Fund-level Investor Sentiment and Mean-variance Relation: Evidence From Singapore-listed ETFs

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Abstract

This paper tests the influences of fund-level sentiment on the mean-variance relation in ETF market. We find that in low (high)-sentiment periods, the expected excess return is positively (negatively) related to the conditional variances. Sentiment traders undermine the otherwise positive risk-return tradeoff and even twist it into a negative one in high-sentiment periods. The impact of sentiment is stronger during the global pandemic.

Keywords: exchange-traded funds, investor sentiment, mean-variance relation

1. Introduction

The relationship between mean return and conditional volatility is a central issue in finance and has been debated for decades. The classical asset pricing model insists on a positive risk-return tradeoff, which is supported by researchers like French et al. (1987), Baillie and DeGennaro (1990), Ghysels et al. (2005) and Pástor et al. (2008). However, there are also studies supporting a negative relation like Campbell (1987), Breen et al. (1989), Nelson (1991), Lee et al. (2002) and Brandt and Kang (2004). Some researchers find mixed results of both a positive and negative relationship (Turner et al., 1989; Glosten et al., 1993) and some find an insignificant relationship (Chan et al., 1992; Theodossiou & Lee, 1995; Bali et al., 2005; Bollerslev & Zhou, 2006).

Behavior financial theories gradually recognize the existence of noise traders and highlight the role of investor sentiment in market (Fama, 1965; Black, 1986; De Long et al., 1990; Barberis et al., 1998; Brown, 1999; Brown & Cliff, 2005; Baker & Wurgler, 2006). Yu and Yuan (2011) find that excess returns are positively related to conditional variances under low-sentiment regimes and unrelated to variances under high-sentiment regimes. The presence of sentiment-driven traders would have strong influences on stock markets when sentiment is high, which weakens the positive mean-variance relation. Shen et al. (2017) and Wang (2018) also get similar results.

Exchange-traded funds (ETFs) have grown fast these years and arisen investors' interest due to its low expense ratios and fewer broker commissions when compared to purchasing the stocks individually. While in ETF markets, the related literature about the impact of sentiment on mean-variance relation is scarce. Most of the literature concerns about the effect of sentiment on ETF returns (Chen et al., 2017; Lee et al., 2021; Swamy et al., 2019), ETF price deviation (Ma et al., 2018) and the effect on return volatility (Yang & Chi, 2021). Chau et al. (2011) find that sentiment-driven noise trading causes a positive feedback trading activity in ETF market. Clifford et al. (2014) argues that the naive extrapolation bias results in the return chasing in ETFs.

In this paper, we contribute to the literature by studying the mean-variance relation in ETF market. Besides, we extend this question under the two-regime setting and explore the influences of investor sentiment on the mean-variance relation. Prior literature mostly uses market-wide sentiment, but we construct composite measure of fund-level sentiment. We use daily data of 37 ETFs listed on the Singapore Exchange from June 27, 2019 to June 28, 2022. The fund-level sentiment index is constructed by applying the first principal component analysis used by Baker and Wurgler (2006) of four sentiment proxies suggested by Yang and Chi (2021). We employ GARCH, GJR-GARCH and the moving average model to estimate the ETF return volatility.

Our results show that the positive risk-return tradeoff exists in low-sentiment periods while sentiment-driven noise trading cause too much turbulence in high-sentiment periods, which not only weaken the otherwise positive relation but also twist it into a negative one. The results are robust to three volatility models. We also conduct the regression in different subperiods. In Pre-Covid and Post-Covid periods, the expected excess return is unrelated to conditional variance under high sentiment regime, while during Covid period, the mean-variance

relation is negative, suggesting that the impact of sentiment is stronger in global pandemic.

The reminder of this paper proceeds as follows. Section 2 develops the hypothesis. Section 3 provides the data, constructs the composite sentiment index and introduces the three volatility models. Section 4 presents and discusses the main empirical results. Section 5 reports the robustness check and Section 6 concludes the remarks.

2. Hypothesis Development

Traditional financial theories imply a positive risk-return tradeoff as Merton (1973)'s intertemporal capital asset pricing model (ICAPM) shows, but they leave little space for noise traders, investors who have no access to inside information and act irrationally on noise, defined by Black (1986).

Earlier researchers like Fama (1965) notice that irrational investors and rational arbitrageurs trade against each other so the asset price is not far away from its fundamental value.

De Long et al. (1990) focus on the limits of arbitrage in exploiting noise traders' misperceptions. The arbitrageurs are likely to have risk-aversion and restricted horizons, so their willingness to beat against noise traders would be limited. The price would be even further and arbitrageurs suffer great loss.

In their model, noise traders could be optimistic or pessimistic about the market, which makes price misalign with intrinsic value. The net impact of investor sentiment on mean returns relies on the relative importance of the price pressure effect and hold more effect.

Furthermore, the misperceptions of noise traders also affect the returns through its impact on market formation of risks. The net effect depends on the interaction of Friedman effect and create-space effect. The Friedman effect implies that noise traders have poor market timing, and asset prices tend to be adversely impacted with a rise in misperceptions of noise traders. The sentiment-induced trading also reduces the rational investors' holding in risky asset and create space for noise traders.

Yu and Yuan (2011) have two implications in their paper. The first one is the mean-variance relation is weakened when noise traders hold more risky assets and have stronger influences on asset prices. The second implication is noise traders are reluctant to have short positions when their sentiment is high. These two implications lead to the main argument that sentiment traders undermine an otherwise positive risk–return tradeoff during high-sentiment periods in the stock market.

Since an ETF is a basket of securities that can be traded on a stock exchange the same way that a regular stock can. Therefore, we hypothesis in ETF market, the mean-variance relation is also different under two sentiment regimes. We propose following hypothesis in this paper.

Hypothesis: In ETF market, the mean-variance relation is positive during low-sentiment periods, but sentiment traders undermine the otherwise positive mean-variance relation during high-sentiment periods.

3. Data

In this paper, we use daily data of 37 ETFs listed on the Singapore Exchange, which can be downloaded from WRDS database and Wind database. We use 6-month T-Bill yield as the risk-free rate, and the daily data can be retrieved from the website of Monetary Authority of Singapore. Since the issuance of 6-month T-bills ceased on December 27, 2013 and resumed on June 27, 2019, our sample period spans from June 27, 2019 to June 28, 2022, covering 877 days.

3.1 Investor Sentiment Index

Baker and Wurgler (2006) construct their investor sentiment index based on the first principal component of five standardized market-based sentiment proxies. Following Yang and Chi (2021), Kim and Ha (2010), Yang and Zhou (2015) and Chen et al. (2010), we select four proxies, namely relative strengthen index (RSI), Bull and Bear Index (BBI), up days (UPD) and trading volume (Volume) as the proxies for individual fund-level sentiment of ETFs.

Relative strengthen index (RSI) is often used to show whether the market is oversold or overbought. It is defined as follows.

$$RSI_t = 100 * RS_t/(1 + RS_t)$$

$$RS_t = \frac{\sum_{t=1}^{6} \max(P_t - P_{t-1}, 0)}{\sum_{t=1}^{6} \max(P_{t-1} - P_t, 0)}$$

where P_t is the closing price of ETF i at day t. A given day's ETF-level RSI_t shows whether the ETF's gains are larger than losses. If RSI >50, the ETF's gains are greater than losses, otherwise, the ETF's losses are greater than gains. An RSI of 70 suggests that the market is overbought, while an RSI of 30 suggests that the market is oversold.

Bull and bear index (BBI) is a commonly-used market index to gauge whether current market is in a bull market or a bear market. It is calculated by taking a weighted mean of several moving average lines of different days as follows.

$$BBI = (MA_3 + MA_6 + MA_{12} + MA_{24})/4$$

where MA_3, MA_6, MA_{12} and MA_{24} represents the moving average of the closing price at day 3, day 6, day 12, and day 24 respectively. If the closing price of ETF is below BBI, this suggests that there exist more pessimistic investors in the market and the trend is possibly to go downward. This will trigger a "sell" signal. Otherwise, there are more optimistic investors in the market, and the trend is possibly to go upwards. This will trigger a "buy" signal.

Up days (UPD) can be served as a sentiment indicator to detect undertones for a trend change. Within the trading period, the index calculates the number of days when the closing price of ETF i at day t is higher than the closing price of ETF i at day t-1.

Trading volume (Volume) carries information about the market and can serves as a sentiment proxy (Baker & Stein, 2004), so it is used by many researchers to construct composite investor sentiment index.

In this paper, we construct fund-level investor sentiment based on the first principal component of four above market-based sentiment proxies. And each of the proxies has first been standardized. The fund-level sentiment index is defined as follows.

$$Sent_{i,t} = \mu_{i,RSI}RSI_{i,t} + \mu_{i,BBI}BBI_{i,t} + \mu_{i,UPD}UPD_{i,t} + \mu_{i,Volume}Volume_{i,t} \qquad (1)$$

where $Sent_{i,t}$ denotes the fund-level sentiment, $RSI_{i,t}$ denotes the Relative strengthen index, $BBI_{i,t}$ denotes the Bull and bear index, $UPD_{i,t}$ denotes Up days within the trading period, and $Volume_{i,t}$ denotes the trading volume of ETF i at day t.

3.2 Conditional Variance Model

3.2.1 GARCH and Asymmetric GARCH Models

Since the volatility of asset returns cannot be observed directly, the GARCH family models are employed by many researchers to estimate the volatility process (Yu & Yuan, 2011; Yang & Jia, 2016; Yang & Chi, 2020). Bollerslev (1986) extend the ARCH model by Engle (1982) and proposes the generalized ARCH (GARCH) model. Glosten, Jagannathan and Runkle (1993) allows asymmetry in the ARCH process and propose the GJR-GARCH model.

In this paper, we apply the GARCH (1,1) model and the GJR-GARCH (1,1) model to estimate daily ETFs' return volatility.

The GARCH (1,1) model is set as equation (2) and (3).

$$R_{i,t} = \theta_0 + \sum_{j=1}^{12} \theta_{i,j} R_{i,t-j} + \varepsilon_{i,t} \qquad (2)$$

and

$$\sigma_{i,t}{}^2 = \alpha_0 + \alpha_1 \varepsilon_{i,t-1}{}^2 + \gamma \sigma_{i,t-1}{}^2 \qquad (3)$$

where $R_{i,t}$ represents the daily excess returns of ETF i on day t. It is calculated as the daily closing price return

minus the risk-free rate. $\sigma_{i,t}^2$ represents the estimated conditional variance of ETF i on day t.

The GJR-GARCH (1,1) model is set as equation (2) and (4).

$$\sigma_{i,t}^2 = \alpha_0 + \alpha_1 \varepsilon_{i,t-1}^2 + \alpha_2 \varepsilon_{i,t-1}^2 I_{i,t-1} + \gamma \sigma_{i,t-1}^2 \tag{4}$$

where $I_{i,t-1} = 1$ if $\varepsilon_{i,t-1} < 0$ and $I_{i,t-1} = 1$ if $\varepsilon_{i,t-1} \geq 0$.

3.2.2 Moving Average Model

Another commonly-used method is the moving average model for volatility estimation, proposed by Brock et al. (1992). The conditional variance is calculated as follows.

$$\sigma_{i,t}^2 = \frac{\sum_{d=0}^{22-1}(R_{i,t-d} - \bar{R}_\iota)^2}{22 - 1} \tag{5}$$

where $\sigma_{i,t}^2$ represents the estimated conditional variance of ETF i on day t. $R_{i,t-d}$ represents the daily excess return of ETF i on day t-d, $\bar{R}_\iota$ is the daily average excess return of ETF i from day t-21 to day t. For each ETF, we use the past 22 days rolling window, and 22 is the approximate number of trading days in one month.

4. Empirical Results

4.1 Summary Statistics

Table 1 reports the summary statistics. The average return and excess return of ETF is -0.02% and -0.78% respectively. The fund-level sentiment has a mean of -0.0043 and standard deviation of 1.02, fluctuating from -8.71 to 8.80. The mean of the volatility calculated by GARCH model (VOL^G) and GJR-GARCH model (VOL^A), is 18.52 and 17.26 respectively. The mean of the volatility calculated by moving average model (VOL^M) is 10.50.

4.2 Mean-variance Relation

Following Yu and Yuan (2011), we test the mean-variance relation in the ETF markets. The panel regression is set as follows.

$$R_{i,t} = a + \beta VOL_{i,t} + \epsilon_{i,t} \tag{6}$$

where $R_{i,t}$ is the daily excess returns of ETF i on day t and $VOL_{i,t}$ is the conditional variance of ETF i on day t.

To test whether the risk-return tradeoff is undermined in the high-sentiment regime, we estimate the following two-regime equation.

$$R_{i,t} = a_1 + \beta_1 VOL_{i,t} + a_2 D_{i,t-1} + \beta_2 D_{i,t-1} VOL_{i,t} + \epsilon_{i,t} \tag{7}$$

where $D_{i,t}$ is a dummy variable for the high-sentiment regime. $D_{i,t} = 1$ if $Sent_{i,t-1} > 0$ and $D_{i,t} = 0$ if $Sent_{i,t-1} \leq 0$. $Sent_{i,t}$ is the fund-level sentiment of ETF i on day t.

We expect β has a positive sign. Investors have higher compensation for bearing higher risks, showing a traditional positive risk-return tradeoff.

We expect β_1 has a positive sign since in low-sentiment periods, the sentiment traders do not cause too much turbulence to the positive risk-return tradeoff.

We expect β_2 has a negative sign since in high-sentiment periods, the risk-return tradeoff is undermined by sentiment traders.

Table 2 reports the estimation results for equation (6) and (7). We can see that under one-regime setting, the mean–variance relation (β) is weak and ambiguous. Only when we use volatility calculated by GJR-GARCH model, the coefficient β is significant, though the magnitude (0.0011) is small. The R^2 of the regression is low when using volatility calculated by other two models, which is less than 0.1%.

Under two-regime setting, during low-sentiment periods, the mean-variance relation (β_1) is highly significant at 1% level, regardless of which volatility model we choose. β_1 is 0.0039, 0.0054, and 0.0059 when we use volatility calculated by GARCH model, GJR-GARCH model and moving average model.

However, during high-sentiment periods, such a positive mean-variance relation is weakened. β_2 is -0.0110, -0.0125, and -0.0197 when we use volatility calculated by GARCH model, GJR-GARCH model and moving average model, all at 1% significance level. According to the test statistics, $\beta_1 + \beta_2$, which stands for the coefficient of the mean–variance relation during high-sentiment periods, is significantly different from zero. With the three volatility models, the estimates are -0.0071, -0.0071 and -0.0138 respectively. This suggests that sentiment traders cause too much turbulence and even twist the positive risk-return tradeoff into a negative one. Besides, the data fit much better in the two-regime equation than the one-regime equation since the R^2 rise from less than 0.1% to more than 5%.

Our conclusions are robust across different volatility models. Although we get different results under the one-regime setting, the three conditional variance models lead to same conclusions under the two-regime setting. We find during low-sentiment periods, there exists a positive risk-return tradeoff in ETF market, which indicates that investors taking higher risks are compensated with higher returns when the market is dominated by the rational traders. But sentiment traders weaken an otherwise positive risk–return tradeoff during high-sentiment periods. This is consistent with Yu and Yuan (2011)'s finding in stock markets.

What distinguish us from them is that in their paper, during high-sentiment periods, the stock market's expected excess return is unrelated to variance. But we observe a significantly non-zero relation in ETF market during high-sentiment periods. When the market is dominated by the sentiment-driven traders, the mean-variance relation become negative. This supports Campbell (1987), Brandt and Kang (2004), Yang and Yang (2021).

According to De Long et al. (1990), the effect of noise traders on expected returns is also through its impact on the market's formation of risk. It depends on the dominance of Friedman effect and create-space effect. On the one hand, noise traders have poor market timing, which makes them buy high and sell low. The changes in the noise traders' misperceptions about risks lead to lower expected returns, which is indicated by Friedman effect. On the other hand, noise traders benefit more because they crowd out rational arbitrageurs and create space. Our results show that during low-sentiment periods, the create-space effect dominates the Friedman effect, while during high-sentiment periods, the negative effect from poor market timing cannot be offset by the positive effect from the space noise traders create.

Another empirical pattern is about the predictive power of the sentiment dummy (a_2). Our results indicate that such predictive power is insignificant at the one-day horizon, and this is consistent with Yu and Yuan (2011)'s finding in one-month horizon and also supports Brown and Cliff (2005). Besides, the interaction term is significant, which supports the moderator (Baron & Kenny, 1986) (Note 1) hypothesis by Baron and Kenny (1986). Sentiment is a moderator that affects the direction of the relation between mean and variance, so a moderator-interaction effect is said to occur in this case.

5. Robust Check

Over our sample period, the World Health Organization (WHO) has declared Covid-19 a global pandemic on March 11, 2020. And Singapore announced a significant easing of Covid-19 restrictions on March 24, 2022, which is regarded as its most decisive step forward to live with the virus. Therefore, we split our sample period into three segments: June 27, 2019 to March 11, 2020 (Pre-Covid), March 12, 2020 to March 24, 2022 (During Covid) and March 25, 2022 to June 28, 2022 (Post-Covid).

We run our regression in subperiods and Table 3-5 shows the results. We find that our main conclusions are still robust. In low-sentiment periods, the excess return is significantly positively related to conditional variance. In high-sentiment periods, the positive risk-return tradeoff is weakened. However, the magnitudes are different. In

Pre-Covid and Post-Covid periods, we cannot reject the zero relation between the risk and return except for the volatility calculated by moving average model, according to the test statistics. But in Covid periods, the risk-return tradeoff is significantly negative during high-sentiment regimes, which is consistent with our prior conclusions. With the three volatility models, the coefficients are -0.007, -0.0071 and -0.0141 respectively, which is close to our previous results in Table 2.

This suggest that compared to other two subperiods, sentiment traders in global pandemic not only weaken but also twist the otherwise positive mean-variance relation Moreover, after taking different subperiods into consideration, the main conclusions are impressively robust across the three conditional variance models.

6. Conclusions

Numerous researchers study the mean-variance relation and obtain mixed results over the past years. Their findings become more complicated since the role of investor sentiment has been recognized. Most of their studies concentrate on stock market, but with the fast growth in ETF market, this topic has not been explored so deeply.

In this paper, we test the effect of fund-level sentiment on the relationship between expected excess returns and conditional variance in ETF market. We use daily data of 37 Singapore-listed ETFs from 06/27/2019 to 06/28/2022. Four market-based sentiment proxies are selected based on Yang and Chi (2021), and fund-level sentiment index is constructed by applying the first principal component analysis. For robustness, we choose three conditional variance models, namely GARCH, GJR-GARCH and moving average model to estimate the daily return volatility. The two-regime setting is similar to Yu and Yuan (2011). Our findings in ETF market are summarized below.

During low-sentiment periods, the expected excess return is positively related to the conditional variance. Investors bearing high risks are compensated with high returns. This supports the positive risk-return tradeoff implied by classical financial theories. During high-sentiment periods, Yu and Yuan (2011) find in stock market, the expected excess return is unrelated to the conditional variance. However, we find in ETF market, the mean-variance relation is negative. We further conduct the regression in subperiods, and the results show that in Pre-Covid and Post-Covid period, the risk-return tradeoff is not significant under high-sentiment regime, while during Covid period, negative risk-return tradeoff exists. This suggests that the effect of noise trading driven by sentiment on mean-variance relation is stronger during global pandemic and crisis. The positive risk-return tradeoff is undermined and turns out to be negative in high-sentiment periods.

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Appendix A

Table 1. Summary Statistics

This table reports the summary statistic of return, excess return, fund-level sentiment and volatility of excess returns of ETFs. VOL^G, VOL^A, VOL^M is the daily return volatility calculated by GARCH (1,1), GJR-GARCH (1,1) and moving average model for ETF respectively. The sample period starts from June 27, 2019 to June 28, 2022, including a total of 877 days.

Variable	Mean	Median	S.d.	Min	Max
Return (%)	-0.0150	0	3.1819	-100.1898	59.1364
Excess return (%)	-0.7846	-0.5767	3.2461	-100.5198	57.9664
Sentiment	-0.0043	-0.1055	1.0172	-8.7139	8.7952
VOL^G	18.5241	1.0048	160.1586	0	5904.4519
VOL^A	17.2582	1.0978	146.6512	0	3699.7338
VOL^M	10.5014	0.6820	81.5433	0	1456.8290

Table 2. Mean-variance Relation

This table reports the results for equation (6) and (7).

$$R_{i,t} = a + \beta VOL_{i,t} + \epsilon_{i,t} \tag{6}$$

$$R_{i,t} = a_1 + \beta_1 VOL_{i,t} + a_2 D_{i,t-1} + \beta_2 D_{i,t-1} VOL_{i,t} + \epsilon_{i,t} \tag{7}$$

where $R_{i,t}$ is the daily excess returns of ETF *i* on day *t* and $VOL_{i,t}$ is the conditional variance. $D_{i,t}$ is a dummy variable for the high-sentiment regime. $D_{i,t} = 1$ if $Sent_{i,t-1} > 0$ while $D_{i,t} = 0$ if $Sent_{i,t-1} \le 0$. $Sent_{i,t}$ is the fund-level sentiment of ETF *i* on day *t*. Panel A, B, C reports the results for using volatility calculated by GARCH model, GJR-GARCH model and moving average model respectively.

Panel A. GARCH volatility

Model	$a(a_1)$	$\beta(\beta_1)$	a_2	β_2	R^2
One-regime	-0.7936[***]	0.0003			0.0002
(6)	(0.0144)	(0.0003)			
Two-regime	-0.7986[***]	0.0039[***]	0.0488	-0.0110[***]	0.0706
(7)	(0.0365)	(0.0009)	(0.0499)	(0.0008)	
Test		F-statistic		p-value	
H_0: $\beta_1 + \beta_2 = 0$		117.99[***]		0.0000	

Standard errors in parentheses. [*] $p < 0.1$, [**] $p < 0.05$, [***] $p < 0.01$.

Panel B. GJR-GARCH volatility

Model	$a(a_1)$	$\beta(\beta_1)$	a_2	β_2	R^2
One-regime	-0.8061[***]	0.0011[***]			0.0023
(6)	(0.0216)	(0.0003)			
Two-regime	-0.8217[***]	0.0054[***]	0.0672	-0.0125[***]	0.0787
(7)	(0.0439)	(0.0001)	(0.0554)	(0.0005)	
Test		F-statistic		p-value	
H_0: $\beta_1 + \beta_2 = 0$		134.68[***]		0.0000	

Standard errors in parentheses. [*] $p < 0.1$, [**] $p < 0.05$, [***] $p < 0.01$.

Panel C. Moving average model

Model	$a(a_1)$	$\beta(\beta_1)$	a_2	β_2	R^2
One-regime	-0.8018[***]	0.0002			0.0000
(6)	(0.0121)	(0.0004)			
Two-regime	-0.7963[***]	0.0059[***]	0.0314	-0.0197[***]	0.0554
(7)	(0.0318)	(0.0010)	(0.0535)	(0.0009)	
Test		F-statistic		p-value	
H_0: $\beta_1 + \beta_2 = 0$		1594.26[***]		0.0000	

Standard errors in parentheses. [*] $p < 0.1$, [**] $p < 0.05$, [***] $p < 0.01$.

Table 3. Regression Results in Subperiods (GARCH Volatility)

Model	$a(a_1)$	$\beta(\beta_1)$	a_2	β_2	R^2
2019/06/27-2020/03/11					
One-regime	-1.7208[***]	-0.0018			0.0011
(6)	(0.0420)	(0.0034)			
Two-regime	-1.6622[***]	0.0090[***]	-0.0597	-0.0247[**]	0.0510
(7)	(0.0581)	(0.0010)	(0.0365)	(0.0090)	
Test		F-statistic		p-value	
H_0: $\beta_{1}+\beta_{2}=0$		2.74		0.1091	
2020/03/12-2022/03/24					
One-regime	-0.4039[***]	0.0002			0.0001
(6)	(0.0134)	(0.0002)			
Two-regime	-0.3753[***]	0.0037[***]	-0.0505	-0.0107[***]	0.0808
(7)	(0.0405)	(0.0009)	(0.0363)	(0.0007)	
Test		F-statistic		p-value	
H_0: $\beta_{1}+\beta_{2}=0$		294.07[***]		0.0000	
2022/03/25-2022/06/28					
One-regime	-1.6752[***]	0.0040			0.0001
(6)	(0.0178)	(0.0063)			
Two-regime	-1.6672[***]	0.0248[***]	-0.0128	-0.0438[**]	0.0045
(7)	(0.0321)	(0.0077)	(0.0558)	(0.0200)	
Test		F-statistic		p-value	
H_0: $\beta_{1}+\beta_{2}=0$		1.17		0.2872	

Standard errors in parentheses. [*] $p < 0.1$, [**] $p < 0.05$, [***] $p < 0.01$.

Table 4. Regression Results in Subperiods (GJR-GARCH volatility)

Model	$a_{(a_1)}$	$\beta_{(\beta_1)}$	a_2	β_2	R^2
2019/06/27-2020/03/11					
One-regime	-1.7478***	0.0004			0.0000
(6)	(0.0415)	(0.0035)			
Two-regime	-1.6962***	0.0115***	-0.0521	-0.0262**	0.0498
(7)	(0.0575)	(0.0013)	(0.0404)	(0.0106)	
Test		F-statistic		p-value	
$H_{0:}\ \beta_{1+}\beta_{2=0}$		1.84		0.1862	
2020/03/12-2022/03/24					
One-regime	-0.4184***	0.0009***			0.0021
(6)	(0.0225)	(0.0002)			
Two-regime	-0.4027***	0.0051***	-0.0278	-0.0122***	0.0900
(7)	(0.0529)	(0.0001)	(0.0452)	(0.0003)	
Test		F-statistic		p-value	
$H_{0:}\ \beta_{1+}\beta_{2=0}$		332.16***		0.0000	
2022/03/25-2022/06/28					
One-regime	-1.6803***	0.0054			0.0003
(6)	(0.0170)	(0.0051)			
Two-regime	-1.6917***	0.0327***	-0.0400	-0.0327*	0.0069
(7)	(0.0329)	(0.0098)	(0.0553)	(0.0164)	
Test		F-statistic		p-value	
$H_{0:}\ \beta_{1+}\beta_{2=0}$		0.00		0.9983	

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Regression Results in Subperiods (Moving Average Volatility)

Model	$a_{(a_1)}$	$\beta_{(\beta_1)}$	a_2	β_2	R^2
2019/06/27-2020/03/11					
One-regime	-1.7596[***]	0.0016[*]			0.0002
(6)	(0.0131)	(0.0008)			
Two-regime	-1.6807[***]	0.0184[***]	-0.1375[**]	-0.0319[*]	0.0263
(7)	(0.0285)	(0.0042)	(0.0615)	(0.0169)	
Test		F-statistic		p-value	
H_0: $\beta_{1}+\beta_{2=0}$		1.11		0.3004	
2020/03/12-2022/03/24					
One-regime	-0.3963[***]	-0.0002			0.0000
(6)	(0.0092)	(0.0004)			
Two-regime	-0.3577[***]	0.0053[***]	-0.0608[*]	-0.0194[***]	0.0661
(7)	(0.0280)	(0.0011)	(0.0347)	(0.0010)	
Test		F-statistic		p-value	
H_0: $\beta_{1}+\beta_{2=0}$		11813.21[***]		0.0000	
2022/03/25-2022/06/28					
One-regime	-1.6829[***]	0.0090			0.0006
(6)	(0.0165)	(0.0061)			
Two-regime	-1.6867[***]	0.0380[***]	0.0144	-0.0638[***]	0.0097
(7)	(0.0296)	(0.0089)	(0.0560)	(0.0210)	
Test		F-statistic		p-value	
H_0: $\beta_{1}+\beta_{2=0}$		2.97[*]		0.0935	

Standard errors in parentheses. [*] $p < 0.1$, [**] $p < 0.05$, [***] $p < 0.01$.

Note

Note 1. In Baron and Kenny (1986)'s paper, a moderator is a qualitative or quantitative variable that affects the direction and/or strength of the relation between an independent and a dependent variable.

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