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Stock market return predictability: Google pessimistic sentiments versus fear gauge

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Abstract: This study aims at comparing Google Search Volume Indices (GSVIs—including market crash and bear market) and VIX (Investor Fear Gauge Index) in terms of explaining the S&P 500 returns. The VIX is found a more robust predictor of stock market returns than Google indices, and it does granger cause the GSVIs more robustly. In addition, in vector auto-regression model, VIX has more prominent effect of its past values on both Google indices. Finally, using the autoregressive distributed lag (ARDL) and nonlinear ARDL models, contrary to prior literature, we find significant symmetric negative relationship between changes in VIX and S&P 500 returns.

Subjects: World Wide Web; Corporate Finance; Investment & Securities; Financial Statement Analysis

Keywords: investors' pessimistic sentiments; Google Search Volume; ARDL; NARDL; stock market returns; volatility index

JEL code classifications: C22; G02; G12

1. Introduction

Investor sentiment is the overall attitude of investors toward a particular security or financial market. This concept has engaged the researchers and academicians since the work of Keynes (1936). According to the classical finance theory, there is no room for investor sentiments (irrational

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PUBLIC INTEREST STATEMENT

Recently, both academics and practitioners have started to embrace the idea of behavioral biases of investors (investor sentiments) and their impacts on pricing of the assets. However, it is really difficult to capture and measure the variety of sentiments that matters to investors. Researchers have started to construct a laundry of such measures using both qualitative and quantitative methods. This study using Google Search Volume Index and Chicago Board Options Exchange's Volatility Index as proxies of the pessimistic sentiment indices compares in both explaining broader market (S&P 500) returns and question whether such a relation is symmetric or asymmetric using autoregressive models. Findings suggest that volatility index as a better representative of investor sentiments that Google Search-based indices, and it has a symmetric relationship with the S&P 500 market index, which is contrary to prior literature.

behavior). Classical theories suggest that there exists a competition among rational investors in the market that leads the security prices to the fundamental values which is actually the discounted value of expected cash flows. If there is any kind of irrational behavior because of the noise traders, then arbitragers' activities pull the prices back to the equilibrium level. But the arbitrage is not as easy as theoretically stated. There are many limits to arbitrage making some stocks costly to arbitrage. Further, it is stated by Shleifer and Vishny (1997) that arbitrage becomes ineffective when prices are far away from fundamental values. De Long, Shleifer, Summers, and Waldmann (1990) incorporate the role of investor sentiments in financial market.

Short-term movements in asset prices can be better explained by investor sentiment other than any fundamental factor (Baek, Bandopadhyaya, & Du, 2005). Numerous studies use the investor sentiment to understand the change in asset prices. Previous studies use the direct as well as the indirect measures of investor sentiments. Direct measures are based on the surveys like AAII (American Association of Individual Investors survey), Investors Intelligence Survey, Consumer Confidence Survey, Google Search Volume Indices, and many more. While indirect measures use the financial or economic variables as the proxy for investor sentiments like put–call ratio, trading volume, Baker and Wurgler Index, and many more.

Different researchers use the different proxies for measuring the sentiments. As put–call ratio is used by Dennis and Mayhew (2002), Barron's Confidence Index is used by Lashgari (2000); Net Cash Flow into Mutual Funds is used by Randall, Suk, and Tully (2003); Risk Appetite Index (RAI) is used by Kumar and Persaud (2002); Issuance Percentage is used by Baker and Wurgler (2006), while Whaley (2000) uses the Volatility Index (VIX-Investor Fear Gauge); Klemola, Nikkinen, and Peltomäki (2016) employ the Google Search Volume Index (GSVI) and Bull-Bear Spread from American Association of Individual Investors data, and Brown and Cliff (2005) also use the Bull-Bear Spread and the Investors Intelligence Survey to measure the investor sentiment. However, this study tries to compare an investor-specific measure (VIX) and a generalized GSVI measure of pessimistic sentiments (i.e., market crash and bear market) in terms of stock market return predictability. Beside this, we also test which one of these better conveys investor sentiments.

The purpose of this study is to make use of investors' pessimistic sentiments through Google Trends Volume to predict the future stock market returns by employing the Ordinary Least Square Approach and later vector auto-regression is applied to confirm the results. Klemola et al. (2016) find the significant relationship between Google Search Volume data and future S&P 500 returns. But now, the Google has changed its methodology of calculating Google Search Volume Trend data. This study suggests that whether the Google's new methodology of collecting trend data is still worthwhile to predict the near-term future returns.

Another measure of investor sentiment, VIX (Investor Fear Gauge), is considered as *the world's premier barometer of investor sentiment* by Chicago Board Options Exchange (CBOE). It is used by Dash and Moran (2005) as an investor sentiment's broad signal for returns of hedge funds. VIX is also considered as a confrontational tool for market timing (see Bittman, 2007; McEwan, 2004). Furthermore, the *Wall Street Journal* reports on VIX movements regularly (see, e.g., Ball 2007; Ovide 2008). One more contribution to the literature on investor sentiment as Fisher and Statman (2000), Klemola et al. (2016), Otoo (1999), and Solt and Statman (1988) by using the GSVI and to Durand, Lim, and Zumwalt (2011) and Whaley (2000) by employing the VIX as a tool to gauge the pessimistic investor sentiment. As VIX measures the volatility incorporating the investor perception about volatility in market. So, we compare the Google Search Volume Index (GSVI) and VIX (Investor Fear Gauge Index) to determine which of the indices better capture the other. This attempt provides the ideal measure for academia and practitioners who study market behavior.

Furthermore, Durand et al. (2011) depict that "Changes in the VIX drive variations in the expected returns of the factors included in the Fama and French three-factor model augment with a momentum factor." Furthermore, the relationship between VIX and portfolio market returns is studied by

Banerjee, Doran, and Peterson (2007). Fleming, Ostdiek, and Whaley (1995) find the evidence of large negative contemporaneous relation with significant asymmetry between changes in CBOE old VIX (now named as VXO) and stock index returns. Giot (2005) also reports the asymmetric return with respect to S&P 100 returns and depicts that negative stock index returns are more associated than positive returns with greater changes in VIX. This asymmetric relation is found to be stronger in S&P 100 when make compared to Nasdaq 100. This leads us to find the symmetric/asymmetric relationship between VIX and S&P 500 returns.

The results find the symmetric relation of VIX with the stock market returns. Further, VIX is proved as the possible predictor of S&P returns more robust than GSVIs. Additionally, VIX also granger causes the GSVIs more strongly than otherwise. These results are also confirmed by vector autoregressive models. This paper is providing the evidence of negative significant linear relationship between investors' fear gauge and S&P 500 returns.

The paper is organized as follows: Section 2 provides the data and methodology. Section 3 provides the results, and Section 4 concludes the study.

2. Data and methodology

We use weekly data from 1 January 2004 to 31 December 2015. The data on VIX are taken from CBOE (Chicago Board Options Exchange). Data for opening prices and volume of S&P 500 are obtained from Yahoo Finance, and GSVI data are obtained from Google Trends.

For GSVI, two different terms are being used: "Market Crash" and "Bear Market." Google has changed its methodology of trend data. Previously, it is, how many searches have been done for a specific search term on a Google Web search on that specific week, relative to the total number of searches done for the same specific search term on Google Web search over time. In the relative mode, the data are scaled by Google to the average traffic for the specific search term during the time period selected (Klemola et al., 2016). Now, volume trends' data results are proportionate to the time and location of a query.[1]

To test the possible relationships between variables, weekly logarithmic change of S&P 500 weekly opening prices, weekly logarithmic change of the volume of S&P 500 returns, ΔVIX, and ΔGSVI are calculated. ΔGSVI is calculated as change in Google Search Volume as the ratio of last three weeks' average.

Table 1 reports the descriptive statistics of the data. The mean of the main dependent variable S&P 500 returns is 0.0012 with the standard deviation of 2.38% which indicates relatively small variation as compared to S&P 500 volume with the standard deviation of 7.25%. S&P 500 returns and its volume are negatively skewed. Table 1 also shows that VIX has highest standard deviation among all investors' pessimistic sentiment indices taken in this study. Google indices (Market crash ad Bear market) are negatively skewed and VIX is positively skewed.

Table 2 shows the correlation between the variables taken in this study. VIX and Google indices are significantly positively correlated to each other. Sentiment indices (VIX and Google indices) are significantly positively correlated with the volume of S&P 500. The highest significant correlation is 0.304879 (significant at 1%) between Market Crash and change in S&P 500 volume. While with the S&P 500 returns, VIX and Marker Bear are negatively correlated, and Market crash is positively correlated. Furthermore, the possible relation between sentiment indices and S&P 500 returns is explained in Sections 2.1–2.3.

2.1. VIX and S&P-500

The relationship between VIX and portfolio market returns is studied by Banerjee et al. (2007). Fleming et al. (1995) find the evidence of large negative contemporaneous relation with significant

Table 1. Descriptive statistics

	ΔCrash	ΔBear	VIX	ΔVIX	S&P 500 Returns	ΔVOL
Mean	−0.0004	0.0003	19.3810	0.0022	0.0012	0.0003
Median	−0.0111	0.0045	16.4518	−0.0873	0.0018	−0.0003
Maximum	8.9	2.4785	71.802	17.436	0.1147	0.3546
Minimum	−9.0395	−3.1004	10.015	−15.894	−0.1684	−0.3278
Std. Dev.	0.7484	0.41954	9.24238	2.4367	0.0238	0.0725
Skewness	−0.4104	−0.7324	2.46738	0.8970	−0.5038	−0.0228
Kurtosis	76.4077	12.3025	10.7391	13.8552	9.56648	7.0049
Observations	622	622	622	622	622	622

Notes: This table reports the descriptive statistics of ΔCrash and ΔBear. Furthermore, the descriptive statistics of weekly first difference S&P 500 returns, volume of S&P stock market and VIX are also reported here.

Table 2. Correlation

	ΔCrash	ΔBear	S&P 500 Returns	ΔVOL	ΔVIX
ΔCRASH	1				
ΔBEAR	0.326351	1			
SPRET	0.068136*	−0.0518	1		
ΔVOL	0.304879***	0.194338***	−0.12791***	1	
ΔVIX	0.148218***	0.23788***	−0.54209***	0.282728***	1

Notes: Table 2 reports the correlation between the given variables: ΔCrash, ΔBear, weekly logarithmic change S&P 500 weekly opening prices, weekly first difference of volume of S&P 500, and weekly first difference of VIX.

*Coefficient significance level of 10%.

**Coefficient significance level of 5%.

***Coefficient significance level of 1%.

asymmetry between changes in CBOE old VIX (now named as VXO) and stock index returns. Giot (2005) also finds the asymmetric returns with respect to S&P 100 index and depicts that negative stock index returns are more associated than positive returns with greater changes in VIX. This asymmetric relation is found to be stronger in S&P 100 when compared to Nasdaq 100. This leads us to our following hypothesis;

H1: VIX has asymmetric relationship with S&P 500 returns.

Recently, Shin, Yu, and Greenwood-Nimmo (2014) advance a nonlinear ARDL co-integration approach (NARDL) as an asymmetric extension to the well-known ARDL model of Pesaran and Shin (1998) and Pesaran, Shin, and Smith (2001), to capture both long-run and short-run asymmetries in a variable of interest. We adopt this modeling approach for our purpose of confirming the possible direction of the relationship of VIX to the S&P 500 returns.

In its traditional form, the linear ECM (error correction model) specification without asymmetry in short- and long-run dynamics takes the following form;

$$\Delta \mathrm{SP}_t = \mu + \rho_{\mathrm{sp}}\mathrm{SP}_{t-1} + \rho_{\mathrm{vix}}\mathrm{VIX}_{t-1} + \sum_{i=1}^{p=1} \alpha_i \Delta \mathrm{SP}_{t-i} + \sum_{i=0}^{q=1} \beta_i \Delta \mathrm{VIX}_{t-i} + \varepsilon_t \tag{1}$$

Here, SP is S&P 500 returns, and VIX is investors' fear gauge. $\Delta\mathrm{SP}_t$ defines the weekly logarithmic change of S&P 500 returns at level; SP_{t-1} is first lag of S&P 500 returns; VIX_{t-1} is first lag of VIX; $\Delta\mathrm{SP}_{t-i}$ defines the weekly first difference for S&P 500 opening prices with the lags up to lag *i*; $\Delta\mathrm{VIX}_{t-i}$ defines the weekly first difference for VIX with the lag up to lag *i*; μ is intercept of equation; and ρ_{sp}, ρ_{vix}, α_i, and

β_i are slope coefficients. ρ_{sp} and ρ_{vix} parameters are estimated to represent the long-run coefficients; α_i and β_i parameters are estimated to represent the short-run coefficients; and ε_t is error term.

Even though the model in Equation (1) enables the investigation of the short- and long-run relationships between variables, it becomes impertinent when these relationships are nonlinear and/or asymmetric, which is the case for investors' fear gauge and stock market returns as we point out in the introduction. That is why a nonlinear and asymmetric ECM is of great interest. We thus adopt the co-integrating NARDL model of Shin et al. (2014) that allows for short- and long-run asymmetries.

This model uses the decomposition of the independent variable VIX in VIX^+ and VIX^- as the partial sum of positive and negative changes in VIX to incorporate the short-run and long-run asymmetries in model. As

$$\text{VIX}_t^+ = \sum_{i=1}^{t} \Delta\text{VIX}_i^+ = \sum_{i=1}^{t} \max(\Delta\text{VIX}_i, 0)$$

And

$$\text{VIX}_t^- = \sum_{i=1}^{t} \Delta\text{VIX}_i^- = \sum_{i=1}^{t} \min(\Delta\text{VIX}_i, 0)$$

ΔVIX_i^+ shows the positive changes in VIX, ΔVIX_i^- shows the negative changes in VIX, VIX_t^+ represents the partial sum of ΔVIX_i^+ and VIX_t^- represents the partial sum of ΔVIX_i^-.

When the asymmetries in the short- and long-run dynamics are introduced into the standard ECM, Shin, Yu, and Greenwood-Nimmo (2014) showed that Equation (1) is extended to obtain a more general co-integration model as follows;

$$\begin{aligned}\Delta\text{SP}_t =& \mu + \rho_{sp}\text{SP}_{t-1} + \rho_{vix}^+\text{VIX}_{t-1}^+ + \rho_{vix}^-\text{VIX}_{t-1}^- + \sum\nolimits_{t=1}^{p} \alpha_i \Delta\text{SP}_{t-1} \\ &+ \sum\nolimits_{i=0}^{q} (\beta_i^+ \Delta\text{VIX}_{t-1}^+ + \beta_i^- \Delta\text{VIX}_{t-1}^-) + \varepsilon_t\end{aligned} \tag{2}$$

The superscripts (+) and (−) are decomposition in positive and negative changes as defined above, ρ_{vix}^+ and ρ_{vix}^- slope coefficients capture the long-run asymmetry, while β_i^+ and β_i^- capture the short-run asymmetry. Further, the long-run symmetry can be tested by using a Wald test of the null hypothesis $\theta^+ = \theta^-$ with $\theta^+ = -\rho_{vix}^+/\rho_{sp}$ and $\theta^- = -\rho_{vix}^-/\rho_{sp}$ being the positive and negative long-run coefficients. The short-run adjustment to a positive and a negative shock in the VIX is captured by the parameters β_i^+ and β_i^-, respectively. The short-run symmetry can equally be tested by using a standard Wald test of the null hypothesis $\beta_i^+ = \beta_i^-$ for all $i = 0, \ldots, q-1$. The model in Equation (2) reduces to the traditional ECM if both null hypotheses of short-run and long-run symmetries are not rejected. The non-rejection of either the long-run symmetry or the short-run symmetry will yield the co-integrating NARDL model with short-run asymmetry in Equation (3) and with long-run asymmetry in Equation (4), respectively.

$$\Delta\text{SP}_t = \mu + \rho_{sp}\text{SP}_{t-1} + \rho_{vix}\text{VIX}_{t-1} + \sum\nolimits_{t=1}^{p} \alpha_i \Delta\text{SP}_{t-1} + \sum\nolimits_{i=0}^{q} (\beta_i^+ \Delta\text{VIX}_{t-1}^+ + \beta_i^- \Delta\text{VIX}_{t-1}^-) + \varepsilon_t \tag{3}$$

$$\Delta\text{SP}_t = \mu + \rho_{sp}\text{SP}_{t-1} + \rho_{vix}^+\text{VIX}_{t-1}^+ + \rho_{vix}^-\text{VIX}_{t-1}^- + \sum\nolimits_{t=1}^{p} \alpha_i \Delta\text{SP}_{t-1} + \sum\nolimits_{i=0}^{q=1} \beta_i \Delta\text{VIX}_{t-i} + \varepsilon_t \tag{4}$$

Here, the β_i^+ and β_i^- captures the short-run asymmetry, mentioned in Equation (3), and ρ_{vix}^+, ρ_{vix}^- captures the long-run asymmetry mentioned in Equation (4).

2.2. Pessimistic investor sentiments and S&P 500

Many studies find the statistically significant relationship between investor sentiment and future stock market returns (see, e.g., Brown & Cliff, 2005; Fisher & Statman, 2000, 2003). Another study Klemola et al. (2016) finds the relationship between GSVI and future near-term market returns taking S&P stock volume as control variable, and Whaley (2000) finds the negative relationship between VIX and stock market returns but our study focuses on two different proxies (GNSVI and VIX) for investor sentiment to measure the future stock market returns to check which one of the indices better forecasts the stock market returns. This leads to the following hypothesis to address the first objective of the study.

H2: Investors' pessimistic sentiments forecast the future stock market returns.

To test possible relationship between ΔGSVI, ΔVIX, and future S&P 500 returns as proposed in H2, we use following Ordinary Least Squares (OLS) models:

$$(\Delta S\&P_t) = \beta_0 + \beta_1(\Delta \mathrm{GSVI}_{t-1}) + \beta_2(\Delta \mathrm{VOL}_{t-1}) + e_t \tag{5a}$$

$$(\Delta S\&P_t) = \beta_0 + \beta_1(\Delta \mathrm{VIX}_{t-1}) + \beta_2(\Delta \mathrm{VOL}_{t-1}) + e_t \tag{5b}$$

$$(\Delta S\&P_t) = \beta_0 + \beta_1(\Delta \mathrm{VIX}_{t-1}) + \beta_2(\Delta \mathrm{GSVI}_{t-1}) + \beta_3(\Delta \mathrm{VOL}_{t-1}) + e_t \tag{5c}$$

Here, $\Delta S\&P_t$ shows the weekly logarithmic change of the S&P 500 weekly opening prices, $\Delta \mathrm{VOL}_{t-1}$ defines the weekly logarithmic change for volume of S&P 500 returns with lag of one week, $\Delta \mathrm{GSVI}_{t-1}$ defines the first difference for GSVI with a lag of one week, and $\Delta \mathrm{VIX}_{t-1}$ defines the weekly difference of investor fear gauge with a lag of one week. β_0 is intercept, and e_t is error term; β_1, β_2, and β_3 are slope coefficients of each equation separately.

Moreover, this study also uses vector auto-regression (VAR) analysis to analyze possible erogeneity of GSVI as the possible predictor of S&P 500 returns. We use the following VAR model:

$$(\Delta S\&P_t) = \beta_0 + \sum_{s=1}^{i} \beta_s(\Delta S\&P_{t-s}) + \sum_{i=1}^{i} \beta_i(\Delta \mathrm{Index}_{t-i}) + \sum_{v=1}^{i} \beta_v(\Delta \mathrm{VOL}_{t-v}) + e_t \tag{6}$$

Here, $\Delta S\&P_{t-s}$ defines the weekly logarithmic change of S&P 500 opening prices with different weekly lags; $\Delta \mathrm{Index}_{t-i}$ defines the weekly first differences of VIX and Google indices with different weekly lags; $\Delta \mathrm{VIX}_{t-i}$ defines the weekly first difference of VIX with different weekly lags; $\Delta \mathrm{GSVI}_{t-i}$ defines the first difference of GSVI with different weekly lags; and $\Delta \mathrm{VOL}_{t-v}$ defines the weekly logarithmic change for weekly S&P 500 volume with different weekly lags. Equation (6) defines the general VAR models. Here, four lags are considered for the estimation of VAR. β_0 is intercept, and βi and βv are slope coefficients. Results are reported in Table 4.

2.3. VIX and GSVI

Another purpose of this study is to compare the indices; GSVI and VIX to check which one of the indices better captures the market pessimistic sentiments. To our understanding, the GSVI takes into account the sentiments of participants who are not necessarily investing in the stock markets. This group of participants includes both real investors and people who just want to know market trends. Whereas, VIX specifically taken into account the views and sentiments of actual investors. This leads to our next hypothesis:

H3: The Google sentiment indices can better capture sentiments than VIX.

The possible relationship between VIX and GSVI is tested by applying the VAR model and Granger Causality. The estimated VAR models with the lags of four weeks are;

$$(\Delta \mathrm{VIX}_t) = \beta_0 + \sum_{i=1}^{i} \beta_i(\Delta \mathrm{VIX}_{t-i}) + \sum_{v=1}^{i} \beta_v(\Delta \mathrm{GSVI}_{t-v}) + e_t \tag{7}$$

$$(\Delta \text{GSVI}_t) = \beta_0 + \sum_{v=1}^{i} \beta_v (\Delta \text{GSVI}_{t-i}) + \sum_{i=1}^{i} \beta_i (\Delta \text{VIX}_{t-v}) + e_t \tag{8}$$

Here, ΔVIX_{t-i} defines the weekly first difference for VIX with the lag up to four week, and $\Delta GSVI_{t-i}$ defines the first difference for GSVI with the lags up to four weeks. β_0 is intercept; βi and βv are slope coefficients; and e_t is error term.

Additionally, redundancy is checked among investors' pessimistic attention proxies. Time series regression of ΔVIX and ΔGSVI (ΔCrash and ΔBear) is performed as

$$\Delta \text{GSVI} = \propto + \beta \Delta \text{VIX} + \varepsilon_{it} \tag{9}$$

$$\Delta \text{VIX} = \propto + \beta \delta \text{GSVI} + \varepsilon_{it} \tag{10}$$

$$\Delta \text{VIX} = \propto + \beta_1 \Delta \text{Crash} + \beta_2 \Delta \text{Bear} + \varepsilon_{it} \tag{11}$$

Here, $\propto$ is intercept; β, β_1, and β_2 are slope coefficients; and ε_{it} is error term. If ΔVIX captures the change in Google indices, then the $\propto$ should be equal to zero or negative otherwise. Same apply to the Equations (10) and (11).

3. Results

The results of Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test are shown in Table A1 (see Appendix A). In the test equations, we use the intercept term only. The results of both tests show that variables are stationary at level. Accordingly, we estimate Equations (1–4), and the maximum lag order considered is 1 as per the SC and HQ criteria (see Table A2 in Appendix A). The Johansen co-integration test indicates co-integration between the VIX and S&P 500 returns. Results are shown in Table A3 (see Appendix A). These lead us to next step of ARDL and NARDL estimation. Specification models are estimated using the Equations (8–11). The obtained results are reported in Table 3. Wald tests are then conducted to examine the hypotheses of short-run and long-run symmetries. Wald test shows that long-run and short-run symmetries cannot be rejected for the relationship of VIX and S&P 500 returns.

In short, addressing the H1, it is concluded that investor fear gauge has significant symmetric relationship with stock market return. As the null hypothesis is the existence of asymmetric relation, so we reject the null hypothesis. On the basis of this symmetry, we proceed to our next hypotheses results.

Table 4 reports the regression estimates of OLS model (Equation 1) taking the S&P 500 returns as dependent variable and S&P stock volume as a control variable. Addressing the hypothesis H2, the results report that both proxies of pessimistic investor sentiments negatively predict the future S&P 500 returns. Estimated coefficients of both terms of GSVI are negative in sign but only "Market Bear" significantly predicts the S&P 500 returns with the p-value < 0.01. Table 3 provides evidence that VIX is more prominent predictor of S&P returns as compared to GSVIs. Furthermore, volume as control variable has significant relationship in both regression models. Additionally, adjusted R-square values are also reported in Table 4.

Results given in Table 5 show that for the Google Search Volume Index (Bear Market), different lags of change in Bear have a negative relationship with future S&P 500 returns supporting the H1. The change in Bear with the lag of one week has the largest estimated coefficient with the t-statistics of −3.56. Additionally, different lags of S&P 500 returns have positive relationship with change in Bear Market. The S&P 500 returns with the lag of one week has the largest estimated coefficient.

For the Google Negative Search Volume Index (Market Crash), different lags of change in Crash have a negative relationship with future S&P 500 returns. The change in Market Crash with the lag of four weeks has the largest estimated coefficient. Additionally, different lags of S&P 500 returns have positive relationship with change in Market Crash. For different lags of S&P 500 returns, the

Table 3. Estimation of symmetric and asymmetric relationship between VIX and S&P500 returns

Without asymmetry (ARDL)		NARDL with LR asymmetry		NARDL with SR asymmetry		NARDL with LR & SR asymmetry	
Variable	**Coefficient**	**Variable**	**Coefficient**	**Variable**	**Coefficient**	**Variable**	**Coefficient**
C	0.023918***	C	0.000444	C	0.023943***	C	0.000409
LOGSP(-1)	−1.15607***	LOGSP(-1)	−1.15871***	LOGSP(-1)	−1.15426***	LOGSP(-1)	−1.15861***
LOGVIX(-1)	−0.00779***	LOGVIXPOS(-1)	−0.00786***	LOGVIX(-1)	−0.00792***	LOGVIXPOS(-1)	−0.00789***
DLOGSP(-1)	−0.05758*	LOGVIXNEG(-1)	−0.00798***	DLOGSP(-1)	−0.05852*	LOGVIXNEG(-1)	−0.00801***
DLOGVIX	−0.10889***	DLOGSP(-1)	−0.05632*	DVIXPOS	−0.10513***	DLOGSP(-1)	−0.0561*
DLOGVIX(-1)	−0.08945***	DLOGVIX	−0.10884***	DVIXPOS(-1)	−0.09011***	DVIXPOS	−0.10658***
		DLOGVIX(-1)	−0.08948***	DVIXNEG	−0.11436***	DVIXPOS(-1)	−0.09141***
				DVIXNEG(-1)	−0.09023***	DVIXNEG	−0.11233***
						DVIXNEG(-1)	−0.08794***
R^2	0.702682	R^2	0.70319	R^2	0.702791	R^2	0.703242
F-statistic	290.2253***	*F*-statistic	242.0489***	*F*-statistic	206.399***	*F*-statistic	180.6932***
AIC	−5.07891	AIC	−5.0774	AIC	−5.07125	AIC	−5.06954
SC	−5.03604	SC	−5.02738	SC	−5.01402	SC	−5.00515
		Wlr	1.049674	Wsr	0.085118	Wsr	0.926483
						Wlr	0.004826

Notes: This table reports the symmetric/asymmetric relationship between VIX and S&P 500 returns. Further asymmetric relationship is expended into three models, one with long-run asymmetry, one with short-run asymmetry, and other with both long-run and short-run asymmetries. Estimated models are given as;

$$\Delta \mathrm{SP}_t = \mu + \rho_{sp}\mathrm{SP}_{t-1} + \rho_{vix}\mathrm{VIX}_{t-1} + \sum_{i=1}^{p=1} \alpha_i \Delta \mathrm{SP}_{t-i} + \sum_{i=0}^{q=1} \beta_i \Delta \mathrm{VIX}_{t-i} + \varepsilon_t \quad (1)$$

$$\Delta \mathrm{SP}_t = \mu + \rho_{sp}\mathrm{SP}_{t-1} + \rho^{+}_{vix}\mathrm{VIX}^{+}_{t-1} + \rho^{-}_{vix}\mathrm{VIX}^{-}_{t-1} + \sum_{t=1}^{p} \alpha_i \Delta \mathrm{SP}_{t-1} + \sum_{i=0}^{q} (\beta^{+}_i \Delta \mathrm{VIX}^{+}_{t-1} + \beta^{-}_i \Delta \mathrm{VIX}^{-}_{t-1}) + \varepsilon_t \quad (2)$$

$$\Delta \mathrm{SP}_t = \mu + \rho_{sp}\mathrm{SP}_{t-1} + \rho_{vix}\mathrm{VIX}_{t-1} + \sum_{t=1}^{p} \alpha_i \Delta \mathrm{SP}_{t-1} + \sum_{i=0}^{q} (\beta^{+}_i \Delta \mathrm{VIX}^{+}_{t-1} + \beta^{-}_i \Delta \mathrm{VIX}^{-}_{t-1}) + \varepsilon_t \quad (3)$$

$$\Delta \mathrm{SP}_t = \mu + \rho_{sp}\mathrm{SP}_{t-1} + \rho^{+}_{vix}\mathrm{VIX}^{+}_{t-1} + \rho^{-}_{vix}\mathrm{VIX}^{-}_{t-1} + \sum_{t=1}^{p} \alpha_i \Delta \mathrm{SP}_{t-1} + \sum_{i=0}^{q=1} \beta_i \Delta \mathrm{VIX}_{t-i} + \varepsilon_t \quad (4)$$

*Coefficient significance level of 10%.
**Coefficient significance level of 5%.
***Coefficient significance level of 1%.

Table 4. OLS estimation results

Model	C	ΔBear(-1)	ΔCrash(-1)	ΔVIX(-1)	ΔVOL(-1)	Adj *R*-sq
5a (1)	0.00126	−0.006667***			−0.024199*	0.01949
5a (2)	0.00126		−3.02E-05		−0.03162**	0.00613
5b	0.001259			−0.00304***	−0.00279	0.095736
5c (1)	0.001258	−0.003441		−0.002922***	−3.19E-05	0.097701
5c (2)	0.00126		0.000648	−0.003053***	−4.71E-03	0.094648

Notes: Table 4 reports the Ordinary Least Square for Equation (1) given as;

$$(\Delta S\&P_t) = \beta_0 + \beta_1(\Delta GSVI_{t-1}) + \beta_2(\Delta VOL_{t-1}) + e_t \tag{5a}$$

$$(\Delta S\&P_t) = \beta_0 + \beta_1(\Delta VIX_{t-1}) + \beta_2(\Delta VOL_{t-1}) + e_t \tag{5b}$$

$$(\Delta S\&P_t) = \beta_0 + \beta_1(\Delta VIX_{t-1}) + \beta_2(\Delta GSVI_{t-1}) + \beta_3(\Delta VOL_{t-1}) + e_t \tag{5c}$$

Here $\Delta S\&P_t$ shows the weekly logarithmic change of the S&P 500 weekly opening prices, ΔVOL_{t-1} defines the weekly logarithmic change for volume of S&P 500 returns with lag of one week, $\Delta GSVI_{t-1}$ defines the first difference for GSVI.

*Coefficient significance level of 10%.

**Coefficient significance level of 5%.

***Coefficient significance level of 1%.

t-statistics ranges from 1.90 to 2.72. The S&P 500 returns with the lag of one week has the largest estimated coefficient. For the investor's fear gauge index (VIX), different lags of change in Crash have a negative relationship with future S&P 500 returns. The change in VIX with the lag of four weeks has the largest estimated coefficient with the t-statistics of −10.884. The S&P 500 returns with the lag of one week has the largest estimated coefficient (see Table 5).

Addressing the H2, the results report that both proxies of pessimistic investor sentiments negatively predict the future S&P 500 returns. Negative relation shows that investors expect bad returns after the good returns. Results depict the VIX as the more prominent predictor of S&P 500 returns as compared to GSVIs. So, we suggest that proxies for pessimistic investor sentiments convey information about predictability of stock returns but do not fully reflect the investor sentiments. However, these findings suggest that investors who are not aware of the complex decision-making procedure of investment, may use the proxies (GSVI and VIX) to make optimal decisions. As data for GSVI and VIX are easy accessible to investors.

Table 6 reports the results of VAR. Results show that GSVIs contain some information to explain the investors' fear gauge index, VIX with different weekly lags. For the investors' fear gauge, different lags of change in VIX have a significant negative relationship with the change in Bear Market up to lags of three weeks. The change in VIX with the lag of third week has the largest estimated coefficient with the *t*-statistics of −3.04. Additionally, different lags of change in Bear Market have positive relationship with change in VIX. The change in Bear Market with the lag of one week has the largest estimated coefficient with the *t*-statistics of 2.42 (see Table 6).

For the investors' fear gauge, different lags of change in VIX have a significant negative relationship with the change in Market Crash. For different lags of change in VIX, the *t*-statistics ranges from −2.76 to −4.13. The change in VIX with the lag of third week has the largest estimated coefficient. Additionally, different lags of change in Market Crash have positive relationship with change in VIX. The change in Market Crash with the lag of fourth week has the largest estimated coefficient with the *t*-statistics of 2.79 (see Table 6).

The Granger causality test is also being used to explain which of one the indices (VIX and GSVI) captures the other. Granger causality test is applied to explain the causality of variation in one variable because of other variable one by one. As Granger (1969) demonstrates the causality of

Table 5. VAR estimation results

Variable	S&P 500	ΔBear	ΔVOL	S&P 500	ΔCrash	ΔVOL	S&P 500	ΔVIX	ΔVOL
C	0.001488	−0.00683	0.001043	0.001443	−0.01322	0.001153	0.002092**	−0.07722	0.001144
SPRET(-1)	−0.09885**	1.713983***	0.142839	−0.07805*	3.049641***	0.098164	−0.3912***	25.58728***	0.231274
SPRET(-2)	0.033089	1.199125*	−0.16266	0.028682	2.220856**	−0.1703	−0.0316	12.14456**	−0.20385
SPRET(-3)	−0.0716*	1.174379*	−0.05983	−0.07322*	2.124862*	−0.08503	−0.14211***	12.35746**	−0.20346
SPRET(-4)	−0.01361	1.483207**	0.215174*	−0.00471	2.151778*	0.221636*	−0.10546**	11.04582**	0.222862
ΔIndex(-1)	−0.00925***	−0.41209***	0.016482**	−0.00081	−0.6268***	−0.00161	−0.00491***	0.091026*	0.001954
ΔIndex(-2)	−0.00248	−0.40597***	0.011664	−0.00094	−0.43463***	0.004326	−0.00135***	0.123535**	0.000866
ΔIndex(-3)	−0.00558**	−0.32531***	0.013044*	−0.00226	−0.32181***	0.013704***	−0.00071	0.132201**	−0.00221
ΔIndex(-4)	−0.00167	−0.1465***	0.009926	−0.00673***	−0.19544***	0.006153	−0.00149***	0.045141	−0.00101
ΔVOL(-1)	−0.03683**	0.055663	−0.40311***	−0.03772**	0.5529	−0.38231***	−0.00971	2.614023*	−0.39573***
ΔVOL(-2)	−0.02449	−0.3213	−0.32661***	−0.02216	−0.68722	−0.32488***	−0.00406	1.055653	−0.32571***
ΔVOL(-3)	−0.02286	−0.1493	−0.30645***	−0.01746	−0.79775*	−0.34446***	−0.00972	1.332646	−0.29326***
ΔVOL(-4)	−0.00887	−0.40317*	−0.22333***	0.012526	−0.2376	−0.23614***	0.013656	0.258714	−0.21263***
Adj. R-sq	0.034904	0.226435	0.180547	0.04386	0.287155	0.185074	0.196271	0.037617	0.177522
F-statistic	2.859571	16.05047	12.32847	3.358594	21.71217	12.67701	13.55601	3.009718	12.09764
AIC	−4.64923	0.865901	−2.58361	−4.65855	1.944709	−2.58915	−4.8322	4.606784	−2.57992

Notes: Table 5 reports the vector auto-regression results of Equation (6) given as;

$$(\Delta S\&P_t) = \beta_0 + \sum_{s=1}^{i} \beta_s(\Delta S\&P_{t-s}) + \sum_{i=1}^{i} \beta_i(\Delta \mathrm{Index}_{t-i}) + \sum_{v=1}^{i} \beta_v(\Delta \mathrm{VOL}_{t-v}) + e_t \tag{6}$$

Here, $\Delta S\&P_{t-s}$ defines the weekly logarithmic change of S&P 500 with different weekly lags, $\Delta GSVI_{t-i}$ defines the first difference of GSVI with different weekly lags (GSVI refers to "Market Crash" and "Bear Market") and ΔVOL_{t-v} defines the weekly logarithmic change for weekly S&P 500 volume with different weekly lags.

*Coefficient significance level of 10%.

**Coefficient significance level of 5%.

***Coefficient significance level of 1%.

variations of X factor by Y factor and vice versa by the GC test. Table 7 reports the results of Granger causality (GC) test. This test will explain either any of the indices; Google Negative Search Volume Index and VIX Index could cause the other one and otherwise (Table 7).

Results suggest that change in VIX contains information that helps to forecast the Market Crash and Bear Market, and Google sentiment indices (Market crash and Bear market) also contain some information to explain the change in VIX. This can be summarized as change in VIX granger causes the GSVI and otherwise also. Furthermore, Table 8 shows the results of time series regression. Insignificant intercept with absolute value of approximately zero and significant βs shows that VIX is being explained by the pessimistic investors' attention toward market. On the other hand, results of model 5b show that VIX is fully capturing one of the Google indices that is Market Crash.

Addressing the H3, results in Table 8 show that change in VIX contains information that helps to explain the Market Crash and Bear Market, and Google sentiment indices (Market crash and Bear market) also contain some information to explain the change in VIX. But VIX is fully capturing one of the Google indices that is Market Crash. These findings suggest the investor fear gauge (VIX) as more robust measure of investor sentiment for academia and practitioners who study market behavior.

Further, money managers may also be able to use these new insights to pull their long-term and short-term investing strategies. Using VIX (an indirect measure) and GSVI (a direct measure) as investor sentiment can definitely help individual investors to make optimal decisions that when to invest and where to invest. It could be interpreted as when investors are pessimistic, the stock return tends to go down. Likewise, when investors are optimistic, stock returns tend to go up. This phenomenon helps investors to take optimal decision regarding investing their money. As optimal decision-making must intake investor sentiments along with the fundamental factors.

Table 6. VAR results of VIX and GSVI

	ΔVIX	ΔBear	ΔVIX	ΔCrash
C	0.002173	−0.00037	0.002324	−0.00201
ΔVIX(-1)	−0.03138	−0.01567**	−0.02455	−0.03861***
ΔVIX(-2)	0.001839	−0.01671***	0.013371	−0.03849***
ΔVIX(-3)	0.056588	−0.01959***	0.04395	−0.04447***
ΔVIX(-4)	−0.01977	−0.00906	−0.02783	−0.03022***
ΔGSVI(-1)	0.676919**	−0.40308***	0.414559***	−0.61225***
ΔGSVI(-2)	0.444782	−0.40101***	0.274525	−0.44879***
ΔGSVI(-3)	0.499864*	−0.29791***	0.441663***	−0.32014***
ΔGSVI(-4)	0.009859	−0.14253***	0.420603***	−0.15851***
Adj. *R*-sq.	0.005144	0.230907	0.013155	0.318257
F-statistic	1.398811	24.15545	2.028086	37.00419
AIC	4.633614	0.853747	4.625529	1.893743

Notes: Table 6 shows the vector auto-regression results of following equations:

$$(\Delta \mathrm{VIX}_t) = \beta_0 + \sum\nolimits_{i=1}^{i} \beta_i(\Delta \mathrm{VIX}_{t-i}) + \sum\nolimits_{v=1}^{i} \beta_v(\Delta \mathrm{GSVI}_{t-v}) + e_t \tag{7}$$

$$(\Delta \mathrm{GSVI}_t) = \beta_0 + \sum\nolimits_{v=1}^{i} \beta_v(\Delta \mathrm{GSVI}_{t-i}) + \sum\nolimits_{i=1}^{i} \beta_i(\Delta \mathrm{VIX}_{t-v}) + e_t \tag{8}$$

Here $\Delta \mathrm{VIX}_t$ defines the daily first difference for VIX with the lag of one week and $\Delta \mathrm{GSVI}_t$ defines the first difference for GSVI with the lag of one week.

*Coefficient significance level of 10%.

**Coefficient significance level of 5%.

***Coefficient significance level of 1%.

Table 7. Granger causality results of VIX and GSVI

Panel A				**Panel B**			
Dependent variable: ΔVIX				**Dependent variable: ΔVIX**			
Excluded	χ^2	**df**	**Prob.**	**Excluded**	χ^2	**df**	**Prob.**
ΔBear	8.023793	4	0.0907	ΔCrash	13.03229	4	0.0111
All	8.023793	4	0.0907	All	13.03229	4	0.0111
Dependent variable: ΔBear				Dependent variable: ΔCrash			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
ΔVIX	25.88565	4	0.000	ΔVIX	55.57464	4	0.000
All	25.88565	4	0.000	All	55.57464	4	0.000

Notes: This table presents the Granger causality results. ΔVIX, ΔBear, and ΔCrash define the change in VIX and Google indices. Table is divided into two columns. Each with the individual Google index.

Table 8. Results of time series regression

Model	**Dep. var.**	**C**	**ΔCrash**	**ΔBear**	**ΔVIX**	R^2	**Adj.** R^2
5a	ΔBear	0.000227			0.040954***		
5b	ΔCrash	−0.00054			0.045521***		
6a	ΔVIX	0.002	0.4826***			0.021969	0.020391
6b	ΔVIX	0.001		1.3817***		0.056587	0.055065
7	ΔVIX	0.001	0.257226*	1.2319***		0.062163	0.059133

Notes: This table shows the time series regression results of given models.

$$\Delta \text{GSVI} = \propto + \beta \Delta \text{VIX} + \varepsilon_{it} \quad (9)$$

$$\Delta \text{VIX} = \propto + \beta \delta \text{GSVI} + \varepsilon_{it} \quad (10)$$

$$\Delta \text{VIX} = \propto + \beta_1 \Delta \text{Crash} + \beta_2 \Delta \text{Bear} + \varepsilon_{it} \quad (11)$$

*Coefficient significance level of 10%.

**Coefficient significance level of 5%.

***Coefficient significance level of 1%.

Additionally, in classical finance theory, investor sentiments do not play any role in determining stock prices and stock returns. This study takes investor sentiments into account and depicts that sentiments have significant effect on stock prices, thus asset pricing models augmented with sentiments-based factors would result in better pricing of assets in the markets.

4. Conclusion

This study employs investors' pessimistic sentiments through Google Trends Volume and VIX to predict the S&P 500 returns. To check the symmetric/asymmetric relationship of VIX with stock returns, this study employs models like ARDL, NARDL with only long-run asymmetry, NARDL with only short-run asymmetry, and NARDL with both long-run and short-run asymmetries. Contrary to existing evidence, we find that VIX has significant symmetric relationship with S&P 500 returns.

Further, we find that investors' pessimistic sentiment proxies (Google indices and VIX) predict the future S&P 500 returns; however, VIX shows more robust return predictability than Google indices. Although Google has changed its methodology for providing search term volume data, the shifts in bear and crash market indices have still able to predict the S&P 500 returns. It suggests that Google Search Volume data can be further used for estimating or predicting the stock market movements. These findings may be explained as, because of the pessimistic sentiments, investor turn to expect negative stock returns after good returns and otherwise. That's the reason the relationship between pessimistic investor sentiment and stock returns is negative.

In addition, this compares the two proxies of pessimistic investor sentiments, investor fear gauge and Google Search Volume indices. Our results suggest that the VIX (investor's fear gauge) may be used by academics and practitioners as robust measure of investor sentiments and for optimal decision-making.

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Note
1. https://support.google.com/.

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Appendix A

Table A1. Results of unit root tests

	Augmented Dickey-Fuller (ADF) test statistic		Phillips-Perron (PP) test statistic	
	t-statistic	Prob.	*t*-statistic	Prob.
Spret	−26.5031	0.000	−26.5015	0.0000
VIX	−3.30681	0.015	−3.36388	0.0126
dVIX	−24.8473	0.000	−24.8473	0.0000
dvixPOS	−21.8636	0.000	−21.8636	0.0000
dvixNEG	−24.7383	0.000	−25.1603	0.0000

Notes: only the intercept term is included in the test equation, and SIC criterion is used to select the optimal lag order in ADF and PP test equations.

Table A2. Maximum lag order consideration

Lag	SC	HQ
0	−6.617847	−6.62666
1	−6.757831*	−6.784259*

Table A3. Co-integration test

Unrestricted co-integration rank test (Trace)				
Hypothesized trace 0.05				
No. of CE(s)	Eigen value	Statistic	Critical value	Prob.**
None*	0.256122	193.5412	15.49471	0.0001
At most 1*	0.017645	10.9842	3.841466	0.0009

Trace test indicates 2 co-integrating eqn(s) at the 0.05 level
*Denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) *p*-values

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