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Abstract

This study provides an empirical analysis to determine whether leveraged exchange-traded funds are contributing to excess intraday volatility. The study, which is centered around the introduction dates of six leveraged ETFs, uses high-frequency TAQ data for the S&P 500 constituent stocks to compare volatility before and after the introduction dates. Realized volatility is calculated for the morning, afternoon, and entire trading day during the twenty trading days before, and twenty trading days after each date of interest. There has been a lot of debate recently about whether leveraged ETFs could be increasing swings in intraday volatility. Up until now, this debate has persisted almost exclusively among practitioners and professionals. This study is the first in-depth, academic approach to the problem. Making use of the rich TAQ database to measure intraday volatility around the event days, some suspicions are confirmed while others are not.

1 Introduction

Review of Leveraged ETF Dynamics

Before diving into the problem at hand, it is worthwhile to review the dynamics of leveraged ETFs (LETFs) to better understand the role these financial instruments play in the marketplace. LETFs, like their vanilla ETF counterparts, are exchange traded funds that track the return some index, commodity, or basket of assets. The difference, obviously, is that LETFs use leverage to obtain some multiple of the return of its underlying assets. LETFs can be designed to offer long exposure of $2\times$ or $3\times$ or, conversely, short exposure of $-2\times$ or $-3\times$ the underlying index return.

While leveraged funds have existed for decades, leveraged ETFs in particular have seen an increase in volume in recent years because of their attractive features for traders and investors. With over 100 LETFs trading in the US, short-term traders can easily express a directional speculation on a variety of indices, sectors, or commodities. Also, because leverage is explicitly embedded in the security, investors can hedge their portfolios in the short-term without the need to enter into the swaps, options, or futures markets or without having to trade on margin. As LETFs become more popular, there is an increased concern among some that these financial instruments could be contributing to greater volatility in the market, especially near the end of the trading day.

The main reason behind this concern is due to the fact that at the end of each trading day, LETFs must re-balance their portfolios to maintain a constant exposure ratio and guarantee the same level of promised returns during the next trading day. What is most troubling to some, and also counterintuitive, is that no matter what the return of the underlying index is for the day is, both long and short LETFs must re-balance by trading in the same direction as the index return for that day.

It is worthwhile to demonstrate an example to illustrate why LETF re-balancing always results in pro-cyclical trading at the end of the day. As Cheng and Madhavan (2009) explain, LETFs can use a combination of futures, swaps, and equities to achieve their promised leveraged returns. Total return swaps are generally used by LETFs since these swaps are easily customizable and guarantee a desired multiple of returns relative to the underlying index. A total return swap is simply an agreement between two parties to exchange the total return of the underlying's performance for a specified time period and notional amount. Whether these swaps are used or whether a leveraged position in the actual underlying or futures is used to achieve the fund's desired return is unimportant. Any trading of derivatives is known to ultimately affect trading in the market (for example, if a long position in the futures market is taken, the corresponding market maker is accepting a short position in the futures market and must hedge by taking a long position in the actual underlying securities). In the examples below, we will look at both long and short LETFs and the re-balancing needed at the end of each trading day. Assume in both cases an initial index value of $100.00 and also an initial fund net asset value (NAV) of $100.00.

Table 1: Example of 2X Long LETF Rebalancing

Period	Index Level	Index Return	Fund Return	Fund NAV	Exposure Needed	Change in Exposure
n = 0	100	-	-	100	200	-
n = 1	110	10%	20%	120	240	+40
n = 2	100	-9.09%	-18.18%	98.18	196.36	-43.63

Table 2: Example of 2X Short LETF Rebalancing

Period	Index Level	Index Return	Fund Return	Fund NAV	Exposure Needed	Change in Exposure
n = 0	100	-	-	100	-200	-
n = 1	110	10%	-20%	80	-160	+40
n = 2	100	-9.09%	-18.18%	94.55	-189.09	-29.09

As demonstrated above, when the value of the underlying index increases (positive return), both long and short LETFs must rebalance by trading in the same direction. The long LETF must *increase* its exposure, and the short LETF must *decrease* its *negative* exposure (net positive change in exposure). Conversely, when the underlying index decreases (negative return), both long and short LETFs must decrease their exposure. This means that regardless of the index return for any given day, both long and short LETFs must engage in pro-cyclical trading at the end of the day. It is this pro-cyclical trading by LETFs that some argue is exacerbating market volatility toward the end of the trading day.

Prior Research

LETFs have been under fire in recent years. Some money managers blame LETFs for contributing to increased volatility in the stock market, especially toward the end of the trading day due to rebalancing. For example, in one recent New York Times article[1], Douglas A. Kass, founder and president of Seabreeze Partners Management, is quoted as describing LETFs as the "new weapons of mass destruction," referencing Warren Buffett's famous line that derivatives are "weapons of mass destruction." Describing the effect LETFs have on the market, Mr. Kass says, "They've turned the market into a casino on steroids. They accentuate the moves in every directions - the upside and the downside."

In addition, Harold Bradley and Robert E. Litan of the Kauffman Foundation[2] write about the potential effects of the LETF rebalancing on the market, stating "The S.E.C., the Fed and other members of the new Financial Stability Oversight Council, other policy makers, investors and the media should pay far more attention to the proliferation of ETFs and derivatives of ETFs." This sentiment has been echoed by many other people in the field of money management.

However, some professionals hold an opposing view. Michael Rawson, CFA and ETF analyst for Morningstar[3], recently wrote an article arguing that LETFs are not to blame for increased market volatility. In the article, he expresses skepticism, pointing out that leveraged and inverse ETFs account for just 3.2% of all U.S. ETF assets, and that it is hard to imagine that such a small segment of the market could impact market volatility.

Deshpande, Mallick, and Bhatia (2009), showed that the percentage of market capital traded by LETFs for the S&P 500 account for only 0.0079% of total volume. Even though volume in LETFs has increased since 2009, this suggests that any impact LETFs might have on volatility would be very small.

William J. Trainor Jr. (2010) of East Tennessee State University studied volatility of the S&P 500

[1] Andrew Ross Sorkin. (October 11, 2011) "Volatility, Thy Name is E.T.F." The New York Times, DealBook Column.

[2] Bradley, H., Litan, R.E. (Nov 12, 2010) "Choking the Recovery: Why New Growth Companies Aren't Going Public And Unrecognized Risks Of Future Market Disruptions." The Ewing Marion Kauffman Foundation.

[3] Michael Rawson.(December 26, 2011) "Leveraged ETFs Aren't the Cause Of Increased Market Volatility" news.morningstar.com/articlenet/article.aspx?id=450684 as of June 1, 2012

during the financial crisis, a time of extremely high volatility and the period when LETFs began to come under fire. He showed that while volatility did increase in the afternoon, volatility increased uniformly throughout the day and so the rise in volatility can not be driven by rebalancing. Volatility has since reached stable levels.

To my knowledge, this is the first in-depth academic study of this issue which takes advantage of the rich high-frequency TAQ data. This study provides something more concrete by means of an event study centered around the introduction dates of several LETFs. If LETFs are in fact contributing to excess intraday volatility, there are significant implications regarding market efficiency and portfolio management. If LETFs continue to gain traction among investors, we could expect and even further rise in volatility as well as predictability in the direction of the market during the final minutes of trading.

2 Data and Methodology

This study is centered around six LETFs that were introduced into the market over four introduction dates. The six LETFs are comprised of three long LETFs with each of their respective short counterparts. All correspond to the S&P500 as their underlying. Table 3 shows the introduction date, name, ticker, and leverage ratio for each LETF:

Table 3: Intro Dates for Leveraged ETFs

Introduction Date	Name	Ticker	Leverage
June 21, 2006	ProShares Ultra S&P500	SSO	2X
July 13, 2006	ProShares UltraShort S&P500	SDS	-2X
November 7, 2007	Guggenheim 2x S&P500	RSU	2X
	Guggenheim Inverse 2x S&P500	RSW	-2X
June 25, 2009	ProShares UltraPro S&P500	UPRO	3X
	ProShares UltraPro Short S&P500	SPXU	-3X

To compare intraday volatility around these introduction dates, information from the Trade and Quote (TAQ) database is used. TAQ data provides tick-by-tick trades and quotes for many securities, including the S&P 500 constituent stocks that are of interest for this study. Using a computer program written in C++ and Python programming languages, this TAQ data was extracted for all of the S&P 500 stocks for each introduction date and for twenty trading days before, and twenty trading days after each introduction date. This data is then merged with data from the Center for Research in Security Prices (CRSP). This database gives us the market capitalization, price, and daily volume for each stock is merged with the TAQ database in order to control for these variables in the regression analysis.

Controlling for market cap, price, and volume is important because, in theory, a company with a smaller market cap should be relatively more affected by any change in trading activity than a company with a large market cap. Likewise, a company with low trading volume should be relatively more affected by any change in trading activity than a company with a large market cap. Because of the finite tick size of one cent, any fluctuation in prices due to a change in trading activity is likely to have a greater effect on shares that trade at lower prices relative to shares that trade at higher prices.

The measure of interest in this study is the integrated volatility over a specific period of time. Realized volatility can usually be used to estimate this measure and is calculated simply by taking the sum of squared, continuously compounded returns over a period of time. For example, let S_t denote the price of a security at time t, and $X_t = logS_t$, then realized volatility can be expressed by:

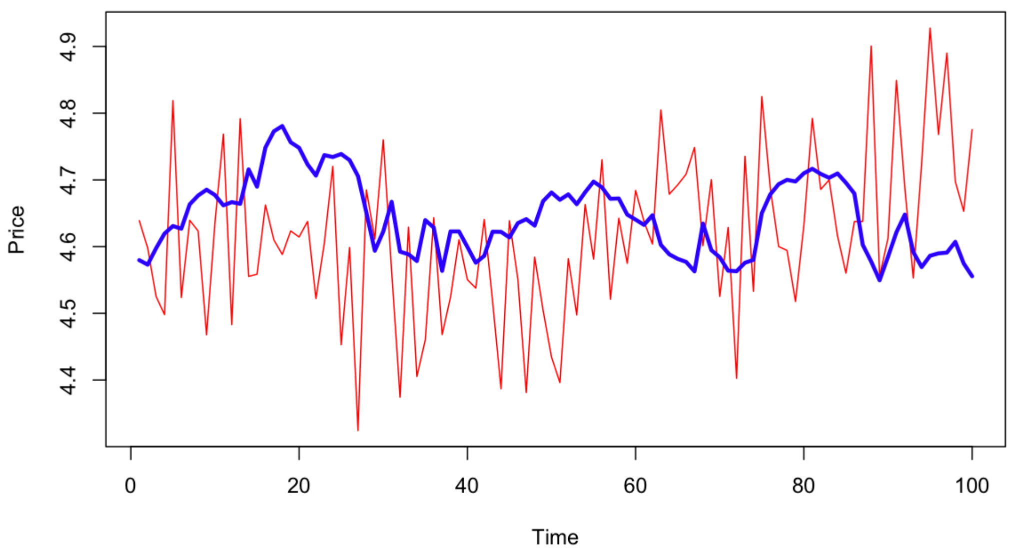
$$[X, X]_T = \sum_{t_i} (X_{t_{i+1}} - X_{t_i})^2,$$

In theory, using realized volatility is an efficient and unbiased method of estimating integrated volatility since it follows, theoretically, that:

$$plim \sum_{t_i} (X_{t_{i+1}} - X_{t_i})^2 = \int_0^T \sigma_t^2 dt.$$

It would seem from the theoretical result above that with an increasingly frequent sample, that the sum of squared returns would, in the limit, provide a perfect measure of integrated volatility. Therefore, it would seem that with TAQ data, we are in a good position to estimate realized volatility. This would be true if not for the reality of market microstructure noise. When working with high-frequency data, such as the TAQ data used in this study, a problem arises in that taking the sum of squared returns results in capturing only the microstructure noise instead of the underlying volatility. Market microstructure noise, which is primarily represented by the bid-ask spread, can manifest itself as large swings in the stock price because the market maker sells at a higher price, and buys at a lower price relative to the true value of the security. Figure 1 represents two security price paths through time. The thick, blue line represents a path without noise. This is the path that would exist in an ideal, continuous stochastic world. However, reality (modeled by the thin, red line) is that microstructure noise has a profound effect on the behavior of any asset path.

Figure 1: Graph of a security price path through time with microstructure noise (thin red line) and without microstructure noise (thick blue line).



In analyzing high-frequency data, the accuracy of realized volatility in estimating true volatility is seriously compromised by noise. Using realized volatility at high-frequencies results in the estimation of only the noise when we would otherwise think we are measuring volatility.

Aït-Sahilia, Mykland, and Zhang (2005) develop a more advanced estimator, which is referred to as the Two-Scales Realized Volatility (TSRV) estimator. It combines sub-sampling, averaging, and bias-correcting to measure realized volatility while stripping out all noise without having to sacrifice any data. A brief overview of how this estimator is developed is worthwhile, which includes the introduction of five estimators, each successively better than the last, beginning with the "fifth-best" and finally arriving at the "first-best" estimator, which provides a greatly improved method for estimating realized volatility in the presence of market structure noise.

2.1 Two-Scales Realized Volatility

For the following estimators, let the security return process take the form:

$$Y_{t_i} = X_{t_i} + \epsilon_{t_i}$$

where X_{t_i} is the true return and ϵ_{t_i} is the noise around the true return.

The Fifth-Best Estimator

The fifth-best estimator, $[Y,Y]_T^{(all)}$, simply computes realized volatility over all available data

$$[Y,Y]_T^{(all)} = \sum_{t_i}(Y_{t_{i+1}} - Y_{t_i})^2.$$

This method completely ignores noise. This approach is devastating to the estimation of integrated volatility, because as the number of samples n over a given time period $[0,T]$ increases, we end up with:

$$\sum_{t_i,t_{i+1}\epsilon[0,T]}(Y_{t_{i+1}} - Y_{t_i})^2 = 2nE\epsilon^2 + O_p(n^{\frac{1}{2}})$$

where O_p is the noise component and completely drowns out volatility. We end up with an estimate the volatility of the noise only.

The Fourth-Best Estimator

The fourth-best estimator, $[Y, Y]_T^{(sparse)}$, rather than ignoring noise altogether, more closely reflects the standard practice in the empirical finance literature:

$$[Y, Y]_T^{(sparse)} = \sum_{t_i} (Y_{t_{i+1}} - Y_{t_i})^2.$$

Rather than using every bit of trade data, which can occur several times in a given second, samples are taken more sparsely at a lower frequency, say every five minutes.

The Third-Best Estimator

While the fourth-best estimator samples at an arbitrarily chosen frequency, the third best estimator, $[Y, Y]_T^{(optsparse)}$, attempts to pinpoint an *optimal* sampling frequency.

$$[Y, Y]_T^{(optsparse)} = \sum_{t_i} (Y_{t_{i+1}} - Y_{t_i})^2.$$

This is done buy minimizing the mean squared error (MSE) through solving the following integral:

$$n^*_{sparse} = (E\epsilon^2)^{\frac{1}{3}} \left(\frac{T}{8} \int_0^T 2H'(t)\sigma_t^4 dt \right)^{\frac{1}{3}} (1 + O_p(1)).$$

The Second-Best Estimator

The previous two estimators, while improving on the fifth-best estimator, still fall short in the sense that they do not utilize all available data. Statistically, it is inefficient and wasteful to throw away data. The second-best estimator, $[Y, Y]_T^{(avg)}$, takes the average of the estimators $[Y, Y]_T^{(k)}$ across K grids of average size $\bar{n}$:

$$[Y, Y]_T^{(avg)} = \sum_{k=1}^{K} [Y, Y]_T^{(k)}$$

where

$$[Y,Y]_T^{(k)} = \sum_{t_i} (Y_{t_{i+1}} - Y_{t_i})^2.$$

The full grid of data points G is divided into K non-overlapping sub-grids $G^{(k)}, k = 1, ..., K$. To reduce bias, the optimal number of subgrids, $K^* = \frac{n}{\bar{n}^*}$, can be solved by:

$$\bar{n}^* = \left(\frac{T}{6(E\epsilon^2)^2} \int_0^T \sigma_t^4 dt \right)^{\frac{1}{3}}$$

Bias is reduced even further by the first-best estimator.

The First-Best Estimator

The first-best estimator, corrects the bias of the second-best estimator:

$$\widehat{\langle X, X \rangle}_T = [Y,Y]_T^{(avg)} - \frac{\bar{n}}{n}[Y,Y]_T^{(all)},$$

This estimator combines the second-best estimator (an average of realized volatilities estimated over subgrids) and the fifth-best estimator (realized volatility estimated using all of the data). The result is a centered, bias-corrected estimator for the integrated volatility despite the presence of microstructure noise. One further improvement is made as a small-sample adjustment:

$$\widehat{\langle X, X \rangle}_T^{(adj)} = \left(1 - \frac{\bar{n}}{n}\right)^{-1} \widehat{\langle X, X \rangle}_T$$

Using this methodology, the Two-Scales Realized Volatility estimator is applied to my data set to measure realized volatility for the morning, afternoon, and entire trading day for each day during the period of 20 trading days before and 20 trading days after each introduction date. The use of C++ is implemented to dramatically improve calculation time. Since the argument exists that volatility should increase in the afternoon relative to the morning due to LETF rebalancing, the difference in volatility between the afternoon and morning is also calculated for each day. An additional measure, pricing error, is included. (Pricing error is a common measure used in microstructure research as an indicator of market inefficiency). The volatility measures of interest in this study are denoted as follows:

- TSRV - Realized volatility for the entire trading day (10:00am - 4:00pm).
- TSRVm - Realized volatility for the morning (10:00am - 1:00pm).
- TSRVa - Realized volatility for the afternoon (1:00pm - 4:00pm).
- TSRV(a-m) - The difference in afternoon and morning volatility.
- PE - Pricing error (a measure of market inefficiency).

Information on summary statistics, t-tests, and regression analysis is covered in the next section.

3 Results

Summary Statistics and T-Tests

Table 4 reports the summary statistics as well as T-stats and p-values for each of the volatility measures. Panel A shows these results with respect to Date 1, June 21, 2006. The results show that volatility actually *decreased* after the introduction of the ProShares Ultra S&P500 (SS0 - 2x Long) leveraged ETF. Volatility across the entire trading day decreased (see column [1]), and both morning volatility and afternoon volatility decreased (see columns [2] and [3], respectively). Afternoon volatility decreased more than morning volatility, so as expected the difference between afternoon and morning volatility also decreased (see column [4]). This runs contrary to the arguments that volatility should increase, and that afternoon volatility should increase more relative to morning volatility when LETFs are traded in the market. Column [5] shows that pricing error also decreased.

Panel B reports the summary statistics as well as T-stats and p-values for each of the volatility measures with respect to Date 2, July 13, 2006. The results show that volatility *increased* after the introduction of the ProShares UltraShort S&P500 (SDS - 2x Short) leveraged ETF. Column [1] shows that volatility across the entire trading day increased, and both morning volatility and

Table 4: Summary Statistics with T-stats (p-values) comprising panels A - E.

Panel A. Date 1 - June 21, 2006 - SSO (2x Long)					
	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Std Dev (pre)	0.1249	0.1132	0.0599	0.0969	0.000235
Std Dev (post)	0.0734	0.0592	0.0518	0.0483	0.000171
Std Dev (post - pre)	-0.1249	-0.054	-0.0081	-0.0489	-0.000064
Mean (pre)	0.2166	0.1593	0.1430	-0.0162	0.000259
Mean (post)	0.1756	0.1325	0.1107	-0.0218	0.000225
Mean (post-pre)	**-0.0410**	**-0.0268**	**-0.0324**	**-0.00556**	**-0.000034**
T-stat	**-17.10**	**-12.69**	**-24.38**	**-3.11**	**-6.95**
(p-value)	**(<0.0001)**	**(<0.0001)**	**(<0.0001)**	**(0.0018)**	**(<0.0001)**

afternoon volatility increased (shown in columns [3] and [4], respectively). Afternoon volatility increased less than morning volatility, so the difference between afternoon and morning volatility decreased (see column [4]). Column [5] shows that pricing error increased. This outcome is completely opposite to the result on Date 1.

Panel B. Date 2 - SDS (2x Short)					
	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Std Dev (pre)	0.0718	0.0554	0.0502	0.0344	0.000138
Std Dev (post)	0.2182	0.0730	0.2088	0.2053	0.000317
Std Dev (post - pre)	0.1464	0.0176	0.1586	0.1709	0.000179
Mean (pre)	0.1648	0.1228	0.1069	-0.0159	0.000205
Mean (post)	0.2216	0.1675	0.1393	-0.0282	0.000235
Mean (post-pre)	**0.0568**	**0.0447**	**0.0325**	**-0.0122**	**0.00003**
T-stat	**13.30**	**27.17**	**8.08**	**-3.14**	**4.79**
(p-value)	**(<0.0001)**	**(<0.0001)**	**(<0.0001)**	**(0.0017)**	**(<0.0001)**

Panel C reports the summary statistics as well as T-stats and p-values for each of the volatility measures with respect to Date 3, November 7, 2007. The results show that volatility *increased* after the introduction of the Guggenheim 2x S&P500 (RSU - 2x Long) and Guggenheim Inverse 2x S&P500 (RSW - 2x Short) leveraged ETFs. Column [1] shows that volatility across the entire trading day increased, and both morning volatility and afternoon volatility increased (shown in columns [3] and [4], respectively). Afternoon volatility increased more than morning volatility, so the difference between afternoon and morning volatility increased only slightly (see column [4]). Column [5] shows that pricing error increased, though not significantly. This outcome is consistent with the result on the previous Date 2.

Panel C. Date 3 - RSU (2x Long) and RSW (2x Short)					
	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Std Dev (pre)	0.1225	0.1005	0.0812	0.0865	0.000141
Std Dev (post)	0.1789	0.1231	0.1343	0.1312	0.000287
Std Dev (post - pre)	0.0564	0.0226	0.0531	0.0447	0.000146
Mean (pre)	0.2489	0.1760	0.1707	-0.00529	0.000196
Mean (post)	0.2836	0.2006	0.1963	-0.00428	0.000198
Mean (post-pre)	**0.0347**	**0.0247**	**0.0257**	**0.00101**	**0.0000026**
T-stat	**15.71**	**15.22**	**16.03**	**0.63**	**0.80**
(p-value)	**(<0.0001)**	**(<0.0001)**	**(<0.0001)**	**(0.5294)**	**(0.4221)**

Panel D reports the summary statistics as well as T-stats and p-values for each of the volatility measures with respect to Date 4, June 25, 2009. The results show that volatility *decreased* after the introduction of the ProShares UltraPro S&P500 (UPRO - 3x Long) and ProShares UltraPro Short S&P500 (SPXU - 3x Short) leveraged ETFs. Column [1] shows that volatility across the entire trading day increased, and both morning volatility and afternoon volatility increased (shown in columns [3] and [4], respectively). Afternoon volatility decreased more than morning volatility, so the difference between afternoon and morning volatility decreased, although only slightly (see column [4]). Column [5] shows that pricing error decreased, though not significantly.

Panel D. Date 4 - UPRO (3x Long) and SPXU (3x Short)					
	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Std Dev (pre)	0.9780	0.9736	0.1061	0.9690	0.000600
Std Dev (post)	0.1487	0.1067	0.1081	0.0616	0.000456
Std Dev (post - pre)	-0.8293	-0.8669	0.002	-0.9074	-0.000144
Mean (pre)	0.3112	0.2332	0.1989	-0.0343	0.000218
Mean (post)	0.2671	0.2074	0.1651	-0.0421	0.000211
Mean (post-pre)	**-0.0441**	**-0.0259**	**-0.0338**	**-0.0078**	**0.000006**
T-stat	**-4.52**	**-83.19**	**-22.60**	**-0.81**	**-0.42**
(p-value)	**(<0.0001)**	**(<0.0001)**	**(<0.0001)**	**(0.4155)**	**(0.4038)**

Panel E reports the overall summary statistics as well as T-stats and p-values for all of the dates pooled together. When the data from all dates are pooled together, as column [1] shows, there is a decrease in volatility across the entire day, however it is not even significant at the 0.1 level. Column [2] shows an insignificant decrease in morning volatility, but a significant decrease in afternoon volatility (shown in column [3]). The difference between afternoon volatility and morning volatility decreased (shown in column [4]) and pricing error also decreased, though not significantly (see column [5]). While most of these results are not significant, they are unsupportive of the claim that LETFs are contributing to excess volatility.

Panel E. All Dates (Pooled)					
	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Std Dev (pre)	0.6232	0.6178	0.0920	0.6126	0.000399
Std Dev (post)	0.1677	0.1071	0.1338	0.1176	0.000353
Std Dev (post - pre)	-0.4555	-0.5107	0.0418	-0.495	-0.000046
Mean (pre)	0.2603	0.1907	0.1714	-0.0193	0.000213
Mean (post)	0.2541	0.1892	0.1650	-0.0241	0.000212
Mean (post-pre)	**-0.00625**	**-0.00149**	**-0.00637**	**-0.00484**	**-0.000001**
T-stat	**-1.60**	**-0.39**	**-6.38**	**-1.28**	**-0.42**
(p-value)	**(0.1096)**	**(0.6947)**	**(<0.0001)**	**(0.1993)**	**(0.6753)**

Table 5 reports some additional T-Tests performed regarding total trading volume (TV), morning trading volume (TVm), afternoon trading volume (TVa), and the difference between afternoon and morning trading volume($TV(a\text{-}m)$) of the S&P 500 stocks around each LETF introduction date. The results are consistent in that where volatility increased (or decreased) as shown in Table 4, volume also increased (or decreased). Column [1] shows that for Date 1, trading volume decreased during the morning, afternoon, and entire trading day. The difference between afternoon and morning trading volume decreased. Column [2] shows that for Date 2, trading volume increased during the morning, afternoon, and overall, while the difference between afternoon and morning trading volume decreased. Column [3] shows that for Date 3, trading volume increased during the morning, afternoon, and overall. The difference between afternoon and morning trading volume also increased. Columne [4] shows that for Date 4, morning, afternoon, and overall trading volume decreased as well as the difference between afternoon and morning trading volume. Column [5] shows that when all dates are pooled together, there is no significant change in trading volume, though the difference between afternoon and morning trading volume does decrease significantly.

Table 5: Additional T-Stats (p-values) regarding Total Volume (TV) traded for the S&P500 during the morning, afternoon, and entire trading day around each introduction date.

T-values (p-values)	*Date 1* [1]	*Date 2* [2]	*Date 3* [3]	*Date 4* [4]	*All Dates* [5]
TV	-3.38 (0.0007)	4.32 (<0.0001)	4.69 (<0.0001)	-1.85 (0.0639)	-0.06 (0.9482)
TVm	-3.06 (0.0023)	5.14 (<0.0001)	3.88 (0.0001)	-1.06 (0.2874)	0.46 (0.6441)
TVa	-3.55 (0.0004)	3.39 (0.0007)	5.23 (<0.0001)	-2.61 (0.0092)	-0.58 (0.5603)
TV(a-m)	-1.85 (0.0647)	-3.80 (0.0001)	4.55 (<0.0001)	-4.21 (<0.0001)	-2.82 (0.0049)

Regression Analysis

Volatility measures *TSRV, TSRVm, TSRVa, TSRV(a-m),* and *PE* are regressed on log prices (*logprc*), log market cap (*logmktcap*), log volume (*logvol*), and a dummy variable, "post," which is equal to 1 after the introduction date, or 0 before the introduction date. The equations below are estimated for each time period. Coefficients are reported along with p-values. Statistical significance at the 0.01, 0.05, and 0.10 levels is denoted by ***, **, and *, respectively.

$$TSRV_{i_t} = \beta_0 + \beta_1 logprc_{i_t} + \beta_2 logmktcap_{i_t} + \beta_3 logvol_{i_t} + \beta_4 post_{i_t} + \epsilon_{i_t}$$

$$TSRVm_{i_t} = \beta_0 + \beta_1 logprc_{i_t} + \beta_2 logmktcap_{i_t} + \beta_3 logvol_{i_t} + \beta_4 post_{i_t} + \epsilon_{i_t}$$

$$TSRVa_{i_t} = \beta_0 + \beta_1 logprc_{i_t} + \beta_2 logmktcap_{i_t} + \beta_3 logvol_{i_t} + \beta_4 post_{i_t} + \epsilon_{i_t}$$

$$TSRV(a-m)_{i_t} = \beta_0 + \beta_1 logprc_{i_t} + \beta_2 logmktcap_{i_t} + \beta_3 logvol_{i_t} + \beta_4 post_{i_t} + \epsilon_{i_t}$$

$$PE_{i_t} = \beta_0 + \beta_1 logprc_{i_t} + \beta_2 logmktcap_{i_t} + \beta_3 logvol_{i_t} + \beta_4 post_{i_t} + \epsilon_{i_t}$$

Table 6 reports the regression analysis results for June 21, 2006 (Date 1). Findings that volatility *decreased* are significant across the board and consistent with the summary statistics and t-tests.

Table 6: Regressions for Date 1 - SSO (2x Long)

	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Intercept	0.1230***	0.0757***	0.0943***	0.0187	0.00096***
	(<0.0001)	(<0.0001)	(<0.0001)	(0.2118)	(<0.0001)
logprc	0.0293***	0.0266***	0.0130***	-0.01362***	-0.00008***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
logmktcap	-0.0562***	-0.0437***	-0.0337***	0.0100***	-0.00005***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
logvol	0.0617***	0.0478***	0.0376***	-0.0102***	0.00003***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
post	-0.0320***	-0.0198***	-0.02681***	0.0070***	0.00003***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Adj R^2	0.2597	0.1863	0.3592	0.0106	0.1910

Table 7 reports the regression analysis results for July 13, 2006 (Date 2). Findings that volatility *increased* are significant across the board and consistent with the summary statistics and t-tests.

Table 7: Regressions for Date 2 - SDS (2x Short)

	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Intercept	0.0275	0.0750***	-0.0251	-0.1001***	0.0008***
	(0.4078)	(<0.0001)	(0.4358)	(0.0019)	(<0.0001)
logprc	0.0251***	0.0275***	0.0087**	-0.0187***	0.00082***
	(<0.0001)	(<0.0001)	(0.0398)	(<0.0001)	(<0.0001)
logmktcap	-0.0593***	-0.0495***	-0.0333***	0.0162***	-0.00010***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
logvol	0.0702***	0.0523***	0.0446***	-0.0078***	0.00003***
	(<0.0001)	(<0.0001)	(<0.0001)	(0.0042)	(<0.0001)
post	0.0421***	0.0338***	0.0231***	-0.01074***	0.00002***
	(<0.0001)	(<0.0001)	(<0.0001)	(0.0066)	(<0.0001)
Adj R^2	0.1396	0.4726	0.0672	0.0061	0.1394

Table 8 reports the regression analysis results for November 7, 2007 (Date 3). Findings that volatility *increased* are significant across the board and consistent with the summary statistics and t-tests.

Table 8: Regressions for Date 3 - RSU (2x Long) and RSW (2x Short)

	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Intercept	0.0131	0.0119	0.0131	0.0012	0.00065***
	(0.2924)	(0.3355)	(0.2924)	(0.9275)	(<0.0001)
logprc	0.0543***	0.0557***	0.05426***	-0.0014	0.00002***
	(<0.0001)	(<0.0001)	(<0.0001)	(0.4329)	(<0.0001)
logmktcap	-0.0587***	-0.0646***	-0.05866***	0.0060***	-0.0007***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
logvol	0.06168***	0.0684***	0.0617***	-0.0067***	0.00004***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
post	0.0156***	0.0132***	0.0156***	0.0023	-0.00001*
	(<0.0001)	(<0.0001)	(<0.0001)	(0.1496)	(0.0650)
Adj R^2	0.1758	0.2114	0.1758	0.0027	0.0494

Table 9 reports the regression analysis results for June 25, 2009 (Date 4). Findings that volatility *decreased* are significant across the board and consistent with the summary statistics and t-tests.

Table 9: Regressions for Date 4 - UPRO (3x Long) and SPXU (3x Short)

	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Intercept	0.2410***	0.1681**	0.1882***	0.0199	0.00081***
	(0.0022)	(0.0321)	(<0.0001)	(0.7991)	(<0.0001)
logprc	-0.0055	0.0070	-0.0189***	-0.0259**	-0.00007***
	(0.6070)	(0.5076)	(<0.0001)	(0.0142)	(<0.0001)
logmktcap	-0.0834***	-0.0674***	-0.0465***	0.0209***	-0.00005***
	(<0.0001)	(<0.0001)	(<0.0001)	(0.0061)	(<0.0001)
logvol	0.0928***	0.0732**	0.0532***	-0.0199***	0.00002***
	(<0.0001)	(<0.0001)	(<0.0001)	(0.0036)	(<0.0001)
post	-.03831***	-0.0212**	-0.0306***	-0.0093	-0.00001
	(<0.0001)	(0.0276)	(<0.0001)	(0.3311)	(0.4366)
Adj R^2	0.0238	0.0128	0.4394	0.0003	0.0303

Table 10 reports the regression analysis results for all dates pooled together. With all data pooled together, much of the statistical significance is lost. However, it is worth noting that the coefficient estimates for *post* are all negative. Though not significant in most cases, the coefficient estimate for *TSRVa* (-0.0078) is significant at a level less than 0.0001.

Table 10: Regressions for all dates pooled together

	TSRV [1]	*TSRVm* [2]	*TSRVa* [3]	*TSRV(a-m)* [4]	*PE* [5]
Intercept	0.1052***	0.0929**	0.0603***	-0.03098	0.00078***
	(0.0008)	(0.0305)	(<0.0001)	(0.2927)	(<0.0001)
logprc	0.0377***	0.0305***	0.0206***	-0.0098**	-0.00005***
	(<0.0001)	(<0.0001)	(<0.0001)	(0.0148)	(<0.0001)
logmktcap	-0.0847***	-0.0656***	-0.0513***	0.0143***	-0.0004***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
logvol	0.0933***	0.0705***	0.0582***	-0.0123***	0.00002***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
post	-0.0085**	-0.00317	-0.0078***	-0.0046	-0.000001
	(0.0270)	(0.3984)	(<0.0001)	(0.2245)	(0.2680)
Adj R^2	0.0363	0.0218	0.2224	0.0006	0.0354

4 Conclusion

The reaction of volatility in the stock market was not uniform in each of the introduction dates involved in this study. Volatility and trading volume increased significantly after July 13, 2006 (when SDS - 2x Short was introduced) and after November 7, 2007 (when RSU - 2x Long and RSW - 2x Short were introduced). However, volatility and trading volume decreased significantly after June 21, 2006 (when SSO - 2x Long was introduced) and after June 25, 2009 (when UPRO - 3x Long and SPXU - 3x Short were introduced). With data from all dates pooled together, there was no significant increase in volatility attributable to the introduction of LETFs. It may be popular to blame LETFs or other complex financial instruments for causing excess volatility in the stock market, but it in the case of leveraged ETFs, it is not clear that this argument has any merit.

Even though there may be no clear conclusion to make from this study about the effects leveraged ETFs have on intraday volatility in the stock market, this study opens the door for subsequent studies that can be done to further analyze this issue. For example, this study does not take into account changes in systematic volatility around the introduction dates. A further study could control for the volatility of the entire market, including stocks that are not part of the S&P 500, to better isolate changes in volatility due to the introduction of LETFs.

It is important to continue to study this and related issues. As the financial marketplace grows more and more complicated every day, it is important to improve understanding of the role that financial instruments play in the market. Changes in volatility have significant implications for asset prices, especially options, as well as for the behavior of individual and institutional investors. A better understanding of how leveraged ETFs and other complex financial instruments contribute to volatility will lead to more informed investing and therefore more efficient markets.

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