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Asymmetric Effects of Long and Short Selling Positions: Evidence from US Stock Markets

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Abstract

This paper investigates the effects of short/long positions on the return volatility of the market using high frequency, intra-day data from 2009 to 2020. We employ an asymmetric EGARCH model and find evidence of high persistence of return volatility. We cover the long periods of increased market turbulence over the decade. We show the time-varying volatility of the US stock market and emphasize the asymmetric effects of positive/negative shocks in the extreme market conditions and the destabilizing effects of short selling activities on the financial markets. Our results provide significant implications for portfolio management, especially for profitable short-selling strategies in turbulent periods.

1. Introduction

The effects of short selling on the global financial market are a continuing debate among policymakers and academia. Short selling is an important mechanism in determining the prices of stocks. The Global Financial Crisis (GFC) in 2008 triggered restrictions and bans imposed on short selling activities by governments and regulators to prevent further decline in market prices. Market players have blamed short sellers for crashes however, academic research finds the restrictions and bans on short selling activities adversely affect the market performance.

The extant literature finds the restrictions of short selling led to price inflation (Boehmer et al., 2010; Beber & Pagano, 2013; Diether et al., 2009; Lobanova et al., 2010; Autore et al., 2011), destroying effects on market quality (Lee and Piqueira, 2016; Boehmer et al., 2013; Sobaci et al., 2014), and stocks with high stock interest achieved negatively abnormal returns (Boehmer et al., 2010). Market volatility is used as a proxy measure of risk in financial markets. The restrictions on short selling have been documented to cause higher market volatility (Boehmer et al., 2013; Bris et al., 2007), reduce return volatility (Chen et al., 2016; Zhao et al., 2014; Chang et al., 2014).

While most literature has extensively investigated the impact of the bans and stricter regulations on short selling in the financial market, we follow Bohl et al., (2016) and Kao et al. (2020) to investigate the relationship between return volatility and short selling by introducing short trading position as a variable. We focus on the

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behavior of return volatility during different time periods of the decade. Bohl et al. (2016) investigated the impact of short selling restrictions on stock return volatility. Using the asymmetric Markov-switching GARCH model, they found evidence that the financial crises were accompanied by an increase in volatility persistence, a destabilizing impact of the restrictions on stock volatility. Kao et. al. (2020) examined the relationship between return and trading volume between S&P 500 and the VIX Future Index. They apply the GJR-GARCH model to demonstrate that the threshold exists in both the contemporaneous and lead-lag relationships between return-volume and volatility-volume.

We contribute to the stream of literature and apply the asymmetric Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model to the effect of short selling on return volatility and focus on the impact of investors who use both long and short selling strategy on the market. To the best of our knowledge, we are the first to extensively investigate the asymmetric impact of long-short positions and the market return volatility.

We first provide an empirical analysis of the impact of short selling on return volatility in the US market. We find evidence of high volatility persistence. This indicates the destabilizing effect of short selling activities during periods of increased market turbulence.

Second, we use high-frequency daily data from August 2007 to September 2020 and focus on the asymmetric effects of short selling on return volatility. We show the time-varying volatility of the US stock markets and emphasize the asymmetric effects of positive and negative shocks in extreme market conditions such as a pandemic (Covid-19). Our results show short selling activities increase (decrease) return volatility in bearish (bullish) markets.

The remainder of the paper is structured as follows. Section 2 gives a brief overview of existing literature on short selling. Section 3 provides empirical methods. Section 4 discusses the results of the study and section 5 concludes.

2. Literature Review

The activities of short selling in the financial markets have become a topical issue particularly after the global crisis in 2008. Critics of short selling have attributed the cause of market shocks to the behavior of short sellers. They argued the destabilizing impact of short selling on the market. The negative view on short selling activities is shared by policymakers and regulators of the financial market. The collapse of two of the largest investment banks; Bear Stearns and Lehman Brothers in 2008 was attributed to short selling which caused panic in the market and signaled the global financial crisis in 2008 (McGavin, 2010).

Empirical findings on bans of short selling conclude on the impact to price discovery process, liquidity, and market efficiency. Beber and Pagano (2013) argue that short selling bans reduced market liquidity. On price discovery, Boehmer and Wu (2013) conclude short selling contributes significantly while Engelbert et al. (2018) argue short selling decrease the price efficiency. Short selling contributes to market efficiency (Chen et al. 2016; Zhao et al., 2014; Chang et al., 2014). We focus our study on the impact of short selling on return volatility.

Return volatility plays an important role in financial markets. Volatility is used as a proxy for market risk and its importance applies to securities pricing, asset allocation, and risk management. Short selling activities have been argued by various researchers to either increase or decrease the market volatility. Sobaci et al (2014) investigated the dynamic relationship between short selling activity and volatility using a VAR(p)-cDCC-FIEGARCH (1, d,1) approach on the Borsa Istanbul. The conclude increase in short selling activities is associated with decreased volatility. Caceres et al. (2014) study the different types of short-sale bans on the Spanish stock market. Using panel data and different risk measures, they show evidence that market volatility was reduced during total and partial bans. Zhao et al. (2014) observed lower volatility when they investigated the impact of short sale constraints on the Chinese stock market using an event study approach.

Some researchers argue contrarily that short selling activities increase market volatility. Henry and McKenzie (2006) study the relationship between traded volume and volatility on the Hong Kong stock market. using the Multivariate GARCH model, they find evidence of greater volatility attributed to short selling activities. Helmes et al. (2017) argued short selling increases intraday volatility when they study the Australian stock using a fixed-effect panel method. Studies by Henry et al. (2015) Chan and Feng (2016), Boehmer et al. (2013) have found evidence to support the theory that short selling increases volatility in the market. Our paper aims to contribute to the literature on the impact of short selling on return volatility during market shocks. We use recent time-series data (2009-2020) and economic models, applying structural breaks to investigate the impact of short and long positions on the return volatility. We apply the exponential GARCH model to capture the persistent and asymmetry of return volatility.

The Autoregressive Conditional Heteroskedasticity (ARCH) proposed by Engle (1982) and its extension of GARCH by Bollerslev (1986) has been widely used in the modeling and forecasting of volatility. The ARCH and GARCH capture volatility clustering and leptokurtosis but not the leverage effect. The asymmetry or leverage effects allow the conditional volatility to be affected by both positive and negative shocks of the same magnitude (Charles & Darnes, 2019). The model uses a log-volatility which is expressed as a combination of past values and past values of negative and positive parts of the innovations (Francq et al., 2013). This allows for volatility asymmetries in financial data and does not place positive restrictions on the volatility coefficients.

The EGARCH model has been applied to various financial assets. Sakarya and Ekinci (2020) study Exchange Traded Funds (ETFs) flows in foreign exchange uncertainty by using EGARCH on Borsa Istanbul. Do et al. (2020) investigated the volatility spillover between 3 types of China's shares using the EGARCH model. Mansur and Elyasiani (2017) apply the EGARCH model to investigate the significant factors for co-skewness and co-kurtosis in hedge fund returns using monthly data from 1993 to 2014. We apply the EGARCH model in this study to capture the asymmetric and persistence effects of short selling activities on return volatility.

3. Data and Methods

We use the daily trading volumes of short/long selling data from August 2009 to September 2020 in this research. The short selling data are provided by the Financial Industry Regulatory Authority (FINRA) upon request. The short selling data published by FINRA includes only trades that are publicly disseminated[1]. The daily market prices for the New York Stock Exchange Composite Index (^NYA) are also used to represent the general stock market in this study for the same period. The Index is a float-adjusted market capitalization-weighted index. It includes all common stocks listed on the NYSE which includes ADRs, REIT, tracking stocks, and foreign listings. The inclusion of all stocks in all industries justifies our selection of the index as the best representation of the market.

Table A1 in the Appendix shows the descriptive statistics of the returns and short selling trading volumes. The time series of the index and its return shows they are negatively skewed with excess kurtosis on the returns of the index. The excess kurtosis in the index returns and the short/long position volumes indicate the series are leptokurtic which implies higher peaks at the mean. The short selling trading volumes show a positively skewed series. The test statistic of the Ljung-Box test significantly shows a linear dependence for all the series and an indication of the ARCH effect which supports the use of the EGARCH model. The Jarque-Bera test concludes non-normality in all series. The non-normality of the series is a common characteristic of financial data and Fama (1964) found evidence of non-normality of monthly stock returns. A normally distributed financial data has observations that line on the straight line (Loy et al., 2016).

This paper uses the exponential GARCH (EGARCH) proposed by Nelson (1991) to investigate the impact of long-short selling positions on the market price volatility for the period between 2009 and 2020.

The conditional variance of EGARCH (1,1) is specified as follows

$$In(\delta_t^2) = \omega + \alpha\left[\frac{|\varepsilon_{t-1}|}{\delta_{t-1}} - \sqrt{\frac{2}{\pi}}\right] + \Upsilon\frac{\varepsilon_{t-1}}{\delta_{t-1}} + \beta\ln(\delta_{t-1}^2) \tag{1}$$

Where δ_{t-1}^2 is the variance estimation of the previous period, $\frac{\varepsilon_{t-1}}{\delta_{t-1}}$ is the effect of leverage and asymmetry and Υ the leverage parameter. If $\Upsilon \neq 0$, the impact of news is asymmetric while $\Upsilon < 0$, indicates the leverage effect. The impact of shocks on the conditional variance is measured by α and β measures the persistence.

We follow a similar approach to Chen et al. (2011) to include additional regressors; the trading volumes of short position (V_t^{SP}) and long position (V_t^{LP}) used as the explanatory variable to the conditional volatility of GARCH and EGARCH models.

The variables V_t^{SP} and V_t^{LP} are defined as follows;

$$V_t^{SP} = \frac{SV_t}{SV_{t-1}} \text{ and } V_t^{LP} = \frac{LV_t}{LV_{t-1}} \tag{2}$$

Where SV_t and LV_t are the trading volumes for the short and long positions respectively. This gives the significance of the impact of short/long positions on the conditional variance of the returns of the NYSE Composite Index.

[1] FINRA provides daily short selling volumes for all listed stocks. We process data and aggregate the total short and long positions for each day. Data is available upon request.

The variance equations of the models are given below;

$$In(\delta_t^2) = \omega + \alpha\left[\frac{|\varepsilon_{t-1}|}{\delta_{t-1}} - \sqrt{\frac{2}{\pi}}\right] + \Upsilon\frac{\varepsilon_{t-1}}{\delta_{t-1}} + \beta\ln(\delta_{t-1}^2) + \lambda_1 V_t^{LP} + \lambda_2 V_t^{SP} \tag{3}$$

Where λ_1 and λ_2 are the estimated parameters for long and short positions respectively.

The distribution of innovations for the GARCH models is assumed to be normally distributed. The assumption however does to suit financial times series with excess kurtosis. We use the Generalized Error Distribution (GED) to depict the leptokurtosis of the series.

The density function of GED random variable normalized to have a mean = 0 and variance = 1 as described by Nelson (1991) is expressed as

$$f(z) = \frac{v\exp\left[-\left(\frac{1}{2}\right)|Z/\lambda|^v\right]}{\lambda 2^{(1+1/v)}\Gamma(1/v)} \qquad -\infty < z < \infty \tag{4}$$

where $\Gamma(\cdot)$ is the gamma function, and

$$\lambda = \left[2^{(-2/v)}\Gamma(1/v)/\Gamma(3/v)\right]^{1/2} \tag{5}$$

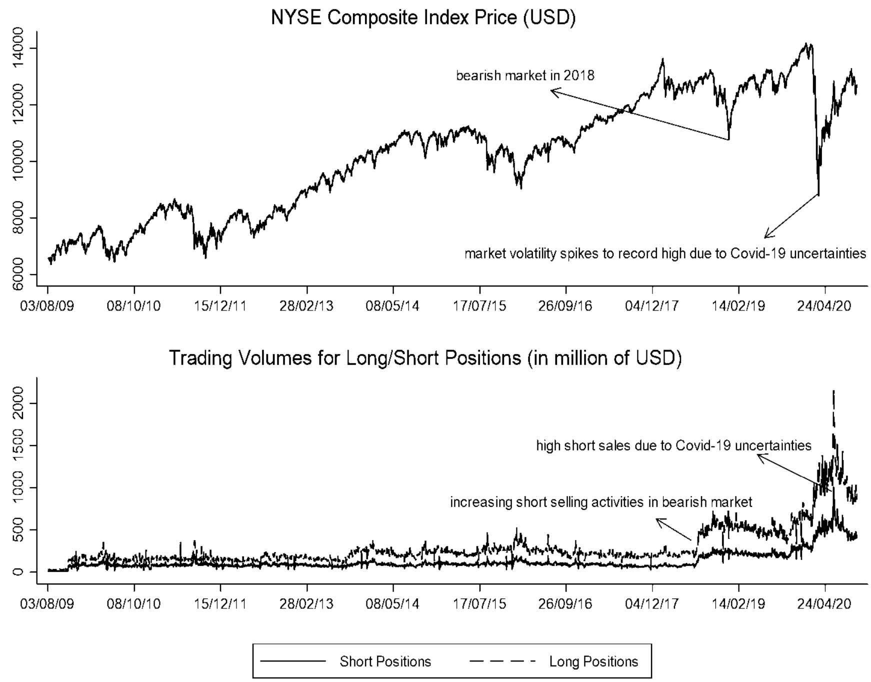
v denotes the shape parameter, z follows a standard normal distribution when $v = 2$.

4. Results

Our empirical analysis provides several results which explain the time-varying behavior of short selling effects on return volatility First, we analysis the impact of short and long positions on return volatility from 2009 to 2020 and show that short positions increase market volatility in the baseline regressions presented in tables 1 and 2. Second, we considered the impact of short selling under different time- periods. We use the Bai-Perron test to estimate structural change points and show that short selling activities increase (decrease) return volatility in bearish (bullish) markets.

Fig. 1 depicts the daily price changes of the market (^NYA) during the empirical period from August 3, 2009 to September 30, 2020 and the corresponding trading volumes (in millions of dollars) of the short/long positions by investors in the same period. The index price soars and exhibits a long-running bullish market over the period with occasional falls in prices which are quickly recovered. Fig. 1 also shows a steady pattern in investors' use of short selling as a trading strategy in a bullish market from 2009 to 2018. The follows the various restrictions and regulations enacted by the regulators after the 2008 financial crisis. The financial year 2018 is considered as the worst performing year for stocks since the financial crisis largely attributed to the 4th quarter performance. Investors' uncertainties and concerns due to the trade wars between the largest economies led to increased volatility in the market and the tumultuous performance in December 2018 meant the benchmark indices could not meet the performance of 2017. The return of NYSE CI fell 11.88% by end of the year 2018. The Dow, S&P 500, Nasdaq all fell in 2018 by 5.6%, 6.2% and 4% respectively. This led to an increase in short selling activities in Q4, 2018.

Figure 1 NYSE Composite Index and Long/Short Trading Volumes

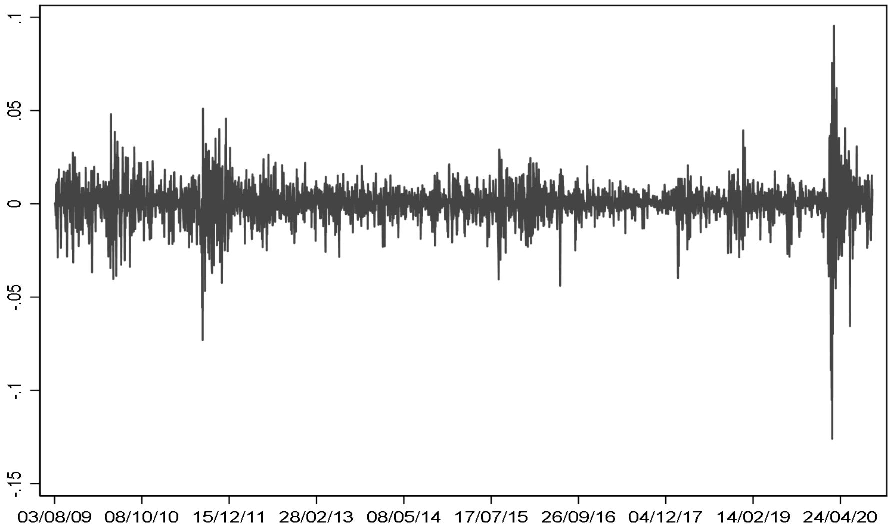


Notes: NYSE Composite Index daily trading prices are obtained from New York Stock Exchange website (ftp://ftp.nyxdata.com) and short selling daily trading volumes provided by FINRA. All data are sampled from 3 August, 2009 to 30 September, 2020. Index prices on indicated on the y-axis of the first graph while trading volumes are indicated on the x-axis of the second graph in millions of USD. Period time is indicated on the x-axis of both graphs.

The market recovery in 2019 is attributed to the policy shift of the Federal Reserve of the US (Fed). While the Fed hiked its interest rate to 2.5% in 2018, it cut the rate in 2019 to the range of 1.50% to 1.75% which gain investors' confidence. The benchmark indices all ended the year with significant returns. The market again suffered its worst performance with the onset of the Covid-19 which was declined a pandemic by the World Health Organization (WHO) on March 11, 2020. The market exhibited an exponential fall in prices as shown in Fig. 1 as global economic activities were put on hold to fight the pandemic. The market volatility spiked to a record high since the global financial crisis on 16th March 2020 as indicated in Fig. 1. This is also replicated in the exponential increase in short selling activities with the uncertainties of the effects of the pandemic on the global markets.

Fig. 2 depicts the return volatility of the index. The series exhibit clustering and the standard deviation value of (1.12%) implies relatively high volatility. The impact of the pandemic is visibly captured in Fig.2 and Fig. 3, the estimated conditional volatility series. Both show the highest volatility throughout studies. The estimated volatility was stable and ranges from 0.0000 to 0.0020 from 2009 to 2019. It however jumps to highs above 0.0060 in 2020 due to the uncertainties caused by the pandemic. The periods of high volatility can be associated with market drops in prices.

Figure 2 NYSE Composite Index Returns



Notes: NYSE Composite Index daily log-returns are computed from the daily index prices. Returns range from -0.15 to 0.10 on the y-axis. All data are sampled from 3 August 2009 to 30 September 2020 indicated on the x-axis.

We first run the GARCH model estimates for the return of NYSE CI as summaries in Table 1. The EGARCH (1,1) estimates using the Generalised Error Distribution (GED) indicate a strong leverage effect in the returns of the market. The positive coefficient of the asymmetric effect (-0.1583), significant at 1% level indicates negative innovations are more destabilizing than positive innovations. The estimates also show a strong volatility persistence ($\alpha + \beta$). The garch effect coefficient in both GARCH (1,1) and EGARCH (1,1) significant at 1% shows the volatility of the index is strongly driven by their past volatility. This implies the presence of volatility clustering and common phenomena in stock markets (Duppati et al. 2017).

Table 1 GARCH Models Estimates for Return Volatility

	GARCH (1,1)	*EGARCH (1,1)*
constant	0.0000	-0.3020
	(0.0000)	(0.0508)
α	0.1700***	0.2119***
	(0.0121)	(0.0233)
β	0.8110***	0.9680***
	(0.0122)	(0.0053)
Ƴ	-	-0.1583***
		(0.01544)
Log Likelihood	9368.099	9488.438

Notes: *, **, *** Statistically significant at the 10%, 5% and 1% significant level. The parameter estimates follow GED.

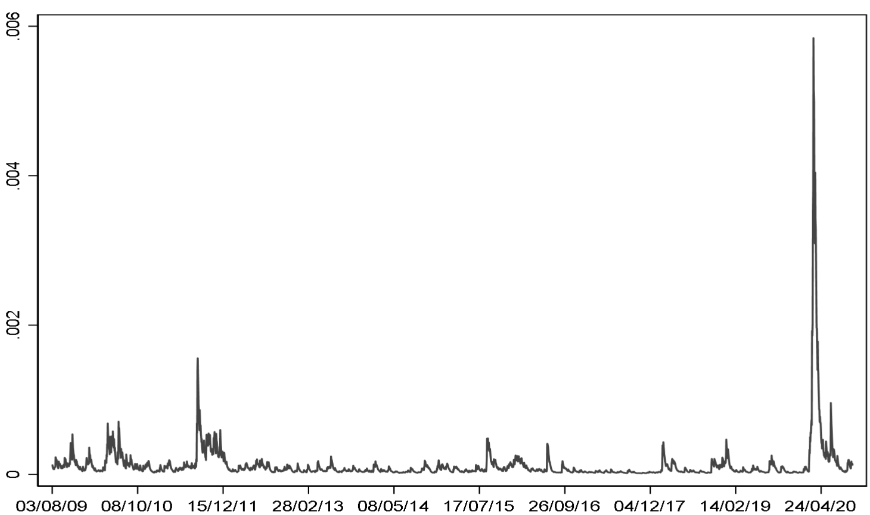
Table 2 provides the GARCH estimates and shows the effect of short selling on the return volatility of the market. The EGARCH (1,1) estimates show the weak arch and strong garch effects on the return volatility during short selling activities. There is the presence of high volatility persistence in the returns during short selling activities. The high persistence parameter indicates volatility shocks take a longer time to dissipate and implies a destabilizing effect of short selling on the market volatility (Bohl et al., 2016). The coefficient of the asymmetric effect (-0.1843) significant at 1% implies the positive coefficient shows negative shocks prove to increase the market volatility more than negative stocks (Fakhfekh et al., 2016; Jeribi et al., 2015). The coefficient of short positions is 2.5158 and significant at 1%. This implies short selling activities on the market increase the return volatility. The traditional buy-and-hold strategy used by traders reduces the return volatility as indicated by the coefficient of the long position (-1.1378). The results are consistent with higher orders of the EGARCH model estimates. The asymmetric effects and high volatility persistence are captured as summarized in table 1. The estimated risk premium of the expected returns is negatively correlated with the conditional variance with negative constant values in all orders of the EGARCH model. This result is consistent with the findings of Nelson (1991). The higher orders of the EGARCH model exhibits similar results to the EGACH (1,1).

Table 2 Short Selling Effects on Return Volatility

	GARCH (1,1)	*EGARCH (1,1)*	*EGARCH (1,2)*	*EGARCH (2,1)*	*EGARCH (2,2)*
constant	0.0007	-0.5651	-0.6694	-0.6261	-0.8407
	(0.0001)	(0.0006)	(0.0708)	(0.0648)	(0.0834)
α_1	0.1718***	0.2809***	0.3405***	0.1023**	0.1630***
	(0.0204)	(0.0260)	(0.0334)	(0.0484)	(0.0439)
γ_1		-0.1843***	-0.2369***	-0.2333***	-0.2227***
		(0.0181)	(0.0237)	(0.0284)	(0.0283)
α_2				0.2027***	0.2724***
				(0.0478)	(0.0425)
γ_2				0.0490*	-0.0757***
				(0.0296)	(0.0303)
β_1	0.8063***	0.9437***	0.5962***	0.9375***	0.4016***
	(0.0201)	(0.0062)	(0.0560)	(0.0066)	(0.0522)
β_2			0.3376***		0.5149***
			(0.0589)		(0.5177)
Short Position	1.4306	2.5185***	3.3588***	2.7015***	3.4106***
	(2.1673)	(0.4789)	(0.5453)	(0.4673)	(0.5546)
Long Position	-0.333	-1.1378**	-1.5614***	-1.2652***	-1.4271**
	(2.0967)	(0.4861)	(0.5503)	(0.4786)	(0.5656)
Log Likelihood	9451.46	9553.12	9568	9562.54	9591.82

*Notes: *, **, *** Statistically significant at the 10%, 5% and 1% significant level. Robust standard errors are in parentheses. The parameter estimates follow GED.*

Figure 3 Estimated Conditional Volatility of NYSE Composite Index



Notes: Estimated conditional volatility of the NYSE Composite Index obtain from NYSE website. Conditional volatility ranges from 0 to 0.006 on the y-axis. All data are sampled from 3 August 2009 to 30 September 2020 indicated on the x-axis.

4.1 Time-Varying Effects of Short Selling on Return Volatility

We present the main results of our analysis in table 3. The aftermath of the financial crisis resulted in stricter regulations in short selling activities. The global financial markets did recover from the crises and have been marked with periods of low/high performance. The period between 2009 to 2017 is characterized by increased trading activities on the stock markets as more companies result in raising funds on the stock markets to borrow. The market sentiment over the period has largely been bullish as investors gain confidence coupled with policy interventions by governments. The year 2018 however ended the long bullish global markets. The year ended with falling market prices accompanied by increase short selling activities as shown in Fig. 2. The uncertainties involved in the trade wars between large economies led to the bearish market in 2018. The markets however recovered in 2019 with policy interventions as US Fed cuts its rate to between 1.5 - 1.75%. This resulted in investors' confidence in the market with the benchmark of most indices ending the year with positive returns.

The financial market has experienced several shocks which affect the behavior of investors and traders after the global crisis. We study the impact of long and short positions under different periods. Using the Bai-Perron test, we test and estimate for structural breaks in the return series of the NYSE Composite Index. We find strong evidence of structural breaks significant 1%. We then estimate the breakpoint dates of the market shocks. We divide our data into 5 different sub-periods; period 1 (03/08/2009 - 09/08/2011), period 2 (10/08/2011 - 12/02/2016), period 3 (16/02/2016 - 30/5/2018), period 4 (31/05/2018 - 16/03/2020) and period 5 (17/03/2020 - 30/09/2020). Figure A1 in the Appendix shows the Bai-Perron Plot for the NYSE CI Returns.

Table 3 below, illustrates the EGARH (1,1) estimates under different periods. Volatility clustering with parameter (α) exists across all the periods. This implies larger shocks will increase the return volatility to a greater extender than smaller shocks. The strong clustering can be attributed to the speculative nature of the long-short trading strategies. Investors and traders increase their short (long) positions when prices start to fall(rise). The high garch (β) estimates significantly indicate the presence of persistence in the return volatility. The current return volatility across all periods is strongly driven by its past volatility.

The effects of the long and short positions on the return volatility of the NYSE CI are asymmetric. The estimates for the asymmetric effect (Υ) are negative across all periods and statistically significant at 1%. This implies negative shocks are found to increase the return volatility of the NYSE CI more than positive shocks. This finding is consistent with the literature on equity markets. We give the possible explanation that during market turbulence, negative information (buy low and sell high) is evident in the NYSE CI which leads to an increase in the return volatility.

Period 1 consists of the first 2 years of economic recovery after the financial crisis. Market regulators enact new and stricter laws to govern the activities of short selling. The coefficient of short positions is positive, which indicates an increase in volatility but not significant. The possible explanation is that investors and traders during this period were yet to adapt to new regulations and market recovery. Periods 2 and 3 show a stable economic recovery and activities. Investors' confidence in the financial market increased. The coefficients of short positions are positive and statistically significant. Short positions increase the return volatility in periods 2 and 3. Investors and traders increase their trading positions to mitigate their risk exposure and maximize their returns.

Period 4 was characterized by market uncertainties. This caused a downturn in the financial markets. The major developed markets all returned negative at the end of 2018, however recovered in 2019. The coefficient of the short positions is negative and weakly significant at 10%, indicating decreased volatility. This implies investors and short traders can use short selling as a hedging tool to reduce their risk Bianchi and Drew (2012). Period 5 saw the onset of the Covid-19 pandemic. The World Health Organization (WHO) declared Covid-19 as a pandemic on March 11, 2020 however the US reported its first case in early February 2020. The pandemic has affected all sectors of the global economies and led to an increase in the global market risk volatility (Zhang et. al., 2020). The Covid-19 pandemic uncertainties resulted in an exponential fall in prices which was the highest since the financial crises in 2008. The coefficient of the short position is positive, indicating increase volatility but insignificant. we explain our findings that the pandemic did not have a significant impact on the return volatility. Investors and traders can profit from long/short trading strategies and make decisions that involve a degree of uncertainty and risk at different time periods (Kapounek et al, 2021).

Our analysis across the different periods shows the time-varying behavior short positions have on the return volatility over the period. While period 4 findings indicate reduced volatility, the remaining periods indicate an increase in return volatility with periods 2 and 3 statistically significant. Our results show that short selling activities increase (decrease) return volatility in bearish (bullish) markets. Investors and traders can use short positions as a hedging tool to reduce their risk exposure (Bianchi and Drew 2012).

Table 3 EGARCH (1,1) Estimates for Different Periods

	Full Period	*Period 1 (03/08/2009 - 09/08/2011)*	*Period 2 (10/08/2011 - 12/02/2016)*	*Period 3 (16/02/2016 - 30/05/2018)*	*Period 4 (31/05/2018 - 16/03/2020)*	*Period 5 (17/03/2020 - 30/09/2020)*
constant	-0.5651	-1.0500	-0.5018	-0.5404	-0.6403	-0.2873
	(0.0006)	0.02501	(0.0970)	(0.2306)	(0.2037)	(0.1368)
α	0.2809***	0.0683	0.2587***	0.2843	0.3224***	0.3470***
	(0.026)	(0.0728)	(0.03621)	(0.0702)	(0.0875)	(0.0415)
β	0.9437***	0.8875***	0.9514***	0.9499	0.9373***	0.9691***
	(0.0062)	(0.0272)	(0.0099)	(0.0223)	(0.0202)	(0.0151)
ϒ	-0.1843***	-0.3104***	-0.1378***	-0.1530***	-0.2430***	-0.3165***
	(0.0181)	(0.05563)	(0.0277)	(0.0391)	(0.0455)	(0.0109)
Short Position	2.5185***	1.5727	4.7265***	3.3606***	-3.9004*	6.4315
	(0.4789)	(0.9653)	(0.7955)	(1.1914)	(2.2525)	(3.3409)
Long Position	-1.1378**	-1.0863	-2.8857***	-0.4301	6.0840***	-5.5078
	(0.4861)	(0.9628)	(0.7749)	(1.2403)	(2.2444)	(3.3470)
Log Likelihood	9553.12	1602.22	3860.19	2172.61	1604.4	388.82
Obs.	2810	510	1135	576	451	138

*Notes: *, **, *** Statistically significant at the 10%, 5% and 1% significant level. Robust standard errors are in parentheses. The parameter estimates follow GED*

5. Robustness Analysis

We check the robustness of our results and test the hypothesis that there is no difference in the US stock markets. We apply our analysis to 3 different market indices. We use the Dow Jones Industrial Average, the S&P 500 Index, and Nasdaq Composite Index. Table 4, 5 and 6 below provide the EGARCH estimates for the 3 markets respectively.

Table 4 EGARCH (1,1) Estimates for Dow Jones Industrial Average

	Full Period	*Period 1* *(03/08/2009 - 09/08/2011)*	*Period 2* *(10/08/2011 - 12/02/2016)*	*Period 3* *(16/02/2016 - 30/5/2018)*	*Period 4* *(13/02/2016 - 30/05/2018)*	*Period 5* *(17/03/2020 - 30/09/2020)*
constant	-0.6385	-0.9684	-0.5231	-0.6787	-0.4902	-0.4195
	(0.0687)	(0.2350)	(0.1123)	(0.2241)	(0.1444)	(0.2342)
α	0.2889***	0.0914	0.2738***	0.2735***	0.2284***	0.2593*
	(0.2583)	(0.0676)	(0.0375)	(0.0669)	(0.0841)	(0.1269)
β	0.9363***	0.9007***	0.9498***	0.9365***	0.9510***	0.9527***
	(0.0070)	(0.0243)	(0.0115)	(0.0216)	(0.0150)	(0.0284)
ϒ	-0.2007***	-0.3229***	-0.1822***	-0.1726***	-0.2723***	-0.1341
	(0.0193)	(0.0561)	(0.0283)	(0.0420)	(0.0480)	(0.1012)
Short Position	1.8509***	1.4996	3.6146***	2.121	-3.2675	-1.1281
	(0.5270)	(0.9758)	(0.7821)	(1.4071)	(2.3974)	(3.6681)
Long Position	-0.5368	-1.1040	-1.7611**	0.9661	5.3045**	5.1745
	-0.5317	(0.9631)	(0.7716)	(1.3865)	(2.3790)	(3.9851)
Log Likelihood	9705.59	1719.25	3947.56	2186.46	1541.68	372.39
Obs.	2810	510	1135	576	451	138

Notes: *, **, *** Statistically significant at the 10%, 5% and 1% significant level. Robust standard errors are in parentheses. Estimates follow GED

Table 5 EGARCH (1,1) Estimates for S & P 500 Index

	Full Period	***Period 1*** **(03/08/2009 - 09/08/2011)**	***Period 2*** **(10/08/2011 - 12/02/2016)**	***Period 3*** **(16/02/2016 - 30/5/2018)**	***Period 4*** **(13/02/2016 - 30/05/2018)**	***Period 5*** **(17/03/2020 - 30/09/2020)**
constant	-0.7020	-1.0041	-0.5820	-0.6509	-0.6146	-0.4677
	(0.0707)	(0.2395)	(0.1200)	(0.2263)	(0.1654)	(0.2568)
α	0.3098***	0.0829	0.2852***	0.2706***	0.2882***	0.2924**
	(0.0262)	(0.0686)	(0.0360)	(0.0723)	(0.0744)	(0.1216)
β	0.9294	0.8949***	0.9436***	0.9386***	0.9390***	0.9468***
	(0.0073)	(0.0253)	(0.0125)	(0.0218)	(0.0168)	(0.0292)
ϒ	-0.2069***	-0.3153***	-0.2040***	-0.2060***	-0.2954***	-0.0628
	(0.0184)	(0.0551)	(0.0304)	(0.04466)	(0.0447)	(0.1148)
Short Position	2.2080***	1.5632*	3.9944***	2.5338*	-4.3835*	2.7132
	(0.5399)	(0.9427)	(0.8484)	(1.3608)	(2.2832)	(5.7795)
Long Position	-0.7297	-1.1180	-1.9876**	0.5000	6.6474**	1.3716
	(0.5456)	(0.9315)	(0.8372)	(1.4084)	(2.3241)	(5.8508)
Log Likelihood	9623.09	1658.42	3897.54	2189.46	1564.87	382.42
Obs.	2810	510	1135	576	451	138

Notes: *, **, *** Statistically significant at the 10%, 5% and 1% significant level. Robust standard errors are in parentheses. Estimates follow GED

Table 6 EGARCH (1,1) Estimates for NASDAQ Composite Index

	Full Period	*Period 1 (03/08/2009 - 09/08/2011)*	*Period 2 (10/08/2011 - 12/02/2016)*	*Period 3 (16/02/2016 - 30/5/2018)*	*Period 4 (13/02/2016 - 30/05/2018)*	*Period 5 (17/03/2020 - 30/09/2020)*
constant	-0.72144	-1.1205	-0.6529	-0.9682	-0.7030	-0.5306
	(0.0762)	(0.2910)	(0.1295)	(0.2983)	(0.1937)	(0.1426)
α	0.2584***	0.1059	0.2272***	0.2459***	0.2837***	0.2556**
	(0.0263)	(0.0663)	(0.0346)	(0.0754)	(0.0796)	(0.0115)
β	0.9247***	0.8802***	0.9343**	0.9053***	0.9266***	0.8931
	(0.0081)	(0.0313)	(0.0139)	(0.0300)	(0.0207)	(0.1834)
Ƴ	-0.1794***	-0.2833***	-0.1849***	-0.2045***	-0.2550***	0.2187
	(0.0176)	(0.0508)	(0.0284)	(0.0486)	(0.0502)	(0.1146)
Short Position	1.8757***	1.9855**	3.4131	1.6711	-3.7921	2.7311
	(0.5490)	(0.9888)	(0.7930)	(1.4361)	(2.5071)	(5.6988)
Long Position	-0.5177	-1.4673	-1.5237*	1.6749	6.2978**	1.2484
	(0.5527)	(0.9878)	(0.7907)	(1.4305)	(2.4445)	(4.6490)
Log Likelihood	9095.53	1600.62	3722.73	2046.05	1439.28	347.54
Obs.	2810	510	1135	576	451	138

Notes: *, **, *** Statistically significant at the 10%, 5% and 1% significant level. Robust standard errors are in parentheses. Estimates follow GED.

There is high volatility persistence across the 3 major indices indicates the destabilizing effects of short selling across developed markets (Bohl et al., 2016). The negative asymmetric coefficient is statistically significant across the markets. This indicates negative shocks increase the market volatility more than positive shocks (Fakhfekh et al., 2016; Jeribi et al., 2015). This phenomenon is common across the financial markets. Barunik and Kocenda (2019) conclude that negative shocks dominate forex volatility connectedness. The asymmetric effect also indicates short selling is dominated by informed investors, fund managers, and traders in developed markets. The negative constant values indicate the expected risk premium of the expected returns of the 3 markets are all negatively correlated with the conditional variance of the EGARCH model. -.

The positive coefficient of short selling in all 3 markets shows an increase in volatility after the GFC. This is significant in periods 2 and 3 for all markets. These periods are charateristised by market recovery and increased financial confidence. This result is consistent with our findings in table 3. Period 4 impacted by market uncertainties shows a reduction in return volatility. This is consistent across all markets and proves there is no difference in the US markets and indicate interdependence of developed markets during periods of increased volatility (Fidrmuc et. al. 2020).

6. Conclusions

This paper studies the effect of short selling activities on return volatility. We focus on the time-varying volatility behavior of the US stock markets. We apply the asymmetric EGARCH model to investigate the relationship between short selling trading volumes and the return volatility of the NYSE CI.

The results of the studies show high volatility persistence in the return volatility during short selling activities. This implies a destabilizing effect of short selling on the financial market which is consistent with the work of Bohl et al. (2016). We also discovered positive shocks prove to increase the market volatility less than negative stocks (Fakhfekh et al., 2016; Jeribi et al., 2015) which reflects the asymmetric effect observed in stock markets.

We analyze the impact of short selling activities during market shocks under 5 different periods. Using the Bai-Perron test, we estimate the structural change points and find evidence of high persistence and volatility clustering across all periods. We show the time-varying volatility behavior of the US market over the period. Our results show short selling activities increase (decrease) return volatility in bearish (bullish) markets. Our findings indicate during the extreme market turbulence (pandemic), the short selling activities did not have any significant impact on return volatility. Investors and traders can use the negative information (buy low and sell high) to increase their portfolio returns.

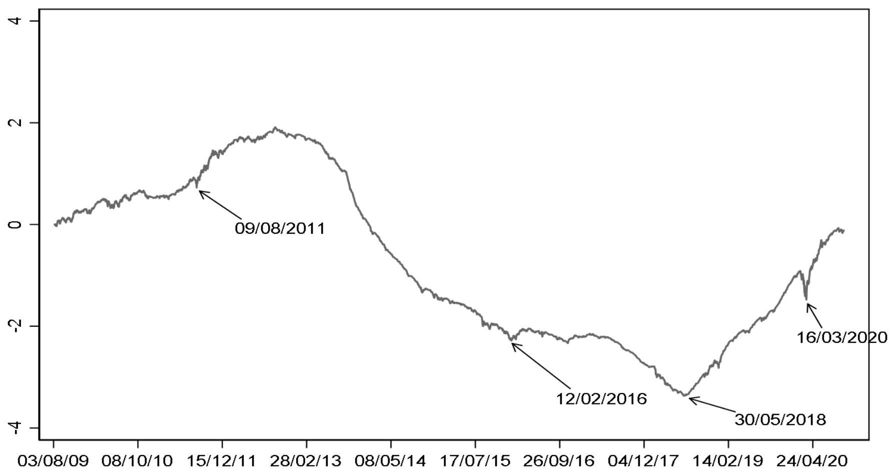
This contribution is beneficial to investors and portfolio managers to use short-term strategies during such market conditions. The market regulators are also cautioned in the implementations and formulations of policies during these extreme market conditions.

APPENDIX

Table A1 Summary Statistics

	NYSE Composite Index	***Returns of NYSE***	***Short Postions (Vol. in Dollars)***	***Long Postions (Vol. in Dollars)***
Mean	10181.87	0.00	130366213.33	293527362.17
Max.	14183.20	0.10	1006381051.00	2168739929.00
Min.	6352.11	-0.13	9794749.00	22101125.00
S.D	2042.84	0.01	111422050.80	240771841.60
Skewness	-0.11	-1.02	2.95	2.65
Kurtosis	1.83	18.80	13.47	11.71
Jarque-Bera	165.61	29724.81	16914.01	12179.93
Ljung-Box Q (40)	100900.00	265.00	90845.00	90549.00
Obs.	2810	2810	2810	2810

Figure A1 Bai-Perron Cusum Plot of NYSE Composite Index



Notes: With 99% confidence bands around the null. The structural breaks dates are estimated to capture the market shocks in the return of the NYSE CI. The dates are used to divide our data into five sub-groups.

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