Winter 2018

Pay for Performance: Do Higher Expense Ratios of Levered and Inverse ETFs Lead to Lower Tracking Error?

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PAY FOR PERFORMANCE: DO HIGHER EXPENSE RATIOS OF LEVERED AND INVERSE ETFS LEAD TO LOWER TRACKING ERROR?

by

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A Thesis Submitted in Partial Fulfillment
of the Requirements for a Degree with Honors
(Accounting and Finance)

The Honors College

University of Maine

December 2018

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ABSTRACT

Levered and inverse Exchange Traded Funds (LETFs) are a recent and controversial innovation in financial engineering. These ETFs set out to achieve daily returns that are a multiple (2x, 3x) or negative multiple (-1x, -2x, -3x) of an underlying index. Since their inception in 2006, research has overwhelmingly concluded that these ETFs fail to meet their stated objectives over long holding periods. However, there has been debate over the causes of this error, and the holding period at which the tracking begins to break down.

This thesis sets out to analyze the relationship between the expense ratios of LETFs and their tracking error. Influenced by the methods of Bansal and Marshall (2015) as well as Lu, Wang, and Zang (2012), I calculate tracking error of LETFs and use regression analysis to estimate changes in tracking error attributable to changes in expense ratio. The sample is analyzed by each target multiple, and analysis is performed for holding periods of 1, 5, 10, 21, 63, and 126-days.

Through the research process, I find that for -1x, -3x (HP: 126 days) and 2x LETFs, paying a higher expense ratio can produce lower levels of tracking error. The data also supports previous research claiming LETFs tracking error increases as holding period increases. Results did vary for some holding periods and target multiples. Varying results are likely due to the effects of compounding on LETF returns and market conditions like volatility and direction of returns.

ACKNOWLEDGMENTS

I must first acknowledge the support group I have had for my entire life. My Father, Dr. John Paul Carrier as well as my Mother, Paula Carrier. Without the support I have had from both of you, I would not be here today, a graduate of the University of Maine. You have shown me all the doors that open as the result of hard work, dedication, and education.

Second to them would be the rest of my loving family, Alex Carrier, Camden Carrier, Jamie Navarro, Rob Carrier, and Michael Navarro as well as Patty O'Brien, and the May, Vickers, and Wentzel families. Family will always come first, and I am lucky to have all of you as family. I hope someday that Annabel, Ollie, Jack, Molly, Sara, Sophie and Abby can read this thesis and be inspired to complete one themselves.

I would also like to thank my Thesis advisor and chair, Dr. Stephen Jurich. You have helped shape me into a finance researcher and guided me through this extremely challenging process. LETFs are some of the most complicated financial instruments on the market today, and you have aided my learning more than you know. I know that I would not have been able to complete this thesis without you, and I owe you many thanks.

Thank you to my committee members as well: Matt Skaves, Wendy Coons, Dave Barrett and Mark Haggerty. Thank you all for accepting my invitation to be on the committee of this thesis. It quite literally would not have gotten off the ground without you all agreeing to join.

Lastly, thank you to all my friends, who are too many to list. You have made my three and a half years here the best years of my life. You guys didn't help me much with this Thesis, but you all mean the world to me.

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1. INTRODUCTION

1.1 ETF's History

One of the most significant innovations of financial engineering in recent years has been the creation of exchange traded funds (ETFs). It all started in 1993 with the very first ETF Standard & Poor's Depository Receipts, commonly referred to as "spiders." What was unique about spiders, was its ability to replicate the performance of the S&P 500 index while taking the form of a single security that is traded like a stock (Gastineau and Marshall, 2011). By the early 2000's, index-tracking ETFs were common, with many sponsor companies releasing their own. Sponsors also added ETFs that tracked other popular indexes, like the Dow Jones Industrial Average and the Nasdaq 100. The creation of ETFs offered a cheaper, more liquid, way to get exposure to markets when compared to alternatives like index-mutual funds.

The main benefits of an ETF over a mutual fund comes from flexibility and expenses. ETFs typically have a very low expense ratio as compared to mutual funds, which can have expense ratios nearing 10%. ETFs will also never have commission expenses or any kinds of loads, which make it much easier to get a "mutual fund" level of exposure for a much cheaper price. Lastly, ETFs can be traded throughout the day like stocks, so they are a more liquid instrument than mutual funds, especially close-ended funds which can only trade at the end of each day after NAV is calculated.

It was found by Agapova (2011) that ETFs and conventional index funds are substitutes, although not perfect substitutes. The introduction of ETFs contributed more to market completeness and opened up a new option for investors to use, but it did not shake the mutual fund market enough to replace them. As of 2018, the total net assets of US

investment companies for respective instruments was $18.7 trillion in mutual funds and $3.4 trillion in exchange traded funds. Those numbers are up from where they were in 2010, $5.7 trillion and $1 trillion respectively (Investment Company Institute, 2018). Since 1993, there have been more than 1,500 ETFs introduced in the US and over 5,000 around the world. This shows just how much ETFs have skyrocketed onto the mainstage of financial trading.

1.2 LETF Development

It didn't take long after the early popularity of ETFs for someone to engineer a financial derivative using ETFs. In 2006, the first leveraged and inverse ETFs (LETFs) were introduced. These LETFs were designed to perform at a multiple of their underlying index. So a levered S&P 500-tracking ETF with a multiple of 2 would hypothetically give an investor two times the return of the S&P 500 for that day. If the S&P 500 were to go up $10, and if an investor were to have one unit of this LETF, then that investor's position should increase by $20. The first LETFs were offered by ProFund Advisors LLC and were for multiples of 2x, -1x and -2x. Since then, the number has increased significantly, with many sponsors getting into the mix. There has also been the addition of 3x and -3x target LETFs.

There have been multiple studies that have shown these levered and inverse ETFs do not perform in-line with their benchmarks over the long term. There is debate over when this performance breaks down, but it has been accepted that any holding period longer than one year would result in an inaccurate return compared to the stated multiple (Lu, Wang and Zhang (2012). Sponsor websites provide additional information on the

performance and structure of their levered and inverse ETFs. They also explicitly state that LETFs are not for the casual investor and should be traded by experienced professionals only. Here is an example of a warning from Direxion's website regarding their LETF – Direxion Daily S&P 500 Bull 2x Shares (SPUU):

> "This leveraged ETF seeks a return that is 200% the return of its benchmark index ***for a single day***. **The fund should not be expected to provide two times the return of the benchmark's cumulative return for periods greater than a day"**

A sponsor's website for each LETF outlines much more than just this warning. It has performance metrics, objectives, as well as a link to their prospectus, fact sheet, daily holdings and other descriptive information. The prospectus for SPUU and daily holdings for a different LETF, Proshares UltraShort QQQ (QID), can be found at Appendix D and E respectively. The prospectus includes more detailed information on the fund and also further explains the risks of the LETF. The fact sheet includes information on the LETFs holdings and can provide a detailed understanding of what these LETFs are made of. One thing to note here is how Direxion names their LETFs as compared to their competitor ProShares. They explicitly state in the name that it is the *Daily* negative two times return of the S&P 500. This is both an effort to be more transparent to their customers and an extra encouragement to use these instruments for daily trading.

Interestingly, because these levered ETFs are designed to only produce their multiple for a day, they have much higher trading volumes than traditional ETFs. The experienced professionals that are tasked with trading these instruments understand the risk of LETFs, so they often will sell their shares at the end of the day. In the United States

during 2009, leveraged ETFs accounted for almost 40% of the total trading volume of ETFs (both traditional ETFs and LETFs). This is an impressive amount because at this time, and still today, traditional ETFs account for a much larger share of the total Assets Under Management (AUM) of all ETFs. For example, the SPDR S&P500 ETF, the largest traditional ETF, had $224.82 billion in AUM in 2016, and the largest leveraged ETF in this study's data set is $3.58 billion (Statista, 2017). So, although much more of the money is placed in traditional ETF's, the LETFs are traded much more frequently because they are typically not treated as buy and hold instruments.

1.3 LETF Structure and Rebalancing

One major reason why levered and inverse ETFs can achieve their target multiple for a day, but not for a long period, is due to daily rebalancing. The following section explains the levered ETF structure, how levered ETFs are rebalanced, and how levered ETFs lose their target multiple as time goes on.

First, understand that ETFs are not traded as funds, or shares, but as units. So, let's say we have a theoretical LETF named "Fox." It is designed to do 2x the S&P 500 index, and it begins with a price of $100 per unit. If an investor buys one unit of Fox at $100, then the fund sponsor will borrow another $100 and invest the investor's money and the borrowed money ($200) into the S&P. If the S&P goes up 3% that day, then the investor is at $206. If the investor does not rebalance, then the investor won't borrow anymore, and his or her leverage multiple will now be $206/$106 or 1.94 rather than 2.00. As each day passes, this gets more and more skewed, and the return begins to look very ugly.

To incorporate rebalancing, we must bring in another variable and that is index price. Say that the index stands at 1000 at the beginning of all of this. Just like before, the investor starts with $100 and the sponsor borrows another $100, with a 3% increase the index would grow to 1030. If a fund does rebalance, the sponsor would end up with the $206, then subtract the $100 borrowed to get $106 worth of equity for the investor. Now, on day two the sponsor must borrow $106 to match investor equity in order to maintain the multiple of 2 and each unit now has $212 invested in the index. Suppose, on day two the index decreases 4%, to 988.8. The $212 also decreases by 4% and comes down to $203.52. Once the sponsor subtracts the $106 borrowed they end up with $97.52 investor equity which is an 8% decline from $106 where the investor began the day. This is exactly twice the 4% decline, so the daily objective is met once again. However, when you look at the results over the two days, you see that the overall change does not meet the benchmark multiple. Over the two days the index went from 1000 to 988.8, a decrease of 1.12%. So with the multiple of two, the investor would expect Fox to come down 2.24%, or twice the decrease from the index. However, the decrease in investor equity from $100 to $97.52 is a 2.48% decrease.

This relative shortfall in performance over longer holding periods has been well documented (Mackintosh, 2008; Trainor and Baryla, 2008). Because of this, levered and inverse ETFs have been labeled as inherently dangerous, but I believe they are important to having a complete and competitive market. Because it has only been 12 years since their creation, there is still a lot for us to learn about these unique financial instruments. As mentioned above, tracking error and holding period return has been the focus of most ETF research, but what about the price you pay for them?

1.4 Expense Ratios

Levered and inverse ETFs pay for their expenses through a charged expense ratio, typically an annual percentage of your investment. This pays for managers salaries, transaction costs, marketing, administration, and any other operating expenses of the funds. A fund's annual report provides more information on these expenses and how they come together to create the percentage they report. The ProShares 2018 Annual Report explains their administration and Custodian fees to J.P. Morgan Chase, the Listing, Data and Related fees for listing their funds on exchanges, as well as the $185,000 Trustee fee paid annually to each individual trustee for their services as a Board member.

A fund must set an expense ratio so investors know the price they are paying for their investment. Although they must charge the set expense ratio, LETF's replication strategies often create varying expenses that can be larger than anticipated. If expenses become greater than what the stated expense ratios can cover, then the fund "waives" or "reimburses" these expenses and the fund's net income decreases. A fund can recoup these losses over a five-year period, limited to the lesser of the expense limitation at the time of recoupment or the expense limitation at the time of waiver/reimbursement (Proshares, 2018). This means that if an LETF had an expense ratio of 0.90% in 2016 and expenses of 1.00% it would waive 0.10% of expenses resulting in a loss of 0.10%. If it increased its expense ratio to 1.00% in 2017 but only had expenses up to 0.89% it could recoup its loss from 2016 but only 0.01%. A LETF could set a higher expense ratio for a longer period and pass on more of their expenses to the investor but would likely suffer more by

decreasing the fund's competitiveness. As mentioned earlier, a low expense ratio is one of the main advantage's ETFs have over mutual funds. Because of this, it is important to keep these ratios as low as possible.

LETFs that have a more complicated, and therefore more expensive, replication strategy would be expected to have higher expense ratios. This can be observed in the sample of this Thesis. The funds with a lower target ratio typically have lower expense ratios. The inverse (-1x) ETFs have the lowest expense ratios of all. These funds don't have to use leverage and can enter low cost short positions on the underlying index or ETF. The triple levered (3x) and triple inverse (-3x) have the highest expense ratios in the sample, due to the cost of obtaining this leverage.

As a fund's Assets Under Management (AUM) grow over time, the fund is sometimes able to decrease its expense ratio. ProShares UltraPro S&P500, a 3x LETF, had an expense ratio of 0.95% from 2014-2017, with AUM from approximately $559 million and $880 million. The fund was able to drop its expense ratio to 0.92% in 2018 as its AUM increased to $1.4 billion (Proshares, 2018). However, AUM can fluctuate by a large amount from year to year and any change in expense ratio must be approved by the fund's board of directors, so changes like this are less frequent and relatively insignificant.

1.5 Importance

The first reason this Thesis provides value is that it explores the importance of expense ratio and performance over different holding periods. There is literature that suggests LETFs can track their index accurately for up to 6-months (Hill and Foster, 2009) or even a year (Lu, Wang, and Zhang, 2012). If an investor agrees and wants to use a LETF

as a buy and hold instrument, expense ratio could be of more importance. However, day traders can be just as sensitive to expenses. No significant relationship between expense ratio and tracking error over short holding periods would show to a daily investor that paying the lowest expense ratio is worth it because it will not affect daily return.

Another reason is that it provides an analysis into expense ratios over a recent period. Much of the research previously done on LETFs does not focus on their expense ratios and tracking error. Lots of LETF research was done soon after their inception in the late 2000s and early 2010s, during high volatility as a result of the financial crisis, and a period of market development as LETFs were being created and also dissolved. Since 2010, the market cap of ETFs has increased from about $1 trillion to nearly $3.5 trillion today. This has increased liquidity and performance of LETFs, according to Osterhoff and Kaserer, (2016). As these LETFs become more prevalent and efficient, expense ratios may become a higher point of interest for future research.

Lastly, previous research (Lu, Wang, and Zhang, 2012; Elton, Gruber, Comer and Li, 2002; and Dorocakova, 2017; among others) has focused on popular LETFs that track common indexes like the S&P 500, the Dow Jones Industrial Average, and the Russell 2000. The sample for this Thesis includes a variety of LETFs tracking a variety of indexes including the S&P Small Cap 600 Index and the Russell 1000 Financial Services Index, to name a few.

2. LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

2.1 Tracking Error and Holding Period

Most of the literature on LETFs labels them as a dangerous investment, with some going as far as warning investors to avoid them completely. The common conclusion of finance research is that LETFs underperform their underlying benchmarks due to the compounding effect. This is based on the principle that the geometric mean (average return) of a series of numbers will be lower for a series that has greater variance. LETFs are designed to create more variance in the form of higher or lower returns as defined by their target multiple. As a simple example, assume you have $100 in a 2x LETF. It had a 20% decrease to $80 when the index decreased 10%. The next day a 10% increase causes the index to increase from $90 to $99 and the LETF from $80 to $96. The fact that the index fails to return to $100 is evidence of the compounding problem, while the LETF ending at $96 explains the exacerbation of this effect due to leverage. As each day passes and the index rises and falls, this problem contributes to increasing tracking error.

Charuput and Miu (2011) use regression analyses to find that tracking error for LETFs increases with a longer holding period. More specifically, they identified that after a holding period of one week, expected returns often begin to deteriorate. After a one-month holding period, actual returns can vary significantly from target returns.

Lu, Wang, and Zhang (2012) conclude that the “2x” target LETFs can perform to twice their underlying index’s returns for a holding period of up to 1 year. They also discover that the “-2x” LETFs relationship with its underlying index breaks down after just

one quarter. These results seem to agree with those from Charupat and Miu (2011) that bearish LETFs have significantly more tracking error on average than bullish funds.

2.2 Tracking Error and Volatility

Avellaneda and Zhang (2010) find that for their sample of 56 LETFs tracking error is higher during periods of high volatility. Their conclusion is that it takes a LETF more round-trip transactions to achieve the desired leverage in a period of high volatility. As the number of transactions increase, the compounding effects on returns become more significant. The article ends with an addendum stating regulators had recently issued notices concerning the suitability of LETFs as buy-and-hold investments.

Holzhauer, Lu, McLeod and Mehran (2013) also conclude that expected market volatility, as measured by the Chicago Board Options Exchange Volatility Index (VIX), has significant effects on the daily tracking error of LETFs. They also find that these effects are stronger as target multiples increase, and strongest for inverse ETFs. Although their sample is from 2006 to 2009, a period where the VIX hit an all-time high, they are able to show that higher volatility is related to worse tracking error.

As foreshadowed by the addendum in Avellaneda and Zhang (2010), regulators now require fund sponsors to explain the effects of volatility on their stated or expected returns in a fund's prospectus. The figure below, from ProShares UltraProQQQ's prospectus, shows estimated fund returns while assuming 1) no dividends paid, 2) no Fund expenses, and 3) borrowing/lending rates of 0%.

Figure 1: Chart from ProShares UltraPro QQQ showing volatility effects on returns

Estimated Fund Returns

Index Performance		One Year Volatility Rate				
One Year Index	Three times (3x) the One Year Index	10%	25%	50%	75%	100%
-60%	-180%	-93.8%	-94.7%	-97.0%	-98.8%	-99.7%
-50%	-150%	-87.9%	-89.6%	-94.1%	-97.7%	-99.4%
-40%	-120%	-79.0%	-82.1%	-89.8%	-96.0%	-98.9%
-30%	-90%	-66.7%	-71.6%	-83.8%	-93.7%	-98.3%
-20%	-60%	-50.3%	-57.6%	-75.8%	-90.5%	-97.5%
-10%	-30%	-29.3%	-39.6%	-65.6%	-86.5%	-96.4%
0%	0%	-3.0%	-17.1%	-52.8%	-81.5%	-95.0%
10%	30%	29.2%	10.3%	-37.1%	-75.4%	-93.4%
20%	60%	67.7%	43.3%	-18.4%	-68.0%	-91.4%
30%	90%	113.2%	82.1%	3.8%	-59.4%	-89.1%
40%	120%	166.3%	127.5%	29.6%	-49.2%	-86.3%
50%	150%	227.5%	179.8%	59.4%	-37.6%	-83.2%
60%	180%	297.5%	239.6%	93.5%	-24.2%	-79.6%

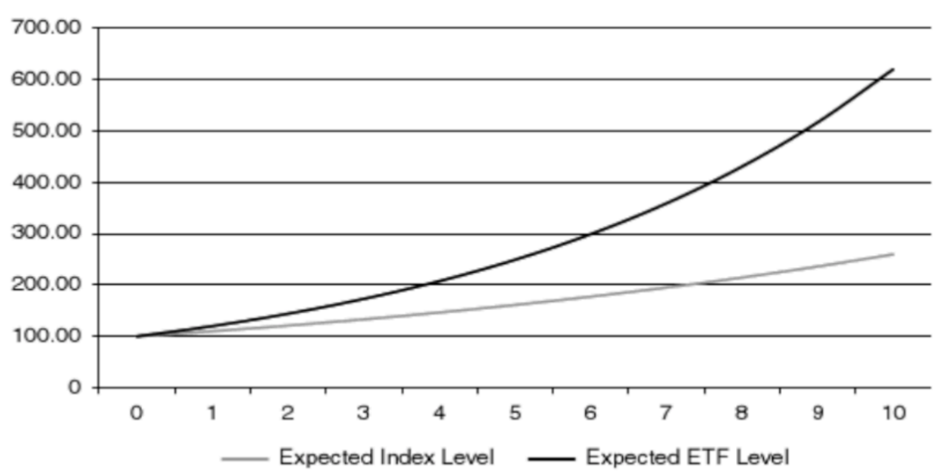
A table like this can be found in every LETF's prospectus. Notice how even a low volatility rate can create huge fluctuations as returns increase and decrease. At 10% market volatility, a 40% decrease in the index would result 41% underperformance to target for a 3x ETF. Although it is unlikely a casual investor would read this, it is evidence of regulators attempting to increase transparency and openness to the risks of LETF trading as a result of research explaining these deficiencies.

2.3 Tracking Error and Compounding Effects

The effects of compounding that cause a difference between target and actual returns are more significant in rising markets than in falling markets. Abner (2010) provides an example of how a "2x" levered ETF can outperform its underlying index significantly over a 10-day holding period in a trending market. Tables and graphs of his example showing performance deviation over 10 days for rising, "flat", and dipping markets are featured in the figures below.

Figure 2: LETF performance in 10% per day rising market (Abner, 2010)

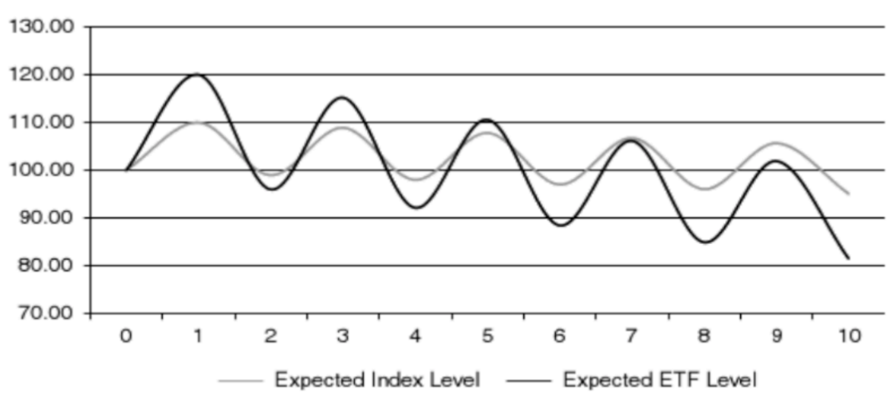
Days Elapsed	Daily Market Performance	Expected Index Level	Expected 2x Leveraged Long ETF Level	Daily ETF Performance
0	0.00%	100.00	100.00	
1	10.00%	110.00	120.00	20.00%
2	10.00%	121.00	144.00	20.00%
3	10.00%	133.10	172.80	20.00%
4	10.00%	146.41	207.36	20.00%
5	10.00%	161.05	248.83	20.00%
6	10.00%	177.16	298.60	20.00%
7	10.00%	194.87	358.32	20.00%
8	10.00%	214.36	429.98	20.00%
9	10.00%	235.79	515.98	20.00%
10	10.00%	259.37	619.17	20.00%
10-Day Cumulative Change		**159%**	**519%**	



An index with 10% increases over 10 days would expect to have a 159% cumulative change over that period. A "2x" LETF should produce twice as much as its benchmark, or 20% returns per day over the same period. One would expect this to result in 318% increase, however 20% returns over 10 days produce cumulative returns of 519%.

Figure 3: LETF performance in a flat market (Abner, 2010)

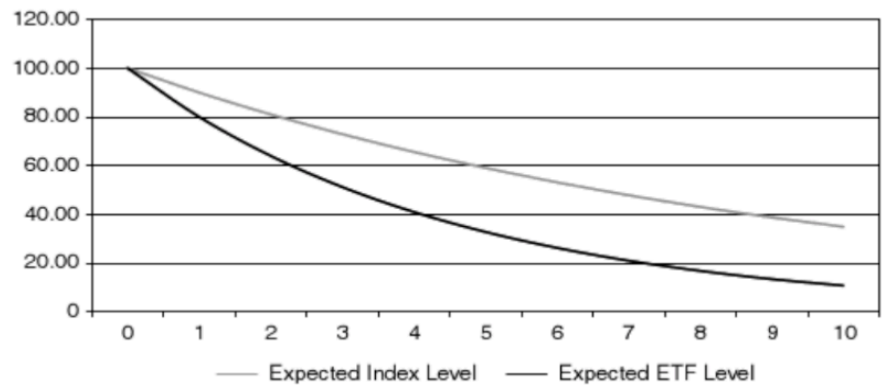
Days Elapsed	Daily Market Performance	Expected Index Level	Expected 2x Leveraged Long ETF Level	Daily ETF Performance
0	0.00%	100.00	100.00	
1	10.00%	110.00	120.00	20.00%
2	−10.00%	99.00	96.00	−20.00%
3	10.00%	108.90	115.20	20.00%
4	−10.00%	98.01	92.16	−20.00%
5	10.00%	107.81	110.59	20.00%
6	−10.00%	97.03	88.47	−20.00%
7	10.00%	106.73	106.17	20.00%
8	−10.00%	96.06	84.93	−20.00%
9	10.00%	105.67	101.92	20.00%
10	−10.00%	95.10	81.54	−20.00%
10- Day Cumulative Change		**−4.90%**	**−18.46%**	



The difference in 10-day cumulative change for a flat market, going up 10% and down 10% every other day, would be -4.90% for a benchmark, and would be -18.46% for the "2x" LETF, as opposed to the intuitive -9.8%. As you can see in the chart, expected ETF returns would be better at first, but as time goes on, compounding causes those returns to become worse and worse.

Figure 4: LETF performance in 10% per day dipping market (Abner, 2010)

Days Elapsed	Daily Market Performance	Expected Index Level	Expected 2x Leveraged Long ETF Level	Daily ETF Performance
0	0.00%	100.00	100.00	
1	−10.00%	90.00	80.00	−20.00%
2	−10.00%	81.00	64.00	−20.00%
3	−10.00%	72.90	51.20	−20.00%
4	−10.00%	65.61	40.96	−20.00%
5	−10.00%	59.05	32.77	−20.00%
6	−10.00%	53.14	26.21	−20.00%
7	−10.00%	47.83	20.97	−20.00%
8	−10.00%	43.05	16.78	−20.00%
9	−10.00%	38.74	13.42	−20.00%
10	−10.00%	34.87	10.74	−20.00%
10-Day Cumulative Change		**−65%**	**−89%**	



The LETF here ends up with less underperformance than expected (-89% rather than -130%), however, mathematically it is impossible for the index or ETF to hit a value below zero. As the market dips 10% each day, that dip becomes infinitely smaller and smaller. This is the reason that the compounding effect is less significant in a dipping market than a rising one.

This is an extreme example and uses mathematics as opposed to empirical data, but the concept remains the same. The compounding effects on returns of LETFs is an important concept for investors to consider when looking at putting money into LETF's. However, all LETFs within a target group have to deal with this disadvantage, and Lu,

Wang, Zhang (2012) show that this compounding effect can be mitigated for periods up to 1 year.

2.4 Tracking Error and Dividend Distributions

Elton, Gruber, Comer and Li (2002) analyzed the spider (SPY) ETF and find that ETFs underperform their underlying index because of transaction costs and holding dividend distributions in cash accounts. Gastineau (2004) also found underperformance of inverse or levered ETF to be attributable to their handling of dividend distributions.

A LETF may have holdings of the securities that make up its benchmark index. An example of a LETF with holdings of the underlying securities is provided by ProShares (2018). The annual report shows that ProShares UltraPro QQQ generated its 3x multiple by using 76% exposure in underlying securities, 214% in swaps and 10% futures. Some funds will accumulate dividends paid by those securities into cash accounts. The time they sit in cash accounts before getting reinvested, if they are ever reinvested, can result in an opportunity loss and variation from the index. Elton, Gruber, Comer and Li (2002) show that 9.95 basis points of underperformance for Spiders was attributable to holding dividends in cash accounts.

Charupat and Miu (2014) explain that typically funds will use those dividend distributions to help offset management fees and then will distribute any remaining money to the unit holders. These dividends are likely used to cover the “waived” or “reimbursed” expenses that the fund suffered and are unable to recoup in the future.

2.5 Tracking Error and Expense Ratio

Agapova (2011) determined that the introduction of ETFs created a substitute for conventional index funds. Within the sample of 11 ETFs and 171 conventional index funds, she finds that ETFs have lower tracking error, net of fees. Because ETFs are able to offer much lower expense ratios than conventional index funds, often at levels of 0.2-0.4% or lower, less of the variance is attributable to the expense ratio. As any financial instrument's expense ratio increases, it eats away at a small percentage of return and although index funds may track the index more accurately, the price you pay for that accuracy is not better than the extremely small price you pay for an ETF.

Rompotis (2011) concludes that his sample of 27 ETFs can better perform or match the performance of their underlying index for a period of a year or longer. He also attributes tracking error to expenses of the fund, as well as age and risk of the ETF. Through regression analysis, Rompotis finds that a higher expense ratio will significantly affect the tracking error of the fund, but admits it is not the only contributing factor. Because the expense ratio of ETFs can have an impact on their tracking ability, it could also be the case for LETFs as well. Levered and inverse ETFs also have higher expense ratios than regular or "plain vanilla" ETFs. If there is a relationship between expense ratio paid and tracking ability, the value may be more significant for LETF investors.

Due to the previous research on LETFs and tracking error, as well as ETFs and their expense ratio as it relates to tracking error, I believe there could be a significant relationship between expense ratios and tracking error of LETFs. Revealing a relationship between the two in this Thesis would provide a basis for further research into expense ratios and

performance. Although expense ratios of LETFs are relatively low when compared to other securities, paying for performance should always be a focus of investors.

3. RESEARCH QUESTION & HYPOTHESES

As I learned about levered ETFs in BUA 353 in the Fall of 2017, I was intrigued by these unique instruments. The ability to earn 3x returns on the S&P 500 as markets were rising with each day had me thinking of huge percentage returns above those who invested in the index. Soon we learned these LETFs may not be what they seem and can have significant return variance from its target. I began thinking to research on actively vs. passively managed mutual funds. Paying higher expense ratios for actively managed funds has proven to be fruitless in most cases. Because of this, I thought there could be something worth exploring in expense ratios of LETFs and their returns.

QUESTION:

> Does a higher expense ratio of a leveraged or inverse ETF lead to better performance of that ETF? Where performance is based on return relative to their underlying benchmark (tracking error).

From this question, and an evaluation of the literature on ETFs and LETFs, I was able to develop three hypotheses to test.

Hypothesis #1: *Paying for a higher expense ratio will produce higher tracking error for levered and inverse ETFs.*

From the work of Agapova (2011) on ETFs and index funds, and Rompotis (2011) on ETF performance, I believe that a higher expense ratio will eat away at returns and produce a higher tracking error for the LETF. A low expense ratio could be the separation in performance of LETFs with similar objectives. As compounding and volatility affect all

LETFs, and most handle dividend distributions in a similar way, the price you pay may be the only way to reduce tracking error. If I uncover a significant positive relationship between expense ratio and tracking error, this hypothesis would be proven true.

<u>Hypothesis #2</u>: *The higher a levered or inverse ETF's target multiple, the higher its tracking error will be.*

According to Charupat and Miu (2014) the effects of compounding are more severe for LETFs with higher target ratios. The compounding effect is one of the most significant reasons that LETFs fail to meet their target multiple over holding periods longer than a day. Holzhauer, Lu, McLeod and Mehran (2013) also claim the negative effects of volatility on tracking error are more significant for LETFs with higher target ratios. Because the compounding effect and effects of volatility are exacerbated for LETFs with higher target ratios, I expect to find the -3x and 3x LETFs to have higher tracking error than all other target groups.

<u>Hypothesis #3</u>: *Those with bearish (bullish) multiples will have worse (better) tracking error and higher (lower) expense ratios.*

The work of Lu, Wang, and Zang (2012) showed that expected returns of LETFs begin to break down after one quarter for -2x LETFs but not until a year for a 2x LETF. Along with Charupat and Miu (2011) findings that bearish funds have higher tracking error than bullish, I believe that the inverse ETFs will have higher tracking error than their

levered counterparts. Additionally, Charupat and Miu (2014) explain that bearish LETFs must face higher transactional costs and therefore have higher expense ratios, so I believe these funds will have higher expense ratios than bullish LETFs.

4. SAMPLE SELECTION & METHODOLOGY

4.1 Data

The sample of 54 levered and inverse ETFs from 2017 were pulled from ETF.com. This was a reliable first source for information on the LETFs. The website has brief descriptions of the funds as well as links to their websites. Data for AUM, expense ratio, and spread for the LETFs was also taken from ETF.com and descriptive statistics for this data can be found in Table 1 below.

Table 1: Descriptive Statistics – AUM, Expense Ratios, Spread

The table reports the descriptive statistics of all 54 LETFs for the year 2017. AUM represents Assets Under Management in millions of dollars. AUM is calculated by summing the market value of all securities, derivatives and swaps agreements owned by the fund. The expense ratio is the price paid to cover expenses of the fund, expressed as a percentage of investment. Spread is the difference between a LETF's Ask and Bid price at a given time.

Variables	*Mean*	*Median*	*Std. Dev.*	*Minimum*	*Maximum*
Full, n= 54					
AUM	$435.85	$137.49	708.31819	$2.06	$3,580
Expense Ratio	0.96%	0.95%	0.000953	0.56%	1.11%
Spread	0.18%	0.09%	0.00193	0.02%	0.84%
Panel A: Leveraged					
2x, n= 12					
AUM	556.31	167.20	811.21	3.57	2,510.00
Expense Ratio	0.90%	0.95%	0.10%	0.67%	0.95%
Spread	0.14%	0.08%	0.18%	0.02%	0.62%
3x, n= 13					
AUM	859.11	622.84	1,027.88	38.77	3,580.00
Expense Ratio	1.00%	0.95%	0.06%	0.95%	1.11%
Spread	0.13%	0.10%	0.12%	0.02%	0.36%
Panel B: Inverse					
-1x, n= 7					
AUM	330.29	260.39	491.54	4.73	1,400.00
Expense Ratio	0.89%	0.95%	0.15%	0.56%	0.95%
Spread	0.09%	0.04%	0.11%	0.03%	0.32%
-2x, n= 11					
AUM	126.18	26.66	246.00	2.34	829.78
Expense Ratio	0.94%	0.95%	0.02%	0.89%	0.95%
Spread	0.33%	0.25%	0.28%	0.03%	0.84%
-3x, n= 11					
AUM	181.06	128.13	164.00	2.06	419.32
Expense Ratio	1.02%	0.95%	0.09%	0.90%	1.11%
Spread	0.16%	0.09%	0.16%	0.04%	0.58%

After the sampling of LETFs was completed, transaction level data for the LETFs was obtained from the Center for Research in Security Prices (CRSP). Agapova (2011), Elton, Gruber, Comer and Li (2002), Lu, Wang, and Zhang (2012), and many others have

used CRSP for accurate and expansive U.S. ETF historical data. Because of this and the access granted from my advisor, I decided that CRSP would be the most adequate source. “Plain vanilla” ETFs data also came from CRSP, so all return data could come from a single and reliable source. The data for both the LETFs and plain ETFs collected from CRSP included daily percentage returns, daily volume, price (bid/ask average), company name, PERMNO, and number of shares outstanding.

Appendix A provides a list of the LETFs in the sample. Appendix B provides a description and definition of the variables used in the analysis.

4.2 Descriptive Statistics

The sample included 25 leveraged and 29 inverse ETFs. This is made up of 12 LETFs with a “2x” target multiple, 13 with a “3x” target, 7 with a “-1x” target, 11 with a “-2x” target and 11 with a “-3x” target. The largest expense ratio is 1.11% and belongs to the Direxion Daily S&P Biotech Bear 3X Shares, Ticker: LABD (-3x) and the Direxion Daily Semiconductor Bear 3x Shares, Ticker SOXS (-3x). Notice here that the LETFs with the highest expense ratios are bearish, and three times multiple. This would seem to support Charupat and Miu (2014) concept that bearish and high multiple LETFs have higher expenses than bull or low multiple LETFs. The lowest expense ratio is 0.56% and belonged to Direxion Daily S&P 500 Bear 1X Shares, Ticker: SPDN (-1x). The entire sample has a mean expense ratio of 0.96%. Table 2 below provides descriptive statistics for all LETFs by target multiple.

Table 2: Descriptive Statistics by Target Multiple

This table reports descriptive statistics of LETFs by target multiple for a 6-month holding period. Volume is the number of shares traded in a day. The expense ratio is the price paid to cover expenses of the fund. Returns represents the percentage daily returns over the time period. Plain Ret represents the return of the underlying or "plain vanilla" ETF. Target represents daily *expected* return of the LETF based on the target multiple.

Full, n= 6750	*Mean*	*Median*	*Std Dev*	*Max*	Min
Volume	1,065,924.23	221,756.00	1,964,390.94	22,998,238.00	-
Expense Ratio	0.00956	0.00950	0.00095	0.01110	0.00560
Returns	-0.00003	-0.00030	0.01724	0.13031	-0.13145
Plain Ret	0.00092	0.00098	0.00685	0.03110	-0.04406
Panel A: Leveraged					
2x, n= 1500					
Volume	251,295.97	23,968.5	468,944.45	3,034,047	0
Expense Ratio	0.00903	0.00950	0.00095	0.00950	0.00670
Returns	0.00177	0.00140	0.01364	0.08345	-0.07918
Plain Ret	0.00093	0.00098	0.00659	0.02912	-0.04406
Target	0.00185	0.00197	0.01317	0.05825	-0.08811
3x, n= 1625					
Volume	1,040,122	491,151	1,298,868.67	8,679,270	0
Expense Ratio	0.01000	0.00950	0.00059	0.01110	0.00950
Returns	0.00251	0.00243	0.02149	0.09372	-0.13145
Plain Ret	0.00089	0.00093	0.00728	0.03110	-0.04406
Target	0.00267	0.00278	0.02184	0.09330	-0.13217
Panel B: Inverse					
-1x, n= 875					
Volume	498,076.48	210,047.00	803,433.92	6,114,375.00	-
Expense Ratio	0.00886	0.00950	0.00135	0.00950	0.00560
Returns	-0.00084	-0.00093	0.00549	0.02123	-0.02860
Plain Ret	0.00088	0.00093	0.00549	0.02912	-0.02144
Target	-0.00088	-0.00093	0.00549	0.02144	-0.02912
-2x, n= 1375					
Volume	736,100.39	23,928.00	1,383,393.82	12,542,116.00	-
Expense Ratio	0.00945	0.00950	0.00017	0.00950	0.00890
Returns	-0.00190	-0.00202	0.01380	0.07597	-0.06322
Plain Ret	0.00100	0.00107	0.00680	0.02912	-0.04406
Target	-0.00199	-0.00215	0.01360	0.08811	-0.05825
-3x, n= 1375					
Volume	2,676,284.97	940,603.00	3,280,456.35	22,998,238.00	-
Expense Ratio	0.01015	0.00950	0.00082	0.01110	0.00900
Returns	-0.00259	-0.00289	0.02189	0.13031	-0.09414
Plain Ret	0.00090	0.00097	0.00744	0.03110	-0.04406
Target1	-0.00270	-0.00290	0.02232	0.13217	-0.09330

Note that the sample sizes represent 125 days (6-months) for each LETF. Thus, for the "2x" target, n= 1500 because there are 12 LETFs with that target multiple. Target data is the "Plain Ret" data multiplied by the funds target multiple. For example, the mean "Plain Ret" for 3x is 0.089%, and the Target value is 0.267%, or 0.089% * 3. The minimum of 0 for volume shows that on some day(s) there was an LETF that was not traded.

Expense ratios are the smallest for the "-1x" LETFs. These seven funds have a mean expense ratio of 0.886% and a minimum of 0.56%. These funds don't need to obtain significant leverage and instead provide individual investors a cheaper and simpler way to short an index. Of the seven LETFs, six of them are provided by ProShares and one is provided by Direxion. The Direxion -1x ETF (ticker: SPDN) has an impressively low expense ratio, which is also the lowest in the entire sample at just 0.56%. The six Proshares inverse ETFs have expense ratios of 0.95% with the exception of the Proshares Short S&P 500, (ticker: SH) at 0.89%. For 2017, SPDN had the highest tracking error of the group. SH had the second highest tracking error for the group. The fact that both track the S&P 500 implies there may be a relationship between the performance or direction of the index they track and their tracking error. However, the fact that the inverse ETF with the lowest expense ratio produced the highest tracking error is an important anecdotal observation. This also differs from the expectations of Charupat and Miu (2014) that the higher an LETFs expense ratio, the more it would be expected to underperform its index.

The 3x and -3x targets are the only fund groups that have expense ratios above 1%. All 3x LETFs have a mean expense ratio of 1.0% and -3x have a mean of 1.01% These are both higher than even the maximum (0.95%) from any other target group. The 2x grouping has a minimum of 0.67% and a mean of 0.903%. Compare this to the -2x target group with

a minimum of 0.89% and a mean 0.945%, the higher price paid for the -2x group further solidifies the claim from Charupat and Miu (2014) that bearish LETFs face higher transactional expenses than other funds.

4.3 Tracking Error

Tracking error is the measurement for levered and inverse ETF performance. A perfectly operating LETF would have a tracking error of 0, any deviation away from zero is considered underperformance. Some investors may consider higher than expected return, or less negative than expected return as better performance, however a fund's performance should be measured relative to its objective. For this thesis tracking error is calculated using this equation:

$$TE = f_t - (Li_t)$$

Where, TE represents tracking error, f_t is the LETFs actual return, i_t is plain vanilla ETF return, and L is the fund's target multiple. The study on leveraged ETF performance by Bansal and Marshall (2015) uses this equation to find tracking error of 2x and 3x LETFs. For a positive target multiple, underperformance is a negative tracking error. However, calculating tracking error this way causes a negative target multiple to have a positive tracking error when it is underperforming. This may seem complicated, but it is not and does not affect the results of my analysis. Simply put, tracking error is the deviation away from zero, regardless of sign. Table 3 below reports tracking error descriptive statistics by target ratio for a holding period of 1, 5, 10, 21, 63, and 126-days.

Table 3: Tracking Error Descriptive Statistics by Target Ratio

This table reports descriptive statistics for tracking error for the 54 LETFs over various holding periods.

Tracking Error	*Mean*	*Median*	*Std Dev*	*Maximum*	*Minimum*
2x, n= 1500					
1 day	-0.00007937	-0.000091	0.0067824	0.058535	-0.07244
5 days	-0.00071683	-0.0004585	0.00929	0.083662	-0.0636
10 days	-0.0013116	-0.0009285	0.0115841	0.055351	-0.06038
21 days	-0.0027446	-0.0018015	0.0150971	0.061067	-0.06772
63 days	-0.006882	-0.0054975	0.0180745	0.082463	-0.0905
126 days	-0.0123738	-0.0102905	0.023951	0.099994	-0.11855
3x, n= 1625					
1 day	-0.00016043	-0.000146	0.0032105	0.027087	-0.02936
5 days	-0.0010025	-0.000794	0.0066257	0.044061	-0.08563
10 days	-0.0019576	-0.001572	0.0093425	0.05073	-0.08036
21 days	-0.0040449	-0.003209	0.0114962	0.067964	-0.09904
63 days	-0.0107976	-0.009203	0.0109889	0.032626	-0.1326
126 days	-0.0179502	-0.01711	0.014373	0.100808	-0.13464
-1x, n= 875					
1 day	0.000047983	0.00004	0.0015455	0.014679	-0.01089
5 days	0.000216853	0.000249	0.0014527	0.01083	-0.01137
10 days	0.000422616	0.000457	0.0015555	0.014606	-0.01176
21 days	0.000881851	0.000975	0.0018055	0.015796	-0.0169
63 days	0.0024057	0.002598	0.0025462	0.021834	-0.01475
126 days	0.0037628	0.003987	0.0033411	0.023806	-0.01263
-2x, n= 1375					
1 day	0.000087498	0.000103	0.0046316	0.029803	-0.05279
5 days	0.00057978	0.000383	0.0076694	0.051207	-0.04018
10 days	0.0011751	0.000779	0.0107661	0.052887	-0.0489
21 days	0.0025543	0.001531	0.0147531	0.065847	-0.05411
63 days	0.0059244	0.004708	0.0173649	0.083787	-0.06719
126 days	0.0091553	0.006424	0.0232801	0.11488	-0.06285
-3x, n= 1375					
1 day	0.000107489	0.000107	0.0038898	0.027636	-0.03072
5 days	0.00074352	0.000548	0.007352	0.085123	-0.0444
10 days	0.0014005	0.001139	0.0103336	0.078199	-0.05056
21 days	0.0029096	0.002193	0.0127144	0.098132	-0.06994
63 days	0.0068645	0.006117	0.0124179	0.128537	-0.03996
126 days	0.0079232	0.007742	0.0175529	0.123266	-0.11148

Note that within the columns for mean and median, tracking error increases for all target multiples as holding periods increases. For the inverse (-1x) LETFs, the one-day holding period has a TE (0.0000479) or .00479%. However, increasing to a one-week holding period shows the tracking error becomes five times greater (0.00021685). Across the data set there is a similar pattern. Not only does tracking error increase, it increases by the multiple increase in holding period. This means that tracking error for a 10-day HP to a 21-day would nearly double, and from 21-day to 63-day it would be close to triple. To show this further, see that the inverse LETFs 20-day HP tracking error is 0.000881 which is nearly twice that of the 10-day (0.00021685). The -3x tracking error for a holding period of 10-days is 0.00140, and the tracking error for 21-days is 0.00291 - almost three times as much. This increasing tracking error over longer holding periods supports the work of Charupat and Miu (2011).

The positive target multiples have higher amounts of tracking error (farther from zero) than the negative target multiples. This would vary from the results of Charupat and Miu (2014) who state that LETFs with negative target multiples experience higher levels of tracking error due to their bearish nature and the transaction costs of creating those returns. The inverse (-1x) ETFs had the lowest amount of tracking error for all target groups at every holding period. For a holding period of 6 months the inverse group was able to average a tracking error of just 0.37% which is nearly three times less than the next closest group which was -2x at 0.92%. The inverse group also had a maximum tracking error for 6 month holding period of 2.38% a much lower maximum than other target groups, 11.86% (2x), 13.46% (3x), 11.48% (-2x) and 12.33% (-3x).

The 2x LETFs appear to have less average tracking error than the 3x target group throughout the holding periods. The -1x multiple also has less tracking error than -2x and -3x target groups. Lastly, the -2x has lower tracking error than the -3x over all holding periods, with the exception of 6 months. This would agree with Charupat and Miu (2014) and Holzhauer, Lu, McLeod and Mehran (2013) who determined that LETFs with higher target ratios will experience higher levels of tracking error.

4.4 Methodology

This thesis uses a tracking error approach from (Bansal, Marshall 2015) with common statistical regression methods to test the impact of expense ratio on tracking error. This method differs from tracking error calculations used by Charupat and Miu (2011, 2014), Agapova (2011), and Shum and Kang (2013) among others, for a reason. Their method uses a regression of an ETF or LETF's change in NAV returns to its underlying index change in NAV returns to measure a funds tracking error. However, a fund's NAV is free from any management expenses so there would be no relationship between these returns and an LETFs expense ratio (Rompotis, 2011). The approach used in this study allows me to use a simpler measure of tracking error and then use regression analysis to look for a causal relationship between that error and the LETFs expense ratio.

4.4.1 "Plain Vanilla" ETF Proxy

This study also compares the returns of a sample of LETFs to the returns of plain vanilla ETFs which track the same indexes as the given LETF. A "plain vanilla" is an unlevered ETF that simply tracks an index without leverage. This method is also used by Lu, Wang, and Zang (2012) in their testing of leveraged ETF returns. Using plain vanilla

ETFs as a proxy is an acceptable analysis method because of their ability to track an index more efficiently than conventional index funds. Agapova (2011) claims that the difference in means of tracking error between conventional funds and ETFs is significant. The lower amount of tracking error for ETFs in her sample suggests that ETFs can track the underlying indexes more efficiently than conventional index funds. Agapova also states that tracking error is the important factor for investors expecting return of the underlying index, which is even more important to investors expecting a stated multiple of return on that index. The ability to use plain vanilla ETFs provided important analysis validity by allowing us to take all return data from a single source, the Center for Research in Security Prices.

4.4.2 Time Period Selection

Deciding on a time period and duration for the return data was based on Lu, Wang, and Zhang (2012) who concluded that a holding period of one year can still produce adequate returns for 2x LETFs. Because of these results, I felt that one year would be a sufficient maximum period for return data. Later in the thesis process, when we began regression analysis on the Statistical Analysis Software, I experienced issues with the size of data files going from SAS to Excel. In order to keep data files to a manageable size, I did not include the holding period of 1-year in the results. I decided to use holding periods of 5, 21, 63, and 126 days because of work done by Charupat and Miu (2014) and Lu, Wang & Zhang, (2012). These time periods are also logical benchmarks, one week, one month, one quarter, and $\frac{1}{2}$ year based on trading days.

Selecting data from the year 2017 was intended to provide results on recent data. Data for only 251 days per LETF aided in keeping data size reasonable (original N=13554). As ETF and LETF markets continue to develop, we may be able to uncover information that was not found by previous research. Using recent data may help the analysis of performance now more than research done previously, because LETF markets are more mature and LETFs have become more liquid and better performing as time has passed. Using data from a single year in this study serves as a way to observe short- and long-term performance while slightly mitigating the effects of trending markets.

4.4.3 Data Preparation

From the list of LETFs, I copied all tickers into CRSP to produce return data for every day of 2017. Due to trading days of the particular year, the data ranges from January 3, 2017 to December 29, 2017. Along with daily percentage returns, I also pulled daily volume, price (bid/ask average), company name, PERMNO, and number of shares outstanding data.

Once sample data was extracted from CRSP and imported to Excel, the next step was to match each LETF with the underlying plain vanilla ETF that could serve as a proxy for the underlying index. It was imperative to understand exactly which index or plain vanilla ETF the fund is tracking. For a LETF like *ProShares Short S&P500,* it is rather obvious it tracks the S&P500, or for the purpose of this study, the ETF ticker: SPY. For others, it required searching sponsor and LETF websites to read through prospectuses or daily holdings to give more insight into each fund's structure. However, for some it was

challenging and resulted in a decision to remove any LETFs with doubt of target index from the data set.

Once all plain vanilla ETFs were found, their return data was also pulled from CRSP and imported to Excel. Next, I added three columns next to the LETF return data (f_t). The columns are Plain Return (i_t), Target (Li_t), and Tracking Error (TE). For each LETF, I copied all 251 days data of returns for its plain vanilla ETF and pasted it into the Plain Return column. Then, to create the data for the Target column, I multiplied the data in the Plain Return column by the respective LETF's target multiple (2x, 3x, -1x, -2x, -3x). I followed the equation below for tracking error used by Bansal and Marshall (2015) to calculate tracking error in the final column.

$$TE = f_t - (Li_t)$$

As mentioned previously, this measure of tracking error produces negative tracking error for levered ETFs when they underperform and positive tracking error for inverse ETFs. It was not possible to take the absolute value of all negative tracking errors because the analysis requires adding tracking error of each day for the holding period to get total tracking error for the period. Absolute values of each day would result in an extremely high and inaccurate tracking error for levered ETFs. One could take the absolute value of the *holding period tracking error* of an LETF to solve the signage issue. However, that complexity would add more work than value and the issue can be addressed with this simple explanation and the understanding that for the purpose of this Thesis tracking error is the deviation away from 0.

Once the Excel file was complete with all relevant data for the analysis, the final step was to add binary variable columns to help the processing capability of the Statistical

Analysis Software, referred to as SAS. To do this I created five new columns in the file, pos2, pos3, neg1, neg2, neg3. Next, I used simple "IF" logic, to assign a 1, or 0, in the column indicating a "yes" or "no" to that given target ratio. For example, ProShares Ultra S&P 500 (Ticker: SSO) has a 2x target multiple, so the formula "=IF(I2155="2x",1,0)" where I2155 is a cell within the "Target Ratio" column, will return 1 in the pos2 column and 0 in all other columns. Using the simple binary of 0 and 1 helps SAS quickly identify the pieces of data required for analysis.

4.4.4 Statistical Analysis Software

The complete Excel file was imported to SAS for the final descriptive statistics and regression analysis. With the help of Thesis Advisor, Dr. Stephen Jurich, I began writing the code SAS would use to process the LETF data. The first step was to run descriptive statistics for volume, expense ratio, returns, plain returns and target returns on the full sample of LETFs as well as each target group. The code for the analysis of the entire sample looks like this:

```
proc means n mean median std max min data=etf2;
var volume expense_ratio returns plain_ret target;
run; quit;
```

This is telling the system to run the sample size, mean, median, standard deviation, max and min analysis for variables volume, expense ratio, returns, plain returns, and target within the data set "etf2". Next, the same analysis would be done but the binary variables would be used to sort the data by target multiple, to get more detailed descriptive statistics. The code `proc sort data=etf2; by neg1; run; quit;` will sort the data to only show data for LETFs with a 1 in the neg1 column. A code very similar to the one used for the

entire sample is repeated for this set of neg1 LETFs, and the process is repeated for each target multiple. These descriptive statistics for the LETFs are combined into Table 2.

Next, I used SAS to develop tracking error for holding periods of 5, 10, 21, 63, and 126 days. The code for this can get complicated. I will explain the process for a five day holding period, but note that this process is repeated for each holding period. The code for this process will develop an ongoing summation of five day holding periods for each LETF. The first measure will be tracking error for days 1-5, the second will be days 2-6, third will be 3-7, and so on for 126 days – this process is an example of a lag argument. The code looks like this:

```
data etf3; set etf2;
lag1te=lag1(track_error);
lag2te=lag2(track_error);
lag3te=lag3(track_error);
lag4te=lag4(track_error);
lag5te=lag5(track_error);
run; quit;

data etf4; set etf3;
sum5te = lag1te + lag2te + lag3te + lag4te + lag5te;
run; quit;

data etf5; set etf4;
if lag1te ne permno then delete;
run; quit;
```

Creates a new column with tracking error -1 day, -2 days, -3 days, etc.

Sum5te is a new variable, representing 5-day holding period tracking error, which I will use in SAS to run descriptive statistics and regression analysis. The last section tells SAS to delete previous entries where a change in permno is detected. This is to avoid calculating tracking error for two different LETFs due to the construction of the return data.

Once this process was completed for each holding period, I had variables *sum5te, sum10te, sum21te, sum63te, and sum126te*.

Using similar code for the descriptive statistics of the LETFs, I was able to quickly calculate descriptive statistics for tracking error of different holding periods for all target multiples. These statistics are provided in Table 3.

The last and most important step was to perform the regression analysis on expense ratios and tracking error. Because of the work and planning done before hand, this final step was simple coding. The regression code is as follows: `proc reg data=etf5; model sum5te = expense_ratio; by pos2; run; quit;` The code written here would give us regression results for tracking error and expense ratio for 2x LETFs with a holding period of 5 days. This process would be repeated for pos2 sum10te, pos2 sum21te, and so on. And then that entire process would be repeated again for every target multiple. All of the final regression data was then aggregated into Table 4, which can be found in Section 5 of this Thesis. Note that the code above would produce only the results for the top right corner of Table 4, 2x target multiple at 5 day holding period.

5. RESULTS

Testing Hypothesis #1 is the main objective of this study and the focus of significant casual regression analysis. Hypothesis #2 and Hypothesis #3 are testable based on pure observation rather than statistical analysis. For the second two, I observed the sample to test if the tracking error and expense ratio data matched trends found in previous ETF research. For this Thesis, the regression line equation of $y = mx + b$ labels the dependent variable of y as tracking error, and independent variable of x as expense ratio, where b is the starting value or intercept for tracking error. Table 4 below reports the regression results for expense ratio impact on tracking error of levered and inverse ETFs.

Table 4: Regression Results by Target Ratio.

Regression results where dependent variable = tracking error, independent variable = expense ratio. ***, and ** represent significance at the 1%, and 5% level respectively.

Expense Ratio Reg	2x Estimate (t-stat)	3x Estimate (t-stat)	-1x Estimate (t-stat)	-2x Estimate (t-stat)	-3x Estimate (t-stat)
5 days					
Intercept	-0.00001305	0.00005354	0.00067016**	-0.00012	-0.00166
	(-0.01)	(0.02)	(2.05)	(0.01)	(-0.68)
Expense Ratio	-0.07791	-0.10561	-0.05118	0.07408	0.23714
	(-0.31)	(-0.38)	(-1.4)	(0.06)	(0.98)
R-Square	0.0001	0.0001	0.0023	0.00	0.0007
10 days					
Intercept	0.00286	0.00051548	0.0013***	-0.00095	-0.00366
	(1.00)	(0.13)	(3.72)	(0.06)	(-1.06)
Expense Ratio	-0.46227	-0.24731	-0.09886	0.22479	0.49876
	(-1.46)	(-0.63)	(-2.54)	(0.13)	(1.47)
R-Square	0.0014	0.0002	0.0073	0.00	0.0016
21 days					
Intercept	0.00955	0.00181	0.00271***	-0.00403	-0.0082
	(2.56)	(0.37)	(6.74)	(-0.19)	(-1.93)
Expense Ratio	-1.3615***	-0.58537	-0.20633***	0.69738	1.09415***
	(-3.32)	(-1.21)	(-4.60)	(0.30)	(2.62)
R-Square	0.0073	0.0009	0.0237	0.0001	0.005
63 days					
Intercept	0.02979***	-0.0003531	0.00799***	0.01186	-0.00925**
	(6.81)	(-0.08)	(14.77)	(0.46)	(-2.24)
Expense Ratio	-4.05923***	-1.04445**	-0.63015***	-0.62821	1.58689***
	(-8.43)	(-2.25)	(-10.44)	(-0.23)	(3.91)
R-Square	0.0453	0.0031	0.1111	0.00	0.011
126 days					
Intercept	0.05802***	-0.01217**	0.01363***	0.04444	0.02637***
	(10.28)	(-2.00)	(20.27)	(1.29)	(4.50)
Expense Ratio	-7.79249***	-0.5777	-1.11393***	-3.73587	-1.81709***
	(-12.54)	(-0.95)	(-14.84)	(-1.03)	(-3.16)
R-Square	0.095	0.0006	0.2015	0.0008	0.0072

5.1 -1x Target

The inverse LETFs showed a significant negative relationship between expense ratio and tracking error for holding periods of 21, 63, and 126 days. This refutes Hypothesis #1 by showing that paying for a higher expense ratio can decrease tracking error for inverse ETFs. According to my results, for a holding period of 21 days, each basis point increase in expense ratio would be expected to produce a 0.21% decrease in tracking error. Increasing the holding period to 126 days and the same increase could save 1.11% in tracking error for the period. This suggests there may be a good reason to pay for a higher expense ratio for an inverse ETF if you're planning to hold it for a period longer than a few weeks. This likely has to do with their simple engineering when compared to the LETFs that use derivatives contracts to achieve leverage, whereas these ETFs simply take your money and flip it by shorting the underlying security. -1x ETFs are lumped in with leveraged and inverse ETFs because their objective is different from that of a typical ETF. However, they don't use leverage as -2x, and -3x ETFs do. Because of this, they do not have to rebalance daily and therefore do not experience the increased effects of compounding due to leverage. There is much less significance in the remaining results, which I believe is a sign of the effects of compounding on the sample of LETFs.

The finding that a higher expense ratio can lead to better performance of an inverse ETF may also have significant connection to how the is ETF is constructed. The SPDN inverse ETF (Previously discussed in Section 4.2 *Descriptive Statistics*) had a significantly lower expense ratio (0.56%) than most inverse ETFs (Range from 0.89%-0.95%). I believe SPDN's expense ratio is this low because of its simple construction. A look into the daily holdings of Direxion Daily S&P500 Bear 1x as of 11/15/2018 is in Figure 5 below. As of

that date, the fund consisted of a single shorted S&P 500 Index swap worth $13,418,748 and a combination of assets to equally offset this liability.

Figure 5: Direxion Daily S&P500 Bear 1x Daily Holdings, 11/15/2018

Security Description	Shares	Price	Market Value
S&P 500 INDEX SWAP	(4,967.00)	2,701.58	(13,418,747.86)
BANK OF NEW YORK CASH RESERVE	10,363,306.60	1.00	10,363,306.60
GOLDMAN FINL SQ TRSRY INST 506	2,905,505.52	1.00	2,905,505.52
GOLDMAN FINL SQ TRSRY INST 506	4.12	1.00	4.12

This framework is much simpler than one like ProShares Short Dow30 (Ticker: DOG). DOG's daily holdings look similar to SPDN's except for the amount of transactions they use and how much cash they hold (Figure 6). DOG also happens to charge a much higher expense ratio at 0.95% than SPDN. But, as our results tell us, this more complicated and expensive time-deferred maturity framework seems to mitigate tracking error for inverse ETFs better than a cheaper method. The details of how managers come to these numbers, what each strategy is, and which is more effective is beyond the scope of this Thesis.

Figure 6: ProShares Short Dow 30 Daily Holdings, 11/15/2018

Security Description	Maturity Date	Shares	Price	Market Value
DJ Industrial Average SWAP Goldman Sachs International		(3,497)	(87,694,294)	
DJ Industrial Average SWAP Citibank NA		(1,548)	(38,835,323)	
DJ Industrial Average SWAP Societe Generale		(1,035)	(25,967,823)	
DJ Industrial Average SWAP Credit Suisse International		(902)	(22,618,648)	
DJ Industrial Average SWAP Deutsche Bank AG		(785)	(19,689,045)	
DJIA MINI 12/21/2018 (DMZ8)		(115)	(14,415,250)	
DJ Industrial Average SWAP Bank of America NA		(269)	(6,738,930)	
DJ Industrial Average SWAP UBS AG		(134)	(3,358,329)	
DJ Industrial Average Index SWAP BNP Paribas		(40)	(1,003,220)	
UNITED STATES TREASURY BILL	11/15/18	33,000,000		33,000,000
UNITED STATES TREASURY BILL	12/13/18	32,000,000		31,946,551
UNITED STATES TREASURY BILL	1/3/19	25,000,000		24,924,373
UNITED STATES TREASURY BILL	12/6/18	9,000,000		8,988,575
UNITED STATES TREASURY BILL	11/23/18	8,000,000		7,996,218
UNITED STATES TREASURY BILL	11/29/18	7,000,000		6,994,208
UNITED STATES TREASURY BILL	12/20/18	7,000,000		6,985,351
UNITED STATES TREASURY BILL	12/27/18	7,000,000		6,981,931
UNITED STATES TREASURY BILL	1/31/19	5,000,000		4,975,563
UNITED STATES TREASURY BILL	2/28/19	5,000,000		4,966,057
UNITED STATES TREASURY BILL	3/28/19	5,000,000		4,956,636
UNITED STATES TREASURY BILL	1/10/19	4,000,000		3,986,109
UNITED STATES TREASURY BILL	1/17/19	4,000,000		3,984,250
UNITED STATES TREASURY BILL	2/7/19	4,000,000		3,978,510
UNITED STATES TREASURY BILL	2/14/19	4,000,000		3,976,479
UNITED STATES TREASURY BILL	1/24/19	3,000,000		2,986,729
UNITED STATES TREASURY BILL	2/21/19	3,000,000		2,980,992
UNITED STATES TREASURY BILL	3/7/19	3,000,000		2,978,253
UNITED STATES TREASURY BILL	3/14/19	3,000,000		2,976,882
UNITED STATES TREASURY BILL	3/21/19	3,000,000		2,975,404
Net Other Assets / Cash		220,252,007		220,252,007

The sample of -1x LETFs had less tracking error in all holding periods than the higher leveraged -2x and -3x LETFs. These findings agree with Charupat and Miu (2014) and confirm Hypothesis #2 that the higher target multiple LETFs will have higher tracking error than lower targets. These findings are likely due to the effects of compounding and the theory that compounding effects are exacerbated by higher target ratios.

5.2 -2x Target

For any holding period, there is no significant relationship found between expense ratio and tracking error for the -2x target group. There are many potential explanations for this result, however my expectation is this result is due to the unity in expense ratios for the -2x group. All eleven of the LETFs except for one have an expense ratio of 0.95%, the other has an expense ratio of 0.89%. Because there was very little variation in expense ratios, it is difficult to find a statistically significant connection between this price and the tracking error.

The sample of -2x LETFs had more tracking error in all holding periods than their lower leveraged -1x cohorts as well as less tracking error than the more levered -3x target group. This agrees with Charupat and Miu (2014) as well as Hypothesis #2 that the higher target multiple LETFs will have higher tracking error than lower targets.

In regard to Hypothesis #3, the -2x LETFs had less tracking error in all holding periods than their bullish counterparts but they also had higher expense ratios than the 2x target group. At a holding period of 126 days, -2x LETFs had a mean tracking error of 0.91%, and the 2x LETFs had a mean tracking error of 1.24% over the same period. Table 3 reports tracking error data. This would refute the claim of Charupat and Miu (2011) and Lu, Wang, and Zhang (2012) that bearish funds have more tracking error than bullish. However, when looking at expense ratios of -2x and 2x in Table 2, the mean -2x expense ratio is 0.945% and the 2x is 0.903%. The higher expense ratios of the -2x group confirms the second half of Hypothesis #3 and Charupat and Miu (2014) findings that bearish LETFs have higher expense ratios than bullish.

5.3 -3x Target

The results for the -3x target grouping may be the most puzzling of all. There is a significant positive relationship between expense ratio and tracking error with a holding period of 21 and 63 days, but it becomes a significant negative relationship at a holding period of 126 days. The results for a holding period of 21 or 63 days would support Hypothesis #1, that a higher price produces higher tracking error. However, the 126-day results refute it.

The explanation for these results relates to the effects of compounding in a trending market. As shown by Abner (2010), the direction of the underlying ETF's return will impact the direction and size of tracking error for a LETF. Because of this concept and the understanding that higher leveraged ETFs experience more of the compounding effect, the change in direction of the relationship makes a little more sense.

Although there is variation in the results for -3x over different holding periods, the negative relationship for expense ratio and tracking error at a holding period of 126 days is in agreement with results for -1x and 2x target groups with the same holding period.

The sample of -3x LETFs had more tracking error in all holding periods than their lower leveraged -2x and -1x partners. These findings agree with Charupat and Miu (2014) as well as Hypothesis #2 that the higher target multiple LETFs will have higher tracking error than lower targets.

Similarly to the -2x and 2x LETFs, the -3x target group had higher expense ratios than their 3x counterparts, consistent with findings of Charupat and Miu (2014). The -3x group had a higher mean expense ratio (1.01% vs. 1.00%) as well as a lower minimum, showing there were higher expense ratios for -3x LETFs than the 3x group (Table 2 and

Appendix A). However, the -3x LETFs had lower tracking error than the 3x LETFs (Table 3) which refutes the first half of Hypothesis #3 and the findings of Charupat and Miu, 2011; Shum and Kang 2013) that bearish LETFs have more tracking error than bullish.

5.4 2x Target

For the sample of 12 double levered ETFs in the data set, there was a statistically significant negative relationship between expense ratio and tracking error that grows as holding period increases. At a holding period of 21-days, each basis point increase in expense ratio would expect to produce a 1.36% decrease in tracking error. Increasing the holding period to 126-days will result in a 7.79% decrease in tracking error for each increase of the same increment. The t-stat also grows from -3.32 at 21-days to -12.54 at 126 days showing that the relationship gets stronger as holding period increases. One significant difference from these results and the results for -1x and -3x is the magnitude of estimate results. At a holding period of 126-days, a one basis point increase in expense ratio would only expect to decrease tracking error 1.11% and 1.82% for the -1x and -3x target group respectively, which is much less than 7.79%. These results refute Hypothesis #1 and lead us to believe that paying for a higher expense ratio can actually produce lower tracking error for 2x LETFs. Ignoring the possible effects of compounding on the LETF returns, this could show investors that the tracking error (only 1.24% for a holding period of 126-days) can be reduced by paying for the most expensive LETFs in their target group.

The sample of 2x LETFs had less tracking error in all holding periods than the 3x LETF group. As is the case for all target groups, these findings confirm Charupat and Miu

(2014) claims as well as Hypothesis #2, that more levered (higher target ratio) LETFs will have higher tracking error than lower targets.

The results for 2x target ratio relating to Hypothesis #3 reflect the same results mentioned in Section 4.2. The 2x LETFs had more tracking error in all holding periods than their bearish counterparts (Table 3), but they also had lower expense ratios on average than the 2x target group (Table 2). This result disagreed with the claim of Shum and Kang, 2013; Charupat and Miu, 2011) that bearish funds have more tracking error than bullish. This result also confirms Charupat (2014) that bullish LETFs should have lower expense ratios than bearish.

5.5 3x Target

The 3x target group showed no significant relationship between expense ratio and tracking error for any holding period except for 63 days. Because there is no growing significance like there is for the 2x and -1x groups, this one period of significance is likely due to chance. Although the results returned significance to the 5% level, most of the other significant results were to the 1% level. The R^2 for this relationship is also the lowest of any statistically significant relationship, furthering the point that this result may be a false positive. The only other group without a significant relationship was the -2x target group. Section 4.2 discusses the uniformity of -2x LETF expense ratios. Unlike the -2x group, the sample of 3x LETFs has a wide variety of expense ratios and was still unable to uncover a significant relationship. A variety of expense ratios removes data quality as a reasonable explanation for the lack of a relationship. This leads me to make the conjecture that compounding had a significant effect on 3x returns. The results show no relationship

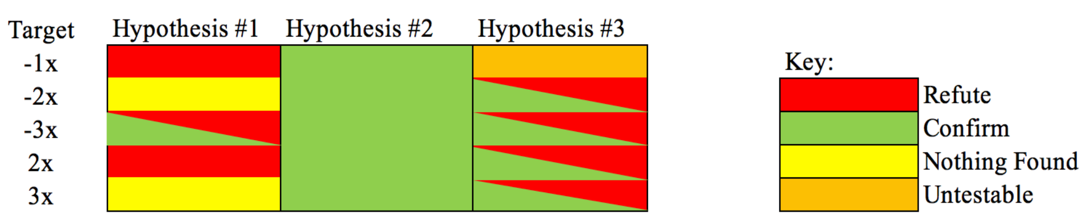
between expense ratio and tracking error for 3x target group, and, because of this, I am unable to reject or confirm Hypothesis #1 for the group.

Hypothesis #2 expected the higher levered ETFs to have more tracking error than their lower levered partners. The 3x target group confirmed this hypothesis and had higher tracking error than the 2x ETFs for every holding period. A higher target group (more levered) having more tracking error agrees with findings of Charupat and Miu (2014) that the effects of compounding are more significant for LETFs with more leverage.

The 3x target group had higher tracking error than the -3x group which disagrees with Hypothesis #3, but it did have lower expense ratios which confirms the second half of Hypothesis #3. These results refute Charupat and Miu (2011) but confirm the findings of Charupat and Miu (2014), that bullish LETFs typically have lower expense ratios because of their lower transaction costs.

5.6 Results Further Discussion & Recommendation for Future Research

Figure 7 below shows the results of this Thesis for hypothesis by target ratio.



Hypothesis #1 was refuted by the regression results which showed a significant negative relationship between expense ratio and tracking error for -1x, 2x, and -3x LETFs. The -3x did confirm Hypothesis #1 over a holding period of 21 and 63 days. Because there were varying results for the -3x target group and no significant results for the 3x and -2x target ratios, I hesitate to accept my results for the -1x, -3x (HP of 126) and 2x LETFs as

absolute. However, I do trust the analysis I have conducted and think there is more work to be done. Controlling for the effects of compounding, volume, volatility, and market trends may help paint a clearer picture of the relationship between expense ratios and tracking error. In my opinion, the compounding effect is the largest reason why I was unable to find significant results for more of the sample.

Hypothesis #2 was confirmed across the board for nearly all holding periods. LETFs with higher target ratios, or more leverage, experienced higher levels of tracking error. These results serve as evidence of the compounding effect. As holding period increases, tracking error will also increase due to the effects of compounding, and this effect is exacerbated by higher tracking errors. This has been shown by Charupat and Miu (2011), Lu, Wang amd Zang (2012), and Bansal and Marshall (2015) among others and inclined me to blame the compounding effect for variation in my regression results.

For the final hypothesis, I found results across the board that agree with Charupat and Miu (2014) that bullish ETFs will have higher expense ratios than bearish LETFs. However, I also had data that refuted Charupat and Miu's (2011) claim that bullish ETFs have better, or lower, tracking error than bearish ETFs. In the sample, nearly all bullish ETFs actually had more tracking error than their inverse counterparts. Because I confirmed part of the hypothesis but refuted the second part, I entered a $\frac{1}{2}$ box for Hypothesis #3 in Figure 7 above.

The R^2 of the regression analysis were low for all target multiples and holding periods. The highest R^2 of all the regression results is 0.2015, for the -1x target group at a 126-day holding period. Typically, a low R^2 would be an indicator that a large proportion of the variance in tracking error is not attributable to changes in expense ratio. However, it

is common to have a low coefficient of determination for a regression analysis on LETFs and their return data. Elton, Gruber, Comer, and Li (2002), Agapova (2011), Charupat and Miu (2011) among others were able to come to significant conclusions despite having R^2 that were at similar levels

While this Thesis has provided more insight into the pricing and performance of LETFs, further research can be done to help investors make informed decisions when trading LETFs. I believe it would be insightful to do a Sponsor vs Sponsor test to see if there is any significance to how each provider prices or structures their LETF. There were only two providers for the sample, Direxion and ProShares, and each had a different make up of daily holdings. They also had a much different range of expense ratios. Because of this, each sponsor may have significantly different replication strategies for certain target ratios or indexes. I feel that research comparing tracking error of ProShares LETFs tracking the S&P500 to Direxion LETFs also tracking the S&P500 would help investors understand differences in providers, which is just as important as understanding the difference between a Chevy and a Ford.

The analysis conducted in this Thesis could be improved in future research. Using a more complex model put forth by Charupat and Miu (2014) to control for the effects of financing (transaction costs) and compounding may provide more insight as to what proportion of the tracking error is attributable to each variable. However, this method uses the NAV method for calculating tracking error which would mitigate our ability to assess the expense ratio's role in creating this error. This Thesis could also benefit from a more advanced statistical analysis where factors like volume, volatility, and market direction are taken into account. Because LETFs are extremely complicated instruments that have well

documented tracking error, it has also been well documented that many factors can contribute to this error. As a result, it can be difficult to account for all these factors while looking for causality in a single one. As outlined by the literature review, expense ratios have been of less focus in LETF literature. However, as the other components of tracking error become clearer, more precise research can be conducted on expense ratios and their relationship with tracking error.

6. CONCLUSION

In conclusion, this Thesis set out to further understand the relationship between a levered or inverse ETF's expense ratio and its tracking error. The Thesis used a sample of 54 Index tracking LETFs and return data for the period January 3, 2017 to December 29, 2017. During the research process, I used the tracking error equation from Bansal and Marshall (2015) and regression analysis on tracking error and expense ratios to test for a causal relationship between the two.

The guiding Hypothesis #1 was refuted by the results of a regression analysis on tracking error and expense ratio over multiple holding periods. Generally, the results support the claim that an increase in expense ratio can decrease tracking error of LETFs, and that this relationship is more significant for longer holding periods. However, results did vary based on target multiple and holding period, and one target group had results that flipped from positive to negative as holding period increased. Because of the varying results, further research is needed to understand the relationship between tracking error and an LETF's expense ratio. Specifically, a model that controls for compounding, volatility, benchmark index and market trends would provide a much better conclusion on the issue.

With respect to the second two hypotheses, the results were able to overwhelmingly confirm Hypothesis #2 and provide further evidence that tracking error is larger for more levered ETFs over all holding periods. This result is likely due to the exacerbating effects leverage can have on the compounding effect. Results relating to Hypothesis #3 both confirm and refute it. The results showed that bearish LETFs had better tracking error than bullish ETFs, refuting Hypothesis #3. However, results also showed bearish LETFs had higher expense ratios, confirming the expectations of Hypothesis #3.

This Thesis has added to the growing pool of valuable LETF research. As relatively new instruments, there is still much to be learned about the behavior of these levered securities. The negative causal relationship between expense ratio and tracking error found in this Thesis could be important to investors who are confident in LETF performance over holding periods between 21 and 126 days. If investors enter their position with an understanding of compounding and LETF tracking error, they may want to pay a higher price to decrease this tracking error, so long as the higher price does not outweigh the benefits of lower tracking error. Further research is needed before these results can be applied to investing without a disclaimer.

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Appendix A: List of LETFs included in the data set, grouped by target ratio

Ticker	Fund Name	Underlying ETF	Objective	Expense Ratio
SH	ProShares Short S&P500	SPY	-1x	0.89%
PSQ	ProShares Short QQQ	QQQ	-1x	0.95%
RWM	ProShares Short Russell2000	IWM	-1x	0.95%
DOG	ProShares Short Dow30	DIA	-1x	0.95%
SPDN	Direxion Daily S&P 500 Bear 1X Shares	SPY	-1x	0.56%
MYY	ProShares Short MidCap400	MDY	-1x	0.95%
SBB	ProShares Short SmallCap600	SLY	-1x	0.95%
SDS	ProShares UltraShort S&P500	SPY	-2x	0.89%
QID	ProShares UltraShort QQQ	QQQ	-2x	0.95%
DXD	ProShares UltraShort Dow30	DIA	-2x	0.95%
TWM	ProShares UltraShort Russell2000	IWM	-2x	0.95%
BIS	ProShares UltraShort Nasdaq Biotechnology	IBB	-2x	0.95%
SKF	ProShares UltraShort Financials	XLF	-2x	0.95%
MZZ	ProShares UltraShort MidCap400	MDY	-2x	0.95%
REW	ProShares UltraShort Technology	XLK	-2x	0.95%
SIJ	ProShares UltraShort Industrials	DIA	-2x	0.95%
SDD	ProShares UltraShort SmallCap600	SLY	-2x	0.95%
SSG	ProShares UltraShort Semiconductors	SOXX	-2x	0.95%
SQQQ	ProShares UltraPro Short QQQ	QQQ	-3x	0.95%
SPXU	ProShares UltraPro Short S&P500	SPY	-3x	0.90%
TZA	Direxion Daily Small Cap Bear 3x Shares	IWM	-3x	1.10%
SPXS	Direxion Daily S&P 500 Bear 3X Shares	SPY	-3x	1.10%
SDOW	ProShares UltraPro Short Dow30	DIA	-3x	0.95%
FAZ	Direxion Daily Financial Bear 3X Shares	XLF	-3x	1.10%
LABD	Direxion Daily S&P Biotech Bear 3X Shares	XBI	-3x	1.11%
SRTY	ProShares UltraPro Short Russell2000	IWM	-3x	0.95%
SOXS	Direxion Daily Semiconductor Bear 3x Shares	SOXX	-3x	1.11%
ZBIO	ProShares UltraPro Short Nasdaq Biotechnology	IBB	-3x	0.95%
SMDD	ProShares UltraPro Short MidCap400	MDY	-3x	0.95%
SSO	ProShares Ultra S&P 500	SPY	2x	0.90%
QLD	ProShares Ultra QQQ	QQQ	2x	0.95%
UYG	ProShares Ultra Financials	XLF	2x	0.95%
DDM	ProShares Ultra Dow30	DIA	2x	0.95%
BIB	ProShares Ultra NASDAQ Biotechnology	IBB	2x	0.95%
UWM	ProShares Ultra Russell2000	IWM	2x	0.95%
MVV	ProShares Ultra MidCap400	MDY	2x	0.95%
USD	ProShares Ultra Semiconductors	SOXX	2x	0.95%
SAA	ProShares Ultra SmallCap600	SLY	2x	0.95%
UXI	ProShares Ultra Industrials	DIA	2x	0.95%
SPUU	Direxion Daily S&P 500 Bull 2x Shares	SPY	2x	0.67%
SMLL	Direxion Daily Small Cap Bull 2X Shares ETF	IWM	2x	0.72%
TQQQ	ProShares UltraPro QQQ	QQQ	3x	0.95%
FAS	Direxion Daily Financial Bull 3x Shares	XLF	3x	1.02%
UPRO	ProShares UltraPro S&P500	SPY	3x	0.95%
SPXL	Direxion Daily S&P 500 Bull 3x Shares	SPY	3x	1.04%
TNA	Direxion Daily Small Cap Bull 3x Shares	IWM	3x	1.11%
SOXL	Direxion Daily Semiconductor Bull 3x Shares	SOXX	3x	1.02%
UDOW	ProShares UltraPro Dow30	DIA	3x	0.95%
LABU	Direxion Daily S&P Biotech Bull 3X Shares	XBI	3x	1.08%
URTY	ProShares UltraPro Russell2000	IWM	3x	0.95%
MIDU	Direxion Daily Mid Cap Bull 3x Shares	MDY	3x	1.08%
FINU	ProShares UltraPro Financial Select Sector	XLF	3x	0.95%
UBIO	ProShares UltraPro Nasdaq Biotechnology	IBB	3x	0.95%
UMDD	ProShares UltraPro MidCap400	MDY	3x	0.95%

Appendix B: Metrics of Measurement

Terminology	Definition	Calculation
Expense Ratio	The price that the investor pays to cover the expenses of the fund. This figure is expressed as a percentage of the value of your investment in the fund.	This is selected by the fund provider and varies based on their target objective, fund construction, transactional costs, and other variable expenses.
AUM	The total market value of all the fund's financial assets at a given time.	Sum of the market value of all securities, derivatives and swaps agreements owned by the fund.
Volume	The number of shares of the LETF that are traded that day.	Sum of all trades during trading hours.
NAV	The value of each share's portion of the fund's underlying assets, calculated at the close of the trading day.	$\frac{(Fund\ Assets - Liabilities)}{\#\ of\ Shares\ Outstanding}$
Tracking Error	The deviation between an LETF's return and the underlying index or underlying ETF's return multiplied by the fund's target multiple.	$TE = f_t - (Li_t)$ Where: TE = tracking error f_t = LETFs actual return i_t = plain vanilla ETF return L = target multiple
Return	The percentage increase of the LETF over a period of time. For the case of our study it is the percentage return of the LETF over one-year.	Summation of daily return percentages for the holding period.
Bid-Ask (Spread)	The amount that an ask price exceeds a bid price for an LETF.	$Ask\ price - Bid\ price = Spread$ $\frac{Spread}{Ask\ Price} = Spread\ \%$

Appendix C: SAS code used for Regression analysis

```
***tracking error HP 1 year, Regression with expense ratio
proc reg data=etf2;
model track_error = expense_ratio;
run; quit;

proc reg data=etf2;
model track_error = expense_ratio neg2 neg3 pos2 pos3;
run; quit;

proc reg data=etf2;
model track_error = expense_ratio neg2 neg3 pos2 pos3 volume;
run; quit;

proc reg data=etf2;
model track_error = expense_ratio neg2 neg3 pos2 pos3 volume bidask;
run; quit;

proc reg data=etf2;
model track_error = expense_ratio bidask;
run; quit;
***tracking error holding period;
data etf3; set etf2;
lag1te=lag1(track_error);
lag2te=lag2(track_error);
lag3te=lag3(track_error);
lag4te=lag4(track_error);
lag5te=lag5(track_error);
lag1ticker=lag1(permno);
lag2ticker=lag2(permno);
lag3ticker=lag3(permno);
lag4ticker=lag4(permno);
lag5ticker=lag5(permno);
lag6ticker=lag6(permno);
run; quit;

data etf4; set etf3;
sum5te = lag1te+lag2te+lag3te+lag4te+lag5te;
run; quit;

data etf5; set etf4;
if lag1ticker ne permno then delete;
run; quit;

proc means n mean median std max min data = etf5;
var sum5te track_error;
run; quit;
```

Appendix D: Direxion Daily S&P 500 Bull 2x Shares (SPUU) First Page of Prospectus

Direxion ETFs | Funds

Summary Prospectus February 28, 2018
Direxion Shares ETF Trust

Direxion Daily S&P 500® Bull 2X Shares

Ticker: SPUU
Listed on NYSE Arca

Before you invest, you may want to review the Fund's prospectus, which contains more information about the Fund and its risks. You can find the Fund's prospectus and other information about the Fund, including the Fund's statement of additional information and shareholder report, online at http://www.direxioninvestments.com/regulatory-documents. You can also get this information at no cost by calling Fund Investor Services at 866-476-7523 or by sending an e-mail request to info@direxionshares.com, or from your financial intermediary. The Fund's prospectus and statement of additional information, both dated February 28, 2018, and the most recent shareholder report, are incorporated by reference into this Summary Prospectus.

Important Information Regarding the Fund

The Direxion Daily S&P 500® Bull 2X Shares (the "Fund") seeks ***daily leveraged*** investment results and is very different from most other exchange-traded funds. As a result, the Fund may be riskier than alternatives that do not use leverage because the Fund's objective is to magnify the daily performance of the S&P 500® Index (the "Index"). This means that the return of the Fund for a period longer than a trading day will be the result of each trading day's compounded return over the period, which will very likely differ from 200% of the return of the Index for that period. As a consequence, longer holding periods, higher volatility of the Index and greater leverage increase the impact of compounding on an investor's returns. During periods of higher Index volatility, the volatility of the Index may affect the Fund's return as much as, or more than, the return of the Index. Further, the return for investors that invest for periods less than a trading day will not be 200% of the performance of the Index for the trading day.

The Fund is not suitable for all investors. The Fund is designed to be utilized only by knowledgeable investors who understand the potential consequences of seeking daily leveraged investment results, understand the risks associated with the use of leverage and are willing to monitor their portfolios frequently. The Fund is not intended to be used by, and is not appropriate for, investors who do not intend to actively monitor and manage their portfolios. An investment in the Fund is not a complete investment program.

Investment Objective

The Fund seeks daily investment results, before fees and expenses, of 200% of the daily performance of the Index. **The Fund does not seek to achieve its stated investment objective for a period of time different than a trading day.**

Fees and Expenses of the Fund

This table describes the fees and expenses that you may pay if you buy or hold shares of the Fund ("Shares"). Investors purchasing Shares in the secondary market may pay costs (including customary brokerage commissions) charged by their broker.

Annual Fund Operating Expenses (expenses that you pay each year as a percentage of the value of your investment)

Management Fees	0.50%
Distribution and/or Service (12b-1) Fees	0.00%
Other Expenses of the Fund	1.04%
Acquired Fund Fees and Expenses	0.07%
Total Annual Fund Operating Expenses	1.61%
Expense Cap/Reimbursement[1]	-0.94%
Total Annual Fund Operating Expenses After Expense Cap/Reimbursement	0.67%

[1] Rafferty Asset Management, LLC ("Rafferty" or the "Adviser") has entered into an Operating Expense Limitation Agreement with the Fund. Under the Operating Expense Limitation Agreement, Rafferty has contractually agreed to waive all or a portion of its management fee and/or reimburse the Fund for Other Expenses through September 1, 2019, to the extent that the Fund's Total Annual Fund Operating Expenses exceed 0.60% of the Fund's average daily net assets (excluding, as applicable, among other expenses, taxes, swap financing and related costs, acquired fund fees and expenses, dividends or interest on short positions, other interest expenses, brokerage commissions and extraordinary expenses).

Any expense waiver or reimbursement is subject to recoupment by the Adviser within the following three years only if overall expenses fall below the lesser of this percentage limitation and any percentage limitation in place at the time. This agreement may be terminated or revised at any time with the consent of the Board of Trustees.

Example - This example is intended to help you compare the cost of investing in the Fund with the cost of investing in other mutual funds. The example assumes that you invest $10,000 in the Fund for the time periods indicated and then redeem all of your shares at the end of those periods. The example also assumes that your investment has a 5% return each year and that the Fund's operating expenses remain the same. Although your actual costs may be higher or lower, based on these assumptions your costs would be:

1 Year	3 Years	5 Years	10 Years
$68	$416	$787	$1,832

Portfolio Turnover

The Fund pays transaction costs, such as commissions, when it buys and sells securities (or "turns over" its portfolio). A higher portfolio turnover rate may indicate higher transaction costs and may result in higher taxes when Fund shares are held in a taxable account. These costs, which are not reflected in Annual Fund Operating Expenses or in the example, affect the Fund's performance. During the most recent fiscal year,

Appendix E: Proshares Ultra Short (QID) – Daily Holdings – 10/11/18

Fund Ticke	Fund Name	Security Description	Maturity Date	Shares/Contracts	Exposure Value	Market Value
QID	ProShares UltraShort QQQ	NASDAQ 100 Index SWAP Deutsche Bank AG	.	-20214.77	-141834731.13	
QID	ProShares UltraShort QQQ	NASDAQ 100 Index SWAP Societe Generale	.	-17455.44	-122474237.81	
QID	ProShares UltraShort QQQ	NASDAQ 100 Index SWAP Credit Suisse Interr	.	-8937.83	-62711301.03	
QID	ProShares UltraShort QQQ	NASDAQ 100 Index SWAP Bank of America N	.	-6886.83	-48320748.29	
QID	ProShares UltraShort QQQ	NASDAQ 100 Index SWAP Goldman Sachs Int	.	-6476.93	-45444694.95	
QID	ProShares UltraShort QQQ	NASDAQ 100 Index SWAP Morgan Stanley & (	.	-4713.07	-33068744.23	
QID	ProShares UltraShort QQQ	NASDAQ 100 Index SWAP UBS AG	.	-4195.73	-29438941.16	
QID	ProShares UltraShort QQQ	NASDAQ 100 Index SWAP Citibank NA	.	-4156.69	-29164972.18	
QID	ProShares UltraShort QQQ	PowerShares QQQ (QQQ) SWAP Morgan Star	.	-803.22	-2091135.08	
QID	ProShares UltraShort QQQ	NASDAQ 100 Index SWAP BNP Paribas	.	-142	-996327.38	
QID	ProShares UltraShort QQQ	PowerShares QQQ (QQQ) SWAP Goldman Sa	.	-227.74	-592923.05	
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	12/13/2018	64000000		63817600
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	11/08/2018	42000000		41968320.66
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	12/06/2018	41000000		40900424.12
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	11/15/2018	40000000		39953000
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	11/23/2018	15000000		14974887.45
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	11/01/2018	14000000		13995161.18
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	11/29/2018	14000000		13971803.58
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	12/20/2018	14000000		13953906.96
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	12/27/2018	14000000		13947045.98
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	02/28/2019	10000000		9919965.3
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	03/28/2019	10000000		9899753.1
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	01/03/2019	9000000		8961575.58
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	01/31/2019	9000000		8944074.63
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	01/17/2019	7000000		6963667.34
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	02/07/2019	7000000		6953766.96
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	02/14/2019	7000000		6950466.25
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	01/10/2019	6000000		5971753.32
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	01/24/2019	6000000		5965725
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	02/21/2019	6000000		5954668.32
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	03/07/2019	6000000		5948712.48
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	03/14/2019	6000000		5945876.88
QID	ProShares UltraShort QQQ	UNITED STATES TREASURY BILL	03/21/2019	6000000		5942938.32
QID	ProShares UltraShort QQQ	Net Other Assets / Cash		296178860.61		296178860.61

AUTHOR'S BIOGRAPHY

Grant Carrier was born March 27, 1995 to his loving parents Paul and Paula Carrier. He was raised in the coastal town of Falmouth, Maine. He graduated from Saint Dominic's Academy in 2013 among the top of his class. At St. Dom's he was also a three-sport athlete, State Champion in Golf, and a finalist for the Tavis Roy Award for the top player in the State. He then pursued junior hockey in Massachusetts as well as education in Alabama, before transferring to the University of Maine for the fall of 2015. Throughout the last three and a half years, he has been pursuing a double major in Finance and Accounting as well as a minor in Psychology. Throughout his time in Orono, Grant been an active member of the Men's Club Hockey team and served as the club's President for his senior year.

After graduating with a perfect GPA, Grant plans to obtain his CPA and pursue a career in public accounting. He will begin a job at RSM US, formerly McGladrey, in Boston, MA as a tax associate in January 2019.