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LIETF TRADING BEHAVIOR DURING U.S. – CHINA TRADE WAR

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ABSTRACT

This paper examines the trading behavior of investors in Leveraged and Inverse Exchange-Traded Funds (LIETFs) during the early phase of the U.S.–China tariff trade war, from January to November 2018. Using panel data models, we analyze LIETF reactions to 17 trade-war news events identified by China Briefing. The study focuses on the 12 most liquid LIETFs tracking the S&P 500 and Nasdaq-100 indices, with trade and quote data obtained from Reuters DataScope Select. Our first objective is to test whether LIETF investors' trading activity changes significantly around trade-war announcements, and our results provide strong support for this hypothesis. To further explore trading dynamics, we construct two measures of abnormal activity—the abnormal buy–sell ratio and the abnormal order imbalance—and test whether LIETF investors can predict subsequent market movements. We find little evidence of such predictive ability. Finally, we assess short-term momentum behavior: while investors display trend-chasing in intraday intervals of less than 30 minutes, they tend to bet on reversals of the underlying indices over longer intervals. Overall, this study contributes to understanding how investors in leveraged products respond to geopolitical shocks. Given the growing asset base of U.S.-listed LIETFs and the regulatory importance of investor behavior during periods of heightened uncertainty, our findings are relevant to academics, practitioners, and market supervisors.

Keywords: *Leveraged and Inverse Exchange-Traded Fund (LIETF), Order imbalance, News reaction, Trend-chasing behavior, Trade informativeness, Sophisticated investors, U.S.-China trade war news*

1. INTRODUCTION

Exchange-Traded Funds (ETFs) and related products have expanded rapidly across global markets over the past three decades. According to Cerulli Associates, assets in U.S. ETFs surpassed $10 trillion for the first time in November 2024 (Konish, 2024, CNBC; cnbc.com) and now standing at $14.7 trillion (Koudelka et al., 2025). ETFs provide investors low-cost access to virtually any asset class in major U.S. and international markets, as well as to established investment styles (e.g., value, growth, large- and small-cap, sector-based) (Broman, 2016). ETF shares are created when an Authorized Participant deposits a basket of securities with the ETF sponsor in exchange for ETF shares. This creation and redemption mechanism—often conducted in-kind—helps mitigate arbitrage opportunities when ETF prices deviate from their net asset values (NAVs).

The academic literature offers mixed evidence on the broader impact of ETFs. On the one hand, ETFs improve informational efficiency (Glosten, Nallareddy & Zou, 2021; Li & Zhu, 2022) and enhance price discovery (Wallace, Kalev, & Lian, 2019). On the other hand, concerns include their potential to amplify volatility in underlying assets through arbitrage channels (Ben-David et al., 2018; Filippou, He, Li, & Zhou, 2025) and the influence of non-fundamental demand in ETF arbitrage activity (Brown, Davies, & Ringgenberg, 2021). ETFs also play a critical role in transmitting global shocks and driving cross-country return co-movement. Country ETFs traded in the U.S. are highly transparent and liquid, allowing them to incorporate U.S. shocks quickly; these shocks are then transmitted to international markets through price discovery and arbitrage mechanisms at the next day's opening (Kalev & Wallace, 2024; Filippou, Gozluklu, & Rozental, 2024).

Within this landscape, a distinct and more speculative category has emerged: Leveraged and Inverse Exchange-Traded Funds (LIETFs). These products allow traders to take magnified long or short positions on benchmark indices—typically at multiples of −3, −2, −1, 2, or 3—by employing derivatives and daily rebalancing (Cheng & Madhavan, 2009; Charupat & Miu, 2011). LIETFs can also be purchased on margin, further increasing effective leverage, which positions them at the riskier end of the ETF spectrum.

While exchange-traded funds (ETFs) are generally designed for buy-and-hold investors, LIETFs are predominantly traded by short-horizon investors who engage in smaller transactions and generate significantly higher turnover than traditional ETFs. Owing to the end-of-day rebalancing of leveraged ETFs, the associated increases in trading volume and volatility are most strongly pronounced near the close of the trading session (Cheng & Madhavan, 2009).

Another key distinction is that, unlike conventional ETFs—whose units are created and redeemed in kind—LIETFs employ a cash-based creation and redemption process (Charupat & Miu, 2011). This structural feature not only defines the arbitrage bounds between market prices and net asset value (NAV) but also provides an ideal setting to examine how trading activity and order imbalances under extreme market conditions contribute to deviations from NAV and influence price informativeness and market efficiency (Chordia, Roll, & Subrahmanyam, 2005).

This paper contributes to the debate on whether LIETFs serve as harmful speculative vehicles or valuable instruments for information discovery. We focus on the second year of Donald J. Trump's presidency (January–November 2018) and analyze LIETF investor behavior during U.S.–China trade-war news events. Using an event-study approach and data on the 12 most liquid LIETFs tracking the S&P 500 and Nasdaq-100 indices, we test whether investors trade on information or engage in excessive and uninformed risk-taking.

Our contribution is threefold. First, we propose two novel measures of abnormal LIETF trading activity: the abnormal buy–sell ratio and abnormal order imbalance. Second, we apply these metrics to investigate whether LIETF investors demonstrate predictive ability around major policy announcements. Third, we find only limited evidence of superior forecasting skill among LIETF investors. Given the growing scale of leveraged ETF markets in the U.S., these findings have important implications for both researchers and regulators.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 presents the data and methodology. Section 4 reports the empirical results. Section 5 discusses the findings, and Section 6 concludes.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2. 1. REGULATORY CONCERNS

Market regulators and practitioners have expressed concerns about the risks posed by LIETFs. For instance, senior officials at the SEC have warned that leveraged ETFs "*pose real risks to American families*," questioning their appropriateness for retail investors. Jim Ross, one of the designers of the first U.S. ETF in 1993 (the SPDR on S&P 500, *SPY*), has similarly cautioned that products offering multiple returns on underlying securities may be too dangerous for the average investor. In an interview in Tokyo, Ross emphasized that leveraged ETFs require "*extreme education for the end investor to be using them*." He further added that, in his view, "*we do not see a place*" for such products (Bloomberg News, 2018; Investors.com).

Whether LIETFs destabilize markets remains a subject of academic debate. Due to their daily rebalancing feature, LIETFs are often considered contributors to late-day volatility; however, empirical studies do not support this claim (Ivanov & Lenkey, 2018; Li & Zhao, 2014; Trainor, 2010). Recent reports highlight growing market attention: Bloomberg reported record LIETF trading volumes in late 2024 (Tsekova & Hajric, 2024), while The Economist (2025) noted that these high-risk instruments are often favored by speculative traders rather than sophisticated investors, making them prone to sudden and substantial losses. (The Economist, 2025; Economist.com).

2. 2. THEORETICAL LITERATURE

Miller (1977), in his seminal paper, developed a theory of differences of opinion. His model explains cyclical variation in investor behavior by noting that market sentiment and price levels are dynamic, influenced by the flow of information before, during and after news releases. Each period represents a distinct phase opinion formation and resolution: (i) Pre-news days: opinion is diverse and unanchored, leading to optimism; (ii) News-day releasees: opinion begins to align, triggering price adjustments; and (iii) Post-news days: the market corrects toward a more unified assessment of the asset's value. More recently, Bollerslev, Li and Xue (2018) derived an explicit expression for the elasticity of expected trading volume with respect to price volatility.

Kyle (1985) developed a strategic model of informed investor behavior, in which the informed trader incorporates private information is incorporated into prices gradually. His model provides a foundation for studying the informational role of derivative markets. Options markets have long served as a natural laboratory for investigating information-based trading. Black (1975) first proposed that informed traders might prefer options to stocks due to their embedded leverage. Subsequent research has explored the interaction between options and stock markets (e.g., Chan, Chung, & Johnson, 1993; Easley, O'Hara, & Srinivas, 1998). Easley et al. (1998) develop an asymmetric information model in which informed traders choose between options and stocks depending on leverage and expected profits. Their empirical evidence strongly supports the role of options markets as venues for informed trading.

2. 3. EMPIRICAL LITERATURE

Blume, MacKinlay and Terker (1989) examine order imbalances and stock price movements on October 19 and 20, 1987 on the NYSE. The authors use dollar volume at the ask price minus dollar volume at the bid price over 15-minute intervals. The study finds a strong association between imbalance and return, with the effect being much stronger for firms in the S&P 500 than for those outside the index. Brown, Walsh, and Yuen (1997) analyze the relationship between buy and sell order imbalances and stock returns using Australian market data. Applying Granger causality tests, the authors find short-term (but not persistent beyond one day) bidirectional causality between order imbalance and stock returns.

Patel, Putniņš, Michayluk, and Foley (2020) show that new information is incorporated first into option prices before being transmitted to stock prices, with higher-leverage options contributing more substantially to price discovery. These results, together with those of Ge, Lin, and Pearson (2016), align with the predictions of Black (1975) and Easley et al. (1998), suggesting that informed traders gravitate toward high-leverage instruments.

Roll, Schwartz, and Subrahmanyam (2010) introduce the options-to-stock (O/S) trading volume ratio to capture relative activity across markets, showing that informed trades influence both time-series and cross-sectional variation in O/S. Ge et al. (2016) further demonstrate that embedded leverage drives the predictive power of option trading volumes for stock returns. Similarly, Johnson and So (2012) find that O/S carries a negative cross-sectional signal of private information and provides predictive power for returns of the underlying securities, with short-sale costs identified as the primary driver.

Recent evidence indicates that sophisticated investors use ETFs for information-based trading. Li and Zhu (2022) show that short sellers employ ETFs for "synthetic shorting" to circumvent stock-level short-sale constraints. Huang, O'Hara, and Zhong (2021) find that industry ETFs facilitate informed trading and enhance market informational efficiency by enabling risk hedging. Eglīte, Štaermans, Patel, and Putniņš (2023) further show that ETFs can serve as vehicles for concealing insider trading.

Gao, Han, Li, and Zhou (2018) provide strong evidence of intraday time series momentum (ITSM), showing that the first half-hour return of the trading day significantly predicts the last half-hour return for a sample of U.S. ETFs tracking the broader U.S. market, various U.S. sectors, and emerging markets. More recently, Li, Sakkas, and Urquhart (2022) extend this evidence globally, linking ITSM to market characteristics such as liquidity and volatility.

2. 4. HYPOTHESES DEVELOPMENT

This paper examines the relationship between trade informativeness and the trading behaviour of LIETF investors in response to news events with market-wide implications. Three alternative hypotheses are tested in this study. The hypotheses are set in alternative form.

Based on the review of the literature, the first hypothesis posits that the trading behavior of LIETF investors would vary between the period prior to the release of the news, the period when the news is released, and the period after the news is released. The hypothesis is defined as:

H_1: LIETF trading volumes and order imbalances change significantly around trade-war news events.

The second hypothesis tests whether the LIETF investors are informed. If investors were informed, abnormal trading volumes in LIETFs would predict larger future market index moves that match their outlook. Apart from the anecdotal evidence based on media releases, to best of our knowledge, there are no skillful trading activities or evidence of informed trading of LIETFs around major market news announcements. The second hypothesis is defined as:

H_2: The abnormal LIETF trading activity predicts future index returns.

If H_2 holds, LIETF trading volumes and order imbalances reflect informed (skillful) trading. Since LIETFs provide leveraged exposure and the flexibility to trade in rising (bull) and falling (bear) markets, investors with forecasting ability or strong convictions about news outcomes can effectively impound their information through these products. If H_2 is rejected, it suggests that LIETF investors are largely speculative, making little contribution to price efficiency. In that case, the final hypothesis, $H_{3,}$ considers whether LIETF investors' trading reflects short momentum-driven strategies instead.

H_3: LIETF investors exhibit trend-chasing behavior.

2. 5. SUMMARY

Overall, the literature highlights that leveraged financial instruments, such as options and LIETFs, can serve as important venues for information-based trading due to their embedded leverage and flexibility. However, evidence on LIETFs specifically remains scarce. While regulators and practitioners warn about their risks, empirical research has yet to establish whether LIETF investors are informed traders or merely speculative participants. By testing whether LIETF trading conveys predictive information or reflects momentum-driven behavior around U.S.–China trade war news events, this study seeks to fill this gap and contribute to the broader debate on the role of leveraged instruments in price discovery and market stability.

3. RESEARCH METHODOLOGY, MODEL SPECIFICATION AND DATA SOURCES

3. 1. RESEARCH METHOD

The paper utilizes a panel data regression to test our second hypothesis whether the abnormal LIETF trading activity predicts future index returns. To define the trading order imbalance variable, consistent with Chordia, Roll and Subrahmanyam (2005), we first assign the dollar traded volume in each transaction as buyer- (seller-) initiated based on the Lee and Ready (1991) algorithm. A trade is a buyer- (seller-) initiated if it is closer to the ask (bid) of the prevailing quote. We start with calculation of cumulative buy (sell) values between the (t-1)th- and tth-interval for the i-th LIETF. Intervals of 5-, 15-,30- and 60-minute intervals are considered during the continuous trading session (9:30 a.m. to 4:00 p.m.) on NYSE and NASDAQ. Next, we estimate the percentage change of the cumulative buy (sell) values. Finally, the difference between the two percentage changes ($\Delta BuySell_{i,t}$) is our main predictor variable of interest to test H_2 using the following regression model:

$$\begin{aligned} Ret_{i,t} = \beta_0 + \beta_1 \Delta BuySell_{i,t-1} + \beta_2 \Delta BuySell_{i,t-2} + \sum_k \beta_k Controls_{i,t} \\ + \textstyle\sum_j \beta_j Weekday\_FE + \sum_l \beta_l LIETF\_FE + \varepsilon_{i,t}, \end{aligned} \quad (1)$$

where $Ret(t)$ is the return of the underlying index in the t-th time interval, $Controls(t)$ are price volatility and market liquidity of the corresponding LIETF in the concurrent time interval. While Parkinson (1980) high-low range volatility measure is utilized to estimate the volatility, the market liquidity is proxied by the quoted spread which is the difference between the best bid- price (highest price a buyer is willing to pay) and the best ask-price (lowest price a seller is willing to accept).

For robustness, we also derive a second predictor variable, namely the Abnormal Order Imbalance ($AOIB_{i,t}$); the details are set in the Appendix. The panel regression model to test H_2 is as follows:

$$Ret_{i,} = + AOIBi,t-1 + \sum \beta k Controls_{i,t} + \sum \beta j Weekday\_FE + \sum \beta_l\, LIETF\_FE + \epsilon i,t. \quad (2)$$

Finally, to investigate the potential motivation for trading LIETFs around news announcement we examine whether such traders are motivated by chasing short-term momentum (H_3). The following panel regression is estimated to test our third hypothesis:

$$\begin{aligned} OIB_{i,t} = \beta_0 + \beta_1 Ret_{i,t-1} + \beta_2 Ret_{i,t-2} + \beta_3 Ret_{i,t-3} + \beta_4 Ret_{i,t-4}\, \beta_4 Ret_{i,t-4} \\ + \sum_k \beta_k\, Controls_{i,t} + \sum_j \beta_j Weekday\_FE + \sum_l \beta_l LIETF_{FE} + \epsilon_{i,t} \end{aligned} \quad . \quad (3)$$

where $OIB_{i,t}$ denotes the order imbalance level in the tth time interval, Ret_{t-k} denotes the kth lag term of return of the underlying index, all other variables are defined above.

3. 2. DATA SOURCES

LIETFs can be identified from the ETF Database (http://etfdb.com/). This database provides comprehensive information regarding ETFs, such as the issuer, expense ratio, average trading volume, asset under management (AUM), benchmark index, etc. In particular, we use the ETF screener provided by ETF Database to obtain the list of U.S. equity LIETFs. The initial set of filters that we have applied are as follows: (i) Asset class: Equity; (ii) Size: Large-Cap; (iii) Region: U.S. and; (iv) Attributes: Leverage factor of 1.25, 2, 3, −2, and −3.

The major indices we have chosen are the S&P 500 Index and the Nasdaq-100 Index, two of the most representative indices in the U.S. market. Out of 103 LIETFs in the U.S., 12 track either the S&P 500 Index or the Nasdaq-100 Index. The total AUM of these 12 LIETFs is $13.67 billion, or equivalently, 49.01% of the entire LIETFs space (58.36% of total AUM in the large-cap LIETFs space) in the U.S.A. Of these 12 LIETFs, one of them has a leverage factor of 1.25; three of them have a leverage factor of 2; three of them have a leverage factor of 3; two of them have a leverage factor of −2; and three of them have a leverage factor of −3. The complete list of the LIETF samples is shown in Table 1. In the subsequent analyses, we use the abbreviation SPX to represent the S&P 500 Index and NDX to represent the Nasdaq-100 Index.

Table 1. List of LIETFs, January 1, 2018, to November 1, 2018

Symbol	ETF Name (Index tracked)	Leverage/ Inverse X-Factor	Total Assets ($MM)
PPLC	Portfolio+ S&P 500 ETF (SPX)	1.25	$78.25
SSO	ProShares Ultra S&P 500 (SPX)	2	$2,472.27
QLD	ProShares Ultra QQQ (NDX)	2	$1,834.10
SPUU	Direxion Daily S&P 500 Bull (SPX)	2	$6.74
TQQQ	ProShares UltraPro QQQ (NDX)	3	$4,352.91
UPRO	ProShares UltraPro S&P 500 (SPX)	3	$1,515.86
SPXL	Direxion Daily S&P 500 (SPX)	3	$1,123.71
SDS	ProShares UltraShort S&P 500 (SPX)	–2	$775.52
QID	ProShares UltraShort QQQ (NDX)	–2	$250.70
SQQQ	ProShares UltraPro Short QQQ (NDX)	–3	$581.84
SPXU	ProShares UltraPro Short S&P 500 (SPX)	–3	$419.28
SPXS	Direxion Daily S&P 500 Bear (SPX)	–3	$257.35

Notes: SPX and NDX are the S&P 500 and NASDAQ-100 indices, respectively. X-Factor is positive (negative) integer for the leverage non-inverse (leverage inverse) ETFs.

Source: compiled by authors from ETF Database https://etfdb.com/etfs/leveraged/ and https://etfdb.com/etfs/inverse/

LIETFs trade and quote data are collected from Thomson Reuters DataScope Select for the sample period of January 1 till November 1, 2018. From the the initial universe of 13,477,129 transactions and twice an many quote data on the prevailing ask- and bid-quotes around these executed trades. After eliminating trades with zero volume and limiting the analysis to the continuous trading session, the dataset consists of 13,475,671 trades. For the total sample of trade war news-days, we account for 4,893,796 trades and a volume of 68.67 billion dollars.

The major news related to the trade war between the U.S. and China is collected through the website of China Briefing, which is the publication vehicle of the Dezan Shira & Associates (the company that produces it).

The major news related to the trade war between the U.S. and China was collected from the website of China Briefing, which is published by Dezan Shira & Associates.

Following a manual filtering procedure, a total of 17 news events were obtained. Our sample source is consistent with the list provided by Reuteres. The initial trade news appears in early February 2028, following the formats of Bown (2021) and Chen, Fang, and Liu (2023). Table 2 provides the date and a summary of each event.

Table 2. List of 17 important U.S-China trade war news, Feb. 7, 2018 – Nov. 1, 2028

Data	Description of the important trade war related news events
2018-02-07	The U.S. "global safeguard tariffs" – placing a 30% tariff on all solar panel imports.
2018-03-23	The U.S. imposes a 25% (10%) tariff on all steel imports with few exceptions.
2018-04-02	China imposes tariffs (from 15% to 25%) on 128 products (worth $3 billion).
2018-04-03	The U.S. Trade Representative (USTR) releases an initial list of products for 25% tariff.
2018-04-04	China reacts to USTR's initial list and proposes 25% tariffs to 106 products.
2018-04-17	China announces antidumping duties of 178.6% on imports of sorghum from the U.S.
2018-05-07	U.S. and China engage in trade talks in Beijing (May 3-7). Talks end with no resolution
2018-05-29	U.S. reinstates tariff plans after a brief truce.
2018-06-16	China revises its initial tariff list to include a 25% tariff on 545 products.
2018-07-06	U.S. implements first China tariffs and begins collecting a 25% tariff on 818 products.
2018-08-02	U.S. tariffs revisions: The USTR considers a 25% tariff rather than a 10% one on List 3
2018-08-03	China announces a second round of tariffs on U.S. products
2018-08-23	U.S. and Chinese representatives meet in Washington DC (Aug. 22-23) - no success
2018-09-07	Trump threatens new tariffs
2018-09-17	U.S. finalizes tariffs on $200 billion of Chinese goods (List 3)
2018-09-18	China announces retaliation for U.S. tariffs –go into effect on September 24.
2018-10-30	U.S. reportedly prepared to announce tariffs on remaining Chinese products

Source: compiled by authors from China Briefing from https://www.china-briefing.com/news/the-us-china-trade-war-a-timeline (accessed on March 18, 2023)

4. RESULTS

4. 1. DESCRIPTIVE STATISTICS

Table 3 shows the summary statistics of the aggregate average trading activities of LIETFs around the news events. Panel A (Panel B) provides the mean values of the following: number of trades, dollar-volume traded, dollar-volume buy- & sell-values during the *Pre-news*, News- and *Post-news* periods. Overall, we observed that all reported statistics are decreasing monotonically; while the highest number is for the *Pre-news*, the lowest one for the *Post-news* sub-samples. The t-statistics—based on the difference between the *News-day* and each of the *Pre-*, *Post-news*-day sub-samples—were statistically significant at levels smaller than the 1% level of significance. The findings reported in Table 3 provide support to our first hypothesis (H_1) that LIETF investors behave differently during around the trade-war news events. Our observations suggested that the LIETF investors may have become more risk-averse around the impactful news events, which reduced their trading activities.

Table 3. Summary statistics of trading activities of LIETFs

Sub-Period	Mean No of Trades	Mean Values (All Trades ($MM)	Mean Buy-Values ($MM)	Mean Sell-Values ($MM)
Panel A: SPX				
Pre-news	33,660***	$551.2***	$242.3***	$252.1***
News-day	31,258	$513.1	$226.9	$231.0
Post-news	27,210***	$477.7***	$213.8***	$211.7***
Panel B: NDX				
Pre-news	43,063**	$541.1**	$246.4**	$243.7**
News-day	42,769	$544.6	$251.2	$246.0
Post-news	35,888***	$473.2***	$216.6***	$213.8***

Notes: The *t*-statistics are based on the difference between each of the *Pre-*, *Post-* & *News-day*, where *, ** and *** denotes 10%, 5% and 1% statistical level of significance, respectively.

Source: Author` s calculation

Transaction-level analysis in Table 4 has highlighted differences in trade values across sub-periods.

Table 4. Summary statistics of average number of trades (thousands)

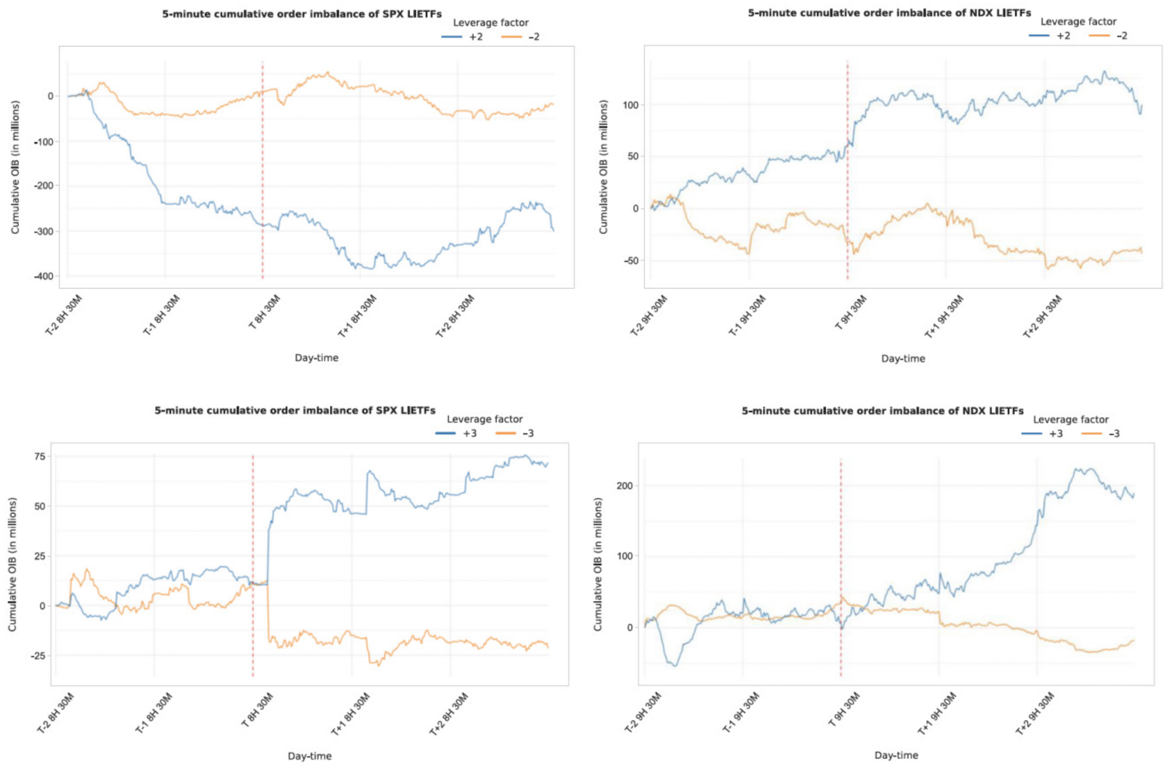
Sub-Period	Average	10th Percentile	50th Percentile	90th Percentile
Panel A: SPX Trades				
Pre-news: Buy	16.85	1.88	7.96	33.69
Pre-news: Sell	16.86	1.91	8.01	33.10
News-day: Buy	17.00	1.51	7.91	33.98
News-day: Sell	17.13	1.73	7.94	33.33
Post-news: Buy	18.28	1.93	8.53	35.89
Post-news: Sell	17.98	1.99	8.62	34.42
Panel B: NDX Trades				
Pre-news: Buy	13.19	1.29	6.92	25.74
Pre-news: Sell	12.90	1.25	6.70.	25.93
News-day: Buy	13.21	1.26	6.72	25.97
News-day: Sell	13.19	1.27	6.72	26.26
Post-news: All	13.18	1.24	6.72	25.87
Post-news: Buy	13.78	1.33	6.89	27.07
Post-news: Sell	13.69	1.27	6.86	27.14

Source: Author` s calculation

On average trades are higher for the *News*- than *Pre-news days*. Also, *Post-news days* are higher than *News-days*. Notably, trade values increased in the post-news period rising to 18.28 (13.78) to 17.98 (13.69) thousands for SPX-LIETFs (NDX-LIETFs), suggesting more aggressive trading behavior among remaining participants.

Figure 1 depicts the 5-minute cumulative order imbalance ($COIB_{i,t} = \Sigma_{j=1}^{t} OIB_{i,j}$) of the SPX-LIETFs and NDX-LIETFs from $t-2$ to $t+2$. The blue line and orange line represent the non-inverse and inverse leveraged ETFs, respectively. The red dashed line indicates the opening time on day t, the news release day. The cumulative order imbalance is shown in the y-axis and is expressed in millions of dollars. Panel A shows the cumulative order imbalance plots for LIETFs with leverage factors of +2 and −2. Panel B shows the corresponding plots for LIETFs with the leverage factor of +3 and −3.

Figure 1. 5-minute cumulative order imbalance of LIETFs



Source: Author` s calculation

From 5-minute cumulative order imbalance plots, non-inverse leveraged ETFs indicated upward trends, while inverse leveraged ETFs downward trends around news events. There are two possible explanations: (1) bullish sentiment on the underlying indices increased buying pressure for non-inverse ETFs and selling pressure for inverse ETFs or (2) LIETFs were used for hedging, though this would imply short positions in underlying portfolios—a hypothetical argument that we were not able confirm due to unavailable holdings data.

Pearson correlation matrix of LIETF's 5-minute cumulative order imbalance with different leverage factors is reported in Table 5. In particular, the correlation between SPX ±3X, NDX ±2X, and NDX ±3X LIETFs were high and statistically significant; the correlation coefficients of -0.92 (t-statistics of −46.45), −0.52 (t-statistics of −12.02) and −0.91 (t-statistics of −44.59), respectively. The significant negative correlations of the LIETFs' order flows indicated that investors are consistent in their views on the future movement of the underlying indices. These negative correlations could also be attributed to investors' reliance on their beliefs about the future direction of the market. For example, an investor seeking to trade in the 3X SPX-LIETFs but without prior knowledge about the future movement of the S&P 500 Index may infer a trading decision based on the order flow information of the −3X SPX ETFs. Suppose investors observed a large positive (negative) order imbalance of inverse ETFs. These investors may learn from the order flow information and have updated their existing beliefs about a decrease (increase) in future returns of the S&P 500 Index in the short term. Therefore, they would be likely to enter a short (long) position in the non-inverse ETFs.

Table 5. Correlation matrix of leverage factors

Factor (+/ –)	2 X	3 X		–2 X	–3 X
Panel A: SPX					
2 X	1.00				
3 X	−0.70***	1.00			
–2 X	−0.07	−0.01		1.00	
–3 X	0.65***	−0.92***		−0.05	1.00
Panel B: NDX					
2 X	1.00				
3 X	0.77***	1.00			
–2 X	−0.52***	−0.74***		1.00	
–3 X	−0.53***	−0.91***		0.70***	1.00

Notes: *** denotes statistical significance at 1% level.

Source: Author` s calculation

4. 2. FORECAST ABILITY OF LIETFS TRADERS

Recall that the main question being examined in this subsection is whether LIETF investors can predict future returns of the underlying indices. There are two possible motivations for investors to trade in LIETFs. On the one hand, these traders may be speculators with no superior knowledge about the future market direction and could be purely attracted by the high leverage, low entrance fees and convenience of LIETFs. Essentially, this type of investor considers LIETFs as a "gambling" instrument to bet against the short-term view of the underlying indices. On the other hand, due to the riskiness of trading these products, people who trade LIETFs can also be professional traders and possess superior skills which allow them to predict future market movements. Hence, this (latter) group of investors may include LIETFs in their portfolios for high-conviction trades or hedging purposes. In the former case, traders can be regarded as noise traders, and their trading activities should have no predictive power on the underlying indices. In contrast, in the latter case, a greater amount of buying activities of the non-inverse (inverse) leveraged ETFs should be positively (negatively) correlated with the future return of underlying indices, assuming these investors are not trading for hedging purposes. It is reasonable to argue that these two groups of traders (speculators and professional traders) can co-exist; nonetheless, we are interested which group of investors dominates the market-LIETFs.

Two variables were considered to examine our H_2 whether LIETF investors have superior predictability of future market returns. The first variable, *ΔBuySell*, is the percentage difference between cumulative buy and sell values; the second variable is abnormal order imbalance. If the LIETFs trades were initiated by informed traders, it is anticipated that both estimates of β_1 and β_2 to be significantly positive (negative) for non-inverse (inverse) LIETFs. We estimated the regression model based on Eq. (1). The results shown in Table 6 are mixed: few only were significant with the expected positive coefficient for β_1 and β_2.

Table 6: LIETFs return predictability based on cumulative buy- and sell-values

Variable	5-minute	15-minute	30-minute	60-minute
Panel A: Leverage only (Non-Inverse) ETFs				
$\Delta BuySell_{(t-1)}$	-5.1×10^{-6} (–0.86)	1.5×10^{-5} (1.20)	-9.2×10^{-5} (–0.86)	7.0×10^{-5}*** (10.03)
$\Delta BuySell_{(t-2)}$	2.3×10^{-5}** (2.00)	4.9×10^{-5}*** (2.62)	2.5×10^{-5}** (2.48)	-3.3×10^{-5}** (2.00)
Constant	0.00047 (0.14)	0.019** (1.98)	0.014 (0.71)	–0.070* (–1.72)
Obs.	21,508	6,944	3,340	1,470
Adj. R^2 (%)	0.035	0.12	0.083	1.4
Panel B: Leverage Inverse ETFs				
$\Delta BuySell_{(t-1)}$	1.3×10^{-6}** (2.01)	-1.5×10^{-6}*** (–2.63)	-1.6×10^{-5} (–0.35)	-5.5×10^{-5} (–0.29)
$\Delta BuySell_{(t-2)}$	2.0×10^{-8}*** (19.10)	-2.9×10^{-8}*** (–20.69)	1.8×10^{-5} (0.54)	3.0×10^{-4}** (2.34)
Constant	0.0024 (–1.26)	0.020** (–2.02)	0.012 (0.57)	–0.075 (–1.56)
Obs.	28,664	8,665	4,049	1,660
Adj. R^2 (%)	0.013	0.079	0.054	0.74

Notes: The dependent variable is $Ret_{(t)}$. Control variables are *Volatility* and *QSpread*. All panel data regressions are with *Weekday* and *LIETF* fixed effect. *, ** and *** denotes 10%, 5% and 1% statistical level of significance, respectively.

Source: Author` s calculation

Next, the results of the estimated with Eq. (2) regression model using the second predictor variable—the abnormal order imbalance—are reported in Table 7. For both inverse and non-inverse LIETFs across all time intervals, we did not observe a statistically significant relationship between abnormal order imbalance and future returns. Although the coefficient for the inverse LIETFs at 60- minute intervals was significant at the 10% level, this sign of this number does not align with our second hypothesis.

Overall, the results from both panel regression estimation have questioned the validity of our second hypothesis, namely the abnormal LIETF trading activity cannot predict future index returns. Hence, we can conclude that LIETFs' investors were primarily speculative around important major market news announcements.

Given that there was no evidence found that LIETF investors have superior information or skills to predict future returns, we tested next whether these traders were chasing the short-term momentum.

Table 7: Return predictability by abnormal order imbalance of LIETFs traders

Variable	5-minute	15-minute	30-minute	60-minute
Panel A: Leverage only (Non-Inverse) ETFs				
$AOIB_{(t-1)}$	-5.2×10^{-6} (–1.25)	6.1×10^{-6} (0.25)	7.7×10^{-5} (1.17)	-8.9×10^{-5} (–0.76)
Constant	0.012 (0.87)	0.045 (1.36)	–0.24** (–2.55)	0.076** (2.84)
Obs.	7,769	2,678	1,450	793
Adj. R^2 (%)	–0.0066	–0.13	0.038	6.71
Panel B: Leverage Inverse ETFs				
$AOIB_{(t-1)}$	-4.4×10^{-6} (–1.00))	4.0×10^{-7} (0.02)	-3.1×10^{-5} (–0.42)	3.8×10^{-4}* (1.70)
Constant	0.00072 (0.14)	0.0038 (0.22)	–0.029 (–0.59)	–0.19* (–1.80)
Obs.	9,121	3,077	1,691	920
Adj. R^2 (%)	–0.038	0.065	–0.055	7.92

Notes: The dependent variable is $Ret_{(t)}$. $AOIB_{(t-1)}$ is computed by taking the difference between abnormal buy-values (*ABV*) and abnormal sell-values (*ASV*), where abnormal buy (sell)-values equal to the percentage difference between the total buy (sell)-values in the current interval and the running 75th percentile of buy (sell)-values of the previous 120 intervals. Control variable is *Volatility*. All panel data regressions are with *Weekday* and *LIETF* fixed effect. *, ** and *** denotes 10%, 5% and 1% statistical level of significance, respectively.

Source: Author` s calculation

4. 3. ARE LIETF INVESTORS TREND CHASERS

In the next stage of our study, we investigated whether LIETF investors are trend-chasers. We have already showed that order flows of LIETFs provided no valuable insights regarding the future returns of the underlying indices. If there is no evidence that LIETF investors have superior information or skills to predict future returns, are these traders motivated by chasing momentum? We estimated the empirical regression model provided by Eq. (3). If LIETF investors are primarily short-term trend-chasers, then we should expect the coefficients of the past returns to be positive for the non- inverse leveraged ETFs and negative for the inverse leveraged ETFs. The results are depicted in Table 8. Two important findings emerged.

First, the lagged returns were highly correlated with the order imbalance level. At 5-minute, 15-minute and 30-minute intervals, there was a strong positive relationship between the first two lagged terms of index returns and the order imbalance level for non-inverse leveraged ETFs (i.e., both β_1 and β_2 are greater than zero). Similarly, we found a negative relationship between the corresponding variables for inverse leveraged ETFs. These results are statistically significant (at the 1% level). Our findings provided evidence that LIETF investors engage in trend-chasing behavior.

Second, we observed that in longer time intervals (i.e., 60 minutes), the positive (negative) relationship between past returns and present order imbalance level faded away for non-inverse (inverse) leveraged ETFs. We observed an inverse relationship between past returns and current order imbalance at 60-minute intervals. This finding is symmetric between the non-inverse leveraged ETFs and inverse leveraged ETFs.

Table 8. Regression analysis on the trend-chasing behaviour of LIETF investors

Variable	5-minute	15-minute	30-minute	60-minute
Panel A: Leverage only (Non-Inverse) ETFs				
$Ret_{(t-1)}$	0.72*** (8.82)	0.52*** (2.85)	0.72*** (2.74)	–0.85 (–1.59)
$Ret_{(t-2)}$	0.25*** (3.45)	0.46*** (2.88)	0.96*** (4.10)	0.036 (0.69)
Constant	0.10*** (4.27)	0.27*** (3.23)	0.42** (2.50)	0.92** (2.03)
Obs.	21,508	6,944	3,340	1,470
Adj. R^2 (%)	0.91	2.01	2.03	7.41
Panel B: Leverage Inverse ETFs				
$Ret_{(t-1)}$	–0.32*** (–7.39)	–0.23** (–2.24)	–0.35** (–2.84)	–0.43 (–1.29)
$Ret_{(t-2)}$	–0.18*** (–4.26)	–0.26*** (–2.94)	–1.02*** (–6.43)	0.19 (0.68)
Constant	0.01 (0.80)	0.043 (0.90)	0.075 (0.82)	0.31 (1.30)
Obs.	26,864	8,665	4,049	1,660
Adj. R^2 (%)	0.48	1.82	4.51	8.70

Notes: The dependent variable is the LIETF's order imbalance – $OIB_{i,t}$. The ind. variables $Re_{(t-k)}$, where k=1,2,…,5 are the k-th lag term of the index returns. The first two lagged return variables are reported. The control variables for current and lagged price volatility based on the underlying stock index and quoted spread of the corresponding LIETF are not reported. All panel data regressions are with *Weekday* and *LIETF* fixed effect. *, ** and *** denotes 10%, 5% and 1% statistical level of significance, respectively.

Source: Author` s calculation

In summary, these findings offered substantial support for our third hypothesis. LIETF investors demonstrated trend-chasing tendencies during short-term trading periods (intervals under 30 minutes) and engaged in contrarian strategies, anticipating reversals of the underlying index, during longer intraday intervals.

5. DISCUSSION, POLICY RECOMENTADIONS, LIMITATIONS AND FUTURE RESEARCH

5. 1. DISCUSSION

Our research extends the literature on price informativeness of leveraged instruments by showing that LIETF trading activity contains limited predictive value for future index returns. While prior studies demonstrated that embedded leverage could provide return predictability through the trading of leveraged products such as options and other derivatives (Roll et al., 2010; Johnson & So, 2012; Ge, Lin, & Pearson, 2016), we found little evidence that LIETF investors possess superior skill in forecasting market direction. Instead, LIETF trading patterns appear consistent with trend-following rather than informed trading, suggesting that these markets are not driven by investors with significant informational advantages. This distinguishes LIETFs from other exchange-traded products, such as industry or broad-based ETFs which, according to recent research, can facilitate informed trading, synthetic shorting, or even the concealment of insider activity (Li & Zhu, 2022; Huang, O'Hara, & Zhong, 2021; Eglīte et al., 2023).

5. 2. POLICY RECOMENTADIONS

Our findings highlight key policy implications. Due to embedded leverage, LIETFs can greatly increase both gains and losses, posing high risks for inexperienced investors. The lack of evidence that LIETF investors are skilled implies that many may unknowingly accept risks exceeding their established tolerance levels. These concerns are consistent with ongoing regulatory debates. The Securities and Exchange Commission (SEC) has already scrutinized leveraged products, proposing in 2019 to standardize approval frameworks, and later permitting the launch of ETFs with leverage up to 200% without prior SEC approval (Shubber & Henderson, 2020). A further concern is that the daily rebalancing mechanism of LIETFs may contribute to heightened late-day volatility in financial markets, as funds must adjust positions in the direction of contemporaneous asset returns. For regulatory authorities, our findings highlight the importance of maintaining robust oversight, ensuring transparent disclosures, and promoting investor education. For retail investors, our empirical results indicate that LIETFs are predominantly used as speculative instruments rather than for long-term investment purposes. Consequently, it is advisable to exercise caution and apply careful consideration when engaging with these products.

5. 3. LIMITATIONS & FUTURE RESEARCH

The study has certain limitations that suggest possible directions for future research. First, extending the sample period beyond the initial Phase One stage of the tariff trade war in 2018 to cover U.S.–China tariff relations through January 2021, including the early Biden era, would provide a broader perspective. Second, cross-country evidence could reveal whether similar dynamics hold in markets with different regulatory frameworks, levels of investor sophistication, and product designs. Third, examining the intraday mechanisms through which LIETFs may amplify volatility—particularly during rebalancing windows—would enhance understanding of their broader market impact. Fourth, linking investor-level characteristics with trading outcomes could clarify whether specific groups of LIETF traders, such as institutional versus retail participants, display differential skill or risk exposure. Fifth, subsequent research could integrate comprehensive data on both retail and institutional holdings. Finally, given the swift expansion of increasingly complex and speculative investment instruments (e.g., The Economist, 2025), there is a clear need for more in-depth analysis of these “spicier” products. Future research could usefully explore the long-term viability of short-term speculative trading and assess its broader implications for the stability of underlying spot indices as well as overall systemic risk. These important questions remain open and merit careful investigation in subsequent studies.

6. CONCLUSION

This study examines how LIETF investors react to U.S.–China trade war news events. After such news releases, trading activity generally decreased, suggesting increased risk aversion, while more active investors raised order sizes and used more assertive strategies. Order imbalance data indicates patterns of short-term consensus and positive sentiment. Abnormal trading activity, assessed via the buy-sell ratio and order imbalance, does not significantly predict future index returns. Overall, LIETF investors tend to pursue prevailing trends in the short term and seek reversals over longer periods. Our findings suggest that speculative activities rather than information-based trading influence LIETF market behavior. These results highlight regulatory considerations and advise that retail investors evaluate the risks associated with LIETFs.

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Data Availability

The authors do not have permission to share data.

Conflict of Interest

The authors declare no conflict of interest.

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APPENDIX A

Consistent with Chordia et al. (2005), the order imbalance ($OIB_{i,t}$) of the ith LIETF is given by:

$$OIB_{i,t} = BV_{it} - SV_{it}, \tag{A1}$$

where BV and SV are the dollar-volume of buy-trades and sell-trades, respectively.

The total buy-values and sell-values are calculated within each interval for each LIETF. Let us assume there are p buy-trades and q sell-trades in time interval t, then the total buy-values and sell-values of LIETF i in interval t are denoted by:

$$TotalBV_{i,t} = \sum_{j=1}^{p} BV_{i,j}, \tag{A2}$$

$$TotalSV_{i,t} = \sum_{j=1}^{q} SV_{i,j}. \tag{A3}$$

While using the previous 120 intervals, we compute the running 75 th percentile of buy-values and sell-values for each interval, which are denoted by $B75$ and $S75$, respectively. The abnormal buy-values ($ABV_{i,t}$) and abnormal sell-values ($ASV_{i,t}$) in the tth interval are:

$$ABV_{i,t} = \begin{cases} \frac{TotalBV_{i,t} - B75_{i,t}}{B75_{i,t}}, & if\ Total\ BV_{i,t} > B75_{i,t} \\ 0, & otherwise \end{cases}, \tag{A4}$$

similarly,

$$ASV_{i,t} = \begin{cases} \frac{TotalSV_{i,t} - B75_{i,t}}{B75_{i,t}}, & if\ Total\ SV_{i,t} > B75_{i,t} \\ 0, & otherwise \end{cases}. \tag{A5}$$

The abnormal order imbalance is given by:

$$AOIB_{i,t} = ABV_{i,t} - ASV_{i,t}. \tag{A6}$$