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A Machine Learning-Based Prediction of Stock Price Crash Risk Using Micro and Macro-Level Determinants

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This research study investigates the impact of macro and micro-level indicators of the stock price crash risk. We used the daily stock prices of 15 top-performing stocks listed in the S&P 500 index. We choose these specific companies based on their trading volume. We used data ranging from Jan 2010 to Dec 2022 for all the companies. In the first step, we calculated the monthly series of stock price crash risk using the negative skewness approach. In a similar pattern, we use monthly data of macro indicators, which are exchange rate, interest rate, and economic policy uncertainty. In addition, we use trading volume and short selling as micro-level determinants of individual stock price crash risk (SPCR). We deploy four different models to forecast the stock price crash risk and the impact of individual determinants on the SPCR. These models include linear regression, support vector regression, a single-layer perceptron model, and a multilayer perceptron model. The findings suggest that both the micro (firm) level and macro-level potential predictors are highly significant. The overall accuracy of machine learning models improved significantly when macro-level indicators were incorporated. Furthermore, machine learning models, especially SLP and MLP, outperform linear regression.

Keywords: *Crash Risk; Economic Uncertainty; Machine Learning; Stock Markets.*

Introduction

A stock market crash is a phenomenon when stock markets experience a significant decline in stock prices. It happens when the number of sellers exceeds the number of buyers (Toporowski, 1993). The pressure of selling equities accelerates the stock market crash. Such a scenario causes panic in both individual and institutional investors (Fleitas, Fishback, & Snowden, 2018). The literature regarding stock price crash risk is dominated by "bad news hoarding" theory. It argues that the likelihood of stock price crash risk increases if managers withhold bad news for an extended period of time. When such accumulated bad news is released, it leads to an abrupt decline in stock prices. In addition, any news related to economic instability may also trigger the negative movement of stock prices. Recently, different indices of economic uncertainty have been used in the literature. These indices are constructed on the basis of news projecting that the uncertainties prevail in the economies (Brogaard & Detzel, 2015; Jens, 2017). Several studies have focused on the linkage between economic uncertainty indices and stock returns. However, the relationship between economic policy uncertainty (EPU) and stock price crash risk (SPCR) is still underexplored. EPU and SPCR have a positive relationship since during high EPU periods, managers hold bad news, which is a major predictor of

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SPCR. Therefore, high EPU leads to high volatility in the earnings and cash flows of firms. Consequently, managers tend to distort financial information for the sake of projecting smooth earnings and avoiding short-term pressures. Furthermore, EPU triggers information asymmetries among insiders and outsiders (Nagar, Schoenfeld, & Wellman, 2019). In their research, it is argued that EPU has great potential to influence SPCR because it affects the bad news hoarding behavior of managers. Hence, high EPU is followed by the likelihood of SPCR.

There has been a bulk of literature that showed a growing interest in the investigation of economic and financial consequences of economic policy uncertainty (EPU) (See (Luo & Zhang, 2020; Phan, Iyke, Sharma, & Affandi, 2021; Sahinoz & Erdogan Cosar, 2018)). Some of the studies focused on the impact of EPU on investment behavior and efficiency (see (Bernanke, 1983; Bloom, Bond, & Van Reenen, 2007; Jens, 2017; Rodrik, 1991)). Special attention has been given to the impact of EPU on asset pricing (Pastor & Veronesi, 2012). It is argued that higher EPU causes low stock prices and high expected future stock returns. Furthermore, high political risk leads to high volatility in stock markets (Boutchkova, Doshi, Durnev, & Molchanov, 2012). EPU is considered a crucial risk factor in asset pricing (Brogaard & Detzel, 2015). Among the macro indicators of stock price crash risk, EPU acts as a major predictor because the construction of EPU indices focuses on the use of economic uncertainty news published in major newspapers at the country level (Al-Thaqeb & Algharabali, 2019). This news covers all the information regarding monetary policy, fiscal environment, and economic uncertainty, which are critical for stock market performance, especially stock price crash risk.

Among the firm level indicators of SPCR, short-sale bans is an important factor. E. C. Chang, Luo, and Ren (2014) concluded that revoking the ban led to an increase in price efficiency and a decrease in stock return volatility. X. Li and Wang (2017) suggested that, even in an emerging economy like China with a less developed stock market in comparison with US and Europe, short selling played a pivotal role in stabilizing stock prices and enhancing market quality. The question of whether short selling can successfully mitigate the risk of stock price crashes at the firm's level remains open to discussion. Similarly, the high liquidity of stocks is closely linked to an increased risk of stock price crashes. This causal relationship is investigated by the decimalization of stock trading, serving as an external shock to liquidity. Analogously, research indicates that the capital market itself increases the propensity to hold onto bad news, increasing the risk of future price collapses. X. Chang, Chen, and Zolotoy (2017) validate the notion that the disclosure of negative news could prompt short-term investors to sell their stocks by finding a positive association between crash risk and stock liquidity, which they use as a stand-in for this incentive. However, their methodology does not clearly state how exactly stock liquidity affects crash risk, either directly or indirectly through the sporadic investor channel.

The literature regarding SPCR is mostly tilted either towards the micro (firm) level determinants or uses traditional econometric models. However, stock price crash risk is exposed to both firm-level as well as macro-level determinants. Therefore, this research study fills the existing gap by using advanced machine learning models of support vector regression (SVR), a single layer perceptron (SLP) model and a multilayer perceptron model (MLP). We use these models because traditional time series models are unable to address the problems of outliers and nonlinearities. We use trading volume and short selling as a micro (firm) level indicators of stock price crash risk. Whereas, exchange rate, interest rate and EPU have been used as macro level predictors of individual stock price crash risk.

The contribution of this research study is multifold.

- Firstly, we investigate the impact of micro (firm level) and macro-level indicators on individual stock price crash risk which is under explored in the existing literature. Among macro indicators, we use the news-based economic policy uncertainty (EPU) index. This indicator is quite rarely used in literature, especially in the context of SPCR. In addition, exchange rate and interest rate have not been considered in previous studies to predict SPCR
- Secondly, we compare the forecasted results of individual SPCR based on micro level predictors with the results generated based on macro-level indicators such as exchange rate, interest rate and EPU.
- Lastly, we forecast the firm level SPCR by using machine learning models i.e. SVR, SLP and MLP. We use these models because of their strength to manage the nonlinearity and outliers present in the financial time series data sets.

The rest of the paper is organized as follows: the second section presents the literature review of stock price crash risk, and the third section discusses the methodology in detail. The fourth section presents the results along with the discussion and literature support followed by the conclusion.

Literature and Hypothesis Development

The firm-specific stock price crash risk refers to the probability of noticing extreme negative values in their distribution after balancing the return portions that move together with the common factors (L. Jin & Myers, 2006; J. B. Kim, Li, & Zhang, 2011a, 2011b). In a similar study, L. Jin and Myers (2006) investigated whether the information asymmetry between internal and external customers can have any sort of impact on crash risk. More precisely, they found that non-transparent stocks are more likely to crash because the management holds the bad news regarding such stocks. Hutton, Marcus, and Tehranian (2009) found that when the ambiguity or murkiness of the stocks is increased, the chances of crash risk are high. They tested it by using the accruals in absolute quantity as a proxy. Francis, Hasan, and Li (2016) have further extended this finding by adding that real earnings management (REM) also has an increasing impact on crash risk. Furthermore, the impact of REM is more significant and noticeable as compared to accrual earnings management (AEM).

The extensive literature on stock price crashes is related to the lack of balancing and asymmetry in the returns for every individual stock (Callen & Fang, 2015b; J. Chen, Hong, & Stein, 2001; J. B. Kim & Zhang, 2014). Many

prospective studies have been introduced to estimate this asymmetry in crash risk, and most of the studies relate these findings to diversified independent variables to determine the possible outcomes of crashes in stock prices. Investors in stock markets always strive for higher returns on their investments, especially with stocks having higher negative skewness, suggesting that skewness can be referred to as the priced risk factor (Conrad *et al.*, 2013; Harvey & Siddique, 2000). The present-day disturbance or agitation in the stock market also shows that investors are at crash risk. Barter investors try to be more focused on financing in the stocks of smaller firms compared to the larger ones (Barber & Odean, 2013), and the crash in stock prices of these companies' portfolios can be more destructive for their personal assets. Therefore, grasping what affects investors deemed crash risk has the possibility of protecting the value of shareholders. Most of the latest experimental studies on the factors determining crash risk come behind the agency theoretical framework of L. Jin and Myers (2006), in which the information asymmetries between both internal and external customers contribute to the existence of crash risk. This uneven information permits managers to conceal substandard news for an expanded time period for the sake of earning compensation, saving employment and lowering the litigation chances emerging from substandard news declarations (Kothari *et al.*, 2009).

Theoretically, the concept crash risk is constructed on the opinion that the managers of a firm have a propensity to hold back any substandard news for an expanded period, which resultantly allows such type of news to pile up. If managers succeed in stopping the circulation of bad information regarding the firm in the stock market, the dispensation of the returns in stocks should be asymmetric (Hutton *et al.*, 2009; Kothari *et al.*, 2009). When the pile of disturbed news passes a specific gateway, it is disclosed to the market in bulk, which results in a huge downturn in the price of stock.

Although financial reporting obscurity and the consequences on stock crash risk have gone well with the usual research approach, other definite procedures could also result in stock price crashes. Bleck and Liu (2007) in their proposed model used the traditional cost financial reporting of historical data allowing the manager to carry on with a substandard investment opportunity, thereby acquiring benefits before the maturity of the project. This is eased by the help of outside customers who are not able to evaluate the project's market value until the completion of the project. Moreover, (Benmelech, Kandel, & Veronesi, 2010) proposed a model that adds that managers with contracts in equity-based markets must continue with low NPV projects to increase the value of their remuneration packages. The main idea of these models is that managers should be compensated for piling up bad news to the forerunner for a stock price crash. Finally, the manager must reveal the bad news that will end up causing the stock price to drop. When the assembled substandard news leaks out quickly in the market, stock prices continue to decrease, which eventually leads to a crash.

EPU and Stock Price Crash Risk

Economic Policy Uncertainty (EPU) and stock price crash risk are positively correlated (Bates, 2012). Most of the literature has focused on the impact of EPU on volatility and stock returns whereas, its influence on the stock return's third moment is still under-explored. It is expected that the EPU is positively associated with the SPCR as the managers' incentives and aptitudes to withhold any depraved news, which is a significant factor of crash risk, and are both reinforced during periods when EPU is quite high. A high EPU results in increased variation in both earnings and cash flow of companies, which results in managers' larger tendency to misrepresent financial information so that the performance pressures may be alleviated (Luo & Zhang, 2020). Furthermore, greater EPU leads to a high information asymmetry among the investors sitting outside and the corporate insiders (e.g., Nagar *et al.*, 2019)), which upsurges investors' dependence on the company disclosures while creating investment choices and managers' capability to influence earnings. Hence, we assume a greater EPU to be followed by a high crash risk in stock price particularly between stocks with larger valuation vagueness.

EPU is meaningfully and positively related with combined crash risk at the market level (Luo & Zhang, 2020). A similar argument has been built by Brogaard and Detzel (2015) which conclude that EPU generates systematic risk in the stock markets and its impact could not be completely diversified. X. Jin, et. al (2019) argue that EPU is related with SPCR through its association with manager's behavior of hoarding bad news and the investors' varied opinions. In this context, EPU has the power to have an impact on stock price risks which are firm specific as it impacts management's bad news hoarding conduct, which is a significant factor of crash risk as advised by above-mentioned research studies. More precisely, we assume that EPU impacts both managers' skills and incentives to hold any bad news. Companies' operations face larger vagueness in times of high EPU, resulting in more downturns in future cash flows and profits. High EPU is also anticipated to have negative effects on the short-term performance of firms. Hence, the management has greater incentives to change earnings to level the firm's performance and to reduce short-term performance pressures throughout greater EPU times. Furthermore, investors have to face larger valuation vagueness and information asymmetry whenever the values of EPU are higher and have to trust more on the disclosures done by managers' while evaluating firm value (Nagar *et al.*, 2019). Management consequently has higher skills to hide bad news and change earnings. The EPU is expected to positively relate with the individual level SPCR to the extent that managers' incentives and skills to reserve bad news are strengthened when EPU is high, as specified in our first hypothesis:

H1: Firm-specific stock price crash risk increases with economic policy uncertainty.

Short Selling and Stock Price Crash Risk

According to Hong and Stein (2003), constraints on short sales created hindrance in pessimistic investors' trading activities, causing stock prices to dominantly reflect positive news. This information imbalance allowed negative views to gather up, eventually reaching a critical threshold and triggering a crash of stock prices. G. Chen and Zhang (2009) built up on Hong and Stein (2003) model of heterogeneous beliefs, proposing that lifting short-sale bans could alleviate the occurrence of these stock price crashes. China gradually began lifting short-sale bans for selected stocks in a designated list since March 2010 (Luo & Ren, 2016). Analyzing Chinese companies' data from 2010 to 2012, E. C. Chang et al. (2014) concluded that revoking the ban led to an increase in price efficiency and a decrease in stock return volatility. Looking at a broader time frame between 2009 to 2014, X. Li et al. (2017) suggested that, even in an emerging economy like China with a less developed stock market in comparison with US and Europe, short selling played a pivotal role in stabilizing stock prices and enhancing market quality. The question of whether short selling can successfully mitigate the risk of stock price crashes at the firm's level remains open to discussion.

Diamond and Verrecchia (1987) suggested that the removal of short-sale constraints can give returns which are less negatively skewed. On the contrary, Hong and Stein (2003) argue in their work that constraints on short selling correlate positively with the skewness of stock returns. In a recent study, Saffi and Sigurdsson (2011) analyze weekly stock return skewness, revealing that easing short selling constraints lead to increased negative skewness and less frequent sharp positive returns. However, their study found no evidence supporting an increase in the frequency of sharp negative returns with higher lending supplies. Considering the ambiguous outcomes and conflicting predictions from past literature, we postulate that easing short-sale restrictions makes the correction of stock prices to their fundamental value in a timely way, thus reducing the price crash risk. Contrarily, during acute shorting, more negative information is put into the price, which is likely to lead to a drop in insider sales. Short selling promotes corporate transparency by constraining earnings management (Fang, Huang, & Karpoff, 2016), and also deters insider trading which lowers litigation risk for inside managers.

H2: Firm-specific stock price crash risk increases with short selling.

Trading Volume and SPCR

The high liquidity of stocks is closely linked to an increased risk of stock price crashes. This causal relationship is investigated by the decimalization of stock trading, serving as an external shock to liquidity. The impact of this phenomenon is particularly prominent in firms having a higher ownership ratio held by ephemeral investors and non-block holders. Notably, companies with greater liquidity exhibit a high level of probability of experiencing unfavorable future earnings revelations. These, in turn, trigger boosted selling by ephemeral investors, although not by block holders. The liquidity factor urges managers to withhold negative news, boosted by the apprehension that its disclosure would prompt sales by transient investors. Finally, a combined release of negative information emerges simultaneously, causing a market crash (X. Chang *et al.*, 2017). Analogously, research indicates that the capital market itself increases the propensity to hold onto bad news, increasing the risk of future price collapses. X. Chang et al. (2017) validate the notion that the disclosure of negative news could prompt short-term investors to sell their stocks by finding a positive association between crash risk and stock liquidity, which they use as a stand-in for this incentive. However, their methodology does not clearly state how exactly stock liquidity affects crash risk, either directly or indirectly through the sporadic investor channel. Callen and Fang (2015a) add to this narrative by showing that short interest in stocks is a leading predictor of future crash risk. This is consistent with the theory that short sellers can identify managerial tendencies to withhold bad news, leading them to initiate pre-emptive short positions ahead of price declines. Further studies, e.g. Ni and Zhu (2016) and Habib and Hasan (2017), explore how novel corporate tactics and regulatory reforms, respectively, might impact the likelihood of a stock market crash.

H3: Firm-specific stock price crash risk increases with trading volume.

Literature Regarding Machine Learning

The literature regarding stock price crash risk using machine learning focuses on a specific domain that mostly provides implications in the form of warning systems for stock market crashes. Coudert and Gex (2008) use the logit model to estimate the stock market crisis by using risk aversion indicators and find it significant. The major reason behind the stock price crash is the burst of price bubbles. Herwartz and Kholodilin (2014) investigated the determinants of stock price crash risk and found that the price-to-book ratio is a significant explanatory factor behind the emergence of price bubbles. They used in-sample and out-of-sample approaches for their analysis. In a similar pattern, W.X. Li et.al (2015) also use a logit model to forecast stock market crises by using options and futures as features in their model. Their findings provide significant explanatory power of options and futures to predict stock market crises.

The forecasting of time series financial variables has been one of the most studied topics in finance literature. A few studies have used neural network models to forecast financial asset prices. (See, e.g. (Bagheri, Mohammadi Peyhani, & Akbari, 2014; Cervello-Royo *et al.*, 2015; Chiang *et al.*, 2016). Some researchers propose a hybrid model that is the combination of ANN and PCA to obtain better forecasted results of financial time series data sets (X. Zhong & Enke, 2017). H. Y. Kim and Won (2018) present a combined approach of statistical machine learning to improve the predictive capacity of the financial forecasting system. However, combinations of deep learning and statistical machine learning approaches provide more accurate results.

H4: The predictive power of ML models increases with macro indicators of stock price crash risk.

In forecasting SPCR, the combined use of micro (firm)-level and macro-level features in machine learning forecasting systems is still unexplored. Therefore, this research study aims to fill this gap in literature.

In the existing literature using machine learning models, studies either attempt to forecast stock prices or stock returns. See (Jabeen *et al.*, 2022; Maqsood *et al.*, 2020). In addition, event-based social media sentiment is used in these studies to forecast stock market data. In this context, forecasting of SPCR has received little attention and needs to be explored further by considering firm level as well as macroeconomic determinants.

Data and Methodology

In this section, we discuss the data description, and a detailed methodology used for the estimation of stock price crash risk.

Data

We collected the daily data set of 15 top performing stocks from Jan 2010 to Dec 2022 listed in S&P 500 index. We have taken the top performing blue-chip companies that represent the stock market. These stocks include the financial and non-financial sector industries. In the financial sector, 4 companies have been chosen which provide financial services. On the other hand, the remaining 11 stocks have been chosen from the non-financial sector. These stocks are traded in the New York Stock exchange and NASDAQ. The data set includes 5 companies from the technology sector, 2 stocks from healthcare, 2 stocks from energy and communication services and one stock from consumer cyclical and airlines industry each. All the 15 stocks have been selected based on their current high trading volume. In addition, this data set covers the major sectors. In this context, the data set covers a major part of Business and trading. The daily frequency of data set comprising 15 companies makes it suitable to use advance forecasting models for machine learning because they require the large data points to understand the complex relationship among the variables. In addition, 12-year span covering daily data points of 15 companies adds an advantage of generalizability of the forecasted results. Furthermore, when the stock price crash triggers, it initially hits the large companies containing the major share of the stock markets and then moves to small stocks. Therefore, we have considered the data set of top performing stocks. We calculated the stock price crash risk of all the stocks monthly. Among macroeconomic determinants, we used exchange rate, interest
rate and EPU. Trading volume and short selling have been used as a micro (Firm) based indicators of individual SPCR.

Variables

Calculation of Stock Price Crash Risk

We calculated the monthly stock price crash risk of all the 15 companies using a negative skewness approach, which is consistent with (J. Chen et al., 2001). We used Eq. 1.

$$NCSKEW = -\left[n(n-1)^{\frac{3}{2}}\sum W_{it}^{3}\right] \Big/ (n-1)(n-2)\left(\sum W_{it}^{2}\right)^{\frac{3}{2}} \quad (1)$$

NCSKEW is the negative conditional skewness. It is calculated by taking the negative of the third moment of daily individual stock returns. We calculated the monthly negative conditional skewness of all the stocks using this approach. Here n denotes the number of daily data points of individual stock prices.

Macro Indicators

Interest Rate

Interest rate is a major macroeconomic variable that affects the investment decision in the stock market. Hence, we used the country-level monthly policy rate as a proxy of interest rate to determine its impact on the stock price crash risk.

Exchange Rate

We use the exchange rate in terms of USD to GBP since our targeted stocks are the top 15 actively traded stocks of the S&P 500 index. These stocks are traded in NYSE.

Economic Policy Uncertainty

We use the EPU index constructed by Baker, Bloom, and Davis (2016). It is constructed based on news regarding the economy published in major newspapers. They applied textual data mining techniques to construct the EPU index based on selected words regarding uncertainties prevailing in an economy. We used the monthly frequency of the EPU index of the USA since the selected firms are USA-based firms. We have used the two measures of the conventional EPU index. One is a component index which is based on state-level disagreement, tax expiration, and CPI disagreement. The second measure is the news-based policy uncertainty index.

Micro (Firm level) Indicators

Volume

We use the trading volume of the individual stocks as a company-specific micro indicator to predict the stock price crash risk. We selected the top 15 stocks on the basis of their current trading volume in the NYSE. These stocks are also listed in the S&P 500 index.

Short Selling

We use short selling as a micro indicator to predict the stock price crash risk. A short-selling dummy is inserted in our data set during the period in which there exists a negative relationship between the closing price and trading volume of the relevant stock. At first, we used the structural break approach of Bai and Perron (1998) to find out the periods in which there is an inverse relationship between stock price and its trading volume. In the second step, we insert a dummy to represent the short-selling regimes.

Financial Model

The linear regression model is a widely used machine learning technique for prognostic analysis. The syndicate between the dependent and independent variables is calculated and approximated using these linear regression models. We use the following form of regression presented by Eq 2.

$$CR = \beta_0 + \beta_1 EPUTC + \beta_2 EPUN + \beta_3 E + \beta_4 I + \beta_5 vol + \beta_6 SS \quad (2)$$

Here, CR is the stock price crash risk. The regression model is designed in such a way as to find a best-fit linear line or linear relationship among the independent and dependent variables. As the weights of coefficients are different, which then produces a different line of regression, the optimum values for coefficients are to be obtained to construct a best fit line, which in our case we have done using the objective functions. In other words, the mapping function that makes a link between the independent and dependent variables is authenticated by using the cost function. The difference between the line made by the predicted values and that of the actual values is referred to as the error term or residual. This residual is calculated for each instance or the data point, and the added value of these residuals is referred to as the sum of residuals.

Support Vector Regression

Support vector regression (SVR) is another type of regression technique that is also a generalized version of support vector machines. SVRs are able to compute both linear and nonlinear regression problems (Adcock & Gradojevic, 2019; H. Zhong, Wang, Jia, Mu, & Lv, 2019). Mostly, the working of SVR is similar to SVM, but the difference lies in an objective to estimate the most fitted line within a given range of data. The distance between the hyperplane and the boundary line is called the threshold value. The best fitted line is referred to as the line having the maximum number of data points. Generally, while solving regression problems, SVR is a very useful approach and is used for estimating different types of prediction problems. Given in Eq.3., the SVR model establishes a functional calculator by using a fraction of the given data set.

$$f(x) = w^T \emptyset(x) + b \quad (3)$$

In equation (3), the weights of EPU, interest rate, exchange rate, trading volume, short selling and their coefficients are denoted by $w \in R^n$, where b is the constant term. Moreover, $\emptyset(.)$ defines the mapping, and (x) in R^n defines the input variables containing the independent variables. The SVR model sets a threshold error tolerance ε around the linear regression line. Most importantly, this is done in such a way that the accuracy of the instances is not compromised. Hence, it is called the ε-insensitive portion, in which the residuals outside this portion are minimized. The loss function is mathematically shown below:

$$L(\xi) = \begin{pmatrix} 0 & |\xi| \le \varepsilon \\ |\xi| - \varepsilon & |\xi| > \varepsilon \end{pmatrix} \quad (4)$$

In equation (4), ξ describes the differentiating point from the ε-insensitive portion. The mathematical form of this challenge function is given below.

$$Min: \frac{1}{2}||w||^2 + C\sum_{I=1}^{n}(\xi_i + \xi^*{}_i)$$
$$s.t \begin{Bmatrix} y_i - w^T x - b \le \varepsilon + \xi_i \\ w^T x + b - y_i \ge \varepsilon + \xi^*{}_i \\ \xi_i, \xi^*{}_i \ge 0 \end{Bmatrix} \quad (5)$$

By combining the Lagrangian dual function, the optimization problem defined in the above equation (5) can be easily solved. In equation (3), the weights of EPU, interest rate, exchange rate, trading volume, short selling and their coefficients are denoted by $w \in R^n$, where b is the constant term. Moreover, $\emptyset(.)$ defines the mapping, and (x) in R^n defines the input variables containing the independent variables. The SVR model sets a threshold error tolerance ε around the linear regression line. Most importantly, this is done in such a way that the accuracy of the instances is not compromised.

Single Layer Neural Network

Single-layer neural networks (SLPs) are the basic and simplest form of artificial neural networks (ANNs). ANNs, or artificial neural networks, are mathematical, numerical and statistical models that emulate the human brain and are very effective approximation techniques for solving regression problems and performing predictive modelling. ANNs are high-powered modelling algorithms designed to build relationships between independent and dependent variables by first training them on large data. The nerve cells in ANNs are attached to each other at more than one level of the predictive model being used, which is the same as the way neurons are connected inside the brain. These nerve cells are often referred to as nodes. Each nerve in the model obtains input data from either the environment or through other nerve cells in the network. Computers are artificially programmed in such a way that they act like brain cells linked with one another in the ANN. Disturbance in one or more ANN units does not stop it from building an outcome, and this strong property of the ANN provides the model with fault tolerance. One salient feature of ANNs is their potential and capability to open the input patterns without any set rules and checks. The application of artificial neural networks includes pattern recognition, forensics, medical sciences, natural and environmental sciences, among others (Abiodun *et al.*, 2018).

A simplified form of ANN is a single-layer neural network that contains only an input and an output layer. The total number of nodes in the input layer is the number of independent variables used at the time of training the model. In this research study, the SLP algorithm takes the input vector of independent variables denoted as:

$x = (EPU, I, E, Vol, SS)$

Each x_{in} is given to the separate nodes at the input layer of the model. In the next step, the outcome of the nodes from 1 to n is calculated by using equation (6)

$$\left(u_1 = \left(\sum iw_i x_i + b\right), u_2 = \left(\sum iw_i x_i + b\right) \ldots . u_n \left(\sum iw_i x_i + b\right)\right) \quad (6)$$

In the above equation (6) $u_1 \ldots u_n$ represents the total nodes in the input layers, which are micro and macro indicators of SPCR, while w_i denotes the weights in the case of each node connection. More precisely, each input is multiplied by the weight attached to it. These weights, in true essence, define the length and range of the connections between the hidden nodes within the SLP model. Inside the processor of SLP, every weighted input is added together.

When an input weight equals zero, a bias is introduced to obtain a nonzero outcome. In the next step, the SLP model starts its learning process by tuning the weights, and the same process continues by estimating the model residual, which is the difference between the expected model outcome and the actual value of the explanatory variable. The same process continues several times or for a settled number of repetitions until the model ends with minimum residual values. In this study, the SLP model was trained for 20 ages/epochs with a learning rate of 0.01 and array size of 4. The starting weight values of layers are initiated with the Glorot uniform method, which is also known as Xavier uniform initialization. These weights become optimal throughout the training phase from start to end by using the "Adam" weight optimizer (Kingma & Ba, 2014). The coefficient values generated through this regression model are saved after the training phase and later, may be utilized to calculate the values of the dependent variables for any observations or tested data.

Multilayer Neural Network

A well-known form of a feed-forward artificial neural network is a multi-layered neural network. The existence of concealed layers between the input and output layers differentiates single-layer neural networks from multilayer neural networks. The number of concealed units in various layers is called nodes with nonlinear activation functions. Back propagation is an approach of supervised learning that is used to train multilayer neural networks. The MLP model is more prominent than the classical linear regression due to its multiple-layered design as well as nonlinear activation functions. A single concealed layer in neural networks is referred to as a conventional ANN or a multilayer perceptron. In every layer of the MLP model, contrasting activation functions are introduced after the transfer function. In this study, the design of the MLP model comprises five layers, which is equal to the number of independent variables in the model. The ReLu not only surpasses the logistic sigmoid function but also the hyperbolic tan function. It can control the problems associated with gradient disappearance and explosion while also making the merging speed steady. Equation (7) depicts the mathematical form of ReLu (Nair & Hinton, 2010)

$$ReLu(x) = \begin{cases} x & if \quad x > 0 \\ 0 & if \quad x \leq 0 \end{cases} \tag{7}$$

As the underlying architecture is fully connected, it confirms that each concealed unit is connected with every other node or concealed unit of the preceding layer with some weight value. Therefore, the result of every node u is depicted in equation (8)

$$u = \varphi\left(\sum iw_i a_i + b\right) \tag{8}$$

Equation (8) depicts that w_i is the weight assigned to each link between nodes, a_i represents the input the bias term is referred to as b is and φ represents the activation function i-e ReLu on concealed layers. Finally, the outcome of the node has the value $(\sum iw_i a_i + b)$, which represents the approximate value of the dependent variables. "Adam", the weight optimizer, dynamically updates the weights and bias values of parameters during the training session of the model. The numerical calculation for those weights and biases is depicted below:

$$\Delta W_1(t+1) = -\frac{x_\lambda}{r} W_1 - \frac{x}{n}\frac{\partial C}{\partial W_1} + m\Delta W_1(t) \tag{9}$$

$$\Delta B_1(t+1) = -\frac{x}{n}\frac{\partial C}{\partial B_1} + m\Delta B_1(t) \tag{10}$$

The symbols $W, x, B, l, n, t, m, \lambda,$ and C in the above equations represent the weights, rate of learning, bias, layer count, instances of training, updating step, momentum, regularization parameter, and loss function. Furthermore, the tuning parameters of the suggested model contain a learning rate set to 0.01, a batch size of 4, and epochs of 20. At the beginning of the training process, the weights are provided with initial values b using the Glorot uniform method, also called Xavier uniform initialization, and during the later stages, the values of these weights are dynamically updated in consecutive epochs. When an epoch ends, the residual term is calculated based on the mean squared error between the actual and forecasted values of the variables. The mathematical form of the loss function being used is depicted below:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{11}$$

While viewing equation (11), N shows the total instances of examples in dataset $D = (y_i, x_{i1}, \dots \dots x_{ip})_{i=1}{}^{n}$, while y_i represents the actual output of the SPCR, and $\hat{y}_i$ shows the forecasted value of the SPCR. When the epochs are ended, the finalized values of the coefficients are saved, which will further be used for the testing data (i.e. unobserved data) during the future by using the interest rate, exchange rate, EPU indices, trading volume, and short selling to calculate the forecasted values of an SPCR.

Results and Discussion

This section discusses the results of the descriptive statistics, ADF unit root test and regression coefficients of the individual SPCR parameters. For coefficient estimation, we use linear regression, support vector regression, a single-layer perceptron model and a multilayer perceptron model. We also present the results of the evaluation matrices generated with and without macro-level determinants of SPCR.

Descriptive Statistics

In this part, we present the descriptive statistics of the relevant variables regarding stock price crash risk.

Table 1

Descriptive Statistics Apple

	Crash Risk	EPUTC	EPUNS	Exchange rate	Interest rate	Volume
Mean	1.778	142.13	163.20	1.432	0.655	995.69
Std. Dev.	0.286	46.437	69.167	0.149	0.876	1271.48
Jarque-Bera	5708.64***	1554.2***	4543.25	184.22***	1554.31***	32673***
Probability	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2340	2340	2340	2340	2340	2340

***,* show significance at 1 % and 10 %

The results of the Jarque-Bera test are also reported. The JB test statistics show that all the variables are non-normal i.e. interest rate, exchange rate, economic policy uncertainty news sentiment, trading volume and stock price crash risk. The above Table 1 shows the descriptive statistics of all the variables collectively. The mean value of crash risk is 1.778 with a standard deviation of 0.286. The total number of observations is 2340 for all the variables.

Unit Root Test

In the time series data, the problem of unit roots is quite common. We investigated the existence of the unit root problem unit augmented Dickey Fuller (ADF) test. If data has a unit root problem, then regression models do not provide reliable results. The results of the ADF test are reported in Table 2

Table 2

ADF Unit Root Test

Variables	Level	Tabulated Test statistics at 5 %
CR	-24.421	-2.863
EPUTC	-7.547	-2.863
EPUN	-7.459	-2.863
Volume	-3.668	-2.863
Exchange rate	-6.791	-2.863
Interest rate	-11.334	-2.863
Volume	-4.869	-2.863

*** shows significance at 1 %

If the data set has a problem of Stationarity, then the mean and variance of the series become time-dependent; hence, modelling does not provide reliable results. Therefore, it is necessary to investigate whether the data set has a unit root problem. The results show that all the variables are stationary at level because their ADF test stats are greater than tabulated test statistics, which rejects the null of the unit root problem. The calculated ADF test statistics and tabulated ADF test statistics are reported in Table 2.

Forecasting of Firm-level Stock Price Crash Risk

In this section, we present the forecasted results of the individual SPCR of the top 15 performing stocks listed in S&P 500. We use four different models for the prediction of stock price crash risk. For evaluation matrices, we used the mean absolute error, mean squared error and root mean squared error.

Forecasting of SPCR using only Micro (Firm) level Indicators

In the first step, we predict the individual SPCR using only micro level indicators such as trading volume and short selling.

Table 3

Forecasting of SPCR using Micro Level Indicators

	MAE	MSE	RMSE
Linear Regression	0.3787	0.128	0.345
SVR	0.365	0.233	0.314
SLP	0.366	0.105	0.283
MLP	0.237	0.112	0.195

The evaluation matrices show that machine learning models provide better forecasted results. We used the LR, SVR, SLP and MLP models to forecast the individual SPCR. The results of the MLP model are more accurate than those of the linear regression, SVR and SLP models. The results reported in Table 3 confirm H4 which state that machine learning models perform better than the linear regression model. The MLP model is more prominent than the linear regression model due to its multiple-layered design as well as nonlinear activation functions. A single concealed layer in neural networks is referred to as a conventional ANN or a multilayer perceptron. In every layer of the MLP model, we introduced contrasting activation functions after the transfer function. Therefore, the MLP model outperformed the rest of the models used to predict SPCR. The results are reported in Table 3.

Forecasting of Individual SPCR using both Micro (Firm) and Macro level Indicators

In this step, we predict the individual SPCR using both micro and macro level determinants. Exchange rate, Interest rate and EPU are used as macro level predictors. Whereas short selling and trading volume are used as firm level predictors. The results are reported in the following Table 4.

Table 4

Forecasting of Stock Price Crash Risk using Macro and Micro-Indicators

	MAE	MSE	RMSE
Linear Regression	0.172	0.034	0.280
SVR	0.168	0.033	0.201
SLP	0.165	0.030	0.192
MLP	0.129	0.026	0.165

The evaluation matrices show that machine learning models provide better forecasted results. We used the LR, SVR, SLP and MLP models to forecast the individual SPCR of the top 15 performing stocks. The results of the MLP model are more accurate than those of the linear regression, SVR and SLP models. The results reported in Table 4 confirm H4 which states that machine learning models perform better than the linear regression model. The MLP model is more prominent than the linear regression model due to its multiple-layered design as well as nonlinear activation functions. A single concealed layer in neural networks is referred to as a conventional ANN or a multilayer perceptron. In every layer of the MLP model, we introduced contrasting activation functions after the transfer function. Therefore, the MLP model outperformed the rest of the models used to predict SPCR. The overall accuracy of the MLP model has improved by 10 %, 11 %, and 3 % according to MAE, MSE, and RMSE evaluation matrices after the incorporation of macro-level determinants of SPCR.

Results of Linear Regression and Machine Learning Models

In this part of the research, we discuss the outcome of Eq. 2, which estimates the coefficients of economic policy uncertainty sentiments, exchange rate, interest rate, trading volume, and short selling.

Table 5

Determinants of Stock Price Crash Risk

	β_o	β_1	β_2	β_3	β_4	β_5	β_6
Linear	0.457***	0.301	**0.435****	0.027	0.013	-0.004	**0.447***
Regression	**(0.000)**	(0.114)	**(0.036)**	(0.347)	(0.441)	(0.199)	**(0.097)**
SVR	**0.228*****	0.889	0.778	0.404	**0.194***	-0.587	**1.254****
	(0.000)	(0.267)	(0.436)	(0.136)	**(0.078)**	(0.489)	**(0.044)**
SLP	**0.004*****	**0.127****	**0.783****	**0.057*****	**0.152*****	**0.980*****	**0.668*****
	(0.000)	**(0.037)**	**(0.034)**	**(0.000)**	**(0.000)**	**(0.004)**	**(0.000)**
MLP	**0.115***	**0.206****	**0.448*****	**0.963*****	**0.020*****	**-0.585*****	**0.985*****
	(0.055)	**(0.045)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**

*, ** and *** indicate significance of coefficients at 10 %, 5 % and 1 %, respectively.

The results of the coefficients of all the explanatory variables are reported in Table 5. We estimate Eq. 2 considering the crash risk of top 15 stocks listed in S&P 500 index and traded in NYSE. We used 4 different approaches for the estimation of coefficients of all the determinants of stock price crash risk. These approaches include linear regression, support vector regression (SVR), the single layer perceptron model (SLP) and the multilayer perceptron model (MLP). We present estimated coefficients along with their respective probabilities in parentheses. The results of the SLP and MLP models are highly significant. The coefficients of EPUTC, EPUN, exchange rate (E), interest rate (I) and short selling are positive and significant. A depreciation in domestic currency and increase in the domestic interest rate causes capital outflow from the economy that leads to instability in stock markets. The coefficient of economic policy uncertainty news sentiment turns out to be positive and significant, which supports the fact that economic uncertainty leads to stock market instability. In the case of MLP model, the coefficient of trading volume is negative, which means that stocks with high trading volume are less likely to crash. The overall effect of short selling is positive and significant which means that an increase in short selling increases the likelihood of stock price crash risk. Machine learning models, especially SLP and MLP, provide more accurate results than linear regression models. Economic policy uncertainty and crash risk have a positive relationship because when EPU increases, managers tend to withhold bad news. In addition, high EPU leads to low earnings and cash inflows to companies, which ultimately makes managers distort financial information for the sake of presenting better short-term performance. (See, e.g. (Boutchkova *et al.*, 2012; Pastor & Veronesi, 2012; Pastor & Veronesi, 2013). In addition, it is argued that EPU increases the information asymmetry among insiders and outsiders (Nagar *et al.*, 2019).

Conclusion

This study investigated the impact of micro and macro-level indicators of the stock price crash risk of individual-level stocks. For empirical analysis, we use data from Jan 2010 to Dec 2022. First, we calculated the monthly series of the stock price crash risk. We used the negative conditional skewness approach to calculate the stock price crash risk. In a similar pattern, we use monthly data of macro indicators, which are the exchange rate, interest rate, and economic policy uncertainty indices of the USA. In addition, we used trading volume and short selling as a micro (Firm) level determinant of stock price crash risk. We deployed four different models to forecast the stock price crash risk. These models included linear regression, support vector regression, a single-layer perceptron model, and a multilayer perceptron model. The overall findings suggest that both the micro and macro-level potential predictors are highly significant. Our results rendered strong support for the hypothesis that higher EPU increases the likelihood of SPCR. Furthermore, machine learning models, especially SLP and MLP, outperformed the linear regression. The forecasting evaluation matrices complement these findings and endorse the importance of incorporating both micro and macro-level determinants of stock price crash risk at the individual stock level. The results of the study provide insights for both investors and policymakers. While constructing portfolios, investors should be very careful about stocks that are highly sensitive to macro-level indicators, especially exchange rates, interest rates, and economic policy uncertainty. Similarly, policymakers should take care of news and apply circuit breakers to avoid stock crashes. In future studies, data sets regarding stock price crash risk need to be enhanced to incorporate further micro and macro-level determinants in empirical testing. In addition, a comparative study among different stock markets may also be focused on.

This research study used the panel data set of only US based individual stocks. We also used limited number of macroeconomic variables because of the unavailability of the data sets in high frequency. In addition, we considered the data set of a single stock market, USA which is a developed stock market. The future research studies may consider the data sets of multiple stock markets and conduct a comparative analysis among the developing and developed stock markets. This may provide further insights into the determinants of stock price crash risks.

Appendix: List of Companies

Name	Symbol	Exchange	Sector
Intel Corporation	INTC	Nasdaq	Technology
Apple Inc	APPL	Nasdaq	Technology
NVIDIA Corporation	NVDA	Nasdaq	Technology
Microsoft Corporation	MSFT	Nasdaq	Technology
Advanced Micro Devices,Inc	AMD	Nasdaq	Technology
Alphabet Inc	GOOGL	Nasdaq	Communication Services
Bank of America	BAC	NYSE	Financial
Morgan Stanley	MS	NYSE/Nasdaq	Financial Services
U.S.Bancorp	USB	NYSE/Nasdaq	Financial Services
Citigroup Inc	C	NYSE/Nasdaq	Financial Services
Pfizer Inc	PFE	NYSE	Healthcare
Abbott Laboratories	ABT	NYSE/Nasdaq	Healthcare
Amazon	AMZN	Nasdaq	Consumer Cyclical
Exxon Mobil Corporation	XOM	NYSE/Nasdaq	Energy
United Airlines Holdings	UAL	Nasdaq	Airline/Industrials

List of Abbreviations

SPCR	Stock Price Crash Risk
NYSE	NewYork Stock
SLP	Single layer Perceptron Model
MLP	Multilayer Perceptron Model
SVR	Support Vector Regression
Vol	Trading Volume of stocks
SS	Short Selling Dummy
I	Interest Rate
E	Exchange rate
EPU	Economic Policy Uncertainty

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