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An Analysis of the Role of Short Selling in Detecting Default Risk

Almuhannad Alsaif [1]

Abstract

Default risk has been a significant factor for various organizations in this volatile business environment. The primary objective of this study is to examine the effect of short interest ratio on default risk. In this paper, data from 500 publicly traded US non-financial firms for the period from 2000 to 2023 are used, and the comparison of static and dynamic panel data models is done for estimating and forecasting default risk. Several factors were utilized to determine the probability of default, including gross profit margin, quick ratio, debt-to-equity ratio, stock return, and market capitalization. The study indicates that firm size and profitability are relevant factors in the mitigation of default risk. While debt and short stakes measure financial risks. This study contributes essential insight to the understanding of default risk, giving regulators and investors critical tools for analyzing organizations' financial health.

Keywords: Default risk, Short interest levels, Debt to equity ratio, Dynamic panel probit model.

[1] CEO, ChartChats, Saudi Arabia.

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1. Introduction

Short selling is a well-known strategy where investors sell the borrowed shares to earn profit from the foreseeing price declines, bearing the potential for positive and negative ramifications on a firm's financial stability. It can also be divided into two categories: knowledgeable and ignorant short-selling. An investor's belief that a stock is overpriced, supported by in-depth fundamental and technical analysis, is the foundation of informed short selling. Insightful short sellers access the financial health of organizations, decision-making, and industry trends for trading decisions. This approach was highlighted by (Dechow et al., 2001; Desai et al., 2002, and Engelberg et al., 2012), identifying potential vulnerabilities. Alternatively, some short sellers opt for a momentum- driven strategy based on market sentiments and trends. (Curtis and Fargher, 2014; Lamont and Stein, 2004).

On the contrary, corporate financial failures arose as a substantial global concern specifically after the 2008 crisis followed by the 2019 pandemic crisis which led to economic distress. Major stock market indices experienced precipitous declines at an unprecedented pace (Baker et al., 2020). A subset of credit risk known as default risk is the possibility that a borrower will miss payments on a debt. In financial markets the role of short-sellers is contentious and the purpose is widely debated. Critics argue that short sellers intensify market volatility and instability, while proponents claim they improve market efficiency and promote price discovery. Short sellers must act as informed traders to contribute positively to market efficiency.

Simultaneously, it is crucial to establish patterns of how short interest levels correlate with default risk influencing firms' future stock and financial stability. This is because defaults are rare occurrences that often result in bankruptcy and liquidation. Hence the correlation between short interest levels and default risk rating has garnered significant attention in financial research. Several prior studies have highlighted the crucial role of short-selling in shaping firm-level financial performance. For example, Meng et al. (2023) found that in the Chinese stock market, short selling reduces default risk, especially in companies that the authors describe as operating in a low information environment and under weak corporate governance systems. The impact became visible after approximately two years with more efficient control and management of the financial aspects, improved accountability, and corporate governance. Also, short-sellers have better access to credit and debt financing as compared to long-sellers. These research studies demonstrate short- selling's potential to enhance the market discipline of company behaviors. Additionally, Cheng and Zhang (2024) establish that removing short-selling restrictions leads to better rating precision but lowers rating reliability for firms over comparative firms with limits. This shows that short-selling pressures drive rating agencies to prioritize accuracy over stability. Furthermore, these organizations rely less on ratings in debt contracts, showing a preference for stability over accuracy in the face of short-selling risks.

Some of the current research has argued that the relationship between future returns and short interest varies across firms and is most evident in companies with high default risk. In this regard, the study by Guo and Wu (2019) is relevant. This paper examines credit risk as a moderator of the association between future stock returns and short selling; the study finds that short interest is most sensitive to stocks with the lowest credit risk. Indeed, the study discovered that low stock grades that observed meaningful declines in short interest surpassed those with considerable boosts by 1.09% in the subsequent month. This paper investigates this concept in a novel setting: the relationship between default risk and short interest levels, where informational obstacles are greater for short sellers than for credit rating agencies. Prior research shows that a decline in rating often results in negative equity returns. This research investigates whether these downgrades can be predicted by short sellers after anticipating the likelihood of default changes, as well as whether they can forecast these downgrades using other rating-specific data.

Both academics and practitioners need to understand how short interest levels are associated with the risk of default. For investors, such information can be used to actively trade on the stock market, especially in identifying stocks that are expected to perform badly or well depending on their short interest and credit risk standings. The findings of the current study can assist policymakers and regulators in observing market and firm stability as well as in responding to possible vulnerabilities linked to large short sales in firms in trouble. Furthermore, by recognizing and evaluating the influence of credit risk on the informative part of short selling within the framework of financial markets, this study adds to the corpus of existing knowledge.

1.1 Research Objectives

The study's primary goal is to analyze how short interest rates are connected with default risk and how this connection affects future stock returns. Specifically, the study aims to:

1. Examine the relationship between short interest rates and enterprise default risk.
2. Investigate how firm-specific financial factors influence default risk.

1.2 Research Hypothesis

H_1: High levels of short interest are positively and significantly correlated with higher default risk ratings.

H_2: Firm-specific characteristics including debt level, firm size, and profitability have an impact on the risk of default.

2. Literature Review

The stock market is a complex ecosystem where multiple factors influence a company's financial health and performance. Among these, short interest levels and default risk are key indicators for assessing market sentiment and corporate creditworthiness. Short interest represents the bears that investors have with regard to the future outlook of a firm and default risk is an indication of firms' ability to service their obligations. The objective of this study is to examine the relationship between the two variables to establish the level of congruency between market sentiment as measured by short interest and the rating agencies' evaluation of default risk.

Short-selling activities have increased significantly in the last two decades and there is a lot of literature on the impact of equity short interest on assets' prices. At the same time, financial distress has been confirmed to impact the predicted asset returns to a very large extent. In a dynamic asset pricing equilibrium, price, volume, and short interest rates are all determined endogenously. Since market anomalies are common in low-credit quality firms and during credit quality deterioration Avramov et al. (2013), it is important to investigate returns, short selling, and credit risk. It is, therefore, possible that credit risk could partly account for the relationship between short interest and stock returns. Semczuk (2024) finds that low short-interest levels mean the total number of shares of a particular stock that have been sold but not bought back. Short selling means selling the shares you did not own but borrowed and purchasing the same ones after the price has dropped, at the current prices. Short interest levels are therefore used as indicators of the market sentiment particularly investors' ability to doubt the ability of certain stocks to perform well in the future. Short interest is calculated by the number of shares sold short multiplied by the total number of shares that are freely sold in the market known as float shares. Additionally, Henry et al. (2015) examine whether short sellers can predict significant changes in the default risk of a firm and credit rating downgrades. This study demonstrated that short interest in a company's equity is 40% greater in the month preceding a rating downgrade than the previous year. Short sellers gain from focusing on companies with an erroneous or skewed probability of default, as downgrades dramatically lower equity returns. Furthermore, short sellers improve efficiency by lowering post- downgrade and lead bond yield to spread abnormal stock returns. Short interest rates have been linked to a higher probability of default. Low short-interest ratios are associated with negative investor sentiments and expected decline in a firm's financial health, which is viewed as credit risk. Therefore, monitoring short interest levels might help to gain an understanding of the market's perceptions of a company's default risk since short-sellers tend to expect adverse events, including default. In the same manner, Guo and Wu (2019) examine the role of credit risk as a moderator of short selling and future stock returns. According to their findings, short interest has the highest ability to predict future returns in assets with the lowest ratings. In particular, low-grade equities with the maximum declines in short interest outperformed equities with the maximum increase in short interest by 1. 09% the following month while exports were 04% lower in the same period. This difference variation sustains even after the regulation of cross-sectional variables and organizational features specifically evident during the tenure of low liquidity and higher investor sentiments. Research explores an interesting pattern that companies with a high rate of short selling are more prone to default risk. This holds even after the presence of various business factors particularly during low liquidity and market optimism. Considerably, companies with increasingly short interest underperform which increases the chances of default risk. Thus, findings suggest that monitoring short interest levels are early warning indicator about a firm's financial health and credibility serving as a valuable measure for the prediction of default risk by tracking which we can gain valuable insights and mitigate the risk of default.

2.1 Theoretical Mechanism

When it comes to the prediction of default risk, integrating the theoretical models along with real-world data is vital for accurate estimations. Regarding this, a study conducted in 2004 by Semczuk found that, in comparison to companies with lower pre-disclosure short-selling rates, those with higher short-selling rates before any disclosure saw noticeably poorer stock returns six months after a credit decline. A related study by Dechow et al. (2001) highlights the effectiveness of this strategy in helping astute short sellers make money by identifying businesses with shaky financial foundations. These studies highlight the importance of using theoretical frameworks with empirical data to forecast the default risk. In addition to this, Firms compensate lenders for default risk by paying a spread above the default-free interest rate. Default probabilities vary by credit rating: AAA-rated firms have a 0.02% annual default rate, A-rated firms 0.1%, and CCC-rated firms 4%. In case of default, losses average 49% for senior secured bonds, 68% for subordinated bonds, and 81% for zero-coupon bonds, highlighting the importance of security and collateral. Christophe et al. (2010) emphasize using quantitative models to predict default risk, considering firm-specific and macroeconomic factors. Diversified portfolios are recommended to mitigate default risk, as focusing on individual firms is not viable due to the limited upside potential of debt investments. Previous studies used a variety of models to measure and predict real-world defaults and bankruptcies. Notably, Henry et al. (2015) widely used Z-scores, and Guo and Wu's (2019) use of multivariate discriminant analysis is effective in predicting default and bankruptcy. Multivariate discriminant analysis combines numerous characteristics into a single score to predict the possibility of default or bankruptcy. However, the accuracy of these forecasts is determined by the predictive factors' quality and relevance, as well as the quality of the data. As a result, applying multivariate discriminant analysis to predict bankruptcy risk requires careful selection of acceptable factors and dependable data sources.

The analysis strengthens previous research that looked at the relationship between short interest rates and default risk. Short selling is usually associated with low financial health and elevated default risk because of the ability of investors to take advantage of firms' financial distress (Dechow et al., 2001; Desai et al., 2002). Curtis and Fargher (2014) believe that short selling improves the market's effectiveness in identifying such firms, although momentum-driven short selling may be a reaction to broader market trends. Furthermore, short interest is connected with market fluctuations participates in the formation of prices, and amplifies fluctuations in crises (Baker et al., 2020). Several researchers such as Guo and Wu (2019) examine short-term effects, but there are still voids concerning industry characteristics and the long-term effect of short interest over time. This research seeks to fill these gaps by investigating distinct industry characteristics and the impact of corporate governance on the short interest-default risk nexus.

3. Data and Methodology

This section provides a depth analysis of the data set, identification of variables, and the modelsused for estimation.

3.1 Dataset

The study used the data comprising 500 publicly listed non-financial companies in the United States from 2000-2023 extracted from Bloomberg. Financial ratios, stock market indicators, and short-selling metrics are considered to examine the default risk using an unbalanced panel data methodology.

3.2 Research Variables

3.2.1 Dependent Variables

The study's dependent variable is binary, with '1' denoting a default firm and '0' denoting no defaultfirm. According to a study by Pindado et al. (2008) and Khan et al. (2020), companies whose EBIDTA has been negative for three straight years are defaulted.

3.2.2 Independent Variables

A total of seventeen independent variables are used that are further categorized into three groups. Out of which, thirteen are financial ratios, three are stock market indicators and one of them is a short selling measure. These factors were chosen based on VIF and Multicollinearity. The variablesare described as follows:

- **Financial Variables**

In assessing the impact of short selling on companies facing default risk, financial ratios like Return on Assets (ROA), Return on Capital Employed (ROCE), Gross Profit Margin (GPM),and liquidity metrics such as the Quick Ratio (QR) and Cash Ratio (CR) are critical. A strongROA indicates efficient asset utilization, while a high ROCE suggests effective capital deployment, both of which strengthen financial stability (Altman, 1968). Lower GPM can increase default risk by limiting funds for debt repayment. Liquidity measures like QR and CRare vital for meeting short-term obligations (Keasey and Watson, 1991). Other key metrics include total debt-to-asset (D/A) and debt-to-common equity (D/E) ratios, which assessleverage, and inventory turnover (IT), which reflects operational efficiency. These indicators provide a comprehensive view of a firm's financial health in the context of short-selling vulnerabilities.

- **Market Variables**

In addition to financial ratios, market-related metrics like stock return, market capitalization todebt, and trading volume are crucial for assessing the financial health of companies engaged in short selling. Declining stock returns signal weakened investor confidence and deteriorating financial stability, increasing default risk (Merton, 1974). Chava and Purnanandam (2009) found a correlation between falling stock prices and heightened short-selling activity. High debt relative to market capitalization also elevates default risk, as shrinking market value and heavy debt burdens can signal financial distress (Ohlson, 1980). Trading volume further reflects investor sentiment; rising volume during declining prices often signals increased short selling, as informed traders act on negative market outlooks (Diether et al., 2002)

- **Short Selling Factor**

The short-interest ratio is a measure of how many days at average daily trading volume it wouldtake for short sellers to close their positions and it captures market sentiment and or the pressurefirms undergo. A high short-interest ratio indicates a bearish view and could compound
problems if a company is in trouble, or its economic situation is less than solid. Asquith et al. (2005) also reported that firms with high short-interest ratios underperformed in the long run. Moreover, Diether et al. (2002) were able to demonstrate that among high short-interest ratios trading is more active; therefore, suggesting more market action.
The descriptive statistics for the variables are presented in Table 1.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Log (Short Interest Ratio)	7,999	0.349	0.459	-3.000	2.888
Return on Assets	7,999	-0.043	0.531	-27.247	3.127
Return on Capital Employed	7,999	0.038	0.051	-0.105	0.792
Gross Profit Margin	7,999	0.261	1.845	-58.754	36.406
Quick Ratio	7,999	0.003	0.096	0.000	8.569
Working Capital to Total Assets	7,999	-0.007	0.291	-18.059	0.127
Cash Ratio	7,999	0.003	0.096	0.000	8.569
Asset Turnover	7,999	0.722	1.514	-0.194	70.478
Working Capital turnover	7,999	0.002	0.939	-29.721	71.359
Inventory Turnover	7,999	0.064	0.394	0.000	16.269
Total Debt to Common Equity	7,999	0.253	1.395	0.000	31.357
Total Debt to Total Assets	7,999	0.087	1.374	0.000	52.664
CL to Total Asset Ratio	7,999	0.520	3.278	0.000	99.874
Firm Size	7,999	6.170	4.190	-12.830	16.150
Stock Return	7,999	0.162	2.668	-1.000	95.569
Trading Volume	7,999	12.820	4.172	-5.565	20.837
Log (Market Cap to Debt)	7,999	0.970	0.921	-3.000	6.114

4. Econometric Model

4.1 Static Panel Logit Model

The study utilizes a panel logit model to assess the influence of short selling on a company's defaultrisk, which corresponds to the methodology employed by Li (2023). This model, which is a logistic regression variation, is intended to forecast and explain categorical variables that fall into the 0 and 1 categories. Using the logistic curve, logistic regression explains the interaction between independent and dependent variables. Below is a thorough mathematical explanation of the logit model.

The initial step involves the transformation of the dependent variable (Y) through a process knownas the logit function, as delineated below:

$$Logit\ (Y\ ) = \ ln(odds) = \ a\ +\ k1x2\ +\ k2x2\ + \cdots . + knxn \quad (1)$$

Where odds refer to the odds of Y being equal to 1

$$Odds = \frac{Probability}{1 - Probability} \quad (2)$$

And odds can be defined mathematically as;

$$Probability = \frac{Odds}{1 + Odds} \tag{3}$$

Odds can be transformed into probabilities by the following expression:
The right-hand side of the first equation does not ensure that the values lie between 0 and 1. Hence, taking exponential on both sides of the equation.

$$e^{\ln(\text{odds})} = \text{odds} = e^{(\text{a + k1x1 + k2x2 + ...+ knxn})} \tag{4}$$

Dividing both sides of Eq. by (1+odds):

$$\frac{Odds}{(1 + odds)} = \frac{e^{(a + k1x1 + k2x2 + ...+ knxn)}}{1 + e^{(a + k1x1 + k2x2 + ...+ knxn)}} \tag{5}$$

Now the equation looks like

$$Probability = \frac{e^{(a + k1x1 + k2x2 + ...+ knxn)}}{1 + e^{(a + k1x1 + k2x2 + ...+ knxn)}} \tag{6}$$

Equation yields the probability for a particular group (Y=1, representing defaulted firms), rather than the logarithm of the odds for the same. The outcomes derived from Eq above manifest withinthe range of 0 and 1. Moreover, to ensure validity, robustness, and reliability, different diagnostictests are used which pre-diagnostic tests include multicollinearity, VIF, panel unit root, and the Hausman test. While post-diagnostic tests include Wooldridge's test for autocorrelation and to examine the heteroscedasticity in panel data presence of models, researchers frequently use diagnostic tests such as the Breusch-Pagan test or the White test.

4.1.1 Dynamic Panel Probit Model

The Dynamic Panel Probit model involves a binary dependent variable together with the panel data and contains the lagged dependent variable for each region to account for the persistence overthe strong period. However, it is noteworthy while using this model that the chance of an event forinstance default at time t is partly determined by events that occurred in previous time t-1 and otherfactors. In this context, the dynamic panel probit model also incorporates all the exogenous variables of interest and the lagged dependent variable but also controls for past behavior and otherunobserved heterogeneous characteristics at the entity level. Arellano and Bond (1991) also explain how to estimate the dynamic panel model.

Wooldridge (2005) proposed the following method for modeling a dynamic panel with a limited dependent variable: the unobserved effect should be dispersed by the beginning value and the exogenous variables. Subsequently, Wooldridge (2005) suggested an improvement to Chamberlain's (1980) method of handling dynamic panel models the problem of initial conditions was however addressed. They also suggested the distribution of the unobserved effects by using the initial value of the dependent variable and the exogenous variables. This is useful in estimating in dynamic panel probit modelsby correcting for endogeneity bias that incorporates both, the dynamic character of the process aswell as unobserved individual effects. In the context of this study, the dynamic panel probit modelcan be expressed as follows:

$$Y *_{it} = \alpha \,.\, y_{i(t-1)} + \beta \,.\, X_{it} + c_i + \epsilon_{it} \quad (7)$$

$$Y *_{i0} = \Upsilon_0' X_{i0} + \epsilon_{i0} \quad (8)$$

Where initial conditions are:

$$\begin{cases} Y\_it = 1\,(Y * \_it > 0) \\ Y\_i0 = 1\,(Y * \_i0 > 0) \end{cases} \quad (9)$$

The dynamic probit model assumes a random effects specification for unobserved heterogeneity.

$$c_i\text{:} \;\; c_i = pc_i + u_{it} \quad (10)$$

Given the binary nature of the dependent variable, the probability of Y_{it} = 1Is:

$$P(Y_{it} = 1) = \varphi(\alpha\, y *_{i(t-1)} + \beta\, X_{it} + c_i) \quad (11)$$

Where,

Φ represents the standard normal distribution's cumulative distribution function

(or CDF).

Hence, the final dynamic panel probit model can be expressed as:

$$P(y_{it} = 1 | y_{i(t-1)}, X_{it}, c_i) = \varphi(\alpha\, y *_{i(t-1)} + \beta X_{it} + c_i) \quad (12)$$

Where,

$(lagged\ y_{it})$ is the dynamic component.

5. Results and Discussion

5.1 Static Panel Logit Model Results

Table 2 summarizes the analysis findings using the static panel logit model which shows various crucial factors influencing default probability are revealed. The results show that the Short InterestRatio is crucial in explaining the default risk which denotes a positive correlation with default risk. An increase in one unit of short interest will increase default risk by 0.195%, implying that short sellers predict future financial risk. This aligns with the findings by Guo and Wu (2019). Also, the Return on capital employed is inversely related to default risk which shows that an increase in a company's profitability will decrease the probability of default risk. Whereas, the Cash ratio depicts a positive relation with default risk implies that an increase in one unit of Cash Ratio will increase default risk by 0.170%. This corresponds with the result by Arnold (2014) in which the study also established the direct relationship between the risk of default and Managerial Cash. Besides that, the Inventory Turnover and Total Debt to Common Equity also show a positive relationship with default risk meaning that higher debt levels and faster inventory turnover of firmslead to more probability of default (Billings,1999). In contrast, the coefficient estimate for Firm Size is negative, showing that size constraints have a negative impact on default risk suggesting that large firms are less likely to default. These findings are in line with the study by Rapposelli et al. (2023), which denotes that larger firms tend to have lower default risk due to their financial strength and stability. Furthermore, Trading Volume is strongly associated with default risk, implying that rising trading activity often signals financial instability, which leads firms toward default risk. In contrast, the Market Cap-to-Debt ratio compares a company's market value to its debt, with a higher ratio suggesting that the company's equity significantly outweighs its debt Thisimplies market confidence and provides a financial buffer, lowering the risk of default bypositioning the company to better meet its obligations, raise funds, or restructure debt if necessary (Graham and Leary, 2011). Thus, while increased debt raises default risk, a strong market capitalization can mitigate this effect.

Table 2: Static Model Results

	Coefficient	**Average MarginalEffect dy/dx**	**P>|z|**
Log (Short Interest Ratio)	0.195	0.048	0.099**
Return on Capital Employed	-4.757	-1.160	0.000*
Gross Profit Margin	-0.131	-0.032	0.406
Log (Quick Ratio)	-0.149	-0.036	0.166
Log (Cash Ratio)	0.170	0.041	0.030*
Asset Turnover	0.060	0.015	0.371
Working Capital Turnover	0.017	0.004	0.873
Inventory Turnover	0.650	0.159	0.029*
Total Debt to Common Equity	0.123	0.030	0.126
Total Debt to Total Assets	0.027	0.007	0.572
CL to Total Asset Ratio	0.015	0.004	0.619
Firm Size	-0.268	-0.065	0.000*
Stock Return	0.009	0.002	0.521
Trading Volume	0.063	0.015	0.005*
Log (Market Cap to Debt)	-0.126	-0.031	0.088**
LR $chi^2(15)$	245.830		
Prob > chi^2	0.000		

Note: * and ** indicate the significance of confidence interval at 5% & 10%, respectively.

5.2 Dynamic Panel Probit Model Results

Table 3 presents the estimated outcomes of the dynamic panel data probit model. Consistent withthe previous research by Besley et al. (2020), Default Risk$_{(t-1)}$ has a large positive and highly significant coefficient implying that a firm default in the previous period is often likely to be in default in the current period. The study established that previous status as a defaulter is a strong predictor of further default. The model also describes that the coefficient of Total Debt-to-Common Equity is 0.078 which is applicable in establishing the financial leverage of a company as this ratio rises, that means an increased proportion of cash is used in servicing this debt becauseinterest and the principal amount are often due and payable put pressure on the cash flow, hence increased possibility of default during the lean period in the economy (Atrill and McLaney, 2015). This is because firms with high levels of debt become financially leveraged, even in periods of economic difficulties (Adrian et al., 2024). Also, Firm size is inversely linked with default risk which means, a larger firm size reduces the probability of default risk. Nevertheless, these resultshighlight the interdependence between profitability, financial solvency, debt management, and market forces on default risk rates.

Table 3: Dynamic Probit Model Results

	Coefficient	**Average MarginalEffect dy/dx**	**P>|z|**
Default Risk (0)	0.091	0.007	0.491
Default Risk(t-1)	2.521	0.182	0.000*
Log (Short Interest Ratio)	0.123	0.009	0.154
Return on Capital Employed	-0.500	-0.036	0.533
Gross Profit Margin	-0.041	-0.003	0.127
log Quick Ratio	-0.125	-0.009	0.183
log Cash Ratio	0.124	0.009	0.112
Asset Turnover	0.011	0.001	0.576
Inventory Turnover	0.100	0.007	0.280
Total Debt to Common Equity	0.078	0.006	0.034*
Total Debt to Total Assets	-0.010	-0.001	0.638
CL to Total Asset Ratio	0.019	0.001	0.238
Firm Size	-0.108	-0.008	0.000*
Stock Return	0.001	0.000	0.908
Trading Volume	0.030	0.002	0.131
Log (Market Cap to Debt)	-0.100	-0.007	0.066**
constant	1.016		0.026*
Wald chi^2	1,795.280		
Prob > chi^2	0.000		

Note: * and ** indicate the significance of confidence interval at 5% & 10%, respectively.

According to these results, the study effectively supports the hypotheses mentioned in thisresearch. To begin with, the study tests the first hypothesis that relates short interest rates to firms'default risk and establishes that higher short interest leads to a higher probability of default. Second, important indicators influencing the default risk, Firm Size, and Profitability are recognized, expressing to an extent to which they enhance or decrease the frequency of defaults, thus supporting the second hypothesis.

6. Conclusion

This research work utilizes two models, namely dynamic panel data probit and static panel logit to determine default risk for US non-financial firms by using various variables. The results offer valuable insights into the factors influencing default risk, emphasizing the significant role of short interest. By integrating firm size profitability, and debt metrics, the analysis establishes a comprehensive framework for predicting default risk. These measures help minimize indexvariability and create a reliable benchmark for estimating default risk. The results reveal that firm size and profitability have a negative effect on default risk while high debt and short interest ratiohave a direct effect on default risk. This study helps to expand upon prior research by consideringshort interest and default risk both historically and through contemporary econometric procedures.This research expands prior research in terms of explaining various aspects of short selling and default risk through a combination of different theoretical approaches, while also providing policymakers and investors with useful insights. The models demonstrated that the static panel probit model offers a more comprehensive understanding of the persistence of default risk, as it accounts for firm-specific characteristics. The research hypothesis was tested and validated, confirming that high levels of short interest are strongly associated with increased default risk. Also, the variables; debt, size, and profitability of the firm size were observed to highly influencedefault risk. The study enhances the understanding of how short interest can act as an early warningsignal for default risk, providing crucial insights for investors and regulators aiming to mitigate financial risks in firms.

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Appendix

Table 1: Panel Unit Root

Variables	Z-Statistics	p-value
Fisher-Type Test		
Default Risk	-7.722	0.000*
log(Short Interest Ratio)	-23.898	0.000*
Return on Assets	-28.993	0.000*
Return On Capital Employed	-33.539	0.000*
Gross Profit Margin	-18.869	0.000*
log(Quick Ratio)	-29.174	0.000*
Working Capital to Total Assets	-20.835	0.000*
log(Cash Ratio)	-28.833	0.000*
Asset Turnover	-22.032	0.000*
Working Capital Turnover	-51.409	0.000*
Inventory Turnover	-38.246	0.000*
Tot Debt to Common Equity	-15.147	0.000*
Total Debt to Total Assets	-12.947	0.000*
CL to Total Asset Ratio	-22.451	0.000*
Firm Size	-13.731	0.000*
Stock Return	-48.867	0.000*
Trading Volume	-9.417	0.000*
log(Market Cap to Debt)	-21.496	0.000*

Note: * and ** indicate the significance of confidence interval at 5% & 10%, respectively.

Table 2: Variance inflating Factor (VIF)

Variable	VIF	1/VIF
log(Quick Ratio)	4.730	0.211
log(Cash Ratio)	4.570	0.219
Total Debt to Total Assets	2.260	0.442
Firm Size	2.000	0.500
CL to Total Asset Ratio	1.900	0.527
Trading Volume	1.890	0.529
Return on Assets	1.500	0.666
Working Capital to Total Assets	1.310	0.762
log(Market Cap to Debt)	1.230	0.811
log(Short Interest Ratio)	1.110	0.899
Asset Turnover	1.100	0.909
Gross Profit Margin	1.060	0.945
Inventory Turnover	1.040	0.962
Tot Debt to Common Equity	1.030	0.973
Stock Return	1.020	0.979
Return on Capital Employed	1.020	0.980
Working Capital turnover	1.000	1.000
Mean VIF	1.750	