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## Article

# How fears index and liquidity affect returns of ivol puzzle before and during the Covid-19 pandemic

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## FINANCIAL ECONOMICS | RESEARCH ARTICLE

# How fears index and liquidity affect returns of ivol puzzle before and during the Covid-19 pandemic

Khoa Dang Duong<sup>1</sup>, Man Minh Tran<sup>1</sup>, Diep Van Nguyen<sup>2</sup> and Hoa Thanh Phan Le<sup>3\*</sup>

**Abstract:** This study examines the impacts of investor sentiment and liquidity on the idiosyncratic volatility (IVOL) anomaly returns in Vietnam before and during the COVID-19. We construct an internet search-based measure of sentiment (FEARS) from the Google Trends Search Volume Index of Vietnam's financial and economic search terms from December 2010 to December 2020. We employ Two-Stage Least Squares (2SLS) regressions and univariate portfolio testing to examine the existence of IVOL anomaly in Vietnam after controlling for FEARS sentiment index and liquidity proxies. Our findings document the persistence of the IVOL anomaly in the Vietnam stock market before the pandemic. However, the IVOL anomaly disappears during the pandemic. In addition, increasing investor fear sentiment reduces stock returns during the pandemic. Our robustness tests indicate that the IVOL anomaly persists in the high FEARS, low FEARS, and high turnover subsample before the pandemic. Our results contribute new evidence of how the FEARS index and liquidity help explain the IVOL puzzle before and during the pandemic. Our findings align with the trade-off theory, the efficient market theory, the attention-driven theory, and prior literature.

**Subjects:** Finance; Corporate Finance; Investment & Securities; Risk Management

**Keywords:** COVID-19 pandemic; investor sentiment; google search volume; IVOL; liquidity; Vietnam

**JEL:** G11; G12; G14

## 1. Introduction

Investor sentiment is a factor not mentioned in classical financial theory. This theory holds that investors are rational individuals. Their competition in the market will gradually reach equilibrium through portfolio diversification. This theory argues that price equals the discount of expected cash flows and that returns primarily depend on systematic risk. Besides that, if there are a minority of irrational investors, the arbitrageurs will balance their demand. Therefore, the price is not changed.

While many empirical studies on sentiment exist, there is still no uniform method to measure sentiment. Baker and Wurgler (2007) argue that the current question is whether sentiment affects stock returns but how to measure sentiment effectively. From that base, Da et al. (2015) built the "Financial and Economic Attitudes Revealed by Search" (FEARS) index based on daily Google search queries to measure the sentiment impact of millions of US households on the stock market. The FEARS index proves that it is an effective sentiment indicator. It is easy to build, collect data, and directly reflect investor sentiment through the Internet search behavior of households.

Besides sentiment, liquidity relates to investor attention and stock returns. The capital market equilibrium theory suggested that investor attention influences stock pricing. The poor diversification in the model arises when investors know only certain stocks in the market. That requires less well-known stocks to provide higher returns to offset the risk. The attention of investors on these stocks will increase the liquidity and stock price. Therefore, liquidity is a common factor that can measure market sentiment and determine stock returns. Liu (2015) proves that increased investor optimism increases market liquidity and leads to higher mispricing.

Recently, IVOL has always been one of the most concerned asset pricing topics. More than 687 different research papers on IVOL anomaly have been published since 2018. IVOL anomaly performs as a helpful factor in explaining aggregate market volatility. Several recent studies show a close relationship between IVOL and economic uncertainty. Specifically, Malagon et al. (2018) examine the effect of liquidity on the relationship between IVOL and returns. The results show that liquidity can accurately explain the price of high IVOL stocks for up to 9 months after the recession. Furthermore, Vo et al. (2020) test the influence of abnormal returns on the IVOL-returns relationship in the context of an emerging market like Vietnam. The result indicates that investors can make IVOL strategy profit from stocks with positive abnormal returns. Recently, Mohrschladt and Schneider (2021) indicated that IVOL anomaly only exists in the market when investor sentiment causes stock values to deviate from their fundamental values. While prior studies document mixed explanations for IVOLs, the IVOL puzzle in different market sentiment is relevant and require further examination.

Several motivations motivate us to conduct this study in Vietnam. Firstly, the Vietnamese stock market has remarkably high liquidity risk in the ASEAN region (Naufa et al., 2019). However, the State Securities Commission of Vietnam shows that the average trading value in Vietnam increased 3.2 times from July 2016 to July 2021. In there, the average transaction value in 2020 continued to grow by 29.66% despite the impacts of the pandemic. These figures indicate that a transition market like Vietnam always brings opportunities and risks for investors.

Secondly, individual investors dominate the Vietnamese stock market. The Vietnam Securities Commission report that Vietnam has about 3,479,945 individual trading accounts, accounting for more than 99% of trading accounts on the market in July 2021. Ali et al. (2020) show that most individual investors in the market behave irrationally because they often speculate on overvalued or undervalued stocks. Our sample descriptive statistics indicate that the average IVOL in Vietnam is 9.347%, three times higher than Ali et al. (2020). The higher IVOL indicates that Vietnamese investors are exposed to severe residual risks. Therefore, this study aims to help retail investors understand the impacts of idiosyncratic risks and construct trading strategies on IVOL anomalies to generate returns in different market sentiments.

Finally, we strive to construct a sentiment index in the Vietnam stock market because individual investors have no official sentiment index. We extend the Nguyen and Pham (2018) to study the impact of FEARS on the Vietnamese market. In short, we are motivated to test whether a search-based sentiment indicator affects the stock returns in Vietnam. The FEARS index also serves as an ex-ante indicator for individual investors to adjust their expected returns accordingly.

This paper employs the Two-Stage Least Squares (2SLS) regressions and portfolio sorting methodologies to estimate the returns of the IVOL anomaly after controlling for market sentiment and liquidity factors in the Vietnam stock market. We follow Da et al. (2015) to build the FEARS index, proxying for market sentiment in Vietnam. We follow Ang et al. (2009) to compute the IVOL anomaly. We add trading volume VND into the model as two factors proxy for liquidity. We further examine whether the IVOL puzzle persists in different market sentiments before and during the pandemic.

Our study generates the following striking results. Firstly, our findings figure out the persistence of the IVOL anomaly in the Vietnam stock market before the pandemic, even after controlling for

sentiments, liquidity, and other factors. Our results align with hypothesis 1, Ang et al. (2009), Qadan et al. (2019), and Duong et al. (2021). However, the IVOL anomaly disappears during the pandemic. This finding is consistent with Duong et al. (2021) and the market efficiency theory.

In addition, increasing investor fear sentiment reduces stock returns during the pandemic. These findings align with attention-driven theory, Da et al. (2015), Nguyen and Pham (2018), and Kostopoulos et al. (2020). The result implies that investor sentiment decreases during the pandemic, reducing stock returns in Vietnam. However, a higher FEARS index favorably increase stock returns before the pandemic. The results are consistent with Nguyen and Pham (2018); and the heterogeneity of investors theory of Da et al. (2015).

Furthermore, the turnover ratio significantly negatively affects returns before and during the pandemic. Our findings imply that stocks with high turnover typically earn lower returns because of lower liquidity risk. This result is similar to Gu et al. (2018), Hung and Yang (2018), and Amihud and Mendelson (2008). Finally, DVOL had a significant positive effect on returns before and during the pandemic. It also aligns with Chung and Chuwonganant (2018) and the liquidity preference theory.

Our robustness tests indicate that the IVOL anomaly persists in the high FEARS, low FEARS, and high turnover subsample before and during the pandemic. Furthermore, the portfolio sortings suggest that investors earn arbitrary profit from the IVOL anomaly in the low FEARS sentiment period, before COVID-19, and with high turnover stocks. Our findings align with Ang et al. (2009), Guidolin and Ricci (2020), and Duong et al. (2021).

Our paper is unique in the following ways. Firstly, our study is similar to Da et al. (2015) because our primary interest is constructing an effective sentiment index in Vietnam. Our study deviates from Da et al. (2015); Nguyen and Pham (2018) as we construct the FEARS index in Vietnam using monthly instead of daily frequency. It is because monthly data allows us to reduce noise compared to daily and weekly data. Furthermore, monthly frequency also suggests that the retail sentiment responds to returns more clearly than the sudden effects of discrete events. We also complement the study of Vo et al. (2020) by analyzing the IVOL puzzle in different market sentiments and during the pandemic.

Our paper contributes evidence that the IVOL puzzle persists in the Vietnamese stock market. Vietnam is a transition market in which individual investors significantly dominate (Tran et al., 2018). As a result, mispricing and information asymmetry problems prevent information from fully reflecting on stock prices. Therefore, our study suggests that policymakers reduce information asymmetry, increase market efficiency, and establish an official indicator of sentiment in Vietnam. Our study also supports individual investors in forming a profitable trading strategy in various market sentiments and during the pandemic.

Our research is structured as follows. Section 2 provides the literature review. Section 3 provides an overview of the data used in the study. Section 4 provides empirical analysis together with discussion, and section 5 concludes.

## 2. Literature review

### 2.1. Idiosyncratic volatility anomaly and stock returns

The capital asset pricing model (CAPM) relies on Markowitz's portfolio theory. This theory holds that investors always try to keep their portfolios in equilibrium. Therefore, the only systematic risk exists in the model, while IVOL is minimized through portfolio diversification. However, recent studies document the persistence of IVOL puzzles across stock markets.

Ali a et al. (2020), Ali B et al. (2020), and Bergbrant and Kassa (2021) report a positive relationship between the idiosyncratic risk and expected returns. Their results are consistent with the

trade-off theory of Bettis and Mahajan (1985), implying that investors venturing into high-risk investments can yield correspondingly high returns. Specifically, Ali a et al. (2020) suggest that individual investors hold undiversified portfolios to expect premiums for bearing the residual risks. Ali B et al. (2020) also show similar results in the Singapore market, especially with small-cap stocks due to their fast-growing nature. Moreover, Bergbrant and Kassa (2021) prove that the positive IVOL-returns effect is robust in the US market.

In contrast, Ang et al. (2009), Qadan et al. (2019), and Duong et al. (2021) indicate an inversed relationship between IVOL and expected stock returns. Especially, Ang et al. (2009) report that the IVOL puzzle is a global phenomenon as it shows robust negative IVOL-returns in 23 countries. These results are consistent with the prospect theory of Kahneman and Tversky (1979), which implies that the disposition-prone investors usually hold stocks with unrealized capital losses in the long term to wait for future recovery. As a result, these stocks become overpriced and reduce the stock returns subsequently.

In addition, Berggrun et al. (2016) and Vo et al. (2020) suggest that IVOL has a statistically insignificant impact on stock returns. The results are consistent with the efficient market theory when there is no relation between risk and returns. Specifically, Berggrun et al. (2016) report that the IVOL anomaly disappears in the Latin American Integrated Market. Meanwhile, Vo et al. (2020) argue that the IVOL anomaly disappears due to the lack of opportunities for investors to diversify their investment portfolios.

In summary, the existing literature document mixed findings of the IVOL puzzle. The positive effect of IVOL on returns is consistent with the trade-off theory, while the adverse impact aligns with the prospect theory. From there, we put forward the first hypothesis to test the specific impact of IVOL on returns:

H1: The IVOL anomaly exists in the Vietnam stock market.

## **2.2. FEARS index, search-based sentiment, and stock returns**

Recent sentiment studies have mainly focused on the search-based method. Search-based is a superior method in several respects to the previous methods. Through Internet, search behaviors can extract investor sentiment directly. Because individuals only search if they are interested in economic and financial issues (Da et al., 2015). The search-based method outperforms the market-based because sentiment based on seeking behaviors is unaffected by other economic factors. Search-based measures also have external verification, whereas survey-based ones have not (Da et al., 2015). Furthermore, Google is an open-source that makes it easier to find data, and Google Trends is a tool that allows searches based on past search data.

Tan and Tas (2019) and Swamy and Dharani (2019) examine the effect of Google search on stock returns. The results show that an increase in SVI (search volume index) can lead to a corresponding increase in returns. These results are consistent with the attention-driven theory, implying that increased investor attention may lead to temporary positive price pressure, which increases stock returns accordingly. Specifically, Tan and Tas (2019) suggest that stock prices in the Turkish market are mainly driven by investor attention. Therefore, the strategy of buying high-attention stocks and selling low-attention stocks brings significant profits. Similarly, Swamy and Dharani (2019) also indicate that higher SVI can predict positive returns in the subsequent three weeks.

On the other hand, Da et al. (2015), Nguyen and Pham (2018), and Kostopoulos et al. (2020) document an adverse impact of the FEARS index on stock returns. The FEARS indicator is a search collection of economic and financial terms representing a negative mood. The results show that an

increase in FEARS leads to a reduction in stock returns. These results are consistent with the heterogeneity of investors theory (Da et al., 2015). This theory suggests that the emotional decisions of some investors can push the value of stocks beyond their fundamental value. Da et al. (2015) show that rising FEARS index can reduce returns until the reverse effect happens in the next two days. This reversal phenomenon is mainly due to temporary mispricing (Da et al., 2015).

From existing literature, we propose the second hypothesis to test the impact of the FEARS index on stock returns.

H2: FEARS index has a negative relationship with stock returns in Vietnam.

### **2.3. Liquidity and stock returns**

Amihud and Mendelson (2008) argue that investors often demand higher returns for holding illiquid stocks. Gu et al. (2018); and Hung and Yang (2018) also show a negative relation between turnover and Taiwan stock returns. Meanwhile, Y. Y. Chang et al. (2010) indicate that the higher the trading volume reduces the stock returns.

In contrast, Darby et al. (2021); and Wen et al. (2021) show that turnover is positively related to returns. Meanwhile, Chung and Chuwonganant (2018) indicate that dollar trading volume shock usually leads to positive excess returns in NYSE, AMEX, and NASDAQ stocks from January 1990 to December 2012. These results are consistent with the liquidity preference theory. This theory implies that investors usually prefer liquidity assets to avoid losing capital due to the unforeseen impact of market risk.

We propose the third and fourth hypothesis to test the liquidity effect on stock returns in Vietnam as follow:

H3: Turnover significant negative impact on stock returns in Vietnam.

H4: Trading volume positively impacts stock returns in Vietnam.

### **2.4. Other factors and stock returns**

Firm size and book-to-market ratio are two essential factors in the CAPM model. However, their results are still inconsistent and controversial. In addition, Walkshäusl (2019) suggests that large firm size reduces stock returns. Similarly, Duong et al. (2021) confirm that large-cap stocks tend to get lower returns than small-cap stocks. Meanwhile, Vo and Bui (2016) argue that firm size positively impacts the returns in Vietnam. Duong et al. (2021) show that Stocks with high book-to-market ratios tend to offer high returns about book-to-market ratio. Cakici and Zarembo (2021) also prove that the book-to-market ratio positively impacts stock returns. However, Vo et al. (2020) report that stocks with a high book-to-market ratio often reduce returns accordingly in the Vietnam market.

In addition, reversal is also a controversial factor. Specifically, Bali et al. (2011) show that reversal reduces expected returns, while Hung and Yang (2018) suggest that reversal positively affects subsequent stock returns.

## **3. Data and methodology**

### **3.1. Constructs FEARS index**

We download a 149-word list of Da et al. (2015) to construct the FEARS index. Initially following the Harvard IV-4 Dictionary and the Lasswell Value Dictionary classified as economic word and either positive or negative showing in this word (Tetlock, 2007). We translate all the English words



into Vietnamese. To make sure the Vietnamese words have the same power as English words, we keep both stress and non-stress words. We collect top-10 related words to the original 149 words in Google Trends Vietnam. After removing duplicate and non-economic words that are not inter-dependent with economic meaning, we have a list of 191 words. As Google trends allow downloading data from 2004 so we download the monthly SVI (Search Volume Index) each of 191 terms on the Google Trends from January 2004 to December 2020.

Then we calculate the monthly log change of SVI  $j$  on month  $t$  as:

$$\Delta SVI_{j,t} = \ln(SVI_{j,t}) - \ln(SVI_{j,t-1})$$

We follow Da et al. (2015) to minimize the outliers and heteroskedasticity by winsorizing SVI at a 5% and 95% level. Then, we standardize each time series following Baker and Wurgler (2006). After adjustments, we have  $\Delta ASVI$  or adjusted  $\Delta SVI$ .

The final step is to identify the most important search terms for returns. We run a regression of monthly  $\Delta ASVI$  on VN index returns to determine the relationship between search terms and market behavior returns. Following Tetlock (2007), the negative search terms in the language are more interconnected with investor sentiment. We focus on using the top 30 most significant negative  $t$ -statistic words to construct the FEARS index following Da et al. (2015) and Nguyen and Pham (2018). We define the FEARS index on month  $t$  as:

$$FEARS_t = \sum_{i=1}^{30} \frac{\Delta ASVI_t}{30}$$

$\Delta ASVI_t$  is the adjusted search volume index change at rank  $i$  from November 2010 to December 2020. We rank the negative  $t$ -statistic from the most extensive ( $i = 1$ ) to the smallest ( $i = 191$ ). FEARS index on month  $t$  is the average  $\Delta ASVI$  of 30 negative search terms on month  $t$ . The top 30 negative words are reported in Table 1.

### 3.2. Other data

We collect daily stock price data of all the stock listed in HSX and HNX from [cafef.vn](http://cafef.vn), which provides free source data in Vietnam. Financial data are collected on FiinPro, the reliable commercial data provider in Vietnam. Following FAMA and FRENCH (1992), we scraped financial and utility industry firms. We follow Hung and Yang (2018) to exclude stocks with fewer than ten trades per month to eliminate bias estimates. We follow Jegadeesh and Livnat (2006) to winsorize all variables at the 5% and 95% levels to mitigate outlier problems. However, to ensure the accurate reflection of search behavior (FEARS index) on Vietnam stock returns, we choose the observation starting from 2010 for several reasons. Firstly, the statistics from the world bank show that the Internet started to become popular in Vietnam in 2010. Specifically, the ratio of internet users in the total population was 30.6% in 2010, which is significantly higher than 7.6% in 2004. Secondly, 2010 marked the recovery and expansion of Vietnam's stock market. We also remove observations that do not have sufficient information to calculate required variables. Our final data sample has 36,569 firm-month observations spanning from December 2010 to December 2020.

### 3.3. Methodology

We focus on using the two-stage least square (2SLS) regression method to replace the Ordinary least square (OLS) or Fama&Macbeth (1973) method in previous studies. The 2SLS method has the advantage of overcoming autocorrelation, heteroskedasticity, and endogeneity issues. Common endogeneity phenomena include omitted explanatory variables, simultaneity bias, and errors in variables. As a result, these issues lead traditional OLS methods to produce biased and inconsistent estimates. We provide the OLS diagnostic tests, and the results suggest that the 2SLS approach is preferred in Table 2.



We use firm-level regressions to examine the effect of IVOL, FEARS index, REV, fundamental factors (BM, SZ), and two alternative measures of liquidity level (TURN, DVOL) on stock returns. Following Vo et al. (2020), we build each model by considering how each factor affects the existence of IVOL. Model (1) tests the single impact of IVOL on stock returns, following Vo et al. (2020). Following Da et al. (2015), we build model (2) to examine the impact of investor sentiment on stock returns. In model (3), we follow FAMA and FRENCH (1992) to investigate further the effect of fundamental variables such as a book to market ratio and firm size on stock return. In model (4), we follow Vo and Bui (2016) to add liquidity variables such as trading turnover and DVOL (VND trading volume). In model (5), we follow Hung and Yang (2018) to estimate the impact of all variables in the model, including the reversal effect on stock returns.

**Table 1. Top 30 negative T-Statistic words**

No.	Vietnamese Search Terms	English Search Terms	T-Statistic
1	SJC GIÁ VÀNG	SJC GOLD PRICE	-3.89
2	GIÁ VÀNG HÔM	GOLD PRICE IN	-3.11
3	LÃI GỬI TIẾT KIỆM	SAVING INTEREST RATE	-2.93
4	GỬI TIẾT KIỆM NGÂN HÀNG	DEPOSIT BANK	-2.86
5	VÀNG HÔM NAY	GOLD TODAY	-2.84
6	GIÁ VÀNG HÔM NAY	GOLD PRICE TODAY	-2.8
7	LÃI SUẤT GỬI TIẾT KIỆM	SAVING DEPOSIT RATE	-2.8
8	CHỨNG KHOÁN VIỆT NAM	VIETNAM SECURITIES	-2.52
9	MA CHUNG KHOAN	SECURITIES CODE	-2.51
10	VÀNG 9999	GOLD 9999	-2.49
11	SO TIET KIEM	SAVING	-2.21
12	BẢNG GIAO DỊCH CHỨNG KHOÁN	SECURITIES TRADING PANEL	-2.15
13	SAN GIAO DỊCH CHUNG KHOAN	STOCK EXCHANGE	-1.92
14	ĐAU TƯ CHUNG KHOAN	SECURITIES INVESTMENT	-1.9
15	GIÁ VÀNG	GOLD PRICE	-1.85
16	KINH TẾ VIỆT NAM	VIETNAM ECONOMY	-1.79
17	GIÁ VÀNG SJC	SJC GOLD PRICE	-1.78
18	LÃI TIẾT KIỆM	SAVING RATE	-1.73
19	VÀNG 9999 GIÁ	GOLD 9999 PRICE	-1.59
20	LAI SUAT NGAN HANG	BANK INTEREST RATE	-1.54
21	ĐỊNH GIÁ TÀI SẢN	ASSET PRICING	-1.36
22	NHẬN BẢO HIỂM THẤT NGHIỆP	RECEIVE UNEMPLOYMENT INSURANCE	-1.33
23	GIA CHUNG KHOAN	STOCK PRICES	-1.24
24	TÀI SẢN TÀI CHÍNH	FINANCIAL ASSETS	-1.2
25	BANG GIA TRUC TUYEN	ONLINE PRICE LIST	-1.18
26	LÀM BẢO HIỂM THẤT NGHIỆP	UNEMPLOYMENT INSURANCE	-1.14
27	LAI SUAT GUI TIET KIEM NGAN HANG	SAVING INTEREST RATE	-1.12
28	CHỨNG KHOÁN TRỰC TUYẾN	ONLINE SECURITIES	-1.11
29	KINH TẾ SUY THOẠI	ECONOMIC DEPRESSION	-1.06
30	LAI SUAT	INTEREST RATE	-1.05

**Table 2. Estimation selection process**

Procedure	Result
Hausman test	Chi-square = 7, P-value = 0.00. The selection test results between FEM and REM show that FEM is suitable.
Likelihood ratio test	F(512,360) = 1.27, P-value = 0.00. The selection test results between FEM and OLS show that FEM is suitable.
Heteroskedasticity test	F(513) = 4606.230, P-value = 0.00. The results show that the model has a heteroskedasticity problem.
2SLS method	We propose to use 2SLS regression to overcome heteroskedasticity and minimize endogeneity in the model.

$$R_{i,t} = \beta_0 + \beta_1 IVOL_{i,t} + \epsilon_{i,t} \quad (1)$$

$$R_{i,t} = \beta_0 + \beta_1 IVOL_{i,t} + \beta_2 FEARS_{i,t} + \epsilon_{i,t} \quad (2)$$

$$R_{i,t} = \beta_0 + \beta_1 IVOL_{i,t} + \beta_2 FEARS_{i,t} + \beta_3 LnBM_{i,t} + \beta_4 LnSZ_{i,t} + \epsilon_{i,t} \quad (3)$$

$$R_{i,t} = \beta_0 + \beta_1 IVOL_{i,t} + \beta_2 FEARS_{i,t} + \beta_3 LnBM_{i,t} + \beta_4 SZ_{i,t} + \beta_5 TURN_{i,t} + \beta_6 DVOL_{i,t} + \epsilon_{i,t} \quad (4)$$

$$R_{i,t} = \beta_0 + \beta_1 IVOL_{i,t} + \beta_2 FEARS_{i,t} + \beta_3 BM_{i,t} + \beta_4 SZ_{i,t} + \beta_5 TURN_{i,t} + \beta_6 DVOL_{i,t} + \beta_7 REV_{i,t} + \epsilon_{i,t} \quad (5)$$

COVID-19 is an unusual event and has an unpredictable impact on the market. Therefore, to avoid interference in the model and evaluate whether FEARS index, IVOL and other factors affect stock returns, we separate the sample by the time when COVID-19 began to affect in Vietnam. We determine COVID-19 in Vietnam from December 2019.

Following FAMA and FRENCH (1992), Fama & French (1993), firm size (SIZE) and book to market (BM) are fundamental anomaly factors in Vietnam. Size is a market capitalization announcement of a firm at the end of June every year. Moreover, BM is the book value of equity plus deferred taxes to the market value of equity measured at the end of the previous year. Following Duong et al. (2021), Reversal (REV) in the month  $t$  is the stock returns over the month  $t-1$ . We set variables belonging to the liquidity group into the model. We follow Duong et al. (2021) to calculate turnover (TURN) by taking the total number of shares outstanding divided by trading volume over the previous month. Furthermore, we follow Bhushan (1994) to define the trading volume VND (DVOL) as the stock price in VND multiplied by the number of shares traded. The formula and variable definitions are in detail in Table 3.

## 4. Empirical results and discussions

### 4.1. Descriptive statistics

Table 4 presents the summary statistics on FEARS, IVOL, short-term reversal, turnover, book-to-market ratio, firm size, market value, and trading volume VND. Through the data, the average firm size is 26, the average turnover is  $-3.076\%$ , and IVOL is  $9.347\%$ . These results are close to the study of Vo and Bui (2016). Besides that, we also focus on FEARS. The average FEARS index is

**Table 3. Variable definitions**

<b>RET</b>	Monthly return of stock <i>i</i> is the last day returns <i>d</i> in month <i>t</i> $Ret_{i,t} = (\text{Close price}_{d,t} - \text{Close price}_{d-1,t}) / \text{Close price}_{d-1,t}$
<b>REV</b>	Following Duong et al. (2021), the reversal in the month <i>t</i> is the stock returns over the month <i>t</i> -1.
<b>TURN</b>	Following Duong et al. (2021), to calculate the total number of shares outstanding divided by trading volume over the previous month. The formula is: $\text{Turnover} = (\text{Trading volume} / \text{Shares outstanding}) * 1000$
<b>BM</b>	Following FAMA and FRENCH (1992), the book to market ratio is the market value of stock in the previous calendar year and the book values of common stock.
<b>SZ</b>	Following Bali et al. (2011), the firm size is the logarithm of a stock's market value at the end of month <i>t</i> .
<b>IVOL</b>	$\epsilon_i^t$ : We follow Ang et al. (2009) to compute the IVOL of stock <i>i</i> in month <i>t</i> , the standard deviation of daily residuals returns from the Fama-French three-factor model in month <i>t</i> . Is the idiosyncratic return on day <i>d</i> . $IVOL_{i,t} = \sqrt{\text{var}(\epsilon_i^t)}$
<b>DVOL</b>	Following Bhushan (1994), trading volume VND (DVOL) is the stock price in VND multiplied by the number of shares traded.
<b>FEARS</b>	Following Da et al. (2015), FEARS is the top 30 $\Delta ASVI$ of most significant negative <i>t</i> -statistic words in month <i>t</i> : $FEARS_t = \sum_{i=1}^{30} \frac{\Delta ASVI_t}{30}$

−0.034. The standard deviation of FEARS is 0.209, the 5th percentile is −0.287, and the 95th percentile is 0.319.

#### 4.2. Pearson correlation matrix

Table 5 shows the Pearson correlation matrix between seven variables. The correlation matrix table shows some notable points among the variables in the model. Firstly, the correlation coefficients between IVOL and FEARS index are negative. At the same time, IVOL positively correlates with TURN and DVOL. Secondly, the correlation coefficient between TURN and DVOL is about 0.515. The result consists of Vo and Bui (2016) that two liquidity variables have substitution

**Table 4. Descriptive statistics**

Variable	N	Mean	Std.	Median	5th Pctl	95th Pctl
RET (%)	36,569	1.097	11.105	0.000	−16.168	21.583
LnBM	36,569	2.658	2.295	2.067	0.512	6.559
LnSZ	36,569	26.000	1.701	25.834	23.573	29.125
REV (%)	36,569	1.099	11.050	0.000	−16.071	21.429
LnTURN (%)	36,569	−3.076	2.399	−2.718	−7.698	0.256
LnDVOL	36,569	11.441	3.030	11.448	6.211	16.380
IVOL (%)	36,569	9.347	3.505	8.852	4.518	15.774
FEARS	36,569	−0.038	0.209	−0.063	−0.287	0.319

Notes: The table reports sample mean, standard deviation, median, the 5th percentile, 95th percentile. We take the natural logarithm of variables such as BM, SZ, TURN, and DVOL. The sample period is from December 2010 to December 2020.

**Table 5. Pearson correlation matrix**

Variables	FEARS	LnBM	LnSZ	REV	LnTURN	LnDVOL	IVOL
FEARS	1	−0.078***	0.080***	0.029***	−0.004	0.072***	−0.027***
LnBM		1	−0.622***	0.055***	0.067***	−0.282***	0.091***
LnSZ			1	−0.024***	0.038***	0.591***	−0.151***
REV				1	0.009*	0.111***	−0.007
LnTURN					1	0.515***	0.154***
LnDVOL						1	0.026***
IVOL							1

Notes: The table shows a Pearson correlation matrix for seven control variables. When using two-tailed tests, all correlate variables in this table are significantly different from zero at least at 1% level. The sample period is from December 2010 to December 2020. \*\*\*, \*\*, \* denote the p-value at 1%, 5%, 10%, respectively.

ability. Thirdly, the FEARS index positively correlates with REV. We also perform the VIF test to check for multicollinearity issues. The mean VIF is 1.66, indicating no multicollinearity issue in our sample (C. P. Chang et al., 2021).

#### 4.3. Two-Stage Least Squares (2SLS) regression results

Table 6 shows the estimation results of the five models before and during the pandemic, respectively. The results show that IVOL is significant and negatively related to returns in all models before COVID-19. Our findings indicate the persistence of the IVOL puzzle and support the first hypothesis, which implies that stocks with higher IVOL have lower returns. Our results align with Ang et al. (2009), Qadan et al. (2019), and Duong et al. (2021). However, Panel B of Table 6 reports the positive relationship between IVOL and stock returns in Vietnam during the pandemic. These results are consistent with Duong et al. (2021) and the market efficiency theory that IVOL is not statistically significant in the COVID-19 under the influence of multiple factors in the firm-level regression. This result does not support the first hypothesis.

Table 6 reports that the FEARS index also shows different effects before and during the pandemic. Specifically, panel A of Table 6 indicates that the FEARS index positively and statistically significantly affects stock returns before the pandemic. While our results are inconsistent with Da et al. (2015) and Nguyen and Pham (2018), they align with Nguyen and Pham (2018). The Vietnamese stock market is less efficient, so it responds to a decline slower but rebound faster than the US market (Nguyen & Pham, 2018). Therefore, the predictability of the monthly FEARS index on stock returns is compatible with a transition market such as Vietnam. Our results are consistent with the heterogeneity of investors theory of Da et al. (2015). Besides, the result of the FEARS index before COVID-19 is not supporting the second hypothesis.

On the other hand, panel B of Table 6 figures out that the higher FEARS index adversely reduces stock returns during the pandemic. Notably, the impact of the FEARS index on returns is increased by approximately ten times compared to before the pandemic. Sun et al. (2021) suggest that the pandemic spreads negative sentiment in the market, leading to unforeseen and chaotic effects. Therefore, the investor sentiment becomes lower during the pandemic, creating pressure to lower the prices and reduce stock returns in Vietnam. Our results align with attention-driven theory, Da et al. (2015), Nguyen and Pham (2018), and Kostopoulos et al. (2020). Thus, the result of the FEARS index during COVID-19 supports the second hypothesis.

Table 6 reports that the turnover ratio significantly negatively affects returns before and during the pandemic. This result is similar to Gu et al. (2018), Hung and Yang (2018), and Amihud and Mendelson (2008). The results imply that stocks with high turnover typically have low returns. These results also support the third hypothesis. Finally, Table 6 indicates that DVOL had a significant positive effect on returns before and during the pandemic. It also aligns with Chung

**Table 6. Two-Stage Least Squares (2SLS) regression results before and during the pandemic**

	(1)	(2)	(3)	(4)	(5)
<b>Panel A: Before the COVID-19 period</b>					
IVOL	−0.058*** (−3.39)	−0.057*** (−3.35)	−0.078*** (−4.57)	−0.059*** (−3.38)	−0.056*** (−3.24)
FEARS		0.944*** (3.13)	1.190*** (3.95)	1.099*** (3.65)	1.059*** (3.51)
LnBM			0.990*** (10.39)	1.032*** (10.77)	1.019*** (10.62)
LnSZ			−0.039 (−0.87)	−0.198*** (−3.55)	−0.177*** (−3.15)
LnTURN				−0.349*** (−11.22)	−0.337*** (−10.78)
LnDVOL				0.187*** (6.15)	0.168*** (5.44)
REV					0.020*** (3.48)
Constant	1.399*** (8.28)	1.442*** (8.51)	1.941 (1.58)	2.650** (1.98)	2.321* (1.73)
<b>Panel B: During the COVID-19 period</b>					
IVOL	0.199*** (3.44)	0.099* (1.73)	0.064 (1.10)	0.054 (0.91)	0.073 (1.24)
FEARS		−10.937*** (−13.68)	−11.000*** (−13.79)	−10.979*** (−13.77)	−11.565*** (−14.64)
LnBM			1.555*** (4.75)	1.452*** (4.28)	1.545*** (4.60)
LnSZ			0.27 (1.60)	0.037 (0.17)	−0.211 (−0.99)
LnTURN				−0.089 (−0.79)	−0.212** (−1.89)
LnDVOL				0.185* (1.65)	0.436*** (3.84)
REV					−0.157*** (−10.21)
Constant	0.922 (1.55)	2.63*** (4.41)	−4.726 (−1.02)	−1.015 (−0.20)	2.404 (0.47)

Notes: We run a 2SLS regression of the returns in that month on seven variables, including IVOL, FEARS, and five control variables in Table 3. In detail, Model (1) tests the single impact of IVOL on stock returns. Model (2) add the impact of investor sentiment on stock returns. Model (3) investigates further the effect of fundamental variables such as a book to market ratio and firm size on stock return. Model (4) includes the liquidity variables such as trading turnover and DVOL (VND trading volume). Model (5) estimates all variables' impact, including the reversal effect on stock returns. The table reports the time-series averages of the cross-sectional regression slope coefficients and their adjusted t-statistics (in parentheses) in each row. The sample period is from December 2010 to December 2020. \*\*\*, \*\*, \* denote the p-value at 1%, 5%, 10%, respectively.

and Chuwonganant (2018) and the liquidity preference theory. Investors often prefer to choose stocks with high liquidity to limit the possibility of capital loss. Therefore, our findings also support the fourth hypothesis before and during the pandemic.

#### 4.4. Two-Stage Least Squares (2SLS) regression results in sub-samples

Finally, we conduct robustness tests by employing 2SLS estimation in different subsamples by FEARS index and liquidity to test the persistence of the IVOL puzzle more comprehensively. We also consider the impact of each criterion under the influence of COVID-19.

The results indicate how the high FEARS index and low FEARS index have differing effects on stock returns. We define low FEARS period if FEARS index values are less than 0, while the high FEARS period has the FEARS index values are higher than 0. The regression results show that low FEARS (panel A and B of Table 7) has a significant positive relationship with stock returns. In contrast, the high FEARS (panel C and D of Table 7) negatively correlates with stocks returns before and during the pandemic. Specifically, the impact of the low FEARS on stock returns is nearly 12 times stronger than the high FEARS before the pandemic.

Similarly, the impact of the low FEARS is also nearly two times higher than the high FEARS during the pandemic. These results are consistent with Da et al. (2015) and his heterogeneity of investors theory. The results imply that stock prices usually increase when the fear sentiment is low, but stocks prices reverse when the fear sentiment is high. Notably, the impact of low FEARS on stock returns during the pandemic is nearly 32 times higher than before the pandemic. Therefore, our

**Table 7. Two-Stage Least Squares (2SLS) regression results in subsamples**

Constant	FEARS	LnBM	LnSZ	REV	LnTURN	LnDVOL	IVOL
<b>Panel A: Low FEARS before COVID-19</b>							
0.750	2.262***	1.102***	-0.094	0.007	-0.278***	0.144***	-0.056***
(0.47)	(3.43)	(9.84)	(-1.43)	(1.01)	(-7.48)	(3.94)	(-2.73)
<b>Panel B: Low FEARS during COVID-19</b>							
13.473**	72.898***	1.088***	-0.120	0.029	-0.101	0.102	0.087
(2.11)	(15.54)	(2.63)	(-0.45)	(1.16)	(-0.70)	(0.70)	(1.23)
<b>Panel C: High FEARS before COVID-19</b>							
6.513***	-0.186	0.729***	-0.364***	0.050***	-0.479***	0.225***	-0.061*
(2.56)	(-0.31)	(3.90)	(-3.43)	(4.70)	(-8.31)	(3.85)	(-1.85)
<b>Panel D: High FEARS during COVID-19</b>							
1.265	-36.913***	2.148***	0.352	-0.262***	0.188	0.144	0.084
(0.19)	(-31.12)	(4.96)	(1.30)	(-15.25)	(1.33)	(1.01)	(1.08)
<b>Panel E: Low turnover stocks before COVID-19</b>							
5.470**	1.516***	0.986***	-0.341***	-0.052***	-0.180***	0.280***	0.031
(2.24)	(2.99)	(5.70)	(-3.59)	(-5.20)	(-3.02)	(6.03)	(1.04)
<b>Panel F: Low turnover stocks during COVID-19</b>							
-3.382	-9.878***	1.631***	0.040	-0.160***	-0.090	0.413***	0.030
(-0.41)	(-8.35)	(2.92)	(0.13)	(-5.78)	(-0.50)	(2.93)	(0.32)
<b>Panel G: High turnover stocks before COVID-19</b>							
1.105	0.903	1.115***	-0.079	0.010	-0.429***	0.116*	-0.130***
(0.41)	(1.48)	(6.42)	(-0.71)	(1.07)	(-6.73)	(1.84)	(-2.65)
<b>Panel H: High turnover stocks during COVID-19</b>							
-11.770	-11.658***	1.550**	0.296	-0.175***	-0.158	0.235	0.287*
(-1.08)	(-7.28)	(2.42)	(0.67)	(-6.55)	(-0.73)	(1.06)	(1.75)

Notes: We run 2SLS regressions of the returns in that month on seven variables, including IVOL, FEARS, and five control variables in Table 3. In detail, the model is estimated for the period before and during COVID-19. The table reports the time-series averages of the regression slope coefficients and their adjusted t-statistics (in parentheses) in each row. The sample period is from December 2010 to December 2020. \*\*\*, \*\*, \* denote the p-value at 1%, 5%, 10%, respectively.

FEARS index also serves as an ex-ante uncertainty forecast for individual investors, which supports them in adjusting their expected returns before and during the pandemic.

Moreover, the IVOL in both the high and low FEARS groups adversely reduces stock returns before the pandemic. These findings are also similar to prospect theory. Wan (2018) reports that the negative relationship between IVOL and stock returns is robust in high and low sentiment. Besides, the turnover ratio (LnTURN) in both high and low FEARS groups also negatively correlates with stock returns before the pandemic. LnTURN in the high FEARS group has a 0.2% stronger impact than the low FEARS group. In contrast, LnDVOL in the high and low FEARS groups positively impacted returns before the pandemic. LnDVOL in the high FEARS group has a 0.08% stronger impact than the low FEARS group. However, the IVOL, LnTURN, and LnDVOL in low and high FEARS turn insignificant during COVID-19. These results align with Duong et al. (2021)

This section tests whether IVOL and FEARS are robust in different liquidity subsamples. We follow Hung and Yang (2018) to divide the sample into terciles according to turnover criterion with 33.33% low turnover stocks, 33.33% medium turnover stocks, and 33.33% high turnover stocks.

The 2SLS regression results show that the FEARS index of low turnover stocks is statistically significant and positively correlated with returns before the pandemic. In contrast, the FEARS index of high and low turnover stocks adversely reduces stock returns during the pandemic. This result is consistent with our primary findings in Table 6. Moreover, the impact of the FEARS index on returns of low turnover stocks during the pandemic is 6.5 times stronger than before the pandemic. Meanwhile, the effect of the FEARS index of the high turnover stocks is 1.78% higher than the low turnover stocks during the pandemic.

In addition, IVOL is only statistically significant for the high turnover stocks group. Specifically, IVOL has a positive impact on returns before the pandemic, but IVOL turns to a negative impact on high turnover stock returns during the pandemic. Even that, the effect of IVOL on returns during the pandemic is 0.15% higher than before the pandemic. Therefore, these findings are consistent with our preliminary results in Table 6.

Moreover, the turnover ratio of the high and low turnover stocks is statistically significant and harms stock returns before the pandemic. In there, the effect of LnTURN on the returns of high turnover stocks is 0.25% stronger than low turnover stocks. However, LnTURN turns insignificant for high and low turnover stocks during the pandemic. In contrast, LnDVOL of the high and low turnover stocks positively and significantly affect stock returns before the pandemic. Specifically, the influence of LnDVOL on the returns of low turnover stocks is 0.16% higher than high turnover stocks. During the pandemic period, LnDVOL only affect stocks returns of low turnover stocks. Even that, the impact of LnDVOL on returns during a pandemic is 0.13% stronger than before the pandemic.

#### **4.5. Portfolio-level analysis**

This section performs the univariate portfolio sorting method to test whether the IVOL puzzle persists in subsamples of FEARS, liquidity, and pandemic. We follow Hung and Yang (2018) to sort stocks into tercile; the first is the 33.33% lowest monthly IVOL stock portfolio. The second portfolio is 33.33% medium monthly stocks, while the third has the 33.33% highest monthly IVOL stocks.

Tables 8 show the average monthly returns difference between the lowest and highest IVOL portfolios in subsamples of the FEARS index, turnover, and COVID-19. The average returns difference is between the highest IVOL portfolio and the lowest IVOL portfolio. Table 8 indicates that the IVOL anomaly persists in the low FEARS period, before the pandemic and low turnover subsamples. This result aligns with Ang et al. (2009). The results show that investors can earn arbitrary profit by holding low IVOL stocks and selling high IVOL stocks during low FEARS sentiment and before COVID-19. Besides, investors can also build an IVOL strategy based on high turnover stocks.



**Table 8. Equal-weighted and value-weighted portfolios are sorted by IVOL**

Tercile	Low FEARS	High FEARS	Before COVID-19	During COVID-19	Low Turn	High Turn
<b>Panel A: Equal-weight (EW) portfolio:</b>						
Low IVOL	1.115	1.521	1.075	2.599	1.256	1.233
Medium IVOL	0.842	1.550	0.850	2.793	1.189	0.717
High IVOL	0.593	1.302	0.589	2.643	1.399	0.470
Returns difference	−0.522**	−0.219	−0.486**	0.044	0.143	−0.763***
	(−2.06)	(−0.48)	(−2.14)	(0.05)	(0.55)	(−2.96)
Alpha difference	−0.481***	−0.070*	−0.556***	1.835***	0.004	−0.890***
	(−27.49)	(−1.94)	(−34.09)	(44.89)	(0.23)	(−48.66)
<b>Panel B: Value-weight (VW) portfolio:</b>						
Low IVOL	0.842	0.916	0.770	1.647	0.746	0.927
Medium IVOL	0.127	1.782	0.574	1.121	0.428	0.583
High IVOL	0.200	0.924	0.239	1.934	1.179	−0.315
Returns difference	−0.642	0.008	−0.531	0.287	0.433	−1.243**
	(−1.11)	(0.01)	(−1.07)	(0.23)	(0.79)	(−2.28)
Alpha difference	−0.766***	0.136***	−0.708***	2.291***	0.486***	−1.482***
	(−22.60)	(3.01)	(−24.44)	(67.73)	(15.46)	(−44.50)

Notes: This table reports the equal-weight (EW) and value-weight (VW) based on IVOL. Each month, we sort stocks into tercile based on the IVOL. With 33.33% highest, 33.33% medium, and 33.33% lowest IVOL group, respectively. The monthly return difference is the arbitrary returns between high IVOL and low IVOL stocks. Adjusted t-statistics is the value in parentheses. The study spans the months of December 2010 through December 2020. \*\*\*, \*\*, \* denote the p-value at 1%, 5%, 10%, respectively.

Specifically, the results show that building an IVOL investment strategy based on high turnover stocks gives the highest differential returns. Specifically, the equal-weight portfolio shows a return difference is 0.763% per month, while the value-weight portfolio is 1.243% per month. This result is consistent with Duong et al. (2021), Guidolin and Ricci (2020).

## 5. Conclusion

This study examines whether the IVOL puzzle persists after controlling for sentiment and liquidity factors in the Vietnam stock market before and during COVID-19. We follow Da et al. (2015) to construct the monthly FEARS index in Vietnam, representing investor sentiment. Moreover, we follow Ang et al. (2009) to compute IVOL. We examine data from all non-financial companies in Vietnam from December 2010 to December 2020 using the 2SLS estimations. Simultaneously, we perform subsample and univariate sorting methods to test the robustness of our preliminary results.

Our findings document the persistence of the IVOL anomaly in the Vietnam stock market before the pandemic. Specifically, the results imply that higher IVOL reduces stock returns after controlling for sentiments, liquidity, and other factors. Our results align with hypothesis 1, Ang et al. (2009), Qadan et al. (2019), and Duong et al. (2021). However, the IVOL anomaly disappears during the pandemic. This finding is consistent with Duong et al. (2021) and the market efficiency theory.

In addition, increasing investor fear sentiment reduces stock returns during the pandemic. This result is consistent with the second hypothesis that the higher FEARS index reduces stock returns. It also aligns with attention-driven theory, Da et al. (2015), Nguyen and Pham (2018), and Kostopoulos et al. (2020). The result implies that investor sentiment decreases during the

pandemic, reducing stock returns in Vietnam. However, the FEARS index positively correlates with stock returns before the pandemic. The result aligns with the argument of Nguyen and Pham (2018); and the heterogeneity of investors theory of Da et al. (2015).

Furthermore, the turnover ratio significantly negatively affects returns before and during the pandemic. This result is similar to Gu et al. (2018), Hung and Yang (2018), and Amihud and Mendelson (2008). The results imply that stocks with high turnover typically have low returns due to lower liquidity risk. Our results support the third hypothesis. In contrast, DVOL had a significant positive effect on returns before and during the pandemic. It also aligns with Chung and Chuwonganant (2018) and the liquidity preference theory. Investors often prefer investing in stocks with high liquidity to limit the possibility of capital loss. Therefore, our findings also support the fourth hypothesis.

Our robustness tests indicate that the IVOL anomaly persists in the high FEARS, low FEARS, and high turnover subsample before and during the pandemic. Furthermore, the portfolio sortings suggest that investors earn arbitrary profit from the IVOL anomaly in the low FEARS sentiment period, before COVID-19, and with high turnover stocks. Our findings align with Ang et al. (2009), Guidolin and Ricci (2020), and Duong et al. (2021).

Our findings extend literature about the persistence of the IVOL puzzle and FEARS index in Vietnam. Our study provides a helpful reference for market regulators in reducing information asymmetry, increasing market efficiency, and establishing an official indicator of sentiment index in Vietnam. Besides, the results also help individual investors build an arbitrage trading strategy based on IVOL during periods of low FEARS index, before the pandemic, or for high turnover stocks. Our FEARS index also serves as an ex-ante uncertainty forecast for individual investors, which supports them in adjusting their expected returns before and during the pandemic.

However, our study still has some limitations. Specifically, the study does not compare the impact of the daily FEARS index and the reversal time of returns as in the study of Da et al. (2015). On the other hand, the study has not mentioned the impact of the FEARS index and IVOL on different industry groups before and during the pandemic. Therefore, considering the effects of the FEARS index and IVOL on different industry groups is also an exciting topic. Finally, future studies could examine whether the IVOL anomaly persists after controlling for the FEARS sentiment index across developed, emerging markets.

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