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The Effects of Financial Ratios on the Perceived Risk Count for Single Equity VIX

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Abstract

The determinants of fear gauge from March 2005 to September 2019 are empirically examined with attention to the single equity volatility index (VIX). This study utilized Poisson and Negative Binomial Regressions to investigate the link between perceived risk count and its variables at certain levels of quantiles. The Negative Binomial model was chosen based on the highest log-likelihood value and the lowest the Akaike information criterion (AIC) value to analyze the market psychology condition of investors. The result of the return on equity (ROE), cash conversion cycle (CCC), and dividend payout ratio (DPR) are negatively significant in both medium and higher quantile of perceived risk count. The debt ratio and free cash flow (FCF) positively affect the perceived risk count. The impacts of variables on higher quantile have a greater influence on perceived risk count, followed by medium quantile.

JEL classification numbers: G32.
Keywords: Perceived Risk Count, Equity VIX, Poisson and Negative Binomial Regressions.

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1. Introduction

The role played by the volatility index (VIX), so-called fear gauge or fear index, was launched by The Chicago Board of Exchange (CBOE) in 1993. It was increasingly capturing the attention of hedgers and speculators for their trading demand regarding optimism or anxiety. (Gang and Li, 2014) In 2011, the Global Markets of CBOE had launched five single-equity VIX on Amazon, Apple, Goldman Sachs, Google, and IBM. CBOE started VIX futures and options on March 26, 2004, and February 24, 2006. The VIX index can be used to examine investor sentiment measured by the implied volatility of S&P 500 index options. (Bordonado, et al., 2017; Griffin and Shams, 2018) To explore overall uncertainty in the financial market, Robe and Wallen (2016) found that the better measurement for market sentiment for fear or risk was the equity VIX.

Market sentiment related to market psychology affects noise traders' behavior neglecting fundamental valuation and helps clarify the unexplained movement in market changes. According to Karagozoglu and Fabozzi (2017), regarding the investing strategies accompanied by investor sentiment captured from financial and social media databases, the performance of the VIX-Exchange-trade products (ETPs) was superior to a benchmark. For many potential investors and academic scholars, market sentiment measured by VIX was arbitrage opportunities persisting through time. Consistent with this, as sources of information attract attention, the information or opinions disclosed about earnings announcements were expected to outperform the consensus earnings.

Based on the timeframe, the behavior of the VIX can be classified by four types:

1. Short term: trends of intraday data.
2. Medium-term: mean-reverting of daily and weekly data.
3. Long term: staying in the range of monthly data.
4. Unusual term: big spikes for market crashes.

Specifically, the VIX plays the role of contrarian indicator, regarded as mean-reverting. It provides a buying signal when VIX excesses at a certain high level with investor stress up and then reverse downwards. On the other hand, a selling signal indicates that VIX drops below a certain low level, reflecting investor stress and then turns upwards.

Lee, et al. (2005) used the weighted price index of the Taiwan Stock Exchange (TAIEX) to create the volatility index (VXT) in order to seek a good contrarian indicator. The findings supported that the VXT behavior followed mean-reverting patterns. To hedge more efficiently for VIX futures, Kendrick (2012) suggested that the predictive importance of mean-reversion for VIX futures enabled investors to estimate their size positions and hedge remunerations.

Gang and Li (2014) revealed that the risk-returns behavior was connected with sentiment shifts and their changing scales. Fu, et al. (2016) found the relationship between changes in volatility risk and portfolio returns associated with the asymmetric effect. More recently, Ghulam (2019) investigated the multi-directional risk interactions assessed by VIX and VIX-like measures between emerging stock markets. The empirical results showed that there existed persistent and expedited risk transmission. Huang (2014) applied Grey Relational Analysis (GRA) and selected critical elements like the U.S. dollar index, trading index, Commodity Research Bureau (CRB) index. Using these elements as input factors through Artificial Neural Network (ANN) methods, the empirical study showed that Recurrent Neural Network (RNN) could perform with superior ability to predict individual equity VIX.

To the best of our knowledge, studies in the VIX as metrics of risk, mean reversion, or change of sentiment are mainly focused on the importance of stock market returns. However, they did not test the influence of critical financial ratios from the firm-level perspective. The study is motivated by this gap and explores the extent to which financial variables influence the perceived risk of investors proxied by count data of the individual equity VIX with a new approach to enhance insolvency research.

The phenomenon of market psychology for noise traders' behavior is a highly debated stock market issue. Consistent with the evidence of previous studies, which stated the lack of any link between the fear gauge and financial ratios at firm-level status. This study uses Poisson and Negative Binomial Regressions and aims to explore the relationship between perceived risk count and its determinants the certain levels to gain insight into the investors' market psychology condition.

The contribution of this study to the extant literature is that this work tests how the sentiment changes respond to the financial ratios at a firm level. This work incorporates perceived risk count and these financial ratios to understand the different influences at the different levels. This article uses the panel data from CBOE individual equity VIX and financial variables.

The rest of this study is structured as follows. Section two is a literature review, while Section three describes data and methodological approach. Section four presents the empirical results. Section five concludes the conclusion and limitations of this paper.

2. Literature Review

Many studies have long been fascinated by bankruptcy prediction through financial ratios. (Beaver, 1966; Altman, 1968; Ohlson; 1980; and Lennox; 1999) According to Altman's z-score method, the proposed ratios included in "working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value equity/book value of total liabilities, and sales/total assets" as a significant role for measuring credit risk. They found that financial ratios, such as the size, financial structure, performance, and current liquidity, are especially useful in evaluating insolvency predictive.

Ni, et al. (2014) followed a set of financial ratios established by Altman (1968) and Ohlson (1980) and found that the determinants such as liquidity and profit loss have a significant influence in predicting Chinese business failure. José and José (2015) applied z-score ratios and used discriminant analysis techniques for obtaining more accurate business default forecasting. Layla, et al. (2016) reported that a parsimonious Logit model dealt with the profitability ratio, the leverage ratio, and the cash flow ratios that can correctly predict corporate insolvency. Daniel (2016) incorporated the debt factor of Romanian companies and suggested that the debt ratio played an essential role in evaluating the risk levels two years in advance of bankruptcy.

The economists have been continually active in the causes of bank failure. Cooper et al. (1994) and Heffernan (2003) showed that human capital measures like personality, fraud, management deficiencies, or losing customer contact played an influencing role. The empirical literature on the testing probability of failing for U.S. banks has already been reviewed by Abrams and Huang (1987). They found that increased nonperforming loans have higher risk exposures, causing bank failure. It was also CAMEL (Capital Adequacy, Assets, Management Capability, Earnings, and Liquidity) examined by Henebry (1997) who revealed the significant effect of nonperforming loans on total loans on bank failure. Carlos, et al. (2014) revealed that banks' monitoring systems could be used to assess the bank's risk. Monitoring systems included "CAMELS (Capital Adequacy, Assets, Management Capability, Earnings, Liquidity and Sensitivity to Interest Rate Risk)" and "PEARLS (Protection, Effective Financial Structure, Asset Quality, Rates of Return and Costs, Liquidity and Signs of Growth)."

Chen and Chen (2011) used the CAMEL criteria to investigate off-site surveillance on bank rating changes connected with credit risk management procedures. The research results revealed that banks with higher capital to loan ratio and liquid asset ratio could upgrade the probability of long-term creditworthiness. An empirical study of risk analysis by Deni and Adnan (2012) revealed that the return on assets (ROA) was one of the leading causes of the probability of credit default. Glogova and Warnung (2006) used the Value-at-Risk (VaR) to assess credit risk. They measured the bank's economic capital and correlations among systematic risk factors for evaluating off-site banking analysis.

A growing empirical literature investigates whether VIX has impacted market or firm-level returns. Chen (2003) specified that changes in the implied volatility are of interest to investors as a means of measuring future market risk. The investigation, enhanced by Ang, et al. (2006), verified sensitivity changes as the perceived risk can be reflected in firms' returns. Dennis, et al. (2006) examined the relationship between implied volatilities for the S&P 100 equity index and the top 50 U.S firms and stock returns. They indicated that the negatively dynamic relation between stock returns and index volatility innovations existed. However, systematic market-wide factors were superior to aggregated firm-level effects in the asymmetric volatility phenomenon. Whaley (2009) concluded a strong negative concurrent relationship between VIX and stock market returns in the U.S and Europe.

3. Data

The quarterly data has been considered from the CBOE, which consists of five single equity VIXs. We have taken a perceived risk as the dependent variable. It classifies into three certain levels, such as lower (Q1), median (Q2), and higher (Q3) perceived risks based on the quantile. The association of independent and dependent variables (i.e., perceived risk count) is shown in Table 1.

This study collects quarterly data for all independent variables obtained from Macrotrends Net from March 2005 to September 2019. The CBOE data of five single equity VIXs, including Amazon, Apple, Goldman Sachs, Google, and IBM from Investing.com, is used for the following analysis. The independent variables used to estimate the impacts of the perceived risk count of the investor as measured by individual equity VIX are described in Table 1.

3.1 Financial Health

3.1.1 Z Score

The z score Model can help measure a company's financial health to predict financial distress status accurately. It may identify capability for operation and helps to lower the sentiment of the investor when evaluating insolvency. Foo (2015), Foo, et al. (2016), and Foo, et al. (2018) analyzed and compared the relationship between the financial health (z score) and corporate performance (the return on equity, ROE) for the manufacturing sector in China, Hong Kong, India, and Singapore. They found a positive association between ROE and z score, enhancing stakeholders' confidence in investment in these markets. Thus, the likelihood of perceived risk count is expected to decrease with increased financial health.

3.1.2 Tobin's Q

Raja and Kumar (2006) used the discriminate model to predict the probability of financial distress. They found that Tobin's Q value, which is higher than one firm have financially healthy, lowing the likelihood of insolvency. Kazemian, et al. (2017) indicated that firms with higher Tobin's are likely to have a better performance slowing down the possibility of financial distress. Thus, Tobin's Q improves financial health, probably reducing the perceived risk count.

Table 1: The List of dependent and independent variables

Variable	Notation	Formula	Sign
Perceived Risk Count	**RISK**	**Single equity VIX**	
Financial Health			
Z score	ZS	Altman's (1968) Z score= (1.2×A)+(1.4×B)+(3.3×C)+(0.6×D) +(1.0×E) A=Working Capital/ Total Assets B=Retained Earnings/ Total Assets C=Earnings Before Interest & Tax/ Total Assets D=Market Value of Equity/ Total Liabilities E=Sales/ Total Assets	-
Tobin's Q	TQ	Total Market Value /Total Asset Value	-
Technology Competition			
R&D Expenditure	RD	R&D expenditure	+/-
Leverage Finance			
Debt Ratio	DR	Total Debt/Total Asset	+
Financial Liquidity			
Cash Conversion Cycle *	CCC	CCC= DIO+DSO−DPO= DIO = Days of inventory outstanding = (Average Inventory/ Cost of Goods Sold)*365. DSO = Days sales outstanding = Average Account Receivable/ Revenue per day DPO = Days payables outstanding = Average Account Payable/ Cost of Goods Sold per day	-
Profitability			
Return on Equity	ROE	Net Income/ Equity	-
Return on Asset	ROA	Net Income/ Total Asset	-
Dividend Policy			
Dividend Payout Ratio	DPR	Dividend Paid/ Net Income	-
Company Value			
Price to Book Value	PBV	Market Stock Price/ Book Value	+
Cash management			
Free Cash Flow	FCF	FCF = Cash Flow from Operating Activities + Interest Expense -Tax Shield Capital Expenditure	+
Management Efficiency			
Total Asset Turnover Ratio	TAT	Total Sales/ Total Asset	-

Note: * The formula refers to Investopedia.
(www.investopedia.com/terms/c/cashconversioncycle.asp).

3.2 Technology Competition

3.2.1 R&D

Considering a linkage of Altman z score work, Toshiyuki and Mika (2009) revealed a positive relationship between R&D expenditure and the financial performance for the Japanese machinery industry due to its matured technology and low risk with less competition. However, a negative impact of R&D expenditure on the financial performance for the electric equipment industry because of the short life cycle product and aggressive global competition, causing a high risk for investment. Eisdorfer and Hsu (2011) indicated that firms underperformed in technology competition are more likely to file for bankruptcy due to severe technology competition dealing with operational risk and lowering profits and stock prices. Therefore, R&D expenditure may positively or negatively affect financial performance depending on industrial attributes, likely influencing perceived risk count leading to mixed results.

3.3 Leverage Finance

3.3.1 Debt Ratio

Daniel (2016) suggested that the debt ratio can provide a more reliable means for assessing leverage finance, and the results showed a positive relationship between leverage finance and the default risk. Fazzari, et al. (1988) revealed that firms faced with higher leverage have the likelihood of experiencing financial distress due to technical insolvency for repaying problems. The overuse of leverage due to an increased debt ratio will probably increase perceived risk count.

3.4 Financial Liquidity

3.4.1 Cash Conversion Cycle

Liquidity risk measured by the Cash Conversion Cycle (CCC) can reveal the status of the health of a firm reflecting on cash management policies. (Faris and Nassem, 2013) CCC formula considers the time spans required for a company to get cash flows from the production and sales process, such as inventory, account receivables, and bill payment. Iman, et al. (2014) indicated that the company's stakeholders experienced the financial distress risk under a negative CCC if firms were inefficiently dealing with surplus cash with an increase in credit. This paper investigates whether any significant relationship exists between CCC and the probability of the perceived risk count. The longer a firm's CCC, the likelihood of the worse situation of sentiment risk for stakeholders.

3.5 Profitability

3.5.1 Return on Equity and Return on Asset

Lina, et al. (2005) exerted a significantly negative relationship between various financial performances, such as return on equity (ROE) and return on asset (ROA), and insolvency risk index of Taiwanese banks. Likewise, Ikpesu and Eboiyehi

(2018) have concluded that asset tangibility and profitability added explanatory power for influencing financial distress negatively. This study hypothesizes that the higher the financial performance of probability, the lower the perceived risk count for investors.

3.6 Dividend Policy

3.6.1 Dividend Payout Ratio

In the light of signaling theory, Kale, et al. (1990) and Kapoor (2006) reported that dividend yields signal steady cash flows and a firm's future perspective. Jaara, et al. (2018) found that the negative relationship between dividend payout ratio and the default risk which relating to financial gearing to the operation (i.e., debt to equity ratio) and the risk measure (i.e., volatility measure of the ROA). Therefore, the hypothesis of dividend policy is likely to have a negative relationship with the perceived risk count.

3.7 Company Value

3.7.1 Price to book value

Price to book value (PBV) can be measured as an indicator of the company value in evaluating an overvalued or undervalued stock level for the stakeholders. (Marangu and Jagongo, 2014) The empirical results revealed a negative but statistically insignificant relationship between the distress risk and the book-to-market equity ratio because of market inefficiency. (Idrees and Qayyum, 2018) Therefore, there is still a need to enhance the empirical study to accurately measure the impact of PBV on sentiment shifts. This paper analyzes the role of company value in evaluating a positive relationship between PBV and perceived risk count. The stakeholders will probably avoid the high overvalued stock under the consideration of high risk.

3.8 Cash Management

3.8.1 Free Cash Flow

Jensen (1986) found that managers' opportunistic behavior such as over-investments and misusing capitals will likely optimize compensation if low-growth firms have greater FCF rushes risky activities. Thiruvadi, et al. (2016) confirmed that such activities in manipulating cash flow are likely related to increased internal auditing for controlling risk. In contrast, Finishtya (2019) supported the view that firms with good operating cash flow can probably avoid financial distress. Therefore, the relationship between free cash flow and perceived risk count remains ambiguous.

3.9 Management Efficiency

3.9.1 Total Asset Turnover Ratio

The empirical results of Khanna and Poulsen (1995) pointed out that incompetence and inefficient managerial decisions are the main reasons for financial difficulty, while managerial incentives fulfilling stockholder interests enhanced stock market reaction. Likewise, Evans, et al. (2014) reported that skilled CEOs familiar with businesses eager to perform excellently earn bonuses when satisfied stakeholders' needs. Ting (2011) indicated that the probability of a firm's default risk could be reduced by replacing top management. Santosuosso (2014) found a positive relationship between the total asset turnover ratio as proxies of management efficiency and profitability. The results provided a strong signal for the investor to evaluate firms' performance and react to financial distress by quickly divesting assets. Therefore, management efficiency would probably negatively influence the perceived risk count.

4. Methodology

This article used negative binomial distribution to check the significant effect of the variable. The normal distribution is not suitable for the data due to the violation of ordinary least square regression for error terms. This paper compared it with poison distribution to show the novelty of our method. To elaborate more, we discuss both Poison and Negative Binomial Regression and their maximum likelihood estimation procedure for parameters.

This paper uses the panel data to examine estimated counts by analyzing traffic accidents (Quddus, 2008; Wan, et al. 2011), auto insurance claims (David and Jemna, 2015), and loan defaults (Karlis and Rahmouni, 2007).

This empirical study uses the quarterly count number of each single equity VIX as the perceived risk count at the quartile. These count data have discontinuities and non-negative characteristics. Under the normal distribution assumption of the error term, the regression is not suitable. (Chen and Chen, 2002) Therefore, Poisson Regression and Negative Binomial Regression are more suitable for the occurrence pattern. The two models are as follows:

4.1 Poisson Regression

Assume that is the number for the quartile of VIX in the selected time range, and the independent observations of which are. The regression formula of the Poisson distribution probability function can be expressed as: (Greene, 1998; Chen and Chen, 2002).

$$Prob(Y_i = y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, y_i = 0,\ 1,\ 2,....., \qquad \lambda > 0, \tag{1}$$

where λ is the mean and variance of Poisson distribution, and y_i represent a dependent variable. The maximum likelihood of coefficients are as follows:

$$g(\lambda_i) = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k, \tag{2}$$

$$g(\lambda_i) = x_i \beta \,, \tag{3}$$

where β are coefficients.

4.2 Negative Binomial Regression

Due to the omission of variables, data incompleteness, and non-homogeneous, there is an overdispersion for the dependent variable. It leads to the contrary to the assumption of Poisson Regression for "the mean is equal to the variation" phenomenon. Therefore, this paper adopts Negative Binomial Regression for the analysis connected with different assumptions; that is, the variance is different from the mean. The conditional expression for the adjusted probability function model can have the formula:

$$\ln \lambda_i = \beta' x_i + \varepsilon_i \,. \tag{4}$$

Assume that the expected value of the residual follows a gamma distribution, with a mean of 1.0 and a variation of δ^2. Then, substituting the adjusted conditional expression (2) into the probability model can be expressed as:

$$Prob[Y_i = y_i | \varepsilon_i] = \frac{e^{-\lambda_i} \exp(\varepsilon_i) \lambda_i^{y_i}}{y_i!} \,, \tag{5}$$

$y_i = 0,1,2,3,\ldots..$,

The distribution formula under unrestricted conditions is:

$$Prob[Y_i = y_i] = \frac{\Gamma(\theta + y_i)}{[\Gamma(\theta + y_i!)] u_i^2 (1 - u_i)^{y_i}} \,, \tag{6}$$

where $u_i = \theta/(\theta + \lambda_i)$ and $\theta = 1/\alpha$. The variance is:

$$Var[y_i] = E[y_i]\{1 + \alpha E[y_i]\} \,, \tag{7}$$

The model dispersion is:

$$\frac{Var[y_i]}{E[y_i]} = 1 + \alpha E[y_i] \,. \tag{8}$$

4.3 Overdispersion Examination

In order to select a suitable model, the sample dispersion test proposed by (Cameron and Trivedi, 1990) was used. If the sample dispersion is too large and significant, H0 is rejected, and it is not suitable to use the Poisson Regression. A Negative Binomial Regression must be adopted. (Greene, 1998) The test assumptions are:

H_0 : $Var[y_i] = E[y_i]$ ……………………… (Poisson Regression),

H_1 : $Var[y_i] = E[y_i] + \alpha g(\mu_i)$ …………….. (Negative Binomial Regression),

where α stands for parameter value and $g(\mu_i) = \mu_i$ are the sample mean.

5. Results and Discussions

The log-likelihood value and the Akaike Information Criterion (AIC) can be used to determine the best-fitting model (Cleves et al., 2008; Chen and Chen, 2011). As shown in Table 2, the results of the best fitting model are obtained for two different tests. The Negative Binomial model was chosen based on the highest log-likelihood value and the lowest AIC value.

The results provide evidence of overdispersion in the Poisson model in all three quantiles. If we look at the coefficients, the t-ratio is 7.423 and 5.979 in Q3 (i.e., g=mui and g=mui2). Both the values are higher than the criteria value 2.32. Furthermore, similar results indicate that both t-ratio are greater than the criteria value on Q1 and Q2. We confirm that results do not support the Poisson model, and we will choose the Negative Binomial model for perceived risk evaluation in our study.

Table 2: Overdispersion test

	Q1	Q2	Q3
$g(u_i)$	6.987***	9.494***	7.423***
$g(u_i^2)$	6.481***	7.689***	5.979***
Log-likelihood	-469.906	-555.871	-659.672
AIC	3.038	4.123	5.421

Note: *, **, and *** denote 10%, 5% and 1% levels of significant for t ratio.

The empirical result of the Poisson model in Table 3 shows a statistically significant and positive relationship between perceived risk count and the variables like ZS, TQ, and TAT in all quantiles. The results revealed that the likelihood of the increases in financial health (ZS), Tobin's Q (TQ), and total asset turnover ratio (TAT) added explanatory power for influencing financial distress positively. This positive relationship with perceived risk count adds to the evidence presented by Nguyen and Nghiem (2015) and Giordana and Schumacher (2017). This study hypothesizes that the higher the probability of financial performance, the lower the perceived risk count for investors. However, these results are inconsistent with the hypothesis. The coefficient of ROA is a positive and significant effect on the Z score. It tends to imply that the capital-to-asset ratio is mainly responsible for the dynamics of the Z score. The decline in cost efficiency raises the risk of insolvency.

Silva and Majluf (2008) found that family-owned firms positively affect a firm's performance. This positive relationship enhances a firm's performance when using Tobin's Q. In addition, for the variable (TQ), the coefficient for external connections to a company is positive and significant, as Tobin's Q determines. It is beneficial to have extensive family involvement to decrease the risk and maintain a firm's performance, revealing the fewer risk of bankruptcy. Further, managers strive to decrease the likelihood of bankruptcy to improve business stability and protect their investment in firm-specific human capital. As a result, they may take steps to decrease company risk. On the other hand, Membroek (2002) and Nocco and Stulz (2006) confirmed that firms with a risk portfolio were better to make an appropriate strategy in the capital market for enhancing corporate's value.

The results for TAT provide evidence of a significant positive relationship with stock return presented by Patin et al. (2020). The results revealed that total asset turnover ratios significantly affect stock returns reflecting less risk. The significant results for DR and FCF for Q2 and Q3 are consistent with the hypothesis of this study. This finding adds to the evidence presented by Finishtya (2019). Free cash flow helps to improve the financial health of a firm and a higher probability of financial performance. These results show less risk between the FCF and perceived risk count. Beasley, et al. (2005) and Golshan and Rasid (2012) revealed that firms with increasing ROA had a higher risk awareness due to different regulatory requirements.

The statistically significant results negatively correlate with perceived risk count in the Poison model representing RD, CCC, ROE, DPR, and PBV in most results for Q2 and Q3. Even though earlier studies have confirmed that investing in research and development (R&D) improves a company's performance, Ahmed and Jinan (2011) and Antonelli (1989) found that there was a negative relationship between research and development (RD) expenditures and profitability when firms make innovative efforts. Their performance falls below a certain level. The findings indicated that the link between performance and R&D expenditure is not linear but is regulated by a firm's life cycle, which should be considered when determining policy based on market-risk-based performance. Based on the results of R&D expenditures may have both positive and negative impacts on perceived risk count for all five-single equity VIX. These results indicate that the equity VIX Amazon Apple, Google, Goldman Sachs, and IBM dominated the related field facing technology competition with less risk.

The return on equity (ROE) and Cash conversion cycle (CCC) are also negatively significant in both Q2 and Q3. It added to control for negatively influencing financial distress, consistent with this study's hypothesis. The significant results for DPR and PBV also provide evidence of a negative relationship with perceived risk count. These financial ratios are strong factors and give good news for investing in the equity VIX index.

Table 3: Estimation of Poisson Distribution

	Q1		**Q2**		**Q3**	
Variables	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
C	3.204	(0.000) ***	1.636	(0.000) ***	-1.654	(0.000) ***
ZS	0.098	(0.030) **	0.357	(0.000) ***	0.617	(0.000) ***
TQ	49.000	(0.004) ***	116.105	(0.000) ***	274.697	(0.000) ***
RD	-0.183	(0.104)	-0.690	(0.000) ***	-0.739	(0.002) ***
DR	-0.183	(0.108)	1.774	(0.000) ***	4.755	(0.000) ***
CCC	-0.000	(0.120)	-0.000	(0.000) ***	-0.000	(0.028) ***
ROE	-0.154	(0.335)	-0.976	(0.000) ***	-2.418	(0.000) ***
ROA	-	-	6.081	(0.000) ***	14.403	(0.000) ***
DPR	-0.003	(0.220)	-0.009	(0.000) ***	-0.454	(0.232)
PBV	-0.040	(0.000) ***	-	-	-0.168	(0.000) ***
FCF	0.000	(0.235)	0.0029	(0.002) ***	0.023	(0.000) ***
TAT	0.883	(0.000) ***	1.181	(0.000) ***	1.603	(0.000) ***

Note: *, **, and *** denote 10%, 5% and 1% levels of significant for p value.

Table 4 shows the results of the negative binomial distribution. The test results for the ZS were positively significant in all quantiles. The results suggested that the prospect of the increases in financial health (ZS) added clarifying support for influencing financial distress positively. These results conflict with the proposed hypothesis. Giordana and Schumacher (2017) confirmed a positive relationship between Z score and firm performance, but less cost efficiency enhances the risk of insolvency.

Table 4: Estimations Negative Binomial Regression distribution

Negative Binomial						
	Q1		Q2		Q3	
Variables	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
C	3.196	(0.000) ***	2.785	(0.000) ***	-2.214	0.158
ZS	3.848	(0.000) ***	0.293	(0.037) **	0.746	(0.026) **
TQ	-	-	-	-	341.194	(0.012) **
DR	-	-			5.734	(0.001) ***
CCC	-	-	-0.000	(0.028) **	-	-
ROE	-	-	-	-	-2.889	(0.016) **
ROA	-	-	-	-	16.102	(0.002) ***
DPR	-	-	-0.039	(0.025) **	-	-
PBV	-	-	-	-	-0.188	(0.007) ***
FCF	-0.027	(0.002) ***	-	-	0.012	(0.020) **
TAT	-	-	2.462	(0.000) ***	-	-

Note: *, **, and *** denote 10%, 5% and 01% levels of significant for p value.

The mixed results for FCF in Negative Binomial Distribution for Q1 present less impact on perceived risk count, while the significant positive result in Q3 is likely to affect. This negative impact leads to the evidence presented by Finishtya (2019) and revealing that companies with good operating cash flow are less risky. The significant positive result for FCF was consistent with the hypothesis and proved that highly free cash flow and operating activities positively affect perceived risk count on equity VIX. The significant positive value in Q3 for TQ is inconsistent with the study. Silva and Majluf (2008) indicated that an increase in the profitability of equity VIX experienced less likelihood of perceived risk and insolvency. Membroek (2002) pointed out that an adequate risk policy influenced firms to lower debt costs by optimizing the risk-return trade-off inflecting firm value.

The significant result for the DR factor in Q3 is consistent with the hypothesis. The results confirm the probability of an increasingly positive relationship between debt ratio and perceived risk count. The results give evidence to the finding presented by Ma, et al. (2020) that increased debt damages the firm's performance. High leverage and more debt ratio would almost certainly increase the perceived risk count on equity VIX.

The CCC, ROE, and DPR results are negatively significant in Negative Binomial Distribution in Q2 and Q3, respectively. These results are consistent with the hypothesis of this study. The finding for the PBV ratio also has a negative relationship with perceived risk count that is consistent with Siregar and Jahja (2020). Moreover, Philipp and Nadine (2017) showed that the likelihood of profitability as measured by ROA increased with the implementation of risk management due to funding for the required financial resource.

6. Conclusion

This study examined how financial ratios influence changes in sentiments at the firm level. The article employed CBOE individual equity VIX. Based on the financial ratios such as Financial Health, Technology Competition, Leverage Finance, Liquidity, Profitability, Dividend Policy, Company Value, Proprietary Asset, Cash Flow Management, and Management Efficiency. We evaluate whether financial variables influence perceived risks to count to investing in VIX individual equities.

The study utilized Poisson and Negative Binomial Regressions to investigate the link between perceived risk count and the variables at certain levels of quantiles to get insight into the market psychology condition of investors. The Negative Binomial model was chosen based on the highest log-likelihood value and the lowest AIC value.

Most of the findings agreed with the hypothesis of this study. The variables like CCC, ROE, and DPR showed negatively significant in Negative Binomial Distribution in Q2 and Q3 quantiles. These variables are further helpful to control for affecting financial stress negatively. The significant positive result for FCF proved that highly free cash flow and operating activities positively affect perceived risk count. By comparing different quantile levels, the most influential variables associated with higher perceived risk based on Q3 quantile, followed by medium Q2 and lower Q1, have two variables that are significantly influenced. Based on an adequate risk policy, firms have been encouraged to reduce debt related to the optimization trade-off for risk-reward that influenced enterprises' value. The probability of profitability measured by the ROA increased with the implementation of risk management because of the funding of the required financial resources.

This paper gives information to investors in VIX equities, and significant variables were influential factors and gave good news for investing in such investment. Appropriate control of relevant variables at different risk levels implies ensuring the extent to which it can effectively influence risk perception.

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