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An Examination of the Determinants of Optimal Corporate Credit Hegde: Perspectives from Firms Listed in DJIA30 and Nasdaq100

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An Examination of the Determinants of Optimal Corporate Credit Hedge: Perspectives from Firms Listed in DJIA30 and NASDAQ100

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Abstract:

Raising number of corporate defaults could threaten the financial stability, thus modelling credit risk is a key ingredient of financial stability analysis. This paper tries to answer a specific question regarding the drivers of this risk: idiosyncratic risk (industry-specific or firm-specific) and/or systematic risk (macro-economic specific). As a first step, the paper estimates the optimal hedge ratio based on the interest coverage ratio, that acts as a measure for the probability of default. Against this background, the paper applies one of the fundamental-based models of credit risk, known as *hybrid model* after estimating the proposed indicator variable. The suggested model incorporates a number of accounting-based variables (financial ratios: such as measures of profitability, liquidity, and leverage) and a set of macroeconomic variables (such as output growth rate and inflation rate). In doing so, the data sample covers listed firms from both Dow Jones and Nasdaq databases, covering the Q1: 1998 till Q3: 2020. The paper applied the general-to-specific and cross-sectional estimation approach, it concludes with two specific hybrid models for Nasdaq. As for Dow Jones, there was no chance to estimate a hybrid model by including macroeconomic variables, due to the fact that all industries are headquartered in US, which didn't give a room for enough variability and inference. On another note, the hybrid models reveal that inflation has the largest magnitude of impact on the optimal credit hedging ratio, which can be attributed to the fact that higher inflation might constitute a higher risk, in which companies hedge against it by having higher hedging ratio. The opposite happened in case of the GDP growth rate, in other words, higher GDP is associated with lower hedging ratio which gives the market higher level of certainty and confidence.

I. Introduction and Motivation:

Estimating default probabilities for individual obligors is the first step for assessing the credit exposure and potential losses faced by an investor or financial institutions. Default probabilities are also the basic inputs for evaluating both systemic risk and idiosyncratic risk. Estimating default probabilities, however, could be challenging mainly due to limitations on data availability. Fortunately, there are number of models which allow us to overcome these limitations. Among these models; fundamentals-based models, which rely on accounting, systematic market and economic factors, and ratings information (Chan-Lau, 2006).

It must be noted that despite the presence of empirical studies on financial distress, the major issues of failure predictions are far from resolved. It has been stated that the problem is partially due to the fact that the main research findings drawn from the developed countries are difficult to be generalized to different economic setups such as emerging markets. It was also stated that there exists an underlying dissimilarity in market structure and implementation of law and accounting standards. That makes the process to be complicated to apply developed-economy prediction models in developing economies (Zulkarnain and Shamsher, 2004). Given the differences in legal, cultural and regulatory systems, Taffler and Abassi (1984) stated the need for country specific models of corporate failure prediction that should be well developed.

Differing financial ratio benchmarks have led to industry specific models. Altman (1971) provided specific models in manufacturing sector; Mason and Harris (1979) presented specialized models in construction industry, retailing sector by Taffler (1984) and financial institutions sector indicated by Houghton and Smith (1992).

The objective of this study is to contribute to that line of research and to fill the literature gap by presenting a hybrid model to portray the structural relationship between the probability of default, optimal credit hedge ratio and set of macroeconomic and financial variables.

The originality and objective of the paper emerged from filling the literature gap by calculating a novel measure for the optimal hedging ratio which can reflect the probability of default for industry specific and country specific by avoiding the limitations of the traditional financial ratios. In doing so, the proposed model can be used as an early warning system for the financial creditors to safe-guard against default risks of borrowers.

Noteworthy, most of the recent literature on estimating the optimal hedge ratio relied on using the slope coefficient from a simple Ordinary Least Squares (OLS) regression of spot prices on futures prices, where the slope coefficient reflects the ratio of the unconditional covariance to the unconditional variance of the futures prices (Kostika and Markellos, 2007), (Apergis et al 2012) and (Santillán-Salgado et al, 2020). Or equivalently as the product of the correlation coefficient between the changes in the spot and futures prices and the ratio of the standard deviation of the changes in the spot price to the standard deviation of the futures price. The novelty of the metric emerged from the fact that we here utilized for the first time the traditional interest coverage ratio (EBIT and interest) to control for their volatility and to avoid the limitation of the traditional financial ratios.

The paper utilized data for the financial indictors based on Thomas Reuters Finance Center Eikon to cover the idiosyncratic risk variables including proxies for liquidity, profitability and leverage. As for the macroeconomic variables which are used as a proxy for the systematic risk, have been obtained from the International Monetary Fund (IMF) International Financial Statistics (IFS) database including the GDP growth rate and inflation rate.

One policy implication from the analysis while analyzing data, it has been noticed that some industries in both Dow-Jones and Nasdaq encountered negative optimal credit hedge ratio (calculated H-star) which can be explained in the context of commodity prices as the probability of falling price which gives a chance of short-sell position. However, in our case, this situation implies the presence of a negative correlation between EBIT and interest, reflecting also a negative Beta, which gives some insights about the industry of being less risky and consequently we expect maybe lower negative returns from this business.

Another policy implication, also, it has been observed that Systematic risk appears to be symmetric for most of the country sample included in our analysis, in the sense that both GDP growth rate and inflation witnessed co-movements over the period under investigation. This is totally different from the idiosyncratic risk related to the financial indicators presented earlier in this section. The financial indicators and ratios revealed some sort of asymmetry between different industries either for Dow-Jones or Nasdaq.

The main conclusions of the study show that for Dow-Jones industries, there exists a statistically significant relationship between probability of default and the optimal credit hedge ratio. Idiosyncratic risk has been quantified by a group of financial ratios that appeared to be statistically significant being a function in H-star (Optimal Credit Hegde Ratio). These variables include: equity to liability, quick ratio, current ratio, sales-to-receivables, return on assets and capital to total assets.

For Nasdaq industries, general hybrid model showed that two financial indicators were significant which are equity-to-liability and the return on invested capital. A more specific hybrid model specification yielded the significance of equity-to-liability and inflation rate, in which both were significant at 5% with estimated coefficients of -0.0008 and 169.10, respectively. Another specific hybrid model indicated the significance of GDP with an estimated coefficient of -1.052.

It can be grasped that inflation rate had the largest magnitude of impact on the optimal credit hedging ratio, which can be attributed to the fact that higher inflation might constitute a higher risk, in which companies hedge against it by having higher hedging ratio. The opposite happened in case of the GDP growth rate, in other words, higher GDP is associated with lower hedging ratio which gives the market higher level of certainty and confidence.

The following section presents a sample of the most influential works in the literature on modelling the risk hedging and probability of default. The third section introduces the data and the fourth section highlights the methodology used in the empirical section. The fifth section presents the results of the estimations and their interpretation and, finally, the sixth section concludes.

II. Literature Review:

Financial distress is usually associated with some costs to the company; these are known as costs of financial distress. Financial distress lead to enterprise's bankruptcy, therefore financial distress is also called default risk. The financial crisis means that business enterprise loses the ability of payment, has no capability to pay expired liability or expenses and appears asset value less than issued debt. Once the enterprise occurs financial crisis, it will bring great loss for executive and financial institution. Financial distress prediction is of interest not only to managers but also to external stakeholders of company, and it can work as an early warning system.

The most conventional method for estimating optimal hedge ratios is to use the slope coefficient from a simple Ordinary Least Squares (OLS) regression of spot prices on futures prices, where the slope coefficient reflects the ratio of the unconditional covariance to the unconditional variance of the futures prices (Kostika and Markellos, 2007), (Apergis et al 2012) and (Santillán-Salgado et al, 2020).

A growing number of studies focus on the relationship between spot and futures market price fluctuation to measure the hedging effectiveness of different underlying assets using constant and dynamic hedging models. Kharbanda and Singh (2020) study currency futures in India and compare three models for evaluating the effectiveness of hedges. Chiou-Wei al. (2020) analyze US natural gas spot and futures prices in terms of hedging effectiveness. Kumar and Bose (2019) investigate the hedging effectiveness of Nifty index traded on the National Stock Exchange, India and cross-listed Nifty futures traded on the Singapore Stock Exchange and compare the performance of constant and dynamic hedging strategies.

All previous studies find that a dynamic multivariate GARCH model outperforms other static models and improves hedging effectiveness. However, Kumar and Bose (2019) observe that constant hedging models have better hedging effectiveness than time-variant hedging models. Buyukkara et al (2021) tested Optimal hedge ratios and hedging effectiveness in Turkish future market and concluded that Borsa Istanbul (BIST) 30 equity futures contracts provide an efficient hedging mechanism for investors aiming to protect their spot equity portfolios.

Given the adverse economic and financial implications of the default risk, the topic has been researched intensively in both developed and developing countries, likewise. The literature has classified the default probability models broadly into two categories: market-based and fundamental-based models. The paper at hand will be focusing on the fundamental-based models as the other category is far from our scope. Chan-Lau (2006) states that fundamentals-based models include: macroeconomic-based models, credit scoring (or accounting-based) models and the hybrid models. Worth mentioning, the later models generate default probabilities using as explanatory variables a combination of economic variables, financial ratios and ratings data.

Macroeconomic-based models are motivated by the observation that default rates in the financial, corporate, and household sectors increase during recessions. This observation has led to the implementation of econometric models that attempt to explain default indicators, such as default probabilities or default rates, using economic variables. Based on the macroeconomic models, forecasting default probabilities requires choosing an appropriate set of explanatory economic variables, and specifying the function which links the probability of default, with the macroeconomic indicator. The explanatory economic variables usually include GDP, interest rates, productivity indices, equity market returns, the unemployment rate, etc. Examples are given by Vlieghe (2001), Virolainen (2004) and Hoggarth et al (2005).

Table (1): Applications of Fundamentals-based Probability of Default Models

Author(s)	Model Type	Estimation Method	Dependent Variable	Variables Used
Vlieghe (2001)	Macroeconomic-based models	Least Squares	Δ Probability of Default (ΔPD)	real wages, aggregate demand, real interest rates, property prices and bonds spread
Virolainen (2004)	Macroeconomic-based models	Logit	Index (inversely related to PD)	GDP, the industry-specific measures of corporate indebtedness and interest rate
Hoggarth et al (2005)	Macroeconomic-based models	VAR System	Loans Write-offs	output gap, the annual rate of inflation, and nominal interest rate
Bunn et al (2003)	Credit scoring (or accounting-based) models	Maximum Likelihood Probit Model	Probability of Default (survival or failure)	Gross profit to interest payments, debt to assets and current ratio
Thim et al (2011)	Credit scoring (or accounting-based) models	Least Squares	Financial Distress (proxied by long-term debt to total equity ratio and short-term debt to equity ratio)	profitability, liquidity, firm size, solvency, growth and risk
Lennox (1999)	Credit scoring (or accounting-based) models	Probit/Logit	Default Status of Firm i	Sales to receivables, quick ratio, gross cash flows, capital gearing and return on capital

Jayadev (2006)	Credit scoring (or accounting-based) models	Multiple Discriminant Analysis (Z-Score)	Latent Variable	Financial Ratios (current ratio, debt-equity, operating margin, working capital to total assets, net worth to debt and asset-turnover ratio)
Jacobson et al (2005)	Hybrid model	Logit	Probability of Default	Financial variables + output gap, inflation rate, nominal interest rate and real exchange rate
Vermeulen (2008)	Hybrid Model	Logit transformed model	Industry-Specific Default Rate	Return on assets, current ratio, debt-to-asset ratio, GDP growth rate, short- and long-term interest rates and nominal exchange rate

Empirical evidences for the developed countries are given by Vlieghe (2001) modelled the determinants of the aggregate corporate liquidation rate in the United Kingdom. This was carried out from a sample of quarterly data using an autoregressive distributed lag (ARDL) approach which allows for non-stationarity of the variables. To analyze corporate liquidations this paper used the corporate liquidations rate, which is the number of liquidations divided by the stock of companies.

Another empirical work has been applied on Finland based on a macro stress testing model and the default rates are obtained by dividing the number of bankruptcy proceedings instituted by the number of active companies during the time period in question. Default data are available for the following six main industries: agriculture, manufacturing, construction, trade, hotels and restaurants, transport and communication Virolainen (2004).

Among the macroeconomic models some econometric models which allow for feedback between financial distress and the economic variables. The typical econometric framework used in these models is the vector autoregression (VAR) methodology, Once the VAR system is estimated, the sensitivity of default probabilities to shocks to the different economic variables can be quantified using impulse response analysis. Hoggarth et al (2005) use a VAR system to analyze the impact of domestic economic conditions on U.K. banks' loan write-offs, both at the aggregate and at the sectoral level. The economic variables included in their model are the output gap, the annual rate of retail price inflation, and the nominal bank short-term interest rate. The equation estimated for the aggregate write-offs using quarterly data from 1988 Q1 to 2004 Q2.

Another models' strand in literature argues that the probability of default is related to the individual characteristics of corporates, these models are known as credit scoring (or accounting-based) models. The financial ratios used by credit scoring models can be classified broadly as measures of profitability, leverage, debt coverage, growth prospects, and liquidity. In addition, practitioners also include size measures, and activity measures that may signal operating problems. Chan-Lau (2006) states that once the variables are selected, credit scoring models use a variety of statistical techniques for assessing the default probability of a firm, including econometric models and linear discriminant analysis, among others.

Econometric models are usually based on logistic regression and probit models, are similar to those used in macroeconomic-based models. The only difference is that the set of explanatory variables correspond to firm-specific financial ratios rather than economic variables.

In developed countries, Bunn (2003) used a probit approach on a sample of more than 105 thousand firms in UK over the period 1991-2001. The initial model estimated was a standard maximum likelihood probit model. This model estimated the probability of company failure based on both a firm's financial characteristics in the previous year, other firm-level characteristics such as size, industry, and whether the firm is a subsidiary or not, and on macroeconomic effects. It is observed that the company status variable is either failure or survival. The probability of default is then modelled according to the accounting-based model as a function of three financial ratios: gross profit to interest payments, debt to assets and current ratio.

Evidences drawn from the developing countries are given by Thim et al (2011) by applying on the Malaysian stock market, in which they selected randomly a sample of 101 listed companies during the period 2005-2009 where two models are used to analyze the relationships between financial distress and firms' characteristics and risk. The dependent variables were long-term debt to total equity ratio and short-term debt to total equity ratio. The independent variables were profitability, liquidity, firm size, solvency, growth and risk.

Turning to the linear discriminant analysis, conceptually the firms analyzed are divided into two groups, bankrupt and nonbankrupt firms. Altman's Z-score (Altman, 1968) is arguably the most well-known application of credit scoring for bankruptcy prediction. Altman includes as explanatory variables the following financial ratios: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, the market value of equity to the book value of total liabilities, and sales to total assets.

In developed countries, Lennox (1999) applied a probit/logit models on 949 listed firms in UK to determine the status of default of each firm based on the linear discriminant analysis, in which firms are classifies as a dummy variable: non-bankrupt (0) and bankrupt (1). The dummy variable is regressed against a group of financial ratios: sales to receivables, quick ratio, gross cash flows, capital gearing and return on capital.

Evidence from developing countries are given by Jayadev (2006) who employed the multiple discriminant analysis in the framework of z-score, on a defaulters' list of five largest public Indian banks by including different financial ratios. the sample included 56 default companies and another 56 non-default companies. The paper followed the models presented by Altman (2002) and Altman et al (1995). The paper concluded that the financial risk factors considered by banks in their internal rating models are not very effective in distinguishing between default and non-default firms. The accuracy ratio is 68% which can be improved by careful selection of risk factors.

Coming to the third type of models known as the hybrid models, the later are considered recent approaches to estimating default probabilities using as explanatory variables economic variables, accounting data (financial ratios), and in some cases ratings data (Chan-Lau, 2006). Some empirical examples are given by Balzarotti et al (2002), Hamerle et al (2004), Jimenez and Saurina (2005).

Jacobson et al (2005) presented an example of hybrid models, by incorporating both macroeconomic variables along with the financial ratios in modelling the firms' probability of default on 250 thousand firms in Sweden covering the period 1990: Q1 through 1999: Q2. The paper found that financial ratios improves the accuracy of probability of default models by a rate of 30%. The paper used a logit model of the default probability as a function of some financial ratios along with macro-economic variable including: output gap, inflation, nominal interest rate and real exchange rate.

Vermeulen (2008) applied the hybrid model using annual data spanned from 1992-2005 for six industries, by allowing industries to vary according to their sensitivity to the macro-conditions as well as to their balance sheets strength. The paper utilized industry-specific default rate (logit transformed) as the dependent variable being a function of a group of variables; some of which are macro-economic variables and some other are industry-specific financial ratios. As such, the model included three financial variables to control for profitability, liquidity and leverage which were argued in the literature to affect the probability of default. These variables are: return on assets, current ratio and debt to assets ratio. Among the macro-economic variables, growth rate of GDP, short-term and long-term interest rates (to capture the firm's external financing costs on one hand, to reflect the expectations of future inflation and economic growth on the other hand), change in the equity prices, nominal exchange rate (to include the firms' competitiveness).

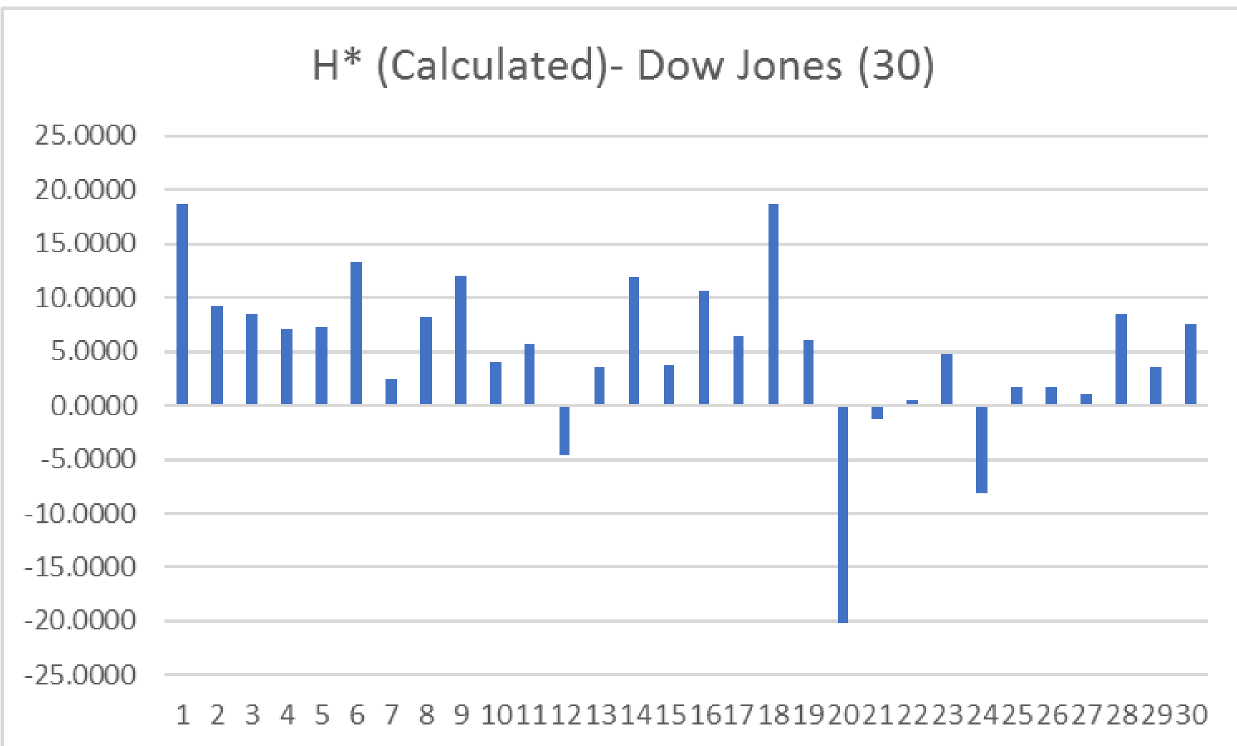
III. Data Description:

The paper at hand is trying to fill the literature gap by coming up with a novel measure for the optimal hedging ratio which can reflect the probability of default (industry specific) and country specific) by avoiding the limitations of the traditional financial ratios. In doing so, the proposed model can be used as an early warning system for the financial creditors to safe-guard against default risks of borrowers. Noteworthy, most of the recent literature on estimating the optimal hedge ratio relied on using the slope coefficient from a simple Ordinary Least Squares (OLS) regression of spot prices on futures prices, where the slope coefficient reflects the ratio of the unconditional covariance to the unconditional variance of the futures prices (Kostika and Markellos, 2007), (Apergis et al 2012) and (Santillán-Salgado et al, 2020). Or equivalently as the product of the correlation coefficient between the changes in the spot and futures prices and the ratio of the standard deviation of the changes in the spot price to the standard deviation of the futures price. The novelty of the metric emerged from the fact that we here utilized for the first time the traditional interest coverage ratio.

The calculated optimal credit hedge ratio is obtained from the following formula: **Optimal Hedging Ratio (h*) for Interest Coverage Ratio that will be discussed in detail in the following section:**

$$= \rho_{EBIT,Interest} \frac{\sigma_{EBIT}}{\sigma_{interest}}$$

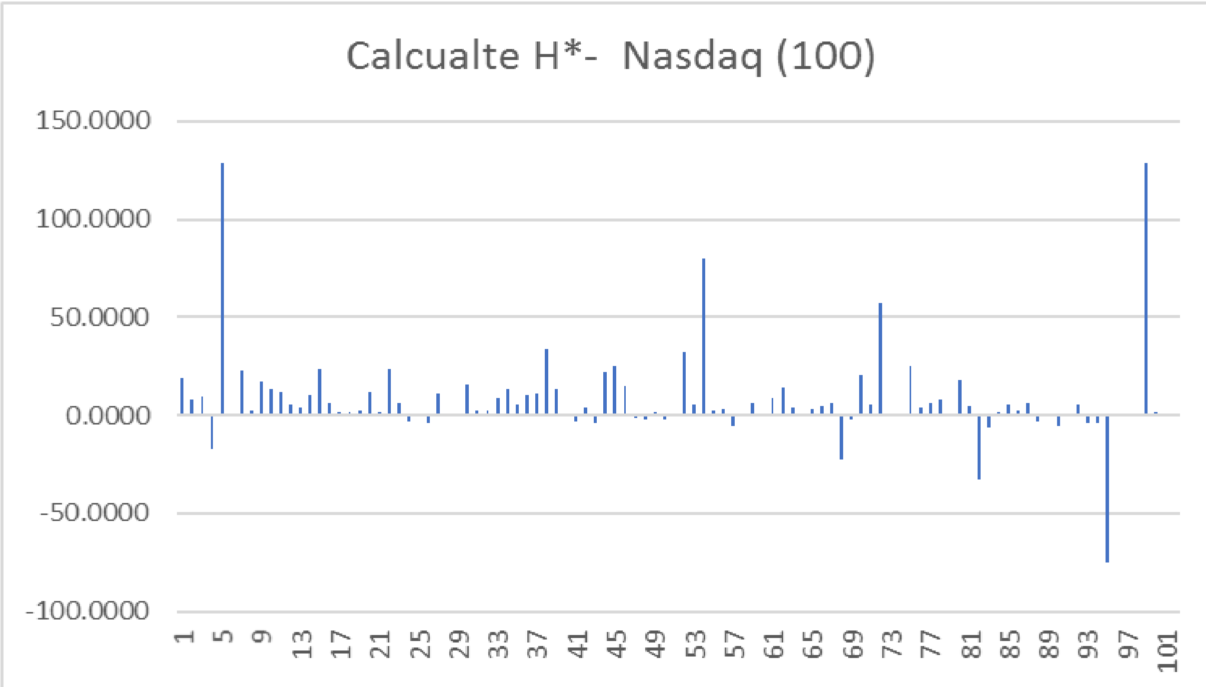
Figure (1): Calculated H* for Dow-Jones (30)



Source: Eikon database, Reuters Finance Center.

The study utilized data for listed industries in both Dow-Jones (30) and Nasdaq (100). The data for financial indicators and ratios were obtained from Eikon database. The data spans from Q1 1998 through Q3 2020. As for the macroeconomic variables, they were obtained from the IMF IFS database regarding GDP growth rate and inflation rate. Knowing that cross-sectional data was utilized, the averages have been calculated over the period under investigation.

Figure (2): Calculated H* for Nasdaq (100)



Source: Eikon database, Reuters Finance Center.

The paper found that some industries in both Dow-Jones and Nasdaq encountered negative optimal credit hedge ratio (H-star) which can be explained in the context of commodity prices as the probability of falling price which gives a chance of short-sell position.

Table (2): Financial Indicators classified as Profitability, Liquidity and Leverage

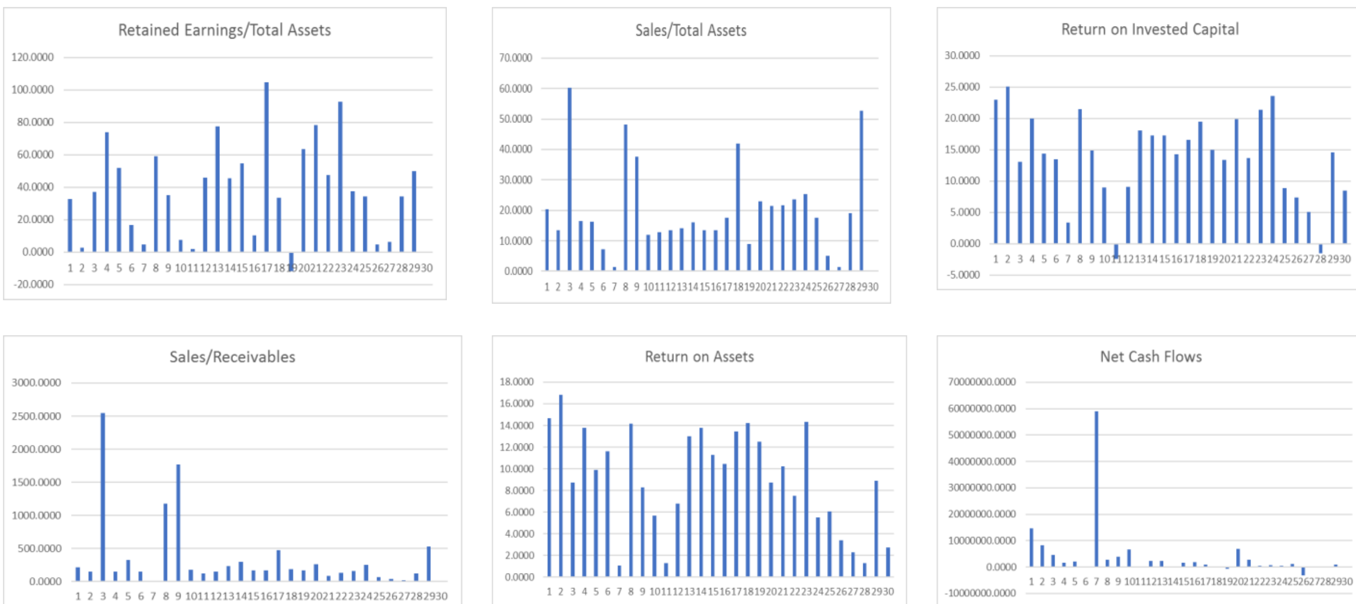
Profitability Ratios	Liquidity Ratios	Leverage Ratios
Retained-Earnings/total Assets	Working Capital/Total Assets	Total Debt / Total Assets
Sales/Total Assets	Market Value of Equity / Book Value of Total Liability	
Sales/Receivables	Quick Ratio	
Net Cash Flows*	Current Ratio	
Return on Capital (ROIC)		
Return on Assets (ROA)		

Source: Eikon database, Reuters Finance Center.
* Net cash flows are calculated as the summation of financing, investing and operating net cash flows.

However, in our case, this situation implies the presence of a negative correlation between EBIT and interest, reflecting also a negative Beta, which gives some insights about the industry of being less risky and consequently we expect maybe lower negative returns from this business.

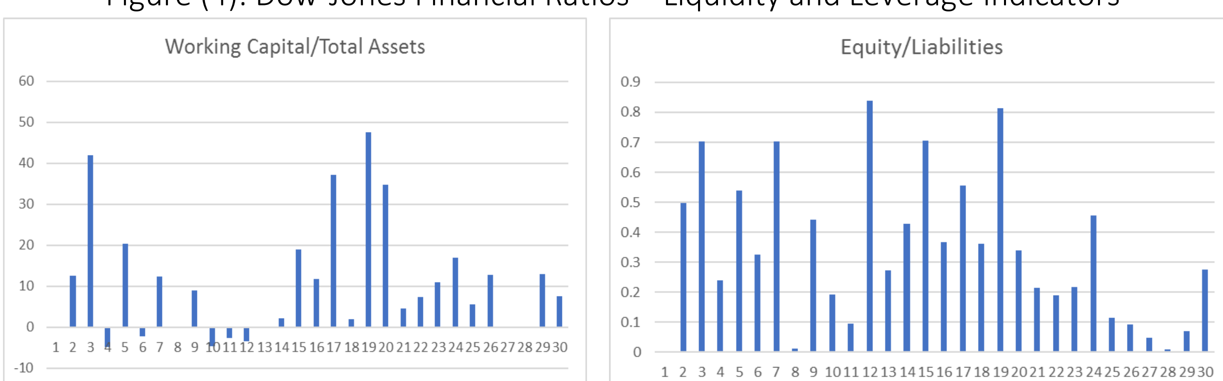
The utilized financial ratios can be classified into three main categories, mainly profitability indicators, liquidity indicators and leverage indicators. In doing so, the paper followed the early work done by Lennox (1999), Jayadev (2006) and Thim et al (2011). As for the macroeconomic variables, the paper utilized the GDP growth rate and inflation rate following Hoggarth et al (2005), Jacobson et al (2005) and Vermeulen (2008). The following four figures display the financial indicators for the 30 industries for Dow-Jones index in addition to Nasdaq 100 industries.

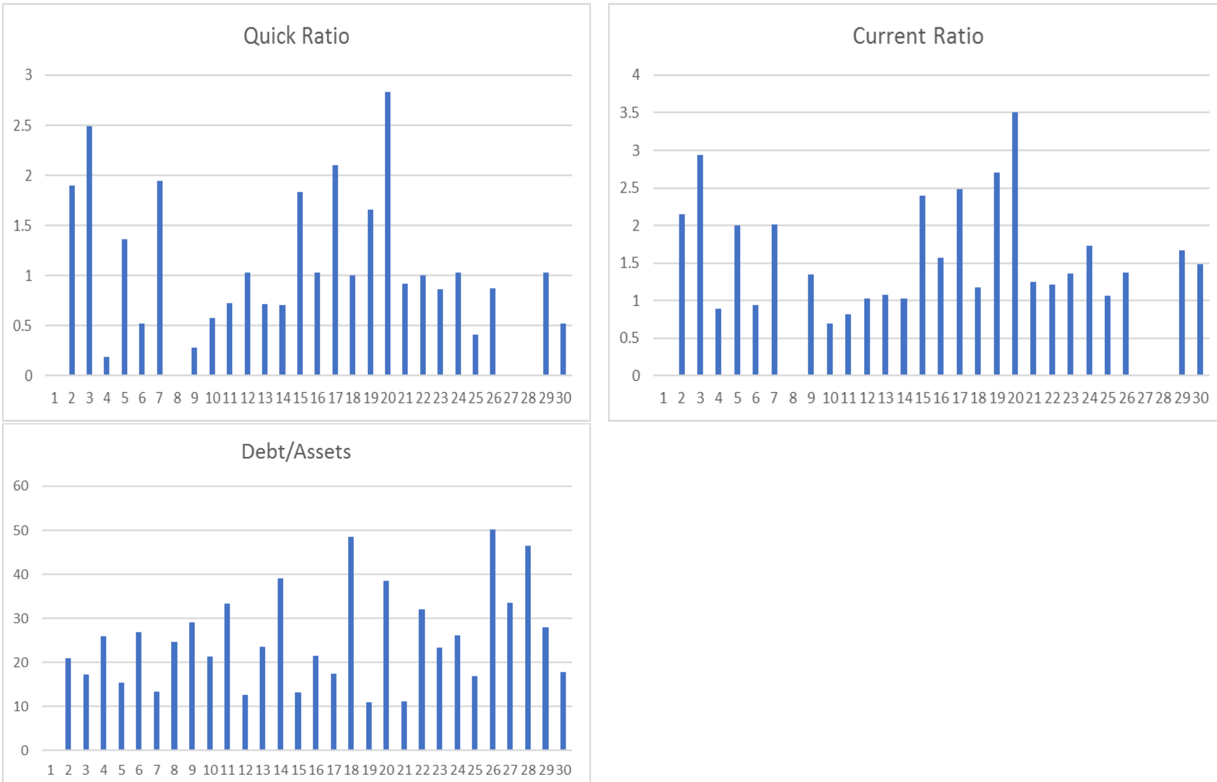
Figure (2): Dow-Jones Financial Ratios – Profitability Indicators



Source: Eikon database, Reuters Finance Center.

Figure (4): Dow-Jones Financial Ratios – Liquidity and Leverage Indicators



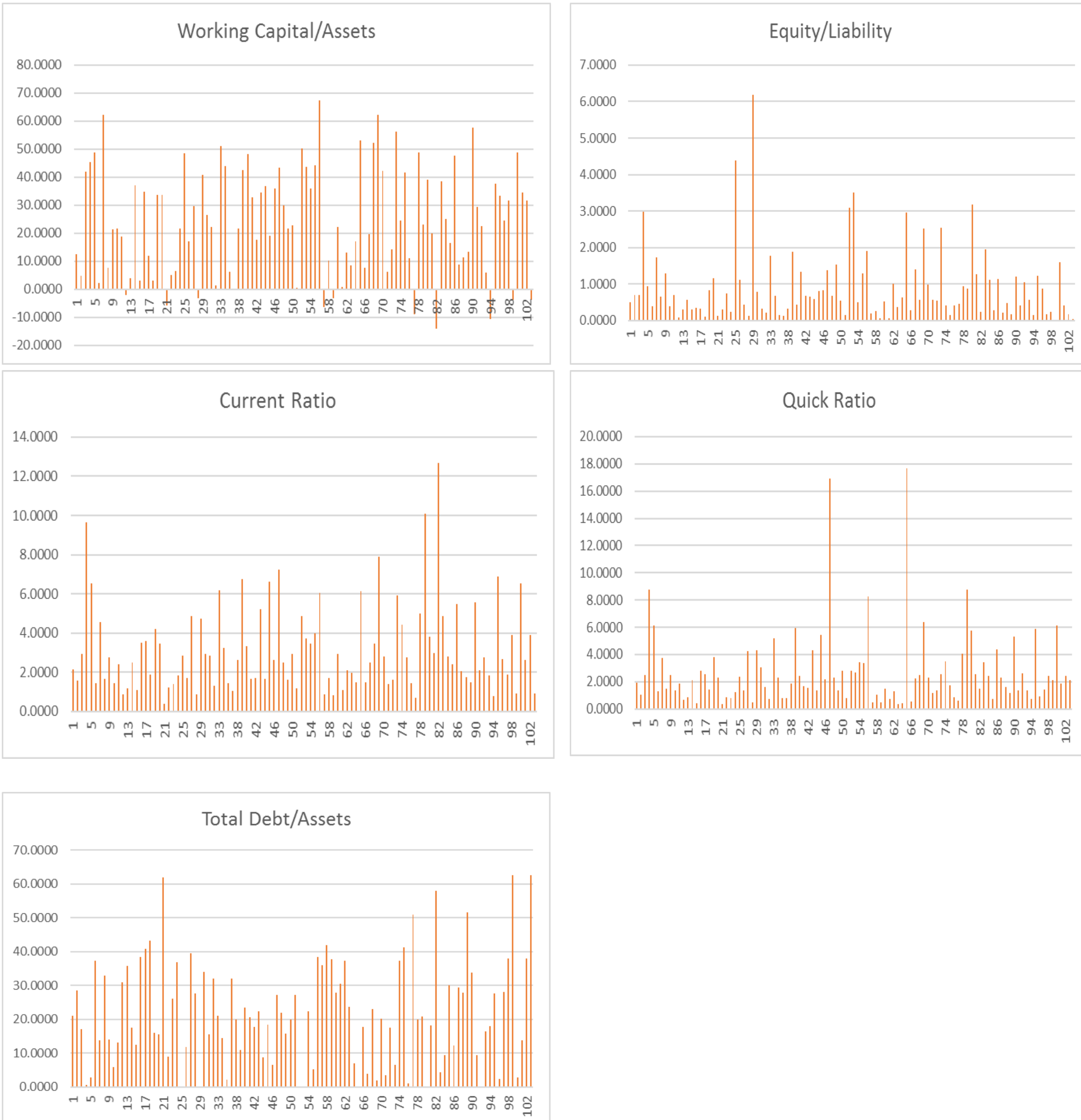


Source: Eikon database, Reuters Finance Center.

Figure (5): Nasdaq Financial Ratios – Profitability Indicators

Source: Eikon database, Reuters Finance Center.

Figure (6): Nasdaq Financial Ratios – Liquidity and Leverage Indicators

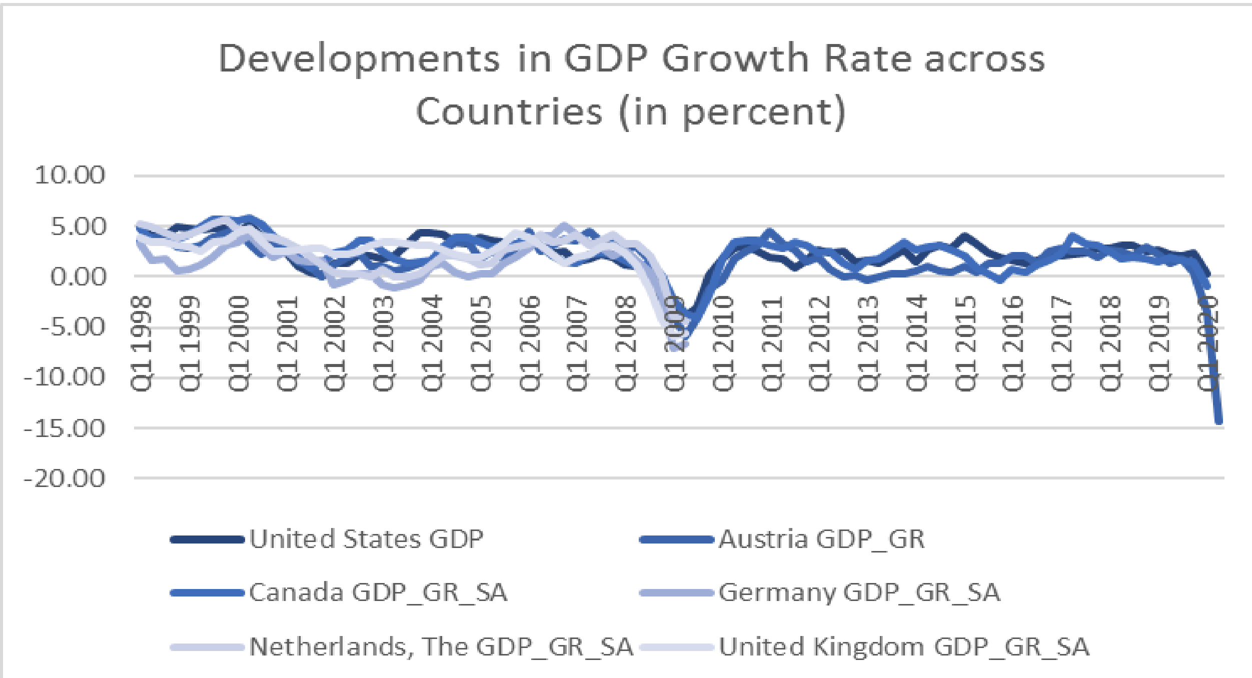


Source: Eikon database, Reuters Finance Center.

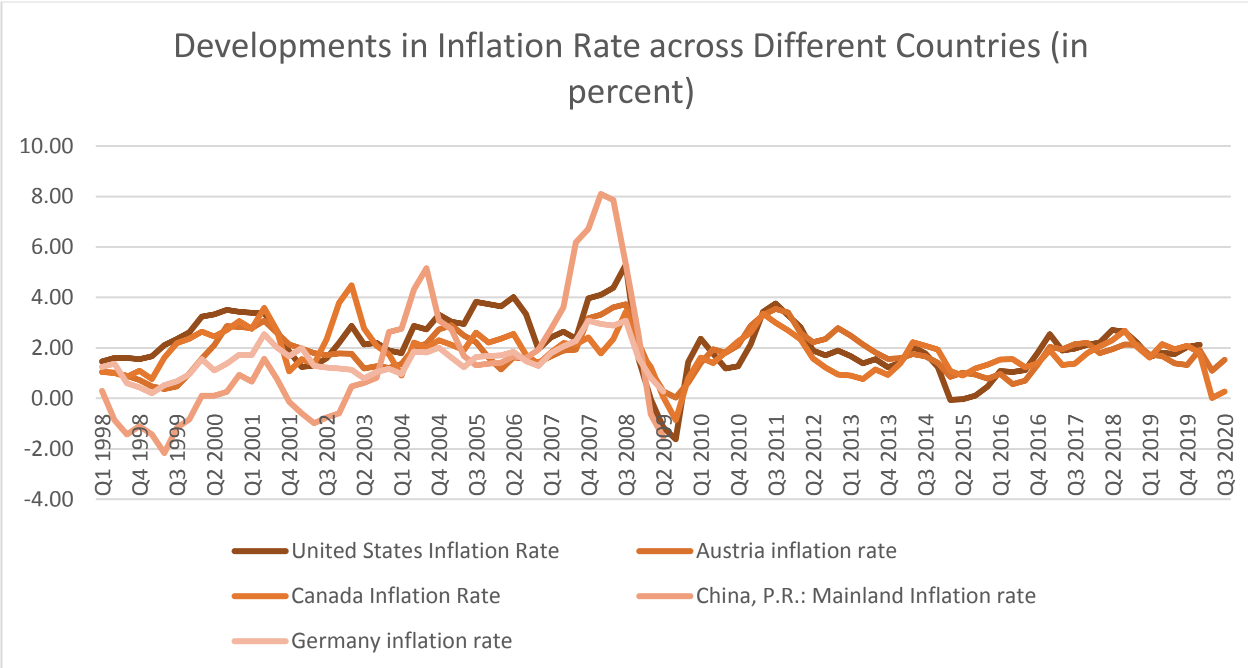
Coming to the macroeconomic variables, the paper utilized both GDP growth rate and inflation rate being the most common macro- variables used in the literature. For Dow-Jones, the paper didn't include the macroeconomic variables because there was a lack of variability since all industries are headquartered in United states and the paper is employing a cross-sectional analysis.

As for Nasdaq, there exists some variability in data because some of the industries are headquartered in countries other than United states which gave a room to apply the hybrid framework.

Systematic risk appears to be symmetric for most of the country sample included in our analysis, in the sense that both GDP growth rate and inflation witnessed co-movements over the period under investigation. This is totally different from the idiosyncratic risk related to the financial indicators presented earlier in this section. The financial indicators and ratios revealed some sort of asymmetry between different industries either for Dow-Jones or Nasdaq.



Source: International Financial Statistics (IFS), IMF.



Source: International Financial Statistics (IFS), IMF.

IV. Methodology:

1. Research Question:

The main research question is concerned with which specific variables are responsible for the prediction of the default risk: idiosyncratic variables, systematic variables or a mixture of both. As such, this study will focus on answering a specific question related to how the predictive power of default risk model can be raised, while relying on an objective indicator variable that will be tailored for this study.

2. Research Design:

The proposed optimal hedging ratio is derived from the traditional interest coverage ratio concept but with a slight twist by including a measure for correlation between EBIT and interest and controlling for their volatility, the proposed measure is given by the following formulas:

Interest Coverage Ratio:

$$= \frac{EBIT}{Interest} \tag{1}$$

Since optimal hedging ratio is given by the following formula,

Optimal Hedging Ratio (h*):

$$= \rho_{ij} \; \frac{\sigma_i}{\sigma_j} \tag{2}$$

Therefore,

Optimal Hedging Ratio (h*) for Interest Coverage Ratio:

$$= \rho_{EBIT,Interest} \ \frac{\sigma_{EBIT}}{\sigma_{interest}} \tag{3}$$

Afterwards, such a measure will be used as the dependent variable of probability of default being a function in a group of macro-economic variables and financial ratios in the framework of a hybrid model.

The empirical framework of that model is given by the equations:

$$Probability\ of\ Default\ (p_i) = \beta_0 + \ \beta_1 \ * Optimal\ Hedging\ Ratio\ (h_i^*) \tag{4}$$

$$h_i^* = f\ (Financial\ ratios, Macroeconomic\ Variables) \tag{5}$$

Where *p* is the probability of default, either industry-specific or country-specific, over a given horizon, and *h** is an indicator variable, which is the optimal hedging ratio calculated in step (3). Here, the proposed hybrid model assumes that the indicator variable is a function of a set of economic and financial variables X = (X_1, X_2, ... , X_n).

V. Estimation Results:

The paper adopted cross-sectional analysis for firms included in Dow Jones (30) and Nasdaq (100), moreover, the analysis depends on the General-to-Specific approach. This section includes the estimation results for the equations (4) and (5) displayed in the methodology section.

1. Dow-Jones Index Results:

P(d) = H-star

The structural default[1] is statistically insignificant and the combined default[2] appeared to have a significant impact associated with the credit hedge ratio at a 10% significance level. R-squared accounted for 0.20 and the estimated coefficient is -0.056, implying that whenever the credit hedge ratio increases, the probability of default declines by 0.056 units.

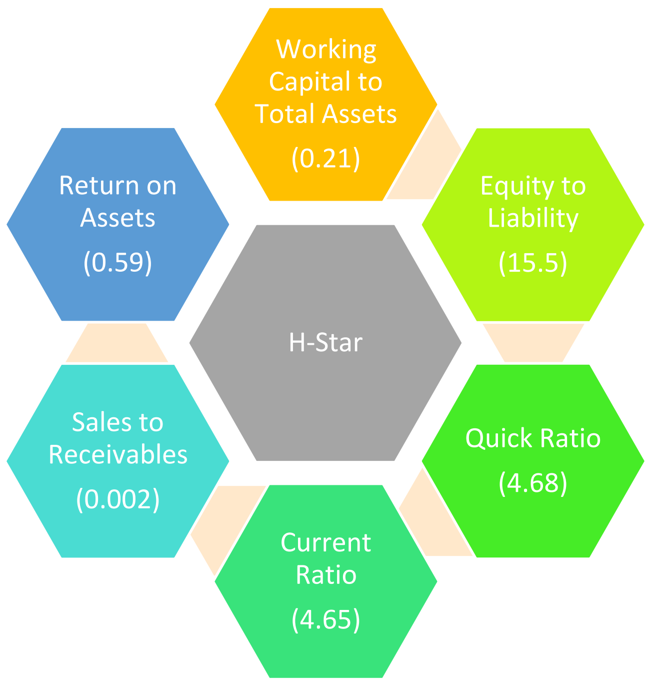
[1] Credit structural probability of default is defined as a decimal that indicates, according to the structural component of the Thomas Reuters StarMine credit risk model, the probability that the company will go bankrupt, or default on its debt obligations, over the next one-year period. The final default probability is equivalent to the probability that the market value of assets will fall below a default point, which is a function of the company's liabilities, within one year.

[2] Credit combined probability of default is defined as a decimal that indicates the probability that the company will go bankrupt, or default on its debt obligations, over the next one-year period.

H-star = F (Financial and Economic Variables), worth to note that we did not include the economic variables because all firms are related to United states so the economic variables lack the variability that could significantly affect the results. Therefore, an estimate of systematic risk was not quantifiable and only idiosyncratic risk has been estimated for Dow-Jones industries.

By applying the general to specific approach, the comprehensive equation indicated that all variables are statistically insignificant except (sales to total assets) which appears to be statistically significant at 10%, with an estimated coefficient of 0.42.

Determinants of Credit Hedge Ratio in Dow-Jones Index:



The rest of variables show a statistical insignificant impact on H-star; these variables include:

- Retained earnings to total assets
- Sales to total assets
- Net cash flows
- Return on invested capital
- Debt to assets

2. Nasdaq Index Results:

P(d) = H-star

The structural default is statistically significant at 5% with an estimated coefficient of -0.016 and R-squared 0.14. The combined default appeared to have a significant impact associated with the credit hedge ratio at a 10% significance level, with an estimated coefficient of -0.003 and R-squared 0.05.

The estimated coefficients for both Dow-Jones and Nasdaq revealed that the optimal credit hedge ratio (H-star) impact on the probability of default is more prevalent in case of Dow-Jones than Nasdaq. This can be attributed to the fact that in Dow -Jones there is some sort of homogeneity in industries as all are related to US, while in case of Nasdaq some industries are headquartered in other countries than United States. That's why the impact is much more prevalent in case of Dow-Jones.

H-star = F (Financial and Economic Variables), worth to note that Nasdaq (100) companies are headquartered in: Argentina, Canada, China (Cayman Islands), China (Mainland), Israel, Netherlands, United Kingdom and United States. This has given the room to include the economic variables to estimate the hybrid models, and include an estimate for the systematic risk along with the idiosyncratic risk.

The general financial model for Nasdaq (100) was comprehensively statistical insignificant. However, a general hybrid model showed that two financial indicators were significant which are equity-to-liability and the return on invested capital at estimated coefficients -0.0006 and 0.8862, respectively.

A more specific hybrid model specification yielded the significance of equity-to-liability and inflation rate, in which both were significant at 5% with estimated coefficients of -0.0008 and 169.10, respectively. Another specific hybrid model indicated the significance of GDP with an estimated coefficient of -1.052, implying that when GDP growth rate increases by 1%, the optimal hedging ratio (H-star) declines proportionally by 1% as well.

It can be grasped that inflation rate had the largest magnitude of impact on the optimal credit hedging ratio, which can be attributed to the fact that higher inflation might constitute a higher risk, in which companies hedge against it by having higher hedging ratio. The opposite happened in case of the GDP growth rate, in other words, higher GDP is associated with lower hedging ratio which gives the market higher level of certainty and confidence, as the systematic risk diminishes with higher level of growth rate and magnifies with higher level of inflation.

VI. Conclusions:

The paper is trying to portray the structural relationship between the probability of default, optimal credit hedge ratio and set of, macroeconomic variables and financial ratios, in the context of a fundamental-based Hybrid model.

The objective of the paper is to come up with a novel metric for optimal hedging ratio which is derived from the traditional interest coverage ratio concept but with a slight twist by including a measure for correlation between EBIT and interest and controlling for their volatility.

The paper adopted the General-to-specific approach in the estimation process. Moreover, cross-sectional data analysis technique has been utilized. In doing so, averages for all included variables have been calculated covering the period Q1:1998 through Q3:2020. Both definition for the probability of default was included in the estimation: structural and combined probability of default.

While analyzing the data, it has been noticed that some industries in both Dow-Jones and Nasdaq encountered negative optimal credit hedge ratio (H-star) which can be explained in the context of commodity prices as the probability of falling price which gives a chance of short-sell position. However, in our case, this situation implies the presence of a negative correlation between EBIT and interest, reflecting also a negative Beta, which gives some insights about the industry of being less risky and consequently we expect maybe lower negative returns from this business.

Also, it has been observed that Systematic risk appears to be symmetric for most of the country sample included in our analysis, in the sense that both GDP growth rate and inflation witnessed co-movements over the period under investigation. This is totally different from the idiosyncratic risk related to the financial indicators presented earlier in this section. The financial indicators and ratios revealed some sort of asymmetry between different industries either for Dow-Jones or Nasdaq.

The main conclusions from the estimation revealed that for Dow-Jones industries, there exists a statistically significant relationship between probability of default and the optimal credit hedge ratio. Additionally, idiosyncratic risk has been quantified by a group of financial ratios that appeared to be statistically significant being a function in H-star. Among these variables: equity to liability, quick ratio, current ratio, sales-to-receivables, return on assets and capital to total assets.

Coming to Nasdaq industries estimation, The general financial model for Nasdaq (100) was comprehensively statistical insignificant. However, a general hybrid model showed that two financial indicators were significant which are equity-to-liability and the return on invested capital. A more specific hybrid model specification yielded the significance of equity-to-liability and inflation rate, in which both were significant at 5% with estimated coefficients of -0.0008 and 169.10, respectively. Another specific hybrid model indicated the significance of GDP with an estimated coefficient of -1.052, implying that when GDP growth rate increases by 1%, the optimal hedging ratio (H-star) declines proportionally by 1% as well.

It can be grasped that inflation rate had the largest magnitude of impact on the optimal credit hedging ratio, which can be attributed to the fact that higher inflation might constitute a higher risk, in which companies hedge against it by having higher hedging ratio. The opposite happened in case of the GDP growth rate, in other words, higher GDP is associated with lower hedging ratio which gives the market higher level of certainty and confidence.

VII. Appendix:

Table (2): Dow-Jones Probability of Default (Structural and Combined)

	Structural PD	Combined PD
H-star	-0.062	-0.557*
No. of Observations	30	30
F-Value	4.476	6.827
R-Square	0.137	0.196

* Significant at 10%.

General-to-Specific Equations

Table : Dow-Jones Determinants of H-Star (General Equation)

	H-star
C	-21.535
Working capital – total assets	-0.467
Equity to liquidity	62.961
Quick ratio	15.174
Current ratio	-10.634
Retained earning to total assets	-0.160
Sales to total assets	0.421*
Sales to receivables	-0.002
N_cash	-.5.50E-07
Return on invested capital (ROIC)	0.447
Debt to assets	0.419
Return on assets	-0.765
No. of Observations	22
F-Value	2.316
R-Square	0.718

* Significant at 10%.

Table (3): Dow-Jones Determinants of H-Star (Specific Equations)

	H-star	No of Observation	F-statistics	R-Squared
Working capital – total assets	0.207**	26	3.860	0.138
Equity to liquidity	15.542**	30	9.611	0.255
Quick ratio	4.679**	26	4.572	0.160
Current ratio	4.654**	26	5.065	0.174
Retained earnings to total assets	-0.047	29	0.948	0.033
Sales to total assets	0.079	29	0.632	0.022
Sales to receivables	0.002**	28	0.982	0.036
N_cash	-2.01E-09	25	0.000	0.000
Return on invested capital (ROIC)	0.160	30	0.627	0.021
Debt to assets	-0.072	29	0.302	0.011
Return on assets	0.594**	30	4.295	0.133

** Significant at 5%.

Table : Nasdaq Probability of Default (Structural and Combined)

	Structural PD	Combined PD
H-star	-0.016**	-0.002
No. of Observations	96	98
F-Value	15.515	5.109
R-Square	0.141	0.050

** Significant at 5%.

Table (4): Nasdaq Determinants of H-Star (General and Specific Equations - Hybrid Equation)

	Hybrid Model (General)	Hybrid Model (Specific 1)	Hybrid Model (Specific 2)
Working capital – total assets	0.065		
Equity to liquidity	-0.0006*	-0.0008**	-0.0005
Quick ratio	1.300		
Current ratio	2.64E-06		
Retained earnings to total assets	0.005		
Sales to total assets	0.107	0.200	0.044
Sales to receivables	-3.983		
N_cash	-0.181		
Return on invested capital (ROIC)	0.886**		
Return on assets	1.466		
Debt to assets	-0.265	-0.118	-0.339
GDP Growth Rate	-1.518		-1.051**
Inflation Rate	-11.92	169.104**	
No of observations	96	98	98
F-statistics	1.987	68.205	1.364
R-squared	0.239	0.745	0.055

*significant at 10% and ** Significant at 5%.

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