | -0.725 | -1.385 | -5.597 | -5.931 |
| | 20 | 0.474 | 0.347 | 0.201 | 0.021 | -0.199 | -0.445 | -0.662 | -1.160 | -1.855 | -7.367 | -7.841 |
| | 25 | 0.574 | 0.503 | 0.263 | 0.033 | -0.246 | -0.712 | -1.049 | -1.135 | -2.621 | -9.169 | -9.742 |
| | 30 | 0.696 | 0.578 | 0.265 | 0.051 | -0.260 | -0.755 | -1.319 | -1.541 | -3.248 | -10.677 | -11.373 |

**Table 3** Hypothetical average returns for (1X) (2X), and (3X) daily compounding LETFs with the S&P 500 as the underlying index. LETFs with positive multiples are shown separately from those with negative multiples. In the third section of each panel, the return of a portfolio which takes equal positions on an LETF and the inverse LETF with the same multiple. The data sample is from Jan, 1960 to March, 2007. Panel A displays (1X) and (-1X) LETF returns. Panel A displays (2X) and (-2X) LETF returns. Panel A displays (3X) and (-3X) LETF returns.

### (1X) Leverage: Panel A

**Volatility Deciles**

| | Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Negative | 5 | -0.277 | -0.234 | -0.233 | -0.157 | -0.100 | -0.098 | -0.177 | -0.097 | -0.007 | -0.154 | 0.123 |
| | 10 | -0.744 | -0.527 | -0.391 | -0.300 | -0.442 | -0.613 | -0.313 | -0.094 | -0.083 | 0.402 | 1.146 |
| | 15 | -1.201 | -0.685 | -0.468 | -0.713 | -0.713 | -0.759 | -0.591 | -0.120 | -0.199 | 0.767 | 1.968 |
| | 20 | -1.540 | -0.974 | -0.866 | -0.701 | -0.912 | -1.044 | -0.693 | -0.443 | -0.443 | 1.358 | 2.898 |
| | 25 | -1.840 | -1.257 | -1.078 | -0.953 | -0.863 | -1.616 | -0.721 | -0.873 | -0.238 | 1.608 | 3.449 |
| | 30 | -2.175 | -1.404 | -1.343 | -0.819 | -1.477 | -1.594 | -1.290 | -1.151 | -0.050 | 1.892 | 4.067 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Positive | 5 | 0.283 | 0.240 | 0.240 | 0.165 | 0.107 | 0.104 | 0.183 | 0.102 | 0.005 | 0.097 | -0.186 |
| | 10 | 0.759 | 0.543 | 0.412 | 0.314 | 0.451 | 0.621 | 0.321 | 0.091 | 0.074 | -0.544 | -1.303 |
| | 15 | 1.226 | 0.712 | 0.496 | 0.730 | 0.722 | 0.772 | 0.604 | 0.116 | 0.184 | -0.997 | -2.223 |
| | 20 | 1.575 | 1.016 | 0.895 | 0.717 | 0.937 | 1.063 | 0.688 | 0.449 | 0.421 | -1.661 | -3.236 |
| | 25 | 1.886 | 1.310 | 1.102 | 0.971 | 0.912 | 1.636 | 0.707 | 0.882 | 0.229 | -2.007 | -3.893 |
| | 30 | 2.235 | 1.471 | 1.369 | 0.832 | 1.521 | 1.621 | 1.277 | 1.136 | 0.065 | -2.370 | -4.605 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Pos + Neg | 5 | 0.003 | 0.003 | 0.004 | 0.004 | 0.004 | 0.003 | 0.003 | 0.002 | -0.001 | -0.028 | -0.031 |
| | 10 | 0.007 | 0.008 | 0.010 | 0.007 | 0.004 | 0.004 | 0.004 | -0.002 | -0.004 | -0.071 | -0.079 |
| | 15 | 0.013 | 0.014 | 0.014 | 0.008 | 0.004 | 0.006 | 0.007 | -0.002 | -0.007 | -0.115 | -0.128 |
| | 20 | 0.018 | 0.021 | 0.014 | 0.008 | 0.012 | 0.010 | -0.003 | 0.003 | -0.011 | -0.151 | -0.169 |
| | 25 | 0.023 | 0.027 | 0.012 | 0.009 | 0.024 | 0.010 | -0.007 | 0.004 | -0.004 | -0.199 | -0.222 |
| | 30 | 0.030 | 0.033 | 0.013 | 0.007 | 0.022 | 0.013 | -0.007 | -0.008 | 0.007 | -0.239 | -0.269 |

**(2X) Leverage: Panel B**

**Volatility Deciles**

| | Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Negative | 5 | -0.547 | -0.461 | -0.458 | -0.306 | -0.192 | -0.191 | -0.348 | -0.190 | -0.018 | -0.366 | 0.182 |
| | 10 | -1.474 | -1.039 | -0.761 | -0.587 | -0.876 | -1.218 | -0.619 | -0.192 | -0.176 | 0.645 | 2.119 |
| | 15 | -2.377 | -1.342 | -0.908 | -1.410 | -1.417 | -1.506 | -1.169 | -0.243 | -0.412 | 1.269 | 3.646 |
| | 20 | -3.045 | -1.906 | -1.703 | -1.385 | -1.799 | -2.068 | -1.392 | -0.880 | -0.905 | 2.349 | 5.394 |
| | 25 | -3.636 | -2.460 | -2.133 | -1.888 | -1.678 | -3.214 | -1.456 | -1.736 | -0.482 | 2.724 | 6.360 |
| | 30 | -4.291 | -2.744 | -2.660 | -1.624 | -2.910 | -3.161 | -2.591 | -2.316 | -0.085 | 3.179 | 7.470 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Positive | 5 | 0.573 | 0.487 | 0.487 | 0.338 | 0.222 | 0.215 | 0.371 | 0.209 | 0.008 | 0.140 | -0.433 |
| | 10 | 1.533 | 1.101 | 0.844 | 0.642 | 0.910 | 1.249 | 0.650 | 0.179 | 0.140 | -1.217 | -2.750 |
| | 15 | 2.478 | 1.452 | 1.018 | 1.477 | 1.452 | 1.557 | 1.222 | 0.227 | 0.353 | -2.191 | -4.669 |
| | 20 | 3.185 | 2.075 | 1.818 | 1.449 | 1.899 | 2.148 | 1.369 | 0.905 | 0.820 | -3.561 | -6.746 |
| | 25 | 3.818 | 2.675 | 2.227 | 1.961 | 1.874 | 3.292 | 1.398 | 1.771 | 0.446 | -4.316 | -8.134 |
| | 30 | 4.531 | 3.008 | 2.765 | 1.679 | 3.086 | 3.269 | 2.537 | 2.253 | 0.143 | -5.089 | -9.620 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Pos + Neg | 5 | 0.013 | 0.013 | 0.015 | 0.016 | 0.015 | 0.012 | 0.011 | 0.010 | -0.005 | -0.113 | -0.126 |
| | 10 | 0.030 | 0.031 | 0.042 | 0.027 | 0.017 | 0.016 | 0.016 | -0.007 | -0.018 | -0.286 | -0.316 |
| | 15 | 0.050 | 0.055 | 0.055 | 0.034 | 0.017 | 0.025 | 0.027 | -0.008 | -0.030 | -0.461 | -0.512 |
| | 20 | 0.070 | 0.085 | 0.058 | 0.032 | 0.050 | 0.040 | -0.012 | 0.013 | -0.043 | -0.606 | -0.676 |
| | 25 | 0.091 | 0.108 | 0.047 | 0.037 | 0.098 | 0.039 | -0.029 | 0.018 | -0.018 | -0.796 | -0.887 |
| | 30 | 0.120 | 0.132 | 0.053 | 0.027 | 0.088 | 0.054 | -0.027 | -0.031 | 0.029 | -0.955 | -1.075 |

**(3X) Leverage: Panel C**

**Volatility Deciles**

| | Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Negative | 5 | -0.811 | -0.682 | -0.676 | -0.447 | -0.277 | -0.278 | -0.514 | -0.278 | -0.030 | -0.638 | 0.173 |
| | 10 | -2.189 | -1.535 | -1.110 | -0.860 | -1.301 | -1.815 | -0.917 | -0.292 | -0.278 | 0.715 | 2.904 |
| | 15 | -3.529 | -1.972 | -1.320 | -2.090 | -2.113 | -2.241 | -1.734 | -0.370 | -0.641 | 1.472 | 5.001 |
| | 20 | -4.516 | -2.795 | -2.510 | -2.053 | -2.662 | -3.074 | -2.097 | -1.309 | -1.387 | 2.912 | 7.428 |
| | 25 | -5.387 | -3.609 | -3.164 | -2.805 | -2.446 | -4.793 | -2.201 | -2.588 | -0.732 | 3.263 | 8.650 |
| | 30 | -6.350 | -4.018 | -3.950 | -2.417 | -4.299 | -4.702 | -3.898 | -3.491 | -0.105 | 3.746 | 10.096 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Positive | 5 | 0.869 | 0.740 | 0.742 | 0.518 | 0.345 | 0.331 | 0.565 | 0.321 | 0.008 | 0.131 | -0.738 |
| | 10 | 2.322 | 1.674 | 1.297 | 0.983 | 1.378 | 1.886 | 0.987 | 0.263 | 0.198 | -2.004 | -4.326 |
| | 15 | 3.756 | 2.219 | 1.567 | 2.242 | 2.191 | 2.355 | 1.853 | 0.333 | 0.506 | -3.551 | -7.307 |
| | 20 | 4.832 | 3.176 | 2.770 | 2.198 | 2.887 | 3.253 | 2.043 | 1.365 | 1.195 | -5.642 | -10.474 |
| | 25 | 5.798 | 4.093 | 3.377 | 2.969 | 2.885 | 4.969 | 2.071 | 2.667 | 0.651 | -6.839 | -12.637 |
| | 30 | 6.890 | 4.613 | 4.188 | 2.541 | 4.696 | 4.943 | 3.778 | 3.350 | 0.235 | -8.043 | -14.933 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Pos + Neg | 5 | 0.029 | 0.029 | 0.033 | 0.036 | 0.034 | 0.027 | 0.025 | 0.022 | -0.011 | -0.253 | -0.282 |
| | 10 | 0.067 | 0.070 | 0.094 | 0.062 | 0.039 | 0.036 | 0.035 | -0.015 | -0.040 | -0.645 | -0.711 |
| | 15 | 0.114 | 0.124 | 0.124 | 0.076 | 0.039 | 0.057 | 0.060 | -0.018 | -0.067 | -1.039 | -1.153 |
| | 20 | 0.158 | 0.190 | 0.130 | 0.072 | 0.112 | 0.090 | -0.027 | 0.028 | -0.096 | -1.365 | -1.523 |
| | 25 | 0.206 | 0.242 | 0.106 | 0.082 | 0.220 | 0.088 | -0.065 | 0.039 | -0.041 | -1.788 | -1.994 |
| | 30 | 0.270 | 0.297 | 0.119 | 0.062 | 0.198 | 0.121 | -0.060 | -0.071 | 0.065 | -2.148 | -2.419 |

**Table 4** Hypothetical average returns for (1X) (2X), and (3X) daily compounding LETFs using 18 popular market indices as the underlying index. LETFs with positive multiples are shown separately from those with negative multiples. In the third section of each panel, the return of a portfolio which takes equal positions on an LETF and the inverse LETF with the same multiple. The data sample is from Jan, 2000 to March, 2007. Panel A displays (1X) and (-1X) LETF returns. Panel A displays (2X) and (-2X) LETF returns. Panel A displays (3X) and (-3X) LETF returns.

**(1X) Leverage: Panel A**

**Volatility Deciles**

| | Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Negative | 5 | -0.453 | -0.353 | -0.301 | -0.220 | -0.162 | -0.051 | -0.063 | 0.087 | 0.076 | -0.247 | 0.206 |
| | 10 | -0.983 | -0.851 | -0.690 | -0.579 | -0.470 | -0.294 | 0.039 | 0.201 | 0.038 | 0.147 | 1.130 |
| | 15 | -1.434 | -1.194 | -1.090 | -1.037 | -0.762 | -0.448 | -0.102 | 0.230 | 0.275 | 0.383 | 1.816 |
| | 20 | -1.772 | -1.596 | -1.536 | -1.308 | -1.120 | -0.576 | -0.334 | 0.187 | 0.505 | 0.561 | 2.333 |
| | 25 | -2.048 | -1.993 | -1.838 | -1.694 | -1.362 | -0.848 | -0.507 | 0.166 | 0.558 | 0.786 | 2.833 |
| | 30 | -2.270 | -2.373 | -2.221 | -1.963 | -1.631 | -1.137 | -0.682 | 0.233 | 0.553 | 0.994 | 3.264 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Positive | 5 | 0.465 | 0.364 | 0.310 | 0.230 | 0.166 | 0.055 | 0.062 | -0.096 | -0.094 | 0.068 | -0.397 |
| | 10 | 1.007 | 0.868 | 0.701 | 0.591 | 0.467 | 0.284 | -0.069 | -0.232 | -0.118 | -0.568 | -1.576 |
| | 15 | 1.471 | 1.216 | 1.110 | 1.040 | 0.752 | 0.421 | 0.047 | -0.310 | -0.428 | -0.991 | -2.462 |
| | 20 | 1.825 | 1.634 | 1.558 | 1.310 | 1.098 | 0.527 | 0.260 | -0.316 | -0.709 | -1.366 | -3.191 |
| | 25 | 2.111 | 2.049 | 1.867 | 1.698 | 1.335 | 0.769 | 0.391 | -0.291 | -0.847 | -1.799 | -3.910 |
| | 30 | 2.348 | 2.437 | 2.250 | 1.969 | 1.604 | 1.054 | 0.536 | -0.403 | -0.912 | -2.172 | -4.519 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Pos + Neg | 5 | 0.006 | 0.005 | 0.004 | 0.005 | 0.002 | 0.002 | 0.000 | -0.005 | -0.009 | -0.090 | -0.095 |
| | 10 | 0.012 | 0.008 | 0.005 | 0.006 | -0.001 | -0.005 | -0.015 | -0.015 | -0.040 | -0.210 | -0.223 |
| | 15 | 0.019 | 0.011 | 0.010 | 0.002 | -0.005 | -0.013 | -0.027 | -0.040 | -0.076 | -0.304 | -0.323 |
| | 20 | 0.026 | 0.019 | 0.011 | 0.001 | -0.011 | -0.025 | -0.037 | -0.064 | -0.102 | -0.403 | -0.429 |
| | 25 | 0.032 | 0.028 | 0.015 | 0.002 | -0.013 | -0.039 | -0.058 | -0.062 | -0.145 | -0.506 | -0.538 |
| | 30 | 0.039 | 0.032 | 0.015 | 0.003 | -0.014 | -0.041 | -0.073 | -0.085 | -0.180 | -0.589 | -0.628 |

**(2X) Leverage: Panel B**

**Volatility Deciles**

| | Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Negative | 5 | -0.895 | -0.695 | -0.594 | -0.430 | -0.319 | -0.099 | -0.127 | 0.165 | 0.136 | -0.677 | 0.217 |
| | 10 | -1.941 | -1.686 | -1.369 | -1.147 | -0.941 | -0.599 | 0.048 | 0.372 | -0.003 | -0.169 | 1.772 |
| | 15 | -2.832 | -2.366 | -2.160 | -2.070 | -1.532 | -0.921 | -0.259 | 0.379 | 0.393 | 0.053 | 2.884 |
| | 20 | -3.493 | -3.153 | -3.049 | -2.611 | -2.260 | -1.201 | -0.741 | 0.246 | 0.794 | 0.134 | 3.628 |
| | 25 | -4.032 | -3.930 | -3.645 | -3.382 | -2.746 | -1.772 | -1.129 | 0.204 | 0.808 | 0.280 | 4.313 |
| | 30 | -4.464 | -4.681 | -4.408 | -3.916 | -3.285 | -2.352 | -1.504 | 0.290 | 0.725 | 0.399 | 4.863 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Positive | 5 | 0.941 | 0.738 | 0.629 | 0.470 | 0.337 | 0.113 | 0.123 | -0.201 | -0.206 | -0.040 | -0.981 |
| | 10 | 2.040 | 1.754 | 1.412 | 1.192 | 0.931 | 0.556 | -0.169 | -0.496 | -0.317 | -1.522 | -3.563 |
| | 15 | 2.980 | 2.454 | 2.239 | 2.083 | 1.494 | 0.815 | 0.039 | -0.701 | -1.006 | -2.506 | -5.486 |
| | 20 | 3.704 | 3.307 | 3.139 | 2.621 | 2.172 | 1.004 | 0.447 | -0.761 | -1.614 | -3.377 | -7.080 |
| | 25 | 4.288 | 4.154 | 3.762 | 3.397 | 2.638 | 1.457 | 0.663 | -0.705 | -1.970 | -4.344 | -8.631 |
| | 30 | 4.773 | 4.938 | 4.526 | 3.941 | 3.172 | 2.019 | 0.920 | -0.971 | -2.164 | -5.133 | -9.907 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Pos + Neg | 5 | 0.023 | 0.021 | 0.018 | 0.020 | 0.009 | 0.007 | -0.002 | -0.018 | -0.035 | -0.359 | -0.382 |
| | 10 | 0.050 | 0.034 | 0.022 | 0.023 | -0.005 | -0.021 | -0.060 | -0.062 | -0.160 | -0.846 | -0.895 |
| | 15 | 0.074 | 0.044 | 0.039 | 0.007 | -0.019 | -0.053 | -0.110 | -0.161 | -0.307 | -1.227 | -1.301 |
| | 20 | 0.105 | 0.077 | 0.045 | 0.005 | -0.044 | -0.099 | -0.147 | -0.257 | -0.410 | -1.621 | -1.726 |

| | Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 25 | 0.128 | 0.112 | 0.059 | 0.008 | -0.054 | -0.158 | -0.233 | -0.250 | -0.581 | -2.032 | -2.159 |
| | 30 | 0.155 | 0.129 | 0.059 | 0.012 | -0.057 | -0.167 | -0.292 | -0.341 | -0.719 | -2.367 | -2.522 |

**(3X) Leverage: Panel C**

**Volatility Deciles**

| | Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Negative | 5 | -1.325 | -1.028 | -0.877 | -0.631 | -0.472 | -0.142 | -0.192 | 0.234 | 0.180 | -1.295 | 0.030 |
| | 10 | -2.875 | -2.505 | -2.037 | -1.702 | -1.414 | -0.914 | 0.028 | 0.513 | -0.121 | -1.003 | 1.872 |
| | 15 | -4.194 | -3.517 | -3.210 | -3.098 | -2.310 | -1.419 | -0.471 | 0.447 | 0.346 | -1.117 | 3.077 |
| | 20 | -5.164 | -4.671 | -4.539 | -3.908 | -3.418 | -1.874 | -1.222 | 0.177 | 0.852 | -1.464 | 3.700 |
| | 25 | -5.956 | -5.812 | -5.422 | -5.060 | -4.148 | -2.772 | -1.864 | 0.106 | 0.732 | -1.741 | 4.215 |
| | 30 | -6.581 | -6.925 | -6.558 | -5.859 | -4.956 | -3.642 | -2.463 | 0.159 | 0.492 | -2.068 | 4.513 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Positive | 5 | 1.429 | 1.124 | 0.957 | 0.719 | 0.513 | 0.175 | 0.183 | -0.316 | -0.338 | -0.321 | -1.750 |
| | 10 | 3.099 | 2.656 | 2.134 | 1.804 | 1.392 | 0.817 | -0.300 | -0.792 | -0.600 | -2.835 | -5.934 |
| | 15 | 4.528 | 3.715 | 3.387 | 3.127 | 2.223 | 1.179 | -0.024 | -1.172 | -1.731 | -4.480 | -9.008 |
| | 20 | 5.638 | 5.018 | 4.741 | 3.929 | 3.218 | 1.429 | 0.560 | -1.337 | -2.708 | -5.903 | -11.541 |
| | 25 | 6.529 | 6.315 | 5.685 | 5.093 | 3.902 | 2.060 | 0.815 | -1.242 | -3.353 | -7.427 | -13.957 |
| | 30 | 7.277 | 7.503 | 6.823 | 5.910 | 4.696 | 2.888 | 1.144 | -1.700 | -3.740 | -8.609 | -15.887 |
| | **Days** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **10-1** |
| Pos + Neg | 5 | 0.052 | 0.048 | 0.040 | 0.044 | 0.020 | 0.017 | -0.004 | -0.041 | -0.079 | -0.808 | -0.860 |
| | 10 | 0.112 | 0.076 | 0.049 | 0.051 | -0.011 | -0.048 | -0.136 | -0.139 | -0.361 | -1.919 | -2.031 |
| | 15 | 0.167 | 0.099 | 0.089 | 0.014 | -0.043 | -0.120 | -0.247 | -0.363 | -0.693 | -2.799 | -2.966 |
| | 20 | 0.237 | 0.174 | 0.101 | 0.011 | -0.100 | -0.223 | -0.331 | -0.580 | -0.928 | -3.684 | -3.921 |
| | 25 | 0.287 | 0.252 | 0.132 | 0.017 | -0.123 | -0.356 | -0.525 | -0.568 | -1.311 | -4.584 | -4.871 |
| | 30 | 0.348 | 0.289 | 0.132 | 0.026 | -0.130 | -0.377 | -0.659 | -0.770 | -1.624 | -5.339 | -5.687 |

**Table 5:** Full-sample standard deviations for major indices

| ticker | Std Dev |
|---|---|
| HYG | 0.0081 |
| DJX | 0.0116 |
| SPX | 0.0124 |
| MID | 0.0137 |
| RUT | 0.0154 |
| NDX | 0.0184 |
| XLF | 0.0203 |
| GDX | 0.0282 |

**Table 6:** Correlation of 10-day returns of the combined portfolio for major indices

| | DJX | GDX | HYG | MID | NBI | NDX | RUT | SML | SPX | XLF |
|---|---|---|---|---|---|---|---|---|---|---|
| DJX | 1.000 | 0.111 | 0.490 | 0.874 | 0.669 | 0.894 | 0.851 | 0.838 | 0.983 | 0.658 |
| GDX | 0.111 | 1.000 | -0.039 | 0.148 | 0.039 | 0.114 | 0.117 | 0.120 | 0.122 | 0.021 |
| HYG | 0.490 | -0.039 | 1.000 | 0.408 | 0.444 | 0.520 | 0.426 | 0.408 | 0.515 | 0.400 |
| MID | 0.874 | 0.148 | 0.408 | 1.000 | 0.643 | 0.860 | 0.972 | 0.968 | 0.916 | 0.667 |
| NBI | 0.669 | 0.039 | 0.444 | 0.643 | 1.000 | 0.680 | 0.669 | 0.637 | 0.679 | 0.365 |
| NDX | 0.894 | 0.114 | 0.520 | 0.860 | 0.680 | 1.000 | 0.853 | 0.830 | 0.927 | 0.646 |
| RUT | 0.851 | 0.117 | 0.426 | 0.972 | 0.669 | 0.853 | 1.000 | 0.994 | 0.897 | 0.696 |
| SML | 0.838 | 0.120 | 0.408 | 0.968 | 0.637 | 0.830 | 0.994 | 1.000 | 0.883 | 0.699 |
| SPX | 0.983 | 0.122 | 0.515 | 0.916 | 0.679 | 0.927 | 0.897 | 0.883 | 1.000 | 0.724 |
| XLF | 0.658 | 0.021 | 0.400 | 0.667 | 0.365 | 0.646 | 0.696 | 0.699 | 0.724 | 1.000 |

**Figure 1:** Cumulative value of fund that begins with $1 of capital, then takes a zero-cost strategy that takes a long position in the combined portfolio with the DJX underlying and a short position in the combined portfolio with the NDX underlying. The position is held for 10 trading days then rebalanced.

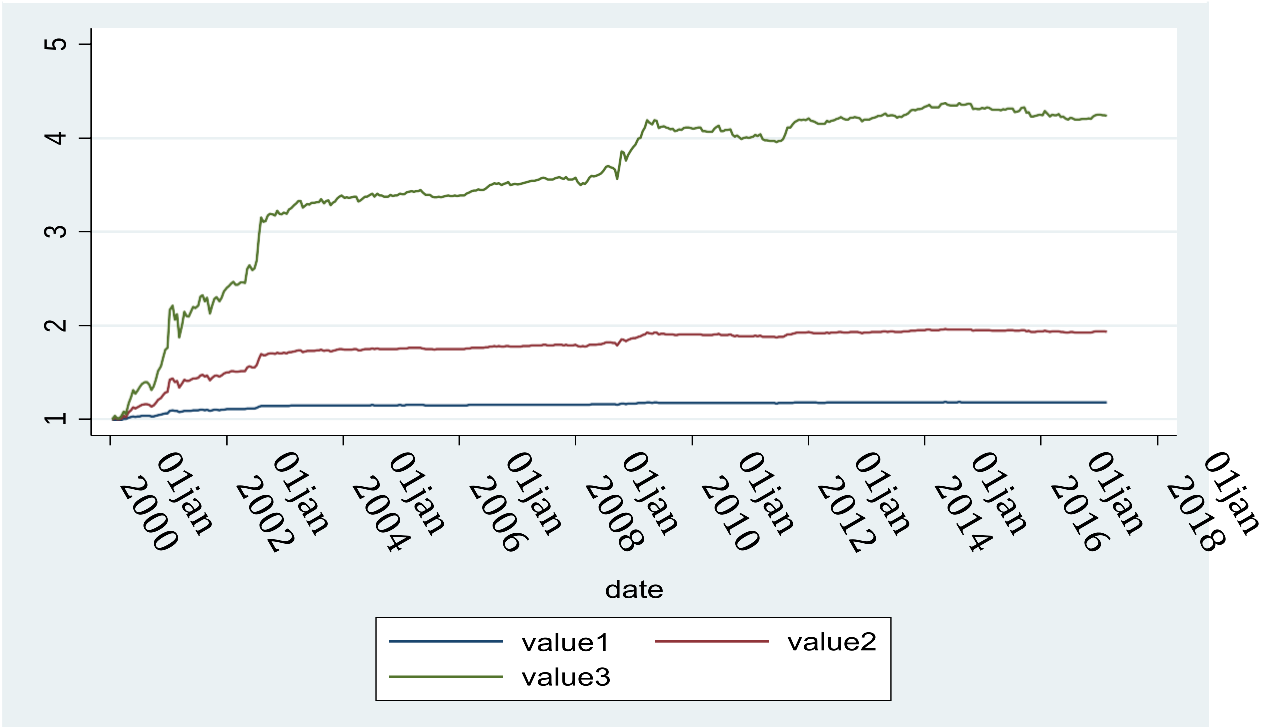
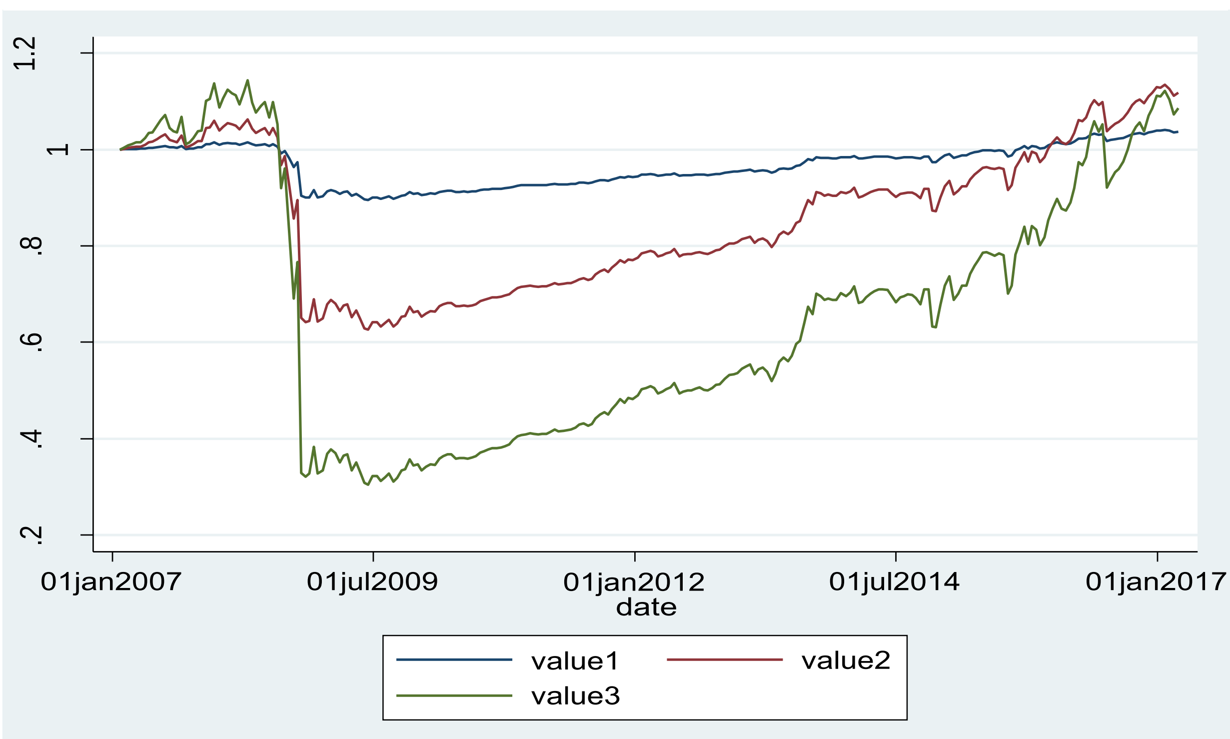



**Figure 2:** Cumulative value of fund that begins with $1 of capital, then takes a zero-cost strategy that takes a long position in the combined portfolio with the IEI underlying and a short position in the combined portfolio with the GDX underlying. The position is held for 10 trading days then rebalanced.



# Chapter 4
Option-Implied Information in Leveraged and Negative ETFs

## 4.1 Abstract

This study will examine the option-implied information derived from exchange traded funds (ETFs), as well as positively leveraged and negatively leverage exchange traded funds (LETF). Preliminary results suggest that daily portfolios created on large deviations from put-call parity outperform their targeted multiples, whereas portfolios created on smaller deviations tend to underperform their respective targets. Furthermore, leveraged ETF raw returns experience relative increases when put-call parity deviations are high. Hedge portfolio that take a long (short) position in high positive (negative) PCP deviations experience an average weekly return of 89 basis points.

## 4.2 Literature Review on Leveraged ETFs

Leveraged and Inverse-leveraged ETFs (both henceforth referred to as LETFs) are like equity options in that they provide an ideal environment attractive to informed investors, i.e., their leverage. Investors who obtain an informational advantage about overall market trends or future macroeconomic policy decisions would see LETFs as simple methods in which to achieve optimal returns.  LETFs are, much like options themselves, theoretically redundant assets. Like options, given the assumptions of complete markets, and informational symmetry, and the absence of trading restrictions, LETFs are easily replicable. But in reality such assumptions do not hold. Furthermore, institutions who market and sell LETFs are likely to have better trading arrangements and more favorable pricing than individual investors. This can possibly be largely attributed to economies of scale. LETFs trade in complex derivatives on a daily basis in order to achieve target multiples. Such large-scale orders on a consistent basis would be attractive to suppliers of the necessary derivative product. Suppliers are more willing to give pricing advantages to buyers in bulk.

Additionally, Due to the compounding-effect, moves in the underlying ETF that indicate a negative return for the LETF are partially offset, as shown by Lu and Wang (2009). The compounding effect increases with investment horizons. Since it is theoretically possible for an LETF to lose more than 100% (due to an increase or decrease of 50% or more in the underlying ETF), yet investors are only beholden to their initial investment, much like equity options there does exist, however slight, a limited downside risk.

LETFs are a relatively new product, first initiated by ProShares in June of 2006.  Thus, research on these products is still in the infant stages. Nonetheless, several studies have found some unique characteristics associated with LETFs. First, it is well established that LETFs do not return the corresponding multiple of underlying ETFs for long investment horizons. This is due to the compounding effect. The goal of LETFs is to produce *daily* returns which are equal to the targeted multiple of the UETF. Thus, when compounding, discrepancies will occur. Lu and Wang (2009) demonstrate this process. A first day return of 10% and a second-day return of 9.09% results in a two-day return of 20% for an UETF. An LETF with a multiple of +2 will experience daily returns of 20% and 18.18%, which, through compounding, implies a two-day return of 41.82% -- a multiple of approximately 2.1. Meanwhile, a corresponding Bear LETF with a targeted multiple of -2 will experience a two-day return of -34.5%, a multiple of -1.72 – again greater than the targeted multiple. Thus, the result of two, fairly even up-moves results in a realized multiple that exceeds the target. Lu and Wang (2009) go on to demonstrate that the opposite for down-moves, and an increased compounding effect in sideways markets.

Thus, Avellandeda and Zhang (2009) suggest the use of geometric returns is more appropriate, due to daily rebalancing. Furthermore, they show that LETFs typically underperform their benchmark multiples. Their study also asserts that holders of LETFs are exposed to excessive levels of volatility. As volatility increases as the number of daily transactions required for rebalancing increases resulting in increased underperformance. In addition to deriving a formula for the return of an LETF as a function of its expense ratio, the interest rate, and the realized return and variance of the UETF, Avellandeda and Zhang (2009) demonstrate that targeted multiples can be achieved using a dynamic hedging strategy. An investor in an LETF holds a time-decay due to the effects of being long convexity (or Gamma) and short variance. In short, both Bear and Bull leveraged ETFs will underperform targeted multiples unless the returns overcome break-even levels which are dependent upon the realized volatility.

The predictive power of options markets has been attributed to informational asymmetry regarding the underlying asset, but asymmetric information has two potential sources. First, traders can become more informed by receiving non-public information, or being tipped of public information ahead of time; insider trading.  Many studies consider the options market’s predictability of individual stocks, and their ability to anticipate the effects of planned and unplanned firm-specific events, such as mergers, earnings surprises, and analyst revisions. It can be persuasively argued that such predictability results from this type of informational advantage. Second, traders can gain an informational advantage by anticipating events with more precision and skill than the general populace, that is, by having superior analytical skills. Because ETFs and LETFs contain multiple equities within them, it is less likely that the movements of individual stocks brought upon by firm-specific events will dominate the movement of the entire fund. Thus, any predictive power inherent in the information implied by ETF and LETF options, it can be argued, is derived from the superior skills LETF option traders have analyzing and anticipating new information.

Recent studies have found predictive power in information implied through the prices of equity options. Much of the evidence links future abnormal stock returns to the implied volatility reflected in options prices. Cremers and Weinbaum (2010) find that deviations from put-call parity predict future equity movements. Along with Xing, Zhang, and Zhao (2010), this study examined the joint effects of put and call implied volatilities. An et al. (2014) examine the separate effects, finding that increasing implied volatility levels measured in call (put) prices are followed by outperformance (underperformance) in the underlying asset returns. Furthermore, as DeMiguel et al. (2013) show, using option-implied information, specifically implied volatility, can improve portfolio performance.

Other studies have examined the predictive power of alternative assets created through option-implied measures. Evidence of a negative relation between the returns of an implied skewness-asset and risk-neutral skewness, according to Bali and Murray (2013), suggest that investors prefer asset returns that are positively skewed, and are willing to accept a lower return for higher skewness. Goyal and Saretto (2009) form volatility-assets and find a positive link between the returns of these securities and the spread between historic and implied volatilities.

The story behind the relationship between contemporary option-implied information and future asset returns is a story of information asymmetry. Informed traders seek the increased leverage of the options market in order to maximize returns and the additional demand created by their volume bids options prices up to abnormally high levels relative to the variance of their underlying assets. High call prices lead to high stock returns and high put prices lead to low stock returns. The sequential trade model developed by Easley et al. (1998) expounds this view, suggesting that if informed trading exists in the options market, then such predictive power should exist. Their research helps confirm the view regarding option markets as a leading indicator of equity market returns. For example, Cremers and Weinbaum (2010) find evidence that deviations in put-call parity are more likely to occur in environments where information asymmetry is high.

These studies have effectively demonstrated the predictive power of options, and produced some evidence that environments of high informational asymmetry add to this predictive power. Moving forward, the nature of the informational asymmetry has also been examined. The degree of private knowledge that arises from insider information can be considered by examining option-implied measure's predictability of significant, informational, firm-level events that alter public perception of the firm's value. For example, Jayaraman et al. (2001) find spikes in option volume ahead of mergers, suggesting that options markets are more conducive to price discovery. Cao et al. (2005), along with several other papers, confirm this view, having found that option-implied volatilities tend to spike before mergers, acquisitions, and takeovers. Similarly, Jin et al. (2012) find predictability ahead of earnings surprises, and Hayunga and Lung (2014) report evidence that option-implied information trading activity increases just ahead of analyst revisions, and in the correct direction. These findings suggest private information accumulated by traders, potentially through tips from managers, analysts, and insiders privy to these firm-specific events.

## 4.3 Motivation and Hypotheses

The link between option-implied information ahead of major, firm-level, informational events yields suggestive, albeit not conclusive, evidence that non-public information rather than market inefficiency drives the predictability of equity option measures. This study will attempt to dichotomize the informational asymmetry inherent in option-price predictability by examining the effect that option prices have just ahead of significant stock movements that are unrelated to firm-specific events; low probability, high-sigma moves that cannot be attributed to such firm-specific events, anticipated or otherwise, but nevertheless affect individual firms uniquely. Any predictive power that option markets may have over these unanticipated moves can be at least partially attributed more to the superior ability some traders have to analyze and interpret publically disclosed information, and the subsequent choice they make to trade in leveraged markets to maximize gains.

Intuition suggests that informed traders can achieve stronger results by trading in leveraged markets. The literature supporting this view has grown substantially since Black (1975) made the suggestion that options markets would provide the ideal leverage and truncated payoffs to the downside to attract informed traders. The subsequent studies confirm this view. However, most that seek to examine the activities of informed traders find that the information asymmetry implied by option-price predictability is derived through traders who have access to non-public information.

The linkage between option markets ahead of firm-specific events appears to dominate the predictable aspect of option-implied information. If firm-specific events lead to asymmetric information due to tipping and subsequently leads to the predictability of options markets, then we might not expect such predictability to exist in options of mutual funds, ETFs, or ETFs that are leveraged in either a positive or a negative direction (LETFs). In such securities multiple firms are present, and thus they are unlikely to be dominated by the movements of a single company. Put another way, if the information implied by the options of ETFs or LETFs has predictive power ahead of the movements of the underlying securities, this would be more indicative of activities performed by traders with superior skills analyzing public information, rather than traders who hold non-public information, or who obtain public information ahead of the general population.

If high levels of realized volatility are associated with the relative underperformance in LETFs, does the option-implied volatility of LETFs have any predictive power regarding the relative performance of an LETF? On the one hand, if option-implied volatility (IV) is a sound predictor of future realized volatility, then high IVs may suggest a future underperformance, at least for longer investment horizons. On the other hand, in equity-options literature, high IVs are associated with abnormal future returns; positive for high call-IVs and negative for high put-IVs. Such large returns (positive or negative) will offset the loss associated with increased volatilities and reduce underperformance or even generate over-performance. One focus of this study will be to examine the relationship between high put and call IVs and future performance of LETFs relative to the targeted multiples.

To achieve this, we will begin by following the example of Cremers and Weinbaum (2010). Using the difference in the implied volatilities as a proxy for deviations in put-call parity, we find preliminary results of a U-shaped relationship between the deviation of put-call parity and the ratio of weekly returns on positively leveraged ETFs and the returns of their underlying ETFs. Very often only the most extreme quintiles prevent a more linear relationship. LETF performance ratios appear to decline as deviations in put-call parity increase from the first quintile to the fourth. But the fifth quintile witnesses a spike in LETF returns that is not observed in the UETF, indicating outperformance of the LETF. This feature appears to disappear over longer investment horizons. This is not surprising as Charapat and Miu (2011) find that LETFs are used by short term traders. According to them, the average holding period for LETFs are about 15 days. Overall, we believe the results support the findings of investors' exposure to volatility, yet extreme IV levels in the call direction suggests the potential for asymmetric information.

Additionally, it is possible that the reason for outperformance is due to a successive string of "positive" moves, which as demonstrated in Lu and Wang (2009), would lead to over performance.

## 4.4 Predictability of Simulations

I first begin by conducting simulations of expected compounding deviations from a hypothetical LETF instrument on the S&P 500 with daily compounding from 1996 to 2015. I simulate the return target by using the actual historical return of the S&P 500 and the targeted multiple of the hypothetical LETF. For example, if the daily return of the S&P 500 is 6%, then to achieve the return of a 2X ETF, I simply multiply the S&P return by the targeted multiple to get 12%. Thus, if the following day achieves an S&P return of -6%, the LETF return will be calculated as -12%. This compounding effect causes deviations from the targeted multiple over multi-day horizons. The two-day return of the underlying index is -0.36%, while the two-day return of the 2X LETF is -1.44%, which is 4 times greater than cumulative return on the underlying index.

Naïve investors are often under the false impression that the return on a LETF will equal the product multiple times the cumulative return of the underlying index for all holding periods. This fallacy is known as the "constant leverage trap." An investor who falls for this trap would expect his or her two-day return to be -0.72% may be surprised to learn their loss is twice as great as the targeted multiple, and four times greater than the loss of the S&P 500.

I extend previous simulations by Loviscek et al. (2014) of the same nature by including option-implied information of the underlying S&P 500 to determine if hypothetical daily LETF product multiples have any relationship with past innovations in options markets.

Table 1a finds that higher volatility corresponds with lower returns. This is unsurprising as down market movements have long been known to be more volatile than an upward trending market. Loviscek et al. (2014) show in their Table 3 that compounding deviations have a positive relationship return magnitudes and tend to have a negative relationship with volatility. Thus, we can expect that any significant predictor of future return or volatility will have some predictive power over directional compounding deviations of LETFs. Such a metric would be of great use to investors of LETF products, as it will allow them to determine if daily compounding is appropriate for their expectations, or if longer compounding horizons would be more suitable. If an investor anticipates high volatility over the next 20 trading days, then perhaps LETF products that compounding monthly would be more suitable than LETF products that compound daily.

In Table 1b I show that past changes in option-implied volatility has some predictive ability of future volatility in the S&P 500. In this panel, I sort three variables independently of each other into quintiles. The variables are past 5-day changes in call implied volatility, put IV, and the IV spread of at-the-money options. I then display the future 10-day volatility of the index. In all cases, we observe that large changes in past implied volatility, whether positive or negative, are indicative of larger observations in future 10-day volatility. The U-shaped distribution indicates some level of predictability in the future volatility of the underlying index.

In Table 2, I offer cumulative 10-day returns of the index following sorted changes in call implied volatility displaying returns on the left side, and the associated performance ratios on the right. This table exposes a problem with examining LETF performance ratios in this manner as in Loviscek et al. (2014). When returns are positive, performance ratios that are higher than targeted multiples represent positive compounding deviations. However, when returns are negative, investors in positively levered ETFs would prefer lower multiples, as they correspond with smaller losses than the naïve investor would expect. It is not unusual, particularly in the smallest quintile in call IV (read: largest negatives) for LETFs to have positive cumulative returns, despite negative cumulative returns in the S&P 500. This causes negative performance ratios which can keep average values low. For these reasons, it is important that performance ratios be examined separately for positive and negative returns in the underlying index.

Tables 3, 4, and 5 does this for changes in call, put, and volatility spreads, respectively. In Table 3, we see that higher changes, whether positive or negative, in call implied volatility predict improved performance ratios than more middling innovations. This holds true weather the underlying index increases or decreases over the 10-day period. On average, investors in daily compounded LETFs will outperform the naïve expectations. This outperformance is typically greater following large changes in implied volatilities. The distribution of returns and performance ratios follow a U-shaped pattern, in contrast to returns on portfolios which exhibit a more linear pattern[10].

I then examine subsamples, splitting the data at post- and pre-end-of-year 2008, around the time the first LETF on the S&P 500 was initiated. Theoretically, option-implied predictability on indices such as the S&P 500 should deteriorate following the introduction of LETF products. This is due to the informed-trading hypothesis of option-implied predictability. If informed traders prefer leverage, and another avenue for leverage is made available, then any predictive information from the original leverage source should be diminished as the informed traders flow funds into the alternative investment. Thus, we should expect that the predictability of options markets on the S&P 500 and other popular indices will decrease once a leveraged ETF is made available.

Table 6 repeats the process for Table 2, displaying average returns and performance ratios among implied volatility and multiple sorts for both sample periods in call options.  We notice that the

[10] See Cremers and Weinbaum (2010)

upward slope in index returns is flatter following the introduction of the LETF. In Table 7 and 8, I rerun Tables 3 and 4 and show that the U-shaped distribution of performance ratios has diminished in the years following LETF trading. When index returns are positive, performance ratios had higher predictability following extreme movements in implied volatility. I believe this to be a symptom of informed traders moving away from the options markets and into LETFs.

In order to continue testing this hypothesis, I will first perform these simulations on other market indices, including the Dow Jones Industrial Average, the S&P 600, the S&P 400, etc. I will also begin empirical tests to see if past LETF volumes measures show any relationship with future movements of the underlying. If informed traders are moving into LETF, then we would expect to find some information within LETFs that signal asymmetry in market knowledge.

## 4.5 Empirical Tests

To measure the impact that deviations in put-call parity (PCP) has on the future return of the LETF, we create first sort deviations in PCP into terciles on day *t*. After sorting upon PCP, we then sort upon targeted multiples of -3X, -2X, -1X, 2X, and 3X creating 15 unique portfolios every trading day and we examine the average weekly returns for each portfolio, the returns of the underlying ETF portfolio, and a "performance ratio" which simply takes the ratio of each LETF return to the return for the underlying ETF. A performance ratio that is equal to the targeted leverage-multiple would be said to be performing on par with the UETF. We repeat this procedure for each day in the sample and report the results in Table 7. There is an evident U-shaped relation between deviations in put-call parity and the performance ratio of the LETF. For positive multiples, the performance ratio outperforms or performs on par with the UETF when deviations from PCP are highly positive or highly negative, yet perform well below the UETF in the middle tercile, where deviations are nearest to zero. At first glance, the relative outperformance of LETFs in low PCP-deviation terciles might seem strange. After all, negative deviations for equity options would tend to suggest a negative return. In fact, we do see negative returns in the LETF for low tercile portfolios. However, due to the compounding effect, the relative performance of the LETF will exceed that of the UETF during periods of successive runs, either in the up or down direction. Thus, Table 7 provides suggestive evidence regarding the predictive power LETF option IVs have on future movements of the UETF. Highly positive (negative) deviations in put-call parity predict successive up (down) moves in the week ahead which, due to the compounding effect results in an outperformance of the LETF relative to the UETF. Later in this study, we will examine this idea further.

LETFs with negative multiples experience a similar pattern of returns relative to the UETF. The shape of the performance ratio, however, follows an inverted U-shape, which may require some explanation. Since the multiples on the LETFs are negative, high deviations in put-call parity are suggestive of high call implied volatilities and low put implied volatilities. A purchaser in call options for an LETF with a negative multiple is positioning himself for a *down* move in the underlying ETF. Which results in an up-move for the LETF. Thus we see the relationship is the same, but appears inverted due to the opposing nature of negative-multiple LETFs.

#### *4.5.1 Changes in call and put implied volatilities*

The procedure is repeated for quintile sorts of LETFs in addition to the terciles. The relationship is similar, but due to the relatively small number of assets in the sample, it has a tendency to be less clean than the results based on tercile sorts. Table 8 displays the results for completeness.

Having unearthed evidence of the predictive power of the conjoined effects of implied volatility for call and put options, we now seek to examine the separate effects. We do this by following the procedure of An, Ang, Bali, and Cakici (2014) who examine the relationship of future equity returns with changes in call-implied volatilities and changes in put-implied volatilities. As before, we form daily portfolios. This time we examine weekly returns for portfolios formed on the intersection of leverage multiple and daily changes in call- and put-implied volatility, with the results respectively displayed in Tables 9 and 10. For positively leveraged ETFs, high daily changes in call-implied volatility have a positive relation with future returns for the LETF, as displayed in Table 9. Weekly LETF returns in the highest tercile outperform those in the lowest terciles by 35bps for double-leveraged ETFs and 55bps for triple-leveraged ETFs. The relationship with the returns for underlying ETFs is also positive, but not as strong. The weekly returns for the underlying ETFs of both double- and triple-leveraged ETFs in the highest terciles outperform the lowest tercile by only 8bps. The result is improving performance ratios from tercile 1 to tercile 3, although the relationship again shows a curvature in its shape. For double-leveraged ETFs, the relationship appears more linear. Performance ratios improve from 1.7 to 1.9 to 2.3 from tercile 1 – 2.

Negatively-leveraged ETFs also experience an increase in weekly returns following a high increase in daily call-implied volatilities. A long position on a call option for a negatively-leverage ETF is a simultaneous short position on the underlying ETF. Thus, daily changes in call-implied volatilities are predictive of high negatively-leverage ETF weekly returns, and low returns for the UETF.

This procedure is repeated for weekly changes in call-implied volatility as well with the results displayed in Table 9b. The results for negatively-leveraged ETFs have reversed. High weekly changes in call-implied volatility for N-LETFs are now associated with declining weekly returns. P-LETF returns on the other hand maintain, or even strengthen following weekly changes in call-implied volatilities. One possible explanation for this is that the increase call-volatilities for N-LETFs have already incorporated themselves into the pricing of N-LETFs by the time portfolios are created. As pointed out by Charupat and Miu (2011), LETFs are short-term trading instruments. Coupled with the well-established finding that traders are averse toward holding assets that move against the broader market, it is reasonable to expect that N-LETFs experience reversals more quickly than their positively-leveraged counterparts.

Table 9c considers monthly changes. Since the average holding-period for LETFs as estimated by Charupat and Miu (2011) is approximately 15 days, we would expect any relationship between changes in call-implied volatilities and future returns to disappear once we consider monthly changes. For the most part, this is what we observe. The exception lies with triple-leveraged ETFs, which experience substantial decreases in weekly returns following large increases in call-IV.

Table 10 considers changes in the put-implied volatilities as predictive agents of future LETF returns and performance. Table 10a sorts based on leverage multiple and daily changes in put-implied volatilities. A high increase in put-IVs is suggestive of a down-move in the LETF, which, for N-LETFs indicates an up-move for the UETF. Thus, we would expect high changes in put-IVs to be related to low future returns for LETFs of all multiples. This is what see in Table 10a, with triple-leveraged ETFs representing the exception.

Performance ratios for double-leverage ETFs increase with high weekly changes in call-IVs while they decrease with high weekly changes in put-IVs. This can be seen in Table 9a and 10a respectively, and represent the only observations with a linear relationship this strong, in contrast to the U-shape or inverted U-shape seen in most performance ratios.

We also consider longer investment horizons of one month and find that the relationship largely disappears for changes in both call and put implied volatilities. The exception is once again the triple-leveraged ETFs, have sharp monthly declines in returns following large changes in IV, whether those changes derive from call or put IVs. The results are displayed on Table 11a and Table 11b.

### *4.5.2 Non-compounding deviation*

Having established a relationship between the option-implied volatility of LETFs and the future returns and performance of the underlying LETF, we now wish to extend our study by decomposing the return deviations of LETF into compounding and noncompounding components. As stipulated by Tang and Zhu (2013), the compounding deviation is computed as the LETF target return (compounded daily) less the naïve target return, which is simply the product of the UETFs return and the leverage multiple. In contrast, the noncompounding deviation is the difference between the actual LETF return and the targeted return, which is computed daily. Such noncompounding deviations can result from management tracking error and market inefficiencies that have nothing to do with the return that is perceived to be lost during the compounding of LETFs. Table 12 examines the noncompounding deviation. The top panel displays the average weekly deviation for each leverage multiple. As we can see, actual returns of LETFs on average tend to fall short of their targeted return (as a reminder, the target return is NOT the same as the naïve return). This shortfall increases with higher absolute leverage multiples. The symmetry between average returns across opposing multiples is striking. Both 1X and (-1X) multiples experience average return shortfalls of 10bps, and 2X and (-2X) multiples both observe shortfalls of 32bps. The symmetry diverts for 3X and (-3X). Noncompounding deviations are 111bps for 3X ETFs and 61bps for (-3X) ETFs.

Sorting by the three IV terciles, we see consistent relationships regarding noncompounding deviation and implied volatilities. The second panel shows that deviations are typically smaller for LETFs with large disparities in put-call parity. This holds across all leverage multiples. The third panel considers changes in call-IV, with noncompounding deviations again shrinking during following large changes. In contrast, yet consistent with prior results, the deviations grow larger following large increases in put-IV.

### *4.5.3 Dividend payments*

The effects that dividend payments of underlying ETFs might have on the implied volatility of LETF options is examined. Preliminary tests find that at-the-money options observe a small decline in volatilities leading up to dividend payment dates and a subsequent rise back to pre-dividend levels in the days following distribution. The decline is small, but consistent across multiples. At this stage the evidence is too sparse to convincingly argue for any dividend effect, but this study will continue to investigate the matter in the future.

## *4.6 Conclusion*

This study provides evidence on the predictive power that option-implied volatilities have on underlying LETF returns and their relative performance to benchmark ETFs. Consistent with the research on equity options, large positive (negative) deviations in put-call parity have weekly returns which outperform (underperform) the other LETF securities. Furthermore, the separate effects of put and call option-implied volatilities are examined. High daily and weekly changes in call (put) implied volatilities are followed by subsequent returns which outperform (underperform) the benchmark ETF.

## 4.7 Tables and Figures

**Table 1:** Panel A shows the 10-day return corresponding with quintile sorting of contemporary standard deviation measurements. Panel B sorts three IV variables independently and displays average future 10-day volatility for each sort

| Panel A | | | | | |
|---|---|---|---|---|---|
| sd(quintile) | 1 | 2 | 3 | 4 | 5 |
| ret10 | 0.0174 | 0.0129 | 0.0110 | 0.0044 | 0.0049 |
| Panel B | | | Future 10-day volatility | | |
| Sorted Variable | 1 | 2 | 3 | 4 | 5 |
| change call_iv | 0.0114 | 0.0090 | 0.0088 | 0.0095 | 0.0142 |
| change put_iv | 0.0112 | 0.0091 | 0.0087 | 0.0095 | 0.0145 |
| change iv spread | 0.0122 | 0.0097 | 0.0093 | 0.0094 | 0.0122 |

**Table 2:** Average returns and performance ratios are displayed for the S&P 500 following sorts on past 5-day changes in implied volatility measures and for hypothetical LETF products.

| | | Returns | | | | Performance Ratios | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | | 1 | 2 | 3 |
| Change Call IV | 1 | -0.0016 | 0.0117 | 0.0401 | 1 | 1.00 | 1.98 | 2.98 |
| | 2 | -0.0007 | 0.0054 | 0.0192 | 2 | 1.00 | 2.00 | 2.00 |
| | 3 | 0.0054 | 0.0192 | 0.0429 | 3 | 1.00 | 2.00 | 2.02 |
| | 4 | 0.0136 | 0.0377 | 0.0736 | 4 | 1.00 | 2.01 | 2.05 |
| | 5 | 0.0346 | 0.0995 | 0.2042 | 5 | 1.00 | 2.03 | 2.11 |

| | | Returns | | | | Performance Ratios | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | | 1 | 2 | 3 |
| Change Put IV | 1 | 0.0100 | 0.0348 | 0.0753 | 1 | 1.00 | 1.99 | 2.02 |
| | 2 | 0.0048 | 0.0046 | 0.0165 | 2 | 1.00 | 2.01 | 2.03 |
| | 3 | 0.0046 | 0.0165 | 0.0363 | 3 | 1.00 | 2.00 | 2.02 |
| | 4 | 0.0066 | 0.0226 | 0.0491 | 4 | 1.00 | 1.99 | 2.01 |
| | 5 | 0.0247 | 0.0816 | 0.1804 | 5 | 1.00 | 2.01 | 2.08 |

| | | Returns | | | | Performance Ratios | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | | 1 | 2 | 3 |
| Change IV Spread | 1 | 0.0075 | 0.0367 | 0.0917 | 1 | 1.00 | 1.99 | 2.02 |
| | 2 | -0.0005 | 0.0013 | 0.0107 | 2 | 1.00 | 1.99 | 2.98 |
| | 3 | 0.0013 | 0.0107 | 0.0285 | 3 | 1.00 | 2.00 | 2.01 |
| | 4 | 0.0148 | 0.0408 | 0.0797 | 4 | 1.00 | 2.01 | 2.04 |
| | 5 | 0.0274 | 0.0763 | 0.1527 | 5 | 1.00 | 2.02 | 2.09 |

**Table 3:** Average returns and performance ratios for the S&P 500 following 5-day changes in call implied volatility sorted into quintiles.

| | | Returns | | | | | Performance Ratio | | |
|---|---|---|---|---|---|---|---|---|---|
| **When 10-Day return < 0** | | | | | | | | | |
| | | Multiple | | | | | Multiple | | |
| | | 1 | 2 | 3 | | | 1 | 2 | 3 |
| Change Call IV | 1 | -0.0848 | -0.1560 | -0.2172 | Change Call IV | 1 | 1.00 | 1.88 | 2.72 |
| | 2 | -0.0688 | -0.0634 | -0.1188 | | 2 | 1.00 | 1.94 | 2.80 |
| | 3 | -0.0634 | -0.1188 | -0.1679 | | 3 | 1.00 | 1.95 | 2.83 |
| | 4 | -0.0667 | -0.1256 | -0.1778 | | 4 | 1.00 | 1.94 | 2.82 |
| | 5 | -0.0961 | -0.1742 | -0.2392 | | 5 | 1.00 | 1.90 | 2.73 |
| **When 10-Day return > 0** | | | | | | | | | |
| | | Multiple | | | | | Multiple | | |
| | | 1 | 2 | 3 | | | 1 | 2 | 3 |
| Change Call IV | 1 | 0.0926 | 0.2017 | 0.3315 | Change Call IV | 1 | 1.00 | 2.07 | 2.25 |
| | 2 | 0.0720 | 0.0726 | 0.1543 | | 2 | 1.00 | 2.05 | 2.19 |
| | 3 | 0.0726 | 0.1543 | 0.2491 | | 3 | 1.00 | 2.04 | 2.19 |
| | 4 | 0.0863 | 0.1857 | 0.3014 | | 4 | 1.00 | 2.07 | 2.23 |
| | 5 | 0.1429 | 0.3265 | 0.5718 | | 5 | 1.00 | 2.12 | 2.39 |

**Table 4:** Average returns and performance ratios for the S&P 500 following 5-day changes in put implied volatility sorted into quintiles.

| | | Returns | | | | | Performance Ratio | | |
|---|---|---|---|---|---|---|---|---|---|
| **When 10-Day return < 0** | | | | | | | | | |
| | | Multiple | | | | | Multiple | | |
| | | 1 | 2 | 3 | | | 1 | 2 | 3 |
| Change Put IV | 1 | -0.0795 | -0.1470 | -0.2053 | Change Put IV | 1 | 1.00 | 1.90 | 2.74 |
| | 2 | -0.0665 | -0.0607 | -0.1152 | | 2 | 1.00 | 1.94 | 2.82 |
| | 3 | -0.0607 | -0.1152 | -0.1642 | | 3 | 1.00 | 1.95 | 2.82 |
| | 4 | -0.0696 | -0.1299 | -0.1828 | | 4 | 1.00 | 1.94 | 2.80 |
| | 5 | -0.1034 | -0.1868 | -0.2556 | | 5 | 1.00 | 1.89 | 2.71 |
| **When 10-Day return > 0** | | | | | | | | | |
| | | Multiple | | | | | Multiple | | |
| | | 1 | 2 | 3 | | | 1 | 2 | 3 |
| Change Put IV | 1 | 0.0977 | 0.2130 | 0.3502 | Change Put IV | 1 | 1.00 | 2.08 | 2.26 |
| | 2 | 0.0726 | 0.0722 | 0.1526 | | 2 | 1.00 | 2.07 | 2.21 |
| | 3 | 0.0722 | 0.1526 | 0.2436 | | 3 | 1.00 | 2.05 | 2.20 |
| | 4 | 0.0833 | 0.1761 | 0.2824 | | 4 | 1.00 | 2.04 | 2.19 |
| | 5 | 0.1431 | 0.3295 | 0.5830 | | 5 | 1.00 | 2.11 | 2.39 |

**Table 5:** Average returns and performance ratios for the S&P 500 following 5-day changes in the implied volatility spread sorted into quintiles.

| | | Returns | | | | | Performance Ratio | | |
|---|---|---|---|---|---|---|---|---|---|
| | | When 10-Day return < 0 | | | | | | | |
| | | Multiple | | | | | Multiple | | |
| | | 1 | 2 | 3 | | | 1 | 2 | 3 |
| Change IV Spread | 1 | -0.0901 | -0.1646 | -0.2278 | Change IV Spread | 1 | 1.00 | 1.91 | 2.74 |
| | 2 | -0.0737 | -0.0634 | -0.1189 | | 2 | 1.00 | 1.91 | 2.77 |
| | 3 | -0.0634 | -0.1189 | -0.1676 | | 3 | 1.00 | 1.94 | 2.82 |
| | 4 | -0.0687 | -0.1282 | -0.1803 | | 4 | 1.00 | 1.93 | 2.79 |
| | 5 | -0.0821 | -0.1518 | -0.2120 | | 5 | 1.00 | 1.93 | 2.77 |
| | | When 10-Day return > 0 | | | | | | | |
| | | Multiple | | | | | Multiple | | |
| | | 1 | 2 | 3 | | | 1 | 2 | 3 |
| Change IV Spread | 1 | 0.1134 | 0.2550 | 0.4383 | Change IV Spread | 1 | 1.00 | 2.08 | 2.30 |
| | 2 | 0.0765 | 0.0715 | 0.1517 | | 2 | 1.00 | 2.05 | 2.19 |
| | 3 | 0.0715 | 0.1517 | 0.2418 | | 3 | 1.00 | 2.06 | 2.20 |
| | 4 | 0.0848 | 0.1825 | 0.2975 | | 4 | 1.00 | 2.07 | 2.23 |
| | 5 | 0.1212 | 0.2717 | 0.4653 | | 5 | 1.00 | 2.10 | 2.33 |

**Table 6**: Average returns and performance ratios are displayed for the S&P 500 following sorts on past 5-day changes in implied volatility measures and for hypothetical LETF products for different sub periods.

| | | Returns | | | Before LETF | | Performance Ratios | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | | | 1 | 2 | 3 |
| Change Call IV | 1 | -0.0048 | 0.0059 | 0.0323 | Change Call IV | 1 | 1.00 | 1.98 | 2.97 |
| | 2 | -0.0043 | 0.0074 | 0.0240 | | 2 | 1.00 | 1.99 | 2.98 |
| | 3 | 0.0074 | 0.0240 | 0.0512 | | 3 | 1.00 | 2.01 | 2.04 |
| | 4 | 0.0111 | 0.0325 | 0.0654 | | 4 | 1.00 | 2.01 | 2.04 |
| | 5 | 0.0397 | 0.1159 | 0.2420 | | 5 | 1.00 | 2.03 | 2.12 |

| | | Returns | | | After LETF | | Performance Ratios | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | | | 1 | 2 | 3 |
| Change Call IV | 1 | 0.0044 | 0.0224 | 0.0544 | Change Call IV | 1 | 1.00 | 1.96 | 2.98 |
| | 2 | 0.0061 | 0.0013 | 0.0098 | | 2 | 1.00 | 2.02 | 2.03 |
| | 3 | 0.0013 | 0.0098 | 0.0263 | | 3 | 1.00 | 1.97 | 2.97 |
| | 4 | 0.0189 | 0.0489 | 0.0913 | | 4 | 1.00 | 2.02 | 2.07 |
| | 5 | 0.0249 | 0.0689 | 0.1332 | | 5 | 1.00 | 2.02 | 2.08 |

**Table 7** Average weekly returns for LETF portfolios formed on the intersection of deviations from put-call parity and various leverage multiples. The top panel lists returns for LETF portfolios. The middle panel displays returns for the UETF portfolios, and the bottom panel displays the ratio of LETF to UETF returns as a performance ratio. Performance ratios represent the average ratio of all assets within a portfolio, as opposed to the ratio of average portfolio returns

| | **Ret5, LETF** | | | | |
|---|---|---|---|---|---|
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| PCPq | | | | | |
| 1 | -0.80% | -0.64% | -0.58% | 0.00% | -0.10% |
| 2 | -0.72% | -0.16% | -0.44% | 0.25% | 0.56% |
| 3 | 0.59% | 0.06% | -0.23% | 0.57% | 0.56% |
| **3-1** | **1.39** | **0.70** | **0.35** | **0.57** | **0.66** |
| | **Ret5, UETF** | | | | |
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| PCPq | | | | | |
| 1 | 0.29% | 0.18% | 0.23% | 0.03% | 0.18% |
| 2 | 0.46% | -0.05% | 0.41% | 0.00% | 0.18% |
| 3 | 0.07% | -0.04% | 0.09% | 0.25% | 0.47% |
| **3-1** | **-0.22** | **-0.22** | **-0.14** | **0.22** | **0.29** |
| | **Performance Ratio (Ret.L/Ret.U)** | | | | |
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| PCPq | | | | | |
| 1 | (6.5) | (2.8) | (2.1) | 2.0 | 2.3 |
| 2 | (2.9) | (1.9) | (1.1) | 1.7 | 2.8 |
| 3 | (2.2) | (2.0) | (0.9) | 2.4 | 2.6 |

**Table 8** Repeats Table7 for quintiles instead of terciles

| | Ret5 | | | | |
|---|---|---|---|---|---|
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| PCPq | | | | | |
| 1 | -0.25% | -0.73% | -0.56% | -0.09% | -0.60% |

| | | | | | |
|---|---|---|---|---|---|
| 2 | -1.41% | -0.36% | -0.55% | 0.05% | 0.39% |
| 3 | -0.32% | -0.19% | -0.41% | 0.43% | 0.69% |
| 4 | 0.03% | -0.09% | -0.33% | 0.27% | 0.40% |
| 5 | 0.60% | 0.15% | -0.23% | 0.73% | 0.40% |
| **5-1** | **0.85** | **0.88** | **0.33** | **0.82** | **1.00** |
| | | | Under_ret5 | | |
| | | | Multiple | | |
| | -3 | -2 | -1 | 2 | 3 |
| PCPq | | | | | |
| 1 | 0.13% | 0.27% | 0.2% | 0.02% | 0.18% |
| 2 | 0.49% | 0.01% | 0.2% | 0.02% | 0.21% |
| 3 | 0.39% | -0.04% | 0.3% | 0.02% | 0.22% |
| 4 | 0.23% | -0.11% | 0.1% | 0.08% | 0.14% |
| 5 | 0.06% | 0.00% | 0.2% | 0.33% | 0.74% |
| **5-1** | **-0.07** | **-0.27** | **0.00** | **0.31** | **0.56** |
| | | | Performance Ratio | | |
| | | | Multiple | | |
| | -3 | -2 | -1 | 2 | 3 |
| PCPq | | | | | |
| 1 | (11.2) | (2.1) | (0.8) | 2.1 | 2.3 |
| 2 | (2.5) | (2.4) | (5.9) | 1.9 | 2.8 |
| 3 | (2.5) | (1.9) | (1.0) | 1.7 | 2.4 |
| 4 | (2.5) | (1.9) | (0.8) | 1.6 | 2.5 |
| 5 | (2.5) | (2.1) | (1.0) | 2.9 | 2.8 |

**Table 9a**

Average weekly returns for portfolios formed on the intersection of daily changes in call -implied volatility and various leverage multiples. The top panel lists returns for LETF portfolios. The middle panel displays returns for the UETF portfolios, and the bottom panel displays the ratio of LETF to UETF returns as a performance ratio. Performance ratios represent the average ratio of all assets within a portfolio, as opposed to the ratio of average portfolio returns

| | | | Ret5, LETF | | |
|---|---|---|---|---|---|
| | | | Multiple | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | -0.52% | -0.29% | -0.46% | 0.05% | 0.29% |
| 2 | -0.32% | -0.26% | -0.35% | 0.33% | -0.03% |
| 3 | -0.09% | -0.03% | -0.34% | 0.36% | 0.84% |
| **3-1** | **0.43** | **0.26** | **0.12** | **0.31** | **0.55** |
| | | | Ret5, UETF | | |
| | | | Multiple | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| 1 | 0.38% | 0.07% | 0.27% | 0.03% | 0.23% |
| 2 | 0.32% | -0.01% | 0.06% | 0.09% | 0.21% |
| 3 | 0.08% | -0.01% | 0.25% | 0.11% | 0.31% |
| **3-1** | **-0.30** | **- 0.08** | **-0.02** | **0.08** | **0.08** |
| | Performance Ratio (Ret.L/Ret.U) | | | | |
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | (6.2) | (2.62) | (2.0) | 1.7 | 2.2 |
| 2 | (2.9) | (1.73) | (0.8) | 1.9 | 2.0 |
| 3 | (2.1) | (2.26) | (1.0) | 2.3 | 2.4 |

**Table 9b**

Average weekly returns for portfolios formed on the intersection of weekly changes in call -implied volatility and various leverage multiples. The top panel lists returns for LETF portfolios. The middle panel displays returns for the UETF portfolios, and the bottom panel displays the ratio of LETF to UETF returns as a performance ratio. Performance ratios represent the average ratio of all assets within a portfolio, as opposed to the ratio of average portfolio returns

| | Ret5, LETF | | | | |
|---|---|---|---|---|---|
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | 0.40% | -0.41% | -0.51% | 0.13% | -0.12% |
| 2 | -0.71% | -0.11% | -0.47% | 0.26% | 0.22% |
| 3 | -0.56% | -0.12% | -0.20% | 0.36% | 0.91% |
| **3-1** | **-0.96** | **0.29** | **0.31** | **0.23** | **1.03** |
| | Ret5, UETF | | | | |
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | 0.13% | 0.07% | 0.40% | 0.09% | 0.26% |
| 2 | 0.38% | -0.02% | 0.45% | 0.10% | 0.14% |
| 3 | 0.24% | 0.03% | -0.10% | 0.04% | 0.34% |
| **3-1** | **0.11** | **-0.04** | **-0.50** | **-0.05** | **0.08** |
| | Performance Ratio (Ret.L/Ret.U) | | | | |
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | (6.8) | (2.38) | (2.0) | 1.9 | 2.4 |
| 2 | (2.3) | (2.35) | (1.0) | 2.3 | 2.6 |
| 3 | (2.2) | (1.96) | (0.8) | 1.8 | 2.6 |

**Table 9c**

Average weekly returns for portfolios formed on the intersection of monthly changes in call -implied volatility and various leverage multiples. The top panel lists returns for LETF portfolios. The middle panel displays returns for the UETF portfolios, and the bottom panel displays the ratio of LETF to UETF returns as a performance ratio. Performance ratios represent the average ratio of all assets within a portfolio, as opposed to the ratio of average portfolio returns

| Ret5, LETF | | | | | |
|---|---|---|---|---|---|
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | -0.34% | -0.22% | -0.33% | 0.24% | 1.43% |
| 2 | -0.62% | -0.20% | -0.48% | 0.29% | 0.30% |
| 3 | -0.20% | -0.22% | -0.25% | 0.23% | -0.34% |
| 3-1 | 0.14 | 0 | 0.08 | 0.01 | -1.77 |

| Ret5, UETF | | | | | |
|---|---|---|---|---|---|
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | 0.27% | 0.01% | 0.31% | 0.14% | 0.36% |
| 2 | 0.25% | 0.00% | 0.16% | 0.06% | 0.21% |
| 3 | 0.41% | 0.10% | 0.02% | 0.06% | 0.24% |
| 3-1 | 0.14 | 0.09 | -0.29 | -0.08 | -0.12 |

| Performance Ratio (Ret.L/Ret.U) | | | | | |
|---|---|---|---|---|---|
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | (2.9) | (2.22) | (2.4) | 1.9 | 2.0 |
| 2 | (5.9) | (2.52) | (1.0) | 2.2 | 2.5 |
| 3 | (2.9) | (1.97) | (0.8) | 1.9 | 2.0 |

**Table 10a**

Average weekly returns for portfolios formed on the intersection of daily changes in put -implied volatility and various leverage multiples. The top panel lists returns for LETF portfolios. The middle panel displays returns for the UETF portfolios, and the bottom panel displays the ratio of LETF to UETF returns as a performance ratio. Performance ratios represent the average ratio of all assets within a portfolio, as opposed to the ratio of average portfolio returns

| Ret5, LETF | |
|---|---|
| | Multiple |

| | -3 | -2 | -1 | 2 | 3 |
|---|---|---|---|---|---|
| PIVq | | | | | |
| 1 | 0.08% | 0.02% | -0.38% | 0.44% | 0.31% |
| 2 | -0.61% | -0.35% | -0.41% | 0.06% | 0.11% |
| 3 | -0.44% | -0.30% | -0.36% | 0.23% | 0.66% |
| **3-1** | **-0.52** | **-0.32** | **0.02** | **-0.21** | **0.35** |
| | | | Ret5, UETF | | |
| | | | Multiple | | |
| | -3 | -2 | -1 | 2 | 3 |
| PIVq | | | | | |
| 1 | 0.05% | 0.03% | 0.18% | 0.17% | 0.27% |
| 2 | 0.50% | -0.09% | 0.37% | 0.00% | 0.17% |
| 3 | 0.28% | 0.09% | 0.13% | 0.06% | 0.33% |
| **3-1** | **0.23** | **0.06** | **-0.05** | **-0.11** | **0.06** |
| | | | Performance Ratio (Ret.L/Ret.U) | | |
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| PIV-q | | | | | |
| 1 | (2.2) | (2.05) | (1.1) | 2.3 | 2.3 |
| 2 | (2.7) | (1.61) | (2.8) | 1.9 | 2.1 |
| 3 | (6.1) | (2.88) | (0.8) | 1.8 | 2.2 |

**Table 4b**

Average weekly returns for portfolios formed on the intersection of weekly changes in put -implied volatility and various leverage multiples. The top panel lists returns for LETF portfolios. The middle panel displays returns for the UETF portfolios, and the bottom panel displays the ratio of LETF to UETF returns as a performance ratio. Performance ratios represent the average ratio of all assets within a portfolio, as opposed to the ratio of average portfolio returns

| | | | Ret5, LETF | | |
|---|---|---|---|---|---|
| | | | Multiple | | |
| | -3 | -2 | -1 | 2 | 3 |
| PIVq | | | | | |
| 1 | -0.48% | -0.34% | -0.37% | 0.37% | -0.11% |
| 2 | 0.31% | -0.29% | -0.49% | 0.11% | 0.58% |
| 3 | -0.83% | -0.03% | -0.33% | 0.28% | 0.39% |
| 3-1 | -0.35 | 0.31 | 0.04 | -0.09 | 0.50 |
| | | | Ret5, UETF | | |
| | | | Multiple | | |
| | -3 | -2 | -1 | 2 | 3 |
| PIVq | | | | | |
| 1 | 0.24% | 0.06% | 0.28% | 0.17% | 0.13% |

| | -3 | -2 | -1 | 2 | 3 |
|---|---|---|---|---|---|
| 2 | 0.23% | 0.01% | 0.43% | 0.09% | 0.28% |
| 3 | 0.33% | 0.02% | 0.02% | -0.02% | 0.29% |
| 3-1 | 0.09 | -0.04 | -0.26 | -0.19 | 0.16 |
| Performance Ratio (Ret.L/Ret.U) | | | | | |
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| PIVq | | | | | |
| 1 | (2.5) | (1.99) | (2.0) | 2.2 | 2.9 |
| 2 | (5.9) | (2.47) | (1.1) | 1.9 | 2.9 |
| 3 | (2.3) | (2.30) | (0.8) | 1.9 | 2.2 |

Table 11a

| Ret20, LETF | | | | | |
|---|---|---|---|---|---|
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | -1.15% | -0.95% | -1.41% | 0.83% | 1.58% |
| 2 | -0.95% | -1.09% | -1.61% | 1.22% | 2.08% |
| 3 | -1.76% | -0.58% | -1.38% | 0.89% | 0.52% |
| 3-1 | -0.61 | 0.37 | 0.03 | 0.06 | -1.06 |
| Ret20, UETF | | | | | |
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | 1.02% | 0.17% | 0.81% | 0.26% | 0.91% |
| 2 | 0.84% | 0.02% | 1.15% | 0.38% | 0.98% |
| 3 | 1.32% | 0.22% | 0.36% | 0.32% | 1.07% |
| 3-1 | 0.31 | 0.05 | -0.45 | 0.06 | 0.16 |
| Performance Ratio (Ret.L/Ret.U) | | | | | |
| | Multiple | | | | |
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | (9.1) | (2.36) | (1.1) | 2.0 | 7.2 |
| 2 | (4.1) | (2.99) | (1.1) | 2.1 | 2.2 |
| 3 | (2.6) | (4.52) | (1.3) | 2.0 | 4.1 |

Table 11b

| Ret20, LETF |
|---|
| Multiple |

| | -3 | -2 | -1 | 2 | 3 |
|---|---|---|---|---|---|
| CIVq | | | | | |
| 1 | -0.28% | -0.88% | -1.26% | 1.04% | 1.99% |
| 2 | -1.03% | -1.15% | -1.83% | 0.78% | 1.82% |
| 3 | -2.58% | -0.64% | -1.37% | 1.15% | 0.38% |
| 3-1 | -2.30 | 0.24 | -0.11 | 0.11 | -1.61 |

Ret20, UETF

| | Multiple | | | | |
|---|---|---|---|---|---|
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | 1.17% | 0.16% | 0.51% | 0.26% | 0.83% |
| 2 | 0.88% | -0.06% | 1.21% | 0.29% | 1.05% |
| 3 | 1.08% | 0.27% | 0.56% | 0.41% | 1.05% |
| 3-1 | -0.09 | 0.11 | 0.05 | 0.15 | 0.22 |

Performance Ratio (Ret.L/Ret.U)

| | Multiple | | | | |
|---|---|---|---|---|---|
| | -3 | -2 | -1 | 2 | 3 |
| CIVq | | | | | |
| 1 | (11.9) | (4.30) | (1.2) | 2.2 | 2.8 |
| 2 | (1.7) | (2.25) | (1.5) | 2.0 | 7.2 |
| 3 | (2.1) | (2.23) | (1.0) | 2.1 | 2.0 |

# Chapter 5
## Conclusion

This dissertation examined how informed (and misinformed) traders seek leverage, their role in price discovery, and their ability to generate abnormal returns in equity price movement and how it relates to market efficiency. In examining the role of highly levered option trades, I find that the lead-lag relationship between options and stocks found in the option-implied volatility spread is driven by interest in OTM options ahead of corporate earnings announcements.  This relationship is reduced otherwise. Additionally, I find that equity traders are able to use the information implied by informed traders to generate abnormal risk-adjusted returns. Examining these returns, I find that evidence to suggest overconfidence and the disposition effect prevalent following earnings announcements, showing that trades found to be correct are quicker to realize equity alphas and also quick to revert volatility spreads to their normal levels. Meanwhile, leveraged trades based on overconfident sentiments exhibit volatility spreads that persist.  Additionally, earnings and post-earnings alphas show that call-driven equity prices are substantially more efficient than those driven by put trades. Alphas for call-driven trades are observed during the earnings period, as opposed to post-earnings like put-driven prices. This suggests that different levels of market efficiency exist between the two types; call-driven equities, which appear to be somewhat stronger than semi-strong form efficiency, and put-driven equities, which appear to be weaker. Finally, a strategic-timing fund is created to determine the economic significance of the leverage indictor variable. The fund generates a CAGR of 12.0% over a 13.5 year period of operation in a steady, non-volatile progression with no obvious response to the depression of 2007-2009.

Next, conducting simulations of return deviations for positive and negative LETFs, I find similarities, but important differences. While both positive and negative LETFs have a negative relationship with the volatility of the underlying index, this relationship appears to be much sharper for negative LETFs, as compounding deviations tend to be higher (lower) during periods of low (high) volatility. I then show that a combined portfolio also has a negative relationship with the volatility of the underlying index, and that positive economic gains are possible, but not near certain, by holding a long-short position with the long (short) position being a combined portfolio in a low (high) volatility market index.

Finally, this study provides evidence on the predictive power that option-implied volatilities have on underlying LETF returns and their relative performance to benchmark ETFs. Consistent with the research on equity options, large positive (negative) deviations in put-call parity have weekly returns which outperform (underperform) the other LETF securities. Furthermore, the separate effects of put and call option-implied volatilities are examined. High daily and weekly changes in call (put) implied volatilities are followed by subsequent returns which outperform (underperform) the benchmark ETF.

The results of this study provide evidence of informed trading occurring in both equity options and LETF options, as well as LETF products themselves. Since both options and LETFs provide attractive environments for informed traders, the two avenues are, in a sense, in competition with each other for informed traders. This suggest a tradeoff exists between LETF products and both their own options and the options their underlying indices. Informed and misinformed traders have the choice of multiple avenues of leverage. Although this goes beyond the scope of this study, a potential extension exists in examining these tradeoffs and providing empirical evidence that such a relationship exists. Such factors that we could consider as relevant would include the liquidity of the options market, as well as the expenditure of options contracts, as measured by implied volatility.

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# Appendix

## A.1 Terms and Variables

| | |
|---|---|
| *combined portfolio*: | Portfolio that takes a long position on a positive LETF and a long position on a negative LETF with the same multiple |
| *Comp deviation*: | difference between the multi-day return of an LETF and its naïve expected return |
| *iv_base*: | The average volatility spread in the base period |
| *iv_post*: | The average volatility spread in the post-earnings period |
| *iv_pre*: | The average volatility spread in the pre-earnings period |
| *LETF*: | Leveraged Exchange Traded Fund (can be positive or negative) |
| *lev_dum*: | Indicator variable equal to one if volatility spread is in the highest quintile and driven by OTM calls |
| *lev_pre*: | Average value of the leverage dummy variable during the pre-earnings period |
| *neg_lev* | Indicator variable equal to one if volatility spread is in the lowest quintile and driven by OTM puts |
| *rlev_pre*: | The ranked *lev_pre* value |
| *rspread_base*: | The ranked volatility spread value of the base period |
| *rspread_pre*: | The ranked volatility spread value of the pre-earnings period |
| *volatility spread*: | Average open-interest weighted difference in the implied volatility of call and put options on a given day (aka "deviations in put-call parity") |
| *xret*: | Excess return of a stock during the 3-day earnings period from *t-1* to *t+1* |

## A.2 Major Market Indices used (Chapters 3 and 4)

| | | |
|---|---|---|
| DJX | EFA | EWJ |
| EWZ | GDX | HYG |
| IEF | IEI | IEMG |
| MID | NBI | NDX |
| RUT | SML | SPX |
| TLT | XLF | |