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Research Article

Volatility Risk Premium, Return Predictability, and ESG Sentiment: Evidence from China's Spots and Options' Markets

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This study investigates the volatility risk premium on the emerging financial market. We also consider the expected return and ESG sentiment. Based on the SSE 50 ETF 5-minute high-frequency spots and daily options data from 2016 to 2021, we adopt nonparametric model-free approaches to calculate realized and implied volatilities. And the volatility risk premium is constructed by subtracting these volatility series. We examine the relations between the volatility risk premium and future excess returns as well as ESG sentiment through multifactor specifications. We find that the volatility risk premium also exists in the Chinese market and is significantly negative. In addition, the statistically positive correlation between the volatility risk premium and aggregate returns is an outlier compared to the empirically negative pattern in developed markets. At last, ESG sentiment is positively associated with the volatility risk premium, especially the impact of environmental and social. This evidence supports the agency theory, which indicates that investors perceive ESG investments as waste resources in a short term and become potentially risky.

1. Introduction

The relationship between return and risk in asset pricing has been an important issue in financial research. In traditional asset pricing studies, scholars often use estimates of stock return variance or volatility to measure financial risk (Markowitz) [1]. Thereafter, the classical intertemporal capital asset pricing model (ICAPM) shows that the asset excess return is positively correlated with the volatility of the market (Merton) [2]. This suggests that volatility is one of the significant risk factors and the study of volatility risk complements asset pricing and risk management.

Volatility can be divided into ex-ante volatility and ex-post volatility. Ex-ante volatility, also known as implied volatility (IV), is generally estimated from options, which is subject to uncertainty; ex-post volatility is a realized volatility (RV), calculated from historical return data, and is free of uncertainty (Bollerslev et al.,) [3]. Both ex-ante and ex-post volatilities can predict future returns, but in recent years, scholars have found that variance risk premiums (VRPs) or volatility risk premiums (VOLRPs) constructed from both can better predict returns (Bollerslev et al.,) [4]. However, the volatility risk premium is unobservable. In this article, a model-free ex-post realized volatility is calculated by summing high-frequency intraday returns squared (Andersen et al., Barndorff-Nielsen and Shephard) [5–7]. And ex-ante implied volatility is calculated by the Black–Scholes formula and model-free methods from options (Black and Scholes, Merton, Britten-Jones and Neuberger, Jiang and Tian) [8–11]. The difference between ex-post realized volatility and ex-ante implied volatility is defined as the volatility risk premium (Carr and Wu) [12].

The relationship between volatility risk premiums and cumulative asset returns has been widely studied in academic works (Carr and Wu, Bollerslev et al., Londono and Zhou) [12–14]. These studies targeted the US market at first and then spread to the global markets (Bollerslev et al., Fassas and Papadamou) [15, 16]. However, the current research focuses more on developed countries. Few scholars pay attention to some emerging markets, such as China whose investment pattern is often different from those of the mature markets (Fassas and Siriopoulos) [17]. Therefore, the return forecasting ability of volatility risk premium in Chinese financial markets today is worth investigating.

Moreover, the volatility risk premium changes over time (Todorov) [18]. Its variation may be caused by market uncertainty, which is determined by multiple micro- and macroeconomic factors [14]. But classical risk factors are unlikely to explain the volatility risk premium (Bollerslev et al., Carr and Wu, BAli and Zhou, Londono and Zhou) [4, 12, 14, 19]. Investor sentiment may serve as a good complementary factor (Baker and Wurgler, Fassas) [20, 21]. In addition, ESG (environmental, social, and governance) is a popular and challenging topic in recent years, but it is hard to measure its characteristics in China (Pastor et al.) [22, 23]. In this article, we employ the ESG sentiment data extracted from newspapers by natural language processing (NLP) to investigate the relationship between ESG sentiment and potential volatility risk.

Compared to previous studies that focus on the Chinese market, we use a longer dataset and high-frequency intraday data (Cong, Zheng and Qin) [24, 25]. Moreover, the monthly nonoverlapping sample and the SSE 50 ETF Volatility Index (iVIX) as an alternative gauge in subperiod are considered to test additional robustness. Our contribution involves two dimensions. On the one hand, the literature on volatility risk premiums is expanded. The existence of the implied volatility risk premium based on Chinese SSE 50 ETF options in emerging markets is verified. Additionally, an abnormal positive relation between the volatility risk premium and asset returns is found in China's financial markets. On the other hand, to the best of our knowledge, our research is the first to discuss the unmeasured characteristic effect of ESG sentiment on the volatility risk premium. And ESG sentiment is positively associated with short-term potential volatility risk, supporting the agency theory.

The rest of the article is organized as follows: Section 2 introduces the related literature. Section 3 describes the model specifications. Section 4 includes the data description and sample selection. Section 5 presents the empirical study and result analysis. Section 6 concludes the article.

2. Related Literature

2.1. Construction of Volatility Risk Premium. First, the volatility risk premium is not directly observable, and therefore proxy variables need to be constructed by extracting realized and implied volatilities from underlying assets (Fassas and Papadamou) [16]. Carr and Wu define the *VRP* as the difference between realized and implied measures. Thus, we adopt this method to estimate the volatility risk premium in this article [12]. However, other academic works such as Bollerslev et al. and Bekaert et al. who refer the VRP as the other way around, that is the difference between the risk-neutral and the physical returns variation, obtain an opposite sign result [4, 26].

Second, the ex-post realized volatility is also latent to observe (McAleer and Medeiros) [27]. Researchers have different ways to estimate the conditional realized volatility, including ARCH and GARCH models, stochastic volatility models (SV), or HAR-RV models (Engle; Bollerslev; Heston; Corsi et al.) [28–31]. However, the results provided by these volatility models are still unsatisfactory; in contrast, the realized volatility constructed based on model-free high-frequency intraday data performs well [27]. In particular, the 5-minute frequency is a trade-off between accuracy and microstructural noise [5, 6]. Therefore, we use the squared returns of the past five minutes to measure ex-post volatility.

Third, regarding the estimation of the ex-ante implied volatility, previous studies simply use the volatility index as a proxy variable for implied volatility, generally (Gonzalez-Perez) [32]. For example, the old VIX introduced in 1993 and the updated VIX in 2003, which were estimated by the nonparametric Black–Scholes and model-free methods, respectively [10, 11]. In China, the Shanghai Stock Exchange (SSE) issued the SSE 50 ETF Volatility Index (*iVIX*) for SSE 50 ETF options. Unfortunately, this official index was suspended on 14 February 2018, after the crash of the Chinese stock market [16, 17]. Therefore, we adopt the Black–Scholes and model-free methods to calculate implied volatility instead of using the iVIX directly.

2.2. Volatility Risk Premium and Returns Predictability. Previous works show that the volatility risk premium is predictive of asset returns. In general, scholars empirically find that the VIX volatility risk premium is significantly and negatively associated with stock returns [4, 12]. However, few studies focus on global equity and other markets, so the verdict is still inconclusive [16, 17].

Volatility risk is the uncertainty of changes in asset price fluctuations and is an important impact on asset returns. When the volatility of returns becomes greater, investors raise the expected value of future returns because they are taking higher risks, which can reduce current prices and thus asset returns over the same period, especially since shocks to negative returns have a larger impact relative to shocks relative to positive returns. Thus, there is an asymmetry, and this leads to the conclusion of a negative correlation between volatility and asset returns in empirical studies (French et al.; Campbell and Hentschel; Fassas and Siriopoulos) [17, 33, 34].

In addition, the volatility risk premium is related to investors' risk aversion. Scholars believe that the difference between physical and risk-neutral measures can be viewed as a proxy variable for the degree of risk aversion in the market. Rational investors view volatility as a risk, and they are willing to cede part of their future returns to hedge against potential volatility risks. So rising volatility leads to lower future returns [4, 12, 21, 26].

It is worth noting that Asia-Pacific markets are different from mature markets in developed countries because the volatility risk premiums of stock indices in Japan and Korea markets are positively correlated with stock returns. Possibly due to the upward jump in underlying asset prices and the gambling sentiment of individual investors, many speculators buy call options in anticipation of the future price spikes [16, 17, 24, 25]. We hypothesize that this anomaly may exist in China because its market is also an emerging market in the Asia-Pacific region. Therefore, we decide to explore the relationship between volatility risk premium and asset returns in China.

2.3. Factors Influencing the Volatility Risk Premium. The volatility risk premium is time-varying, and its changes are influenced by macro-uncertainty and microstructure (Black; BAli and Zhou, Londono and Zhou) [14, 19, 35]. Regarding the macro-level, industrial production, PPI, and monetary policy affect the volatility risk premium [3, 26]. And at the micro-level, systemic risk and size are influencing factors of volatility risk premium [12]. Some scholars also study the dynamic relationship between investor sentiment on asset returns and price volatility based on a micro-perspective (Baker and Wurgler, Bollerslev and Todorov; Fassas) [20, 21, 36]. On the other hand, ESG (environmental, social, and governance) has been a hot topic currently, but it is hard to determine its effect in China. Researchers argue that high returns on green assets strongly reflect environmental concerns and hedges against climate risks as well as investor tastes [22, 23]. Stakeholder theory suggests that institutional ownership is positively associated with environmental and social performance and that institutions are motivated by social and financial returns (Dyck et al.; Chen et al. [37, 38]. Firms with high ESG parity focus more on building long-term firm value and have more stable stock price performance during crises (Broadstock et al.) [39]. However, according to agency theory, the value of a company decreases when the CEO misuses resources (Masulis and Reza) [40]. ESG rating systems may provide incentives for companies to exaggerate social responsibility performance as well as to distract from negative information, exacerbating stock price volatility (Jin and Myers; Kim et al.) [41, 42]. In addition, company managers may exaggerate ESG ratings to build a good image of the company to attract investors' attention (Clementino and Perkins) [43]. In this article, we bridge the gap between these two types of literature by adopting the ESG sentiment based on news as the proxy of firm-specific ESG performance to examine the relationship between the volatility risk premium and ESG sentiment.

3. Methodology

3.1. Estimation of Realized Volatility. The realized volatility (RVOL) as the ex-post realized return variation is calculated at the end of the period. Scholars have two approaches to estimate realized volatility. The first way is to calculate the standard deviation of the daily logarithm returns (Christensen and Prabhala) [44]. The second method is to calculate the conditional variance by summing the squares of the high-frequency logarithm returns and then estimate the realized volatility [4]. This method is adopted for the annualized realized volatility in this article, which is expressed as follows:

$$RVOL_t = \sqrt{\frac{H}{h}\sum_{i=1}^{nh} r_i^2}, \tag{1}$$

where r_i is the 5-min logarithm return. The daily normal trading period is 4 hours from 9:30 am to 11:30 am and 1:00 pm to 3:00 pm, with 48 intraday 5-minute returns. The rolling period is 1 business month, about 20 trading days. Therefore, we have $n = 48$, $h = 20$, and $H = 252$. The ex-post realized volatility is calculated at the end of the rolling windows; correspondently, the historical volatility ($HVOL$) is calculated on the last day of the previous cycle. Therefore, the relationship between $RVOL$ and $HVOL$ is expressed as $RVOL_t = HVOL_{t+h}$.

3.2. Estimation of Implied Volatility. The implied volatility ($IVOL$) as an ex-ante risk-neutral expectation of future return variation is calculated at the beginning of the period. Scholars mainly have two approaches based on the options contracts to estimate the ex-ante implied volatility. The first one is Black–Scholes model (BS), which is used to calculate the original VIX [8, 9]. And the other one is model-free method (MF), which is used to estimate the new VIX [10]. The Black–Scholes model is expressed as follows:

$$C = SN(d_1) - Ke^{-rT}KN(d_2), \tag{2}$$

$$\begin{aligned} d_1 &= \frac{\log S - \ln K + \left(r + 1/2\sigma^2\right)T}{\sigma\sqrt{T}}, \\ d_2 &= \frac{\log S - \ln K + \left(r - 1/2\sigma^2\right)T}{\sigma\sqrt{T}}, \end{aligned} \tag{3}$$

where C is the option price, K is the strike price, S is the spot price, T is the time to maturity, r is the risk-free rate, N is the normal distribution, and σ is the BS implied volatility (BSVOL). Therefore, with the time to expiration, option, strike price, and spot prices, as well as risk-free rate known, the BS implied volatility of the contract can be calculated backward by the model. It is worth noting that the BS model assumes Brownian movement and normal distribution, and the BS implied volatility is calculated by ATM (at-the-money) options contracts.

The model-free method avoids the problem of model bias of the BS model by relying only on the price information of the options and does not require any assumption. In addition, the model-free method can estimate the implied volatility by combining a series of ATM and OTM (out-of-the-money) options contracts, which contain more information [11]. The model-free method is expressed as follows:

$$E\left[\int_0^T \left(\frac{dS_t}{S_t}\right)^2\right] = 2\int_0^\infty \frac{C(T,K) - C(0,K)}{K^2}dK. \tag{4}$$

Problems of the model-free method are discretization error and truncation error when transformed from continuous-time conditions to discrete-time conditions. However, according to Jiang and Tian [11], the errors are proved to be acceptable, and the MF implied volatility (MFVOLt) in the discrete-time condition is expressed as follows:

$$2\int_{K_{\min}}^{K_{\max}} \frac{C(T,K) - \max(S_0 - K, 0)}{K^2} dK \approx 2\sum_{i=1}^{m} \frac{C(T,K_i) - \max(S_0 - K_i, 0)}{K^2} \triangle K, \tag{5}$$

$$\triangle K = \frac{(K_{\max} - K_{\min})}{m, K_i = K_{\max}} - i\triangle K MFVOL_j = \sqrt{E\left[\int_0^T \left(\frac{dS_t}{S_t}\right)^2\right]}, \tag{6}$$

where K is the strike price, S is the spot price, $K_{\max}$ is the maximum strike price of the options, $K_{\min}$ is the minimum strike price of the options, and m is the number of different strike prices.

Moreover, we take the SSE 50 ETF Volatility Index (iVIX) as an alternative measurement to verify the robustness. Although the official publication was discontinued in February 2018 after the crash of Chinese stock market, the iVIX is compared with the implied volatility series we measured as robust tests in a subsample from April 2016 to February 2018.

3.3. Relationship between Realized and Implied Volatilities. We use encompassing regression to examine the relationship between implied volatilities and realized volatility as well as historical volatility [11, 17, 32, 44]. Taking realized volatility as the measure of information content, by checking the univariate and bivariate regression results of both implied volatility and historical realized volatility, if implied volatility encompasses past realized volatility in predicting future realized volatility, then the coefficient of past realized volatility should be statistically insignificant. The regression specifications are as follows:

$$RVOL_{t+h} = \alpha + \beta_{HV} HVOL_t + \beta_{BS} BSVOL_t + \beta_{MF} MFVOL_t + \varepsilon_t. \tag{7}$$

3.4. Estimation of Volatility Risk Premium. The volatility risk premium (VOLRP) is the compensation for taking volatility risk, which is the difference between the physical (P) state and the risk-neutral (Q) state variation. The volatility risk premium cannot be observed directly, so the proxy variable needs to be found. It is defined as follows:

$$VOLR_P^t = E_t^P(\sigma_t) - E_t^Q(\sigma_t). \tag{8}$$

Different models are applied in the literature, and we adopt the method by Carr and Wu in this article [12]. As a linear assumption, the volatility risk premium is the difference between realized and implied volatility series (Bollerslev and Zhou) [45]. And to reduce the heteroscedasticity of both series, the logarithm volatility risk premium (LVRP) is constructed as the difference between the log realized and log implied volatility series [12, 32]. These two alternative specifications are presented as follows:

$$VOLRP_{i,t} = RVOL_{i,t+h-1} - IVOL_{i,t}, \tag{9}$$

$$LVOLRP_{i,t} = \log RVOL_{i,t+h-1} - \log IVOL_{i,t}. \tag{10}$$

3.5. Return Predictability. Taking the performance of the regressions on the excess return of the SSE 50 ETF portfolio as a measurement, we can examine the correlation between the volatility risk premium and asset aggregate returns. If the volatility risk premium is priced, there should be a feedback effect. And we then apply the CAPM to have robust results. The regression models are as follows:

$$R^e_{etf,t+h} = \frac{H}{h}\sum_{i=1}^{h}\left(r_{j,t+i} - r_{f,t+i}\right), \tag{11}$$

$$R^e_{etf,t+h} = \alpha + \beta_i VOLR_P^{i,t} + \varepsilon_t, \tag{12}$$

$$R^e_{etf,t+h} = \alpha + \beta_{mkt} R^e_{mkt,t} + \beta_i VOLR_P^{i,t} + \varepsilon_t, \tag{13}$$

where r_j is the daily natural logarithm return, the risk-free r_f is the rate of 6-month Shibor, $R^e{}_{etf,t}$ is the annualized aggregate excess returns of the SSE 50 ETF, and $R^e{}_{mkt,t}$ is the annualized aggregate excess returns of the stock market.

3.6. ESG Sentiment. We attempt to discover the relationship between the volatility risk premium and neglected variables (Ang et al.) [46]. Since sentiment impacts asset pricing and ESG is becoming an interesting and prevailing issue, ESG sentiment is combined as our mainly challenging variable to extend the literature. Potential risk factors will be controlled. The idiosyncratic belief is sometimes omitted by investors because it cannot be simply and directly observed. Thus, daily turnover is a proxy introduced to control idiosyncratic belief. And P/E is used as a proxy to examine the value effect on volatility risk premium since the value factor is a risk characteristic that has always been of interest to investors. To better figure out the ESG effect, the factors of environment & social and governance are further tested, respectively. Our multifactor regression specifications are as follows:

$$LVOLR_P^t = \alpha + \beta_{esg} ES_G^t + \beta_{turn} TUR_N^t + \beta_{pe} P_E^t + \varepsilon_t, \quad (14)$$

where ESG_t is the ESG sentiment weighted by the amount of daily news. It is ranging from −1 to 1, where 1 is most positive and −1 is most negative. $Turn_t$ is the daily turnover of SSE 50, which represents the idiosyncratic belief and liquidity. And PE_t is the price-to-earnings ratio as a proxy for the value effect.

4. Data

4.1. Data Description. The main purpose of this article is analyzing the volatility risk premium and its return predictability in Chinese financial markets. SSE 50 ETF, CSI 300 Index, and CSI 1000 Index options have been launched since 9 February 2015. Among them, the SSE 50 ETF option is the first contract, and it has existed for a sufficient period with a large trading volume. Therefore, we select the SSE 50 ETF spots and options to study, and 6-month Shibor is taken as risk-free. Data sources are WIND and Oriental Fortune Choice Database.

4.2. Sample Range and Frequency. The sample is selected from 1 April 2016 to 31 March 2021. The first year of SSE 50 ETF options coincides with the excessive boom and bubble-bursting crash of the stock market, which is inferred as a period of sharp market fluctuation from February 2015 to March 2016. And since then, the market has a stationary period. Therefore, our sample spans the period of SSE 50 ETF and options from 1 April 2016 to 31 March 2021, with a total of 5 years or 1217 business days for the empirical tests.

We rely on 5-min SSE 50 ETF spot returns to estimate the daily realized volatility. Since the trading data are impacted by many factors such as intrinsic discontinuity, day-to-day effects, bid-ask spreads, and other market microstructure frictions [5], intraday high-frequency data can be a considerable choice. However, ultra-high frequency data are affected by market noise; it is thus appropriate to use intraday data with a frequency of 5 to 30 minutes [6]. Due to the requirement of a trade-off between accuracy and microstructure noise, our sample frequency is 5 min.

Nevertheless, obtaining SSE 50 ETF option intraday high-frequency data is more difficult than daily trading data for the option-implied volatility. In addition, we propose to explore the relationship between volatility risk premium and ESG sentiment as well as other microstructure variables, which are measured daily. Therefore, implied volatility is estimated based on daily options data in the research.

Moreover, the relevant empirical literature has shown contradictory results from overlapping and nonoverlapping rolling windows. The use of realized and implied volatility series estimated from overlapping data in regression analysis may potentially lead to strong autocorrelation problems in the regression's residuals [12, 16, 17, 44]. To avoid the overlapping problem, we lower the sample frequency and employ the monthly data as nonoverlapping periods for robustness.

4.3. Sample Process. The sample of SSE 50 ETF options is processed as follows [11]. First, the call and put options are filtered by moneyness for each trading day. We select the options at-the-money and out-of-the-money, since these options with large trading volume and high liquidity could be seen as reflections of most investors' expectation of the SSE 50. Second, the options are selected by maturity dates from 7 to 35 trading days. Others with too long or short maturity time will be impacted by the uncertainty of the information or lack of liquidity so that they may not reflect investors' expectation of future returns. Finally, the invalid data sample is eliminated.

4.4. ESG Sentiment Variable. The data source of ESG sentiment is DATAGO Database. It is analyzed from newspapers via natural language processing (NLP). We employ the amount of the news as weight. The sentiment rating is from −1 to 1, where 1 is most positive and −1 is most negative. The ESG sentiment ratings include overall as well as environmental and social as well as governance scores separately and are currently only available by December 2020, with a total of 1156 daily observation data for our empirical study.

5. Empirical Test

5.1. Realized and Implied Volatility Series. Table 1 reports the summary statistics of the volatility series. We calculate time series for different volatilities based on equations (1) through (6). Among them, the realized volatility (RVOL) and historical volatility (HVOL) are calculated from ex-post log returns on the last day of a rolling 20-day business period. And the ex-ante implied volatilities are estimated at the beginning of the 1-month business cycle, approximately. The Black–Scholes implied volatility (BSVOL) is provided for the ATM or OTM calls with the largest trading volume only, while the model-free implied volatility (*MFVOL*) is calculated from both ATM and OTM options. And the information for daily and monthly series is presented in Panels A and B.

Starting with the daily volatility series, the mean of realized volatility is 0.1631 and the standard deviation is 0.1529. The historical volatility is one-period lagged realized volatility, so they have similar summary statistics. The means of both BS and MF implied volatility series are higher than the counterparts of realized volatility. By comparison, the summary statistic of BS implied volatility is similar to realized volatility, while MF implied volatility is relatively more stable with a lower standard deviation. In addition, the skewness and kurtosis of realized volatility is about 1 and 3.5, indicating the distribution of it is positively skewed and slightly leptokurtic. While the skewness of implied volatilities is closer to 0 and the kurtosis is about 3. Particularly, the MF implied volatility is the most conformable with the normal distribution. Therefore, the regressions based on MF implied volatility are inferred to be statistically better specified than those based on BS implied volatility.

Table 1: Summary statistics of 5-min realized and implied volatility series.

	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Observations
Panel A: Daily								
RVOL	0.1631	0.1529	0.3505	0.0698	0.0594	0.9546	3.5484	1217
HVOL	0.1635	0.1541	0.3505	0.0698	0.0595	0.9346	3.5090	1217
BSVOL	0.1819	0.1724	0.4696	0.0397	0.0651	0.5307	3.2149	1217
MFVOL	0.1936	0.1934	0.3668	0.0719	0.0451	0.0894	2.9170	1217
Panel B: Monthly								
RVOL	0.1672	0.1521	0.3505	0.0754	0.0668	1.0680	3.5802	60
HVOL	0.1630	0.1581	0.3303	0.0744	0.0587	1.0371	3.7859	60
BSVOL	0.1878	0.1759	0.3142	0.0621	0.0650	0.1937	2.1043	60
MFVOL	0.1850	0.1877	0.2638	0.1024	0.0385	-0.2619	2.3266	60

Table 2: Correlation matrix of volatility series.

	RVOL	*HVOL*	*BSVOL*	*MFVOL*
Panel A: Daily				
RVOL	1			
HVOL	0.4559	1		
BSVOL	0.5267	0.7442	1	
MFVOL	0.4622	0.6672	0.8369	1
Panel B: Monthly				
RVOL	1			
HVOL	0.4914	1		
BSVOL	0.5168	0.8223	1	
MFVOL	0.4560	0.5742	0.6587	1

Turning to the 60 nonoverlapping monthly observations reported in the Panel B, the monthly volatility series have the similar descriptive statistics as the corresponding values of the daily series, whereas the skewness and kurtosis of implied volatilities are slightly lower relative to the daily counterparts.

Table 2 summarizes the correlation matrix of different volatility series. The correlations between realized volatility and the other volatility series are not as high as previous results in the US market [11], perhaps because the Chinese SSE 50 ETF options market is still in its infancy or the bias of measurements. However, if we take the realized volatility as a benchmark, both BS and MF implied volatility series are correlated with it, which is consisted with the relevant literature. The serial correlation between the realized and historical volatilities is lower because underlying assets are slightly predictable using lagged terms, although the past and future realized series have highly similar patterns. And the results are similar to the monthly volatility series. Overall, the two implied volatilities have the highest correlation, and both contain sufficient historical information and have similar forecasting power for the realized information.

Figure 1 graphs the daily overlapping samples from April 2016 to March 2021. As shown in the figure, both the implied volatility series can track the realized volatility. The BS implied volatility tends to be closer, whereas the MF implied volatility has greater local fluctuations. In general, the BS and MF implied volatility series have similar features and characteristics over the sample period, but they also contain different information content.

Furthermore, the univariate and encompassing regressions are applied with both implied volatility and historical volatility as regressors as an additional robustness [11, 17, 44]. The OLS regression results are provided in Table 3.

We begin by presenting the daily univariate regression results in the first three columns of the top panel. The historical and implied volatility series have a positive and highly statistically significant association with realized volatility. This indicates that all three series contain sufficient information for the realized volatility. However, the two implied volatilities exhibit a better fitting degree since their coefficients and adjusted R^2s are larger, and their interceptions are closer to zero. This evidence implies that the BS implied volatility contains the most information, while the past volatility measurement explains the least of the future variations. The encompassing regressions are reported in the following columns, where the adjusted R^2s are higher than the corresponding values of univariate regressions. And the coefficients of historical as well as either implied volatility are both positively significant perceiving that implied volatility performs better but does not cover all the valid information of historical volatility; in other words, they have slight unique prediction power. However, when the variables *BSVOL* and *MFVOL* are involved together, the former series dominates the latter one since the slope coefficient β_{MFVOL} is statistically insignificant. This evidence suggests that the BS implied volatility subsumes the MF implied volatility perhaps because of the liquidity problem in China's ETF options market [17]. We next consider the monthly nonoverlapping samples in Panel B, and similar empirical results were obtained.

Summing up, the historical volatility as well as the BS and MF implied volatility series are the efficient and biased estimation of future realized volatility since their slope coefficients are positive and interceptions are significantly different from zero. And the information contained by BS and MF implied volatility is similar. Moreover, although they do not encompass historical volatility, their explanation performances are better.

5.2. Volatility Risk Premium and Return Predictability. In this article, BS and MF volatility risk premiums are calculated as $VOLRP_{bs} = RVOL\text{-}BSVOL$; $VOLRP_{mf} = RVOL\text{-}MFVOL$. And the log volatility risk premiums are defined in

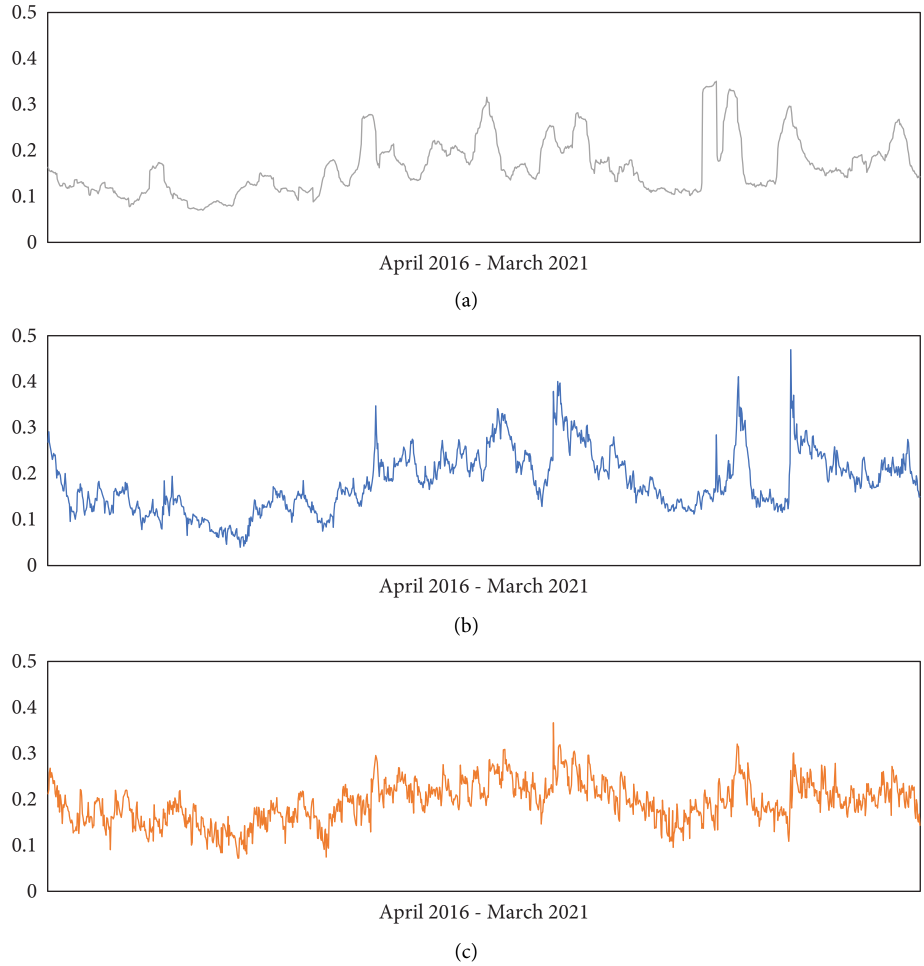

Figure 1: Daily SSE 50 ETF realized and implied volatility series.

an alternative specification as $LVOLRP_{bs} = \log RVOL\text{-}\log BSVOL$; $LVOLRP_{mf} = \log RVOL - \log MFVOL$ (see the descriptive statistics from Table 4 and plots in Figure 2). Besides different formations of volatility risk premiums, we also report the 20-day aggregate excess log returns of the SSE 50 ETF and market in Table 4 to examine the relationship between the volatility risk premiums and expected returns.

We start with the aggregate excess returns that the SSE 50 ETF overcomes the market since the mean of the excess return of SSE 50 ETF ($R^{e}{}_{etf}$) is positive; meanwhile, the corresponding mean value of the market ($R^{e}{}_{mkt}$) is negative. Although the ETF volatiles are stronger, it is more conformable with the normal distribution relative to the market. The averages of all volatility risk premiums are less than zero, which is consisted with previous literature. Among them, $VOLRP_{bs}$ and $VOLRP_{mf}$ tend to be more positively skewed and highly leptokurtic than $LVOLRP_{bs}$ and $LVOLRP_{mf}$. This suggests that $LVOLRP$ may have better statistical specification results than $VOLRP$. Similar patterns are presented in Panel B for the monthly series.

Table 5 summarizes the predictive results of OLS regressions from equations (13) to (14). We find that most daily and monthly volatility risk premium series in Panels A and B show a statistically significant predictive power for future 20-day aggregate excess returns in Chinese spots and options markets. The adjusted R^2s in our findings range from 2% to 6%, approximately. This evidence is consistent with the relevant empirical results in the US [4]. However, we note that the volatility risk premium predicts future aggregate returns with a significantly positive sign at the 1% level. It is prudent to consider the robustness so that we introduce the aggregate excess returns of the stock market into alternative CAPM specification. And this investigation leads to similar results that the predicted coefficients of volatility risk premiums are still highly significant with positive signs. This empirical evidence is an anomaly different from the negative relationship between the underlying asset variation risk premium and returns in the previous literature. Nevertheless, the similar positive patterns are provided in Korean and Japanese stock indexes in Asia, the volatility of volatility, and commodity volatility indexes (KOSPI, NIKKEI 225, SMI, VVIX,VVSTOXX, and white maize) [16, 17]. Although in theory, the volatility risk premium should be negatively associated with the future return because investors regard volatility as a potential risk and rational investors are risk aversion, they are willing to hedge against volatility via giving up a positive excess return [12, 21]. We propose two plausible reasons to account for

Table 3: Univariate and encompassing regressions of volatility series.

RVOL	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Daily							
HVOL	0.4553***			0.1431***	0.2654***		0.1380***
	(17.8532)			(3.9476)	(7.9795)		(3.7794)
BSVOL		0.4811***		0.3837***		0.4263***	0.3480***
		(21.5963)		(11.5742)		(10.4815)	(7.6585)
MFVOL			0.6087***		0.3752***	0.0944	0.0674
			(18.1703)		(8.5550)	(1.6105)	(1.1482)
α	0.0887***	0.0757***	0.0452***	0.0700***	0.0471***	0.0674***	0.0643***
	(19.9828)	(17.6231)	(6.7911)	(15.5272)	(7.2395)	(10.0266)	(9.5412)
Adj. R^2	0.2072	0.2768	0.2130	0.2854	0.2516	0.2777	0.2856
Obs.	1217	1217	1217	1217	1217	1217	1217
Panel B: Monthly							
HVOL	0.5587***			0.2331	0.3894**		0.2109
	(4.2967)			(1.0385)	(2.5059)		(0.9427)
BSVOL		0.5311***		0.3579*		0.3930**	0.2435
		(4.5979)		(1.7646)		(2.5794)	(1.1065)
MFVOL			0.7903***		0.4495*	0.3538	0.3353
			(3.9020)		(1.8978)	(1.3768)	(1.2996)
α	0.0761***	0.0674***	0.0209	0.0619**	0.0205	0.0279	0.0250
	(3.3788)	(2.9382)	(0.5463)	(2.6331)	(0.5592)	(0.7611)	(0.6795)
Adj. R^2	0.2284	0.2545	0.1943	0.2555	0.2615	0.2658	0.2644
Obs.	60	60	60	60	60	60	60

Note. The test statistics are reported with t-values in parentheses. *, **, and *** indicate that the coefficient of regression is significant at the 10%, 5%, and 1% level, respectively.

Table 4: Summary statistics of excess returns and volatility risk premiums.

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
Panel A: Daily								
R^e_{etf}	0.0130	0.0217	1.0015	−0.8233	0.2656	0.0406	3.6459	1217
R^e_{mkt}	−0.0188	−0.0068	0.9889	−0.7571	0.2497	0.1632	4.2350	1217
$VOLRP_{bs}$	−0.0185	−0.0234	0.2016	−0.1933	0.0608	0.6081	4.5392	1217
$VOLRP_{mf}$	−0.0305	−0.0407	0.2156	−0.1545	0.0556	1.2322	5.3456	1217
$LVOLRP_{bs}$	−0.0440	−0.0687	0.4601	−0.3617	0.1414	0.8130	3.6226	1217
$LVOLRP_{mf}$	−0.0889	−0.1019	0.4331	−0.4091	0.1335	0.6912	3.8351	1217
Panel B: Monthly								
R^e_{etf}	0.0146	0.0309	0.7435	−0.5955	0.2726	−0.2431	3.3056	60
R^e_{mkt}	−0.0204	0.0032	0.7393	−0.6039	0.2457	-0.1853	4.0055	60
$VOLRP_{bs}$	−0.0207	−0.0286	0.1753	−0.1360	0.0648	0.8540	4.2305	60
$VOLRP_{mf}$	−0.0179	−0.0258	0.1857	−0.1148	0.0600	1.5168	5.8098	60
$LVOLRP_{bs}$	−0.0535	−0.0702	0.3229	−0.3109	0.1446	0.7252	3.2540	60
$LVOLRP_{mf}$	−0.0649	−0.0734	0.4331	−0.4019	0.1428	0.7476	4.9371	60

this opposing relation. The first possibility is that the SSE 50 ETF returns tend to have upward volatility. And speculators are likely to buy calls due to this price jump propensity [16, 17]. Thus, the SSE 50 ETF options are overvalued with an increasing trading demand. The other one is the high retail investor proportion in China or other Asian regions relative to the US market. Retail investors are inclined to be irrational and have risk preference and appetite compared to the institutional investors [24, 25]. Therefore, this abnormal phenomenon the volatility risk premium predicts future returns with a positive sign is recorded in China's financial markets.

5.3. Robustness Analysis. Our reports on volatility risk premiums rely on the accuracy of our estimations of the Black–Scholes and model-free implied volatility series. However, the CBOE Volatility Index (VIX) is often used simply as a proxy for the S&P 500 implied volatility in the US. Can we employ a similar index as an alternative ex-ante measure in China options market? In June 2015, the Chinese Volatility Index (*iVIX*) is launched on Shanghai Stock Exchange (SSE) to figure out the implied volatility of the SSE 50 ETF options. Unfortunately, the official issue of iVIX was stopped on 14 February 2018, so we cannot employ it as the implied volatility in the whole period. However, to check the robustness, we compare our implied volatility measures with the publish model-free volatility index, *iVIX*, in a short sample period.

Tables 6 and 7 document the summary statistics and correlation matrix of the subsample volatility series. We begin by examining the realized and implied volatility series

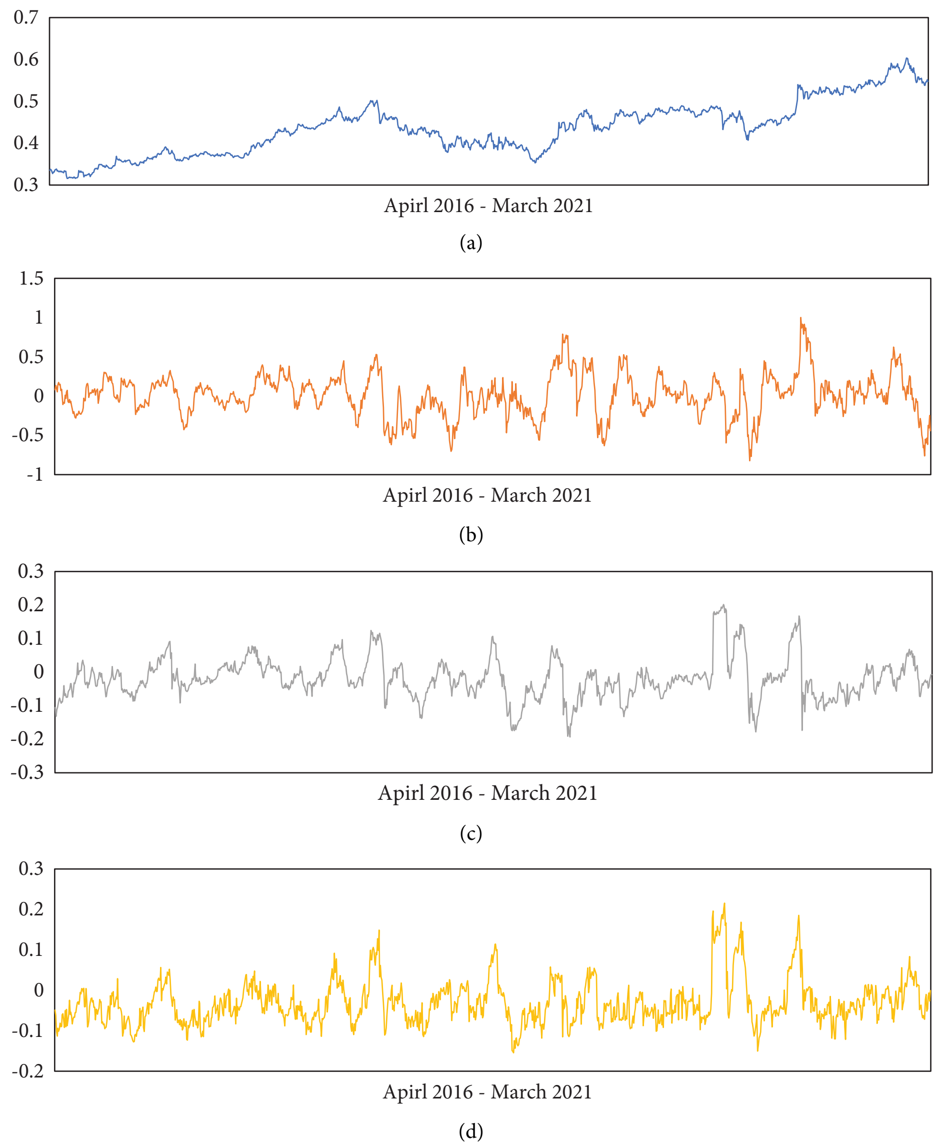

Figure 2: SSE 50 ETF aggregate excess returns and volatility risk premiums.

in the subperiod. The turbulence of the SSE 50 ETF is mild during the subperiod compared with the whole period. Both means and standard deviations of the realized and BS as well as MF implied volatilities decline in this short sample. Turning to the *iVIX* as an alternative option-implied volatility, the average *iVIX* is higher than the realized and BS volatility series but lower than the MF implied volatility. Meanwhile, the *iVIX* has considerably weaker fluctuation among them. And, similarly, the distribution of *iVIX* is right-skewed and leptokurtic. Regarding the correlation matrix, we discover the correlation between the realized and implied volatilities is slightly lower relative to the whole period. Nevertheless, the *iVIX* is highly correlated with the implied volatility series, especially the BS implied volatility. Thus, we speculate that the *iVIX* is calculated by the Black–Scholes model since its methodology was not published in detail.

We next calculate the volatility risk premiums by *iVIX* in subperiod. Table 8 summarizes the subsample excess returns and the volatility risk premium series. Regarding the aggregate future returns, it performs better in this short sample period than the whole sample with higher mean return, lower standard deviation, and slightly negatively skewed. Regarding the volatility risk premiums, on the one hand, the alternative *iVIX* measure also has a negative mean with a similar distribution to model-free volatility risk premium. On the other hand, the descriptive statistics of subsample volatility risk are consistent with the corresponding values of the whole sample.

Finally, we examine the relationship between the alternative *iVIX* volatility risk premium and the aggregate returns in a short time. The empirical univariate OLS results are presented in Table 9. As measured by higher adjusted R^2s, all the terms of volatility risk premium have a stronger

Table 5: Regressions of volatility risk premiums (OLS).

R^e_{etf}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Daily								
$VOLRP_{bs}$	0.6774***				0.3878***			
	(5.4675)				(6.7134)			
$VOLRP_{mf}$		1.0556***				0.4280***		
		(7.8941)				(6.7195)		
$LVOLRP_{bs}$			0.3121***				0.2034***	
			(5.8701)				(8.2740)	
$LVOLRP_{mf}$				0.4059***				0.1976***
				(7.2662)				(7.5207)
R^e_{mkt}					0.9333***	0.9261***	0.9329***	0.9278***
					(66.3942)	(65.3133)	(67.0202)	(66.0076)
α	0.0255***	0.0452***	0.0267***	0.0491***	0.0378***	0.0435***	0.0395***	0.0480***
	(3.2448)	(5.3363)	(3.3990)	(5.4772)	(10.3104)	(10.9008)	(10.8730)	(11.4825)
Adj. R^2	0.0232	0.0480	0.0268	0.0409	0.7889	0.7889	0.7928	0.7908
Obs.	1217	1217	1217	1217	1217	1217	1217	1217
Panel B: Monthly								
$VOLRP_{bs}$	1.1529**				0.4379*			
	(2.1685)				(1.6972)			
$VOLRP_{mf}$		0.3540				0.1396		
		(0.5947)				(0.4988)		
$LVOLRP_{bs}$			0.5173**				0.2293**	
			(2.1724)				(2.0107)	
$LVOLRP_{mf}$				0.1500				0.0797
				(0.6003)				(0.6800)
R^e_{mkt}					0.9597***	0.9806***	0.9586***	0.9805***
					(14.1137)	(14.3593)	(14.2863)	(14.3924)
α	0.0384	0.0209	0.0423	0.0243	0.0433**	0.0371**	0.0465***	0.0398**
	(1.0713)	(0.5663)	(1.1597)	(0.6251)	(2.5352)	(2.1365)	(2.7050)	(2.1791)
Adj. R^2	0.0590	0.0061	0.0593	0.0062	0.7870	0.7772	0.7910	0.7780
Obs.	60	60	60	60	60	60	60	60

Note. The test statistics are reported with t-values in parentheses. *, **, and *** indicate that the coefficient of regression is significant at the 10%, 5%, and 1% level, respectively.

Table 6: Summary statistics of subsample volatility series.

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
Panel A: Daily								
RVOL	0.1248	0.1181	0.2781	0.0698	0.0414	1.8420	7.3831	461
iVIX	0.1484	0.1467	0.3306	0.0831	0.0367	1.0179	5.2484	461
BSVOL	0.1312	0.1284	0.3473	0.0397	0.0428	0.8897	5.2725	461
MFVOL	0.1636	0.1619	0.2956	0.0719	0.0377	0.3412	3.4569	461
Panel B: Monthly								
RVOL	0.1240	0.1190	0.2778	0.0754	0.0418	2.1604	9.0521	23
iVIX	0.1506	0.1506	0.2731	0.0909	0.0390	1.2105	5.4360	23
BSVOL	0.1369	0.1401	0.2683	0.0621	0.0434	0.8739	4.8974	23
MFVOL	0.1643	0.1601	0.2445	0.1024	0.0337	0.3189	2.9931	23

Table 7: Correlation matrix of subsample volatility series.

	RVOL	*iVIX*	*BSVOL*	*MFVOL*
Panel A: Daily				
RVOL	1			
iVIX	0.4070	1		
BSVOL	0.4126	0.9122	1	
MFVOL	0.3024	0.7213	0.8131	1
Panel B: Monthly				
RVOL	1			
iVIX	0.3328	1		
BSVOL	0.4001	0.9408	1	
MFVOL	0.4885	0.5405	0.6177	1

predictability of future excess returns. In particular, the predict power of *iVIX* volatility risk premium is up to around 19%. In addition, all the slope coefficients remain economically positive and statistically significant. It indicates our finding is robust.

To sum up, we exercise subsample and *iVIX* as an alternative measure to test the robustness in this subsection. First, the performances of the volatility series and volatility risk premiums persist in this stable short period. Moreover, the terms of Black–Scholes and model-free implied volatility and risk premium series are similar to the corresponding

Table 8: Summary statistics of subsample excess returns and volatility risk premiums.

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
Panel A: Daily								
R^e_{etf}	0.0483	0.0665	0.5311	−0.5027	0.1816	−0.2446	2.9953	461
$VOLRP_{ivix}$	−0.0236	−0.0282	0.1165	−0.1124	0.0427	0.7885	3.8563	461
$VOLRP_{bs}$	−0.0065	−0.0141	0.1239	−0.1318	0.0457	0.4535	3.0753	461
$VOLRP_{mf}$	−0.0388	−0.0451	0.1486	−0.1275	0.0468	0.8131	3.8654	461
$LVOLRP_{ivix}$	−0.0824	−0.0961	0.2391	−0.2924	0.1236	0.6632	2.7302	461
$LVOLRP_{bs}$	−0.0183	−0.0501	0.4601	−0.2839	0.1478	0.6662	2.8325	461
$LVOLRP_{mf}$	−0.1253	−0.1435	0.3481	−0.4091	0.1390	0.5793	3.1037	461
Panel B: Monthly								
R^e_{etf}	0.0792	0.0449	0.3822	−0.1865	0.1511	0.3919	2.2572	23
$VOLRP_{ivix}$	−0.0266	−0.0384	0.1099	−0.1100	0.0467	0.9979	4.6400	23
$VOLRP_{bs}$	−0.0129	−0.0211	0.1053	−0.1052	0.0467	0.5598	3.4552	23
$VOLRP_{mf}$	−0.0404	−0.0410	0.0333	−0.1148	0.0388	0.0196	2.6330	23
$LVOLRP_{ivix}$	−0.0903	−0.1243	0.2187	−0.2691	0.1287	0.8429	3.0372	23
$LVOLRP_{bs}$	−0.0409	−0.0708	0.2436	−0.2340	0.1418	0.4955	2.1344	23
$LVOLRP_{mf}$	−0.1322	−0.1286	0.0846	−0.4019	0.1222	−0.2210	2.6573	23

Table 9: Regressions of volatility risk premiums (OLS).

$R^e{}_{etf}$	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Daily						
$VOLRP_{ivix}$	1.8458***					
	(10.333)					
$VOLRP_{bs}$		1.3993***				
		(8.0547)				
$VOLRP_{mf}$			1.5587***			
			(9.4012)			
$LVOLRP_{ivix}$				0.5747***		
				(9.1117)		
$LVOLRP_{bs}$					0.3238***	
					(5.8536)	
$LVOLRP_{mf}$						0.4788***
						(8.4410)
α	0.0919***	0.0574***	0.1088***	0.0957***	0.0543***	0.1083***
	(10.5500)	(7.1682)	(10.8005)	(10.218)	(6.5934)	(10.2100)
Adj.R^2	0.1870	0.1219	0.1596	0.1513	0.0674	0.1325
Obs.	461	461	461	461	461	461
Panel B: Monthly						
$VOLRP_{ivix}$	1.3625**					
	(2.1280)					
$VOLRP_{bs}$		1.2008*				
		(1.8297)				
$VOLRP_{mf}$			1.3095			
			(1.6368)			
$LVOLRP_{ivix}$				0.4724*		
				(2.0132)		
$LVOLRP_{bs}$					0.3566	
					(1.6273)	
$LVOLRP_{mf}$						0.3797
						(1.4793)
α	0.1154***	0.0947***	0.1321***	0.1219***	0.0938***	0.1294**
	(3.4109)	(3.0425)	(2.9790)	(3.3532)	(2.9599)	(2.8283)
Adj.R^2	0.1382	0.0964	0.0709	0.1219	0.0697	0.0512
Obs.	23	23	23	23	23	23

Note. The test statistics are reported with t-values in parentheses. *, **, and *** indicate that the coefficient of regression is significant at the 10%, 5%, and 1% level, respectively.

Table 10: ESG sentiment effect on volatility risk premiums (OLS).

Dependent variable	(1) $LVRP_{mf,t}$	(2) $LVRP_{mf,t}$	(3) $LVRP_{mf,t}$	(4) $LVRP_{mf,t+h}$	(5) $LVRP_{mf,t+h}$	(6) $LVRP_{mf,t+h}$
ESG	0.0552*			0.1249***		
	(1.7704)			(3.8283)		
E&S		0.0779*			0.1548***	
		(1.8140)			(3.4374)	
G			−0.0016			0.0288
			(−0.0944)			(1.5896)
TURN	0.4793***	0.4808***	0.4774***	−0.0896**	−0.0872**	−0.0968**
	(11.3874)	(11.4157)	(11.3188)	(−2.0326)	(−1.9745)	(−2.1855)
PE	−0.0072*	−0.0079**	−0.0067*	0.0004	−0.0008	0.0019
	(−1.8415)	(−2.0001)	(−1.7147)	(0.1091)	(−0.2010)	(0.4559)
α	−0.1456***	−0.1634***	−0.1191***	−0.1461***	−0.1742***	−0.0971***
	(−3.5634)	(−3.6156)	(−3.0948)	(−3.4164)	(−3.6767)	(−2.4025)
Adj. R^2	0.1059	0.1060	0.1034	0.0140	0.0116	0.0037
Obs.	1156	1156	1156	1156	1156	1156

Note. The test statistics are reported with t-values in parentheses. *, **, and *** indicate that the coefficient of regression is significant at the 10%, 5%, and 1% level, respectively.

results from the *iVIX*. Therefore, our results of the Black–Scholes and model-free implied volatility and the positive relationship between the volatility risk premium and returns are robust to alternative estimation periods and methods.

5.4. Volatility Risk Premium and ESG Sentiment. To further the research, the impact of ESG sentiment on the volatility risk premium is presented in Table 10. The association between the present log volatility risk premium and ESG sentiment is considered positive, as indicated in column (1). The turnover and value effect, as potential risk factors, are controlled to be robust. Furthermore, we investigate the relationship between current ESG sentiment and future log volatility risk premium. And the correlation is stronger in column (4), with a positive significance at the 1% level. In contrast, unreported results indicate that the relationship between ESG sentiment and excess returns is not statistically significant. In other words, the ESG sentiment cannot forecast future returns, but uncertainty risk may be predicted. Higher ESG sentiment can account for more potential volatility risk, which is compatible with the agency theory, according to which investors infer that ESG investments are abusing resources, hence increasing the unmeasured risk [40].

More importantly, ESG is a multidimensional concept, so the performances of overall *ESG* and the subdimensions *E*, *S*, and *G* may have varying effects on the potential risk. The above study demonstrates that ESG sentiment is positively related to the volatility risk premium. Therefore, which factor is the essential driver of the ESG effect? To answer this question, we examine the impact of firm performances in *E&S* as well as *G* on the volatility risk premium. This further clarifies the relative importance of environmental and social responsibility, and corporate governance. Table 10 also includes the findings of OLS regression using the *E&S* and *G* factors as independent variables, respectively. The slope coefficients of *E&S* are statistically significant, indicating that the association between *E&S* and future volatility risk premium is stronger. However, the correlations between the governance factor and volatility risk premiums lack statistical significance. *E&S* is likewise positively associated with the potential risk measures, as indicated by the sign of the coefficients. One possible explanation is that a high proportion of retail investors pay less attention to hedge against environmental and social risks in China and other emerging countries. Likewise, this evidence also suggests the sustainable development theory that institutional ownership is positively related to *ESG*, especially *E&S* [37, 38].

6. Conclusions

This article aims to establish the dynamic relationship between volatility risk premium and excess returns, as well as impact factors, in an emerging financial market, such as that in China. To achieve this goal, we examine the constructions of volatility risk premiums, compare the methods of calculating implied volatility, and investigate the link between the realized and implied volatilities. And multifactor OLS regressions are used to assess the predictive capacity of the volatility risk premium on future aggregate returns. We conduct further research on the effect of ESG sentiment as an ungauged risk on the volatility risk premium. A longer dataset with high frequency as well as daily and monthly nonoverlapping samples from 2016 to 2021 are applied to describe the characteristics of Chinese SSE 50 ETF spots and options markets in this article.

Overall, our study has several contributions to the relevant academic works in the following ways. First, we expand the current literature by examining the volatility risk premium in China. Although there is extensive literature on variation risk premiums and return forecasting, most academics focus on the developed countries. And few attempts were made to investigate the emerging markets, particularly those in China. The research gap is caused by two reasons: first, emerging markets are still in their infancy, making the risk-return pattern less stable; second, volatility indices as important derivative instruments are often absent in these financial markets, making it difficult to investigate volatility risk premiums. Therefore, we employ a longer dataset and calculate volatility series and define the volatility risk premium to study its return predictability.

In addition, we find an outlier of the relationship between the volatility risk premium and asset returns in China. Generally, the volatility risk premium is negatively correlated with excess returns. Nonetheless, the empirical results of this study show a significantly positive correlation between the volatility risk premium and aggregate returns of SSE 50 ETF, making the Chinese financial markets different from worldwide markets, which have negative relationships. We utilize the alternative predictive specifications, variation measures, subperiods, and monthly nonoverlapping observations to evaluate the robustness. The results demonstrate that the predictive coefficient remains statistically and positively significant.

Finally, we further investigate the relationship between the volatility risk premium and ESG sentiment. The volatility risk premium is seen as a neglected risk. ESG sentiment, a hot-button topic in recent years, is usually ungauged in asset pricing as well. Therefore, we try to fill this gap and explore the underlying connection between them. We find that ESG sentiment is positively associated with the volatility risk premium. Specifically, the slope coefficient of E&S is significantly positive while the corresponding value of the governance is statistically insignificant. The result is consistent with the agency theory that ESG investment is misusing resources and investors assume the short-run volatility risk will be accumulated.

Data Availability

The CSV data that support the findings of this research can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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