

# Interpretable Machine Learning Models for Predicting the Next Targets of Activist Funds

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## Abstract

This work develops a predictive model to identify potential targets of activist investment funds, which strategically acquire significant corporate stakes to drive operational and strategic improvements and enhance shareholder value. Predicting these targets is crucial for companies to mitigate intervention risks, for activists to select optimal targets, and for investors to capitalize on associated stock price gains. Our analysis utilizes data from the Russell 3000 index from 2016 to 2022. We tested 123 variations of models using different data imputation, oversampling, and machine learning methods, achieving a top AUC-ROC of 0.782. This demonstrates the model's effectiveness in identifying likely targets of activist funds. We applied the Shapley value method to determine the most influential factors in a company's susceptibility to activist investment. This interpretative approach provides clear insights into the driving forces behind activist targeting. Our model offers stakeholders a strategic tool for proactive corporate governance and investment strategy, enhancing understanding of the dynamics of activist investing.

*Keywords:* activist funds, shareholder activism, corporate finance, machine learning, SHAP

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## 1. Introduction

Activist funds are a distinct class of investment funds that seek to effect change within their portfolio companies, not just through investment but by actively influencing management and strategic decisions. These funds differentiate themselves from traditional investment vehicles by adopting a hands-on approach, leveraging their stakes in companies to advocate for changes in corporate governance, strategy, management, and operations ([Alu23]). Their ultimate goal is to unlock shareholder value that might not be realized under the current management's approach.

The participation of activists has been growing recent years, particularly after the financial scandals and the financial crisis of 2007-2008 ([DD20]). In 2018, nearly one campaign launched against a new target every day ([Laz18]). Thanks to regulatory reforms that have made shareholder engagement more accessible and weakened corporate defenses, activists can now more easily challenge management to enhance shareholder benefits ([Bri06]). The motivations behind activist investing are diverse. Romito identifies four main types of activist investors ([Rom15]). Some focus on enhancing returns by advising management to issue debt or redirect free cash flow toward dividends or stock buybacks. Others advocate for merging similar competitors to capitalize on economies of scale. Another group prefers

to enhance profitability by separating mismatched divisions within a company. Additionally, some investors aim to streamline operations by maintaining only the most profitable units and spinning off less effective ones. Beyond these financial goals, certain socially responsible funds also promote environmental, social, and governance (ESG) improvements, aiming to foster ethical business practices ([BCR22]).

Studies have demonstrated the benefits of activist interventions in terms of market value, profitability, and governance, although there is ongoing debate about how these benefits vary over time ([DD20], [Fla15], [BBJ15]). Bebchuk et al. conducted an analysis of approximately 2,000 activist interventions from 1994 to 2007, revealing that activist funds often target underperforming companies with stock returns significantly lower than those of industry peers. However, in the five years following these interventions, the performance of the targeted companies generally improved, with them closing two-thirds of their performance gap in terms of return on assets compared to their peers ([BBJ15]). Conversely, Desjardine and Durand analyzed 1,324 campaigns between 2000 and 2016 and found that while shareholder benefits were initially apparent and significant, they were short-lived. These gains often came at a long-term cost to other stakeholders, manifested in reduced cash flow and lower investment spending ([DD20]).

Recognizing potential targets of these activist funds is essential for a wide array of stakeholders. It enables corporations to prepare and defend against unwanted interventions, guides activist investors in selecting firms where they can significantly impact, and offers retail investors opportunities for profit through potential stock price appreciations following activist campaigns.

This study is focused on creating a model that can accurately predict which companies will become targets of activist funds. We analyzed data from firms listed on the Russell 3000 index from 2016 to 2022, along with information on activist campaigns. Our analysis included a wide range of variables encompassing traditional measures of valuation and operations, as well as alternative data points related to ownership structures, governance, and technical indicators. By experimenting with 123 distinct combinations of imputation, oversampling, and machine learning techniques, we were able to determine the most effective model. Furthermore, we utilized Shapley values ([LL17]) to pinpoint the key factors that influence a company’s likelihood of being targeted by an activist fund. This approach not only enhances the predictive accuracy of our model but also provides deeper insights into the dynamics of shareholder activism.

## 2. Literature Review

Several studies explored the valuation analysis strategies of activist funds. Pfirrmann and Eichner’s study based on 30 campaigns between 2013 and 2019, reveals a preference for relative valuation over intrinsic valuations, primarily utilizing Enterprise Value/EBITDA (EV/EBITDA) and Price/Earnings (P/E) ratios ([PE24]). Consistent with findings by Brav et al. ([BJPT08]) and Boyson and Mooradian ([BM11]), it is observed that firms targeted by activists often exhibit lower valuations compared to their fundamental values. Operationally, these firms show robust cash flows from operations and sales growth rates. Furthermore, their asset returns outperform those of their competitors, despite their stock performance trailing behind the broader market. The analysis also highlights that

activist investors typically secure a significant stake in these firms, purchasing between 5% to 10% of equity shares on the market once they have identified their targets.

We broadened the scope of our investigation to how general institutional investors approach company valuation. Bancel and Mittoo conducted a survey among 365 European finance experts holding CFAs or similar qualifications, finding that the most favored valuation techniques are Discounted Cash Flows (DCF) and relative valuation methods, particularly emphasizing the EV/EBITDA and P/E ratios as the top choices for multiples ([BM14]). Similarly, Mukhlynina and Nyborg’s (2016) study involving valuation specialists, such as investment bankers, consultants, and private equity professionals, revealed that a significant portion of these experts employ both multiples and DCF in their valuation practices, with 47% admitting to using both methods but predominantly favoring multiples ([MN16]).

Several studies have explored the evolving focus of activist funds on environmental, social, and governance (ESG) issues. A study by Zhu revealed that activist interventions not only improve the valuations and operations of a company but also steer management practices in a more shareholder-friendly direction. These interventions have led to increased shareholder returns through higher buyback activities and increased dividend payout ratios, as well as reductions in CEO compensation ([Zhu21]). In addition, Barko et al. demonstrated that socially responsible activist funds often choose large, high-profile companies with good financial performance and liquidity but poor ESG scores. Their research indicates that activism focused on corporate social responsibility typically enhances both ESG practices and corporate sales performance, suggesting that ethical investing can coincide with robust financial returns ([BCR22]). The trend towards social responsibility in activism is further supported by research from Albuquerque et al., who developed a model demonstrating that firms decide to engage in CSR activities. Their study noted that over 3,000 institutions, managing assets upwards of 90 trillion USD, have committed to integrating CSR into their due diligence processes ([ADK19]). Additionally, research by Francis et al. underscored the significance of governance-related criteria in target selection, revealing that activist funds are approximately 52% more likely to choose firms with female CEOs. These targets led by women are more cooperative towards activists and tend to see greater improvements in market and operational performance during campaigns ([FHSW21]).

Our research builds upon previous studies to provide fresh insights into shareholder activism. We consider various aspects of companies, including valuations, operations, governance, ownership, stock performance, and technical information, to offer a comprehensive analysis of target selection. Additionally, we employ multiple machine learning techniques to develop a model that predicts potential future targets and to identify the most critical information for making these predictions.

### **3. Methodology**

#### *3.1. Data Collection*

In this study, we analyze the impact of 46 independent variables related to corporate characteristics on the likelihood of a company being targeted by activist investors. These variables are categorized as follows: 10 governance indicators, 3 ownership metrics, 6 technical indicators, 7 return measures, 10 valuation metrics, and 10 operational indicators, with

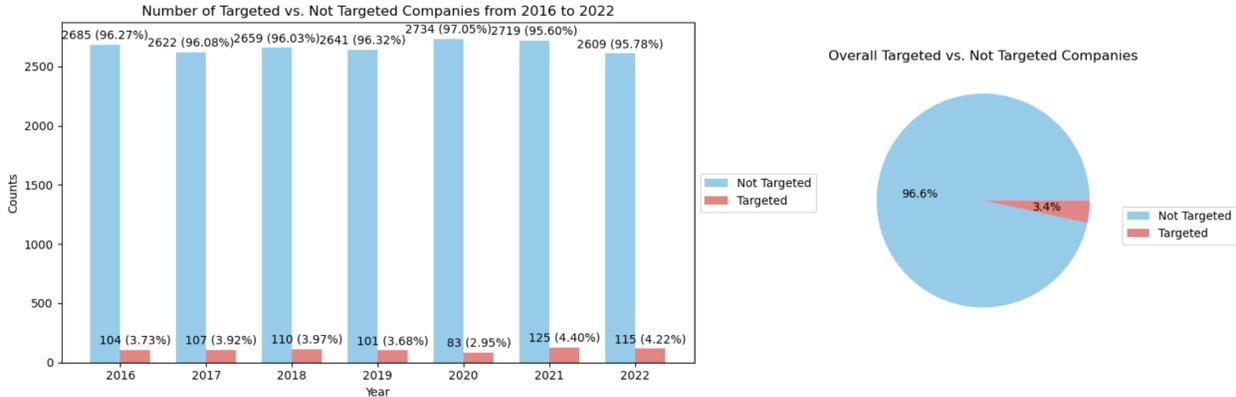


Figure 1: From 2016 to 2022, around 2 to 4% of the companies in Russell 3000 were targeted by activist funds, with the mean value of 3.4% in the entire period.

details presented in Table 1. The independent variables, sourced from the Bloomberg Terminal, comprises year-end snapshots for companies listed on the Russell 3000 index from 2016 to 2022. For the dependent variable that indicates if a company is targeted or not, we utilize data on activist campaigns reported from 2011 to 2022, also obtained from the Bloomberg Terminal. A company is considered a target if it becomes the subject of an activist campaign within the subsequent 12 months. Firms actively under a campaign are temporarily excluded from the dataset and reinstated after the campaign concludes. Our final dataset consists of 19,414 instances, with approximately 3.4% of these companies being identified as targets (see Fig. 1).

### 3.2. Data Preprocessing

#### 3.2.1. Conversion to Ratio Values & Industry Grouping

Some non-ratio values, like capital expenditure, working capital, total compensations to executives, are colinear with the size of the companies. It is therefore inappropriate to directly compare these figures. To account for this, we transform all non-ratio variables into ratio equivalents.

For the operations and valuation categories, values are transformed into percentiles, segmented by industry and year according to the Bloomberg Industry Classification Standard (BICS)<sup>1</sup>. We apply BICS Level 3 grouping when a category contains 10 or more instances. If fewer, we default to BICS Level 2 for classification. This approach allows for straightforward comparisons across different industries.

#### 3.2.2. Data Imputation

There is a significant portion of missing values in the data set (see Fig. 2). For data imputation, we use 4 different methods: mean imputation, K-nearest neighbours (KNN) imputations (k=5) ([BM<sup>+</sup>02]), Multivariate Imputation by Chained Equations using LightGBM (MiceForest)([Ste15]), and Generative Adversarial Imputation Networks (GAIN) ([YJS18]). K-nearest neighbors (KNN) imputation is a technique used to fill in missing values in a

<sup>1</sup><https://assets.bbhub.io/professional/sites/10/BICS-2024-Changes.pdf>

dataset based on the values of its neighboring data points. The missing value is estimated by averaging or taking a weighted average of the values of the  $k$  nearest neighbors to the missing point. Multivariate Imputation by Chained Equations (MICE) is a method used to impute missing values in a dataset by iteratively modeling each variable with missing data as a function of other variables in the dataset. Using LightGBM (Light Gradient Boosting Machine) for MICE involves employing gradient boosting, a powerful machine learning technique, to predict missing values iteratively. LightGBM is particularly efficient for this task due to its ability to handle large datasets and its fast training speed. Generative Adversarial Imputation Networks (GAIN) is a technique used for imputing missing values in a dataset using deep learning and generative adversarial networks (GAN). GAIN is particularly effective for imputing missing values in high-dimensional datasets with complex dependencies between variables.

It’s crucial to highlight that for all imputation methods except for mean imputation, we perform the imputation process within the same category of variables, incorporating the one-hot encoded values of the companies’ year. This approach ensures that imputations are conducted among variables that share predictive relationships and also accounts for overarching yearly trends. To avoid target leakage, we apply these data imputation techniques exclusively to the training set. For the test sets, we insist on median imputation.

### 3.2.3. Data Oversampling

In addressing the challenge posed by the dataset, where only 3.41% of the entries are labeled as targeted, we confronted a significant imbalance between the majority and minority classes. To mitigate this issue and enhance the robustness of our analysis, we implement 4 oversampling techniques. These include Random Oversampling Example (ROSE) ([ZCL15]), Synthetic Minority Oversampling Technique (SMOTE) ([CBHK02]), borderline SMOTE, and Adaptive Synthetic Sampling (ADASYN) ([HBGL08]). Random oversampling (ROSE) performs a random duplicating instances from the minority class(es) until the class distribution is more balanced. SMOTE is a popular method used to address class imbalance in datasets, particularly in the context of binary classification problems. Unlike random oversampling, which simply duplicates instances from the minority class, SMOTE generates synthetic samples for the minority class by interpolating between existing minority class instances. By creating synthetic samples instead of simply duplicating existing minority class instances, SMOTE helps to increase the diversity of the minority class and mitigate the risk of overfitting. Borderline SMOTE and ADASYN are two extensions of SMOTE designed to further address class imbalance in datasets. While SMOTE generates synthetic samples uniformly across the minority class, Borderline SMOTE focuses specifically on those instances that are close to the decision boundary — often the most difficult to classify. It primarily generates synthetic examples near these borderline cases, aiming to strengthen the decision boundary for the classifier. On the other hand, ADASYN adjusts the number of synthetic samples generated for each minority class instance according to their level of difficulty in learning, where more samples are generated for instances harder to learn. This adaptive approach helps in focusing on the regions where the classifier is most likely to benefit from more diverse data.

In our case, oversampling is only applied to training set in order to maintain purity of testing set.

Table 1: Overview of 46 variables. Conversion to percentile compared to industry peers in the same year is done for valuation and operation variables

Category	Variable	Explanation	
Governance	Existence of dual-class voting rights	Dual-class voting hinders activist victory in proxy fights.	
	CEO's tenure	CEO changes suggest company dissatisfaction; new CEOs may be more vulnerable.	
	CEO is female	A company with a female CEO is more likely to be targeted.	
	Board size	Large boards may signal poor governance or conflict of interest.	
	Existence of classified board system	Classified boards increase takeover costs by preventing full board replacement in one election.	
	Existence of poison pill	Poison pills raise takeover costs.	
	Buyback yield	Low repurchases may reflect inadequate shareholder value return.	
	Dividend payout ratio	A low dividend payout ratio could indicate insufficient value return to shareholders.	
Governance	Free cash flow to total compensations to executives	Comparatively high executives compensation points to management inefficiency.	
	Free cash flow to total compensations to board members	Comparatively high board compensation points to management inefficiency.	
Ownership	Free float percentage	Non-float shares typically align with management.	
	Percentage of institutional ownership	High institutional ownership may indicate that there are fewer entities for activists to pursue to launch a campaign.	
	Percentage of insider ownership	Low insider ownership may suggest that company executives and directors have a limited stake in the company's success	
Technical	30-day average trading volume to outstanding shares	High volume allows activists to acquire shares without moving the price.	
	14-day Relative Strength Index	Low RSI indicates stock is oversold; provides favorable entry points.	
	30-day Relative Strength Index	Low RSI indicates stock is oversold; provides favorable entry	
	30-day volatility	High volatility can provide activist funds with favorable entry points.	
	90-day volatility	High volatility can provide activist funds with favorable entry points.	
Return	180-day volatility	High volatility can provide activist funds with favorable entry points.	
	5-year total return	Long-term negative return may indicate shareholder dissatisfaction.	
	4-year total return	Long-term negative return may indicate shareholder dissatisfaction.	
	3-year total return	Long-term negative return may indicate shareholder dissatisfaction.	
	2-year total return	Long-term negative return may indicate shareholder dissatisfaction.	
Return	1-year total return	Short-term negative return may indicate shareholder dissatisfaction.	
	6-month total return	Short-term negative return may indicate shareholder dissatisfaction.	
	3-month total return	Short-term negative return may indicate shareholder dissatisfaction.	
	Valuation	Return on equity (ROE)	Low ROE may indicate inefficiency such that it never returns satisfactory returns to the shareholders.
		Return on invested capital (ROIC)	Low ROIC may indicate inefficient use of invested capital.
Assets to equity		Low asset to equity may signal excessive leverage.	
Earnings per share (EPS)		Low EPS may indicate inefficiency or low profitability.	
Price-earnings ratio (PER)		Low valuation makes a company more attractive to activists.	
Enterprise value to sales		Low valuation makes a company more attractive to activists.	
Tobin's Q ratio		Low valuation makes a company more attractive to activists.	
Price-to-book ratio (PBR)		Low valuation makes a company more attractive to activists.	
EV/EBITDA		Low valuation makes a company more attractive to activists.	
Operation	Enterprise value to asset	Low valuation makes a company more attractive to activists.	
	Free cash flow to capex	Excessive capex may indicate inefficiency, eroding shareholder value, or misaligned with shareholder interests.	
	Current ratio	Excessive working capital ratio indicates inefficiency and low liquidity.	
	EBITDA margin	Low margin indicates the possibility of improvement.	
	Sales to total assets	Sales leverage is an indicator of how efficiently companies use assets.	
	Employee growth rate	High growth rate of employees may indicate excessively aggressive expansion.	
	Free cash flow yield	Excessively high FCF yield may signal insufficient use of cash.	
	Sales growth rate	Low sales growth rate may indicate stagnation of a company.	
	Interest coverage ratio	Low interest coverage ratio may indicate potential risk of insolvency.	
	Cash conversion cycle	High cash conversion cycle might indicate liquidity problem	
Net debt to EBITDA	High net debt compared to EBITDA may indicate excessive debt level.		

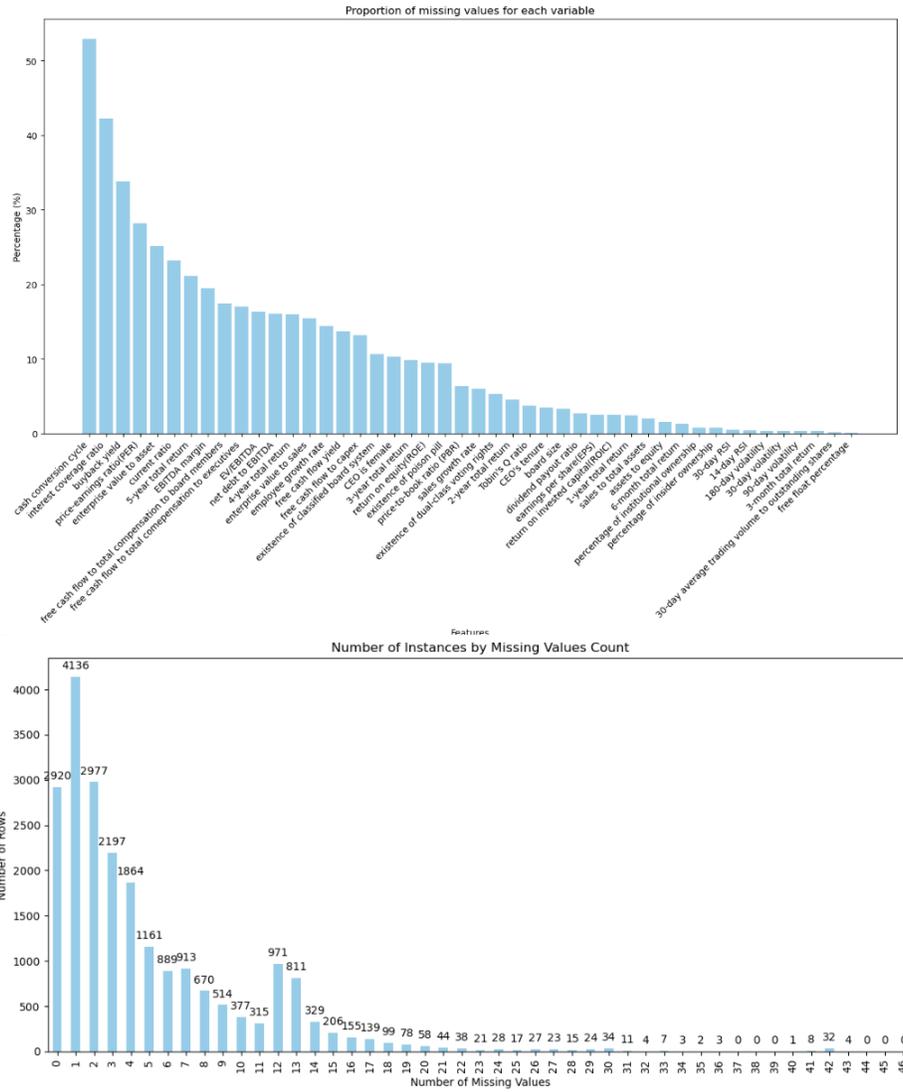


Figure 2: The first subfigure shows the number of instances with different number of missing values for 46 variables. The second subfigure shows the proportion of missing values for each variable.

### 3.3. Model Training & Metrics

We employ six diverse machine learning models in our analysis: logistic regression ([LaV08]), random forest ([Rig17]), XGBoost ([CHB<sup>+</sup>15]), LightGBM ([KMF<sup>+</sup>17]), CatBoost ([PGV<sup>+</sup>18]), and neural networks ([Kro08]). The data is divided, allocating 80% (15,531 instances) for training—this figure increases when oversampling is applied—and the remaining 20% (3,883 instances) for testing. By integrating 4 imputation methods, 5 oversampling strategies (including the option of not oversampling), and 6 machine learning models, we arrive at 120 distinct configurations. Additionally, recognizing the capabilities of LightGBM, XGBoost, and CatBoost to efficiently handle sparse data, we account for these as three extra models using original data without imputation, increasing our total to 123 models.

Considering the significant imbalance within the dataset, we select the AUC-ROC (Area Under the Receiver Operating Characteristic Curve) as our principal performance metric. This choice provides a detailed assessment of a model’s predictive capability, offering insight into its performance across various threshold settings and ensuring robustness against the challenges posed by the dataset’s imbalance.

### 3.4. Model Interpretation Method

In machine learning, there is an inherent trade-off between model complexity and interpretability. Advanced models like neural networks often outperformed simpler alternatives such as linear regression or decision trees in terms of predictive accuracy but typically offered less interpretability. To address the challenge of understanding and interpreting complex models, various methodologies have been developed.

In our study, we employed SHAP (SHapley Additive exPlanations) to analyze and interpret the contributions of different features in our models. Grounded in cooperative game theory, SHAP provided a robust framework for explaining the output of any machine learning model ([LL17]). We chose this method primarily for two reasons. First, the effectiveness of SHAP in highlighting the relative importance of variables was extensively validated in previous research. Second, unlike model-specific tools such as coefficients in linear regression or MDI (mean decrease in impurity) and the number of splits in tree-based models like Random Forest or LightGBM, SHAP is model-agnostic. This universality made it a versatile tool for application across various model architectures.

## 4. Results

### 4.1. Model Performance

In an evaluation of 123 different combinations of imputation, oversampling, and machine learning methods, 11 achieved an AUC-ROC score above 0.7, with 4 surpassing 0.75 in the test set (see table 2). The highest AUC-ROC score observed was 0.782, achieved with a strategy combining KNN imputation, Borderline SMOTE oversampling, and logistic regression. This study highlights the superior performance of machine-learning-based imputation techniques over simpler strategies like median imputation, which was used in only one of the top 11 combinations. Borderline SMOTE was particularly effective, being implemented in 10 of the 11 highest-scoring models. Logistic regression emerged as the preferred method in all four top-performing combinations with AUC-ROC scores above 0.75, whereas ensemble

methods were used in the remaining seven models with scores below 0.75. No neural network models scored above 0.7, suggesting that logistic regression may offer more robustness in smaller datasets compared to more complex methods like ensemble approaches and neural networks.

Table 2: Summary of 11 models that have AUC-ROC (test set) of greater than 0.7

Imputation	Oversampling	ML Method	AUC-ROC
KNN	Borderline SMOTE	Logistic Regression	0.782
Median	Borderline SMOTE	Logistic Regression	0.770
GAIN	Borderline SMOTE	Logistic Regression	0.767
MiceForest	Borderline SMOTE	Logistic Regression	0.752
MiceForest	Borderline SMOTE	Random Forest	0.727
GAIN	Borderline SMOTE	Random Forest	0.709
GAIN	Borderline SMOTE	Light GBM	0.707
KNN	Borderline SMOTE	XGBoost	0.706
KNN	Borderline SMOTE	Random Forest	0.706
KNN	no oversampling	CatBoost	0.701
MiceForest	Borderline SMOTE	CatBoost	0.700

#### 4.2. Model Interpretation

SHAP values calculated for our best-performing model, which utilized KNN imputation, Borderline SMOTE oversampling, and logistic regression, are presented in Fig. 3. The top 10 influential variables in the model include a mix from all categories. The analysis identifies share float as the variable with the highest mean absolute SHAP value. According to the bee-swarm plot shown in Fig. 3, a low share float significantly decreases the likelihood of activist targeting, whereas a high float has a less pronounced effect. Of all return-related variables, only the 4-year total return appeared in the top 10, indicating that activists might consider long-term than short-term underperformance in their target selection process. Short-term technical indicators, specifically the 14-day and 30-day Relative Strength Index (RSI), were also significant, albeit with opposing effects. The model indicates that a high 14-day RSI combined with a low 30-day RSI increases the likelihood of being targeted, suggesting a need for further investigation into the reasons behind this pattern. Traditional valuation and operational metrics such as Tobin’s Q ratio, EV to sales, EV/EBITDA, and ROIC were also prominently ranked among the most influential variables, highlighting their importance in the decision-making process of activist investors.

To ensure robustness, we evaluated the Shapley values of three other top-performing models, each with AUC-ROC scores above 0.75 (refer to Fig. 4). The results confirmed consistency in the variable rankings across the models, with only minor changes in ranks. Some governance-related variables such as the board size and dividend payout ratio. Additionally, given that our models utilized logistic regression, we examined the scaled coefficients to further validate robustness (refer to Fig. 5). While most variable rankings remained consistent, governance-related variables such as the ratio of free cash flow to compensation for board members and the presence of dual-class voting rights were ranked highly. These differences

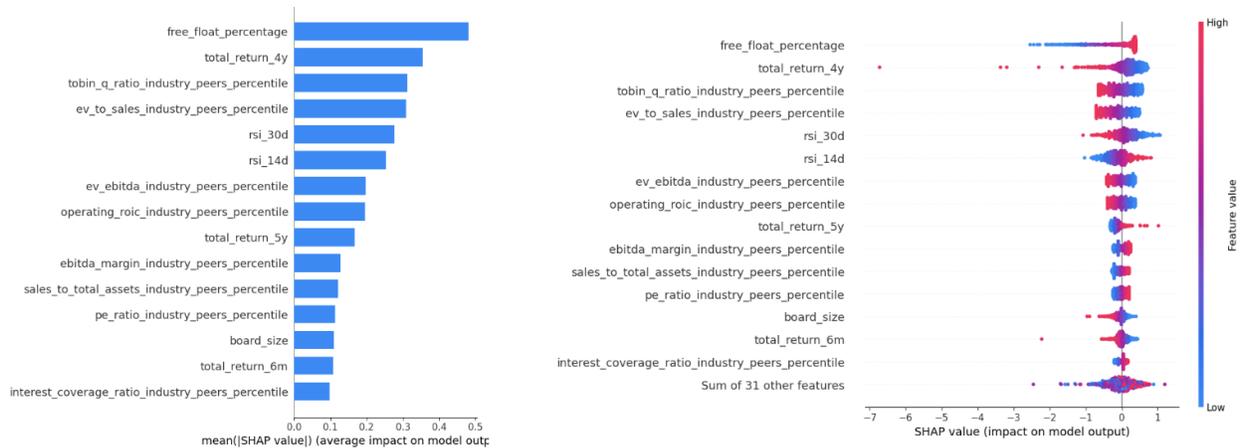


Figure 3: Mean absolute SHAP values for a logistic regression model trained on data processed with KNN imputation and Borderline SMOTE are shown in the first subplot. The second subplot displays individual SHAP values for the top 15 variables across all instances.

could be attributed to various factors, including multicollinearity among variables and the presence of outliers. These findings open up opportunities for a deeper understanding of governance-related factors in target selection, highlighting the need for further investigation into the underlying reasons.

## 5. Conclusion

In this paper, we develop a machine-learning model to predict potential targets of activist funds. Initially, we conduct a comprehensive literature review to identify key factors that influence the likelihood of a company being targeted by activists. Based on this review, we assemble a set of 46 variables providing a detailed overview of a company’s various aspects. Utilizing data from Russell 3000 companies from 2016 to 2022 and activism campaign data from 2013 to 2023, we train models using 123 different combinations of data imputation, oversampling, and machine learning methodologies. The best-performing model achieves an AUC-ROC score of 0.724. Additionally, we employ SHAP analysis to gain deeper insights into the decision-making processes of our model, revealing that a mix of variables related to valuation, operation, technical aspects, returns, and ownership are considered when activists select their targets.

This research has significant theoretical and practical implications. Theoretically, it advances our understanding by constructing a data-driven supervised machine learning model that integrates multiple company aspects and uses SHAP to identify the most influential variables. This comprehensive and systematic approach can serve as a foundation for future studies exploring additional variables. Practically, the model offers several benefits. For activists, it provides a tool to reduce the time and cost involved in screening potential targets. For companies, it enables preemptive measures by indicating the likelihood of being targeted. For other investors, it offers a chance to profit from anticipated improvements in profitability and market value following activist interventions.



Figure 4: Summary plots of SHAP values for three models with AUC-ROC scores above 0.75. The first row features median imputation with Borderline SMOTE and logistic regression; the second row, GAIN imputation with Borderline SMOTE and logistic regression; and the third row, MiceForest imputation with Borderline SMOTE and logistic regression.

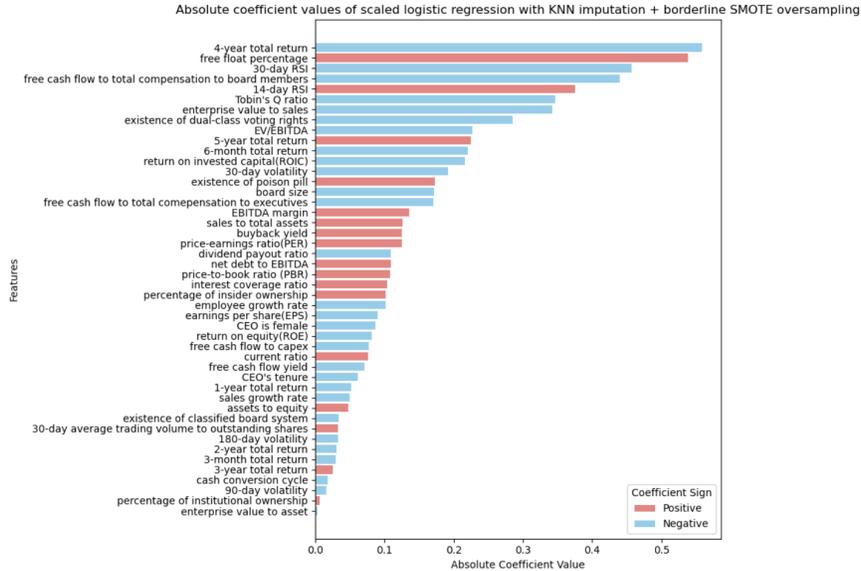


Figure 5: Coefficients in the scaled logistic regression of the best-performing model (KNN imputation + Borderline SMOTE + Logistic Regression)

## 6. Future Directions

The study presents several limitations. First, there is potential for improvement in the data structure. Our model treats multiple entries for the same company at different times as separate instances, which may overlook the unique characteristics and individual effects of different firms, thereby introducing bias. Additionally, our labeling approach categorizes a company as a target only if it becomes a target within the next 12 months, regardless of the exact date the campaign begins. This approach might distort or fail to capture the significance of short-term characteristics, as campaigns are initiated at various times throughout the year. It may also fail to identify companies that exhibit sufficient characteristics of being targeted but were not actually targeted within the study’s timeframe. Therefore, an alternative approach that addresses these issues needs to be explored in the future.

Second, although machine learning models deliver high performance in prediction and SHAP provides a solid understanding of how independent variables impact dependent variables, these approaches fundamentally rely on correlations rather than causations. In the future, we aim to construct a separate causal model that captures the underlying mechanisms of how activists make decisions on their next targets.

Additionally, future research could expand the scope of our study by incorporating time-trend data to observe changes in profitability over time. Another promising avenue would involve analyzing the behavior of activist funds in financial markets outside the US public market, to better understand inter-market heterogeneity and dynamics. This broader perspective could provide deeper insights into the strategies and impacts of activist investments globally.

## Conflicts of Interest

The authors declare no conflict of interest.

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