Hindawi
Complexity
Volume 2023, Article ID 3475079, 21 pages
https://doi.org/10.1155/2023/3475079

WILEY | Hindawi

Research Article

The Influence of Equity Market Sentiment on Credit Default Swap Markets: Evidence from Wavelet Quantile Regression

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Received 6 March 2023; Revised 18 July 2023; Accepted 27 July 2023; Published 16 August 2023

Academic Editor: Sheng Du

Previous studies focused on the fundamental channels of the interaction between the equity market and credit default swap (CDS) market. This paper finds another channel, investor sentiment, that contributes to the impact of the equity market on the CDS market under different time horizons and market conditions within the framework of wavelet quantile regression. It absorbs both the merits of wavelet transform and quantile regression and is advantageous in analyzing heterogeneous time horizons and full conditional distributions. Empirical results show that investor attitude turning optimistic has a negative influence on the deviation of CDS market spread from theoretical value, while the intensification of fear among equity market will enlarge this deviation. Besides, we discovered that the influence of equity market sentiment on the CDS market first increases and then decreases as the time horizon lengthens and that the greater the deviation of CDS spreads from intrinsic value is, the more irrational the CDS market participants are. These findings suggest that the influence of investor sentiment on the credit default swap market is self-reinforced. Our results are robust after controlling for macroeconomic conditions and under different wavelet decompositions. Reasonable suggestions are given to financial institutions, investors, and policy makers based on our findings.

1. Introduction

The credit default swap (CDS), as a crucial derivative for managing credit risk, has been extensively applied by financial institutions since its creation in 1990s. CDS is a contract which offers protection against the default risk by a particular company which is often referred as a reference entity. As the reference entities of the CDS indices are usually traded publicly in the equity market, there is a natural link between the two markets. Along with the financial liberalization, this natural link becomes deeper over the past two decades. The interaction between equity and CDS markets has been frequently recognized in the past research [1–3], most of which attributes the interaction to fundamental information channel. However, except for fundamental information, the irrational channel, such as investor sentiment, is less mentioned in previous related research. As the two markets interact with each other, emotional information also tends to be shared among these markets. The global financial crisis and the subsequent European sovereign debt crisis generated unprecedented levels of fear and risk aversion in the equity market, which materialized in huge turbulence in the credit market [4]. Hence, apart from fundamental information of equity market, it is reasonable that irrational sentiment in the equity market could also influence the CDS market.

Exploring the influence of equity market sentiment on the CDS markets can provide valuable information for both investors and policy makers. Understanding the sentiment influence on CDS markets enables investors to gain further insight into the hedging performance of credit assets and diversification strategies of different assets portfolios. Besides, studying this influence assists financial regulators in preventing possible financial distress or even financial crisis as investor sentiment plays a critical role in the formation and interaction of systematic risk. However, whether and how investor sentiment in the equity market influences the CDS market, especially under different horizons and market conditions, is still unclear.

It is of great importance to analyze the influence of equity market sentiment on the CDS market through various time horizons and under different market conditions. Different types of market participants operate on different horizons when making investment decisions [5] or implementing financial policies; therefore, the time horizons should be considered when analyzing the sentiment influence to meet heterogeneous participants demand. Moreover, these heterogeneous participants, including investors, arbitrageurs, speculators, and policy makers, possess different bounded rationality, preferences, and risk tolerance, responding differently towards CDS spread movements under different market conditions. The consideration of different market conditions is beneficial for them to improve their investment decisions and avoid credit risk, or to choose the appropriate economic measures to promote stability of credit market when they face different market conditions. In addition, previous studies have confirmed that the credit spreads behavior varies with time horizons and market conditions [4, 6–9], and thus, it is necessary to differentiate the sentiment influence between various time horizons and market conditions.

Therefore, the aim of our study is to analyze whether and how investor sentiment in the equity market influences the CDS market through different time horizons and under different market conditions. To fulfill this aim, we choose to implement the wavelet quantile regression approach raised by Yang et al. [10]. With the superiorities of analyzing heterogeneous time horizons and full conditional distributions [10], this approach is most appropriate for our research objective. Wavelet transform is advantageous in analyzing the credit fluctuation among different investment horizons by decomposing the CDS spreads into various time scales, while quantile regression method provides an overall comparison between different market conditions by estimating the sentiment influence on the CDS spreads on different parts of conditional distributions. By integrating wavelet transform and quantile regression method, wavelet quantile regression absorbs the merits of wavelet transform and quantile regression and thus offers investors and policy makers a comprehensive insight for them to make pertinent decisions according to specific market conditions and meets their personalized investment preference on risk aversion and investment horizons.

The main contribution of this paper is as follows: First, as stated above, we highlight the irrational channel between the equity and CDS market by examining the impact of equity market sentiment on the CDS market. Second, we attempt to analyze the influence on the deviation of CDS spreads from the intrinsic value. Previous studies focused on explaining the trends or the changes of CDS spreads or prices [9, 11–13], omitting to distinguish between the impact on the CDS spreads deviation and that on the intrinsic value. Investors in the CDS markets, however, are more concerned about unexpected deviation from the intrinsic value because the unexpected deviation part is corresponding to trading risk [14–16]. Third, our study shows that wavelet quantile regression method is also applicable in the research field of the credit market. Fourth, by investigating the asymmetric characteristics and the speed of the sentiment spillover effect, we found that the spread of fear is much faster than the attitude changing and that the investor sentiment impact on the CDS market is self-reinforced.

The remainder of the article is organized as follows. Section 2 reviews the related literature. Section 3 provides a brief review of the calculation of the investor sentiment proxies, the wavelet decomposition method, and the wavelet quantile regression model. Section 4 provides a detailed description of the data used in this study. Section 5 reports the empirical results and performs a robustness analysis by applying different wavelet families. Section 6 summarizes the main findings.

2. Literature Review

Previous studies have focused on the relationship between credit market and equity market for a long time. In a seminal work, Merton [17] exhibited a structural model which suggests a negative connection between the reference entity's market value of equity and its probability of default. Vassalou and Xing [18] discussed the link between credit and equity markets by a risk-based interpretation for the size and book-to-market effects. After the works, some researchers argued that the equity market generally leads the credit market [9, 19–24]. For instance, Wang and Bhar [23] demonstrated that the influence of equity markets can be measured with two complementary fundamentals, namely, the price channel and the volatility channel. Gatfaoui [9] measured the asymmetric responses of CDS spreads to equity market price and volatility channels with the quantile cointegrating regression approach. In recent years, researchers also recognized the influence of equity market on the CDS spreads in other countries or regions [25–27], or through more advanced approach [28–30]. The above empirical evidence is supported by the liquidity hypothesis: When the liquidity of a market increases, its information share will also rise [31, 32]. Compared with the CDS market, equity market is less institutional and more liquid [21] and thus leads the information share. Different from the above works, some researchers documented that the credit market takes a leading role of the equity market. Acharya and Johnson [33] found evidence of information flow from the CDS market to the equity market, and the information flow always exists, particularly for the periods with negative credit news. This evidence is in line with the phenomenon of hedging by banks with lending exposure and access to privileged information. Xiang et al. [34] observed that the dominant role of CDS over the equity market is enhanced during the subprime crisis. The leading role of the CDS market can be explained by the firm-specific information hypothesis and insider trading hypothesis. The firm-specific information hypothesis suggests that many securities' prices adjust more rapidly to the firm-specific information which is usually reflected in the CDS market, and the insider trading hypothesis indicates that CDS market is more likely to incorporate credit information first attributing to its severer insider trading [3, 33].

Even though no consensus exists regarding the lead-lag relationship among the equity and credit market, it is evident that the two markets are linked closely. Some researchers have found the interaction with each other [1–3, 35]. Fung et al. [1] proposed that the bidirectional feedback effect between the CDS and equity markets is associated with different conditions: The equity market plays a more significant role in the pricing process, while the credit market possesses a more significant role in the volatility process. Breitenfellner and Wagner [2] demonstrated that there is an interactive relationship between stock market returns and the European iTraxx CDS index spread changes post the 2007–2009 financial crisis. Narayan et al. [35] found that the equity market contributes to price discovery in nine sectors while the CDS market contributes to price discovery in six sectors. Chau et al. [3] examined the drivers and dynamics of information share between the equity and CDS market and suggested that the information share of the equity market is usually greater, but the role of CDS market improves during the economic decline.

While these studies have extensively investigated the relationships between the equity and CDS markets, they mainly focused on the influence attributed to fundamental channel, leaving the sentiment channel out of consideration. As mentioned above that the two markets interact with each other, emotional information tends to be shared among these markets [36–42], especially when the market is in extreme conditions which enlarges investors' worries. With lower concern to firm-specific information, less insider trading and fewer institutional participants [3, 21, 31–33], the equity market is more likely to be the source of sentiment that influences the CDS market. Therefore, this study focuses on whether and how investor sentiment in the equity market influences the CDS markets in addition to the fundamentals.

Investor sentiment is defined as the investors' belief about future cash flows and investment risks which is not justified by the fundamental values and the facts at hand [43]. Generally, investor sentiment can be measured by three categories of approaches: the survey-based, search-based, and market-based investor sentiment measures [44]. The survey-based investor sentiment proxies mainly include the University of Michigan Consumer Sentiment Index (MSCI), the American Association of Individual Investor (AAII) index, and the UBS/Gallup Investor Optimism Index. There is one potential weakness for the survey-based measures since people may lack incentive to answer survey questions truthfully or carefully, particularly when questions are sensitive [45]. Besides, the survey-based sentiment measures are usually available at a relatively low frequency (monthly or weekly), which is inadequate for us to analyze the short-term effect of the investor sentiment on the credit market. The search-based proxies are usually based on the Google Trends, Twitter, or search results provided by other search engines. Compared with the survey-based measures, the search-based measures are available at satisfyingly high frequency. However, since the search-based sentiment measures are obtained through complicated natural language analysis and web crawling, these measures vary widely depending on the algorithm used [37]. The market-based sentiment proxies are calculated based on market indicators, such as the Baker and Wurgler's sentiment (BW) index [46], trading volume, mutual fund flows, the investor sentiment endurance index (SE) [47], implied volatility of S&P options (VIX), closed-end fund discount, initial public offering (IPO) first day returns, and IPO volume. Noting that not all investors react to the same exogenous environmental variables in the same manners, the market-based measures have an advantage in reflecting the net effect of different or conflicting attitudes towards the market conditions. Besides, the market-based measures except the BW index are also available at daily frequency.

To fully measure the investor sentiment in the equity market and analyze its impact on the CDS market throughout different time horizons, we adopted two market-based sentiment measures, SE and VIX, under a comprehensive consideration of the advantages and disadvantages of various sentiment measures. Both the SE and VIX index could directly measure the investor sentiment in the US equity market, which enables us to investigate the sentiment channel that contributes to the impact of the equity market on the CDS market. The SE index not only has the strengths of the market-based measures, but also could capture the dynamics of ever-changing valuation opinions and the resilience of the investor sentiment. Moreover, in contrast to many existing investor sentiment indexes which measure the causes of reactions, the SE index directly uses stock price differentials to measure investor reactions to news. Due to the advantages of the SE index mentioned above, it has been used by a great number of studies concerning the influence of investor sentiment on the financial market [37, 48–51]. The VIX index is well known as an "investor fear gauge" by practitioners, which reflects the investor sentiment of fear in the U.S. equity market [52–56]. The greater the fear, the higher the VIX level is. Whaley [57], Simon and Wiggins [58], and Giot [59] used the VIX index as the sentiment proxy and found a negative contemporaneous relationship between sentiment and return. Smales [53] determined that VIX is the preferred measure of sentiment compared with the Baker and Wurgler [46] sentiment measure, the University of Michigan Consumer Sentiment, and the American Association of Individual Investors Bull–Bear Spread in terms of improving model fit and adding explanatory power. Abdelmalek [60] empirically showed that the VIX index is an appropriate fear gauge of market-wide investor sentiment and has a predictive power for future realized volatility. Taking all these into account, we utilize the SE index to study the impact of investors' positive and negative attitude and the VIX index to analyze the influence of investors' fear on the CDS market.

In recent years, wavelet analysis has been applied to investigate the financial assets in different time horizons [5, 61–63] due to the merits of wavelet analysis in different time-scale decomposition. For instance, Yang et al. [63] explored the time-varying dependence structures between G7 and BRICS countries' sovereign CDS spreads from short to long time scales by combining the copula and wavelet methods. Wu et al. [5] examined the comovements between international stock markets in different terms by employing partial and multiple-wavelet coherence analysis. By integrating the wavelet analysis and quantile regression, wavelet quantile regression approach proposed by Yang et al. [10] is advantageous in providing a detailed view of the conditional distribution of explained variables with the merits of wavelet analysis being reserved. Moreover, the wavelet quantile regression approach is robust to outliers, skewness, and heteroskedasticity of explained variables. Since the CDS spreads are generally asymmetric, nonlinear, heavy-tailed, and skew distributed [63], wavelet quantile regression is a preferred choice to comprehensively investigate these properties. Accrued to various advantages the wavelet quantile regression possesses, it has attracted the interest of researchers in the field of finance [64–67]. In the light of the superiorities of wavelet quantile regression in analyzing heterogeneous time horizons and comprehensive market conditions (measured by full conditional distribution), we implemented this approach to achieve the aim of our study and to provide investors and policy makers with suitable suggestions to improve their investment decisions and financial policies.

3. Methodology

3.1. Investor Sentiment Proxies. In this paper, two market-based proxies are adopted to measure the investor sentiment in the equity market. For the first proxy, we utilized the SE index [47, 48] to study the impact of investors' positive and negative attitude. One benefit of this proxy is that it can distinguish the investor sentiment in the equity market. Another benefit is that it can accurately measure the net investor reactions to all news, which will be reflected in the closing prices [68].

During a trading day, investors continuously analyze and respond to various new information, and their reactions are simultaneously quantified into the equity prices. The most optimistic sentiment is reflected in the highest price of the day and the most pessimistic sentiment is built in the lowest price. Other prices between the highest and lowest price are going to cancel out each other, just as different sentiments offset against each other. Eventually, these sentiments will form a lasting main force until the close of the market.

Therefore, we can measure the strength of both optimistic and pessimistic attitudes by estimating the possibility of the highest and lowest prices ultimately becoming closing prices, as presented in the following equation:

$$P_t \times H_t + (1 - P_t) \times L_t = C_t, \tag{1}$$

where P_t refers to the probability that the highest price H_t in the equity market equals the closing price C_t, while $(1 - P_t)$ the possibility that the lowest price L_t is the same as the closing price. By solving the above equation, we could obtain the value of the probability P_t. The investor sentiment proxy SE is specified as follows:

$$SE_t = P_t - 0.5. \tag{2}$$

Hence, if $SE_t > 0$, a majority of investors in the equity market hold positive attitude; if $SE_t = 0$, the strength of optimistic and pessimistic investors is almost the same; and if $SE_t < 0$, a majority of investors hold negative attitude.

For the second proxy, motivated by Dergiades [69], Smales [53, 70], and Song et al. [56], we chose Chicago Board Options Exchange Volatility index (VIX) as the reflection of fear in the equity market, aiming at providing further evidence for the issue of the influence of investor sentiment on credit market from another perspective. VIX is an index of the implied volatility of 30-day options on the S&P 500 calculated from a wide range of calls and puts, reflecting the investors' opinion about the expected movement in the U.S. equity market. Portfolio insurers, who routinely buy index puts are the largest constituents of the S&P 500 index option market and drive changes in the VIX index, providing the VIX index with the colloquial term, the "fear gauge" [57]. Higher values of VIX exhibit greater fear, greater uncertainty, and a greater degree of risk aversion in the stock market.

3.2. Wavelet Decomposition. Wavelet methods have been employed recently to investigate the multitime scale phenomenon in the financial market owing to their superiority in decomposing the financial time series into different timescales series to mimic the different investment horizons of the market participants [71–77].

Wavelet methods can decompose a time series $y(t)$ into the following structure:

$$\begin{aligned} y(t) = {} & \sum_k S_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) \\ & + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t). \end{aligned} \tag{3}$$

In this representation, J denotes the decomposition level, k is a translation parameter, $\phi_{J,k}$ is the scaling function, $\psi_{j,k}$ is the wavelet, $S_{J,k}$ are the scaling coefficients, and $d_{j,k}$ are the detail coefficients. To emphasize the "marriage" involved in building this "family," the scaling function is often referred to the father wavelet and the mother wavelet. The father wavelet describes the smooth trend of the times series while the mother wavelets illustrate the detail and high-frequency components. To be more specific, the father wavelets and the mother wavelets are defined as follows:

$$\begin{aligned} \Phi_{J,k}(t) &= 2^{-J/2}\phi\left(2^{-J}t - k\right), \\ \psi_{j,k}(t) &= 2^{-j/2}\psi\left(2^{-j}t - k\right). \end{aligned} \tag{4}$$

A growing number of wavelet families has been introduced in the financial time series decomposition, for instance, the Haar, Daubechies, Symlets, Coiflets, Morlets, and so on [78–81]. Daubechies wavelet family is one of the most popular wavelet families due to its orthogonal and compact support abilities. The Daubechies wavelet transforms are defined in the same way as the Haar wavelet transform, by computing running averages and differences via scalar products with scaling signals and wavelets. The only difference between them is about how to define these signals and wavelets. The Daubechies wavelet uses overlapping windows, and thus, it is smoother than the Haar wavelets. For the Daubechies wavelet transforms, the scaling signals and wavelets have slightly longer supports and this slight change provides a solid improvement in performing signal processing tasks [82]. In light of the advantages of Daubechies wavelets mentioned above, we used Daubechies 4 wavelets, the simplest one among Daubechies transforms, to decompose data. Moreover, the robustness test demonstrates that the choice of wavelet families has no effect on our main empirical conclusions.

In addition, we consider the maximal overlap discrete wavelet transform (MODWT) [83] on daily data due to its advantages of not requiring the dyadic length (i.e., a sample size divisible by 2^J) and never subsampling the output data. Moreover, the scaling and detail coefficients in it are not shift-invariant based on their sensitivity to circular shift [10].

In summary, the original time series can be decomposed into orthogonal components at different scales and equation (3) can be rewritten as follows:

$$y(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t). \tag{5}$$

Functions $S_J(t)$ and $D_j(t)$ denote the smooth and detail components as follows:

$$S_J(t) = \sum_k S_{J,k}\phi_{J,k}(t), \tag{6}$$

$$D_j(t) = \sum_k d_{j,k}\psi_{j,k}(t), j = 1, 2, \ldots, J, \tag{7}$$

$D_1(t)$, $D_2(t)$, …, $D_J(t)$ in equation (5) represent the detail components of $1-2$ days, $2-4$ days, …, $2^{J-1}-2^J$ days, respectively.

3.3. Wavelet Quantile Regression

3.3. Wavelet Quantile Regression. As one motivation of our research is to study the heterogeneous influence of the investor sentiment on the CDS spreads when they deviate from the intrinsic value to various degrees under different investment time horizons, we used wavelet quantile regression after OLS and quantile regression analysis.

As a standard statistical model, the linear regression model (LRM) is widely used in financial research. However, it emphasizes on modeling the conditional mean of the dependent variable without accounting for the full conditional distributional properties of this dependent variable, only implying appropriate estimations under homoscedasticity and normality assumptions. On the contrary, the quantile regression model (QRM) facilitates analysis of the full conditional distributional properties of the dependent variable, providing robust statistical results unaffected by outlier observations, skewness, and heteroskedasticity of this dependent variable [84]. Following Koenker and Bassett [85], the τ th conditional quantile function of y can be formally expressed as follows:

$$Q_{Y|X}(\tau|x) = \inf\left\{y \in \mathbb{R}: F_{Y|X}(y|x) \geq \tau\right\} = \sum_k \beta_k(\tau)x_k = x'\beta(\tau), \tag{8}$$

where $F_{Y|X}(y|x)$ denotes the cumulative distribution function of y conditioned by x. Define the check function $\rho_\tau(u)$ as follows:

$$\rho_\tau(u) = u[\tau - \mathbb{I}(u \leq 0)], \tag{9}$$

where $\mathbb{I}(\bullet)$ denotes the indicator function. Hence, we can estimate the coefficients $\beta(\tau)$ by minimizing the weighted absolute deviations, given by the following equation:

$$\beta(\tau) = \underset{b\in\mathbb{R}^{\dim(X)}}{\operatorname{argmin}}\, \mathbb{E}\left[\rho_\tau\left(y - x'b\right)\right]. \tag{10}$$

Although the quantile regression has been utilized to explore the influence of equity market on the credit market [9], the quantile regression is incapable of capturing the time and frequency domain of the data. In contrast, the wavelet quantile regression, proposed by Yang et al. [10], applies wavelet analysis based on quantile regression to address the issue of time and frequency domain capture. The wavelet quantile regression is expressed as follows:

$$Q_{Y_{D_j}|X_{D_j}}\left(\tau|x_{D_j}\right) = \inf\left\{y \in \mathbb{R}: F_{Y_{D_j}|X_{D_j}}\left(y_{D_j}|x_{D_j}\right) \geq \tau\right\} = x_{D_j}{}'\beta_{D_j}(\tau), \tag{11}$$

where $F_{Y_{D_j}|X_{D_j}}(y_{D_j}|x_{D_j})$ denotes the conditional distribution function of the wavelet detail components D_j of y given the wavelet detail components D_j of x. Hence, the coefficients $\beta_{D_j}(\tau)$ are also estimated by minimizing the weighted absolute deviations, given by the following equation:

$$\beta_{D_j}(\tau) = \underset{b_{D_j}\in\mathbb{R}^{\dim\left(x_{D_j}\right)}}{\operatorname{argmin}}\, \mathbb{E}\left[\rho_\tau\left(y_{D_j} - x_{D_j}{}'b_{D_j}\right)\right]. \tag{12}$$

The main difference between the wavelet quantile regression and classical quantile regression approach is that wavelet quantile regression analyzes the full conditional quantiles of the dependent variables decomposed by the wavelet transform to explore the relationship between variables from the perspective of frequency and conditional distribution, while classical quantile regression only estimates the conditional quantiles of the raw data. This improvement of wavelet quantile regression over quantile regression allows wavelet quantile regression to capture both short-term and long-term dynamics in the data and to estimate conditional distribution more flexibly and accurately. In practice, the short-term and long-term dynamics provided by wavelet quantile regression are implemented to examine the variation of influence at different investment horizons and the conditional distribution estimates are employed to evaluate the heterogeneous responses under different market conditions [64–67].

4. Data

In this paper, we considered credit market, equity market, and oil market data from Datastream. The dataset consists of 3290 daily observations, covering the period from March 28, 2006, to April 23, 2019. Data availability dictates the sample selection. We performed the empirical analysis on a daily basis.

Credit market data are consisted of midmarket quotes and expressed in basis points. Following Alexander and Kaeck [86], Avino and Nneji [24], and Wisniewski and Lambe [13], we chose CDS indices to measure the North American CDS market, as CDS indices offer an aggregate view of this market. In this research, two five-year CDX indices, including North America High Yield index (CDX.NA.HY) and North America Investment Grade index (CDX.NA.IG), are investigated to examine the influence of equity market sentiment on the CDS markets. We focused on the five-year CDS market, since it is the most liquid CDS market compared with other CDS markets of different terms and is usually recognized as the benchmark of the CDS market. We mainly investigated CDX.NA.HY and CDX.NA.IG rather than other CDS indices since the remaining North America CDS indices, CDX.NA.HY.B, CDX.NA.HY.BB, CDX.NA.IG.HVO, and CDX.NA.XO, are relatively low liquid and there is no available consensus owing to lack of adequate contributions since October 28, 2015, March 25, 2013, April 15, 2016, and December 19, 2013, respectively [87]. CDX.NA.HY consists of 100 noninvestment grade entities domiciled in North America while CDX.NA.IG consists of 125 investment-grade entities. The deviation of market price from theoretical price (hereafter, composite-theoretical spread difference) is calculated as composite spread − theoretical spread for the two series. The composite spread represents the consensus levels of the market participants views generated from the best available sources of market prices. The theoretical spread is the value of a portfolio of single name CDS with a basket that matches the index exactly along with the characteristics that matches the traded index instruments. This can also be seen as the intrinsic value of the index ("Markit CDS indices Pricing User Guide", 2014). The method to calculate the theoretical spread is as follows.

(i) The survival probability of each of the index constituents at each coupon payment date are calculated by using the Markit Composite credit curve and recovery rate for each constituent

(ii) The present value of each index constituent is calculated based on the index trade details

(iii) The present value of the index PV is calculated as the weighted average of the present values of the constituents, and the accrued interest on the index Accrued is calculated as the weighted average of the accrued of the index constituents

(iv) The index theoretical price is calculated as $1 + PV - \text{Accrued}$

(v) The theoretical spread of the CDS index is solved as the flat curve that gives the index PV using the index recovery rate assumption

Therefore, an increase in composite-theoretical spread difference represents that the market participants are more pessimistic towards the credit conditions, and an increase in the absolute value of composite-theoretical spread difference means that the market consensus deviates more from the intrinsic value, and thus, the market participants are more irrational.

We use equity market data to form the measurement of investor sentiment in the equity market. The Standard & Poor's 500 stock market index (S&P 500) composite closing price, highest price, and lowest price are used to construct the investor sentiment index proposed by He and Casey (SE) [47, 48, 88] to reflect the optimistic or pessimistic attitude. In addition, we use the Chicago Board Options Exchange volatility index (VIX) to measure the degree of fear, as this index is usually regarded as the fear index [53, 56, 57, 69, 70]. Higher values of VIX imply greater fear, greater uncertainty, and a greater degree of risk aversion in the equity market.

Equity market data and oil market data are considered to include control variables which are summarized as follows: (1) The SPOT interest rate. We treat the U.S. 5-year Treasury constant maturity rate as a proxy for the spot interest rate, which is consistent with the five-year maturity of the CDX indices [11, 89, 90]. The SPOT interest rate can be seen as a representation for the debt market. (2) The S&P 500 index. S&P 500 index is a widely accepted proxy for the equity market. (3) The WTI oil. The West Texas Intermediate (WTI) oil spot price is regarded as the proxy for crude oil market. Oil price plays an important role in determining activities in many economic sectors, and thus, it can be a major source of instability in the financial market worldwide [8]. Previous studies have found the influence of crude oil prices on the CDS spreads [91, 92]. In general, we have taken into consideration the macroeconomic conditions from the debt market, the equity market, and the oil market as control variables.

Besides, Table 1 outlines the descriptive statistics for these variables. From the first four columns, we find that CDX.NA.HY varies more drastically than CDX.NA.IG, which is in accordance with the characteristics of high-yield entities confronting higher risk of default than investment-grade entities. Then, the skewness, the kurtosis, and the JB-test columns

Table 1: Summary of descriptive statistics.

Variables	Mean	Std. dev	Min	Max	Skew	Kurt.	Jarque-Bera stat	ADF stat	PP stat	DF-GLS stat
CDX.NA.HY	−1.642	46.845	−451.900	172.400	−4.138	29.949	132518.520***	−7.260***	−85.832**	−6.003***
CDX.NA.IG	−4.104	8.063	−61.100	12.200	−3.489	15.363	39083.440***	−6.050***	−74.969**	−5.138***
SE	0.064	0.324	−0.500	0.500	−0.259	−1.278	260.440***	−37.840***	−3514.392**	−7.115***
VIX	19.109	9.201	9.140	80.860	2.476	8.394	13041.600***	−2.220**	−49.023**	−3.436***
SPOT interest rate	2.173	1.158	0.560	5.230	1.059	0.361	634.130***	−1.760*	−5.031	−1.336
S&P 500 index	1698.760	554.409	676.530	2933.680	0.520	−0.775	230.600***	1.820	−5.489	−0.885
WTI oil price	74.248	22.576	26.210	145.660	0.227	−0.695	94.360***	−0.570	−9.59	−1.893
Δ SPOT interest rate	−0.001	0.057	−0.460	0.340	−0.121	4.386	2650.020***	−44.170***	−3234.66**	−2.969**
Δ S&P 500 index	0.502	17.201	−113.190	116.600	−0.508	5.247	3922.200***	−43.500***	−3284.565**	−22.504***
Δ WTI oil price	0.001	1.620	−13.060	16.370	0.010	7.337	7392.310***	−41.980***	−3496.899**	−58.361***

Note. This table reports the main descriptive statistics of the variables under consideration over the whole sample period from March 28th, 2006 to April 23rd, 2019. The main descriptive statistics include the mean, standard deviation, minimum, maximum, skewness, kurtosis, Jarque–Bera test statistics, Augmented Dickey–Fuller test (ADF) statistics, Phillips–Perron test (PP) statistics and Elliott, Rothenberg and Stock's GLS version of the Dickey-Fuller (DF-GLS) test statistics. CDX.NA.HY and CDX.NA.IG are the differences of the composite spread and theoretical spread for the North America High Yield index and North America Investment Grade index, respectively. ***, **, and * denote rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively.

indicate that all those variables are not normally distributed, confirming the essentiality of quantile regression. At last, the results of the Augmented Dickey–Fuller (ADF) test [93, 94], Phillips–Perron (PP) test [95], and Elliott, Rothenberg, and Stock's GLS version of the Dickey–Fuller (DF-GLS) test [96] by the last three columns indicate that the SPOT interest rate, the S&P 500 index, and the WTI oil price are nonstationary in levels but stationary in first difference. Thus, to avoid the spurious regression issue, we first apply differencing to the control variables including the SPOT interest rate, the S&P 500 index, and the WTI oil price.

5. Results and Discussion

We explore the spillover influence of the investor sentiment in the equity market on the North America CDS market by two steps. Thereafter, robustness analysis is implemented to provide further support to our findings.

5.1. OLS and Quantile Regression. In the first step, we applied the OLS regression and quantile regression to get an overall insight of the impact of the US stock market investor sentiment on the North America CDS market by controlling the variables of the US 5-year Treasury constant maturity rate, the S&P 500 price index, and the WTI oil price.

In more detail, we implement OLS and quantile regressions to estimate the following models considering investor sentiment proxy SE as explanatory factors:

$$\mathrm{CDX.NA.HY}_t = \beta_{10} + \beta_{11}\mathrm{SE}_t + \beta_{12}\Delta\mathrm{SPOT}_t + \beta_{13}\Delta S\&P\,500_t + \beta_{14}\Delta\mathrm{WTIoil}_t + \varepsilon_t, \tag{13}$$

$$\mathrm{CDX.NA.IG}_t = \beta_{20} + \beta_{21}\mathrm{SE}_t + \beta_{22}\Delta\mathrm{SPOT}_t + \beta_{23}\Delta S\&P\,500_t + \beta_{24}\Delta\mathrm{WTIoil}_t + \varepsilon_t, \tag{14}$$

where $\mathrm{CDX.NA.HY}_t$ and $\mathrm{CDX.NA.IG}_t$ refer to the composite-theoretical spread difference and Δ is the first difference operator. Then, we consider the other investor sentiment proxy VIX as explanatory variables to estimate the following models:

$$\mathrm{CDX.NA.HY}_t = \beta_{30} + \beta_{31}\mathrm{VIX}_t + \beta_{32}\Delta\mathrm{SPOT}_t + \beta_{33}\Delta S\&P\,500_t + \beta_{34}\Delta\mathrm{WTIoil}_t + \varepsilon_t, \tag{15}$$

$$\mathrm{CDX.NA.IG}_t = \beta_{40} + \beta_{41}\mathrm{VIX}_t + \beta_{42}\Delta\mathrm{SPOT}_t + \beta_{43}\Delta S\&P\,500_t + \beta_{44}\Delta\mathrm{WTIoil}_t + \varepsilon_t, \tag{16}$$

where $\mathrm{CDX.NA.HY}_t$ and $\mathrm{CDX.NA.IG}_t$ also refer to the composite-theoretical spread difference and Δ is the first difference operator.

Panel raw series in Tables 2–5 display the OLS and quantile regression coefficient estimates for seven different quantiles 0.05, 0.1, 0.25, 0.50, 0.75, 0.90, and 0.95. We noticed several specific behaviors for the difference of the composite and theoretical spread under consideration.

Firstly, the quantile of the difference between composite and theoretical spread when the composite spread equals the theoretical spread is 0.45 for CDX.NA.HY, while 0.77 for CDX.NA.IG. However, the arithmetic mean values of the

Table 2: OLS, quantile, and the Daubechies 4 wavelet quantile regression for the influence of SE on CDX.NA.HY.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Raw series								
SE	−10.860***	6.554	−3.596	−10.544***	−11.419***	−13.536***	−16.080***	−17.427***
Δ SPOT	11.468	69.437	18.717	−6.500	−2.108	2.049	1.192	−17.385
Δ S&P 500	0.048	0.058	0.078	0.021	0.025	0.001	0.028	−0.010
Δ WTI oil	0.897	1.880	0.558	0.578	0.495	0.575	0.800	2.370***
Wavelet series D1								
SE	−5.051***	−6.746***	−6.584***	−4.272***	−3.680***	−4.831***	−6.236***	−7.541***
Δ SPOT	3.836*	2.500	8.311**	4.233***	2.652**	2.144	7.185*	5.368
Δ S&P 500	0.108***	0.130***	0.088***	0.094***	0.101***	0.088***	0.094***	0.097
Δ WTI oil	0.181***	0.381**	0.333***	0.082	0.022	0.095*	0.288*	0.459**
Wavelet series D2								
SE	−14.677***	−19.940***	−15.321***	−11.525***	−9.798***	−11.334***	−16.491***	−19.963***
Δ SPOT	8.350**	16.529	10.592**	6.684**	6.665***	9.483***	21.114	25.197**
Δ S&P 500	0.158***	0.157***	0.137***	0.096***	0.092***	0.091***	0.116***	0.165***
Δ WTI oil	−0.125	−0.101	0.127	0.137	0.022	0.061	0.046	0.016
Wavelet series D3								
SE	−24.683***	−35.335***	−26.844***	−18.553***	−16.132***	−19.227***	−25.319***	−38.532***
Δ SPOT	35.767***	61.237	34.839	23.937***	11.083***	10.232**	40.808	37.613**
Δ S&P 500	0.094***	0.213***	0.096***	0.042*	0.023	0.073	0.098**	0.203***
Δ WTI oil	0.064	−0.009	−0.092	−0.323*	−0.135	−0.291**	0.155	0.242
Wavelet series D4								
SE	−34.693***	−46.010***	−40.987***	−29.055***	−25.426***	−29.500***	−36.774***	−45.542***
Δ SPOT	−94.306***	−89.213***	−55.649	−21.391**	−27.350	−29.895	−67.559***	−131.070***
Δ S&P 500	−0.004	−0.096	0.105*	0.110***	0.071**	0.078**	0.036	−0.066
Δ WTI oil	0.628	4.024***	2.782***	0.258	−0.124	0.812***	3.221***	4.808***
Wavelet series D5								
SE	0.188	−19.060**	−17.520***	−23.070***	−19.322***	−23.988***	−10.994***	−9.236
Δ SPOT	−179.247***	−168.918***	−91.199***	−118.081***	−95.299***	−116.754***	−155.108***	−161.013***
Δ S&P 500	−0.482***	−0.151	−0.434***	−0.324***	−0.341***	−0.278***	−0.539***	−0.590***
Δ WTI oil	−5.022***	−5.727***	−2.407***	−1.027***	−0.093	−0.242	−1.932***	−6.051***

Note. This table displays coefficient estimates of the OLS, quantile, and the Daubechies 4 wavelet quantile regression for the influence of SE on CDX.NA.HY. SE denotes the investor attitude proxy; CDX.NA.HY denotes the differences of the composite spread and theoretical spread for the North America High Yield index. ***, **, and * denote rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively.

Table 3: OLS, quantile, and the Daubechies 4 wavelet quantile regression for the influence of SE on CDX.NA.IG.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Raw series								
SE	−2.033***	−0.133	−0.879	−2.140***	−2.333***	−2.307***	−2.518***	−2.746***
Δ SPOT	2.276	11.309	−2.004	1.450	2.510*	1.094	1.218	1.962
Δ S&P 500	0.001	0.030	0.031	0.002	−0.009*	−0.006	−0.009	−0.008
Δ WTI oil	0.108	0.221	−0.009	0.085	0.193	0.067	0.053	0.042
Wavelet series D1								
SE	−1.218***	−1.676***	−1.348***	−0.974***	−0.762***	−1.075***	−1.419***	−1.562***
Δ SPOT	1.889***	1.507	0.808**	0.810***	0.593***	0.717***	1.953***	2.409**
Δ S&P 500	0.019***	0.018***	0.016***	0.017***	0.016***	0.014***	0.014***	0.016
Δ WTI oil	−0.026**	−0.011	−0.029**	−0.025***	−0.010	−0.001	−0.021	−0.059
Wavelet series D2								
SE	−2.662***	−3.396***	−2.841***	−2.130***	−1.781***	−2.124***	−2.765***	−3.754***
Δ SPOT	1.080*	2.933	1.773	0.309	0.025***	−0.008	2.037**	3.399**
Δ S&P 500	0.016***	0.017**	0.017***	0.015***	0.013***	0.013***	0.018***	0.018***
Δ WTI oil	−0.080***	−0.063	−0.017	−0.008	−0.014	0.001	−0.029	−0.055*
Wavelet series D3								
SE	−3.386***	−4.619***	−3.567***	−2.384***	−2.336***	−2.657***	−3.523***	−4.205***
Δ SPOT	3.822***	5.530	3.946***	1.088	−0.780	0.005	1.547	0.511
Δ S&P 500	−0.017***	−0.022	−0.021***	−0.012	−0.004	−0.010**	−0.014**	−0.026**
Δ WTI oil	−0.174***	−0.155	−0.042	−0.132	−0.134***	−0.092***	−0.133**	−0.091

Table 3: Continued.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Wavelet series D4								
SE	−4.045***	−3.164**	−4.576***	−3.929***	−2.804***	−4.015***	−4.961***	−6.685***
Δ SPOT	−5.925**	−5.932	4.847*	6.335***	7.084***	7.832***	6.081**	−4.522
Δ S&P 500	−0.037***	−0.069***	−0.025**	0.002	−0.011*	0.003	−0.022**	−0.027
Δ WTI oil	−0.078	0.400***	0.199**	−0.151	−0.148***	−0.107**	−0.025	0.056
Wavelet series D5								
SE	0.407	3.792	3.087***	−1.543	−0.144	−0.656	−0.010	3.317**
Δ SPOT	5.653**	14.743***	21.074***	14.429***	11.410***	11.266***	5.455*	−3.970
Δ S&P 500	−0.168***	−0.274***	−0.216***	−0.097***	−0.109***	−0.118***	−0.141***	−0.233***
Δ WTI oil	1.261***	1.630***	1.415***	0.633***	0.456***	0.560***	1.266***	2.285***

Note. This table displays coefficient estimates of the OLS, quantile, and the Daubechies 4 wavelet quantile regression for the influence of SE on CDX.NA.IG. SE denotes the investor attitude proxy; CDX.NA.IG denotes the differences of the composite spread and theoretical spread for the North America Investment Grade index. ***, **, and * denote the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4: OLS, quantile, and the Daubechies 4 wavelet quantile regression for the influence of VIX on CDX.NA.HY.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Raw series								
VIX	−1.776***	−4.871***	−3.525***	−1.562***	0.166	1.150***	2.341***	3.397***
Δ SPOT	4.684	−0.592	3.021	3.449	−10.759	8.626	−3.915	−9.808
Δ S&P 500	0.097**	0.053	0.087	0.036	0.027	−0.030	−0.113**	−0.029
Δ WTI oil	0.364	−0.347	−0.478	0.163	0.576	0.436	0.303	−0.224
Wavelet series D1								
VIX	2.024***	1.878	2.230***	2.169***	2.146***	2.226***	2.161***	2.148***
Δ SPOT	2.034	1.244	3.070	−1.572	0.255	−2.080	0.245	2.566
Δ S&P 500	0.068***	0.081***	0.062***	0.058***	0.054***	0.053***	0.066	0.061*
Δ WTI oil	0.100	0.278	0.259	0.030	0.015	0.081	0.105	0.204
Wavelet series D2								
VIX	3.395***	3.288***	3.413***	3.150***	2.877***	3.065***	3.217***	3.309***
Δ SPOT	3.906	20.363**	14.269**	5.467*	1.415	3.175	14.977**	2.827
Δ S&P 500	−0.036***	−0.059*	−0.062**	−0.059***	−0.033	−0.048***	−0.064***	−0.059
Δ WTI oil	−0.035	−0.444	0.164	0.112	0.134*	0.193*	−0.140	−0.305
Wavelet series D3								
VIX	3.119***	2.981***	2.938***	2.653***	2.454***	2.703***	2.847***	3.099***
Δ SPOT	18.964***	29.364	23.416**	23.338***	15.971***	22.000	5.371	3.138
Δ S&P 500	−0.248***	−0.254***	−0.272***	−0.216***	−0.199***	−0.213***	−0.253***	−0.238
Δ WTI oil	−0.088	−0.334	−0.041	−0.240	−0.304**	−0.232	0.088	0.298
Wavelet series D4								
VIX	2.237***	1.483***	1.340***	1.614***	1.473***	1.520***	1.588***	1.425
Δ SPOT	−117.013***	−188.749***	−114.511***	−29.255***	−29.524***	−29.081	−92.095***	−200.180***
Δ S&P 500	−0.449***	−0.645***	−0.438***	−0.294***	−0.254***	−0.315***	−0.468***	−0.600
Δ WTI oil	0.930**	5.024***	3.583***	0.965	0.071	0.785	3.610***	5.386
Wavelet series D5								
VIX	0.984***	0.392**	0.409***	0.680***	1.085***	0.925***	0.526***	0.601
Δ SPOT	−190.683***	−172.359***	−103.498***	−114.618***	−90.835***	−106.445***	−158.278***	−166.137***
Δ S&P 500	−0.419***	−0.512***	−0.620***	−0.563***	−0.628***	−0.582***	−0.594***	−0.742***
Δ WTI oil	−3.663***	−4.845***	−2.599***	−0.901**	−0.326	0.125	−1.757	−5.025***

Note. This table displays coefficient estimates of the OLS, quantile, and the Daubechies 4 wavelet quantile regression for the influence of VIX on CDX.NA.HY. VIX (Chicago board options exchange volatility index) denotes the investor fear proxy. CDX.NA.HY denotes the differences of the composite spread and theoretical spread for the North America High Yield index. ***, **, and * denote the statistical significance at 1%, 5%, and 10% levels, respectively.

composite-theoretical spread difference for CDX.NA.HY and CDX.NA.IG are −1.64 and −4.10, respectively. The quantile value 0.77 and the arithmetic mean −4.10 for CDX.NA.IG are quite puzzling from the view of financial theory, since the expected value of credit market price should be equal to the theoretical price. A possible explanation for this phenomenon is that investors might be psychologically suggested by "investment-grade," believing mistakenly that the riskiness of credit market of investment-grade entities is relatively low, regardless of the whole

Table 5: OLS, quantile, and the Daubechies 4 wavelet quantile regression for the influence of VIX on CDX.NA.IG.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Raw series								
VIX	−0.507***	−1.181***	−0.973***	−0.494***	−0.212***	−0.053	0.032	0.126***
Δ SPOT	0.379	−2.141	−1.113	−0.271	1.211	0.175	0.371	1.134
Δ S&P 500	0.014*	0.013	0.012	0.000	0.003	−0.002	0.000	−0.003
Δ WTI oil	−0.025	−0.022	−0.006	−0.003	0.128*	0.094	0.003	−0.054
Wavelet series D1								
VIX	0.364***	0.370***	0.357***	0.361***	0.370***	0.402***	0.365***	0.378***
Δ SPOT	1.483***	1.934*	0.735	−0.182	−0.051	0.451*	1.141***	1.840
Δ S&P 500	0.014***	0.016	0.017***	0.014***	0.011***	0.010***	0.015***	0.016***
Δ WTI oil	−0.045***	−0.052	−0.055**	−0.034	−0.020***	−0.028***	−0.053***	−0.069*
Wavelet series D2								
VIX	0.480***	0.510***	0.492***	0.506***	0.476***	0.505***	0.473***	0.465***
Δ SPOT	0.469	1.676	−0.245	−0.268	−0.594	0.598	0.142	1.200
Δ S&P 500	−0.014***	−0.016**	−0.011***	−0.012***	−0.009***	−0.012***	−0.011***	−0.017*
Δ WTI oil	−0.078***	−0.132***	−0.040	−0.005	0.014	−0.004	−0.026	−0.071
Wavelet series D3								
VIX	0.444***	0.415***	0.341***	0.323***	0.323***	0.323***	0.370***	0.428***
Δ SPOT	1.402	3.106	1.808	1.222	0.023	−0.551	−1.190	−0.927
Δ S&P 500	−0.064***	−0.082***	−0.062***	−0.046***	−0.037***	−0.044***	−0.064***	−0.075***
Δ WTI oil	−0.196***	−0.188	−0.096	−0.091***	−0.106	−0.112	−0.171***	−0.214
Wavelet series D4								
VIX	0.174***	0.085	0.093***	0.129***	0.124***	0.128***	0.105***	0.115
Δ SPOT	−7.743***	−7.362	1.177	7.816***	6.938***	6.805***	3.923	−10.743
Δ S&P 500	−0.090***	−0.118***	−0.086***	−0.055***	−0.039***	−0.051***	−0.090***	−0.139***
Δ WTI oil	−0.037	0.374***	0.247	−0.071	−0.095**	−0.044	−0.050	0.216
Wavelet series D5								
VIX	−0.090***	−0.082	−0.032	−0.031*	−0.009	−0.015	−0.031	−0.108***
Δ SPOT	6.581**	11.046**	19.540***	14.067***	11.491***	12.144***	6.483**	−4.347
Δ S&P 500	−0.168***	−0.235***	−0.180***	−0.121***	−0.114***	−0.133***	−0.146***	−0.209***
Δ WTI oil	1.143***	1.565***	1.407***	0.582***	0.437***	0.522***	1.202***	2.083***

Note. This table displays coefficient estimates of the OLS, quantile, and the Daubechies 4 wavelet quantile regression for the influence of VIX on CDX.NA.IG. VIX (Chicago board options exchange volatility index) denotes the investor fear proxy. CDX.NA.IG denotes the differences of the composite spread and theoretical spread for the North America Investment Grade index. ***, **, and * denote the statistical significance at 1%, 5%, and 10% levels, respectively.

market condition. The quantile value 0.45 and the arithmetic mean −1.64 for CDX.NA.HY also support this explanation.

Secondly, as displayed in panel raw series of Tables 2 and 3, the investor sentiment proxy SE has a negative impact both on the composite-theoretical spread differences of CDX.NA.HY and CDX.NA.IG, indicating that when the composite spread is smaller than the theoretical spread, investor attitude turning positive in the equity market could increase the gap between the composite spread and the theoretical spread; and that when the composite spread is larger than the theoretical spread, investor attitude turning positive would lower this gap. In other words, the increase of the positive attitude towards American equity market could lower the spread of credit indices compared with rational pricing. Since the spreads reflect the investor perspective of credit market condition, a reasonable interpretation is that the positive attitude in the equity market could spill over to the credit market, even though the credit market condition is not turning better indeed. Otherwise, the recovery of the CDS market should be reflected in the theoretical spreads, and the difference between composite and theoretical spread should be constant. In addition, the coefficient estimates of SE from the panel raw series in Tables 2 and 3 indicate that the influence of investor attitude on the credit spreads is only significant at the quantile levels larger than 0.25, which suggests that if the composite spread is much smaller than the theoretical spread, then the composite-theoretical spread differences are insensitive to the increase of SE. In other words, if the CDS investors views towards the credit worthiness of the reference entities in aggregate credit markets is much more optimistic than the actual credit worthiness, then the enhancement of investor attitude towards equity market will not deviate the investors view on credit market price from intrinsic value further.

Thirdly, panel raw series of Tables 4 and 5 demonstrates that the rise of investor sentiment proxy VIX will enlarge the composite-theoretical spread differences of both CDX.NA.HY and CDX.NA.IG whenever the composite spread is larger or smaller than the theoretical spread, implying that the aggravation of the fear among equity market will impact the credit market such that its investors become more irrational than usual.

Lastly, the influence of investor sentiment of equity market on the high-yield credit market, measured by either SE or VIX, is much larger than that on the investment-grade credit market. This outcome is might be due to that the high-yield credit market, with higher risk of reference entities default and more difficulties to evaluate default risk and recovery rate, causes investors to evaluate credit spread based more on other investors' behavior than on intrinsic value calculation. Another reason is that speculation behavior is more pervasive and active in the high-yield credit market. These findings are consistent with Gatfaoui [9] who showed that the influence of equity market on the credit market depends highly on the CDS rating grades.

In summary, the investor sentiment in the equity market does have a spillover impact on the CDS market. Specifically, the optimistic investor attitude has a negative influence on the composite-theoretical spread difference while the aggravation of fear among equity market will enlarge the deviation of the CDS spread from intrinsic value, reflecting the irrational component in the CDS prices. Besides, the influence of the investor sentiment on the high-yield credit market is much larger than that on the investment-grade credit market.

5.2. Wavelet Quantile Regression. In the second step, we implemented the wavelet quantile regression to obtain an in-depth analysis of the sentiment impact in various horizons and market conditions, which is useful not only for market participants to improve their investment decisions, but also for the policy makers to choose appropriate measures to promote stability in the credit market.

Firstly, we used the MODWT with Daubechies 4 basis to decompose the raw time series into a set of five components, namely, D1, D2, D3, D4, and D5, which represents the investment horizons of 1-2 business days, 2–4 business days, 4–8 business days, 8–16 business days, and 16–32 business days, respectively. Daubechies 4 basis is selected on account of the properties of orthogonality, near symmetry, and compatibility. Figure 1 plots the different time scale wavelet components of the raw data. Subsequently, noting that the decomposed components under wavelet transformation are still stationary in the levels, we applied OLS wavelet regression and wavelet quantile regression to these decomposed components by using models (15)–(18). To be more precise, the following models are used to examine the influence of investor attitude SE on the credit market by OLS wavelet regression and wavelet quantile regression:

$$\mathrm{CDX.NA.HY}_{\mathrm{Dj},t} = \beta_{50} + \beta_{51} SE_{\mathrm{Dj},t} + \beta_{52}\Delta\mathrm{SPOT}_{\mathrm{Dj},t} + \beta_{53}\Delta S\&P\,500_{\mathrm{Dj},t} + \beta_{54}\Delta\mathrm{WTI\ oil}_{\mathrm{Dj},t} + \varepsilon_{\mathrm{Dj},t}, \tag{17}$$

$$\mathrm{CDX.NA.IG}_{\mathrm{Dj},t} = \beta_{60} + \beta_{61}\mathrm{SE}_{\mathrm{Dj},t} + \beta_{62}\Delta\mathrm{SPOT}_{\mathrm{Dj},t} + \beta_{63}\Delta S\&P\,500_{\mathrm{Dj},t} + \beta_{64}\Delta\mathrm{WTI\ oil}_{\mathrm{Dj},t} + \varepsilon_{Dj,t}. \tag{18}$$

Similarly, the following models are implemented to investigate the influence of investor fear VIX on the credit market:

$$\mathrm{CDX.NA.HY}_{\mathrm{Dj},t} = \beta_{70} + \beta_{71}\mathrm{VIX}_{\mathrm{Dj},t} + \beta_{72}\Delta\mathrm{SPOT}_{\mathrm{Dj},t} + \beta_{73}\Delta S\&P\,500_{\mathrm{Dj},t} + \beta_{74}\Delta\mathrm{WTI\ oil}_{\mathrm{Dj},t} + \varepsilon_{\mathrm{Dj},t}, \tag{19}$$

$$\mathrm{CDX.NA.IG}_{\mathrm{Dj},t} = \beta_{80} + \beta_{81}\mathrm{VIX}_{\mathrm{Dj},t} + \beta_{82}\Delta\mathrm{SPOT}_{\mathrm{Dj},t} + \beta_{83}\Delta S\&P\,500_{\mathrm{Dj},t} + \beta_{84}\Delta\mathrm{WTI\ oil}_{\mathrm{Dj},t} + \varepsilon_{\mathrm{Dj},t}. \tag{20}$$

$\mathrm{CDX.NA.HY}_{\mathrm{Dj},t}$ and $\mathrm{CDX.NA.IG}_{\mathrm{Dj},t}$ in equations (17)–(20) refer to the detail components of the composite and theoretical spread difference of the North American High Yield index and North American Investment Grade index, respectively. Δ denotes the first difference operator.

Panel wavelet series in Tables 2–5 display the wavelet quantile regression results, including the coefficient estimates and the statistical significance. According to these tables, almost all investor sentiment (SE and VIX) estimates are significant at the 1% level, except for several quantile coefficients of investor sentiment for D5, suggesting that the impact of investor sentiment in equity market will decay after 32 business days.

Then, we investigated the relationship between the investor sentiment in the equity market and the CDS spreads by analyzing the quantile regression results in Tables 2–5. Not surprisingly, as demonstrated in panel wavelet series in Tables 2 and 3, there is a negative comovement between the investor sentiment proxy SE and the composite-theoretical spread difference in both the high-yield market and the investment-grade market, further confirming our findings in Section 5.1. Besides, at all the quantile levels of CDX.NA.HY and CDX.NA.IG, the influences of SE on the CDS spread difference first increase and then decrease, peaking at the period of 8–16 business days (D4), as the investment horizon lengthens. This result shows that CDS investors respond to the equity market sentiment instantly and that equity market sentiment influences CDS market both in the short term and long term, although this impact first increases and then decreases as the time horizon extends. The empirical evidence also confirms the studies of Shahzad et al. [4] and Hkiri et al. [62] which implied the presence of asymmetries in the short- and long-run relationships between the U.S. CDS spreads and the equity market. Accordingly, policy makers should take

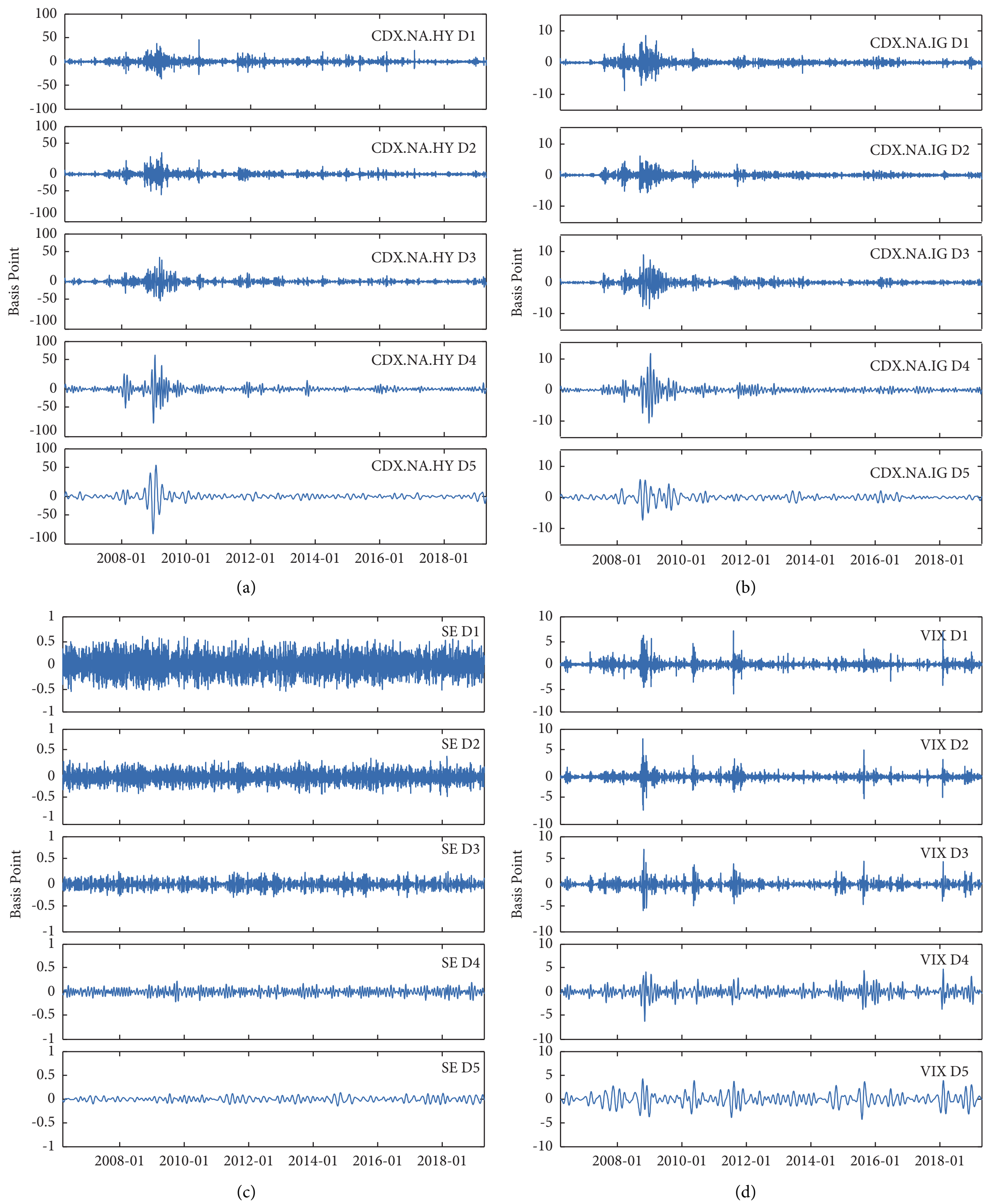

Figure 1: The Daubechies 4 wavelet decomposition series of CDX.NA.HY (a), CDX.NA.IG (b), SE (c), and VIX (d).

pertinent measures for different horizons since the influence of equity market sentiment varies across the time scale. We also recommended that policy makers identify sentiment in the equity market as early as possible to effectively reduce the influence of equity market sentiment on the credit market since such influence become gradually stronger from short term to median term. Additionally, the absolute values of the coefficients at lower or upper tails are much greater than that at middle quantiles. This empirical evidence is in line with the findings of Gatfaoui [9], which indicated that the equity market impacts the aggregate CDS spreads indices strongly at extreme quantiles. Noting that the quantile levels represent the deviation degree of the composite spread from theoretical spread, we find that when the CDS investors' evaluation of spreads deviates further from theoretical value in both the high-yield market and investment-grade market, they tend to become more irrational and distracted by emotion from equity market, leading to further deviations of the CDS spreads from theoretical value. This finding elucidates that the influence of investor sentiment on the CDS market is self-reinforced. Consequently, policy makers need to pay close attention to the change of investor attitude and adopt corresponding measures when the CDS market is in irrational condition where the CDS spreads deviate greatly from theoretical value. Our results are in line with Afonso et al. [97], Blommestein et al. [98], and Breitenfellner and Wagner [2] who emphasized the instability of the relationship between the equity market and the credit market which depends on different market regimes. Similarly, Chen et al. [6], Yang and Hamori [7], and Yang [8] confirmed that the network of CDS market varies with market conditions. These discoveries highlight the asymmetric effects of investor sentiment on different time horizons and market conditions, confirming the advantages of wavelet quantile regression.

Panel wavelet series in Tables 4 and 5 present the comovement between the investor sentiment proxy VIX and the unexpected CDS market price measured by the composite-theoretical spread difference. On the contrary, there is a positive relationship between VIX and the CDS spreads difference, except D5 of CDX.NA.IG, most coefficients of which are insignificant and small in value. This is because the VIX and SE index measure investor sentiment in different manners, as SE describes the range of investor attitude while VIX focuses on the degree of fear. As expected, the fear in the equity market makes the investors attitude turn pessimistic towards the credit market condition, and thus pushes up the composite spread compared with the theoretical spread. Besides, even though the influence trend of VIX over time is quite similar as that of SE on the composite-theoretical differences in both the high-yield and the investment-grade market, the VIX influence peaks at the time horizon of 2 to 4 business days (D2). Therefore, we could conclude that the spread of fear is much faster than the spread of attitude changing to the credit market. This finding is consistent with the hypothesis of risk aversion [99], as investors pay more attention to the risk of markets and respond to the deterioration of market condition more rapidly. Our finding also provides further evidence for the research work of Shahzad et al. [4] which documented that greater risk aversion in the stock market leads to a widening of CDS index spreads. To this end, it is suggested that policy makers identify the equity market fear and take actions earlier to lower the equity market sentiment influence on the credit market compared with the investor attitude. It is worth noting that the impact speed of investor sentiment, either measured by SE or VIX, is identical in the high-yield market and the investment-grade market, which means that different types of the CDS markets will only affect the extent but not the speed of the sentiment impact. In addition, the influence of VIX is much greater at lower or upper quantiles in both the high-yield and investment-grade market, which is consistent with that of SE, further confirming the existence of self-reinforce of the sentiment influence. Likewise, policy makers need to pay more attention to equity market fear and adopt corresponding measures when the CDS market is in irrational condition.

In line with the results in Section 5.1, the influence on CDX.NA.HY is much more pronounced than that on CDX.NA.IG, giving credence to the interpretation that investors evaluate credit spread depending more on other investors' attitude than on the theoretical value calculation when they are faced with higher default probability of reference entities. Accordingly, we suggested policy makers monitor more closely the equity market influence on the high-yield credit market than on the investment-grade credit market.

Meanwhile, we explored the influence of various sectors, namely, the debt market, the equity market, and the crude oil market, on the credit market in the business cycle by analyzing the wavelet quantile regression results of the SPOT interest rate, the S&P 500 index, and the WTI oil spot price in Tables 2–5, respectively. Both the debt market and the equity market have short- and long-term influence on the deviation of CDS spreads, and this influence enlarges as the time horizon extends. Although the oil market does not impact the deviation of CDS spreads in the short term, this market influences the CDS market significantly in the long term. Furthermore, the more irrational condition the credit market is in, the greater influence the three sectors have on the CDS market. This finding offers further evidence for the research work of Yang [8] which revealed that oil sector has different level of influence on the sovereign CDS market when it is in different market condition.

Overall, there is an asymmetric and heterogeneous influence of the investor sentiment in the equity market on the credit market at different time horizons and different spread deviation levels. Concretely, the sentiment influence first increases and then decreases as the horizon extends and the influence level is much higher when the credit market is in extreme conditions where the credit spreads deviate further from theoretical value. The influence of investor sentiment on the CDS market is self-reinforced, which is why the investor sentiment influence first increases and then weakens as investment horizon extends.

5.3. Robustness Analysis. We conducted robustness analysis by using a different wavelet family, the Symlets. Similar to the wavelet family the Daubechies, the Symlets is also common in the financial series analysis. Despite the different wavelet basis, other procedures of empirical analysis are identical, that is, we used the same dataset, decompose them by the same method MODWT, and fit them with the same OLS, quantile, and wavelet quantile regression model.

Figure 2 shows the decomposed details of CDX.NA.HY, CDX.NA.IG, SE, and VIX by the Symlets 2 wavelet, respectively. The regression results are reported in Tables 6–9. Even though the estimated coefficients in Tables 6–9 are not exactly the same as the coefficients derived by the Daubechies 4 wavelet, the difference between the two sets of estimated coefficients is insignificant and negligible. Moreover, the significance levels of the estimate coefficients are consistent between regression results by the Daubechies wavelets and by the Symlets wavelets. Additionally, wavelet quantile regressions by other wavelet families are also conducted and no notable discrepancy has been found between all these

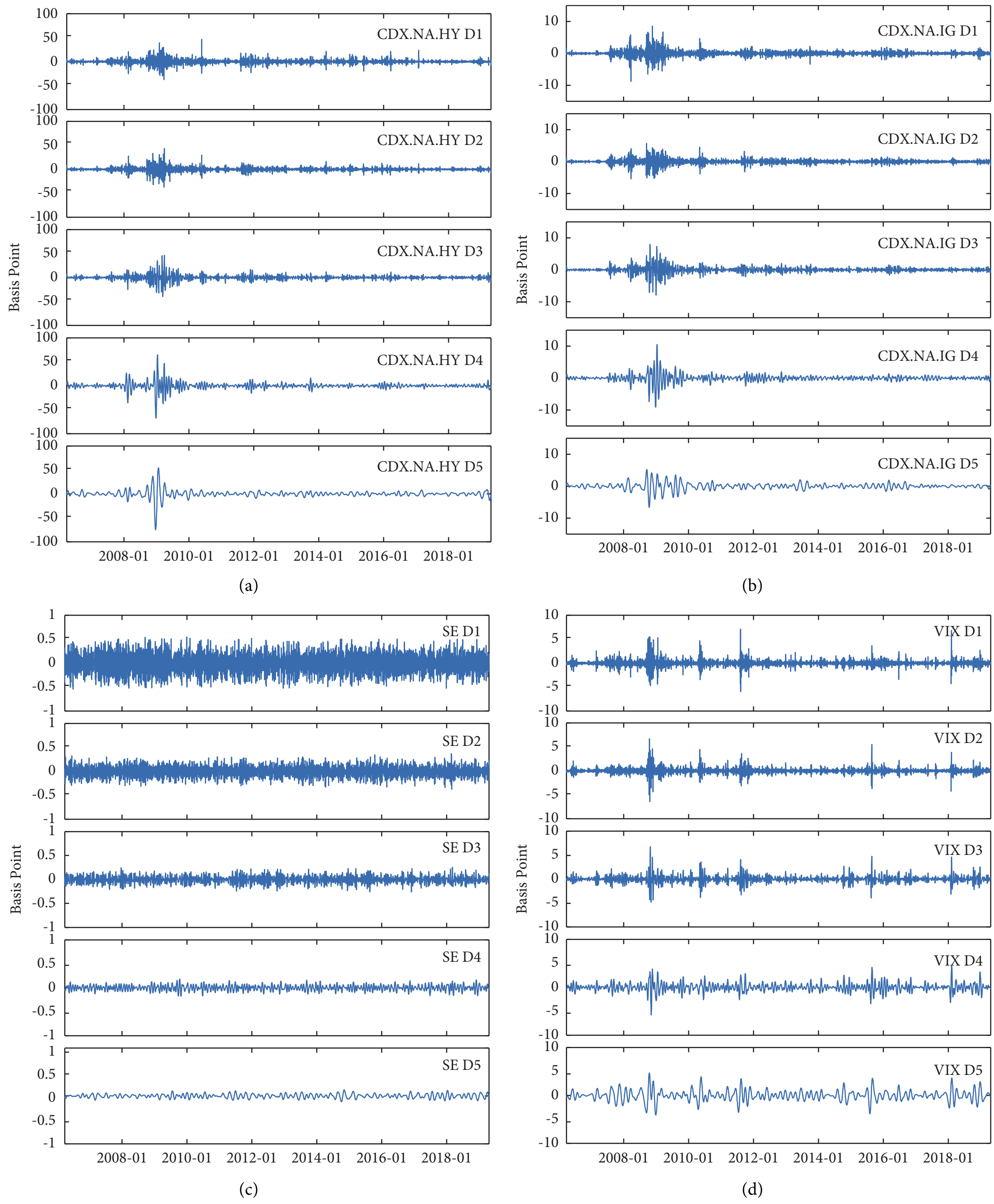

Figure 2: The Symlets 2 wavelet decomposition series of CDX.NA.HY (a), CDX.NA.IG (b), SE (c), and VIX (d).

analyses. The results by other wavelet families are similar and are omitted due to space considerations. Therefore, we could infer that the wavelet quantile regression method is robust in analyzing the impact of the investor sentiment in the equity market on the credit market unaffected by the chosen wavelet basis.

Table 6: OLS, quantile, and the Symlets 2 wavelet quantile regression for the influence of SE on CDX.NA.HY.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Raw series								
SE	−10.860***	6.554	−3.596	−10.544***	−11.419***	−13.536***	−16.080***	−17.427***
Δ SPOT	11.468	69.437	18.717	−6.500	−2.108	2.049	1.192	−17.385
Δ S&P 500	0.048	0.058	0.078	0.021	0.025	0.000	0.028	−0.010
Δ WTI oil	0.897*	1.880	0.558	0.578**	0.495*	0.575*	0.800*	2.370***
Wavelet series D1								
SE	−5.044***	−7.277***	−6.665***	−4.165***	−3.705***	−4.773***	−6.202***	−7.636***
Δ SPOT	3.659*	3.144	6.819**	3.961**	1.414	2.200	7.167*	7.518
Δ S&P 500	0.108***	0.132***	0.084***	0.095***	0.100***	0.087***	0.086***	0.095***
Δ WTI oil	0.168**	0.305	0.298***	0.083	0.059	0.119**	0.265**	0.401
Wavelet series D2								
SE	−14.310***	−18.520***	−15.314***	−11.453***	−9.430***	−11.284***	−16.222***	−19.858***
Δ SPOT	8.158**	15.277	8.032	5.858*	4.029	7.281**	15.422**	21.187**
Δ S&P 500	0.149***	0.129***	0.134***	0.090***	0.091***	0.089***	0.121***	0.143***
Δ WTI oil	−0.080	−0.151	0.145	0.136	0.083	0.129	0.035	0.345
Wavelet series D3								
SE	−24.662***	−36.589***	−26.697***	−18.653***	−15.733***	−19.016***	−26.455***	−39.832***
Δ SPOT	30.491***	51.473**	36.385***	18.272	11.859***	24.825***	38.624	32.797*
Δ S&P 500	0.099***	0.267***	0.080**	0.028	0.029*	0.064***	0.127***	0.230***
Δ WTI oil	−0.082	−0.248	−0.088	−0.235	−0.260**	−0.363**	−0.066	−0.227
Wavelet series D4								
SE	−34.110***	−43.621***	−42.666***	−28.272***	−25.005***	−28.574***	−34.754***	−44.735***
Δ SPOT	−89.425***	−95.705	−51.919	−21.425***	−24.651	−29.444	−57.608	−105.577***
Δ S&P 500	0.015	−0.055	0.161***	0.057	0.045	0.067**	0.038	−0.083
Δ WTI oil	0.057	3.142	1.656	0.158	−0.117	0.759***	2.443***	3.492
Wavelet series D5								
SE	−3.822	−17.785***	−20.659***	−24.853***	−19.991***	−25.761***	−11.535***	−1.635
Δ SPOT	−153.476***	−215.082***	−79.814***	−105.942***	−96.152***	−98.082***	−127.549***	−149.333***
Δ S&P 500	−0.512***	−0.223	−0.504***	−0.314***	−0.314***	−0.250***	−0.656***	−0.838***
Δ WTI oil	−4.368***	−3.285***	−1.253**	−0.703*	−0.115	−0.642	−2.011***	−5.834***

Note. This table displays coefficient estimates of the OLS, quantile, and the Symlets 2 wavelet quantile regression for the influence of SE on CDX.NA.HY. SE denotes the investor attitude proxy; CDX.NA.HY denotes the differences of the composite spread and theoretical spread for the North America High Yield Index. ***, **, and * denote rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively.

Table 7: OLS, quantile, and the Symlets 2 wavelet quantile regression for the influence of SE on CDX.NA.IG.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Raw series								
SE	−2.033***	−0.133	−0.879	−2.140***	−2.333***	−2.307***	−2.518***	−2.746***
Δ SPOT	2.276	11.309	−2.004	1.450	2.510*	1.094	1.218	1.962
Δ S&P 500	0.001	0.030	0.031	0.002	−0.009*	−0.006	−0.009	−0.008
Δ WTI oil	0.108	0.221	−0.009	0.085	0.193	0.067	0.053	0.042
Wavelet series D1								
SE	−1.246***	−1.718***	−1.355***	−0.951***	−0.788***	−1.069***	−1.508***	−1.606***
Δ SPOT	1.974***	2.228**	0.825**	0.709***	0.644***	0.532**	1.626***	2.716***
Δ S&P 500	0.018***	0.018***	0.016***	0.017***	0.016***	0.015***	0.012***	0.015
Δ WTI oil	−0.029**	−0.007	−0.039***	−0.027***	−0.012	−0.004	−0.011	−0.056
Wavelet series D2								
SE	−2.593***	−3.396***	−2.691***	−2.084***	−1.783***	−2.065***	−2.635***	−3.758***
Δ SPOT	0.930	2.853*	2.194*	0.810*	0.009	0.587	1.288**	1.909
Δ S&P 500	0.015***	0.016***	0.012	0.013***	0.012***	0.011***	0.017***	0.020**
Δ WTI oil	−0.071***	−0.075*	−0.002	0.003	−0.002	−0.006	−0.049***	−0.061
Wavelet series D3								
SE	−3.396***	−4.677***	−3.343***	−2.412***	−2.366***	−2.646***	−3.512***	−4.661***
Δ SPOT	3.051**	6.515	2.874	1.130	−0.604	−0.462	0.773	−0.041
Δ S&P 500	−0.015***	−0.025*	−0.022***	−0.011	−0.003	−0.007*	−0.015*	−0.013
Δ WTI oil	−0.172***	−0.113	−0.062	−0.087***	−0.116***	−0.090***	−0.114*	−0.114

Table 7: Continued.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Wavelet series D4								
SE	−3.915***	−2.286*	−4.591***	−3.786***	−2.507***	−3.612***	−4.770***	−6.551***
Δ SPOT	−5.321**	−13.546**	2.373	5.912	5.544	6.892***	8.498	0.736
Δ S&P 500	−0.040***	−0.078	−0.023	−0.004*	−0.016**	−0.007	−0.029***	−0.061**
Δ WTI oil	−0.043	0.332**	0.133***	−0.122***	−0.125**	−0.023	0.157**	0.307
Wavelet series D5								
SE	−0.167	2.423**	2.315	−1.305**	−0.895**	−1.408***	−0.192	1.030
Δ SPOT	5.957**	17.464	26.933***	13.910***	10.419***	9.594***	1.865	−7.742
Δ S&P 500	−0.165***	−0.252***	−0.208***	−0.099***	−0.108***	−0.104***	−0.150***	−0.220***
Δ WTI oil	1.279***	1.661***	1.245***	0.639***	0.519***	0.581***	1.228***	2.416***

Note. This table displays coefficient estimates of the OLS, quantile, and the Symlets 2 wavelet quantile regression for the influence of SE on CDX.NA.IG. SE denotes the investor attitude proxy; CDX.NA.IG denotes the differences of the composite spread and theoretical spread for the North America Investment Grade index. ***, **, and * denote the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 8: OLS, quantile, and the Symlets 2 wavelet quantile regression for the influence of VIX on CDX.NA.HY.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Raw series								
VIX	−1.776***	−4.871***	−3.525***	−1.562***	0.166	1.150***	2.341***	3.397***
Δ SPOT	4.684	−0.592	3.021	3.449	−10.759	8.626	−3.915	−9.808
Δ S&P 500	0.097**	0.053	0.087	0.036	0.027	−0.03	−0.113**	−0.029
Δ WTI oil	0.364	−0.347	−0.478	0.163	0.576	0.436	0.303	−0.224
Wavelet series D1								
VIX	2.060***	2.067***	2.091***	2.193***	2.175***	2.354***	2.304***	2.324***
Δ SPOT	1.845	2.394	1.892	−1.522	0.231	−3.626**	1.965	2.947
Δ S&P 500	0.066***	0.075***	0.073	0.058***	0.050***	0.051***	0.059	0.063*
Δ WTI oil	0.089	0.133	0.226*	0.036	0.009	0.055	0.105	0.159
Wavelet series D2								
VIX	3.384***	3.176***	3.234***	3.151***	2.952***	3.068***	3.299***	3.411***
Δ SPOT	3.381	7.541	14.533**	5.706***	0.116	1.906	12.132*	6.883
Δ S&P 500	−0.039***	−0.044	−0.060**	−0.060***	−0.033***	−0.047***	−0.065**	−0.079*
Δ WTI oil	−0.004	−0.348	0.031	0.119	0.111	0.137	−0.010	−0.016
Wavelet series D3								
VIX	3.118***	3.081***	2.842***	2.667***	2.482***	2.691***	2.948***	3.185***
Δ SPOT	14.483**	23.428	21.365**	22.07***	17.969***	19.591	7.150	−2.654
Δ S&P 500	−0.237***	−0.263***	−0.275***	−0.201***	−0.193***	−0.209***	−0.237***	−0.218***
Δ WTI oil	−0.225	−0.310	−0.554	−0.272*	−0.206	−0.246	−0.258	0.072***
Wavelet series D4								
VIX	2.231***	1.732***	1.362***	1.539***	1.466***	1.385***	1.388***	1.509
Δ SPOT	−110.371***	−208.59***	−98.993***	−29.606	−29.07***	−27.235	−75.576***	−162.944
Δ S&P 500	−0.423***	−0.492	−0.423***	−0.330***	−0.254***	−0.330***	−0.425***	−0.582***
Δ WTI oil	0.427	3.696***	2.821***	1.011***	0.091	0.634**	2.749***	4.666
Wavelet series D5								
VIX	1.126***	0.315**	0.448***	0.684***	1.126***	0.933***	0.695***	0.584
Δ SPOT	−162.21***	−195.144***	−99.937***	−108.599***	−84.027***	−98.922***	−135.733***	−162.937***
Δ S&P 500	−0.502***	−0.579***	−0.717***	−0.579***	−0.632***	−0.559***	−0.722***	−0.776***
Δ WTI oil	−2.913***	−2.513***	−1.433**	−0.283	−0.106	−0.468	−1.486**	−5.647***

Note. This table displays coefficient estimates of the OLS, quantile, and the Symplets 2 wavelet quantile regression for the influence of VIX on CDX.NA.HY. VIX (Chicago board options exchange volatility index) denotes the investor fear proxy. CDX.NA.HY denotes the differences of the composite spread and theoretical spread for the North America High Yield index. ***, **, and * denote the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 9: OLS, quantile, and the Symlets 2 wavelet quantile regression for the influence of VIX on CDX.NA.IG.

Variables	OLS	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Raw series								
VIX	−0.507***	−1.181***	−0.973***	−0.494***	−0.212***	−0.053	0.032	0.126***
Δ SPOT	0.379	−2.141	−1.113	−0.271	1.211	0.175	0.371	1.134
Δ S&P 500	0.014	0.013	0.012	0.000	0.003	−0.002	0.000	−0.003
Δ WTI oil	−0.025	−0.022	−0.006	−0.003	0.128*	0.094	0.003	−0.054
Wavelet series D1								
VIX	0.349***	0.332***	0.303***	0.356***	0.378***	0.397***	0.363***	0.382***
Δ SPOT	1.560***	2.198**	0.479***	0.060	−0.056	0.600**	1.483**	1.622
Δ S&P 500	0.015***	0.019***	0.019***	0.014***	0.011***	0.009***	0.014***	0.015***
Δ WTI oil	−0.048***	−0.073***	−0.059***	−0.037	−0.022	−0.026***	−0.048**	−0.048
Wavelet series D2								
VIX	0.480***	0.494***	0.476***	0.494***	0.484***	0.498***	0.456***	0.500***
Δ SPOT	0.260	0.567	0.517	−0.563	−0.713*	0.363	0.395	0.465
Δ S&P 500	−0.014***	−0.013**	−0.014	−0.011***	−0.009***	−0.013***	−0.012***	−0.014*
Δ WTI oil	−0.070***	−0.070	−0.017	−0.014	−0.002	−0.008	−0.020	−0.076
Wavelet series D3								
VIX	0.444***	0.382***	0.328***	0.319***	0.321***	0.332***	0.384***	0.472***
Δ SPOT	0.748	4.158	1.748	1.901**	0.294	−0.145	−3.072*	−3.691
Δ S&P 500	−0.061***	−0.078***	−0.065***	−0.045***	−0.034***	−0.043***	−0.06***	−0.064***
Δ WTI oil	−0.193***	−0.217	−0.087	−0.076**	−0.117***	−0.103***	−0.111*	−0.219**
Wavelet series D4								
VIX	0.154***	0.076	0.102***	0.125***	0.117***	0.137***	0.089***	0.094
Δ SPOT	−6.763***	−16.886***	−0.977	5.744***	5.420	6.901	7.387**	−2.780
Δ S&P 500	−0.091***	−0.115***	−0.080***	−0.059***	−0.040***	−0.053***	−0.096***	−0.154***
Δ WTI oil	−0.001	0.319*	0.151**	−0.031	−0.081*	0.046	0.137	0.394*
Wavelet series D5								
VIX	−0.099***	−0.079**	−0.050**	−0.045***	0.007	−0.014	−0.018	−0.075*
Δ SPOT	6.820***	18.576	26.711***	14.295***	10.704***	10.801***	4.303***	−6.173
Δ S&P 500	−0.174***	−0.230***	−0.177***	−0.125***	−0.122***	−0.130***	−0.157***	−0.219***
Δ WTI oil	1.145***	1.674***	1.163***	0.606***	0.540***	0.512***	1.161***	2.238***

Note. This table displays coefficient estimates of the OLS, quantile, and the Symplets 2 wavelet quantile regression for the influence of VIX on CDX.NA.IG. VIX (Chicago board options exchange volatility index) denotes the investor fear proxy. CDX.NA.IG denotes the differences of the composite spread and theoretical spread for the North America Investment Grade index. ***, **, and * denote the statistical significance at 1%, 5%, and 10% levels, respectively.

6. Conclusions

In this study, we shed some light on the impact of the equity market sentiment, measured by SE and VIX, on the high-yield and investment-grade CDS markets by implementing quantile and wavelet quantile regression approach. Advantageous in providing a detailed review of time-scale decomposition and conditional distribution, the wavelet quantile regression approach enables exploring the influence of equity market sentiment on the CDS markets through various time horizons and under different market conditions.

The main findings of our study are summarized as follows. First, the empirical evidence first shows that the investor sentiment in the equity market does have a spillover impact on the credit market. Specifically, investor attitude turning optimistic has a negative influence on the composite-theoretical spread difference while the aggravation of fear among equity market will enlarge the deviation of the CDS spread from intrinsic value and thereby increase the irrational component in the CDS prices. Second, the influence of the investor sentiment on the high-yield credit market is much larger than that on the investment-grade credit market, indicating that default risk is more difficult to evaluate, and speculation behavior is more active in the high-yield credit market. Third, we find that even though the equity market sentiment impact on the credit market lasts from short term to long term, the degree of this impact first increases and then decreases. In other words, although participants in the credit markets respond to the investor attitude promptly, it takes two to three weeks for them to react to the investor attitude in the equity market completely. Correspondingly, participants in the credit markets respond to the degree of fear by 2 to 4 business days, which is much more rapid than the response to the investor attitude. Lastly, the greater the deviation of CDS spreads from intrinsic value is, the more irrational the CDS market participants are, indicating that the influence of investor sentiment on the CDS market is self-reinforced, which is why the investor sentiment influence first increases and then decreases as time horizon extends. The regression analyses reach similar results based on different wavelet family decomposition such as the Daubechies and the Symlets, further giving credence to our findings.

Our study has implications for financial institutions and investors. First, the CDS markets are not completely efficient market, and thus investing merely depending on the theoretical value is not desirable. Taking into account the variation of investor sentiment in the equity market could aid in more accurate trading decisions. In addition, financial institutions and investors should respond more promptly to fear than to optimistic attitude, since the influence of fear spread much faster than the influence of investor attitude. They should also pay more attention to investor sentiment in the high-yield market than that in the investment-grade market, as the influence of investor sentiment on the high-yield credit market is much larger than that on the investment-grade credit market.

Meanwhile, several important policies are derived from the findings for policy makers. In the beginning, policy makers should closely monitor the depression of investor sentiment and the degree of fear in the equity market since they have a spillover influence on the CDS market. As the CDS market undertakes the function of credit insurance, the equity market sentiment impact on the CDS market might deteriorate the whole financial markets. However, policy makers ought to be more aware of the financial bubbles in the credit market since investor sentiment turning optimistic could enlarge the deviation of the CDS spread from the intrinsic value.

Data Availability

The data supporting the conclusions of this study are available on request.

Additional Points

Highlights. (i) Wavelet quantile regression is used to examine the influence of equity market sentiment on the CDS market. (ii) Investor attitude turning optimistic has a negative influence on the CDS spread deviation, while the intensification of fear enlarges this deviation. (iii) The influence of equity market sentiment first increases and then decreases as time horizon lengthens. (iv) The influence of equity market sentiment on the CDS market is self-reinforced.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was supported by the National Social Science Fund of China (Grant no. 22BTJ023) and the National Natural Science Foundation of China (Grant no. 71671062).

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