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**Title:** **From Data to Decisions: Role of Machine Learning in Predicting Cash Holdings of Manufacturing Firms in Pakistan**

**Author (s):** Atia Alam[1], Nimra Ansar[1], Syeda Fizza Abbas[1], and Zia Ul Rehman[2]

**Affiliation (s):** [1]Kinnaird College for Women, Lahore, Pakistan
[2]Government College University, Lahore, Pakistan

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Department of Banking and Finance, Dr. Hasan Murad School of Management (HSM)
University of Management and Technology, Lahore, Pakistan

# From Data to Decisions: Role of Machine Learning in Predicting Cash Holdings of Manufacturing Firms in Pakistan

Atia Alam[1*], Nimra Ansar[1], Syeda Fizza Abbas[1], and Zia Ul Rehman[2]

[1]Kinnaird College for Women, Lahore, Pakistan
[2]Government College University, Lahore, Pakistan

## Abstract

Effective cash management is essential to maintain a firm's financial health and sustainability. Hence, this study evaluates the prediction performance of various machine learning (ML) algorithms in identifying firm-specific determinants of cash holdings among the manufacturing firms of an emerging market, namely Pakistan. Using secondary data, the analysis employs ML techniques such as multiple linear regression, LASSO regression, ridge regression, elastic net regression, as well as random forest, gradient boosting, support vector regression, and decision tree models. The findings reveal that random forest and gradient boosting models outperformed others in predicting cash holdings, while the decision tree model exhibited the poorest performance. These insights are valuable for managers and decision-makers in optimizing cash retention, capital allocation, and investment planning. Additionally, policymakers can leverage these findings to develop policies that enhance financial resilience and foster growth in the manufacturing sector of Pakistan.

***Keyword*:** cash holdings, machine learning algorithms, manufacturing firms

**JEL Codes:** C450, C53, D22

## Introduction

Corporate cash holdings have become an increasingly important topic in financial literature, particularly since the early 2000s when companies began to accumulate significant cash reserves to mitigate financial uncertainties. Effective cash management practices are crucial for a firm's stability and liquidity, enabling it to finance its operations, avail investment opportunities, and avoid expensive external financing. Cash is a critical asset, allowing firms to navigate economic fluctuations and maintain operational continuity, even in uncertain conditions (Juliana & Budionno,

*Corresponding Author: atia.a1am@kinnaird.edu.pk

2024). In 2022, US firms accumulated more than $0.7 trillion in cash reserves, highlighting the growing importance of strategic cash management in the current economic landscape (Ahn et al., 2024) Moreover, adequate cash holdings can provide liquidity to manage economic shifts and capitalize on growth prospects, which is vital for sustainable corporate growth.

In Pakistan, the manufacturing sector is a cornerstone of the national economy, contributing approximately 13.6% to the GDP, as of FY 2024 (Government of Pakistan, 2024). This sector also plays a significant role in generating employment, with 25.59% of the total workforce engaged in industrial activities as of 2023 (Trading Economics, 2025). Despite its economic significance, the manufacturing sector faces persistent financial challenges. Ali et al. (2024) indicate that many manufacturing firms struggle with liquidity management, often maintaining excess cash reserves as a precaution against economic uncertainties. Furthermore, Safdar et al. (2019) stated that Pakistani firms maintain meaningful cash buffers to buffer against investment-cash-flow mismatches and to seize profitable opportunities when credit is scarce. In addition to this, strong cash positions support firms' ability to navigate Pakistan's volatile policy environment, marked by exchange-rate fluctuations, interest-rate volatility, and regulatory uncertainty, by providing a self-insurance mechanism that reduces reliance on external debt markets. Juliana and Budionno (2024) highlighted that economic policy uncertainty in Pakistan has led to increased cash holdings among firms, particularly those that are financially constrained and also among large non-state entities.

The manufacturing sector's vulnerabilities were starkly exposed during the economic downturn between 2022 and 2024. High energy costs led to the closure of numerous textile mills across the province of Punjab, resulting in significant job losses and a decline in exports (Sharma, 2025). These events underscore the urgent need for predictive financial tools that can enhance cash planning, ensure business continuity, and support resilient financial decision-making in a volatile economic environment.

Tobin's cash management model emphasizes the need for firms to balance the costs of holding cash—such as opportunity costs—against its advantages, such as maintaining sufficient liquidity for investments and unforeseen events (Tobin, 1956). The model suggests that firms should hold enough cash to cover expected expenditures, while minimizing costs associated with transactions and idle cash. The precautionary motive for holding cash is especially critical, as it allows firms to buffer against unpredictable financial crises. For instance, during the 2008 financial crisis, firms with substantial cash reserves effectively absorbed market shocks and capitalized on undervalued investments. Similarly, the speculative motive supports cash retention to take advantage of favorable opportunities (Thi et al., 2023). Major corporations including Apple and Google have demonstrated this by maintaining significant cash reserves to engage in strategic acquisitions when economic conditions are favorable (Foley et al., 2007).

Despite the recognized importance of cash holdings, there remains a research gap in understanding how to predict optimal cash reserves, particularly in the context of emerging economies. According to a report published by the State Bank of Pakistan (2019), only 25% of businesses in Pakistan retained adequate cash reserves to meet their operating needs, while more than 60% experienced liquidity shortages due to unstable cash flow patterns. These statistics emphasize the challenges faced by businesses in predicting optimal cash holdings within the country's volatile economic landscape. It also highlights the necessity of using advanced prediction tools for financial planning. Traditional forecasting models, such as Ordinary Least Squares (OLS) regression, often prove to be ineffective in capturing the complexities of contemporary financial systems—characterized by large datasets and nonlinear interactions—especially in emerging markets like Pakistan. As these models are limited by their linear assumptions, there is a need for more advanced techniques to accurately model financial complexities. In this regard, the literature identifies machine learning (ML) as a promising solution due to its capacity to handle large datasets, detect nonlinear relationships, and perform effective feature selection (Gao et al., 2024; Toochaei & Moeini, 2023).

This study aims to bridge the research gap by applying various ML algorithms to predict optimal cash holdings in the manufacturing sector of Pakistan. This approach is particularly novel given the dynamic and volatile economic conditions in Pakistan, where firms face high inflation, liquidity constraints, and political instability (Hasan & Chishty, 2024). By leveraging ML techniques such as random forest and gradient boosting, known for their predictive accuracy, this study provides a robust methodology to understand cash holding patterns. Unlike traditional models, ML algorithms adapt to the data, uncover hidden patterns, and improve predictive accuracy through techniques such as hyper-parameter tuning and cross-validation (Gao et al., 2024).

The objective of this research is to evaluate the performance of various ML models in predicting the optimal cash holdings of manufacturing firms in Pakistan. The study seeks to contribute to both the academic literature and practical policy by providing insights into how advanced predictive techniques can better inform financial decision-making. The findings are expected to guide policymakers to formulate policies that enhance the financial resilience and growth of the manufacturing sector, while offering practical implications for managers to optimize cash retention, capital allocation, and investment strategies.

The structure of the paper is as follows: Section 2 provides a review of the relevant literature on corporate cash holdings and ML techniques in finance. Then, the research methodology is outlined, detailing the data collection and analytical techniques employed. Afterwards, the results and their implications are presented. Finally, the paper concludes with a discussion of the findings, their policy implications, limitations, and suggestions for future research.

## Literature Review

### Traditional Approaches to Determinants of Cash Holding

Corporate cash holdings have traditionally been studied through firm-specific financial factors, such as profitability, liquidity, leverage, and firm size. Profitability is often inversely correlated with cash holdings, as profitable firms generate sufficient internal cash flows to finance their operations and investments, reducing the need for cash reserves (Ferreira & Vilela, 2004; Shabbir et al., 2016). In contrast, firms with higher leverage tend to retain more cash to cushion against financial difficulties during unpredictable economic conditions (Jumah et al., 2023). Stability in cash flows is another important factor; companies with more stable cash flows generally hold smaller cash reserves and rely on regular income to meet financial obligations (Dittmar & Mahrt-Smith, 2007). Firm size also plays a key role in determining cash holdings. Larger firms typically hold less cash as they benefit from economies of scale and have an easier access to external funding (Al-Najjar & Clark, 2017). On the other hand, smaller firms often maintain higher cash reserves as a precaution against liquidity shortages, since they face higher costs when acquiring external funding (Ahmad & Adaoglu, 2019).

Despite the insights provided by these traditional approaches, conventional financial models which rely on linear regression and other fundamental econometric techniques have significant limitations. These models often fail to capture the nonlinear and complex relationships between variables, particularly in volatile or uncertain market conditions. This has driven a growing interest in ML techniques, which are better equipped to handle the complexities and nuances of cash holding predictions (Pandya, 2024).

**Machine Learning Approaches to the Determinants of Cash Holdings**

Machine learning (ML) has emerged as a powerful tool for analyzing cash holdings, particularly for managing large, complex datasets that are challenging for the traditional models to handle (Zhong et al., 2021). Studies show that ML algorithms, such as random forest and gradient boosting, outperform conventional methods due to their ability to capture nonlinear interactions and high-dimensional relationships among the variables (Ali & Burhan, 2023). These techniques have been employed increasingly to predict corporate cash holdings, providing enhanced flexibility and accuracy as compared to traditional statistical models (Özlem & Tan, 2022).

For instance, Tan (2022) employed multiple linear regression, LASSO regression, ridge regression, and elastic net regression to predict cash holdings in Turkish firms. The findings revealed that elastic net regression performed the best among all the models in determining cash reserves. Similarly, Farinha et al. (2018) and Özlem and Tan (2022) utilized multiple ML models, including support vector regression, random forest, decision tree, and XGBoost to analyze cash holdings. These studies highlighted that decision tree and XGBoost achieve the highest prediction rates among the tested algorithms.

Wu et al. (2021) utilized decision tree regression technique to predict the cash holdings of Taiwanese high-technology firms, employing methods such as extra trees, logistic model trees (LMT), and random forest (RF). The findings confirmed that random forest exhibited the highest prediction accuracy among the decision tree models. Similarly, Moubariki et al. (2019) investigated cash flow levels in the public sector using decision tree, neural networks, and random forest models, with decision tree showing superior accuracy.

The above stated findings underline the growing adoption of ML techniques for cash flow and cash holding predictions. ML algorithms not only provide more accurate results but also offer flexibility in incorporating diverse financial factors, including profitability, liquidity, leverage, firm size, and growth opportunities. Advanced ML models, such as random forest and gradient boosting, also provide feature importance metrics, enabling firms to identify the most significant factors influencing cash holding practices (Ajiga et al., 2024). Thai and Hoang (2024) examined Vietnamese firms and found that foreign and state ownership leads to higher cash reserves, particularly during financial deficits, highlighting agency and precautionary motives in emerging markets.

Recent literature emphasizes the need for improved modeling of corporate cash holdings in emerging markets, where firms face greater financial volatility and institutional challenges. For instance, Ali et al. (2024) examined the manufacturing firms in Pakistan and found that liquidity constraints and operational uncertainties lead companies to maintain precautionary cash reserves, especially in the absence of robust credit access. Similarly, Thai and Hoang (2024) demonstrated that in Vietnam, state and foreign ownership structures are significantly associated with higher cash reserves, particularly under financial distress, suggesting that governance and control structures shape cash policy. Movaghari et al. (2024) used double ML techniques to identify key drivers of corporate cash policy, such as R&D intensity and asset tangibility, noting shifts from transaction cost to precautionary motives in recent years.

The transition from traditional statistical methods to advanced ML approaches marks a significant shift in financial analysis, offering firms a robust framework to navigate complex economic conditions and improve cash management strategies.

## Research Methodology

### Sample Data

This study examines firm-specific factors influencing cash holding patterns in Pakistan's manufacturing sector, which faces various economic and operational challenges. It analyzes data from 280 non-financial manufacturing firms listed on the Pakistan Stock Exchange (PSX) over an eight-year period (2016–2023) marked by significant economic fluctuations. Financial firms, real estate investment trusts, and firms with missing data for more than two consecutive years or those that defaulted were excluded, resulting in a final sample of 210 firms with 1,680 firm-year observations. To ensure data completeness, missing values were replaced by mean values. The study employs a quantitative approach using secondary data, leveraging 21 financial ratios from firms' balance sheets, income statements, and cash flow statements, to predict cash holdings. A panel data methodology is used to account for both cross-sectional and time-series dynamics in firm behavior.

**Table 1**

*Operationalization of Variables*

| Variables | Measurement | References |
|---|---|---|
| CASH | The ratio of cash and cash equivalents to the total assets | Özlem and Tan (2022) |
| *Profitability Ratios* | | |
| ROA | The ratio of net income to the total assets | Cambrea et al. (2022) |
| ROE | The ratio of net income to the total equity | Manoel et al. (2018) |
| PAS | The ratio of net income to the net sales | Angelovska and Valentinčič (2020) |
| PBS | The ratio of profit before tax to the net sales | Mihai et al. (2018) |
| EPS | Earnings per share | Sarfraz et al. (2022) |
| *Liquidity Ratios* | | |
| CR | The ratio of current assets to current liabilities | Manoel et al. (2018) |
| LIQ | Net working capital less cash and cash equivalents divided by total assets | Shabbir et al. (2016) |
| AR | The ratio of account receivable to the total assets | Mohammadi et al. (2018) |
| AP | The ratio of accounts payable to the total assets | Chen et al. (2014) |

| Variables | Measurement | References |
|---|---|---|
| *Leverage Ratios* | | |
| LEV | Total liabilities divided by total assets | Shabbir et al. (2016) |
| ICR | The ratio of Interest expense to earnings before interest and taxes | D'Mello et al. (2005) |
| *Net Cash Flow Ratios* | | |
| CFOCR | The ratio of net cash flow from operations to current liabilities | Fawzi et al. (2015) |
| CFOTA | The ratio of net cash flow from operations to current liabilities | Khuong et al. (2020) |
| CFOEBIT | The ratio of net cash flow from operations to earnings before interest and taxes to earnings before interest and taxes | Sunmola (2021) |
| *Growth Opportunities Ratio* | | |
| GROW | Percentage change in total assets | Gupta and Pathak (2021) |
| Tobin's Q | The ratio of (sum of market capitalization and total debt) to total assets | Horioka and Terada-Hagiwara (2014) |
| DIV | The ratio of total dividend payments to the total asset | Wu et al. (2021) |
| TANG | Tangible fixed assets divided by total assets | Bhuiyan and Hooks (2019) |
| CAPEX | The ratio of capital expenditure to the total assets | Uyar and Kuzey (2014) |
| FS | Log of Total Assets | Lozano and Yaman (2020) |
| AGE | The foundation year of the firm | Wu et al. (2021) |

## Data Analysis Technique

The study applies a range of ML and statistical models to predict optimal cash holdings in Pakistan's manufacturing sector. The models employed vary in complexity and assumptions about the data, each offering unique advantages in terms of its predictive power (Gao et al., 2024), handling of data characteristics (e.g., multicollinearity, nonlinearity), and interpretability.

### Multiple Linear Regression

MLR is a traditional statistical method that examines the linear relationship between multiple independent variables and a single dependent variable (cash holdings). The model assumes that the relationship between variables is linear and additive. The equation is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon \tag{1}$$

Multiple linear regression provides the coefficients that quantify the impact of each predictor on outcome. The weakness of this techniques is that it assumes a linear relationship between variables and is unable to deal with complex and non-linear data.

### Weighted Least Square Regression

This study employs Weighted Least Squares (WLS) to address heteroscedasticity, a common issue in financial data where the variance of errors is not constant across observations. By assigning appropriate weights, WLS minimizes the impact of heteroscedasticity and provides more efficient and unbiased coefficient estimates. To ensure consistency and comparability with ML models, WLS was applied by splitting the data into training and testing sets. This approach allows for the evaluation of the model's predictive power and mitigates the risk of overfitting, similar to the cross-validation techniques used for ML algorithms.

In addition to its ability to handle heteroscedasticity, WLS serves as a baseline to compare the predictive performance of more complex ML models. While WLS effectively captures linear relationships and offers interpretable results, it is limited in handling nonlinear interactions.

### LASSO Regression

LASSO (Least Absolute Shrinkage and Selection Operator) is a form of linear regression that performs both variable selection and regularization to enhance the predictive accuracy and interpretability of the model (Tibshirani, 1996). It introduces a penalty (α) that reduces some coefficients to zero, effectively removing less important variables. The equation is as follows:

$$\sum_{i=1}^{n} (y_i - \sum_j x_{ij\beta_j})^2 + \alpha \sum_{j=1}^{\rho} |\beta_j| \tag{2}$$

where the first term represents the residual sum of squares (ordinary least squares error). While, the second term is the penalty function that constrains the size of the coefficients (Wu et al., 2021). LASSO regression has the ability to perform feature selection by shrinking insignificant coefficients to zero. Furthermore, it prevents over-fitting in high dimensional data.

**Ridge Regression**

Ridge regression, also known as Tikhonov regularization, is similar to LASSO but applies an L2 penalty to the coefficients, which is the sum of their squared magnitude. The equation is as follows:

$$\sum_{i=1}^{n}(y_i - \sum_j x_{ij\beta_j})^2 + \alpha \sum_{j=1}^{\rho} {\beta_j}^2 \quad (3)$$

This method is particularly effective when predictors are highly collinear because it adds a bias that reduces variance and minimizes over-fitting (Hoerl & Kennard, 1970). However, it does not produce feature selection akin to LASSO regression and can lead to biased estimates.

**Elastic Net Regression**

Elastic net combines the penalties of both LASSO (L1 penalty) and ridge regression (L2 penalty). The penalty function includes two tuning parameters, namely α and λ, which determine the contribution of L1 and L2 penalties:

$$\hat{\beta} = \arg min_\beta \left\{\sum_{i=1}^{n}\left(y_i - \beta_o - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 + \lambda \left(\alpha \sum_{j=1}^{p}|\beta|_j + (1 - \alpha) \sum_{j=1}^{p} \beta_j^2\right)\right\} \quad (4)$$

where $y_i$ is the dependent variable for observation $i$, $x_{ij}$ depicts the value of the *j-th* predictor for observation $i$, $\beta_o$ is the intercept term, $\beta_j$ represents the coefficient for the *j-th* predictor, *n* denotes the number of observations, and *p* indicates the number of predictors. The regularization parameter, which controls the overall strength of the penalty, is depicted by $\lambda$. LASSO L1 penalty is denoted by $\alpha$ = 1, while the Ridge L2 penalty is denoted by $\alpha$=0.

Combining both LASSO and ridge regression makes elastic net regression capable of balancing feature selection and multicollinearity issues.

### Random Forest Model

Random forest is an ensemble learning method that builds multiple decision trees and aggregates their predictions for classification or regression tasks (Breiman, 2001). Each tree is trained on a subset of the data, with the final model output being the average of all tree predictions. The equation governing the prediction process is as follows:

$$h(x) = \Sigma_i\, \omega_j\ \mathrm{I}_{tree}\left(x, \theta_j\right) \tag{5}$$

where $\mathrm{I}_{tree}$ represents each decision tree and $\omega_j$ are weights of the trees. Random forest handles non-linear relationships and complex interactions well. By aggregating multiple trees, it reduces overfitting as compared to a single decision tree. However, it remains computationally intensive for large datasets.

### Gradient Boosting Model

Gradient boosting is another ensemble method which differs from random forest in that it builds trees sequentially (Wu et al., 2021). Each new tree corrects the errors of the previous trees, resulting in a final strong model:

$$f(x) = \Sigma_i\, \gamma_j\ h_j\ (x) \tag{6}$$

where $h_j$ represents each weak learner (tree) and $\gamma_j$ is the weight for each learner. By focusing on the residual errors of previous models, the model iteratively enhances predictive accuracy. This technique has the ability to sequentially correct the errors of previous models and has a strong predictive performance on the structured data. However, it is also computationally expensive and prone to over-fitting. Moreover, it requires careful parametric tuning.

### Support Vector Regression

Support vector regression (SVR) is a supervised learning model that aims to find a hyperplane within a margin that best predicts the continuous outcome variable (Chen et al., 2017). The primary goal is to minimize prediction error while maintaining model simplicity. The kernel function ($\kappa$) is defined as follows:

$$\kappa\left(x_i, x_j\right) = \exp\left(-\,{}^{2_{\sigma^2}}\!\Big/_{\left|x_i - x_j\right|}\right) \tag{7}$$

SVR is effective in handling data with a high dimensionality. Through kernel functions, it can model both linear and non-linear relationships, although it is more sensitive to parameter selection.

### Decision Tree Regression

Decision tree regression involves splitting the data into subsets based on feature values to create a tree-like model of decisions. At each node, a condition is tested to split the data into branches, with final nodes (leaves) representing the predicted outcomes. The equation is as follows:

$$h(x) = T(x, \theta) \tag{8}$$

It is easy to interpret and visualize and remains capable of effectively handling categorical and numerical data. Decision trees are prone to overfitting, especially when the tree is deep (complex). Pruning and setting the maximum depth parameters are commonly used techniques to prevent overfitting.

This study employs linear (multiple linear, LASSO, ridge, and elastic net regression) and non-linear (random forest, gradient boosting method, support vector machine, and decision tree) models for a comprehensive analysis of cash holding determinants. All models are evaluated by splitting the data into training (80%) and testing (20%) sets, with cross-validation to avoid overfitting and improved model generalizability. Moreover, this study uses Mean Squared Error (MSE) and R-squared ($R^2$) as the primary evaluation metrics due to their relevance in financial forecasting. MSE has been selected because it penalizes large prediction errors, ensuring more accurate cash holding predictions, and is commonly used in various ML models including random forest and gradient boosting for its ease of optimization (Breiman, 2001; Zhong et al., 2021). $R^2$ is chosen because it quantifies the proportion of variance explained by the model, making it easier for decision-makers to assess model fit (Ferreira & Vilela, 2004). Although alternative metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) provide additional insights, MSE and $R^2$ are prioritized as they better capture the complexity of predicting cash holdings in manufacturing firms (Toochaei & Moeini, 2023).

## Results

Table 2 presents the summary statistics of the financial ratios used to predict optimal cash holdings in manufacturing firms, organized according to their operational categories. The mean value of cash holdings (CASH) is 1.61, indicating that firms hold, on average, 1.61 units of cash relative to total assets, with a standard deviation of 3.98, suggesting considerable variation across firms. Among profitability ratios, return on asset (ROA) has a mean of 2.14 and a standard deviation of 4.22, while return on equity (ROE) has a mean of 1.26 and a standard deviation of 3.71, indicating moderate variation in profitability across firms. The earnings per share (EPS) shows significant variation, with a mean of 26.56 and a high standard deviation of 81.27. Ratios such as profitability as percentage of sales (PAS, *SD* = 52.31) and profit before tax to sales (PBS, *SD* = 52.28) exhibit substantial fluctuations as well.

Liquidity ratios such as the current ratio (CR) have a mean of 1.96 and a standard deviation of 2.71, suggesting variability in short-term financial health across firms. Accounts receivable (AR) and accounts payable (AP) have standard deviations of 0.17 and 3.17 respectively, indicating more variation in payables. The interest coverage ratio (ICR) stands out with a mean of 70.26 and a very high standard deviation of 4058.24, reflecting extreme differences in interest expense coverage among firms. Leverage ratios show that the leverage (LEV) ratio has a mean of 0.70 and a standard deviation of 1.07, indicating some variability in debt levels across firms. Other leverage measures including capital expenditure (CAPEX, mean = 0.05, SD = 0.16) and dividends (DIV, mean = 0.03, *SD* = 0.15) exhibit lower variability, implying more consistent capital investments and dividend policies.

Considering cash flow ratios, cash flow from operations relative to current liabilities (CFOCR) and to EBIT (CFOEBIT) exhibit standard deviations of 3.13 and 272.91 respectively, indicating considerable variability in operational cash flow. Cash flow to total assets (CFOTA) has a standard deviation of 4.26, reflecting differences in operational cash generation relative to assets. In the growth opportunity ratios category, growth (GROW) shows substantial variation with a standard deviation of 14.05, indicating diverse growth experiences among firms in terms of changes in total assets. Other measures such as net working capital (LIQ, *SD* = 3.31) indicate moderate variability, impacting cash reserves. Lastly, other ratios and variables including firm size (FS) and age (AGE) exhibit means of 9.89 and 3.72, with relatively low standard deviations of 0.89 and

0.42 respectively, suggesting homogeneity in the size and maturity of firms within the sample.

**Table 2**

*Descriptive Statistics*

| | Mean | Standard Deviation |
|---|---|---|
| CASH | 1.61 | 3.98 |
| *Profitability Ratios* | | |
| ROA | 2.14 | 4.22 |
| ROE | 1.26 | 3.71 |
| PAS | -0.22 | 52.31 |
| PBS | -0.54 | 52.28 |
| EPS | 26.56 | 81.27 |
| *Liquidity and Working Capital Ratios* | | |
| CR | 1.96 | 2.71 |
| LIQ | 0.39 | 3.31 |
| AR | 0.12 | 0.17 |
| AP | 2.29 | 3.17 |
| *Leverage Ratio* | | |
| LEV | 0.70 | 1.07 |
| ICR | 70.26 | 4058.24 |
| *Net Cash Flow Ratios* | | |
| CFOCR | 0.39 | 3.13 |
| CFOTA | 1.12 | 4.26 |
| CFOEBIT | -5.71 | 272.91 |
| *Growth Opportunities Ratio* | | |
| GROW | -0.27 | 14.05 |
| TOBIN’s Q | 3.15 | 26.25 |
| DIV | 0.03 | 0.15 |
| TANG | 0.74 | 1.31 |
| CAPEX | 0.05 | 0.16 |
| FS | 9.89 | 0.89 |
| AGE | 3.72 | 0.42 |

## Performance Comparison of WLS Regression and Machine Learning Algorithms

The current study employs various statistical and machine learning techniques to predict cash holdings in manufacturing firms, comparing their performance based on Mean Squared Error (MSE), $R^2$, and adjusted $R^2$ values, as depicted in Table 3. The Weighted Least Square (WLS) regression is used to address heteroscedasticity and unequal variances that violate the assumptions of Ordinary Least Square (OLS). With an $R^2$ value of 0.354, WLS explains 35.4% of the variability in cash holdings, while its MSE of 1.0759 indicates moderate prediction accuracy.

Among the ML algorithms evaluated, LASSO regression yields a low MSE value of 0.0086. However, its $R^2$ value of 0.0401 suggests it captures only 4.01% of the variability in cash holdings, indicating its limited ability to manage the complexities of the financial data. Ridge regression, with an MSE value of 0.0064, outperforms LASSO in accuracy and explains 29.02% of the variance in cash holdings, highlighting the benefits of regularization in reducing overfitting and handling multicollinearity. However, its explanatory power remains moderate. The elastic net regression, which integrates LASSO and ridge penalties, achieves an MSE value of 0.0086 and an $R^2$ value of 0.0432, showing similar limitations to LASSO in effectively capturing data complexities.

The random forest model stands out among the applied techniques, demonstrating a significantly lower MSE of 0.0052 and an $R^2$ of 0.4204, indicating that it explains 42.04% of the variance in cash holdings. This model's strong performance, with both low prediction error and high explanatory power, underscores its capability to handle complex, non-linear relationships within financial data more effectively than the regression-based approaches. Hence, random forest emerges as the most robust model to predict optimal cash holding patterns, surpassing both traditional and penalized regression models in terms of predictive accuracy and explanatory strength.

To summarize, ensemble machine learning models—particularly random forest ($R^2$ = 0.4204) and gradient boosting ($R^2$ = 0.406)—outperform traditional models including WLS ($R^2$ = 0.2635) and MLR ($R^2$ = 0.1377), confirming that ML provides superior predictive power to capture non-linear financial behavior.

**Table 3**

*Evaluation of ML Algorithms*

| ML Techniques | MSE | $R^2$ | Adjusted $R^2$ |
|---|---|---|---|
| WLS Regression | 1.0759 | 0.354 | 0.346 |
| Lasso Regression | 0.0086 | 0.0401 | 0.028 |
| Ridge Regression | 0.0064 | 0.2902 | 0.281 |
| Elastic Net Regression | 0.0086 | 0.0432 | 0.031 |
| Random Forest | 0.0052 | 0.4204 | 0.3797 |
| Gradient Boosting | 0.0053 | 0.406 | 0.3663 |
| Support Vector Regression | 0.0085 | 0.0055 | -0.007 |
| Decision Tree | 0.0101 | -0.118 | -0.132 |

### WLS Coefficient Analysis

The results of the WLS regression depicted in Table IV indicate that several financial ratios play a crucial role in predicting optimal cash holdings in manufacturing firms. Among the profitability ratios, return on assets (ROA), profit before tax to sales (PBS), and profitability as percentage of sales (PAS) show a significant relationship with cash holdings, with ROA and PBS having a positive impact, while PAS showing a negative association. The earnings per share (EPS) ratio remains insignificant. In terms of liquidity, the current ratio (CR) significantly influences cash reserves, while accounts receivable (AR) and accounts payable (AP) show no significant effect. Leverage ratios including leverage (LEV) have a notable negative effect on cash holdings, indicating that higher leverage reduces cash reserves, while the interest coverage ratio (ICR) remains insignificant.

Net cash flow ratios, particularly cash flow from operations relative to current liabilities (CFOCR) and total assets (CFOTA), show a significant positive impact on cash holdings, suggesting that stronger cash flows lead to higher reserves. However, cash flow to earnings before interest and taxes (CFOEBIT) does not significantly affect cash reserves. On the other hand, growth opportunities, measured through the growth in total assets (GROW), have a significant negative relationship with cash holdings, indicating that firms with higher growth prospects tend to hold less cash. Tobin's Q, as another measure of growth opportunities, shows no significant influence on cash reserves.

Other variables also significantly impact cash holdings. Liquidity measured as net working capital (LIQ) negatively affects cash reserves, implying that greater liquidity reduces the need to hold cash. Dividend payout (DIV) and tangibility (TANG) are both negatively associated with cash holdings, indicating that firms with higher dividend payments or more tangible assets tend to hold less cash. Capital expenditure (CAPEX) has a slight but significant negative influence on cash holdings. Meanwhile, firm size (FS) and firm age (AGE) do not show any significant impact on cash reserves.

Overall, the WLS model identifies that the primary determinants of optimal cash holdings in manufacturing firms are profitability, cash flow, liquidity, leverage, dividends, and tangibility. These financial ratios collectively explain a substantial percentage of the variability in cash holdings, reflecting their importance in shaping a firm's cash management strategy.

**Table 4**

*Weighted Least Square Regression*

| Evaluation Metric | Value |
|---|---|
| $R^2$ | 0.354 |
| Durbin-Watson | 2.02 |
| Adjusted $R^2$ | 0.346 |
| Mean Square | 1.0759 |
| *Profitability Ratios* | |
| ROA | -0.138*** |
| ROE | -0.01** |
| PAS | -0.021** |
| PBS | 0.015*** |
| EPS | 0.033 |
| *Liquidity and Working Capital Ratios* | |
| CR | 0.011*** |
| LIQ | -0.21*** |
| AR | 0.019 |
| AP | 0.03 |
| *Leverage Ratio* | |
| LEV | -0.117*** |
| ICR | -0.003 |

| Evaluation Metric | Value |
|---|---|
| *Cash Flow Ratio* | |
| CFOCR | 0.015** |
| CFOTA | 0.132*** |
| CFOEBIT | -0.24 |
| *Growth Opportunities* | |
| GROW | -0.027*** |
| Q | 0.002 |
| DIV | -0.312*** |
| TANG | -0.116*** |
| CAPEX | -0.012*** |
| FS | -0.003 |
| AGE | 0.002 |

***Note.*** ***,** are significant at 1% and 5%, respectively

## Feature Importance Analysis in Machine Learning Models

The feature importance analysis across various M L algorithms reveals key factors driving the prediction of cash holdings in manufacturing firms, as depicted in Table 5. LASSO regression identifies earnings per share (EPS) as the most significant predictor, while interest coverage ratio (ICR) shows the least predictive power, indicating profitability's prominence in determining cash reserves. Ridge regression places importance on return on assets (ROA), cash flow from operations to total assets (CFOTA), and accounts payable (AP), while also highlighting the negative impact of liquidity (LIQ), dividend (DIV), and leverage (LEV) on cash holdings. Elastic net regression mirrors LASSO in its emphasis on EPS as a top predictor, reinforcing the crucial role of profitability in cash management.

The random forest model assigns high significance to current ratio (CR), net working capital (LIQ), cash flow from operations relative to current liabilities (CFOCR), and the interest coverage ratio (ICR), demonstrating the impact of liquidity and cash flow considerations on cash holding decisions. Gradient boosting similarly underscores the influence of LIQ and CR, suggesting that both liquidity management and financial flexibility are key to optimal cash reserves in manufacturing firms. Support vector regression (SVR) also emphasizes LIQ, CR, and CFOTA as critical features, indicating the importance of liquidity and operational cash flow.

Lastly, the decision tree model highlights CR, LIQ, and ICR as significant factors; however, its predictive performance is limited by a tendency to over fit data. Across these ML models, the results consistently point to the centrality of liquidity, profitability, and cash flow considerations in predicting a firm's cash holding patterns.

Across all models, variables related to liquidity (e.g., current ratio, net working capital), profitability (ROA, EPS) and cash flow (CFOTA, CFOCR) emerge as the most influential determinants. This confirms the theoretical expectation that internal financial health drives cash retention strategies. The findings suggest that firms with strong liquidity and profitability metrics can reduce excess cash buffers and reallocate capital more efficiently. This has direct implications for CFOs, risk managers, and policymakers, particularly in the context of Pakistan's economically volatile environment.

These results, when considered collectively, reveal an important strategic insight: while traditional models including WLS provide interpretability, their limited ability to capture complex interactions reduces their practical value in volatile environments, such as that of Pakistan. In contrast, the consistent outperformance of random forest and gradient boosting reflects not just their algorithmic strength but also the multidimensional nature of cash holding behavior—where variables such as liquidity, profitability, and operational cash flow interact nonlinearly. The repeated appearance of certain variables including current ratio and ROA across multiple models suggests a universal pattern of cash retention grounded in the precautionary motive. This cross-model consistency emphasizes that predictive accuracy and theoretical validity are not mutually exclusive, but rather complementary when aligned with context-specific financial challenges.

**Table 5**

*Feature Importance*

| | Lasso Regression | Ridge Regression | Elastic Net Regression | Random Forest | Gradient Boosting | Support vector Regression | Decision Tree |
|---|---|---|---|---|---|---|---|
| Profitability Ratios | | | | | | | |
| ROA | 0.00 | 0.150 | 0.00 | 0.021 | 0.02 | 0.019 | 0.025 |
| ROE | 0.00 | -0.01 | 0.00 | 0.021 | 0.01 | 0.00 | 0.04 |
| PAS | 0.00 | -0.02 | 0.00 | 0.011 | 0.07 | 0.00 | 0.02 |
| PBS | 0.00 | 0.009 | 0.00 | 0.012 | 0 | 0.00 | 0.13 |
| EPS | 0.0003 | 0 | 0.0003 | 0.024 | 0.08 | 0.00 | 0.02 |
| Liquidity Ratios | | | | | | | |
| CR | 0.00 | 0.02 | 0.00 | 0.162 | 0.24 | 0.032 | 0.22 |
| LIQ | 0.00 | -0.15 | 0.00 | 0.149 | 0.21 | 0.040 | 0.175 |
| AR | 0.00 | -0.01 | 0.00 | 0.028 | 0.01 | 0 | 0.031 |
| AP | 0.00 | 0.08 | 0.00 | 0.039 | 0.05 | 0.015 | 0.030 |
| Leverage Ratios | | | | | | | |
| LEV | 0.00 | -0.10 | 0.00 | 0.027 | 0.02 | 0.021 | 0.023 |
| ICR | 0.00001 | 0 | 0.00001 | 0.078 | 0.10 | 0.003 | 0.10 |
| Cash Flow Ratio | | | | | | | |
| CFOCR | 0.00 | 0.03 | 0.00 | 0.085 | 0.13 | 0.004 | 0.022 |
| CFOTA | 0.00 | 0.13 | 0.00 | 0.044 | 0.06 | 0.018 | 0.03 |
| CFOEBIT | 0.00 | 0 | 0.00 | 0.045 | 0.03 | 0.001 | 0.073 |
| Growth Opportunities | | | | | | | |
| GROW | 0.00 | -0.005 | 0.00 | 0.03 | 0.01 | 0.003 | 0.048 |
| Tobin's Q | 0.00 | 0 | 0.00 | 0.03 | 0.01 | 0.004 | 0.020 |
| DIV | 0.00 | -0.12 | 0.00 | 0.027 | 0.03 | 0.017 | 0.15 |
| TANG | 0.00 | -0.08 | 0.00 | 0.044 | 0 | 0.014 | 0.072 |
| CAPEX | 0.00 | -0.07 | 0.00 | 0.036 | 0.05 | 0.010 | 0.029 |
| FS | 0.00 | -0.004 | 0.00 | 0.023 | 0.03 | 0.009 | 0.024 |
| AGE | 0.00 | 0.003 | 0.00 | 0.027 | 0.01 | 0.004 | 0.025 |

## Discussion

This study provides crucial insights into the cash holding patterns of manufacturing firms, highlighting key financial factors influencing their decisions. Effective cash management is essential for firms to finance their operations, mitigate risks, and seize growth opportunities. The Weighted Least Squares (WLS) regression model offers a basic understanding of the relationship between financial ratios and cash holdings but exhibits limited predictive accuracy, as indicated by moderate R-squared and high MSE values (Özlem & Tan, 2022). The model identifies profitability metrics including return on assets (ROA) and profit before tax to sales (PBS) as positive influences on cash reserves, while leverage (LEV), dividend payments (DIV), and tangible assets (TANG) have a negative impact. These results align with trade-off and pecking order theories, which suggest that profitable firms prefer internal funds and maintain lower cash reserves, whereas firms with higher leverage or dividend obligations reduce cash holdings to manage financing costs (Aftab et al., 2018; Aldoseri et al., 2022).

The ensemble machine learning models—random forest and gradient boosting—demonstrate superior predictive accuracy, outperforming traditional regression models with lower MSE and higher R-squared values (Farinha et al., 2018; Özlem & Tan, 2022; Zhang et al., 2021). These models effectively capture nonlinear relationships between financial factors and cash holdings, reaffirming their robustness in financial prediction tasks (Ali & Burhan, 2023). In contrast, ridge and elastic net regression show moderate predictive capabilities but struggle with data complexities (Arturo & Rodriguez-Aguilar, 2023; Tan, 2022). LASSO regression and support vector regression (SVR) perform poorly, with high MSE and low explanatory power, limiting their ability to handle intricate interactions (Sulistiani & Nugraheni, 2022). The decision tree model exhibits significant overfitting, underscoring the need for proper parameter tuning to enhance generalizability (Kim et al., 2022). The feature importance analysis conducted via the random forest and gradient boosting models provides additional insights into the determinants of cash holdings. Liquidity and profitability ratios emerge as the most influential predictors, highlighting their central role in shaping firms' cash management strategies. Current ratio (CR) and net working capital (LIQ) remain particularly significant, indicating that firms with stronger liquidity positions are better equipped to manage short-term obligations, reducing the need for excessive cash reserves. These findings align with the precautionary motive of holding cash, as highlighted by Diaw (2021). The study emphasized that firms operating in volatile environments prefer to maintain liquidity buffers to mitigate unforeseen financial shocks. Similarly, Lozano and Yaman (2020) found that liquidity management significantly influences corporate cash holding decisions, especially in markets where economic uncertainty is prevalent.

Profitability ratios, including ROA and earnings per share (EPS), also exhibit a strong predictive power. Firms with higher profitability maintain lower cash reserves as they generate sufficient internal funds to finance operations and investment opportunities. These results support the pecking order theory, which suggests that profitable firms prioritize the use of internal financing over external borrowing (Aftab et al., 2018; Manoel et al., 2018; Myers & Majluf, 1984). However, Thi et al. (2023) observed that in some emerging markets, highly profitable firms maintain higher cash reserves to buffer against macroeconomic uncertainties and ensure operational stability, suggesting that the relationship between profitability and cash holdings can vary across contexts.

Leverage ratios, particularly LEV and interest coverage ratio (ICR), play a crucial role in determining cash holdings. Highly leveraged firms tend to maintain higher cash reserves to safeguard against financial distress, consistent with the trade-off theory (Kim et al., 1998). These findings align with the results of Chen et al. (2014). They concluded that leverage positively influences cash holdings as firms with higher debt levels tend to maintain more cash to reduce refinancing risks. Conversely, Al-Najjar and Clark (2017) found that firms in highly developed markets tend to hold less cash despite high leverage, suggesting that the relationship between leverage and cash holdings may vary across market contexts.

Tobin's Q (TQ) and capital expenditure (CAPEX) have been identified as moderately important predictors, reflecting firms' tendency to allocate excess cash to growth opportunities under favorable market conditions. This aligns with the speculative motive of cash holdings, where firms maintain liquidity to capitalize on profitable investments under favorable market conditions (Foley et al., 2007). However, Horioka and Terada-Hagiwara (2014) found that in Asian economies, firms with higher Tobin's Q may not necessarily reduce cash holdings, as they often prioritize liquidity to mitigate potential financial risks.

Cash flow ratios, such as cash flow from operations to total assets (CFOTA) and cash flow from operations to current liabilities (CFOCR), also significantly influence cash holdings. These findings are consistent with the work of Fawzi et al. (2015). They demonstrated that firms with a robust cash flow from operations maintain lower cash reserves due to the availability of internal liquidity. However, Cambrea et al. (2022) suggested that in capital-intensive industries, firms may maintain higher cash reserves despite a strong operational cash flow to hedge against economic downturns.

The study also highlights the transactional and speculative motives for holding cash. Firms retain cash to ensure smooth operations, such as supplier payments and wage disbursement, while also navigating inflationary pressures and interest rate fluctuations. The speculative motive is evident in firms that hold cash to capitalize on investment opportunities under favorable market conditions (Foley et al., 2007; Thi et al., 2023). The findings underscore the advantages of using advanced ML techniques in financial analysis, particularly to enhance cash management strategies. The feature importance analysis strengthens these insights by demonstrating that liquidity, profitability, and leverage metrics significantly influence cash retention decisions, reinforcing the validity of established financial theories.

However, the limitations observed in models like decision tree and elastic net suggest the need for tailored approaches, considering the financial and economic context of emerging markets (Özlem & Tan, 2022). Additionally, reliance on historical data and the exclusion of macroeconomic variables restrict the generalizability of the findings, indicating potential areas for further research and refinement. Future research can build on these insights by incorporating macroeconomic variables and considering sector-specific dynamics to further improve model performance and cash management strategies.

While individual results offer valuable insights, it is equally important to consider the broader implications and practical impact of these findings on corporate finance and policy frameworks. The superior predictive power of these ensemble learning models highlights the inadequacy of linear assumptions in financial modeling for emerging markets. Firms and financial analysts should consider integrating non-linear ML approaches into financial planning systems to better forecast liquidity needs. Current ratio and net working capital indicators are directly linked to a firm's short-term solvency. Firms with weak liquidity management are more likely to misjudge optimal cash levels, risking insolvency or idle capital. Policymakers may encourage liquidity benchmarks through corporate governance codes or risk audits.

Firms with consistent profitability tend to manage cash more effectively. This suggests a feedback loop where strong performance improves forecasting accuracy, leading to a more strategic cash use. This reinforces the need for integrated financial planning tools that align performance and cash forecasting. Dependence on internal cash flows underlines the limited access to external financing in Pakistan’s manufacturing sector. Development finance institutions and regulators may consider policy reforms or lending support to reduce firms' reliance on precautionary cash holdings. Decision tree results illustrate the model's tendency to over fit complex, multidimensional financial data. It reinforces the need for robust model selection and validation when deploying AI-based forecasting tools in financial management.

## Conclusion

Efficient cash management plays a crucial role in ensuring the financial health and sustainability of manufacturing firms, especially in emerging markets like Pakistan, where firms face significant economic and operational challenges. This study explored cash holding patterns among non-financial manufacturing firms in Pakistan during the period 2016–2023 using ML techniques to predict optimal cash reserves. The results highlight the superior predictive performance of ensemble models, particularly random forest and gradient boosting, over traditional and regularized regression models. These ML algorithms effectively capture the nonlinear relationships between cash holdings and firm-specific financial indicators, offering a more accurate understanding of cash management dynamics. Liquidity and profitability are identified as key determinants, with metrics such as the current ratio (CR), net working capital (LIQ), return on assets (ROA), and earnings per share (EPS) significantly influencing cash holding strategies.

## Policy Implications

The results of this study carry several practical implications for financial managers, policymakers, and industry stakeholders in Pakistan's manufacturing sector. Firstly, the consistent identification of key predictors—such as liquidity ratios (e.g., current ratio), profitability indicators (e.g., ROA, EPS), and cash flow measures—highlights areas where firms can concentrate their financial monitoring efforts to maintain optimal cash levels. Accurate cash holding forecasts using ensemble ML models including random forest and gradient boosting can significantly reduce the risks of over-hoarding or liquidity shortfalls, enabling more efficient capital allocation and better risk management.

Secondly, the adoption of ML tools can transform traditional financial planning processes. Firms equipped with predictive models can make proactive decisions under uncertainty, especially in the face of volatile cash flows and limited access to external financing—common challenges in emerging markets like Pakistan. Finally, these findings suggest broader policy implications. Regulatory bodies and financial institutions may consider supporting the integration of AI-based decision systems through technical trainings, subsidies, and financial disclosure reforms. Encouraging data driven practices across the manufacturing sector could improve overall financial sustainability and economic stability.

## Limitations and Future Research Directions

This study, while comprehensive, has certain limitations. Firstly, the effectiveness of ML models is highly dependent on the quality and completeness of the data. Although efforts have been made to ensure data accuracy and representativeness, the use of firm-level financial data from a single sector (manufacturing) limits the scope of inference. Secondly, although ensemble models such as random forest and gradient boosting offer high predictive accuracy, they operate as "black box" algorithms, making it difficult to interpret how individual predictions are generated. Future research may incorporate model interpretability techniques such as SHAP (SHapley Additive exPlanations) to provide transparency in prediction logic. Thirdly, the study's contextual specificity—limited to Pakistani manufacturing firms—may restrict its generalizability. Future studies may make cross-sector and cross-country comparisons, integrate macroeconomic indicators, and assess the role of corporate governance in cash management to enhance the broader applicability of the findings.

## Conflict of Interest

The author of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

## Data Availability Statement

The data associated with this study will be provided by the corresponding author upon request.

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