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The Impact of Debt Structure on Future Stock Price Crash Risk: Evidence from Egypt

Abstract

The main objective of the study is to determine the extent impact of debt structure proxies on future stock price crash risk and its different measures in order to mitigate stock price crash risk and help investors to understand better crash risk consequences and modify their investing behavior. Additionally, it is a guide for regulators to better achieve the credit market and to create an intact credit protection system. The study was conducted on a sample of (13) firms representing (40.6%) of the total number of the real estate sector firms listed in the Egyptian Stock Exchange during the period from 2013 to 2019.

The empirical results concluded that firms with high each of trade credit ratio, net trade credit ratio, trade credit to bank credit ratio, and debt structure characteristics have a lower stock price crash risk which was measured as negative conditional skewness of weekly returns, down-to-up volatility, and aggregate stock price crash risk. As for the control variables namely average weekly returns, financial leverage, and return on total assets were negatively significant for all three measures of stock price crash risk. Whilst, the firm size was a positively significant impact on stock price crash risk. While the study indicated that there was an insignificant impact of the bank credit ratio and the control variables namely investor heterogeneity, returns volatility, and market-to-book ratio on stock price crash risk measures in the future. The study also presented valuable recommendations to increase the different monitoring roles of the debt structure proxies in decreasing opportunistic behaviors and alleviating the likelihood of future stock price crash risk in Egypt which finally leads to rationalizing stakeholders' decisions.

Keywords: crash risk, debt structure, bank credit, trade credit.

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تأثير هيكل الديون على مخاطر إنهيار أسعار الأسهم المستقبلية: أدلة من مصر

ملخص البحث

يتمثل الهدف الأساسى للدراسة فى تحديد مدى تأثير هيكل الديون على مخاطر انهيار أسعار الأسهم المستقبلية ومقاييسها المختلفة بغرض الحد من مخاطر انهيار أسعار الأسهم ومساعدة المستثمرين على فهم عواقب مخاطر الانهيار بشكل أفضل وتعديل سلوكهم الاستثماري. فضلاً عن تقديم دليل للمنظمين لوجود سوق ائتمانى أفضل وإنشاء نظام سليم للحماية الائتمانية. وقد أجريت الدراسة على عينة مكونة من (١٣) شركة تمثل (٤٠.٦٪) من إجمالي عدد شركات قطاع العقارات المقيدة في سوق الأوراق المالية المصرى خلال الفترة من ٢٠١٣ م إلى ٢٠١٩ م.

وقد خلصت نتائج الدراسة إلى أن الشركات التي لديها نسبة عالية من الائتمان التجاري، صافي الائتمان التجاري، الائتمان التجاري إلى الائتمان المصرفي، وخصائص هيكل الديون لديها انخفاض فى مخاطر انهيار أسعار الأسهم والتي تم قياسها من خلال معامل الالتواء السالب للعوائد غير العادية الأسبوعية، التقلبات من أسفل إلى أعلى، ومخاطر انهيار أسعار الأسهم الإجمالية. أما بالنسبة للمتغيرات الحاكمة والتى تتمثل فى متوسط العوائد الأسبوعية، الرافعة المالية، ومعدل العائد على الأصول فقد كانت ذات تأثيراً سلبياً على المقاييس الثلاثة لمخاطر انهيار أسعار الأسهم. فى حين كان لحجم الشركة تأثيراً إيجابياً على مخاطر انهيار أسعار الأسهم. بينما أشارت نتائج الدراسة إلى عدم وجود تأثيراً معنوياً لنسبة الائتمان المصرفي والمتغيرات الحاكمة التى تتمثل فى تباين سلوك المستثمرين، وتقلبات العوائد، ونسبة القيمة السوقية إلى القيمة الدفترية على مقاييس مخاطر انهيار أسعار الأسهم المستقبلية.

كما قدمت الدراسة عدد من التوصيات لزيادة الدور الرقابى لهيكل الديون في تقليل السلوك الانتهازى والحد من مخاطر انهيار أسعار الأسهم المستقبلية في مصر مما يؤدي إلى ترشيد قرارات أصحاب المصالح.

الكلمات المفتاحية: مخاطر الانهيار، هيكل الديون، الائتمان المصرفي، الائتمان التجاري.

1. Introduction

The firm-specific future stock price crash risk (hereafter crash risk) can be defined as the probability of sudden but infrequent large price drops in stock price, or an extreme crash in stock value which finally leads to a severe drop in shareholder's wealth (Zhu, 2016; Dang et al., 2018; Cheng et al., 2020). Likewise, it can be defined as the negative skewness in the firm's return distributions or the likelihood of great negative outliers occurring in the firm's return distributions (Habib & Hasan, 2017a; Li et al., 2017; Kim et al., 2019). Additionally, it is considered one of the important risks for firms and stakeholders as it affects the decision making and the risk management of the firm (DeFond et al., 2015; Dang et al., 2018). Thus there is a great increase in attention in understanding the crash risk, as it explains an important part of the amount of change in equity (Gabaix, 2012). It is also considered an essential determinant of the expected returns of the firm (Conrad et al., 2013).

In order to mitigate the crash risk, exploring the factors that affect the likelihood of crash risk has become an important research topic of the capital market participants and becomes a hot theme of academic studies. The debt structure is considered one of the primary monitoring mechanisms that have an effect on crash risk. Following prior studies, the current study notes that Egyptian studies have not paid attention to exploring the role of debt structure, especially those related to bank credit, trade credit, net trade credit, trade credit to bank credit ratio, and debt structure characteristics that may affect on crash risk. So this study seeks to fill this gap by examining how debt structure affects crash risk in the Egyptian environment.

Many prior studies dealt with the nature of the relationship between debt structure proxies and the crash risk, but it was noted that there was a difference between the results of prior studies about the nature of this relationship. Bailey et al. (2011), Xu et al. (2014), and Zi-chao et al. (2018) revealed that the procedures of bank credit are strictly based on contracts between banks and firms which give banks the ability to obtain valuable information by monitoring borrowers and constrain any managers' opportunistic behavior. Besides, McMil-lan

& Woodruff (1999) and Cuñat (2007) documented that Suppliers have strongly motivated to effectively monitor their buyers, they constrain the buyer's opportunistic behavior by menacing to assemble trade credit quickly or finishing business relationships. Moreover, Cao et al. (2018) reported that the firms relying on bank credit and trade credit are also more motivated to improve their governance and information disclosure in order to obtain better bank credit and maintain a long-term relationship with their suppliers and better access to external finance sources. In the same vein, Wang (2017), Liu et al. (2018), and Kao et al. (2018) indicated that debt structure proxies have a negative impact on the crash risk.

On the contrary, Petersen &Rajan (1997) and Raman & Shahrur (2008) reported that suppliers may resort to being permissive in order to preserve a long-term relationship with buyers to achieve lower selling costs and improve operating performance from a stabilized relationship with their buyers. Moreover, Cohen & Frazzini (2008) and Kolay et al. (2016) suggested that suppliers may give concessions to buyers by increasing trade credit which enables them to continue hiding bad news leading to rising crash risk. Whilst, Goto et al. (2015) revealed that the low of the informational advantage of bank credit because banks can only get their borrowers' information about cost, while they can't able to get information about selling activities. In a similar vein, Zichao et al. (2018) reported that debt structure proxies are positively associated with the crash risk.

In the light of the previous discussion, it was observed that there was a difference between the results of prior studies about the relationship between debt structure and crash risk, which requires the necessity of studying and analyzing the relationship between debt structure and crash risk in the Egyptian environment which may differ from the foreign environment. Hence, the current study seeks to fill this gap in order to shine new light on this debate as to whether debt structure alleviates or aggravates crash risk for Egyptian firms.

Accordingly, the current study seeks to answer the following questions to demonstrate more attention about the extent impact of debt structure proxies on the crash risk measures of the real estate sector firms listed in the Egyptian stock exchange:

- What the extent impact of bank credit on crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange?
- To what extent trade credit impact significantly on the crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange?
- What the extent impact of net trade credit on crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange?
- To what extent trade credit-to-bank credit ratio impact significantly on the crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange?
- What the extent impact of debt structure characteristics on crash risk measures of the real estate sector firms listed in the Egyptian Stock Ex-change?

Based on the above questions the current study seeks to realize the following main objectives:

- Determining the extent impact of bank credit on crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange.
- Detecting the significant impact of trade credit on crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange.
- Identifying the extent impact of net trade credit on crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange.
- Describing the significant impact of trade credit-to-bank credit ratio on crash risk measures of the real estate sector firms listed in the Egyptian Stock Ex-change.
- Exploring the extent impact of debt structure characteristics on crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange.

The contribution of this study is mainly revealed in the following aspects: Firstly, it extended on firm-specific crash risk by detecting the role of a new factor such as debt structure in alleviating crash risk. Where the association between debt structure and crash risk has not been examined from the Egyptian perspective. And the current study results indicated that debt structure Influences significantly on crash risk. Secondly, it has several practical implications for different stakeholders, especially to investors. Where most prior studies focus on the implications of debt structure for suppliers and banks, but the current study clarifies the implications of debt structure for investors who try to avoid crash risk and can help them to understand better crash risk consequences and modify their investing behavior. So this study empirically testing the stock market consequences of debt structure by determining the extent impact of debt structure proxies on crash risk measures. Thirdly, conducting the Empirical study on the real estate sector in Egypt, which is considered one of the most important economic sectors in terms of investments, employment, and contribution to the GDP.

The remainder of the study is designed as follows: Section 2 reviews the relevant literature and hypothesis development. While, section 3 describes the empirical methodology represented in sample selection and data source, variables measurement, and model specification. Furthermore, section 4 discusses the empirical results. Finally, the study conclusion presents in section 5.

2. Relevant literature and Hypothesis Development

2.1. Literature Review

2.1.1. Stock price crash risk

Following the prior literature, crash risk can be realized in two groups. The first group relates to the speedy and sudden movement of the stock price, where the crash risk can be defined as the probability of sudden but infrequent large price drops in stock price, or an extreme crash in stock value that causes a severe drop in shareholder's wealth (Zhu, 2016; Dang et al., 2018; Cheng et al., 2020). Whereas, the second group relates to the shape of the return distributions, where the crash risk can be defined as the negative skewness in firm's return distributions or the likelihood of great negative outliers occurring in the firm's return distributions (Habib & Hasan, 2017a; Li et al., 2017; Kim et al., 2019).

Given the importance of this negative risk for firms and stakeholders, numerous previous studies have tried to forecast crash risk by trying to relate it to both internal and external control mechanisms. Where studies on internal mechanisms indicated that crash risk is positively related to each of the tax avoidance (Kim et al., 2011a), managerial equity incentives (Kim et al., 2011b), excess perks consumption (Xu et al., 2014), financial reporting opacity (Hutton et al., 2009; Callen & Fang, 2015), real earnings management (Francis et al., 2016), CEO stock option incentives, board size and inside directors' ownership (Andreou et al., 2016; Park et al., 2018), capable managers (Habib & Hasan, 2017b), earnings smoothing (Chen et al., 2017; Khurana et al., 2018), and overconfident CEOs (Kim et al., 2016; Harper et al., 2020). On the other hand, prior studies revealed a number of determinants that alleviate crash risk, such as corporate social responsibility (Kim & Li, 2014), accounting conservatism (Kim & Zhang, 2016), fair value disclosures (Hsu et al., 2018), and strength of internal control (Chen et al., 2017; Kim et al., 2019).

Similarly, prior studies on external mechanisms reported a number of determinants that mitigate crash risk, such as the institutional investors (Callen & Fang, 2013; Xiang et al., 2019), auditor industry specialization (Robin & Zhang, 2014), the mandatory adoption of International Financial Reporting Standards (IFRS) (DeFond et al., 2015), auditor tenure (Callen & Fang, 2017), trade credit financing (Cao et al., 2018), short-term debt (Dang et al., 2018), and the level of debt financing (Wang et al., 2019). On the other hand, Xu et al. (2013) explored that analyst coverage increases crash risk. Further, Chang et al. (2017) and Chauhan et al. (2017) showed that stock liquidity raises crash risk. Finally, Zichao et al. (2018) indicated that the ratio of trade credit to bank loan also is positively associated with crash risk.

Although the above studies clarified several internal and external controlling mechanisms affecting the likelihood of crash risk, they have not tested the role of debt structure, especially those related to bank credit, trade credit, net trade credit, trade credit to bank credit ratio, and debt structure characteristics, that effect on crash risk. So the current study tends to fill this gap.

2.1.2. Debt structure

The debt structure can be categories into two main sources which are the internal sources and the external sources. The internal sources are common stock, retained earnings, reserves, and preference stock. While, the external sources are bank credit, trade credit, and bonds. The current study focuses particularly on bank credit and trade credit in order to better access the extent of their impact on crash risk. As the percentage of firms bond usage is relatively small, it was excluded in this study about debt structure.

Banks are planning a system that includes agreements and warranty to confirm that they can efficiently monitor borrowers after transactions with firms (Zichao et al., 2018). Byers et al. (2008) referred that bank credit leads to more monitoring of their borrowers. And it is useful for banks to explore and monitor borrowers as they can provide valuable information to the markets (Bailey et al., 2011). Furthermore, Banks incentivize these firms to increase their governance and information disclosure in order to obtain better bank credit. Consequently, banks are acting a positive and helpful role in corporate governance.

As for an informal financing method, trade credit represents the second most essential source of external financing when there is a lack of bank credit (Danielson & Scott, 2004; Saiz et al., 2017). It can be regarded as a short-term financing source (Wu et al., 2012; Chen et al., 2019). It also indicates to the practice of customers financing their operations by deferring disbursements to suppliers (Cao et al., 2018). For instance, Levine et al. (2018) referred that trade credit reached 25% of the firm's total debt in a sample contained 3500 firms in 34 countries during the period 1990-2011.

There are differences between bank credit and trade credit in terms of default risk, monitoring cost, interest rate (Lin et al., 2013; Wu et al., 2014). The cost of trade credit is higher than bank credit due to the higher interest rate in trade credit compared to bank credit. Although it's high cost, trade credit is widely used because of its flexibility and the inability of many firms to obtain bank credit

(Danielson & Scott, 2004), especially, in developing economies where formal finance is insufficient and informal finance is predominant (Lin & Chou, 2015).

As argued by Petersen and Rajan (1997) that suppliers may get information at a low cost, and the information that suppliers usage in monitoring reimbursement appears to be unlike that be used by banks. As such, Jain (2001) explored that suppliers' information advantage will decrease the monitoring cost of trade credit. Moreover, Danielson & Scott (2004) documented that firms can find it less costly to delay trade credit payments comparing with the payment terms of bank credit. Further, Cunat (2007) reported that suppliers have a relative advantage over banks in loaning to customers because suppliers have the capacity to halt providing intermediate goods. Finally, Liu et al. (2018) also explained that trade credit can mitigate buyers' asymmetric information problems comparing with bank credit. On the contrary, Zichao et al. (2018) indicated that suppliers may have motivations to monitor borrowers but the information they could obtain is restricted. Hence, it is too costly for suppliers to monitor as they are not qualified financial institutions. So, the information asymmetry between firms and creditors may be fairly high, particularly when managers are motivated to hoard bad news and gain special advantages.

2.2. Hypothesis development

2.2.1. Bank credit and stock price crash risk

Bank credit is one of the external monitoring mechanisms that have a significantly negative impact on crash risk. Where, the procedures of bank credit are strictly based on contracts between banks and firms which give banks the ability to produce detailed information by monitoring their borrowers which leads to constraining any managers' opportunistic behavior (Bailey et al., 2011; Zichao et al., 2018). Hence, A reduction in managerial opportunism will decrease crash risk consistent with the results of previous studies (e.g., Kim et al., 2011a,b; Xu et al., 2014). Furthermore, the firms relying on bank credit are also financially constrained. Hence, Banks incentivize these firms to improve their governance and information disclosure in order to obtain better bank credit (Bailey et al., 2011). For example, Aintablian and Roberts (2000) reported a significant positive effect of bank credit disclosure on borrower's stock price performance in the future. In the same vein, Harvey et al. (2004) concluded that there was a significantly positive correlation between bank credit disclosure and abnormal returns on borrower's stock for the emerging markets. Thus, the reduction in information asymmetry will reduce crash risk consistent with the results of (Hutton, et al., 2009).

On the other hand, banks can only get information about cost, while they can't able to get their borrowers' information about selling activities compared to trade credit (Biais & Gollier, 1997; Goto et al., 2015). As a result, banks can't mitigate borrowers' asymmetric information problems to a larger extent than trade credit. Consequently, there is a positive relationship between bank credit and crash risk due to the low informational advantage of bank credit.

As such, it was observed that there was a difference between the results of prior studies about the relationship between bank credit and crash risk, which requires the necessity of studying and analyzing the relationship between bank credit and crash risk in the Egyptian environment which may differ from the foreign environment, Thus, this study postulates the main hypothesis as follow:

H_1: The bank credit impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange.

2.2.2. Trade credit and stock price crash risk

Trade credit plays a role as one of the external monitoring mechanisms that have a significantly negative impact on crash risk. Suppliers who lend trade credit have strongly motivated to effectively monitor their buyers, they constrain the buyer's opportunistic behavior by menacing to gather trade credit quickly or finishing business relationships (McMillan & Woodruff, 1999; Cuñat, 2007). Thus, a reduction in managerial opportunism will reduce crash risk. By the same token, the findings of prior studies (e.g., Kim et al., 2011a,b; Xu et al., 2014) showed that crash risk is positively associated with managerial opportunism.

Likewise, the firms relying on trade credit are also more motivated to improve their governance and information disclosure in order to preserve a long-term relationship with their suppliers and better access to external finance sources (Cao et al., 2018). For instance, Aktas et al. (2012) find that the use of trade credit can alleviate information asymmetry, and there is a significantly positive relationship between the use of trade credit and firm value. Goto et al. (2015) also showed that trade credit extension reveals information to suppliers and reduce the degree of information asymmetry. Hence, the reduction in information asymmetry will reduce crash risk (Hutton et al., 2009). Besides, the result of Cao et al. (2018) indicated that firms using more trade credit have a significantly lower crash risk for a sample of Chinese firms. In a similar vein, empirical results of McGuinness et al. (2018) showed that trade credit has a positive impact on firm survival for a sample of SMEs across 13 European countries. Additionally, the conclusions of Liu & Hou (2019) suggested that firms with more trade credit reflect lower stock price synchronicity for a sample of Chinese firms.

On the other hand, suppliers may resort to being permissive in order to sustain a stabilized and long-term relationship with buyers to achieve lower selling costs and improve operating performance (Petersen and Rajan, 1997; Raman and Shahrur, 2008). In the same vein, the results of Cohen & Frazzini (2008) and Kolay et al. (2016) suggested that suppliers may not tend to exert monitoring when buyers are withholding negative information about their financial position for avoiding a decrease of firm value. Additionally, suppliers may give concessions to buyers by increasing trade credit which enables buyers to continue hiding bad news which finally leads to rising crash risk.

In the light of the previous discussion, it was observed that there was a difference between the results of prior studies about the relationship between trade credit and crash risk, which requires the necessity of studying and analyzing the relationship between trade credit and crash risk in the Egyptian environment which may differ from the foreign environment, Thus, this study postulates the main hypothesis as follow:

H_2: The trade credit impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange.

H_3: The net trade credit impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange.

2.2.3. Trade credit to bank credit ratio and stock price crash risk

According to the prior studies, external monitoring mechanisms have a significant impact on crash risk. From the aspect of bank credit, banks could reject the firm's demand for debt when their trade credit was high and used it as a sign of weakness in a firm's business (Danielson & Scott, 2004). In a similar vein, the Study of Zichao et al. (2018) indicated that the monitoring mechanisms of trade credit are weaker than bank credit, and ineffective monitoring could raise the crash risk as managerial opportunistic behaviors are not easy to be detected. It also concluded that the ratio of trade credit to bank credit is positively associated with the crash risk for a sample of Chinese firms.

On the contrary, the procedures of trade credit are simpler and more financial flexibility than bank credit (Danielson & Scott, 2004). Some studies (e.g., Burkart & Ellingsen, 2004; Fabbri & Menichini, 2010; Murfin & Njoroge, 2015) indicated that trade credit suppliers may have informational and monitoring advantages over bank credit. In the same vein, the study of Cuñat (2007) suggested that suppliers have a relative advantage over banks in loaning to buyers because suppliers have the capacity to halt providing intermediate goods.

In the light of the previous discussion, it was observed that there was a difference between the results of prior studies about the relationship between trade credit-to-bank credit ratio and crash risk, which requires the necessity of studying and analyzing the relationship between trade credit-to-bank credit ratio and crash risk in the Egyptian environment which may differ from the foreign environment, Thus, this study postulates the main hypothesis as follow:

H_4: The trade credit–to–bank credit ratio impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange.

H_5: The debt structure characteristics impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange.

3. Empirical Methodology

3.1. Sample selection and data source

The initial sample of the study includes all firms of the real estate sector listed in the Egyptian Stock Exchange during the period of 2013-2019. It is worth observing that the sample period for the debt structure and control variables were from 2013 to 2018, while for crash risk measures were from 2014 to 2019, where the study needs the debt structure and control variables in period (t) to predict the crash risk in period (t+1). Following prior studies (e.g., Chauhan et al., 2017; Dang et al., 2018; Cao et al., 2019), the study excluded the following aspects: Firstly, firms with fewer than 26 trading weeks of stock return data. Secondly, firms with negative total assets and book values of equity. Thirdly, firms with year-end stock prices below one pound. Fourthly, firms with financial statements that were not issued in Egyptian pound. Fifthly firms that were not issued their annual financial statements on 31 December. Sixthly, firms with insufficient financial data for constructing crash risk measures and those with missing values for the debt structure and control variables. Finally, the study's final sample includes (13) firms representing (40.6%) of the total number of the real estate sector firms listed in the Egyptian Stock Exchange. The required data were extracted from the firms' annual financial statements, the Egyptian Stock Exchange, and Investing database.

3.2. Variables Measurement

3.2.1. Stock price crash risk

According to prior studies on crash risk (e.g., Jia, 2018; Ben-Nasr & Ghouma, 2018; Bai et al., 2019), this study employs three measures as dependent variables based on the weekly stock return for each firm on the current week and two weeks forward and backward estimated as residuals from using the following market model (Jin & Myers, 2006; Jia, 2018):

$$R_{it} = \alpha_i + \beta_{1i} R_{m\,(t-2)} + \beta_{2i} R_{m\,(t-1)} + \beta_{3i} R_{mt} + \beta_{4i} R_{m\,(t+1)} + \beta_{5i} R_{m\,(t+2)} + \varepsilon_{it}$$

Where R_{it} is the stock return of firm (i) at week (t), whereas R_m is the value-weighted market return at week (t), while ε_{it} is the random error implies to the stock extremely return of firm (i) at week (t), and (W_{it}) is the extremely negative weekly return for firm (i) at week (t), which calculated as the natural logarithm of one plus the stock extremely return, i.e. ln $(1+\varepsilon_{it})$.

The first measure of crash risk is the negative conditional skewness of weekly returns during the current year symbolized by (Y_1), which is calculated as the negative of the third moment of weekly returns for each firm at a year divided by the standard deviation of weekly returns raised to the third power. As such, (Y_1) for the firm (i) at year (t) is measured by the equation below (Harper et al., 2020):

$$Y_{1it} = -\,[n(n-1)^{3/2}\sum W^3_{it}] \,/\, [(n-1)(n-2)(\sum W^2_{it})^{3/2}]$$

Where W_{it} is the extremely negative weekly return and n is the number of weekly returns during the current year (t).

The second measure of crash risk is down-to-up volatility symbolized by (Y_2), which is measured by the natural logarithm of the ratio of the standard deviation of weekly stock returns (W_{it}) during the "down" weeks (i.e., the weeks in which W_{it} is lower than its annual means) divided by the standard deviation of weekly stock returns (W_{it}) during the "up" weeks (i.e., weeks in which W_{it} is higher than its annual means). Particularly, (Y_2) for the firm (i) at year (t) is computed as the equation below (Habib et al., 2018):

$$Y_{2it} = \log\,[(n_{up}-1)\sum_{Down} W^2_{it}] / [(n_{Down}-1)\sum_{up} W^2_{it}]$$

Where n_{up} and n_{Down} are the number of up and down weeks at year (t) respectively.

The third measure of crash risk is aggregate crash risk symbolized by (Y), which is measured separately computed for firms by the negative conditional skewness of weekly returns and down-to-up volatility, based on Gaio & Raposo (2011), Sodan (2015) methodology. First, firms are ranked according to each of the two individual measures of crash risk. Then aggregate crash risk measure is computed for each firm by averaging its ranking over the two individual crash risk measures. The aggregate measure of crash risk for firms is derived from the following equation:

$$Y_{it}=[Rank\ (Y_{1it})+Rank\ (Y_{2it})]/2$$

Where Y_{it} is the aggregate crash risk of the firm (i) at year (t), whereas Rank (Y_{1it}) is the ranks of the negative conditional skewness of weekly returns of the firm (i) at year (t), while Rank (Y_{2it}) is the ranks of the down-to-up volatility of the firm (i) at year (t).

3.2.2. Debt structure

Following prior studies (e.g., Fisman & Love, 2003; Ge & Qiu, 2007; Lin & Chou, 2015; Zichao et al., 2018; McGuinness et al., 2018; Chen et al., 2019), the current study used the proxies of debt structure as independent variables in order to demonstrate their impact on the crash risk of firms listed in Egyptian Stock Exchange. Accordingly, the bank credit ratio symbolized by (X_1) is measured by the sum of Short-term bank loans and long-term bank loans divided by total assets. While, the trade credit ratio symbolized by (X_2) is calculated as the sum of accounts payable and notes payable, divided by total assets. Whilst, the net trade credit ratio symbolized by (X_3) is computed as the sum of accounts payable and notes payable minus the sum of accounts receivable and notes receivable scaled by total assets. Moreover, the trade credit to bank credit ratio symbolized by (X_4) equals Trade credit to bank credit. Finally, this study employed a dummy variable symbolized by (X_5) to describe the characteristics of debt Structure, Which equals one if the trade credit to bank credit ratio is above the median and zero otherwise.

3.2.3. Control variables

The control variables are the probable determinants that may influence the relationship between debt structure and crash risk. According to prior studies (e.g., Yuan et al., 2016; Habib & Hasan, 2017b; Li et al., 2017; Cao et al., 2018; Yeung & Lento, 2018; Hsu et al., 2018; Sun et al., 2019; Cao et al., 2019) the current study includes seven common control variables; it includes investor heterogeneity symbolized by (Z_1) to control for the change in the turnover ratio which measured by the difference between the average monthly stock turnover in the year (t) and the average monthly stock turnover in the year (t-1), where monthly stock turnover is calculated as the monthly trading volume divided by the total number of stock outstanding during the month. As for past returns, this study includes average weekly returns during the year symbolized by (Z_2) to control for past returns computed as the sum of weekly returns during the year divided by the number of weeks that achieved returns during the year. Furthermore, this study also controls for returns volatility symbolized by (Z_3) which equals the standard deviation of weekly returns during the year.

Additionally, this study adds firm Size symbolized by (Z_4) to control for size effect equals the natural logarithm of total assets. Whilst, this study control for financial leverage symbolized by (Z_5) which measured by total liabilities divided by total assets. Further, this study control for operating performance by return on total assets symbolized by (Z_6) defined as net income scaled by total assets.

While, this study control for Market-to- book ratio symbolized by (Z_7) calculated as the ratio of the market value of equity to book value of equity. Detailed descriptions and measurement of all variables used in study analysis are provided in Appendix A.

3.3. Model specification

The study investigates whether the debt structure proxies will influence on crash risk measures which are negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk, this can be designed by the empirical regressions models as follows:

$$Y_1 = B_0 + B_1X_1 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (1)$$

$$Y_2 = B_0 + B_1X_1 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (2)$$

$$Y = B_0 + B_1X_1 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (3)$$

$$Y_1 = B_0 + B_1X_2 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (4)$$

$$Y_2 = B_0 + B_1X_2 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (5)$$

$$Y = B_0 + B_1X_2 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (6)$$

$$Y_1 = B_0 + B_1X_3 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (7)$$

$$Y_2 = B_0 + B_1X_3 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (8)$$

$$Y = B_0 + B_1X_3 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (9)$$

$$Y_1 = B_0 + B_1X_4 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (10)$$

$$Y_2 = B_0 + B_1X_4 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (11)$$

$$Y = B_0 + B_1X_4 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (12)$$

$$Y_1 = B_0 + B_1X_5 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (13)$$

$$Y_2 = B_0 + B_1X_5 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (14)$$

$$Y = B_0 + B_1X_5 + B_2Z_1 + B_3Z_2 + B_4Z_3 + B_5Z_4 + B_6Z_5 + B_7Z_6 + B_8Z_7 + E_{it} \quad (15)$$

4. Empirical Results

4.1. Data validity test

The extent validity of the study data for statistical analysis can be examined by testing the normal distribution of study variables. Additionally, testing the extent existence of the multicollinearity problem in the study model. Moreover, testing the extent existence of the autocorrelation problem that may affect the accuracy of the study model results. This can be demonstrated as follows:

4.1.1. The normal distribution test

For testing whether the study variables follow the normal distribution, the study relied on the Kolmogorov-Smirnov and Shapiro-Wilk tests. Where the variables follow the normal distribution if the significant value (Sig.) is more than 0.05 (Pallant, 2016). This can be clarified in the table (1) as follows:

Table 1: Results of the normal distribution test

Variable		Kolmogorov-Smirnov		Shapiro-Wilk	
		Statistic	Sig.	Statistic	Sig.
Y_1	Negative conditional skewness of weekly returns	.065	.200	.990	.814
Y_2	Down-to-up volatility	.069	.200	.985	.507
Y	Aggregate crash risk	.099	.056	.950	.057
X_1	Bank credit ratio	.384	.000	.581	.000
X_2	Trade credit ratio	.307	.000	.491	.000
X_3	Net trade credit ratio	.141	.001	.869	.000
X_4	Trade credit to bank credit ratio	.467	.000	.226	.000
Z_1	Investor heterogeneity	.301	.000	.519	.000
Z_2	Average weekly returns	.050	.200	.987	.596
Z_3	Returns volatility	.192	.003	.943	.002
Z_4	Firm Size	.093	.041	.966	.037
Z_5	Financial leverage	.259	.000	.504	.000
Z_6	Return on total assets	.171	.000	.882	.000
Z_7	Market -to- book ratio	.365	.000	.345	.000

The results in the table (1) indicated that the significance values for the Kolmogorov-Smirnov and Shapiro-Wilk tests less than 0.05 which reflects that the study variables did not follow the normal distribution except for negative conditional skewness of weekly returns, down-to-up volatility, aggregate crash risk, and average weekly returns which showed the significance values more than 0.05 and so follow the normal distribution. In accordance with the debt structure characteristics variable, it has not been included in the normal distribution test because it is a dummy variable with binary values not subject to the conditions of the normal distribution.

4.1.2. Multicollinearity test

The study relied on the multicollinearity test to detect the extent existence of the multicollinearity problem in the study model, as this problem leads to the weakness of the study model's ability to explain the effect on the dependent variable. The study used the collinearity diagnostics measure to identify the values of Variance Inflation Factor (VIF) and Tolerance. If the VIF value is less than (10) and the Tolerance value is greater than (0.05), this indicates that there is no multicollinearity problem in the study model (O'Brien, 2007). This can be explained in the table (2) as follows:

Table 2: Results of multicollinearity test

Variable		Collinearity Statistics	
		Tolerance	VIF
X_1	Bank credit ratio	.767	1.303
X_2	Trade credit ratio	.702	1.425
X_3	Net trade credit ratio	.493	2.030
X_4	Trade credit to bank credit ratio	.469	2.134
X_5	Debt structure characteristics	.434	2.302
Z_1	Investor heterogeneity	.778	1.285
Z_2	Average weekly returns	.873	1.145
Z_3	Returns volatility	.627	1.595
Z_4	Firm Size	.485	2.063
Z_5	Financial leverage	.842	1.187
Z_6	Return on total assets	.792	1.263
Z_7	Market -to- book ratio	.859	1.165

The results in the table (2) revealed that VIF values for all study variables are less than (10), and Tolerance values are greater than (0.05), which refers that the multicollinearity problem not existed and the study model's ability in explaining the effect on crash risk.

4.1.3. Autocorrelation test

The study relied on the autocorrelation test to detect the extent existence of the autocorrelation problem in the study model, as this problem leads to an un-real impact of the independent variables on the dependent variable. This test was conducted using the Durbin Watson value (D-W). If this value ranges between (1.5: 2.5), this indicates that there is no autocorrelation problem in the study model (Basheer, 2003). As such, the results of conducting the autocorrelation test reported that (D-W) value was (2.161), which is within the specified range of the test which refers to the non-existence of the autocorrelation problem between the study variables.

4.2. Descriptive statistics

The study relied on the descriptive analysis by dividing the study variables in-to Continuous variables and Interval variables through panel A and panel B. This can be illustrated in the table (3) as follows:

Table 3: Descriptive statistics

Panel A: Continuous variables					
Variable		**Min**	**Max**	**Mean**	**Std. Dev.**
Y_1	Negative conditional skewness of weekly returns	-2.48	1.65	-0.218	0.873
Y_2	Down-to-up volatility	-0.67	0.63	-0.087	0.304
Y	Aggregate crash risk	3.00	77.00	39.500	22.197
X_1	Bank credit ratio	0.00	0.28	0.041	0.079
X_2	Trade credit ratio	0.00	1.14	0.083	0.165
X_3	Net trade credit ratio	-1.28	0.53	-0.084	0.257
X_4	Trade credit to bank credit ratio	0.00	56.76	1.751	8.077
Z_1	Investor heterogeneity	-1.15	0.76	-0.014	0.174
Z_2	Average weekly returns	-0.02	0.02	-0.001	0.008
Z_3	Returns volatility	0.03	0.09	0.053	0.012
Z_4	Firm size	16.98	25.29	20.494	2.153
Z_5	Financial leverage	0.00	6.26	0.622	0.962
Z_6	Return on total assets	-0.03	0.19	0.052	0.054
Z_7	Market -to- book ratio	-18.63	58.90	1.955	7.588

Panel B: Interval variables					
Variable		**(1)**		**(0)**	
		Frequency	**%**	**Frequency**	**%**
X_5	Debt structure characteristics	6	7.7	72	92.3

The results in the table (3) presented the descriptive statistics for all variables used in the regressions for the entire sample. The mean value of negative conditional skewness of weekly returns (Y_1) was (-0.218) with a minimum and a maximum (-2.48, 1.65) respectively, which was similar to that reported by Li et al. (2017), Cao et al. (2018), and Jebran et al. (2020) where reached (-0.205, -0.243, -0.243) respectively, but negative conditional skewness of weekly returns was slightly higher than figures indicated by Park & Song (2018) and Xiang et al. (2019) where reached (-0.471, -0.532) respectively. Additionally, the mean value of down-to-up volatility (Y_2) was (-0.087) with a minimum and a maximum (-0.67, 0.63) respectively, which was similar to that shown by Andreou et al. (2017) and Dang et al. (2018) where reached (-0.104, -0.055) respectively, but down-to-up volatility was slightly higher than figures revealed by Xu et al. (2014) and Sun et al. (2019) Where reached (-0.273, -0.200) respectively. While the mean value of aggregate crash risk (Y) was (39.500) with a minimum and a maximum (3.00, 77.00) respectively.

Moreover, the mean of the bank credit ratio (X_1) was (0.041) with a minimum and a maximum (0.00, 0.28) respectively. This value was lower than the figures reported by Mateut & Chevapatrakul (2018) and Chen et al. (2019) where reached (0.106, 0.363) respectively. While the mean of trade credit ratio (X_2) was (0.083) with a minimum and a maximum (0.00, 1.14) respectively, which was similar to that presented by Aktas et al. (2012) and Cao et al. (2018) where reached (0.082, 0.076) respectively, but trade credit ratio is lower than figures shown by Wang (2017) and Chen et al. (2019) where reached (0.357, 0.251) respectively. Furthermore, the mean of the net trade credit ratio (X_3) was (-0.084) with a minimum and a maximum (-1.28, 0.53) respectively, which was consistent with the reported value (-0.106) by Mateut & Chevapatrakul (2018), but the net trade credit ratio is lower than the figure revealed by Lin & Chou (2015) where reached (-0.013).

Whereas, the mean of the trade credit to the bank credit ratio (X_4) was (1.751) with a minimum and a maximum (0.00, 56.76) respectively, which was lower than the reported value (3.799) in the study of Zichao et al. (2018). As for the interval variable, which was represented in the debt structure characteristics (X_5), it was found that the percentage of firms that included an increase in the trade credit to bank credit ratio compared to the average during the study period reached (6) observations by (7.7%), while the number of observations that included a decrease in the trade credit to bank credit ratio compared to the average during that period (72) observations by (92.3%).

The descriptive statistics for the control variables further reported that the mean value of investor heterogeneity (Z_1) was (-0.014) with a minimum and a maximum (-1.15, 0.76) respectively, which was close to figures revealed by Li & Cai (2016) and Deng et al. (2018) where reached (-0.010, -0.023) respecttively, but investor heterogeneity was higher than figures indicated by Chauhan et al. (2017) and Jebran et al. (2020) where reached (-0.050, -0.059) respectively. However, the average weekly returns (Z_2) was (-0.001) with a minimum and a maximum (-0.02, 0.02) respectively, which was quite similar to figures presented by Wang (2017) and Park & Song (2018) where reached (-0.001, -0.002) respectively, but the average weekly returns was higher than figures reported by Andreou et al. (2017) and Yeung & Lento (2018) where reached (-0.076, -0.079) respectively.

In addition, the mean value of the returns volatility (Z_3) was (0.053) with a minimum and a maximum (0.03, 0.09) respectively, which was consistent with the figures shown by Jia (2018) and Sun et al. (2019) where reached (0.053, 0.051) respectively, but the returns volatility is lower than figures indicated by Deng et al. (2018) and Hsu et al. (2018) where reached (0.066, 0.060) respectively. Whilst, the mean value of the firm size (Z_4) was (20.494) with a minimum and a maximum (16.98, 25.29) respectively, which was similar to the figures revealed by Ben-Nasr & Ghouma (2018) and Chen et al. (2019) where reached (20.877, 21.189) respectively, but the firm size is higher than figures reported by Davydov (2016) and Wu & Hu (2019) where reached (14.400, 16.627) respectively.

Moreover, the mean value of the financial leverage (Z_5) was (0.622) with a minimum and a maximum (0.00, 6.26) respectively, which was consistent with the figures documented by Davydov (2016) and Zichao et al. (2018) where reached (0.650, 0.527) respectively, but the financial leverage was higher than figures documented by Habib & Hasan (2017a) and Cao et al. (2018) where reached (0.170, 0.229) respectively. While, the mean value of the return on total assets (Z_6) was (0.052) with a minimum and a maximum (-0.03, 0.19) respectively, which was quite similar to the figures reported by Li et al. (2017) and Wang et al. (2019) where reached (0.051, 0.050) respectively, but the return on total assets was higher than figures revealed by Deng et al. (2018) and Harper et al. (2020) where reached (0.026, 0.037) respectively. Furthermore, the mean of the market -to- book ratio (Z_7) was (1.955) with a minimum and a maximum (-18.63, 58.90) respectively, which was similar to the figures provided by Li et al. (2017) and Jebran et al. (2020) where reached (1.816, 2.249) respectively, but the market -to- book ratio was lower than figures shown by Jia (2018) and Wang et al. (2019) where reached (3.615, 3.750) respectively.

4.3. The impact of bank credit on future stock price crash risk

The study relied on the regression analysis for detecting the extent impact of bank credit on crash risk measures especially negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk. This can be illustrated by the table (4) as follows:

Table 4: Regression analysis results for the impact of bank credit on future stock price crash risk measures

Variable		Model (1): Y_1		Model (2): Y_2		Model (3): Y	
		B	Sig.	B	Sig.	B	Sig.
X_1	Bank credit ratio	-0.152	.185	-0.194	.342	-8.793	.173
Z_1	Investor heterogeneity	-0.154	.484	-0.014	.532	-2.325	.457
Z_2	Average weekly returns	-57.624	.000	-24.621	.000	-1728.243	.000
Z_3	Returns volatility	-1.144	.497	0.294	.511	5.068	.580
Z_4	Firm size	0.015	.033	0.012	.003	0.507	.042
Z_5	Financial leverage	-0.052	.014	-0.037	.019	-2.372	.002
Z_6	Return on total assets	-1.729	.003	-0.313	.158	-23.056	.036
Z_7	Market -to- book ratio	0.003	.426	-0.002	.147	-0.016	.555
Constant		-0.419	.351	-0.356	.371	28.868	.344
Measurements to assess the accuracy of crash risk							
R		.536		.688		.646	
R^2		28.8%		47.3%		41.8%	
Adj. R^2		20.5%		41.2%		35.5%	
d.f.		(8,69)		(8,69)		(8,69)	
$F_{Stat.}$		7.485		10.741		9.193	
$F_{Tab.}$		2.77		2.77		2.77	
Sig.		.002		.000		.000	

The results in the table (4) reported that the existence insignificant impact of the bank credit ratio on each of the negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk as the significance values were (.185, .342, .173) respectively. This result reflected that there is an insignificant impact of the bank credit ratio on crash risk measures in the future.

Furthermore, the results in the table (4) also suggested that the coefficients of the control variables such as average weekly returns, financial leverage, and return on total assets were negatively significant for all three models, which were consistent with the results of Wang (2017), and Cheng et al. (2020). Whilst, the results reported that the coefficient of firm size was positively significant, which was similar to that presented by Jia (2018), and Cheng et al. (2020). While, the coefficients of others variables such as investor heterogeneity, returns volatility, and market -to- book ratio were insignificant at all three models, which was consistent with that concluded by Wang (2017), Ben-Nasr & Ghouma (2018), and Cao et al. (2019).

Additionally, it concluded from the results for assessing the accuracy of the regression models (1), (2), and (3) that the values of the multiple correlation coefficient reached (.536, .688, .646) respectively, it was also noted that the values of R^2 that reached (28.8%, 47.3%, 41.8%) respectively were consistent with the values of the Adjusted R^2 that reached (20.5%, 41.2%, 35.5%) respectively, which indicates that the size of the study sample was appropriate for the analysis and dissemination of results, as well as the model accuracy and independence of the factors affecting the crash risk. Moreover, the statistical calculated values of F reached (7.485, 10.741, 9.193) respectively, which were higher than the value of F tabulated which amounted to (2.77). Also, the results revealed that the regression models were highly significant as the significance values were (0.002, 0.000, 0.000) respectively.

So as a result, the bank credit ratio impact insignificantly each of negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk, accordingly, it can be accepted the first hypothesis related to "The bank credit impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange".

4.4. The impact of trade credit on future stock price crash risk

The study depended on the regression analysis for testing the extent impact of trade credit on crash risk measures such as negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk. This can be explained by the table (5) as follows:

Table 5: Regression analysis results for the impact of trade credit on future stock price crash risk measures

Variable		Model (4): Y_1		Model (5): Y_2		Model (6):Y	
		B	Sig.	B	Sig.	B	Sig.
X_2	Trade credit ratio	-0.343	.001	-0.333	.041	-7.060	.008
Z_1	Investor heterogeneity	-0.175	.455	-0.021	.498	-3.054	.413
Z_2	Average weekly returns	-57.161	.000	-24.774	.000	-1730.005	.000
Z_3	Returns volatility	-0.895	.519	0.345	.497	11.691	.554
Z_4	Firm size	0.017	.024	0.015	.002	0.657	.036
Z_5	Financial leverage	-0.062	.009	-0.032	.039	-2.254	.001
Z_6	Return on total assets	-1.948	.000	-0.375	.092	-29.913	.027
Z_7	Market -to- book ratio	0.002	.573	-0.004	.143	-0.057	.445
Constant		-0.491	.309	-0.394	.321	25.574	.399
Measurements to assess the accuracy of crash risk							
R		.540		.686		.648	
R^2		29.1%		47.1%		41.9%	
Adj. R^2		20.9%		41 %		35.2%	
d.f.		(8,69)		(8,69)		(8,69)	
$F_{Stat.}$		6.544		10.688		9.233	
$F_{Tab.}$		2.77		2.77		2.77	
Sig.		.002		.000		.000	

The results in the table (5) indicated that the trade credit ratio has a negative and significant coefficient with each of negative conditional skew-ness of weekly returns, down-to-up volatility, and aggregate crash risk as the regression coefficients were (-0.343, -0.333, -7.060) respectively, at significant (.001, .041, .008) respectively. This result revealed that firms with high trade credit ratio have a lower crash risk in the following period, because of Suppliers have strongly motivated to effectively monitor their buyers, so they constrain the managers' opportunistic behavior by menacing to assemble trade credit quickly or finishing business relationships. Additionally, the firms relying on trade credit are also more motivated to improve their governance and information disclosure in order to keep a long-term relationship with their suppliers and better access to external finance sources. This result was consistent with the results of Wang (2017), Cao et al. (2018), and Liu & Hou (2019) that reached existence a negative and significant impact of the trade credit ratio on crash risk measures.

Overall, it revealed from the results for assessing the accuracy of the regression models (4), (5), and (6) that the values of the multiple correlation coefficient reached (.540, .686, .648) respectively, it was also noted that the values of R^2 that reached (29.1%, 47.1%, 41.9%) respectively were agreement with the values of the Adjusted R^2 that reached (20.9%, 41%, 35.2%) respectively. Furthermore, the statistical calculated values of F reached (6.544, 10.688, 9.233) respectively, which were greater than the value of F tabulated which amounted to (2.77). Additionally, the results suggested that the regression models were highly significant as the significance values were (0.002, 0.000, 0.000) respectively.

To sum up, the trade credit ratio has a negatively significant impact on each of negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk, consequently, it can be rejected the second hypothesis related to "The trade credit impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange".

4.5. The impact of net trade credit on future stock price crash risk

The study relied on the regression analysis for identifying the extent impact of net trade credit on crash risk measures which are negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk. This can be clarified by the table (6) as follows:

Table 6: Regression analysis results for the impact of net trade credit on future stock price crash risk measures

Variable		Model (7): Y_1		Model (8): Y_2		Model (9): Y	
		B	**Sig.**	**B**	**Sig.**	**B**	**Sig.**
X_3	Net trade credit ratio	-0.363	.004	-0.324	.040	-7.853	.006
Z_1	Investor heterogeneity	-0.261	.249	-0.026	.478	-4.933	.308
Z_2	Average weekly returns	-57.638	.000	-24.815	.000	-1739.998	.000
Z_3	Returns volatility	-0.183	.584	0.408	.479	35.303	.463
Z_4	Firm size	0.036	.032	0.016	.014	1.007	.025
Z_5	Financial leverage	-0.051	.024	-0.031	.042	-2.028	.017
Z_6	Return on total assets	-2.039	.008	-0.373	.092	-32.136	.019
Z_7	Market -to- book ratio	0.005	.534	-0.004	.148	-0.046	.468
Constant		-0.888	.533	-0.418	.331	16.879	.606
Measurements to assess the accuracy of crash risk							
R		.543		.686		.650	
R^2		29.5%		47.1%		42.3%	
Adj. R^2		21.4%		41%		35.6%	
d.f.		(8,69)		(8,69)		(8,69)	
$F_{Stat.}$		6.614		10.688		9.315	
$F_{Tab.}$		2.77		2.77		2.77	
Sig.		.001		.000		.000	

The results in the table (6) revealed that the net trade credit ratio has a negative and significant coefficient with each of negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk as the regression coefficients were (-0.363, -0.324, -7.853) respectively, at significant (.004, .040, .006) respectively. This result showed that firms with higher net trade credit ratio are related with lower crash risk in the subsequent period, because of effectively monitor managers by Suppliers, besides, the firms' desire to maintain a long-term relationship with their suppliers and better access to external finance sources, which was similar to that revealed by Cao et al. (2018).

In addition, it exposed from the results for assessing the accuracy of the regression models (7), (8), and (9) that the values of the multiple correlation coefficient reached (.543, .686, .650) respectively, it was also noted that the values of R^2 that reached (29.5%, 47.1%, 42.3%) respectively were agreement with the values of the Adjusted R^2 that reached (21.4%, 41%, 35.6%) respectively. Moreover, the statistical calculated values of F reached (6.614, 10.688, 9.315) respectively, which were higher than the value of F tabulated which amounted to (2.77). Also, the results documented that the regression models were highly significant as the significance values were (0.001, 0.000, 0.000) respectively.

Overall, the net trade credit ratio has a negatively significant impact on each of negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk, accordingly, it can be refused the third hypothesis related to "The net trade credit impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange".

4.6. The impact of trade credit to bank credit ratio on future stock price crash risk

The study depended on the regression analysis for testing the extent impact of trade credit to bank credit ratio on crash risk measures such as negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk. This can be demonstrated by the table (7) as follows:

Table 7: Regression analysis results for the impact of trade credit to bank credit ratio on future stock price crash risk measures

Variable		Model (10): Y_1		Model (11): Y_2		Model (12): Y	
		B	Sig.	B	Sig.	B	Sig.
X_4	Trade credit to bank credit ratio	-0.010	.002	-0.303	.007	-0.194	.029
Z_1	Investor heterogeneity	-0.139	.403	-0.016	.522	-2.328	.456
Z_2	Average weekly returns	-58.000	.000	-24.942	.000	-1746.529	.000
Z_3	Returns volatility	-1.751	.442	0.164	.550	5.074	.580
Z_4	Firm size	0.017	.043	0.015	.009	0.653	.042
Z_5	Financial leverage	-0.057	.018	-0.032	.038	-2.158	.012
Z_6	Return on total assets	-1.744	.015	-0.362	.092	-25.640	.028
Z_7	Market -to- book ratio	0.007	.409	-0.004	.176	-0.006	.583
Constant		-0.420	.747	-0.392	.318	27.070	.368
Measurements to assess the accuracy of crash risk							
R		.544		.690		.650	
R^2		29.6%		47.6%		42.2%	
Adj. R^2		21.5%		41.5%		35.5%	
d.f.		(8,69)		(8,69)		(8,69)	
$F_{Stat.}$		6.630		10.831		9.297	
$F_{Tab.}$		2.77		2.77		2.77	
Sig.		.001		.000		.000	

The results in the table (7) reported that the trade credit to bank credit ratio has a negative and significant coefficient with each of negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk as the regression coefficients were (-0.010, -0.303, -0.194) respectively, at significant (.002, .007, .029) respectively. This result reflected that firms with high trade credit to bank credit ratio have a lower crash risk in the future, which conflicts with the result of Zichao et al. (2018) that concluded the existence of a positive and significant impact of the trade credit to bank credit ratio on crash risk measures.

Generally, it provided from the results for assessing the accuracy of the regression models (10), (11), and (12) that the values of the multiple correlation coefficient reached (.544, .690, .650) respectively, it was also noted that the values of R^2 that reached (29.6%, 47.6%, 42.2%) respectively were consistent with the values of the Adjusted R^2 that reached (21.5%, 41.5%, 35.5%) respectively. Further, the statistical calculated values of F reached (6.630, 10.831, 9.297) respectively, which were more than the value of F tabulated which amounted to (2.77). Additionally, the results referred that the regression models were highly significant as the significance values were (0.001, 0.000, 0.000) respectively.

To sum it all up, the trade credit to bank credit ratio has a negatively significant impact on each of negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk, consequently, it can be rejected the fourth hypothesis associated with "The trade credit-to-bank credit ratio impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange".

4.7. The impact of debt structure characteristics on future stock price crash risk

The study relied on the regression analysis for the purpose of assessing whether debt structure characteristics impact significantly crash risk measures particularly negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk. This can be illustrated by the table (8) as follows:

Table 8: Regression analysis results for the impact of debt structure characteristics on future stock price crash risk measures

Variable		Model (13): Y_1		Model (14): Y_2		Model (15): Y	
		B	Sig.	B	Sig.	B	Sig.
X_5	Debt structure characteristics	-0.406	.003	-0.432	.000	-8.218	.012
Z_1	Investor heterogeneity	-0.165	.366	-0.024	.484	-2.847	.424
Z_2	Average weekly returns	-57.172	.000	-24.704	.000	-1730.342	.000
Z_3	Returns volatility	-1.065	.503	0.351	.493	8.166	.568
Z_4	Firm size	0.023	.032	0.017	.005	0.769	.034
Z_5	Financial leverage	-0.060	.013	-0.033	.037	-2.210	.007
Z_6	Return on total assets	-1.657	.022	-0.337	.120	-23.923	.036
Z_7	Market -to- book ratio	0.007	.405	-0.004	.179	-0.009	.586
Constant		-0.558	.668	-0.438	.263	24.239	.420
Measurements to assess the accuracy of crash risk							
R		.550		.696		.653	
R^2		30.3%		48.4%		42.7%	
Adj. R^2		22.2%		42.4%		36 %	
d.f.		(8,69)		(8,69)		(8,69)	
F_{Stat}.		6.745		11.096		9.420	
F_{Tab}.		2.77		2.77		2.77	
Sig.		.001		.000		.000	

The results in the table (8) showed that the coefficients related to a dummy variable which refers to the debt structure characteristics in the regression models (13), (14), and (15) were negative as the coefficients were (-0.406, -0.432, -8.218) respectively at significant (.003, .000, .012) respectively. This result indicated that firms with trade credit to bank credit ratio above the median have a lower crash risk in the future, which conflicts with the result of Zichao et al. (2018) that revealed the existence of a positive and significant impact of the debt structure characteristics on crash risk measures.

Moreover, it concluded from the results for assessing the accuracy of the regression models (13), (14), and (15) that the values of the multiple correlation coefficient reached (.550, .696, .653) respectively, it was also noted that the values of R^2 that reached (30.3%, 48.4%, 42.7%) respectively were agreement with the values of the Adjusted R^2 that reached (22.2%, 42.4%, 36 %) respectively. Further, the statistical calculated values of F reached (6.745, 11.096, 9.420) respectively, which were higher than the value of F tabulated which amounted to (2.77). Also, the results showed that the regression models were highly significant as the significance values were (0.001, 0.000, 0.000) respectively.

So as a result, the debt structure characteristics have a negatively significant impact on each of negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk, consequently, it can be rejected the fifth hypothesis related to "The debt structure characteristics impacts insignificantly on future stock price crash risk measures of the real estate sector firms listed in the Egyptian Stock Exchange".

5. Conclusion

This study investigated the impact of debt structure proxies on crash risk measures which are negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk. Accordingly, the current study examined the extent impact of bank credit on crash risk. Furthermore, scrutinized the significant impact of trade credit on crash risk. Additionally, explore the extent impact of net trade credit on crash risk. Moreover, identified the significant impact of trade credit-to-bank credit ratio on crash risk. Finally, tested the extent impact of debt structure characteristics on crash risk.

Using a sample includes (13) firms representing (40.6%) of the total number of the real estate sector firms listed in the Egyptian Stock Exchange during the period of 2013-2019. The findings reflected that there was an insignificant impact of the bank credit ratio on each of the negative conditional skewness of weekly returns, down-to-up volatility, and aggregate crash risk. While, the study found strong evidence that firms with high trade credit ratio have lower crash risk measures in the following period. The study also found that the net trade credit ratio has a highly negative and significant impact on all three measures of crash risk. Additionally, the results revealed that the trade credit to bank credit ratio has a negative and significant impact on each of the crash risk measures. Further evidence suggested that firms with trade credit to bank credit ratio above the median referring to the debt structure characteristics have lower crash risk measures in the future.

Lastly, the results indicated that the control variables such as average weekly returns, financial leverage, and return on total assets were negatively significant regarding all three measures of crash risk. Whilst, the firm size was a positively significant impact on stock price crash risk. While, other variables such as investor heterogeneity, returns volatility, and market -to- book ratio were not significant at all.

The current study contributes to the existing literature on the determinants of crash risk. Where the study focuses on the different monitoring roles of the debt structure proxies in effecting crash risk and presents new evidence on the economic consequences of the debt structure in decreasing the opportunistic behaviors such as the negative information hoarding, which finally leads to lower crash risk in the following period. Additionally, the study will be valuable to investors who need to recognize the crash risk in the Egyptian Stock Exchange and avoid this risk by using the debt structure information disclosed in financial statements and modify their investing behavior. Furthermore, it is a guide for regulators to better achieve the credit market and to create an intact credit protection system.

However, the main limitation of the current study is the restraining of the sample in the real estate sector firms listed in the Egyptian Stock Exchange. So future studies include the following several aspects: Firstly, conducting more studies in other economic sectors such as basic resources, healthcare and pharmaceuticals, trade and distributors, and banks in order to determine the extent of the difference between those sectors about the impact of the debt structure on crash risk. Secondly, assessing the impact of ownership structure on crash risk and its reflects on the firm's value. Thirdly, detecting the impact of many factors such as stock liquidity, managerial ability, corporate governance, and financial reports quality on crash risk in the Egyptian environment. Finally, investigating the relationship between Accounting Conservatism and the debt structure proxies of firms listed in the Egyptian Stock Exchange.

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Appendix A.

Descriptions and Measurement of variables.

Variable		Measurement	Reference
Dependent Variables			
$\mathbf{Y_1}$	Negative conditional skewness of weekly returns.	The negative of the third moment of weekly returns divided by the standard deviation of weekly returns raised to the third power.	(Gao, et al., 2017) (Harper, et al., 2020)
$\mathbf{Y_2}$	Down-to-up volatility	Natural logarithm of the ratio of the standard deviation of weekly stock returns during the "down" weeks divided by the standard deviation of weekly stock returns during the "up" weeks.	(Kim & Li, 2014) (Habib, et al., 2018)
Y	Aggregate crash risk	The sum of the ranks of negative conditional skewness of weekly returns and the ranks of down-to-up volatility over two.	(Gaio & Raposo, 2011) (Sodan, 2015)
Independent Variables			
$\mathbf{X_1}$	Bank credit ratio	The sum of Short-term bank loans and long-term bank loans scaled by total assets.	(McGuinness, et al., 2018) (Chen, et al., 2019)
$\mathbf{X_2}$	Trade credit ratio	The sum of accounts payable and notes payable, scaled by total assets.	(Dai & Yang, 2015) (Chen, et al., 2019)
$\mathbf{X_3}$	Net trade credit ratio	The sum of accounts payable and notes payable minus the sum of accounts receivable and notes receivable	(Lin & Chou, 2015) (Cao, et al., 2018)

		scaled by total assets.	
X_4	Trade credit to bank credit ratio	Trade credit over bank credit.	(Zichao, et al., 2018)
X_5	Debt structure characteristics	A dummy variable that equals 1 if trade credit to bank credit ratio is above the median and 0 otherwise.	(Zichao, et al., 2018)
Control variables			
Z_1	Investor heterogeneity	The average monthly share turnover in year $_{(t)}$ minus the average monthly share turnover in year $_{(t-1)}$.	(Yuan, et al., 2016) (Cao, et al., 2019)
Z_2	Average weekly returns	The sum of weekly returns during year over the number of weeks that achieved returns during the year.	(Habib & Hasan, 2017) (Dang, et al., 2018)
Z_3	Returns volatility	The standard deviation of weekly returns during the year.	(Chen, et al., 2017) (Sun, et al., 2019)
Z_4	Firm size	The natural logarithm of total assets.	(Li, et al., 2017) (Jia, 2018)
Z_5	Financial leverage	Total liabilities over total assets.	(Gao, et al., 2017) (Yeung & Lento, 2018)
Z_6	Return on total assets	Net income over total assets.	(Park & Song, 2018) (Cao, et al., 2018)
Z_7	Market -to- book ratio	Market value of equity over book value of equity.	(Hsu, et al., 2018) (Zichao, et al., 2018)