

ML techniques in portfolio management
Master thesis research project
Business Administration
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Author:

Giovanni Herbert
University of Twente
P.O. Box 217, 7500AE Enschede
The Netherlands

Graduation committee members:

Dr. Ir. Wouter van Heeswijk
Dr. Marcos Machado

Abstract:

It is generally assumed that with efficient markets, it is not possible to make accurate stock price predictions. With the rise and rapid development of ML models in recent years, this assumption might be proven wrong. ML models are known for their ability to find patterns in large amounts of data. Therefore, this pattern finding ability might be able to identify patterns in stock price data to predict future trends. The purpose of this thesis is to research whether Machine Learning (ML) models can be used to actively trade a portfolio of equities and bonds. Such an ML portfolio would allow for reduced management fees compared to those that financial institutions charge for actively managed portfolios as well as portfolios personalised to an investor's preferences. To determine if ML models can be used for the aforementioned purpose, the ML portfolio should be able to outperform passive portfolios. To examine whether the ML portfolio is able to outperform passive portfolios, the risk-adjusted performance was compared against two benchmark portfolios consisting of a minimum variance portfolio and the market index tracker (following the NASDAQ Composite index). All three portfolios were constructed using the same stocks, as the NASDAQ Composite index was assumed to be the general market for the purposes of this thesis.

During the experiment of this thesis, there were three testing periods to allow for more generalised conclusions on the performance of the ML portfolio. These testing periods were from January to December of the years 2000, 2010, and 2020. The minimum variance portfolio was constructed prior to the start of the testing period based on the ten-year prior stock price data and kept in its original form for the entire duration of the testing period. The market index tracker price was followed during the testing period without any adjustments. The ML portfolio was actively traded on a monthly basis during each testing period. Actively trading the ML portfolio meant that the ML portfolio was reconstructed for every month in every testing period. The reconstruction happened based on the Black-Litterman model that determined the optimal portfolio weights for the fifty companies with the highest expected returns. An Artificial Neural Network (ANN) was used as the ML model to predict the stock prices. These stock price predictions were then used to calculate the expected returns for the Black-Litterman model. The ANN made the stock price predictions based on the training dataset that consisted of ten years of prior stock price information. As the input variable, the market index tracker price from 31-trading days prior to the prediction date.

After the minimum variance and ML portfolios were constructed, the performance was compared against the market index tracker based on (risk-adjusted) performance metrics, including the diversification index, Sharpe ratio, beta, Treynor ratio, and Jensen's alpha. For the diversification index, the minimum variance portfolio outperformed the ML portfolio, both for the individual stock diversification as well as for sector diversification (respectively 95.25 compared to 92.51, and 83.05 compared to 78.06). This showed that the minimum variance portfolio construction methods created more diversified portfolios compared to the Black-Litterman model.

For all the remaining risk-adjusted performance metrics, the minimum variance portfolio outperformed both the ML portfolio as well as the market index tracker. In particular, the Treynor ratio was notable as the minimum variance portfolio outperformed the market index tracker by having a five times higher ratio (0.21 compared to 0.04). This is notable as this shows that the market does not proportionally compensate risk by higher returns, as is one of the assumptions of the CAPM theory. This finding was further displayed by the Jensen's alpha

where the minimum variance portfolio, on average, had an excess return of 5.58 percent. compared to the CAPM expected return. From the portfolio comparison it can be concluded that the ML portfolio was unable to outperform the benchmark portfolio based on the risk-adjusted performance.

The performance of the ANN itself was measured based on the accuracy, R^2 , and error-based metrics. The directional accuracy of the ANN was averaged at 55.04 percent during the three testing periods. The level of accuracy that the ANN achieved during the experiment seems to be too low to construct a benchmark outperforming portfolio, as was observed from the portfolio comparison. The reason why the accuracy was low might be due to the independent variable as the R^2 scores were close to zero in the last two testing periods, showing the chosen input had little ability to explain the variation in the stock prices. The final ML performance metric were the error-based metrics. Between the testing periods, there were differing orders of magnitude for the size of the errors (with median RMSE scores ranging between 2.70 in 2010 and 9.47 in 2020), which made it complicated to generate generalised conclusions. An interesting finding was in relation with the accuracy metric, during the 2010 testing period, the accuracy was at the lowest level of the experiment. In the same 2010 testing period, the error-based metrics were also at the lowest level, showing the lowest difference between the predicted and observed values. This showed that the accuracy might have been misrepresenting the performance of the ANN as lower errors between predicted and observed values better represent the required performance of the ANN.

Concluding, the ML performance metrics showed that the ML model needs to be improved to increase the performance of the ML portfolio. One way to improve the performance of the ANN is by determining what the best independent variable would be. The current independent variable showed too little explaining ability for the stock prices, leading to low accuracy and higher errors.

This thesis contributed mainly to the theory of portfolio management. For the practice, there was no notable contribution as this thesis failed to create an ML portfolio that was able to outperform the benchmark portfolios. In the future, it might be possible to create an outperforming portfolio using a different combination of ML techniques and portfolio construction methods. The theoretical contribution was not directly within the scope of this thesis, however, the findings did indicate that the market does not proportionally compensate risk by higher rewards, as the assumption is for the CAPM theory. This assumption was disproven as the minimum variance portfolio, a portfolio with a low beta, managed to outperform the market index tracker and ML portfolio based on the systematic risk-adjusted performance metric (the Treynor ratio).

Keywords:

Artificial Neural Network, Black-Litterman Model, Machine Learning, Minimum Variance Portfolio, Modern Portfolio Theory, Portfolio Allocation, Risk-Adjusted Performance

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1. Introduction

The aim of active investing is to achieve excess returns on the investment portfolio by actively buying and selling financial assets such as stocks or bonds (Siegel & Waring, 2009). In broad terms, it means having a higher return than the market on your portfolio for the same risk exposure as the market portfolio (Gnägi & Strub, 2020). The aforementioned risk is the standard deviation of the stock prices. The difference between the market return and the portfolio return is called excess return or the Jensen's alpha (Samarakoon & Hasan, 2006), based on the Capital Asset Pricing Model (CAPM) (Horenstein, 2021). CAPM is based on the theory that the expected return of a stock can be calculated using the market risk premium, the risk-free rate, and the beta of that stock. In theory, excess returns can be achieved by good asset selection because there are assets that outperform and underperform the risk adjusted market average performance. However, in practice, this is more difficult to achieve due to the Efficient Market Hypothesis (EMH) (Fama, 1970). This hypothesis states that all assets are priced correctly by the market due to the publicly available information regarding the value, risk, and volatility of the assets. The theoretical implication of this hypothesis is that there are no "cheap" assets. Therefore, finding assets that are under-priced relative to their returns, and therefore, are going to outperform the market in the future, is not an easy task, if at all possible. However, while under the hypothesis' assumptions, the markets are efficient, in reality, the assumptions made in the EMH do not always hold up when faced with contradicting empirical evidence (Basu, 1977; Mayhew, 1995; Nicholson, 1968; O'Sullivan, 2018; Rosenberg et al., 1985; Strebel, 1978).

One reason to choose for a passive investment portfolio is related to the believe in the EMH. People who believe in the EMH, believe that all assets in the market are priced fairly. Therefore, these passive investors will not continuously spend time to find "cheap" stocks that will yield higher returns than other stocks. Instead, these investors would determine their preferred risk level and build a portfolio compliant with this amount of risk by buying a specific proportion of financial assets such as Treasury bonds and stocks. If the preferred risk level of the passive investor is the risk level of the general market, the investor can buy a portfolio equivalent to the market. As it is not reasonably possible to buy all the assets in the market, usually passive portfolios would consist of market index trackers. These trackers may follow popular indices such as the S&P 500, NASDAQ, or the Dutch AEX (CNBC, 2023). According to Anadu et al. (2020), there has been a shift from active to passive investment portfolios held by investors over the past two decades. This means that increasingly more investors chose to invest in the market indices.

One of the market index trackers in which passive investors can invest is the NASDAQ Composite index tracker. Figure 1 shows the prices of the NASDAQ Composite index over the past 49 years. During this period, there has been an average annual return on this index of 11.64 percent. Therefore, on average, a NASDAQ Composite index portfolio has doubled in value roughly every 6.25 years. Table 1 presents an overview of a selection of different asset classes and their returns in the period between 1970 and 2010 (Garcia-Feijoo et al., 2012). When comparing the average annual return of the NASDAQ Composite index portfolio to the asset classes in Table 1, the index portfolio is among the highest performing asset classes. In addition to this return, there are also fewer and lower costs for managing and trading a passive portfolio compared to an actively managed portfolio (Anadu et al., 2020).

Asset class	Return (%)	Standard deviation(%)	Asset class	Return (%)	Standard deviation(%)
Non-US equities: Developed	10.68	59.76	Energy index	13.80	111.00
Non-US equities: Emerging	16.20	83.76	Livestock index	9.24	62.16
Composite index	11.76	69.36	Agriculture index	6.96	71.64
Precious metals index	10.32	79.56	Gold	8.16	67.80
Metals index	11.76	84.72	Treasury Bills (Three months)	6.00	3.60

Table 1. Asset classes returns and standard deviations between 1970-2010. Note. From (Garcia-Feijoo et al., 2012).

Independent of whether the investor chooses an active or passive investment strategy, the risk of the chosen portfolio should always be minimised. The risk of a stock is the standard deviation of the stock price (S. Wang & Xia, 2002). For example, the NASDAQ Composite index portfolio in Figure 1, over the last 49 years, has had a standard deviation or risk of 24.94 percent per year, only outperformed by the Treasury Bills in Table 1.

One way to minimise the risk of a portfolio is by diversifying the portfolio using the correlation of the stocks to reduce the portfolio's unsystematic and therefore, uncompensated risk (Goetzmann & Kumar, 2008). Diversification is possible due to the correlation between stocks; as the number of stocks in a portfolio increases, the standard deviation of the portfolio goes down until it reached the systematic or market risk (Atherton & Yap, 1979).

To determine the optimal portfolio for investors based on the risk and return information of all possible portfolios, the efficient frontier can be used. The efficient frontier represents the highest possible return for every level of portfolio risk (Markowitz, 1952). When the efficient frontier is plotted, as in the example in Figure 2, the Capital Market Line (CML) can be plotted in the same graph from the risk-free interest rate through the tangent of the efficient frontier. The portfolio that is the tangent point of the CML and the efficient frontier is called the tangent portfolio or optimal portfolio (Stoyanov et al., 2007). This optimal portfolio has the highest risk-adjusted performance of all the possible portfolios, represented by the slope of the CML, which is the Sharpe ratio (Hogan & Warren, 1974).

After determining the optimal portfolio, in theory, all investors would hold differing combinations of the optimal portfolio and lend (or borrow) at the risk-free interest rate depending on the investor's individual risk preference (Nielsen & Vassalou, 2006).



Figure 1. NASDAQ Composite index prices 1975-2023. Note. NASDAQ Composite index prices between January 1975 and November 2023. From Refinitiv Eikon (2023).

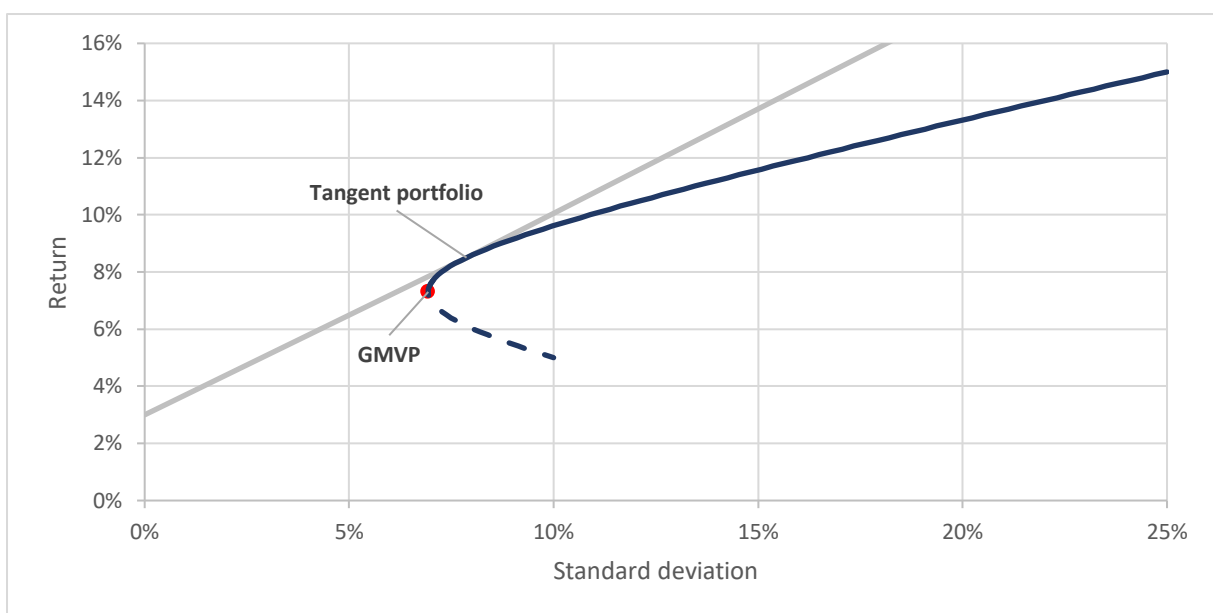


Figure 2. Efficient frontier, the CML, the tangent portfolio, and the Global Minimum Variance Portfolio (GMVP). Note. This figure is an example to demonstrate the aforementioned terms in a visual way, it is not based on any specific market data.

Since the 2010s, machine learning (ML) technologies have been rising (Warin & Stojkov, 2021). This rise was also found in the finance field, especially because of its ability to handle big data analytics (Königstorfer & Thalmann, 2020). Ahmed et al. (2022) mentions that ML technologies can be applied to (active) portfolio management and stock predictions. Active portfolio management was described by Sun et al. (2024) as an optimisation problem in which the investor actively buys and sells equities, monthly, quarterly, or annually, to beat the passive portfolios (Granger et al., 2019). With the rise of ML models that specialise in portfolio optimisation problems in finance (Lestari et al., 2023; Srivastava et al., 2023; Sun et al., 2024; Wolff & Echterling, 2023), the implications of this ML technology on optimising portfolios are potentially also influential for the literature on portfolio management. This thesis aims to add to the existing literature on portfolio management by answering the following main- and sub-research questions:

Main research question:

- Can an ML model, that actively trades an equity portfolio, outperform benchmark portfolios (NASDAQ Composite index tracker and minimum variance portfolio) based on risk-adjusted performance indicators?

Sub questions:

- What are suitable risk-adjusted performance indicators for portfolio evaluation? (Chapter 2.3)
- What ML technique should be used to actively manage a portfolio? (Chapter 2.4)
- How does the ML portfolio compare to the benchmark portfolios based on the risk-adjusted performance indicators? (Chapter 5)
- How accurate are the predictions that were made by the ML model? (Chapter 2.5)

2. Theoretical framework

To answer the research questions of this thesis, some literature and theories need to be covered. In this theoretical framework, this thesis will cover literature and theories that need to be understood before being able to conduct the experiment and answer the research question of this thesis.

The theoretical framework is split in two parts: portfolio management (Chapter 2.1-2.3) and machine learning (Chapter 2.4-2.5). Chapter 2.1 starts with a basic introduction into portfolio management, diversification, and portfolio variance. After these critical topics for this thesis have been introduced, asset allocation methods will be explained in Chapter 2.2, both for the ML generated portfolio as well as for the benchmark minimum variance portfolio. Following this, the key performance indicators for portfolio management will be reviewed in Chapter 2.3, these indicators will be used to compare the portfolios in the experiment in this thesis.

Chapter 2.4 of this theoretical framework compares various machine learning techniques that can be used for the stock price predictions in the experiment of this thesis. Finally, Chapter 2.5 covers the performance metrics that will be used for the machine learning model to determine the accuracy of the predictions.

2.1 Portfolio management and diversification

The foundations of portfolio management theory have been laid by Markowitz (1952). His paper discussed that investors could maximise the expected return of their portfolios by holding diversified portfolios at the investor's given level of risk tolerance. Portfolios are diversified if there are limited covariances between the stocks in the portfolio. According to Markowitz, covariances between stocks can be limited by investing in companies from differing industries.

The aim of diversification is to reduce the level of risk of a portfolio, however, not all risk can be removed with diversification (Markowitz, 1952). There are two types of risk, systematic risk and unsystematic risk (Beja, 1972). Unsystematic risk is the uncorrelated risk that is associated with one particular company, and therefore, by the law of large numbers, can be diversified away (Markowitz, 1952). In contrast, systematic risk is the correlated risk of the entire market, for example, a global recession will influence (almost) all companies the same way. Systematic

risk is also referred to as market risk as this risk cannot be diversified away due to the covariance, and therefore, correlation between stocks.

The correlation between stocks means that, even in a well-diversified portfolio, the systematic risk is still present. This is illustrated in the example in Figure 3. This example shows the portfolio sets of two stocks of differing correlations between -1 and 1. This example shows that except for the portfolio with a perfect negative correlation between the two assets, a certain amount of standard deviation or market risk stays present. In practice, perfect negative correlation between two assets is not achievable (Mao, 1970). In addition to the non-diversifiable market risk, Figure 3 also shows that diversification can reduce the overall portfolio risk lower than the risk of the individual assets.

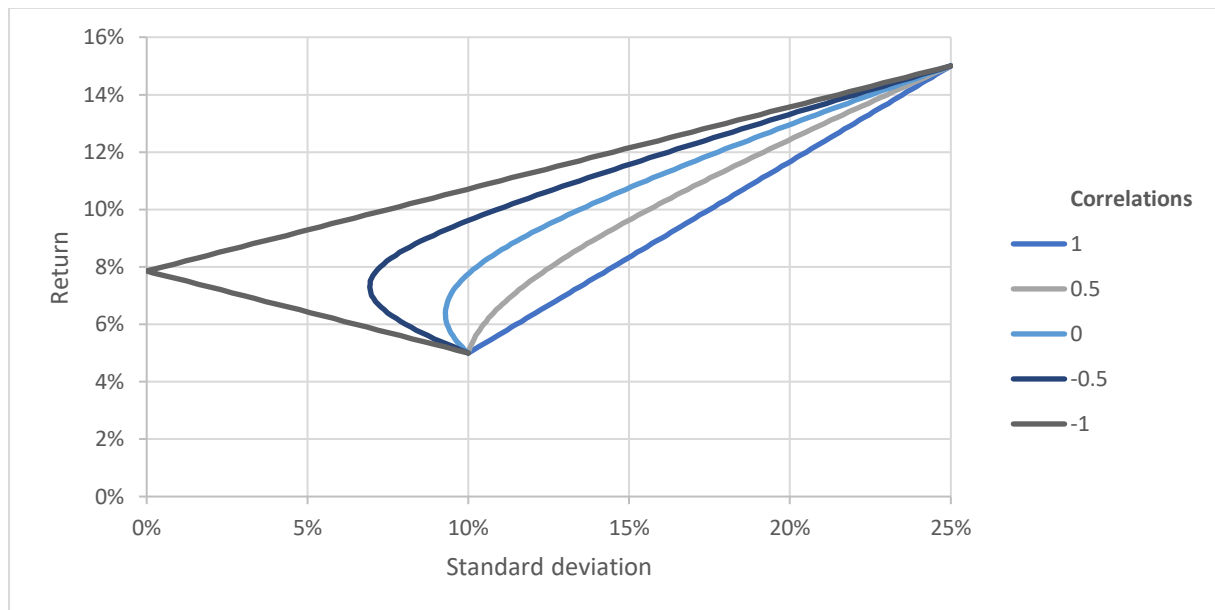


Figure 3. Effect of stock correlation on a portfolio’s return and standard deviation. Note. This figure shows the combined return and standard deviation of two stocks with a return/standard deviation of 5/10 and 15/25 respectively.

The covariance of two stocks can be calculated using Equation 1, using the correlation coefficient of stock A and stock B, and the standard deviation of A and B (σ_A and σ_B).

Given the overall portfolio risk reduction from diversification as can be seen in Figure 3, for portfolio management it is essential to build portfolios that have a low correlation between the stocks in the portfolio. With a low correlation coefficient, it is possible to achieve the highest diversification and therefore, return for any given level of risk.

$$Cov(A, B) = Correlation\ coefficient \times \sigma_A \times \sigma_B \quad (1)$$

Equation 1 also shows that to measure diversification, not only correlation between the stocks but also the standard deviations of the individual stocks should be taken into consideration. Statman et al. (2008) argue that correlation between two assets is not a good indicator for diversification. Instead, Statman et al. propose the return gap as the indicator for diversification. The return gap is presented in Equation 2, where σ is the mean standard deviation of the two stocks and ρ is the correlation.

$$Return\ gap = 2\sigma \sqrt{\frac{1 - \rho}{2}} \quad (2)$$

To apply diversification to a portfolio, it is necessary to be able to evaluate how many stocks need to be held to have a similar amount of diversification compared to the general market, as the general market has only systematic risk and therefore, is by definition, diversified (Beja, 1972). Woerheide (1993) evaluated five different measures of diversification, based on their ability to determine the diversification of stock portfolios, with both evenly and unevenly distributed weights. Woerheide concluded that a Diversification Index (DI, see Equation 3), based on the Herfindahl Index (HI) was the best measure. The Herfindahl Index is a concentration or diversity index that sums the squared stock weights of all the stocks in a portfolio (Nguyen et al., 2022). The output of the Diversification Index was determined to be likely adequately diversified with a value of above 91, while a value of below 85 was likely not an adequately diversified portfolio (Woerheide, 1993). It is possible that a portfolio is adequately diversified despite not reaching the 85-index score, however these scores can be used as general guidelines to determine adequate diversification.

$$DI = (1 - HI) \times 100 = \left(1 - \sum_{i=1}^N W_i^2\right) \times 100 \quad (3)$$

In Equation 4, the formula for portfolio variance (σ_p^2) is presented (Richard Brealey et al., 2023), with N being the number of stocks in the portfolio. Equation 4 shows that when the number of stocks increases, the variance of the stocks is becoming increasingly less important for the total portfolio variance, instead, the covariance between the stocks is becoming increasingly more important. This shows that the aforementioned diversification has an increasingly profound effect on the portfolio variance as the number of stocks in a portfolio increase.

$$\sigma_p^2 = \frac{1}{N} \times Average\ variance + \left(1 - \frac{1}{N}\right) \times Average\ covariance \quad (4)$$

During the experiment of this thesis, Woerheide's aforementioned diversification index will be utilised to compare the ML portfolio against the minimum variance benchmark portfolio. The diversification index will not be used on the market index tracker as the market's risk consists, by definition, only of the systematic risk component, and is therefore completely diversified. During the experiment, Woerheide's guidelines regarding the diversification index will be used to determine whether the ML portfolio and the minimum variance portfolio are adequately diversified.

2.2 Asset allocation methods

The two most famous models for portfolio asset allocation are the mean-variance optimisation (MVO) model and the Black-Litterman model (Liaras et al., 2024; Yang et al., 2020). Yang et al. (2020) found that while in theory the MVO model gives the perfect optimal solution, in practice this model is hard to apply correctly due to inherent assumptions in the model itself, namely: ignoring the fat tail and skewness characteristics of the returns, and the holding period being only one period, leading to inaccurate parameter estimation. In contrast,

the Black-Litterman model was found to have overcome the issues limiting the practical use of the MVO model (Yang et al., 2020). In addition, portfolios created using the Black-Litterman model are generally also better diversified compared to MVO-based portfolios (Sutiene et al., 2024). However, the Black-Litterman model has its own downside, the model requires accurate investor views for the best stocks and weights to be selected (Black & Litterman, 1991).

The Black-Litterman model was originally published in 1991. This asset allocation model takes into consideration both prior financial data, as well as the views from the investor on whether the stock prices for certain stocks will increase or decrease (Walters, 2011). Since this model is partially based on the investor's views of the future market, the accuracy of these predictions also determines the future success of the portfolio. During the experiment in this thesis, these investor views would be generated by the ML model rather than human experts.

Clarke et al. (2011) has found that portfolios created with minimum variance strategies in mind, have outperformed the market, achieving higher cumulative returns in the period from 1968 to 2009. This phenomenon can partly be explained by Clarke et al. using beta as the measure of risk. There is a difference between theory and practice regarding the use of beta from the CAPM equation to predict the expected return of a specific stock. In theory, the stocks' expected return can be calculated using Equation 6, using a market risk premium ($R_M - R_f$) that is the same for every investor (Sharpe, 1964). However, in practice, not every investor has the same market risk premium (Fernandez, 2015), and neither is the market risk premium the same for every level of beta (Platt et al., 2014), and for company specific conditions (McGrattan & Jagannathan, 1995), such as company size (Fama & French, 2004).

Clarke et al. (2011) also found that for minimum variance portfolios, the portfolio weight could be determined solely based on the stock's (co)variance, not needing to include the expected return in the weight calculation. Figure 2 shows such a portfolio constructed using a minimum variance strategy, this is the Global Minimum Variance Portfolio (GMVP). The GMVP is the portfolio on the efficient frontier with the lowest amount of risk, as well as the lowest amount of expected return. Urošević & Vasiljević (2020) suggests that the GMVP is a good benchmark as any portfolio that does not have a higher expected return higher than this portfolio is not optimal. Such a portfolio that does not outperform the GMVP should be avoided as the GMVP has a higher expected return as well as less risk.

To conclude, during the experiment, the ML portfolio will use the Black-Litterman model to determine the appropriate asset allocations. The inputs for this model are the previous financial information that will be collected from Refinitiv Eikon. In addition, the investor views will be derived from the ML's predicted stock prices.

The minimum variance portfolio will be constructed using the minimum variance strategy. This strategy seems the most appropriate as this is an objective way to determine the stock. The minimum variance strategy does not require expected returns, instead the strategy uses (co)variances that can be retrieved from the past financial information. Therefore, as this strategy determines the assets allocations merely on past data, this is the most objective way to create the minimum variance benchmark portfolio.

2.3 Key performance indicators for portfolio management

To evaluate and compare the performance of the portfolios in the experiment of this thesis, comparable performance measures should be used. One of the commonly used performance measures based on mean-variance theory is the Sharpe ratio (Zakamouline & Koekebakker, 2009). The Sharpe ratio can be calculated by using Equation 5.

$$\text{Sharpe ratio} = \frac{R_p - R_f}{\sigma_p} \quad (5)$$

Where R_p is the portfolio return, R_f is the short-term (Treasury bond) interest rate, and σ_p is the portfolio standard deviation or portfolio risk (Lettau & Ludvigson, 2010).

The criticism of the Sharpe ratio as a performance measure is described by Zakamouline et al. (2009) as the measure's dependency on the normal distribution of the portfolio's variance. However, this criticism mainly has implications for hedge funds and investors using options and other derivatives as these risks are not properly measured using the Sharpe ratio. For general portfolio performance using strictly stocks, as the experiment in this thesis, the Sharpe ratio is still an adequate performance measure to compare the portfolios (Clarke et al., 2011; Hollstein & Prokopczuk, 2023; Lorenzo & Arroyo, 2023; Sun et al., 2024; Wolff & Echterling, 2023; Xu et al., 2023). In addition, Schuhmacher et al. (2012) has found that all frequently used performance measures lead to comparable results in ranking to the Sharpe ratio. This finding makes the Sharpe ratio one of the most important, if not the most important, performance measure for portfolio performance.

Another performance indicator for stocks and portfolios is the beta. This indicator measures the systematic risk or variance of a stock or portfolio compared to the general market portfolio and it is derived from Sharpe's CAPM model (1964). This model predicts the return of an investment ($E(r_i)$) by its systematic risk (β_i), the market risk premium ($R_M - R_f$), and the risk-free rate (R_f), as can be seen in Equation 6.

$$E(r_i) = R_f + \beta_i(R_M - R_f) \quad (6)$$

The beta of a portfolio can be calculated by either the weighted average of the betas of the stocks that make up the portfolio or by regressing the portfolio's return against the market's returns (Chong et al., 2018).

From the portfolio beta, yet another performance measure can be calculated, the Treynor ratio (Treynor, 2012). This ratio uses the portfolio beta and the portfolio's excess ($R_p - R_f$) return over the risk-free rate, as can be seen in Equation 7.

$$\text{Treynor ratio} = \frac{R_p - R_f}{\beta_p} \quad (7)$$

The Treynor ratio differs from the Sharpe ratio as instead of the standard deviation, it uses the beta in the numerator of the formula. This means that the risk adjustment of this performance measure is solely based on the systematic risk. As this systematic risk is a non-diversifiable risk, this ratio measures the performance of the performance of a well-diversified portfolio (Treynor, 2012). The experiment in this thesis will make use of diversified portfolios, either in the form of a market index, or the asset selection for the other portfolios as diversification reduces the total risk of the portfolio (Koumou, 2020).

The final portfolio performance measure that will be used in this thesis is Jensen's alpha. This measure shows the deviation from the expected return on the investment portfolio from the CAPM calculation ($E(r_i)$) compared to the actual achieved return on the portfolio (R_p). Jensen's alpha is calculated using Equation 8 (Samarakoon & Hasan, 2006).

$$\text{Jensen's alpha} = R_p - E(r_i) = R_p - [R_f + \beta(R_m - R_f)] \quad (8)$$

In this subchapter, different risk-adjusted performance metrics were discussed. The performance metrics adjust for portfolio risk (Sharpe ratio), market risk (Beta and Treynor ratio), as well as excess return (CAPM and Jensen's Alpha). The performance metrics mentioned in this chapter provide different risk-adjustments to the performance of the portfolios in the experiment of this thesis. The performance metrics should provide sufficient basis for the portfolio performance comparison in the results of Chapter 5.

2.4 ML techniques

There are three popular types of ML model classes that are used for stock price predictions: time series forecasting models (Lim & Zohren, 2021; Mishra et al., 2024; Soni et al., 2022), Artificial Neural Network (ANN) (Lin & Lobo Marques, 2024; Sheth & Shah, 2023; Thakkar & Chaudhari, 2024), and Long Short-Term Memory (LSTM) algorithms (Bansal et al., 2022; Sheth & Shah, 2023; Vuong et al., 2024).

Time series forecasting models are ML models that use consecutive data points to predict the next "out-of-sample" data point or points (Borup et al., 2022). Soni et al. (2022) and Ariyo et al. (2014) have both described the benefits of a time series forecasting model, such as the AutoRegressive Integrated Moving Average (ARIMA), as a model that provides reliable stock price forecasts for the short term.

ARIMA is a linear forecasting model. The model uses three parameters in the model to increase the fit to the data: the lagging parameter, the differencing parameter, and the white noise parameter (Zhang & Meng, 2023). The lagging parameter is used to determine the number of previous values that should be included in the prediction-making process. The differencing parameter is used to make non-stationary data stationary. Stationarity of time series data entails that the data has the same distribution properties (mean and variance) in the past, present, and future (Bektemyssova et al., 2022). The white noise parameter is used to determine how many residuals need to be included in the forecast (Shumway & Stoffer, 2017).

ANN is a form of a neural network. Neural networks are a structure of units or nodes (inspired by biological neurons), connected to each other through coefficients which have been generated by a learning process (Abdi, 1994; Yang & Yang, 2014). During the learning, or training, process, the neural network will estimate the coefficients in the structure of units. After this, the set of coefficients will be evaluated based on a loss function (Wang et al., 2022). This function compares the predicted outcomes with the testing data to determine the difference or error between both. For the purpose of determining the error between the predicted and training data, the mean squared error (MSE) or mean absolute error can be used (Tian et al., 2022). The neural networks generally consist of three types of layers: the input layer, the hidden layers, and the output layer (Vui et al., 2013). ANNs are able to

efficiently work with non-linear data as well as provide competitive levels of accuracy compared to the LSTM algorithms in the next paragraph (Adebiyi et al., 2014).

LSTM algorithms are deep learning-based ML techniques that can be used to forecast time series data. In the basis, LSTM is a recurrent neural network (RNN). RNNs connect the aforementioned units in the neural network recurrently, enabling RNNs to process the sequence of the inputted data (Pawar et al., 2019). The ability to process the sequence of the inputs is important for time series predictions, such as stock prices. However, RNNs do generally not perform well when using long term data. LSTM algorithms correct the shortcoming of the RNN by having a memory cell in its neural network to save data over a longer period of time (Datta, 2022; Istiake Sunny et al., 2020). Datta (2022) mentioned that an advantage of LSTM algorithms is that, due to their memory cells, they are not negatively affected by long past data in the forecasting process. In addition, LSTM algorithms are able to incorporate multiple indicators into the prediction-making process, making them more complete models by including other factors that can also influence the prediction (Ma, 2020).

Stock market data is non-linear and therefore, models that work well with non-linear data such as neural networks. Therefore, ANN and LSTM algorithms are more able to accurately predict the future stock prices compared to linear ML models (Ma, 2020; Selvin et al., 2017). Ma (2020) has compared all three aforementioned ML model classes; ARIMA, ANN, and LSTM. The ANN model outperformed the ARIMA model. For the comparison between the LSTM and the ANN model, the researcher concluded that the time series data that was used had a better fit for the ANN model, leading to a better performing model compared to the LSTM model. Siami-Namini et al. (2018) has found that LSTM-based prediction algorithms are also more accurate in predicting stock prices compared to ARIMA models. Ma (2020) mentioned that the LSTM model might benefit from more indicators to make the predictions compared to just the time series data that will be used in the experiment of this thesis.

While both LSTM and ANN are good ML models to use to predict the stock prices, the conclusion from Ma (2020) makes the convincing argument to choose the ANN model. The decision to go for the ANN model compared to the LSTM is based on the available data for the experiment of this thesis. The data that will be used for the experiment has one input variable (the market index tracker price from 31-trading days prior to the prediction date). With one input variable, the ANN had a better model fit compared to the LSTM according to Ma (2020). Therefore, during the experiment of this thesis, the ANN model will be used to predict the stock prices for the ML portfolio.

2.5 ML accuracy

In addition to the performance measures for the portfolio discussed before, this thesis will also include performance measures for the ML model. The level of accuracy in the predictions of the ML model determine whether the model can generate a portfolio that can relatively consistently outperform the benchmark portfolios. In similar research papers regarding the application of ML models in stock price predictions, ML performance metrics such as RMSE, MAE, MAPE, SMAPE, and R^2 have been used (Bansal et al., 2022; Kumbure et al., 2022; Soni et al., 2022). In this chapter, the aforementioned ML performance metrics will be discussed.

The RMSE can be calculated according to Equation 9, with n being the number of samples of model errors (ε) (Chai & Draxler, 2014). In this case, the model error is the difference between the predicted and observed value. This metric is the square root of the averages of all the squared model errors. This means that a lower RMSE value means that the model is more accurate model compared to a higher output value. As the model errors are squared, this metric is more sensitive to outliers compared to, for example, the MAE metric (Pontius et al., 2008).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \varepsilon_i^2} \quad (9)$$

The MAE is the mean of the absolute model errors, this means that a few big model errors will not disproportionately influence the MAE as it would with the RMSE. The advantage that the MAE has over the RMSE is that it is a simpler metric, this can be seen in Equation 10. In Equation 10, n is the number of model errors (ε) (Chai & Draxler, 2014).

$$MAE = \frac{1}{n} \sum_{i=1}^n |\varepsilon_i| \quad (10)$$

The MAPE is an accuracy metric that is based on the percentage errors, meaning the absolute difference between the observed (y_i) and the predicted value divided by the observed value. Just like the RMSE, the MAPE is sensitive to outliers (Shcherbakov et al., 2013). In addition, another downside of the MAPE is that if the observed value is equal to zero, the formula will not work as it is not possible to divide by zero, however, for stock prices, this should not be a problem as stock prices should be positive values. The MAPE can be calculated from Equation 10.

$$MAPE = \frac{1}{n} \sum_{i=1}^n 100 \times \frac{|\varepsilon_i|}{y_i} \quad (11)$$

The SMAPE is similar to the MAPE metric, however, there are a number of differences between the two metrics. The SMAPE is measured on a scale of 0 to 100 percent, this is different compared to the MAPE as the MAPE does not have an upper limit. This difference between MAPE and SMAPE makes the SMAPE easier to interpret as it is based on percentages. Therefore, a SMAPE score closer to zero percent means a smaller difference between the predictions and the observed values (Makridakis, 1993). Another difference between MAPE and SMAPE is that the MAPE “punishes” overpredictions harder compared to the SMAPE metric (Goodwin & Lawton, 1999), this can be accredited to the lack of an upper limit in the MAPE metric. Therefore, when a SMAPE score is lower compared to the MAPE score, the ML model generally overpredicted the stock prices compared to the actual values.

The SMAPE also has one similar downside compared to the MAPE. When the observed and predicted (p_i) values are the exact opposite values (for example, $y_i = 1$ and $p_i = -1$), the formula does not work as this would result in a division by zero (Shcherbakov et al., 2013).

This should not be a problem for stock price predictions as these values should not be negative. The SMAPE can be calculated according to Equation 12.

$$SMAPE = \frac{1}{n} \sum_{i=1}^n 100 \times \frac{|\varepsilon_i|}{y_i + p_i} \quad (12)$$

In addition to the ML accuracy metrics that were previously discussed, R squared is also a performance metric that is used on price predictions using ML models (Armagan, 2023; Bansal et al., 2022; Charandabi & Kamyar, 2021). R squared (or R²) is the coefficient of determination. The coefficient of determination measures how much of the variation in the dependent variable (stock price) can be explained by the model (Chicco et al., 2021). Chicco et al. (2021) compared the R squared against other ML model performance metrics such as RMSE, MAPE, MAE, and SMAPE and they found that R squared were easier to interpret and, in comparison to SMAPE, even more informative and truthful.

Kumbure et al. (2022) also found that prediction accuracy was an often-used performance metric. Accuracy can be calculated with Equation 13 (Dinga et al., 2019). Within the context of this thesis, the accuracy is measured as the percentage of instances where the ML model correctly predicted the direction in which the stock price went during a monthly period. To give more insights into the accuracy of the ML model, the amount of correct and incorrect predictions can be further analysed. One way to further analyse the accuracy of the ML model is with a confusion matrix. This is a matrix that displays the true positive (TP; positive prediction and positive observation), true negative (TN; negative prediction and negative observation), false positive (FP; positive prediction and negative observation), and false negative (FN; negative prediction and positive observation) predictions (Varoquaux & Colliot, 2023). Within the context of this thesis, there are no clear positive or negative predictions as the ML model does not classify the companies, instead it predicts the stock prices of said companies. Therefore, an adapted version of the confusion matrix will be used. In this adapted confusion matrix, positive and negative will be replaced with increase (I) and no increase (N). An example of what such a confusion matrix would look like is presented in Figure 4. One way to make sense of a confusion matrix is by using the sensitivity and specificity metrics (Varoquaux & Colliot, 2023). On the one hand, sensitivity measures the fraction of the positive (or increased stock prices) retrieved by the ML model, as can be seen in Equation 14. On the other hand, specificity measures the fraction of the negative (or no increased stock prices) retrieved by the ML model, as can be seen in Equation 15. By using both these metrics, it can be evaluated how well the ML can predict both increases and lack of increases in the stock price.

	Observed increase	Observed no increase
Predicted increase	True increase (TI)	False increase (FI)
Predicted no increase	False no increase (FN)	True no increase(TN)

Figure 4. An example of the confusion matrix for this thesis.

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \quad (13)$$

$$\text{Sensitivity} = \frac{TI}{TI + FN} \quad (14)$$

$$\text{Specificity} = \frac{TN}{TN + FI} \quad (15)$$

To conclude, in this chapter, a number of error-based ML accuracy metrics were discussed, these were: RMSE, MAE, MAPE, and SMAPE. These metrics should provide an overview of the difference between the predicted and observed stock prices, where a lower score is better. Another metric that was discussed was the coefficient of determination, or R^2 . R^2 measures the variation of the dependable variable that can be explained by the ML model. Chicco et al. (2021) found that R^2 was a better metric compared to the error-based performance metrics discussed before. However, the error-based performance metrics still provide different insights in the performance of the ML model and therefore, these metrics will be used in this thesis. Finally, prediction accuracy metrics were discussed. These accuracy metrics will demonstrate the ML model's ability to correctly predict the increases and lack of increases in the stock prices.

The ML accuracy metrics that will be used in the experiment of this thesis are the following:

1. Accuracy (including prediction accuracy, a confusion matrix, sensitivity, and specificity);
2. Error-based metrics (RMSE, MAE, MAPE, and SMAPE);
3. And the coefficient of determination or R^2 .

However, accuracy-based metrics are not the only metrics that are important for the evaluation of the performance of an ML model. Other metrics that can also be relevant in such evaluations are explainability and processing time. These metrics are relevant but not critical for the research in this thesis and are therefore excluded due to time constraints. While these two metrics are not included in the experiment of this thesis, they might be utilised in future research opportunities on this topic and will therefore be quickly discussed in this chapter.

Explainability of a model is particularly relevant for neural networks and other deep learning models. These models can be seen as a "black box" where the path from the inputs to the outputs are not clear. Adding explainability to these "black box" models can help to visualise what inputs are more or less important in the decision-making process of the model, making it easier to understand if there are any unwanted biases within the model. In addition to mitigating any results that can be deemed unfair or unethical, explainability can also improve the decision quality by allowing for guidance from the researchers (Hassija et al., 2024).

The other evaluation factor that was mentioned earlier was the processing time. The processing time of the model can be seen as the combined time it takes to train the model on the training data and make the (stock price) predictions. The processing time is relevant as the closer the predictions are made to the actual construction of the portfolio; the more recent data can be used to train the model. In turn, training on the latest data could improve the accuracy of the model. Therefore, the minimisation of the processing time could provide an edge to financial institutes who would want to use ML models to predict the stock prices (Oyewole et al., 2024). As this thesis' experiment will be trained and tested on historical stock

price data, the need for the processing time minimalization is less present and therefore, processing time is not further discussed in the remainder of this thesis.

3. Research design

In this chapter, the research design of this thesis will be discussed. This will happen in three steps; Chapter 3.1 will discuss the general steps that will occur during the experiment of this thesis, Chapter 3.2 will dive deeper in the construction of the minimum variance portfolio, and Chapter 3.3 will explain the process behind the construction of the ML portfolio.

3.1 Overview of the experiment

The research design of this thesis will include the following steps:

1. The experiment starts with collecting the historical stock price data of the NASDAQ Composite index from Refinitiv Eikon, both the index tracker prices itself as well as the individual companies within the index. This data collection will happen on the stock price data between the first of January 1990 and the 31st of December 2020. For this thesis, the dataset will be separated in three subsets of data, as can be seen in Table 2. During the experiment of this thesis, the experiment will be repeated on all three subsets of stock price data. The repetition is chosen as a way to be able to make a more generalised conclusion about the performance of the ML portfolio compared to the benchmark portfolios. Further analysis regarding the collected data for the experiments will be discussed in Chapter 4.
2. The minimum variance portfolio and the ML portfolio will be constructed for the testing period using the steps laid out in respectively Chapter 3.2 and 3.3. For the market benchmark portfolio, the prices of the NASDAQ Composite index tracker during the testing periods will be used.
3. The performance of the ML portfolio and the benchmark portfolios during all data subsets will be evaluated in Chapter 5. The evaluation will happen based on the portfolio risk-adjusted performance metrics from Chapter 2.3 and the ML performance metrics from Chapter 2.5.
4. The results from the experiment in Chapter 5 will be discussed in Chapter 6.2, including limitations (Chapter 6.3) and future research opportunities (Chapter 6.4). Finally, the research question of this thesis will be answered in the conclusion in Chapter 6.5.

Figure 5 shows an overview of the steps for this master thesis in a research framework.

	Training start	Training end	Testing start	Testing end
Data subset 1	1 January 1990	31 December 1999	1 January 2000	31 December 2000
Data subset 2	1 January 2000	31 December 2009	1 January 2010	31 December 2010
Data subset 3	1 January 2010	31 December 2019	1 January 2020	31 December 2020

Table 2. Timeframes within the three subsets of data for the experiment of this thesis.

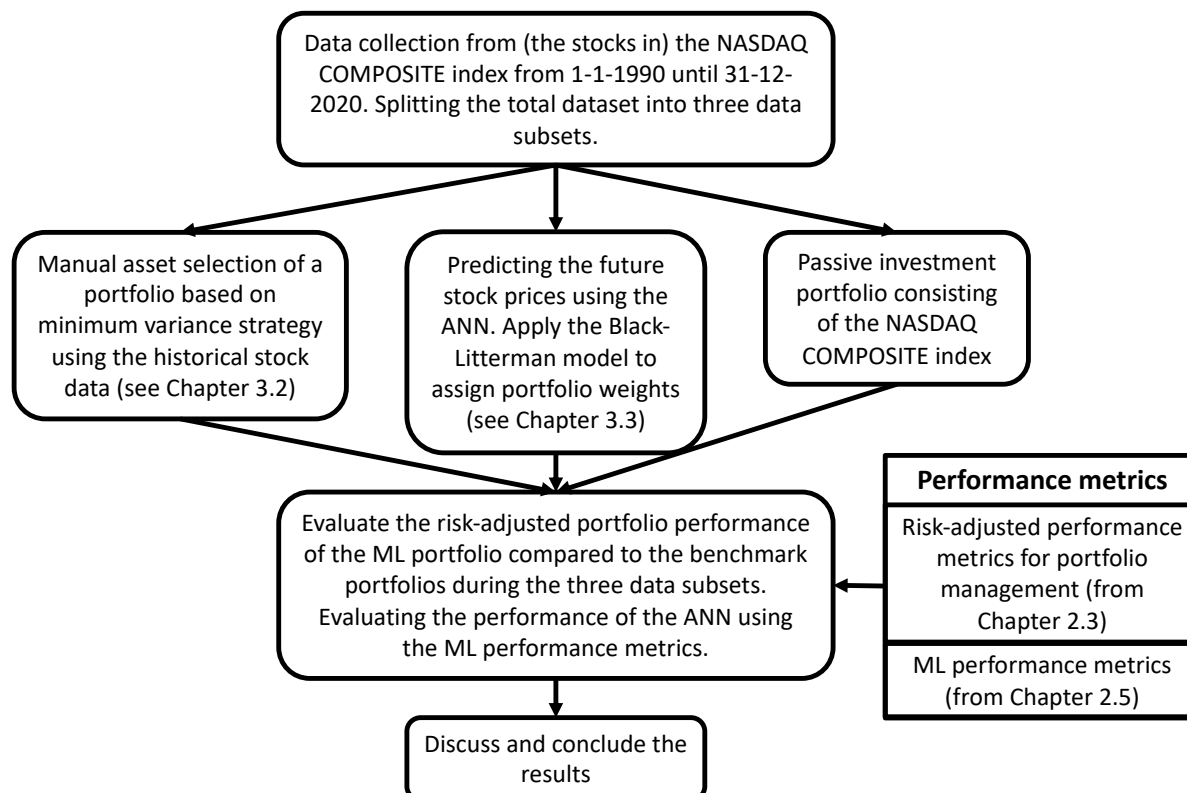


Figure 5. Research framework of this thesis experiment.

3.2 Minimum variance portfolio

To determine the allocations for the minimum variance portfolio, the stocks will be ranked based on their beta during the 10-year training period. The fifty ranked stocks with the lowest (or negative) betas will be selected for the experiment of this thesis. The choice was made for fifty stocks as from fifty stocks onwards, the marginal increase in the diversification index was the lowest. The decreasing marginal increase in diversification index can be seen in Figure 6. In itself, a higher diversification index does not necessarily result in higher returns. However, with a theoretical diversification limit of 98, given equal distribution across all fifty stocks, the minimum variance portfolio is adequately diversified, meaning solely consisting of systematic risk. Increasing the portfolio size to over fifty stocks would increase the complexity of the calculations, but it would not lead to a more diversified portfolio. Therefore, the decision was made to limit the stocks in the minimum variance portfolio to fifty stocks. With the stock selection completed, the portfolio weights need to be determined. The portfolio weights will be determined by minimising the standard deviation of the entire portfolio during the training period by changing the weight allocations of each of the fifty stocks. When the standard deviation minimisation has led to a portfolio of companies and their respective weights, this portfolio will be used for the entire testing period.

The aforementioned stock selection and portfolio construction process will be utilised for all three training periods of the experiment. The portfolio weights for the minimum variance portfolio for each testing period can be found in respectively Appendix A1, B1, and C1.

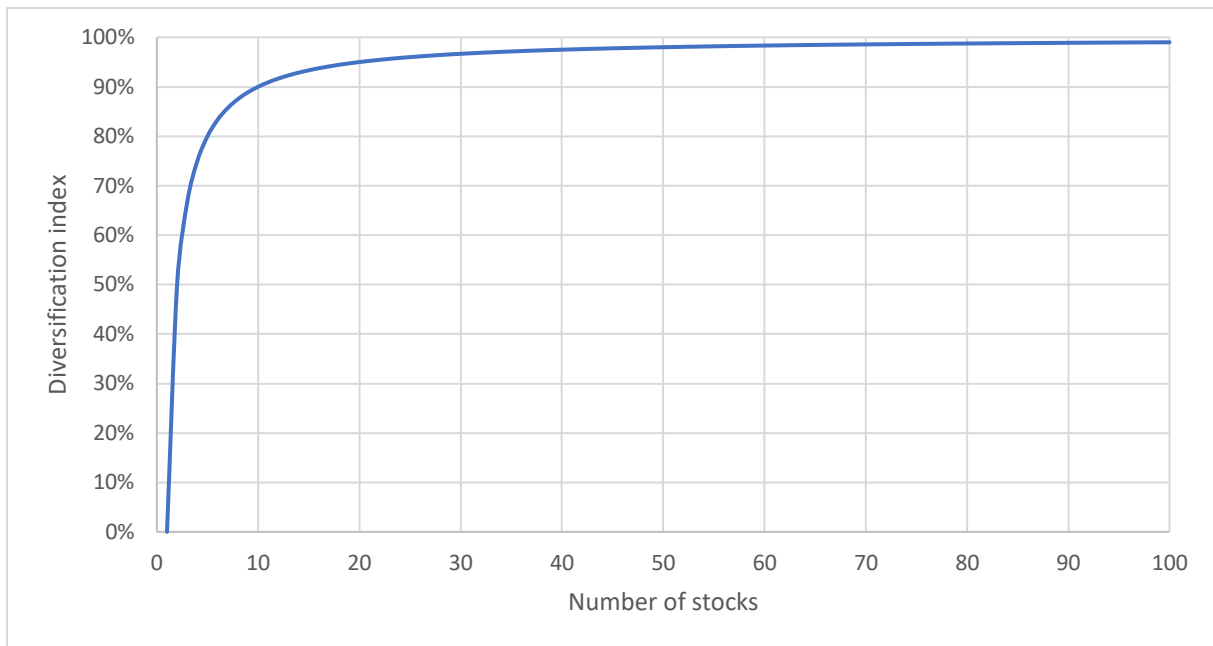


Figure 6. Relation between the number of stocks and the diversification index. Note. For this figure, the diversification index is calculated based on equal portfolio weights.

3.3 ML portfolio

In this chapter, the construction of the ML portfolio will be discussed. Firstly, the intricacies of the ANN will be covered in Chapter 3.3.1. After which the asset allocation using the Black-Litterman model will be explained in Chapter 3.3.2. The chapter will be concluded with a general overview of the process how the ML portfolio is constructed from the input data until the finalised portfolio in Figure 7.

3.3.1 Artificial Neural Network

To determine the asset allocation of the ML portfolio, the ML model will predict the stock prices during the experiment testing year based on the prior 10 years of training data. From the literature review of this thesis, it was found that the ANN would be the most suitable ML model for the specific experiment design that was chosen. While it would be better to also include other ML models, such as the LSTM to have more insights into what the risk-adjusted performance difference would be compared to the ANN, due to time constraints, this is not feasible for this thesis. For the ANN in this thesis, the input variable will be the NASDAQ Composite index tracker price from 31-trading days prior to the prediction date. The time between the input and output variables was chosen to allow for the predictions to be made and a portfolio to be constructed for the coming month. The output variables of the ANN will be the stock prices of every individual company included in the experiment. During the experiment, the entire testing period will be predicted at once with no retraining during each testing period. The ML model will be programmed in the Python programming language using the Keras Deep Learning Package (Keras, 2024) for the ANN.

The specific Keras deep learning model that is used in this thesis is a sequential ANN model. A sequential model is appropriate for creating the ML portfolio as it has one input and one output, as described by Keras (2023b). In Table 3, the particular settings for the sequential ANN model are presented.

ANN settings from Keras	
Layers: Total/Hidden	5/3
Nodes per layer	1/12/10/8/1
Activation function	Rectified Linear Unit (ReLU)
Optimiser	RMSProp
Loss function	Mean Squared Error (MSE)
Epochs	25
Batch size	2
Early stopping monitor	loss
Patience	5

Table 3. Settings for the ANN.

For the experiment of this thesis, an ANN with five layers will be used, consisting of an input layer, three hidden layers, and an output layer. Within the five layers, an architecture of 1/12/10/8/1 nodes per layer was chosen. Figure 6 shows a schematic of the ANN's architecture for the experiment of this thesis.

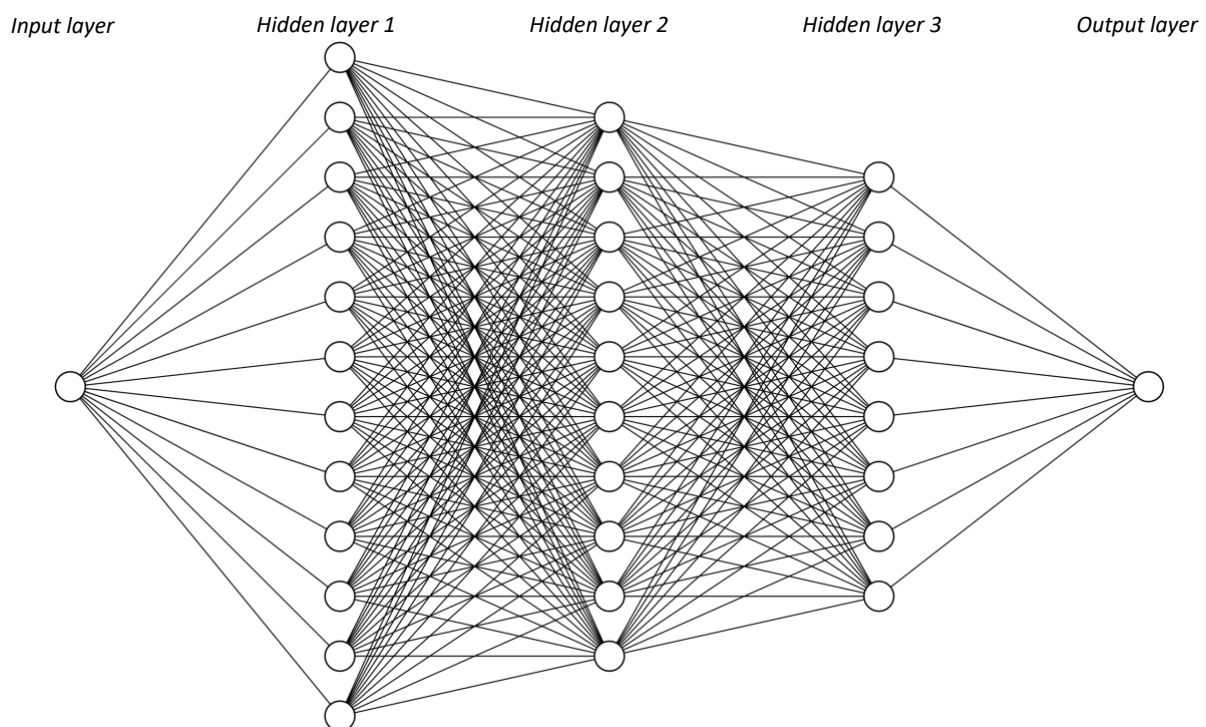


Figure 6. ANN-architecture schematic from this thesis. Note. Created using software by Alexander Lenail (2019).

Activation functions play a vital role in the performance of the ANN, this is because the activation function provides non-linear properties to the ANN (Dubey et al., 2022). In broad terms, an activation function makes a decision regarding whether a node within the network should be activated based on the specified function. The function judges this based on the importance of the node's input to the neural network. The most-used activation function for ANNs is called Rectified Linear Unit or ReLU (Rasamoelina et al., 2020). ReLU is a linear

activation function, this means that the nodes' output value is in proportion to the input value (Lederer, 2021). The ReLU activation function works by replacing the negative values of the nodes by zero while making no adjustments to the positive values. ReLU thanks its popularity to the function's simplicity and performance compared to other activation functions (Dubey et al., 2022). For this thesis, the ReLU activation function will be used.

Neural networks depend on optimisation to make the most accurate predictions (Dogo et al., 2018). The optimisation of a neural network is usually in the form of an iterative process where predictions are repeatedly made based on the training dataset. During the optimisation process, the weights within the neural network are continuously changed to create the most accurate prediction model based on the loss function (Khanal et al., 2022). The optimiser of the ANN in this thesis is called Root Mean Squared Propagation or RMSProp. RMSProp is an optimisation algorithm which optimises the performance of the neural network using an adaptive learning rate (Khanal et al., 2022). The learning rate is the amount of change in neural network weights (Jena et al., 2021). A small learning rate will take more time to reach the optimal weight while a bigger learning rate might miss the optimal weight while trying to optimise the parameters of the neural network. Methods using adaptive learning rates, such as RMSProp, make the training process more efficient by removing the need to manually select a learning rate for the neural network (Ding et al., 2019). In addition, due to the optimiser's ability to select the appropriate learning rate, the performance will also be improved. The improved performance comes from having an appropriate learning rate chosen to optimise the model compared to a manually selected learning rate which might not be the optimal rate (Macêdo et al., 2021).

The loss function of the ANN is used to measure the optimisation of the ANN. A loss function works by generating a set of predictions based on the training data and then comparing the predicted stock prices against the actual stock prices based on a specific formula (Gu et al., 2018). In this thesis, a Mean Squared Error (MSE) loss function will be used. The loss function will input the difference between the predicted and actual values into the formula for the MSE (see Equation 16). A new model with different parameters will then generate a set of predictions and these predictions are then compared against the MSE of the original parameters. The model with the lowest MSE and therefore, the optimal parameters, will then be used to make the predictions on the testing dataset.

$$MSE = \frac{1}{n} \sum_{i=1}^n \varepsilon_i^2 \quad (16)$$

An epoch is defined as the one-time passing of the training dataset through the network (Zupan, 2003). An epoch is part of the optimisation process where every time a new set of parameters is being tested on the training data. The experiment in this thesis will use 25 epochs, and therefore, the training dataset will be passed through the network for a maximum of twenty-five times. The number of 25 epochs was found through a process of trial-and-error as the optimisation process often stopped around ten to fifteen epochs. Therefore, 25 epochs include a margin of error above the usual number of epochs in case the optimisation process takes more trials to find the optimal weights.

For one epoch, the entire training dataset is usually not passed through the network in one time. Often, the training dataset is cut up in batches. One batch is also called one iteration. Within one batch or iteration, there may be multiple training datapoints, this is determined by the batch size. Therefore, the batch size is the amount of training datapoints per iteration (Chahal et al., 2020). Larger batch sizes are better for the scalability and efficiency as there will be less iterations per epoch. However, the downside of larger batch sizes is higher chances of overfitting and lower accuracies (Farkas et al., 2020). During this thesis, a batch size of two will be used. This batch size seems low enough to not compromise on accuracy or overfitting, but it will greatly speed up the training process.

When the training of the neural network approximates the optimal weights and parameters for the specific training dataset, there is less room for improvement left. If the training process keeps continuing when the network has reached this area of small margin improvements, it can even happen that the performance becomes worse due to the noise in the learning (Ying, 2019). To avoid learning past the peak performance of the network, an early stopping monitor can be used. This monitor evaluates the improvements from every epoch based on a certain metric, in the case of this thesis, the metric is the loss from the loss function. When the early stopping monitor “notices” a lack of improvement in the loss of the neural network, it can stop the training process to avoid overfitting and loss of performance (Ying, 2019). However, if the training is stopped too early, underfitting and lower performance might occur. To avoid stopping too early, a patience can be added. A patience is the number of epochs that will be monitored after no improvement has been detected before stopping the training of the neural network (Keras, 2023a).

3.3.2 Black-Litterman model

The stock price predictions from the ANN for the testing period will be used for the portfolio weight allocations. The portfolio weights will be determined using the Black-Litterman model. This model has been, and is currently being used, by investment banks (Cayirli, 2011), such as the Asset Management department of Goldman Sachs (2019). The Black-Litterman model uses a combination of historical stock price data and expert views to determine the appropriate weights for the portfolio. The historical stock price data will be retrieved from Refinitiv Eikon. The expert views will be derived from the ANN’s predictions. The expert views required for the Black-Litterman model are the expected increases or returns of the stock prices during the time period of the to-be-constructed portfolio. The expected returns will be calculated using the increase of the predicted stock prices during the one-month period for which the portfolio will be constructed.

The fifty stocks with the highest expected returns during the one-month period will be chosen for the Black-Litterman model. Similar to the minimum variance portfolio, the fifty stock limit on the portfolio was chosen due to the diversification index nearing the upper limit. When the portfolio is nearing the maximum diversification index, the contribution of the individual stocks to the overall portfolio return will be increasingly smaller, while increasing the complexity of the Black-Litterman model calculations. In addition to the expected returns, the Black-Litterman model also requires the market capitalisation, the historical stock prices, and the market’s historical stock prices. The historical data will be the prior ten years before the month for which the portfolio will be constructed. With the historical data and expected returns described above, the Black-Litterman model calculates a list of both positive and negative weights. A positive weight means buying the stock for the coming month at the price

at the first day of the month and selling on the final day of the month, a negative weight allocation means “short selling” that stock for the coming month. During this thesis, short selling means selling the stock on the first day of the month and buying the stock at the last day of the month to cover the short position.

The Black-Litterman steps will be repeated for every month in all three testing periods. The repetition of the process is required as the ML portfolio in the experiment will be actively traded on a monthly basis during the testing periods. Therefore, during every yearlong testing period, twelve portfolios need to be constructed, one for every month in the year. During the experiments, a transaction costs of 13.8 basis points (or 0.138 percent) (Robert et al., 2012) will be deducted when buying and selling the stocks every month. No additional short selling costs were added during the experiment of this thesis, transaction costs still applied for the stocks with negative weight allocations. Figure 7 shows an overview of the entire construction of the ML portfolio for January 2000 from the input data until the finalised portfolio.

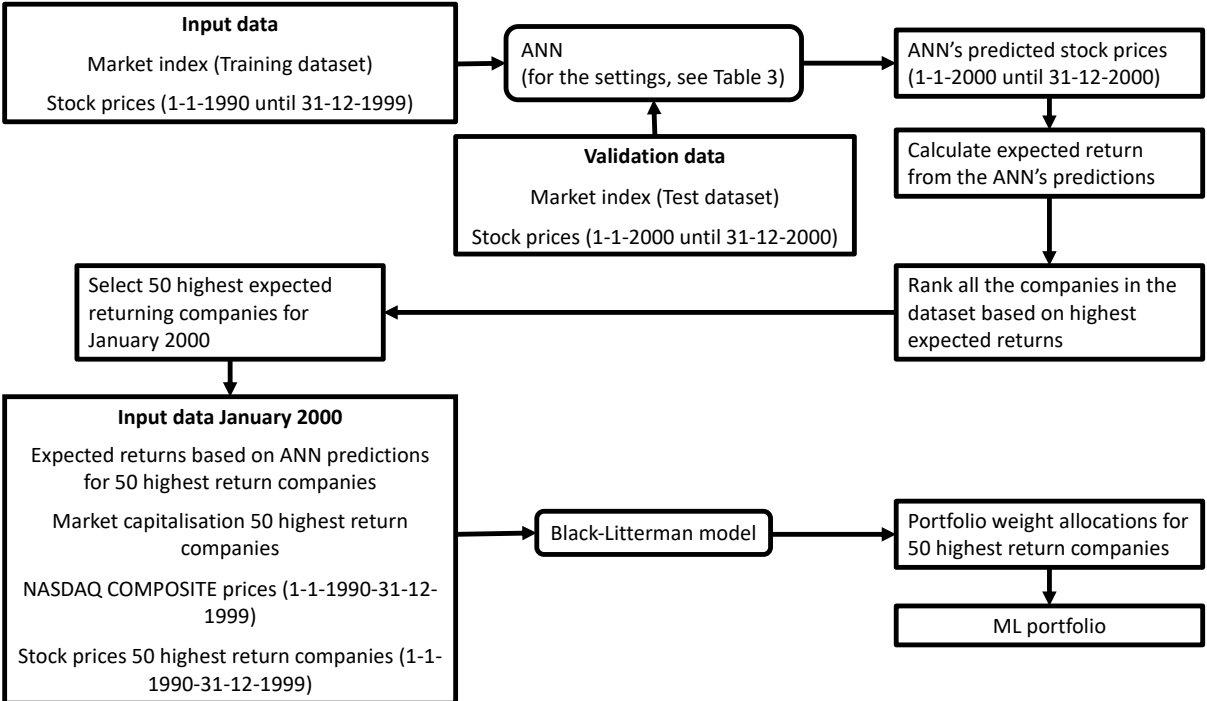


Figure 7. Overview of the construction of the ML portfolio. Note. This figure shows an example of the ML portfolio construction for January 2000.

4. Data preparation

The data for the experiment of this thesis were collected from Refinitiv Eikon. For the minimum variance portfolio and the ML portfolio in the experiment, three datasets were created with daily stock prices of all the stocks in the NASDAQ Composite index for the period between 1990-2000, 2000-2010, and 2010-2020. The choice was made to separate the collected data in three different datasets. This decision was supported by the requirement for significant increase in computing power to prepare one single stock price dataset for all training and testing periods, as well as the lack of benefits for having one single dataset for the three training/testing periods. For the market index tracker, one dataset with daily stock prices of the NASDAQ Composite index tracker for the entire period from 1989-2020 was used as this dataset was less data intensive. The NASDAQ Composite index tracker data was

collected from 1989 instead of 1990 as the index tracker will also be used for the input data of the ANN model. Here, the market index price from 31-trading days prior to the prediction date will be used. Therefore, for the first training period, the input data starts in November 1989 instead of January 1990.

With the collected historical stock price data, data preparation was conducted to make the dataset ready for the use with the ML algorithm as well as with the minimum variance portfolio techniques. The data preparation methods as follows. The companies whose stock price data had missing datapoints were deleted as to allow neither the ML model, nor the minimum variance portfolio, to make predictions and/or calculations based on a more limited amount of data compared to the other companies in the dataset. Companies that did not have any changes in their stock prices in more than 40 percent of the days in the training period were removed. The 40 percent benchmark that was used, was found using trial-and-error based on the number of remaining companies in the datasets. These companies were removed as the companies had little trading activity happening during the training period, meaning that it would be more complicated for the ML model to predict future values. In addition, the low amount of trading activity could also have consequences in practice as it might cause liquidity problems for the actively traded ML portfolio. For the ML portfolio, the stocks from the previous month’s portfolio need to be sold on short notice to be able to purchase the next month’s portfolio. Therefore, stocks with little trading activity were removed from the datasets for both the minimum variance portfolio and the ML portfolio. An overview of the data preparation steps is presented in Figure 8. Table 4 shows number of stocks during each of the training and testing periods. In addition, the number of companies before and after data preparation in all three of the training/testing periods are presented.

Period 1	<i>Number of stocks</i>	Period 2	<i>Number of stocks</i>	Period 3	<i>Number of stocks</i>
1990	293	2000	855	2010	1335
1991	306	2001	914	2011	1381
1992	343	2002	943	2012	1415
1993	380	2003	993	2013	1463
1994	443	2004	1025	2014	1549
1995	493	2005	1078	2015	1675
1996	556	2006	1131	2016	1786
1997	635	2007	1200	2017	1874
1998	699	2008	1268	2018	1996
1999	763	2009	1305	2019	2151
2000	855	2010	1335	2020	2316
BP	855	BP	1335	BP	2316
AP	268	AP	746	AP	1240

Table 4. Number of stocks per year in the NASDAQ Composite index dataset in the three training/testing periods between 1990-2020 and the number of stocks in the experiments before and after data preparation. Note. NASDAQ Composite index was collected from Refinitiv Eikon (2023). Abbreviations used: BP (Before Preparation) and AP (After Preparation).

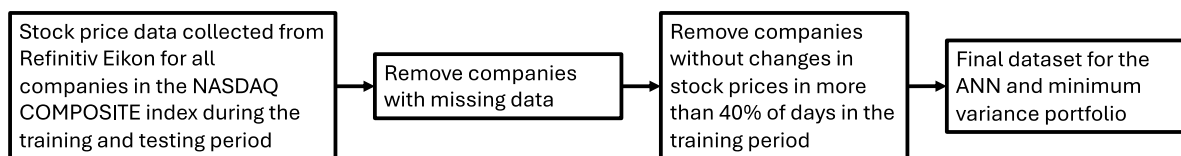


Figure 8. Data preparations for the ML portfolio and the minimum variance portfolio.

5. Results

In this chapter, the results of the experiment during the three decades will be presented. In Chapter 5.1, there will be a general overview of the results during the experiment. In Chapter 5.1.1, the absolute returns and risk of the portfolios will be presented. Chapter 5.1.2 will cover the degree of portfolio diversification during the experiment, both based on individual stock diversification as well as sector diversification. In Chapter 5.2, the portfolios during each of the decades will be compared based on the risk-adjusted performance metrics that were mentioned in the literature review. These performance metrics are the Sharpe ratio (Chapter 5.2.1), beta (Chapter 5.2.2), Treynor ratio (5.2.3), and Jensen's alpha (Chapter 5.2.4).

In the final part of this chapter, the accuracy of the ML model will be evaluated using the following performance metrics; Accuracy (Chapter 5.3.1), R^2 (Chapter 5.3.2), and the error-based ML performance metrics (Chapter 5.3.3). The error-based ML performance metrics include Root Mean Squared Error, Mean Absolute Error, Mean Absolute Percentage Error, and the Symmetric Mean Absolute Percentage Error.

5.1 General results

In this subchapter, the general results of the experiment of this thesis will be presented. During the experiment, the ML portfolio and the benchmark portfolios (minimum variance portfolio and NASDAQ Composite market index tracker) were constructed based on the training data and their respective performances were observed during the testing periods (the years 2000, 2010, and 2020). In Table 5, an overview of the results for the absolute portfolio performance metrics are presented.

5.1.1 Absolute returns and risk

The aim of this thesis is to determine whether a ML portfolio is able to outperform benchmark portfolios based on its risk-adjusted performance. The risk-adjusted performance adjusts the returns of the portfolios, as the name suggests, based on the risk of each portfolio. Therefore, the risk-adjusted performance metrics in Chapter 5.2 are based on the absolute returns and risk of each portfolio. In this subchapter, these absolute returns and risks will be discussed.

Table 5 and Figures 5, 6, and 7 show a comparison of the ML portfolio and the benchmark portfolios in each respective testing period (2000, 2010, and 2020). It can be observed that during every testing period, there was a different portfolio outperforming the other two, both on absolute returns and standard deviation, showing the importance of having multiple training/testing periods. As no generalisations can be made with the differing results from the three testing periods, Table 6 shows the average of the absolute portfolio performance metrics.

	2000			2010			2020		
	MVP	NDC	MLP	MVP	NDC	MLP	MVP	NDC	MLP
Return (%)	8.37	-40.20	-16.41	13.21	16.91	20.99	-1.21	43.64	11.19
Standard deviation (%)	1.96	14.19	7.16	7.47	6.56	7.22	9.29	16.39	8.02

Table 5. Overview of the absolute portfolio performance metrics for the testing periods 2000, 2010, and 2020. Note. The portfolios are abbreviated as MVP (Minimum Variance Portfolio), NDC (NASDAQ Composite market index tracker), and MLP (ML Portfolio).

	MVP	NDC	MLP
Return (%)	6.79	6.78	5.26
Standard deviation (%)	6.24	12.38	7.46

Table 6. Absolute portfolio performance metrics averaged over all three testing periods. Note. The portfolios are abbreviated as MVP (Minimum Variance Portfolio), NDC (NASDAQ Composite market index tracker), and MLP (ML Portfolio).

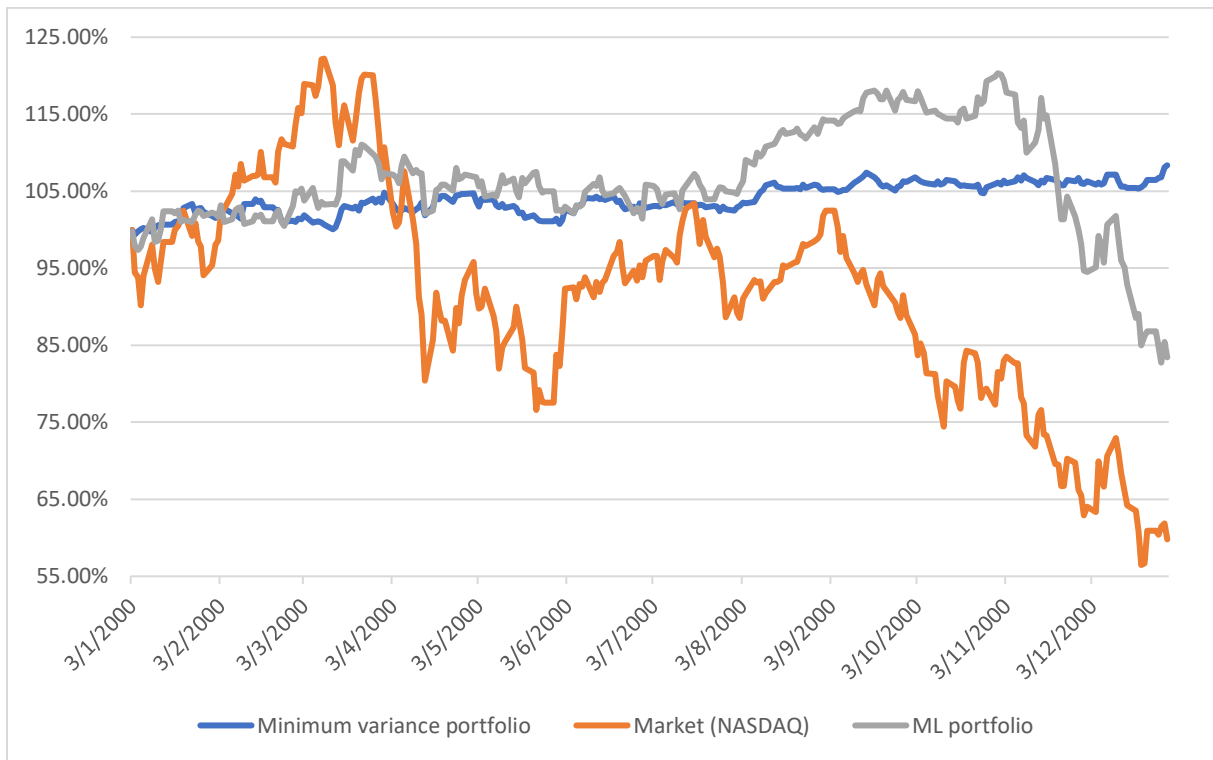


Figure 5. Comparison between the returns (as a percentage of total portfolio value) of the ML portfolio and the benchmark portfolios during the year 2000 based on the training period 1990-1999.

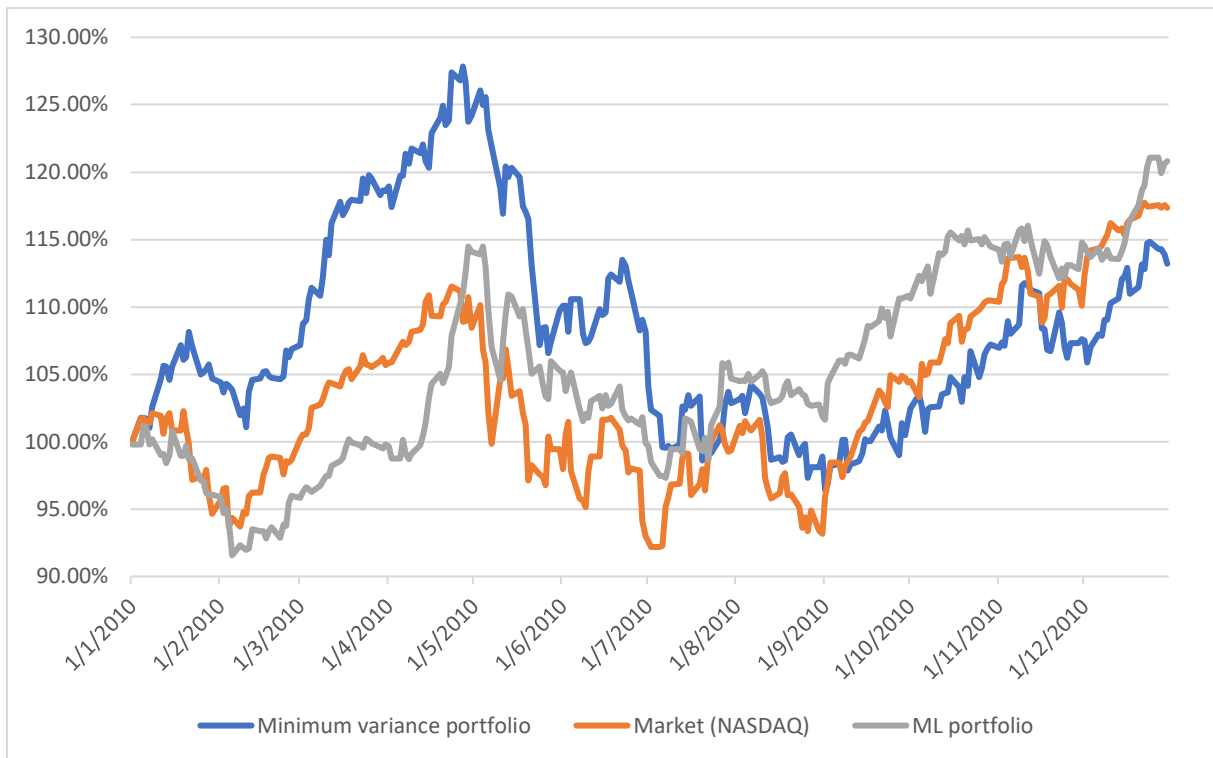


Figure 6. Comparison between the returns (as a percentage of total portfolio value) of the ML portfolio and the benchmark portfolios during the year 2010 based on the training period 2000-2009.

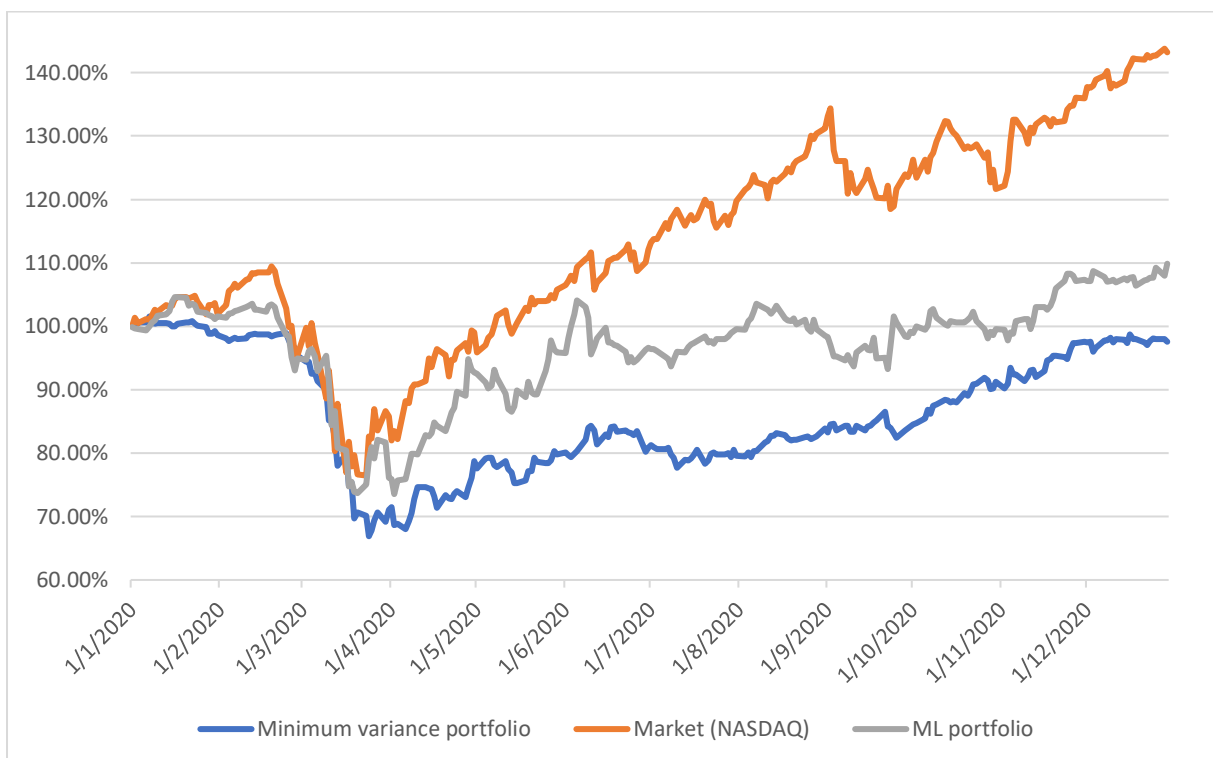


Figure 7. Comparison between the returns (as a percentage of total portfolio value) of the ML portfolio and the benchmark portfolios during the year 2020 based on the training period 2010-2019.

Table 6 shows that the minimum variance portfolio performed with the highest average absolute returns during the three testing periods, slightly outperforming the market index tracker by one basis point. The ML portfolio had the lowest average absolute returns during the three testing periods. The minimum variance portfolio also had the lowest average standard deviation, outperforming the ML portfolio by 1.22 percent point. The market index tracker had the worst average standard deviation during the three testing periods with a standard deviation of 12.38 percent, almost double the standard deviation of the minimum variance portfolio.

5.1.2 Diversification index

In this subchapter, the diversification index will be discussed. As mentioned in the literature review, diversification can be used to reduce the risk by removing the unsystematic risk of a portfolio. As the aim of this thesis is to examine the risk adjusted performance of ML portfolios, reducing the portfolio risk through diversification is an important point of consideration. During the construction of the minimum variance portfolio and the ML portfolio, no specific constraints were added to assure adequate diversification was present. This subchapter will examine the natural ability of both the minimum variance portfolio and ML portfolio construction methods to create a diversified portfolio.

To measure the diversification of a portfolio, the diversification index by Woerheide (1993) will be used. This index is explained in the literature review, and this index gives portfolios a score between 0 and 100, where 100 is perfect diversification. In addition, Woerheide suggested two benchmark levels of the diversification index. These benchmark levels are for likely adequately diversified portfolios (diversification index over 91) and likely not adequately diversified portfolios (diversification index under 85).

	2000		2010		2020		Average	
	MVP	MLP	MVP	MLP	MVP	MLP	MVP	MLP
Diversification index	95.50	92.78	95.03	93.89	95.21	90.85	95.25	92.51
Sector diversification index	79.80	76.83	84.53	82.55	84.82	74.81	83.05	78.06

Table 7. Overview of the diversification index scores for the testing periods 2000, 2010, and 2020. Note. Average column includes the average scores of the three testing periods. The portfolios are abbreviated as MVP (Minimum Variance Portfolio) and MLP (ML Portfolio).

In Table 7, the aforementioned diversification indices of both the minimum variance portfolio and the ML portfolio are presented. The diversification index of the market index tracker is not available; however, it can be assumed to be completely diversified as by definition, the market risk is solely systematic risk. In Table 7, the diversification index is calculated using the weight allocations from the individual companies in the portfolio. The sector diversification index is calculated using the sectors in which the individual companies in the portfolio operate in.

Table 7 shows that the minimum variance portfolio outperforms the ML portfolio consistently based on the diversification index, as well as the sector diversification index. For both the minimum variance portfolio as well as the ML portfolio, the upper benchmark of likely adequate diversification is reached with the individual companies' diversification index, except for the ML portfolio in the 2020 testing period. When looking at the average diversification scores for the three minimum variance and ML portfolios, both portfolios have individual diversification index scores over the 91 benchmark. Due to these average

diversification scores, it can generally be assumed that both the minimum variance portfolio and ML portfolio construction methods lead to adequately diversified portfolios regarding the individual company weight allocations.

The sector diversification index measures the diversification of the portfolio regarding the exposure to the unsystematic risks of any specific sector. As mentioned before, the minimum variance portfolio outperforms the ML portfolio on the sector diversification index, both in every respective testing period as well as with the average sector diversification index. One similarity that both portfolios share is that neither achieved higher sector diversification index scores than the lower benchmark of 85. Despite that the minimum variance portfolio is closer to the minimum benchmark, both portfolios fail to exceed this benchmark, meaning that there is a greater likelihood that the portfolios are not adequately diversified. Inadequate diversification can lead to higher exposures to sector specific risks, potentially increasing the total portfolio risk.

In Table 8, it can be seen that in particular, both the minimum variance portfolio and the ML portfolio have large portfolio weight allocations for the finance sector. These finance allocations are, for both portfolios, more than double the size of the next biggest sector, namely healthcare. The significant weight allocation in the finance sector can also be seen in Figures 8, 9 and 10 for the minimum variance portfolio, and Figures 11, 12, and 13 for the ML portfolio. The distribution of the weight allocations might be able to explain the sector diversification index scores under the lower bound benchmark. Portfolios that have a large portion of portfolio weight allocated to one specific sector may encounter a high exposure to the systematic risks of that sector, in this case, to finance related unsystematic risks. Therefore, while the individual companies' diversification index scores above the upper bound benchmark, the portfolios are likely not adequately diversified when including the sector diversification index.

MVP sectors	Average allocation (%)	MLP sectors	Average allocation (%)
Finance	27.27	Finance	30.70
Healthcare	12.69	Healthcare	13.09
Industrials	10.42	Industrials	13.00
Utilities	10.06	Technology	12.38

Table 8. Top four weight allocations per testing period for the minimum variance portfolio and the ML portfolio.

In Figures 8, 9, and 10, the portfolio weight allocations are presented for the minimum variance portfolio during the years 2000, 2010, and 2020 respectively. In these figures, it can be seen that the portfolios are not equally allocated to all sectors, especially for the aforementioned top four sectors from Table 8. The unequal allocations in Figures 8, 9, and 10 show why the diversification index is under the lowest benchmark for adequate diversification. The largest allocations allow for a significant exposure to industry specific risks, adding a degree of unsystematic risk to the total risk of the portfolio. Due to the inclusion of this unsystematic risk, the portfolio is likely not adequately diversified, just as the diversification index suggests.

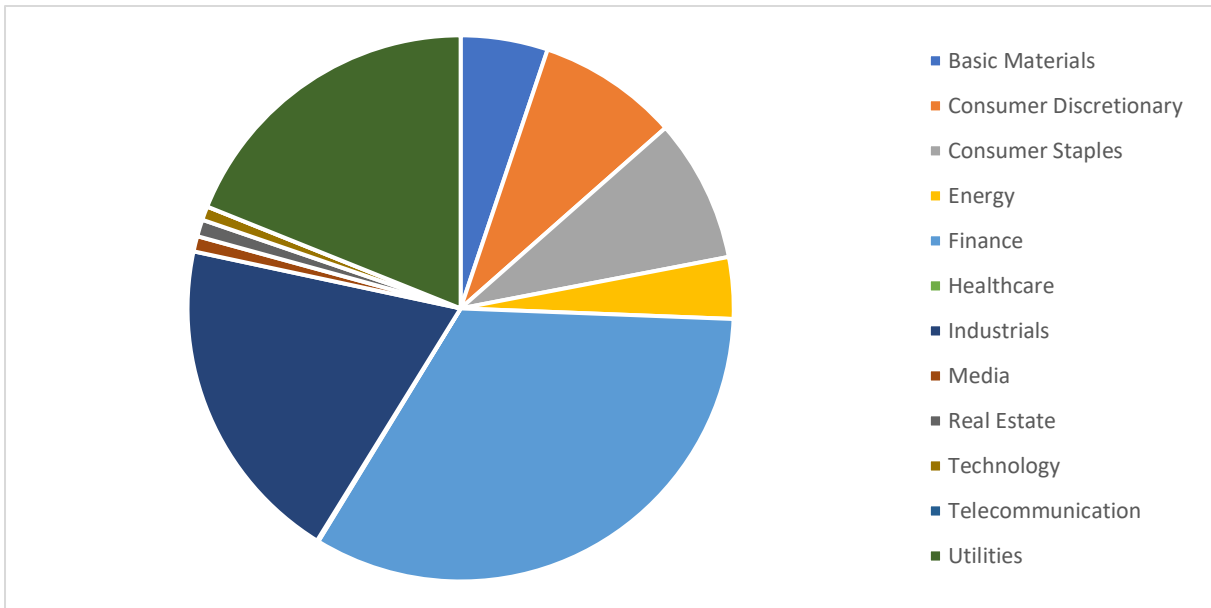


Figure 8. Allocation per sector for the minimum variance portfolio of the year 2000.

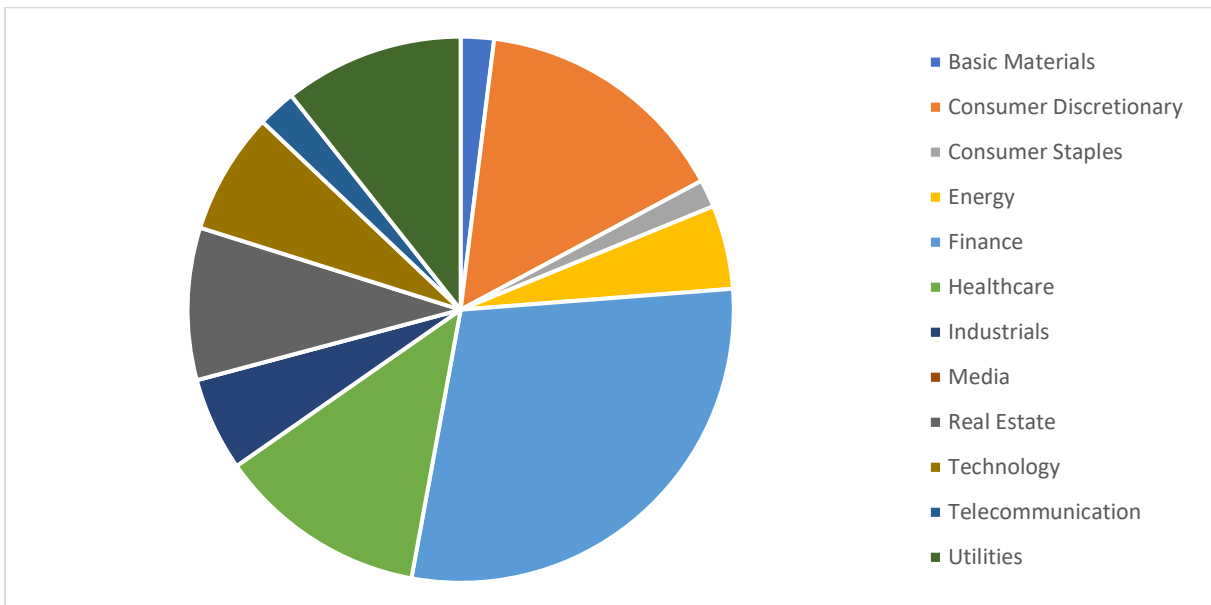


Figure 9. Allocation per sector for the minimum variance portfolio of the year 2010.

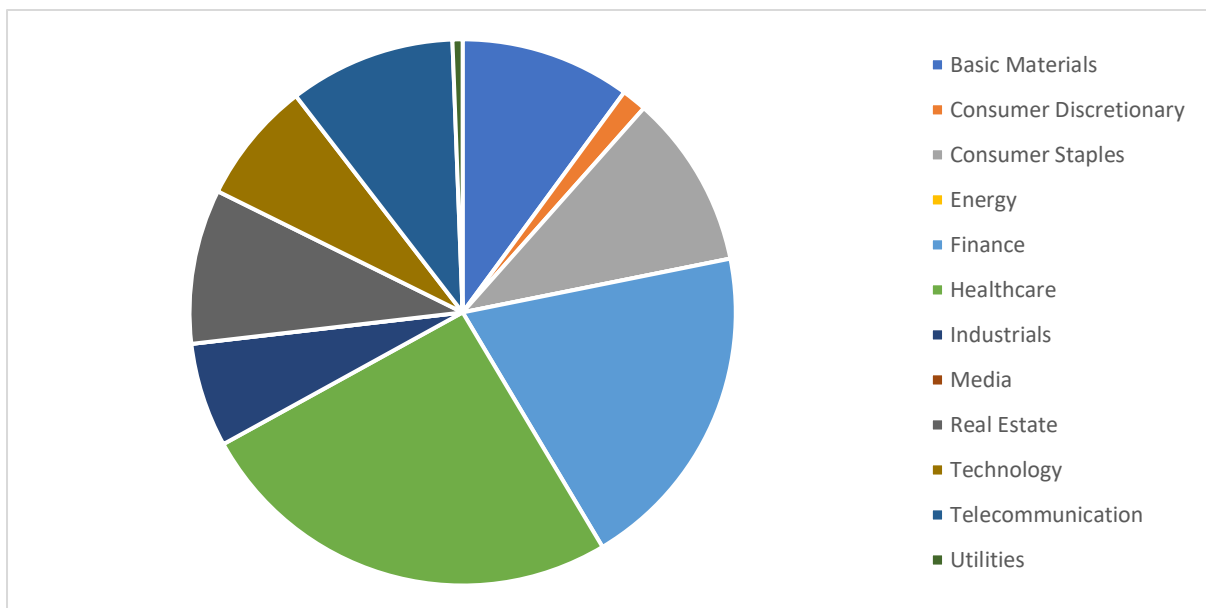


Figure 10. Allocation per sector for the minimum variance portfolio of the year 2020.

Following the portfolio weight allocations for the minimum variance portfolio, Figures 11, 12, and 13 show the weight allocations for the ML portfolios during the three testing periods. In these figures, the weight allocations are displayed on a monthly basis as during the testing periods, a new ML portfolio was constructed every month. As for the diversification of the ML portfolio, it can be seen that, similar to the minimum variance portfolio, the ML portfolio has quite unequal sector allocations. In particular, the portfolio weight allocations for the finance sector can be observed to be generally considerably larger than any other sector, as also can be seen in Table 8. Other sectors with large allocations vary drastically per testing period but do include the healthcare, industrials, and technology sectors. However, while the sectors in itself have varying allocations, every testing period does show a pattern of allocating a considerable portion into only a small number of sectors. Similar to the minimum variance portfolio, this causes higher exposures to sector specific (unsystematic) risk. Therefore, the figures below help explain why the sector diversification index failed to reach the adequate diversification benchmark.

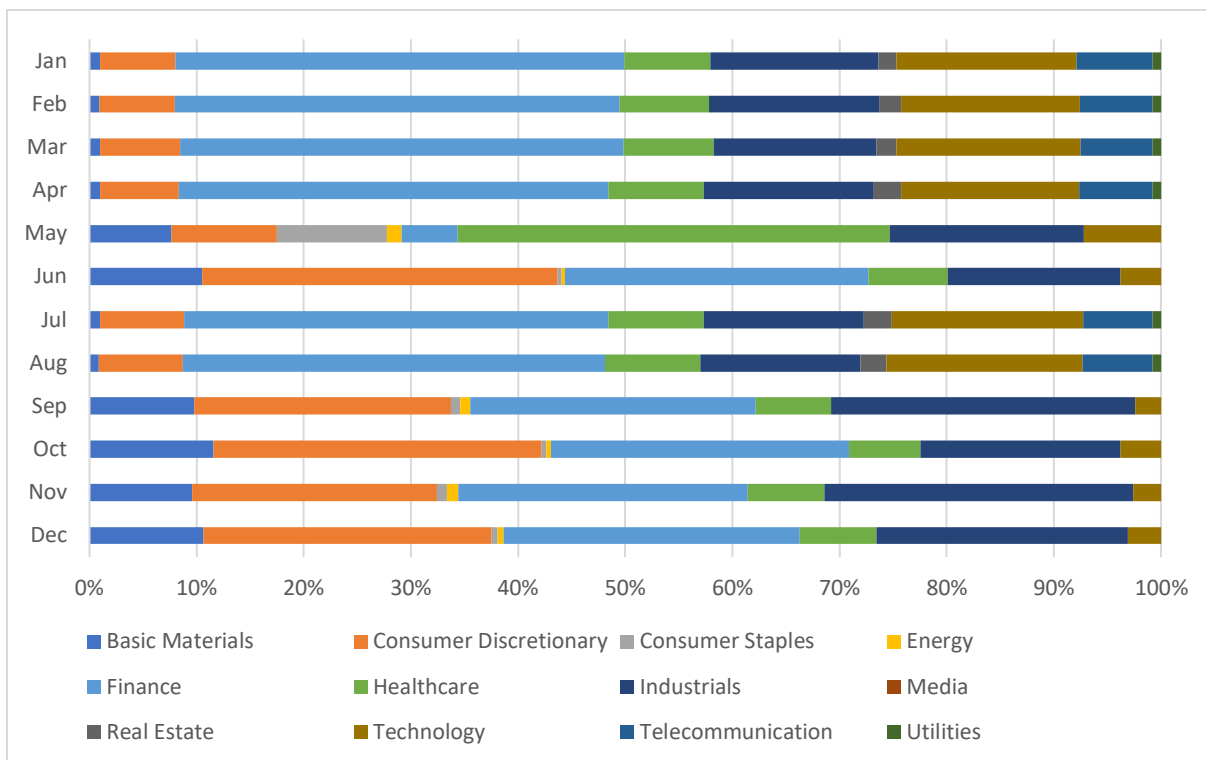


Figure 11. Allocation per sector for the ML portfolio of the year 2000.

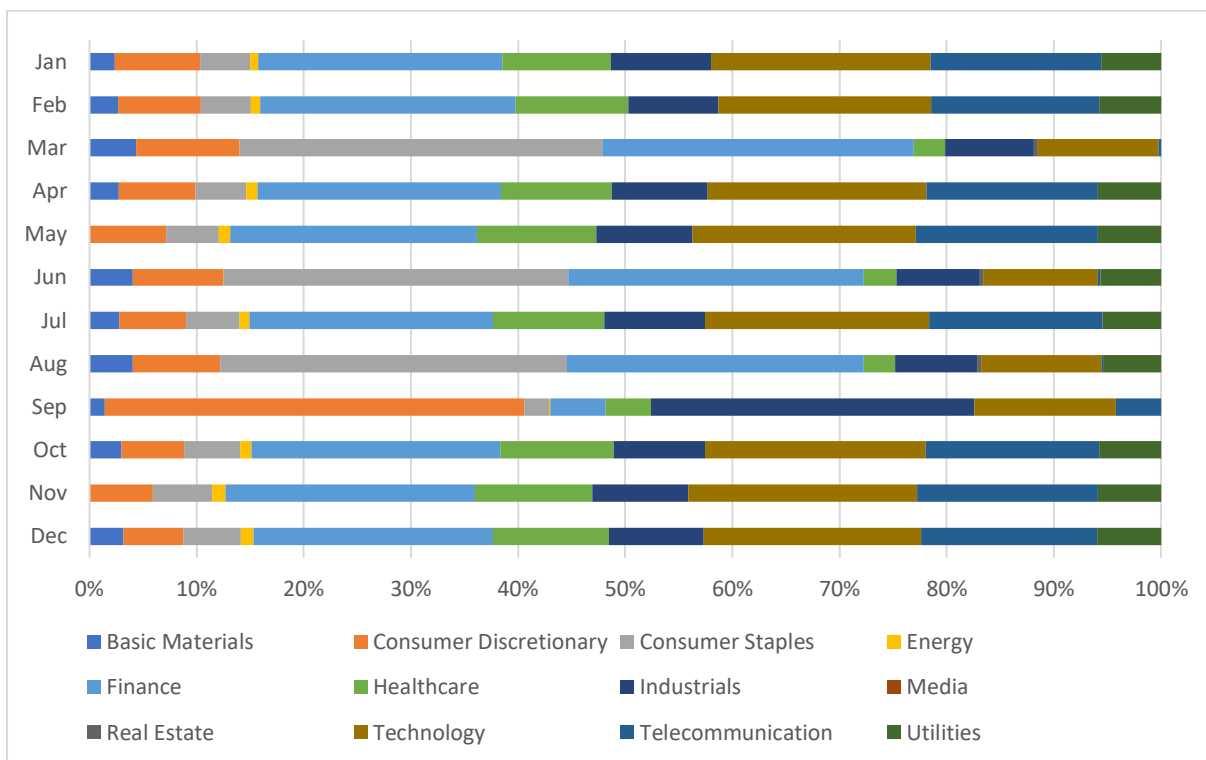


Figure 12. Allocation per sector for the ML portfolio of the year 2010.

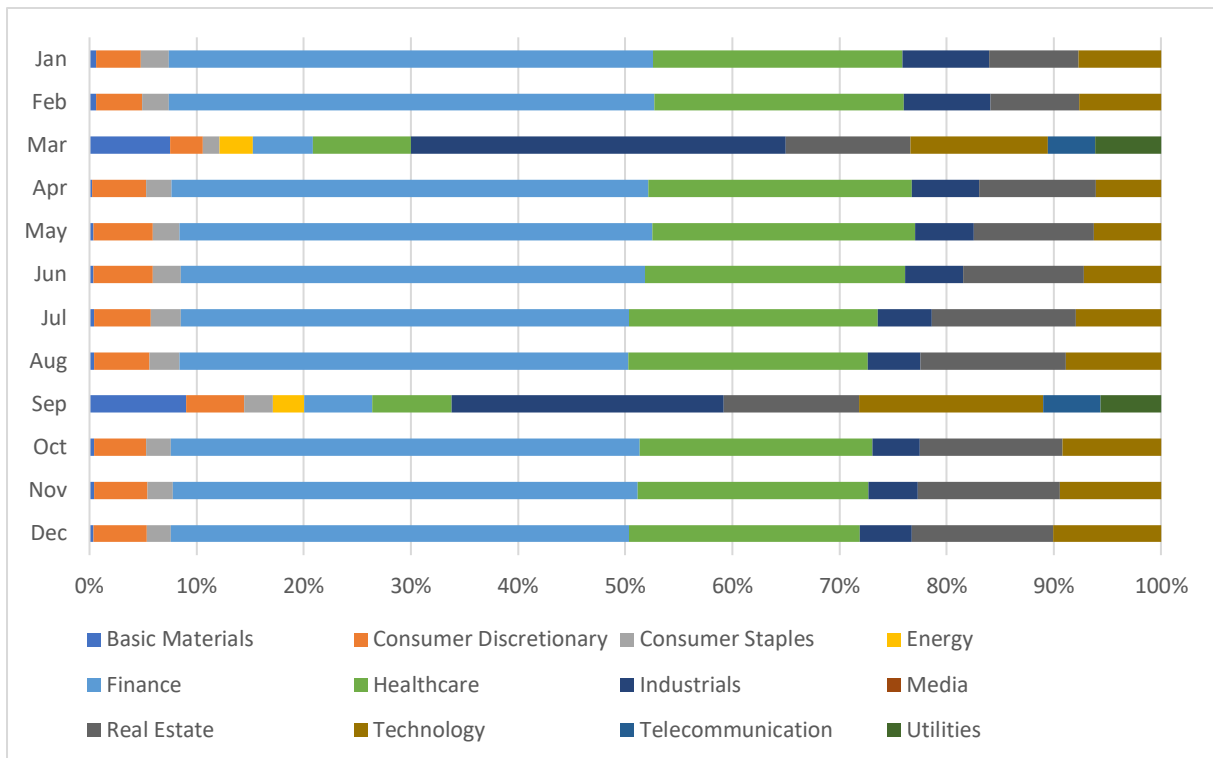


Figure 13. Allocation per sector for the ML portfolio of the year 2020.

5.2 Risk-adjusted performance

In this subchapter, the results of the experiment of this thesis will be put in the context of the risk-adjusted performance. In particular, the ML portfolio and the benchmark portfolios will be compared based on their Sharpe ratio (Chapter 5.2.1), Beta (Chapter 5.2.2), Treynor ratio (5.2.3), and Jensen’s alpha (5.2.4). The equations for these risk-adjusted performance metrics are given in Chapter 2.3. To calculate these metrics, certain assumptions regarding the risk-free rate and the market returns are required for the calculations, the assumptions that were used are given in Table 9. Using the absolute returns and standard deviations from Table 5 and the assumptions from Table 9, the risk-adjusted performances of all three portfolios are calculated for every testing period. The results are presented in Table 10. In the remainder of this chapter, the risk-adjusted performance metrics will be discussed and compared in their respective chapters.

	2000	2010	2020
Risk-free rate based on the 5 Year US treasury bills (%)	6.35	2.07	0.36
Market return (Nasdaq Composite index tracker, %)	-40.19	16.91	43.64

Table 9. Assumptions for the performance metrics calculations during the testing periods 2000, 2010, and 2020. Note. From Refinitiv Eikon (2023, 2024).

	2000			2010			2020		
	MVP	NDC	MLP	MVP	NDC	MLP	MVP	NDC	MLP
Sharpe ratio	1.03	-3.28	-3.18	1.49	2.26	2.62	-0.17	2.64	1.35
Portfolio beta	0.11	1.00	0.10	-0.15	1.00	0.83	0.06	1.00	0.38
Treynor ratio	0.18	-0.47	-2.18	0.72*	0.15	0.23	-0.28	0.43	0.28
CAPM (%)	1.04	-40.20	1.49	-0.22	16.91	14.44	2.80	43.64	16.98
Jensen's alpha (%)	7.32	NA	-17.90	13.42	NA	6.55	-4.01	NA	-5.79

Table 10. Portfolio risk-adjusted performance metrics for the testing periods 2000, 2010, and 2020. Note. The portfolios are abbreviated as MVP (Minimum Variance Portfolio), NDC (NASDAQ Composite market index tracker), and MLP (ML Portfolio). * = The calculations showed a Treynor ratio of -0.72, however, as this negative score was caused by a negative beta instead of a negative return, the absolute beta was used to calculate the Treynor ratio.

5.2.1 Sharpe ratio

Similar to the absolute results, the Sharpe ratios during every testing period result in different rankings for the best performing portfolio. During the 2000 testing period, the market index tracker and the ML portfolio scored similarly with very negative Sharpe ratios. The exception during this testing period was the minimum variance portfolio that not only outperformed the previously mentioned portfolios but actually achieved a positive Sharpe ratio. This can be explained by the absolute positive return for the minimum variance portfolio during this testing period, both other portfolios had negative absolute returns.

During the 2010 testing period, the ML portfolio outperformed the benchmark portfolios. This outperformance can be attributed by the higher absolute performance and medium level of risk compared to the benchmarks during this testing period. All three portfolios reached positive Sharpe ratios during this testing period, hinting at the positive market characteristics during the 2010 testing period (CBS News & Allan Roth, 2011). The other two testing periods had significant market crashes, i.e. the Dot-Com crash in 2000 (CNN & Catherine Tymkiw, 2000) and the crash due to the global COVID outbreak in 2020 (Reuters & Chuck Mikolajczak, 2021).

In the 2020 testing period, the ML portfolio scored between the negative Sharpe ratio of the minimum variance portfolio and the outperforming market index tracker. The difference in Sharpe ratios between the market index tracker and the ML portfolio, shows why the risk-adjustment is important to compare the different portfolios against each other. During the 2020 testing period, the market index tracker had four times higher absolute returns, but this performance was achieved partially due to the higher risk of the portfolio during this period. After the risk adjustment, the market index tracker had a Sharpe ratio of roughly double the ML portfolio, instead of quadruple like the absolute returns.

The ML portfolio outperformed the benchmark portfolios during the 2010 testing period and scored the second place during the other two testing periods, meaning the ML portfolio had a good risk-adjusted performance compared to the benchmark portfolios. However, when comparing the average Sharpe ratios from the three testing periods, a different conclusion might be taken. On average, the ML portfolio had a Sharpe ratio of 0.26, while the benchmark portfolios both scored higher Sharpe ratios (Minimum variance portfolio 0.78 and NASDAQ Composite 0.54). Therefore, the ML portfolio did not outperform the benchmark portfolios based on the Sharpe ratio as the risk-adjusted performance metric.

5.2.2 Beta

In Table 10, the betas of the portfolios during all three of the testing periods are presented. The beta measures how volatile the returns of the portfolio are compared to the returns of the market (which has a beta of 1). In contrast to the Sharpe ratios and the other risk-adjusted performance metrics that will be discussed in this chapter, a higher beta does not mean that the portfolio performed better compared to another portfolio. Therefore, beta can better be used as a measure of systematic risk than a risk-adjusted performance metric in itself.

In all three testing periods, the betas of the minimum variance portfolio and the ML portfolio are lower than the beta of the market index tracker. Therefore, the minimum variance portfolio and the ML portfolio have lower exposures to systematic risk compared to the market index tracker. However, it can be assumed that the market index tracker only has exposure to systematic risk while the other two portfolios might also have a degree of unsystematic risk.

During the 2000 testing period, the ML portfolio had the lowest beta, slightly under the beta of the minimum variance portfolio. During the two later testing periods, the minimum variance portfolio had the lowest beta scores, even having a negative beta during the 2010 testing period. On average, the minimum variance portfolio had a beta of 0.01 across all three testing periods. This can be explained by the construction method of this portfolio. During the construction of the minimum variance portfolio, the stocks with the lowest betas were chosen during the asset selection process. These stocks, therefore, had returns with low volatility compared to the market returns, creating a portfolio with a low beta as well.

For the beta performance metric, no clear best performing portfolio can be chosen as a higher beta is not necessarily better or worse compared to a lower beta. The only conclusion that can be taken from this measure is that the systematic risk of the minimum variance portfolio and the ML portfolio is lower compared to the systematic risk of the market index tracker. In Chapter 5.1, the diversification index showed that the minimum variance portfolio and ML portfolio might not be adequately diversified when accounting for sector specific risks. Therefore, while the systematic risk of these portfolios is lower than the market index tracker, the total risk, including the unsystematic risk, might be higher than the beta suggests. In the following subchapter about the Treynor ratio, the beta will be used to calculate the systematic risk-adjusted performance of the three portfolios.

5.2.3 Treynor ratio

The Treynor ratio is different from the Sharpe ratio as instead of the standard deviation as the method to adjust for portfolio risk, the performance is adjusted for systematic risk using the beta. The differing risk adjustment between the Sharpe and Treynor ratio led to different results and rankings between the ML portfolio and the benchmark portfolios. These results and rankings will be discussed in this subchapter.

During the 2000 testing period, the minimum variance portfolio is the best performing portfolio based on both the Treynor and the Sharpe ratio. This is caused by the positive return in contrast to the negative returns of the market index tracker and the ML portfolio. However, the ranking for these two negatively performing portfolios is reversed compared to the ranking of the Sharpe ratio. The ML portfolio had the worst Treynor ratio during the 2000 testing period, this is caused by the low beta as this multiplies the negative returns compared to the market index tracker.

In the 2010 testing period, the minimum variance portfolio outperformed the ML portfolio in second place and the market index tracker. For this result, a small adjustment had to be

applied to the formula of the Treynor ratio. The minimum variance portfolio had a negative beta during the 2010 testing period, this would also mean a negative Treynor ratio. To adjust for this, the absolute beta was used in the calculation to make a meaningful comparison between the three portfolios.

For the 2020 testing period, the market index tracker managed to outperform the other two portfolios with the same ranking as for the Sharpe ratio. As with the Sharpe ratio, the minimum variance portfolio had the worst risk-adjusted performance as the absolute returns of this portfolio were negative during this testing period while the other portfolios had positive returns. For the ML portfolio, the Treynor ratio score placed the portfolio in the second place of the rankings. However, in proportion, the ML portfolio scored closer to the market index tracker compared to with the Sharpe ratio.

On average the minimum variance portfolio (0.21) had the highest Treynor ratio during the three testing periods of the experiment, followed by the market index tracker (0.04), and the ML portfolio (-0.56). That means that ranking of the average Sharpe ratio and the average Treynor ratio follow the same order, putting the ML portfolio in last place. Similarly to with the Sharpe ratio, it means that the ML portfolio was not able to outperform the benchmark portfolios based on the Treynor ratio as a measure of risk-adjusted performance.

5.2.4 Jensen's alpha using CAPM

Jensen's alpha is a metric of risk-adjusted performance that measures the excess return of the portfolio compared to the expected return calculated by the CAPM. The CAPM's expected return is calculated using the risk-free rate, the beta, and the market risk premium. As the CAPM and the Jensen's alpha are inherently connected, both will be discussed in this subchapter. In Table 10, the CAPM and Jensen's alpha results for the experiment of this thesis are presented. Table 10 shows that the CAPM expected returns of the market index tracker are equal to the absolute returns of the index tracker. In the CAPM, the market's actual and the expected return are the same due to the CAPM being based on the idea of efficient stock markets. When stock markets are efficient, all information is available to all stock market participants and immediately priced into the stock prices (Naseer & Tariq, 2015). Therefore, a stock with less (systematic) risk than the market will have lower returns and a stock with more risk will have higher returns. The market's systematic risk or beta is 1, therefore, the expected and actual returns of the market are identical. For the Jensen's alpha, the market index tracker's excess return is by definition zero, and therefore, the Jensen's alpha is set to not available in Table 10.

During the first testing period, the ML portfolio had the best CAPM expected return, mainly caused by having the lowest beta and therefore, the lowest exposure to the negative market risk premium. The minimum variance portfolio outperformed the market index tracker, this tracker had a very negative expected (and actual) return compared to the slightly positive expected returns of the minimum variance and ML portfolios. During the 2010 testing period, the minimum variance portfolio had a slightly negative expected return, caused by the negative beta. The other two portfolios had positive expected returns, with the market index tracker having the highest expected return out of the three portfolios. During the final testing period, the minimum variance portfolio had again the lowest expected returns, with the market index tracker again outperforming the ML portfolio.

During the comparison of the Jensen’s alpha results, only the minimum variance portfolio and the ML portfolio will be compared. The market index tracker would have excess returns of zero percent during all testing periods, making the inclusion into the comparison useless. During all three testing periods, the minimum variance portfolio outperformed the ML portfolio based on excess returns, even during the 2020 testing period, when both portfolios had negative excess returns. On average, the minimum variance portfolio had an excess return during the three testing periods of 5.58 percent while the ML portfolio had an excess return of -5.71 percent. The average excess returns show that while the beta of the minimum variance portfolio was lower than the ML portfolio, the minimum variance portfolio outperformed the expected return. In contrast, the ML portfolio, on average, underperformed the CAPM’s expected return during the three testing periods. In conclusion, the ML portfolio was not able to outperform the minimum variance portfolio based on the Jensen’s alpha as the risk-adjusted performance metric.

5.3 ML performance metrics

In Chapter 5.1 and 5.2, the performance of the three portfolios was discussed. In Chapter 5.3, the performance of the ML model will be examined. Firstly, the accuracy will be discussed in Chapter 5.3.1, then the coefficient of determination or R² in Chapter 5.3.2. Finally, the error-based ML performance metrics (RMSE, MAE, MAPE, and SMAPE) will be discussed in Chapter 5.3.3. The complete lists with ML performance results are included in Appendix A3, B3, and C3.

5.3.1 Accuracy

In this subchapter, the accuracy of the predictions will be evaluated. The accuracy in this thesis is measured as the accuracy of correctly predicting the direction of the stock price during a one-month period. The options for the direction were the stock price going up, staying the same, and going down. In Table 11, the accuracy of the ANN is presented. On average, the ANN is able to predict the correct direction of the stock price on a monthly basis in 55.04 percent of the predictions that are made.

To give more insight into the accuracy of the ANN, the sensitivity and specificity are included in Table 11. The sensitivity and specificity are calculated based on the confusion matrices in Tables 12, 13, and 14. The sensitivity is the percentage of observed increases that are actually predicted as increases as well by the ANN. On average, the ANN predicted 61.05 percent of the observed increases in stock prices. The specificity is the percentage of observed lack of increases (either stable stock prices or decreases in stock prices) that are correctly predicted by the ANN as lack of increases in stock prices. During the three testing periods, on average, the ANN had a specificity of 45.33 percent. From the sensitivity and specificity, it can be concluded that the ANN has a better ability to correctly identify increases compared to lack of increases in stock prices.

	2000	2010	2020	Average
Accuracy (%)	60.76	49.34	55.01	55.04
Sensitivity (%)	54.22	56.30	72.64	61.05
Specificity (%)	68.12	37.92	29.95	45.33

Table 11. Accuracy metrics of the ANN during all three testing periods of the experiment.

	Observed increase	Observed no increase
Predicted increase	1458 (28.72%)	761 (14.99%)
Predicted no increase	1231 (24.25%)	1626 (32.03%)

Table 12. Confusion matrix for the accuracy of the ANN during the 2000 testing period. Note. Percentages are percentage of total predictions. Percentages do not add up to 100 percent due to rounding.

	Observed increase	Observed no increase
Predicted increase	3132 (34.99%)	2104 (23.5%)
Predicted no increase	2431 (27.16%)	1285 (14.35%)

Table 13. Confusion matrix for the accuracy of the ANN during the 2010 testing period. Note. Percentages are percentage of total predictions.

	Observed increase	Observed no increase
Predicted increase	6073 (42.64%)	4122 (28.94%)
Predicted no increase	2287 (16.06%)	1762 (12.37%)

Table 14. Confusion matrix for the accuracy of the ANN during the 2020 testing period. Note. Percentages are percentage of total predictions. Percentages do not add up to 100 percent due to rounding.

5.3.2 R^2

The R^2 , or coefficient of determination, shows the amount of variation in the dependent variable that can be explained by the independent variable. The R^2 is measured as a percentage between 0 and 100 percent, with higher meaning better explaining ability from the independent variable. In Table 15, the R^2 scores can be seen that for all testing periods during the experiment of this thesis. There is a big difference between the coefficients of determination during the first and the latter two testing periods. During the 2000 testing period, the R^2 score was 44.75, meaning that 44.75 percent of the variation of the dependent variable (the stock price of any specific stock in the testing period's dataset) can be explained by the independent variable (the market index tracker price from 31-trading days prior to the prediction date). During the 2010 and 2020 testing periods, the R^2 score was much closer to zero compared to the first testing period. This means that during the latter testing periods, the independent variable was able to explain less of the variation in the dependent variable, making the independent variable not a great predictor of the stock prices.

R^2 scores close to zero indicate that the model does not have good predicting capabilities as these models would have slightly better stock price predictions compared to a horizontal line at the average of the training data's stock prices (Ozili, 2022).

One reason why the R^2 score was noticeably higher during the first testing period might be due to the number of companies with a R^2 score of zero in each testing period. During the first testing period, 75.62 percent of the companies had a R^2 score of more than zero while this percentage was only 11.93 and 15.92 percent respectively during the 2010 and 2020 testing periods.

To conclude, the low R^2 scores, especially during the two last testing periods might explain why the accuracy of the ANN was not high, as the independent variable that was used might not be the predictor that can explain the most variation in the stock prices of individual companies.

	2000	2010	2020
R ² (Coefficient of determination, %)	44.75	1.63	6.34

Table 15. Median R² results for the three testing periods of the experiment.

5.3.3 Error-based ML performance

In this subchapter of the ML results, the error-based ML performance metrics will be discussed. Error-based ML performance metrics can be used to determine how large the differences (or errors) are between the predicted and observed values. The error-based metrics that will be discussed are the RMSE, MAE, MAPE, and SMAPE, these metrics and their equations were introduced in Chapter 2.5.

In Table 16, there is a clear difference between the median RMSE scores during each testing period. During the first testing period, the RMSE score was almost double the score during the 2010 testing period, while at the same time being half the size of the 2020 testing period's median RMSE score. The same trend for the levels of the RMSE metric can also be observed in the MAE, MAPE, and SMAPE metrics. For all four metrics, the highest scores occurred during the 2020 testing period, while the 2010 testing period had the lowest errors for all metrics used.

The RMSE and MAE should be interpreted as the difference between the predicted and observed stock price, therefore, the median RMSE score of 4.38 from the 2000 testing period means that the predictions made by the ANN were 4.38 dollars away from the observed stock prices. The difference between the RMSE and the MAE metrics is that the RMSE squares the errors, creating a bias regarding larger errors as these create larger squared errors. This bias can be seen in the RMSE having slightly larger scores compared to the MAE metric. Apart from the difference from the RMSE's bias, both the RMSE and the MAE have similar scores, complicating the process of making generalisations regarding the results of the ML performance. Generalising is especially complicated as there is a large difference between the smallest and largest error metrics measured during the different testing periods.

For the MAPE and SMAPE metrics, it can be observed that the MAPE scores are lower compared to the SMAPE scores. The interpretation between the MAPE and SMAPE scores are slightly different as the MAPE has an infinite upper limit while the SMAPE has an upper limit of one hundred percent (Makridakis, 1993). Therefore, on the one hand, the MAPE should be interpreted as the average percentual difference between the predicted and observed stock prices. A MAPE score of 42.80 percent, such as in the 2000 testing period, means that the predicted stock price was, on average, either 42.80 percent higher or lower compared to the observed price.

On the other hand, the SMAPE metric can be interpreted as a percentage-based score where a score closer to zero percent means a smaller difference between the predicted and observed stock prices during the testing period. This makes the SMAPE better to compare across models, as a lower score means that the model was able to predict values closer to the observed values. In the context of this experiment, the SMAPE metric shows that during the 2010 testing period, the model performed the best, followed by the 2000 testing period and the 2020 testing period's model performed the worst out of the three. While the interpretation of these two error-based metrics is different, their conclusions are the same

with the 2010 testing period’s model performing the best and the 2020 model performing the worst.

Another observation can be made using the difference between the MAPE and SMAPE scores. The SMAPE score is higher than the MAPE score during all three testing periods, this might be due to overpredictions made by the ANN. The MAPE metric “punishes” overpredictions harder compared to the SMAPE metric (Goodwin & Lawton, 1999). Therefore, if the MAPE is lower than the SMAPE metric, the ANN likely overpredicted the stock prices during the testing period. When evaluating the predicted and observed stock prices, the ANN overpredicted the stock price, as it predicted higher than observed prices in 61.43 percent of the cases. However, within the context of this experiment, overpredicting can be seen as unfavourable. Optimistic predictions result in higher expected returns, therefore, there is a higher risk of making an underperforming portfolio compared to an ANN that consistently underpredicts the stock prices.

In this subchapter, the error-based metrics were discussed to determine the performance of the ML portfolio during the three testing periods of this experiment. It was unanimously determined that during the 2010 testing period, the ANN performed the best with the smallest errors between the predicted and observed values while the errors were the largest during the 2020 testing period.

	2000	2010	2020
RMSE (Root Mean Squared Error)	4.38	2.70	9.47
MAE (Mean Absolute Error)	3.70	2.34	8.04
MAPE (Mean Absolute Percentage Error, %)	42.80	30.76	57.88*
SMAPE (Symmetric Mean Absolute Percentage Error, %)	47.08	34.24	58.61

Table 16. Error-based ML performance metrics for the three testing periods of the experiment. Note. Median scores for the RMSE and MAE results, average scores for the (S)MAPE results. * = Outliers above 1000 percent were removed from the MAPE results in 2020.

6. Conclusion

In this chapter, the thesis will be concluded. this conclusion is made up of a few different subchapters, firstly, the thesis will be summarised (Chapter 6.1), then the results will be further discussed (Chapter 6.2). After the discussion, the limitations of the experiment in this thesis will be mentioned (Chapter 6.3), and future research opportunities will be presented (Chapter 6.4). Continuing, there will be a managerial conclusion answering the research question that this thesis aimed to answer (Chapter 6.5). The contributions that this thesis brings to both the theory as well as the practice will be discussed (Chapter 6.6). In the final subchapter (Chapter 6.7), the generalisation of this thesis will be mentioned.

6.1 Summary

In recent years, there has been plentiful advancements in the area of Machine Learning (ML). ML techniques can be used to make predictions by training a prediction model on a dataset. One particular activity that would greatly benefit from accurate predictions is active portfolio management. Active portfolio management aims to create (stock) portfolios that will generate a higher return over a given period of time compared to a passive portfolio. The most popular type of passive portfolio is an index tracker. An index tracker consists of the same stocks with

the same portfolio weights as the index (such as S&P 500, NASDAQ Composite, or AEX) that it follows. The deciding factors for investors to determine whether they would prefer a passive or an active portfolio are twofold:

1. The believe in the Efficient Market Hypothesis (EMH);
2. The costs and fees associated with the portfolio.

The EMH states that all assets are priced correctly by the market due to the publicly available information regarding the value, risk, and volatility of the assets. Therefore, if the investor believes in an efficient stock market, a passive portfolio would be a better fit. However, if the investor does not believe in the hypothesis due to the contradicting evidence regarding the assumptions that the EMH is based on, active portfolios could be best suited for the investor's preferences.

For active portfolios, there are additional costs and fees associated with the management of said portfolio. Some of these costs include transactions costs when buying and selling stocks, transaction costs lower the actual returns of the portfolio as a certain percentage of the price of the stock has to be paid to the stockbroker for the service of buying and selling the stocks. Transaction costs are much more heavily associated with active portfolios compared to passive portfolios as active portfolios are traded on a regular basis while the passive portfolio is constructed once, meaning less transaction costs.

Another cost that active portfolio holders have to pay are management fees. Active portfolio management requires expertise and time to determine what stocks will return the highest outperformance, this is more expensive compared to the little management costs of an index tracker. If an investor wants to save on the management and transaction costs, a passive portfolio would again be the best fit.

This thesis focussed on active portfolio management; therefore, the assumption was made that the stock markets are not fully efficient. In particular, this thesis looked at the role of ML techniques in active portfolio management. ML techniques can reduce the required time to analyse different stocks to determine what stocks will outperform the general market, leading to lower management fees for investors. In addition to lower management fees, ML techniques would also allow for personalised active portfolios based on the investor's risk preferences. In theory, the aforementioned benefits of ML active portfolios sound interesting, however, it needs to be verified in practice whether ML active portfolio are actually able to outperform passive portfolios. Therefore, in this thesis, an experiment was conducted to determine the viability of ML (active) portfolios. For the experiment of this thesis, the following research question was constructed: Can an ML model, that actively trades an equity portfolio, outperform benchmark portfolios (NASDAQ Composite index tracker and minimum variance portfolio) based on risk-adjusted performance indicators?

To answer the research question of this thesis, four sub-questions were formed, these were:

- What are suitable risk-adjusted performance indicators for portfolio evaluation?
- What ML technique should be used to actively manage a portfolio?
- How does the ML portfolio compare to the benchmark portfolios based on the risk-adjusted performance indicators?
- How accurate are the predictions that were made by the ML model?

The aforementioned experiment of this thesis consisted of three training/testing periods. The testing periods were one year each and were preceded by a ten-year training period. In each testing period, the NASDAQ Composite index tracker was followed, an ML portfolio was constructed monthly, and a minimum variance portfolio was constructed once per testing period. The ML and minimum variance portfolio were constructed based on the stock price information from the ten-year training period.

The ML portfolio was constructed using stock price predictions by an Artificial Neural Network (ANN), feeding these predictions into the Black-Litterman model to determine the appropriate portfolio weights for the coming month during the testing period. The minimum variance portfolio was constructed by determining the lowest beta companies in each training period's dataset and minimising the fifty lowest beta companies' (co)variances to determine the portfolio weights.

At the end of each of the three testing periods, the performance of the three portfolios was compared. The comparison happened based on a number of risk-adjusted performance metrics as well as some other metrics. These performance metrics included the diversification index, Sharpe ratio, beta, Treynor ratio, and Jensen's alpha. In addition, the performance of the ANN was also be evaluated and compared between the testing periods. ML-specific performance metrics were used for this evaluation, these were accuracy (including sensitivity and specificity), the coefficient of determination (otherwise known as R^2), and error-based performance metrics (Root Mean Squared Error, Mean Absolute Error, Mean Absolute Percentage Error, and Symmetric Mean Absolute Percentage Error).

In the remainder of the conclusion chapter, the results and the limitations of the experiment will be discussed, and areas of future research will be presented. After this, the results will be concluded, and finally the implications of this thesis for both the theory as well as the practice of portfolio management will be mentioned.

6.2 Discussion

In this subchapter, the results from the experiment in this thesis will be discussed. Firstly, the results regarding the portfolio performance will be discussed. In the second half of this discussion, the ML performance metrics will be reviewed to discuss the performance of the ANN.

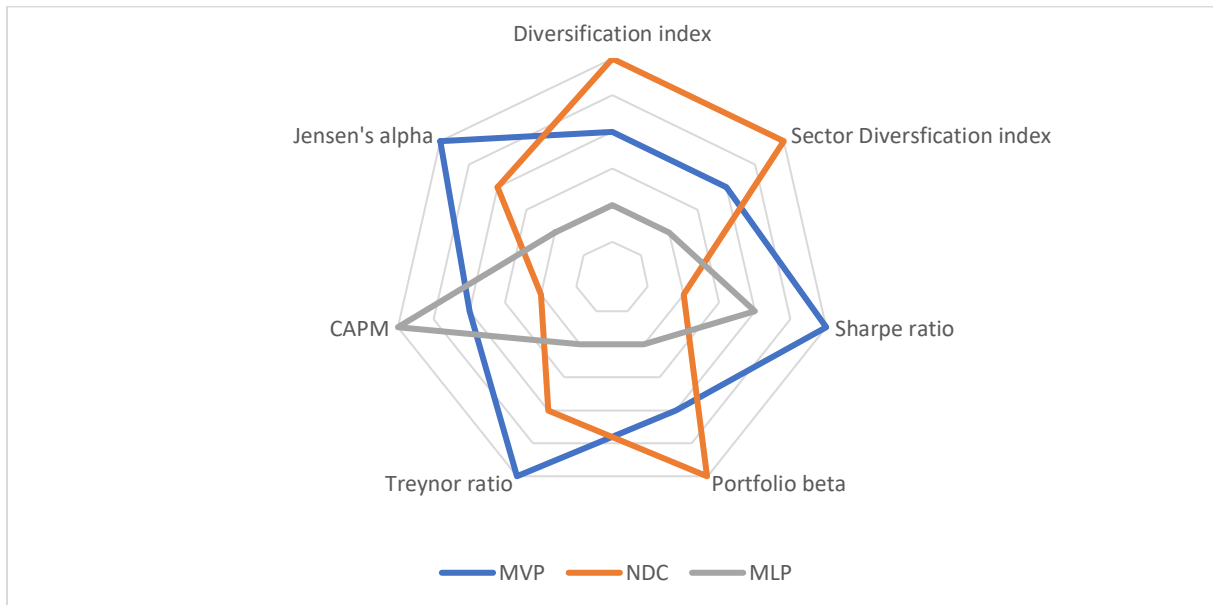


Figure 14. Spider graph of the portfolio performance metrics for the ML portfolio and the benchmark portfolios during the year 2000. Note. The portfolios are abbreviated as MVP (Minimum Variance Portfolio), NDC (NASDAQ Composite market index tracker), and MLP (ML Portfolio). The highest values are on the outside of the spider graph.

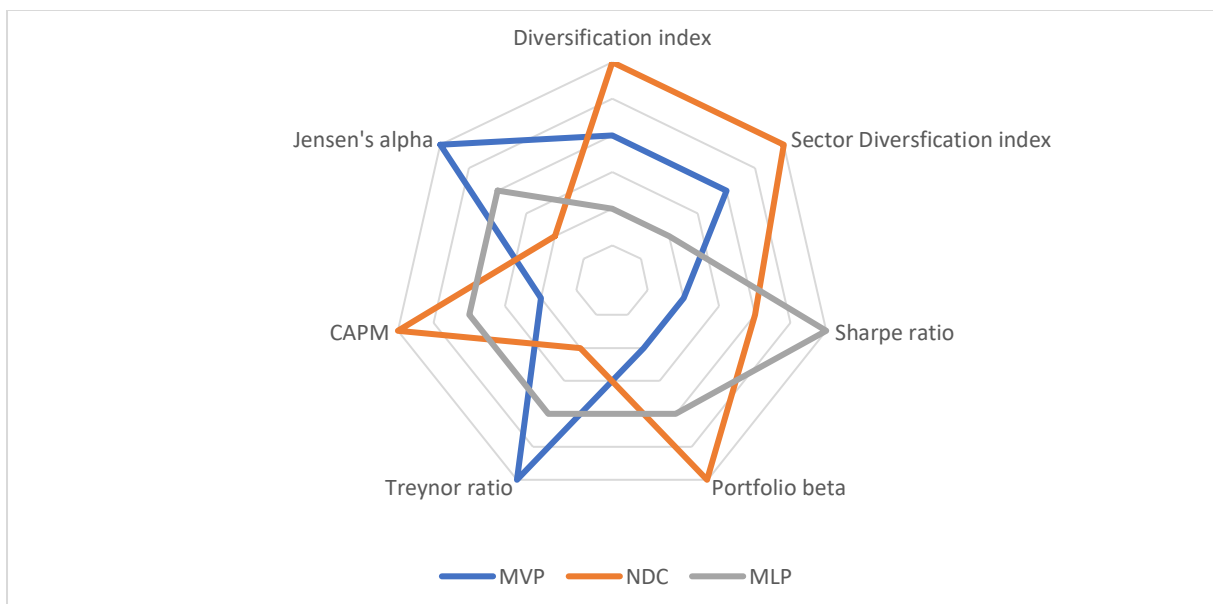


Figure 15. Spider graph of the portfolio performance metrics for the ML portfolio and the benchmark portfolios during the year 2010. Note. The portfolios are abbreviated as MVP (Minimum Variance Portfolio), NDC (NASDAQ Composite market index tracker), and MLP (ML Portfolio). The highest values are on the outside of the spider graph.

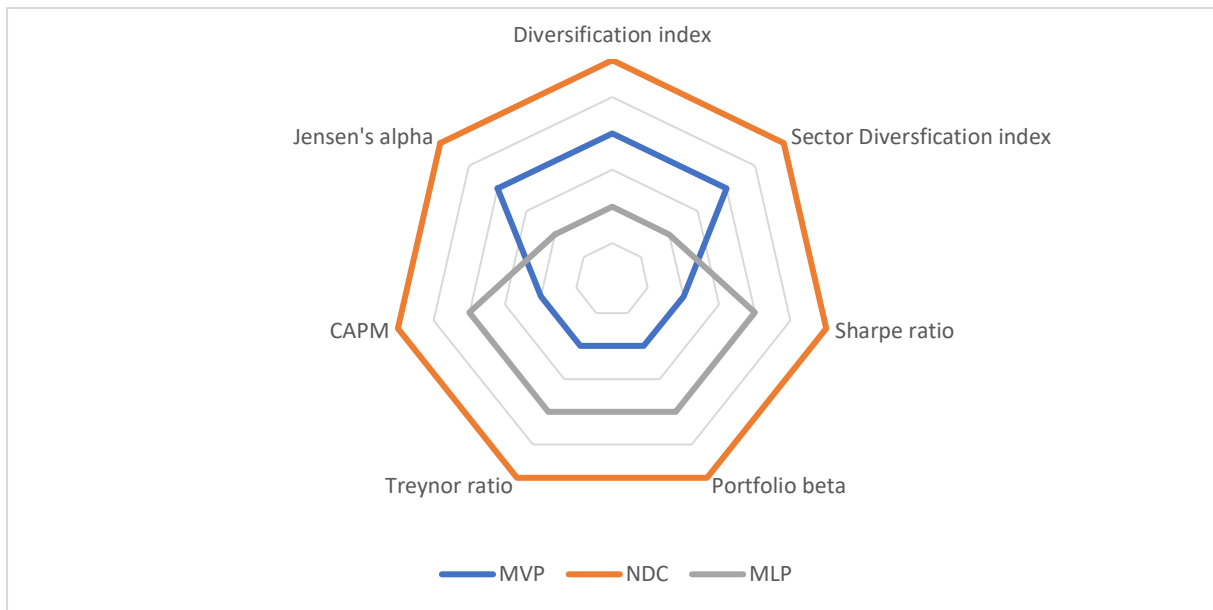


Figure 16. Spider graph of the portfolio performance metrics for the ML portfolio and the benchmark portfolios during the year 2020. Note. The portfolios are abbreviated as MVP (Minimum Variance Portfolio), NDC (NASDAQ Composite market index tracker), and MLP (ML Portfolio). The highest values are on the outside of the spider graph.

In this section of the discussion, the performance of the ML portfolio and the benchmark portfolios during the three testing periods will be discussed. As the research question of this thesis was regarding the ML portfolio's ability to outperform the benchmarks, Figures 14-16 show spider graphs with the ranking of the three portfolios during their respective testing periods.

Starting with the (sector) diversification indices, it was not surprising that the market index tracker had the highest diversification index during all three testing periods. The outperformance by the market index tracker was expected as the market is, by definition, completely diversified. For the minimum variance portfolio and the ML portfolio, it can be observed that the minimum variance portfolio outperformed the ML portfolio during the testing periods on both the diversification index as well as the sector diversification index. The outperformance by the minimum variance portfolio on the (sector) diversification index suggests that the minimum variance portfolio construction method is a better method to reach well-diversified portfolios compared to the combination of the ANN's predictions and the Black-Litterman model from the ML portfolio.

The suggestion that the minimum variance portfolio had a construction method that leads to more diversified portfolios compared to the method for the ML portfolio can also be seen in Table 8 from Chapter 5.1.2 (a duplicate of Table 8 is displayed on the next page for ease of reference). In Table 8, it can be seen that the average allocations for the individual sectors are smaller, admittedly not by a big difference, compared to the allocations of the ML portfolio. Smaller allocations for the biggest weight sectors mean higher allocations for smaller weight sectors, leading to more diversified portfolios. Despite the generally good diversification of both portfolios, improvement is definitely possible as in Table 8, it can be seen that the finance sector has a significantly larger allocation compared to the other sectors for both portfolios. The high average finance portfolio weight allocations might lead to low or negative portfolio returns when a finance specific downturn arises due to, for example, new governmental

regulations. In conclusion, both the diversification index as well as the sector diversification index did not have unexpected results during the three testing periods. During all three testing periods, the ML portfolio was performing the worst when compared to the benchmark portfolios' (sector) diversification indices.

MVP sectors	Average allocation (%)	MLP sectors	Average allocation (%)
Finance	27.27	Finance	30.70
Healthcare	12.69	Healthcare	13.09
Industrials	10.42	Industrials	13.00
Utilities	10.06	Technology	12.38

Table 8 (Duplicated). Top four weight allocations per testing period for the minimum variance portfolio and the ML portfolio.

Following the diversification index, the results from the risk-adjusted performance metrics will be discussed. In Figures 14-16, it can be seen that during each of the testing periods, there was a different portfolio that had the highest Sharpe ratio. Therefore, as the ranking from the spider graph does not present grounds for discussion, a duplicate of Table 10 from Chapter 5.2 is presented below. From Table 10, it can be calculated that during the three testing periods, the minimum variance portfolio had the highest average Sharpe ratio. This is interesting as the aim of the minimum variance portfolio was to have a portfolio with the lowest risk. When looking at the theory from CAPM, the general consensus is that higher risk is rewarded with higher returns. The average Sharpe ratio from the minimum variance portfolio shows that the added risk, which should be present in both the ML portfolio as well as the market index tracker, is not proportionally compensated by higher returns from the market. This disproportional compensation means that it would be more favourable for investors to invest in the minimum variance portfolio compared to the other portfolios as the average risk-adjusted performance was the highest during the three testing periods. This conclusion from the Sharpe ratio is a somewhat unexpected as it means that the minimum variance portfolio had better risk compensation compared to the general market.

The unexpected risk-adjusted performance of the minimum variance portfolio could be explained by the fact that during the chosen testing periods, the minimum variance portfolio did not incur big negative returns while the ML portfolio and the market index tracker did have significant losses during the 2000 testing period, decreasing their average Sharpe ratios.

Continuing with the portfolio beta, the most unexpected result was the beta during the 2000 testing period for the ML portfolio. The beta for the ML portfolio during the first testing period was 0.10, which is unexpected as this is lower than the 0.11 beta from the minimum variance portfolio. The minimum variance portfolio was constructed using the lowest betas during the 10-year training period. The ML portfolio was constructed by choosing the stocks with the highest expected return during each month of the testing period. Therefore, one could expect a higher risk for the ML portfolio compared to the minimum variance portfolio. The portfolio beta is a measure of systematic risk, meaning that the ML portfolio has a low exposure to the systematic risk during the 2000 testing period. This insight in the exposure to the systematic risk might be able to explain the low beta of the ML portfolio. The ML portfolio had a standard deviation of 7.16 compared to 1.96 from the minimum variance portfolio. Expanding on this, while the portfolio beta of the ML portfolio was lower, the portfolio risk was higher than the minimum variance portfolio. Therefore, the low beta could be explained by the exposure to

unsystematic risk, meaning inadequate diversification of the ML portfolio during the 2000 testing period. During the two remaining testing periods, the portfolio betas were as expected with the minimum variance portfolio having the lowest values.

For the next risk-adjusted performance metric, the Treynor ratio, the portfolio beta is used to adjust the performance of the three portfolios based on their systematic risk. Two results stand out from the Treynor ratio results compared to the Sharpe ratio. Firstly, the Treynor ratio of the ML portfolio during the 2000 testing period is more than four times bigger than the market index tracker's ratio while the Sharpe ratio of both of these portfolios was of a similar level. This difference compared to the Sharpe ratio can be explained by the small beta of the ML portfolio compared to the beta of the market index tracker. During the calculation of the Treynor ratio, the risk premium of the portfolio is divided by the portfolio beta. As the beta of the ML portfolio is 0.10, this leads to a multiplication of ten times the (negative) risk premium. Secondly, the minimum variance portfolio had an unexpected result during the 2010 testing period. During this testing period, the minimum variance portfolio had a positive risk premium but a negative portfolio beta. Due to the negative beta, the Treynor ratio would have been negative. However, this is not a fair representation of the systematic risk-adjusted performance of this portfolio as the reason why the ratio is negative is not caused by negative risk premiums but by the portfolio construction method. Therefore, the absolute beta was used to calculate the Treynor ratio. As the minimum variance portfolio had a small absolute portfolio beta, the Treynor ratio was the highest out of the three portfolios in the comparison. This differs from the Sharpe ratio as the ML portfolio had the highest Sharpe ratio during the 2010 testing period while the minimum variance portfolio had the lowest Sharpe ratio. Despite these two expected results, the same conclusion can be taken from the Treynor ratio and the Sharpe ratio. The minimum variance portfolio had the highest average Treynor ratio during the three testing periods while the ML portfolio had the lowest average risk-adjusted performance.

The final risk-adjusted performance metric is Jensen's alpha. This metric is calculated using the excess returns compared to the expected returns from the CAPM calculation. In Table 10, both the CAPM expected returns as well as the Jensen's alpha results are presented. It is noteworthy to mention that the Jensen's alpha discussion will only include the minimum variance portfolio and the ML portfolio as the market index tracker cannot have excess returns from the expected returns. Excess returns are not possible as the expected returns are calculated using the risk-free rate, the market risk premium, and the portfolio beta. For the market index tracker, the market return and expected return are identical as the expected return is calculated in hindsight with the aforementioned variables.

A pattern can be found in the Jensen's alpha results for the relation between the minimum variance portfolio and the ML portfolio. Consistently, the minimum variance portfolio has a higher excess return compared to the ML portfolio, even when the excess returns were negative for both portfolios during the 2020 testing period. The higher excess returns might be able to be explained by the systematic risk compensation. The CAPM expected returns, that are the basis of the excess return calculation, are calculated by multiplying the systematic risk (beta) of the portfolio with the market risk premium and adding the risk-free rate. Therefore, if the multiplication of the portfolio beta and the market risk premium does not adequately represent the risk compensation of the portfolio, the excess returns can be larger.

One specific result that consistently returned was that the minimum variance portfolio outperformed the market index tracker and the ML portfolio on all risk-adjusted performance metrics. This is interesting as the minimum variance portfolio was used as a benchmark as (Urošević & Vasiljevic, 2020) suggested that any portfolio that underperformed the minimum variance portfolio is not an optimal portfolio. Such a portfolio would not be optimal as an underperforming portfolio would either have more risk or less returns compared to the minimum variance portfolio. As the minimum variance portfolio outperformed both of the other portfolios, one can say that these other portfolios were not optimal. It was not expected that the ML portfolio from this thesis would outperform the market index tracker, however, one could have expected the ML to outperform the minimum variance portfolio to “classify” as an optimal portfolio. Therefore, the results of the risk-adjusted performance metrics led to the unexpected discovery that during the testing periods of this thesis, the minimum variance portfolio outperformed both the market index tracker as well as the ML portfolio.

	2000			2010			2020		
	MVP	NDC	MLP	MVP	NDC	MLP	MVP	NDC	MLP
Sharpe ratio	1.03	-3.28	-3.18	1.49	2.26	2.62	-0.17	2.64	1.35
Portfolio beta	0.11	1.00	0.10	-0.15	1.00	0.83	0.06	1.00	0.38
Treynor ratio	0.18	-0.47	-2.18	0.72*	0.15	0.23	-0.28	0.43	0.28
CAPM (%)	1.04	-40.20	1.49	-0.22	16.91	14.44	2.80	43.64	16.98
Jensen's alpha (%)	7.32	NA	-17.90	13.42	NA	6.55	-4.01	NA	-5.79

Table 10 (Duplicated). Portfolio risk-adjusted performance metrics for the testing periods 2000, 2010, and 2010. Note. The portfolios are abbreviated as MVP (Minimum Variance Portfolio), NDC (NASDAQ Composite market index tracker), and MLP (ML Portfolio). * = The calculations showed a Treynor ratio of -0.72, however, as this negative score was caused by a negative beta instead of a negative return, the absolute beta was used to calculate the Treynor ratio.

In the second half of the discussion, the results of the ML performance metrics will be discussed. Firstly, the accuracy metrics will be reviewed, continuing with the coefficient of determination. Finally, the error-based performance metrics will be discussed. The ML performance metrics are presented in Table 17.

In this thesis, the accuracy of the ML model is measured as the accuracy of correctly predicting the direction of the stock price during every month of the testing period. This is chosen as the best way to represent accuracy as it is the most important to determine what stocks will increase or decrease in the following month to construct the ML portfolio. During the three testing periods, the average accuracy of the ANN was 55.04 percent. This seems like a reasonable accuracy for the input data that was used. During the experiment of this thesis, the input data was the market index tracker’s price from 31-trading days prior to the prediction date. While past stock prices can be an indicator for future performance, it does not account for sudden market crashes nor increases. In addition, using the past market index tracker price to determine the stock price of a specific stock also ignores sector specific factors that might influence the stock price. Therefore, the accuracy of the ANN from this experiment seems reasonable although ways to increase accuracy should always be investigated, as will be mentioned in Chapter 6.4.

The sensitivity describes how many of the observed stock price increases are actually predicted by the ANN. The specificity does the opposite, this metric describes how many of the observed lack of stock prices increases are correctly predicted by the ANN. For the sensitivity and specificity, an unexpected result can be seen in Table 17. The proportion of the sensitivity and specificity changes with no relation to the general accuracy metric. The sensitivity seems to be increasing with every new testing period while the specificity seems to decrease. However, there is not a clear link between the accuracy of the ANN and the sensitivity/specificity. A higher accuracy does not mean a higher sensitivity nor specificity. Therefore, it cannot be concluded that there was a relation between the ANN's accuracy and its ability to correctly predict increases nor lack of increases in the stock prices. To continue, it can be observed that generally the sensitivity was higher compared to the specificity, even if the better performances did not necessarily occur in the same testing period. Concluding, it seems that the ANN was generally better at correctly predicting increases in the stock prices compared to lack of increases.

The coefficient of determination or R^2 is the level of variation in the dependent variable that can be explained by the independent variable. That means that the R^2 can be used to observe how good of an indicator the independent variable is to predict the dependent variable. The R^2 did have some unexpected results when comparing between the three testing periods. There was no expectation for the level of explainability of the independent variable, however, there is a big difference in R^2 levels between the testing periods. During the 2000 testing period, the R^2 score of 44.75 percent is much higher compared to the 1.63 percent and 6.34 percent. Therefore, there is not a degree of reliability in the explainability of the variation of the dependent variable from the ANN. To increase the reliability and R^2 results, more or different predictors of the stock price can be used.

The final ML performance metrics that were used during the experiment of this thesis are the error-based performance metrics. These error-based performance metrics consist of the RMSE (Root Mean Squared Error) MAE (Mean Absolute Error) MAPE (Mean Absolute Percentage Error) and SMAPE (Symmetric Mean Absolute Percentage Error). These error-based metrics show the difference between the predicted and observed values during the experiment. Meaning that unlike the previous ML performance metrics, a lower error-based performance means a better performance by the ANN. There is no clear relation between the error-based performance metrics and any of the previous ML performance metrics. An interesting observation is the relation between the accuracy and the error-based metrics in the 2010 testing period. During the 2010 testing period, the accuracy was at the lowest level of the experiment. At the same time however, the error-based metrics were also at their lowest level. This is an interesting observation as while the 2010 testing period was the period where the ANN was the least accurate in predicting the monthly stock price change, the difference between the predicted and observed stock prices was the lowest. However, it cannot be concluded that the accuracy has a negative relation to the error between the predictions and observations as this trend does not hold for the two remaining testing periods.

In general, the ANN's performance left room for improvements on all aforementioned ML performance metrics. This improvement can possibly be achieved through, for example, different and/or more predictors or even a different ML model such as the LSTM algorithm. With an improvement in the performance of the ML model, the performance of the ML

portfolio could potentially also be improved. Therefore, in the next chapter, the limitations of the experiment of this thesis will be discussed. By discussing the limitations of this thesis, the factors that might have led to the ML portfolio's outperformance by the two benchmark portfolios will be mentioned. These factors can then be carefully considered when future research on this topic is conducted.

ML performance metric	2000	2010	2020
Accuracy (%)	60.76	49.34	55.01
Sensitivity (%)	54.22	56.30	72.64
Specificity (%)	68.12	37.92	29.95
R ² (Coefficient of determination, %)	44.75	1.63	6.34
RMSE (Root Mean Squared Error)	4.38	2.70	9.47
MAE (Mean Absolute Error)	3.70	2.34	8.04
MAPE (Mean Absolute Percentage Error, %)	42.80	30.76	57.88*
SMAPE (Symmetric Mean Absolute Percentage Error, %)	47.08	34.24	58.61

Table 17. ML performance metrics for the three testing periods of the experiment. Note. The values displayed are average scores from the testing period except for the RMSE and MAE which are median scores of their respective testing periods. * = Outliers above 1000 percent were removed from the MAPE results in 2020.

6.3 Limitations

In this chapter, the limitations of the research in this thesis will be discussed. The limitations of the experiment mainly have to do with the predictions from the ANN. The limitations that will be discussed in this chapter are in fourfold:

1. Retraining during deployment of the ANN;
2. The choice of the independent variable;
3. The choice of the ML model;
4. And the choice of the training/testing periods used during the experiment.

In the remainder of this chapter, these four limitations will be discussed in further detail.

During the experiment of this thesis, the ANN was not retrained during deployment. Instead, the ANN was trained on the ten-year training dataset and then tested on the entire one-year testing period in one sitting. This approach would not be implemented this way in practice as the independent variable would not be available yet. The independent variable in this thesis was the market index tracker price from 31-trading days prior to the prediction date. Therefore, if the predictions are made for the coming year, there would only be an independent variable for the first 31 trading days. However, as the experiment dealt with stock price data from the past, it was possible to predict the entire testing period at once. The choice for this approach instead of training and predicting for every individual month in the testing period was made as the experiment required significant amounts of computing time and power. Therefore, training only once of the testing dataset saved a drastic amount of time. However, this is a limitation as it did make the prediction process less realistic than it would be in practice, potentially decreasing the prediction ability especially near the ending of the testing period.

The independent variable in this thesis was the NASDAQ Composite index tracker price from 31 trading days prior to the prediction date. This predictor was chosen based on the results of

prior stock price predictions using price data as an input variable (Vijh et al., 2020; Y. Wang, 2014). However, in these articles, the next day stock price was predicted, this is different from the 31-trading day difference between input and output in this thesis. Therefore, the prediction ability of the independent variable was lower than in the aforementioned articles. The lower prediction ability could have had an influence on the performance of the ANN as well as of the ML portfolio, making the choice of the independent variable a limitation of this thesis. Therefore, in future research, more attention should be paid to determining the independent variable(s) with a better prediction ability compared to the predictor used in this thesis.

The choice for the ANN to make the predictions for the ML portfolio was made based on the literature review in Chapter 2 of this thesis. In the literature review, the ANN was determined to have the highest accuracy within the specific context in which the experiment of this thesis would operate. The main determining factor why the ANN was chosen over, for example, the LSTM model is the fact that there was only one independent variable. In the literature review, the ANN performed the best when there was a single predictor variable while the LSTM model performed better when faced with multiple inputs. The choice of the ANN as the only ML model can be seen as a limitation of this thesis. In future research, multiple ML models can be used to determine if a specific ML model can create a better ML portfolio.

The final limitation of this thesis does not only influence the ML portfolio but also the two benchmark portfolios. The chosen timeframes of this thesis were decided completely arbitrary, there was not a specific reason why these timeframes would give the best general representation of the stock market. It could very well be possible that there would be a different best performing portfolio during a different testing period compared to the three periods chosen in this thesis. Increasing the number of training and testing periods could further rule out any unwanted biases regarding any specific portfolio and make a more generalised conclusion about the best performing portfolio.

6.4 Future research

In this chapter, the future research topics will be discussed. These topics can be further researched in future articles to build on the insights from this thesis. The future research topics that are going to be discussed are twofold:

1. Explainable AI,
2. And expanding on the number of testing periods.

Starting with Explainable AI, this future research topic can be used to increase the prediction ability of the ML model. From both the accuracy and the coefficient of determination of the ANN prediction model, it can be concluded that the stock price predictions had room for improvement. The average directional accuracy was 55.04 percent, this seems low as the entire construction and performance of the ML portfolio was based on accurately predicting the stock prices. Therefore, a higher accuracy would mean more accurate expected returns for the construction of the ML portfolio, improving the performance of the ML portfolio in itself. When looking at ways to improve the accuracy of the predictions, the inputs of the ANN should be taken into consideration. In two of the three testing periods, the coefficient of determination was close to zero, meaning that the input could explain very little of the variation of the dependent variable, i.e., the stock price.

A way to determine what input variable(s) has/have the best prediction abilities is by using Explainable AI. Explainable AI can help to show the influence certain input variables have on the prediction accuracy and ability of the ML model. Finding the best input variables for stock price predictions is crucial as it can improve the performance of the ML portfolio. Therefore, utilising Explainable AI in future research can help expand the knowledge on the best input variable(s) for stock price predictions.

In the experiment of this thesis, there were three training/testing periods. The testing periods were the years 2000, 2010, and 2020. During these testing periods, the minimum variance portfolio had the best average risk-adjusted performance out of the three portfolios in the experiment. However, during two of the three testing periods, the years 2000 and 2020, there was a significant decrease in stock prices caused by the Dot Com bubble in 2000 and Covid-19 in 2020. During times with drastic increases or decreases in stock prices, a portfolio with a limited amount of risk will generally have a limited volatility, both upwards and downwards. Therefore, during two of the three testing periods, the minimum variance portfolio had an advantage compared to the higher-risk market index and ML portfolios. Increasing the number of testing periods will make the evaluation of the three portfolios fairer for the higher-risk portfolios. Therefore, in future research the number of testing periods can be increased to determine if this will make a difference on what portfolio can achieve the highest risk-adjusted performance.

In this chapter, two areas of future research were mentioned. These areas can be further researched to determine whether the conclusion of this thesis still holds when certain limitations of the experiment are removed.

6.5 Managerial conclusion

In this thesis, the role of machine learning in portfolio management was researched. In particular, the role that machine learning can play in the construction of actively managed stock portfolios was examined in the form of an experiment. Such a machine learning portfolio would be able to reduce the barrier to entrance for actively managed portfolios. Currently, an actively managed portfolio has significant management fees. These management fees can be reduced with the help of machine learning as it would lower the required manual labour for the asset selection process. The opportunity for machine learning to reduce the barrier to enter actively managed portfolios led to the following research question for this thesis: Can a machine learning model, that actively trades an equity portfolio, outperform benchmark portfolios (NASDAQ Composite index tracker and minimum variance portfolio) based on risk-adjusted performance indicators?

To answer the research question, a machine learning technique called artificial neural network was found to be best fit for the purpose of this experiment. The artificial neural network was trained to predict the expected returns for the stocks in the NASDAQ Composite index (as a representation of the total market) during three different testing periods. These testing periods were the years 2000, 2010, and 2020, where the predictions were based on the ten prior years as the training data. Using the expected returns that were predicted by the artificial neural network, a portfolio was constructed using the Black-Litterman model. This portfolio construction happened on a monthly basis during the three testing periods.

The two benchmark portfolios against which the machine learning portfolio will be compared, as mentioned in the research question, were the NASDAQ COMPINSITES index tracker and a

minimum variance portfolio. The NASDAQ Composite index tracker was directly retrieved from Refinitiv Eikon for all three testing periods. The minimum variance portfolio had to be constructed for the experiment. The construction of this portfolio was done by collecting the fifty lowest beta stocks in the NASDAQ Composite index during the ten years prior to each respective testing period. These fifty stocks would then be collected in a portfolio where the portfolio weights were assigned by minimising the total portfolio standard deviation, leading to the minimum variance portfolio. The minimum variance portfolio remained unchanged during the testing period.

After the three portfolios were constructed, their risk-adjusted performance was compared against each other to determine whether the machine learning portfolio was able to outperform the benchmarks. This comparison happened based on the following risk-adjusted performance metrics: the Sharpe ratio, the beta, the Treynor ratio, and Jensen's alpha. Leaving the beta out of the consideration as a higher or lower beta does not equal better performance, the machine learning portfolio was not able to outperform the benchmark portfolios. Instead, the minimum variance portfolio, on average, outperformed both the machine learning portfolio as well as the index tracker on all remaining risk-adjusted performance metrics. This conclusion meant that the minimum variance portfolio had the best risk compensation out of the three portfolios in the experiment. This is a surprising conclusion as the minimum variance portfolio had a better risk compensation than the general market (the NASDAQ Composite index tracker). From the CAPM theory, an investor is rewarded for taking more risk by receiving higher returns. In this experiment, it was found that this is not always the case as the minimum variance portfolio had lower risks on all risk measures compared to the market index tracker, while still receiving a higher risk compensation. Therefore, while the purpose of this thesis was to determine whether machine learning portfolios could outperform benchmark portfolios, the actual findings were equally interesting as it was contradicting evidence to the CAPM theory was found.

After the comparison on the risk-adjusted performances, the performance of the artificial neural network was also examined to determine the performance during the three testing periods. From this evaluation of the artificial neural network, it was found that the model correctly predicted the direction of the stock prices in 55.04 percent of the cases. The accuracy metric was further supplemented by the sensitivity and specificity of the predictions, here it was found that the sensitivity was generally higher compared to the specificity. This finding means that the artificial neural network is generally better at correctly predicting observed increases compared to lack of increases. For the prediction model, correctly predicting both increases and lack of increases is important, however, the construction of the machine learning portfolio is based on the highest expected returns and therefore, correctly predicting increases in the stock price is more important within the context of this thesis.

The coefficient of determination or R^2 was the next metric of machine learning performance. This metric did not provide a lot of useful insights as two of the three testing periods had very low scores. The 2000 testing period had a surprisingly high R^2 score compared to the other testing periods, meaning a generalised conclusion is complicated to make. However, as the two remaining testing periods had scores close to zero percent explainability of the variance of the dependent variable, it can be concluded that the independent variable might not be the most suitable predictor for the stock prices within the layout of the experiment that was conducted.

The final machine learning performance metrics were error-based metrics. These metrics included the Root Mean Squared Error, Mean Absolute Error, Mean Absolute Percentage Error, and the Symmetric Mean Absolute Percentage Error. While there was not a clear link between the height of the errors and the accuracy of the model, there was an interesting finding. During the 2010 testing period, the directional accuracy of the model was at the lowest of the three testing periods, at the same time the errors between the predicted and observed values was also the lowest. This is interesting as it means that while the model was the worst at predicting the direction of the stock price, it was the best at approximating what the stock price will be. Therefore, the error-based metrics sketch a different image of the performance of the ML model compared to the accuracy metrics.

For the total performance of the ML model, the scores that were measured were not impressive. This might have to do with the independent variable not being the best predictor within the context of this thesis's experiment.

To answer the research question, the actively trading machine learning portfolio was not able to outperform the benchmark portfolios based on the risk-adjusted performance indicators. Instead, the minimum variance portfolio had the best risk-adjusted performance during the three testing periods of this thesis. To improve the performance of the machine learning portfolio, it could help to determine what predictor of the stock price is the most appropriate for the semi-long-term predictions that were made in this thesis.

6.6 Contributions to theory and practice

The experiment of this thesis was relevant as the rise of machine learning techniques leads to more and more applications for these techniques. In particular, this thesis aimed to discover if ML models could be used to actively trade a stock portfolio. The aim of active portfolios is to get a return that is higher compared to passive portfolios, such as the market index tracker. However, the downside of active trading is the high fees and costs, either in management fees for actively managed funds or in time spent analysing stocks by an individual investor.

Using a ML model to automate the active trading of such a portfolio would result in the high returns that are associated with active trading without the high management fees that financial institutions would charge to manage an active portfolio for an investor.

This makes active portfolios more accessible for people with less investable assets, allowing people to use ML portfolios to personally invest, for example, their pension based on their personal risk aversion levels and also based on their personal preferences. These people could invest in all industries on the market or decide to avoid certain industries such as manufacturers of military equipment. This would allow people to let the ML portfolio invest their capital to reach the highest returns based on their individual preferences. However, before ML techniques can be used to create personalised portfolios for individual investors, first it needs to be determined that an ML portfolio can actually outperform passive portfolios based on the risk-adjusted performance. Therefore, this thesis aimed to find out if an ML portfolio can outperform the market index tracker and a minimum variance portfolio.

In the experiment of this thesis, the ML portfolio was unfortunately outperformed by both the market index tracker as well as the minimum variance portfolio. This underperformance by the ML portfolio means that the ML model and the portfolio construction method from this thesis did not reach the desired results. For now, this thesis will have little contributions to practice as the aim to create an ML portfolio that outperforms passive stock portfolios was

not achieved. However, in the future, different combinations of ML models with portfolio construction methods might be used to create an ML portfolio that will succeed to outperform passive portfolios.

A more notable contribution was made to the theory of portfolio management. In particular, the contribution is regarding the risk-adjusted performance results of the minimum variance portfolio is comparison to the results of the (NASDAQ Composite) market index tracker. During the three testing periods, the minimum variance portfolio managed to achieve a higher average risk-adjusted performance compared to the market index tracker. The reason why this is a contribution to the theory is related to the Capital Asset Pricing Model (CAPM), originally thought off by William Sharpe (1964). This pricing model can be used to calculate the expected return of a particular stock or portfolio by using the risk-free rate, the beta of the selected stock or portfolio, and the market risk premium. The theory behind using these variables in the expected return calculation is that a higher beta would be proportionally compensated by the market with higher returns. When the return is proportionally compensated for the amount of risk, the systematic risk-adjusted performance metric (such as the Treynor ratio) should be identical for all portfolios and stocks, regardless of the beta. In the results of this thesis, the average Treynor ratio of the minimum variance portfolio was more than five times higher compared to the Treynor ratio of the market index tracker (0.21 for the minimum variance portfolio compared to 0.037 for the market index tracker). In addition, the Jensen's alpha performance metric shows the excess return compared to the CAPM expected return of the portfolio. On average during the three testing periods, the Jensen's alpha excess return for the minimum variance portfolio was 5.58 percent. The excess return shows that the CAPM expects the minimum variance portfolio to have lower returns than it achieves in reality.

The aforementioned finding from this thesis is contradicting evidence to the CAPM theory as it demonstrates that the return compensation of the market is not increasing proportional to the marginal risk that an investor takes on. Therefore, this thesis adds to the existing criticisms regarding the CAPM theory (Fama & French, 1993; Laubscher, 2002; Liao, 2023; Rossi, 2016).

To conclude, the contribution of this thesis has mostly been on the side of the theory regarding portfolio management. For the practice, the inability of the ML portfolio to outperform the benchmark portfolios led to no new findings from this thesis. For the theoretical side, the contribution has been providing contradicting evidence to the CAPM theory. While disproving the CAPM theory this was not directly in the scope of this thesis, the results of the experiment showed that the return compensation by the market was not proportional to the risk that was being taken. Therefore, the results of this thesis undermine the assumptions of the CAPM.

6.7 Generalisation

Earlier in this thesis, generalisation has been quickly mentioned. However, in this subchapter, it will be further discussed how generalisable the research and conclusion of this thesis are. The experiment of this thesis was designed with generalisation in mind, especially due to the varying conditions that can affect the stock prices and portfolio performances outside just asset selection and allocation. Therefore, while imagining the experiment design, the choice was made to include three testing periods in this thesis' experiment. With these three testing periods, it was possible to make more generalised conclusions regarding the risk-adjusted performances of the three portfolios, i.e., the ML portfolio, the minimum variance portfolio,

and the market index tracker. While adding more testing periods would have made for a more generalisable conclusion, due to time constraints, the choice for three testing periods was deemed sufficient. If the experiment would have consisted of just one testing period, the conclusion would be possibly different depending on the testing period chosen. Concluding, the experiment design has helped to contribute to the generalisation of this thesis.

The sample for the stock price data that was used also has an influence on the conclusion of this thesis. In the previous paragraph, the three testing periods were mentioned as a way to make the conclusion more generalisable. However, the data for the three testing periods in itself had to be chosen as well. The decision for the testing period years 2000, 2010, and 2020 was made due to the differing characteristics between the three periods. During both the 2000 and the 2020 testing periods, there were market crashes due to the burst of the Dot-com bubble as well as the start of the COVID-19 pandemic. However, these two years were dissimilar due to the timing of the market crashes in the year. The Dot-com bubble burst towards the ending of the year, around the autumn months, while the market crash in 2020 was during the beginning of the year, followed by a big rise in stock prices. The 2010 testing period did not feature any significant events (apart from the Flash Crash, which did not have lasting consequences on the stock market prices (Kirilenko et al., 2011)). In addition to the events during the testing period years, another generalisation-aiding characteristic of these three selected years was the number of companies that were included in each testing period. This ranged from 268 companies during the 2000 testing period to 1240 companies during the 2020 testing period.

The aforementioned differences in characteristics help make the conclusion of this thesis better generalisable as the conclusion is tested on three differing datasets during the experiment. As the conclusion is tested on different kinds of data, it is more likely that other data will yield similar results to the results presented in this thesis.

To conclude the discussion of the generalisation of this thesis' research; due to the inclusion of multiple testing periods as well as datasets with varying characteristics, the conclusion of this thesis can be generalised. As the experiment is designed with generalisation in mind, it is likely that the results can be replicated using different datasets. It should be noted that this experiment was conducted on the US stock market, it would be possible that the results might not be identically replicated when stock market data is used from developing economies with less efficient stock markets.

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Appendix A: Results from the 2000 testing period.

Appendix A1: Minimum variance portfolio weight allocations during the 2000 testing period.

Company	Weight	Sector	Beta
ROYAL GOLD	0.24%	Basic Materials	-0.180
SCTY.T.FINL.'A'	0.28%	Technology	-0.078
SENECA FOODS	2.28%	Consumer Staples	-0.048
FIRST BANCORP	1.51%	Finance	-0.019
PAM TRANSPORTATION SVS.	0.03%	Industrials	-0.015
PRIMEENERGY RESOURCES	0.74%	Energy	0.033
ART'S-WAY MANUFACTURING	1.12%	Industrials	0.064
TWIN DISC	8.61%	Industrials	0.069
WEYCO GROUP	2.06%	Consumer Discretionary	0.071
BRIDGFORD FOODS	0.65%	Consumer Staples	0.073
MARINE PETROLEUM TRUST	1.58%	Energy	0.083
MIDDLESEX WATER	2.82%	Utilities	0.090
MARTEN TRANSPORT	0.46%	Industrials	0.090
ALICO	1.87%	Consumer Staples	0.090
DAILY JOURL	0.91%	Media	0.095
US.LIME & MINERALS	0.62%	Industrials	0.097
CAPITAL SOUTHWEST	5.42%	Finance	0.098
DONEGAL GP.'B'	1.34%	Finance	0.099
OLD NATIONAL BANCORP	10.02%	Finance	0.102
VSE	0.81%	Industrials	0.103
ELECTRO-SENSORS	0.45%	Industrials	0.104
WASHINGTON TST.BANC.	1.32%	Finance	0.109
INTERGROUP	0.98%	Consumer Discretionary	0.109
GREAT STHN.BANCORP	1.62%	Finance	0.117
OTTER TAIL	2.66%	Industrials	0.119
MGE ENERGY	1.85%	Utilities	0.120
VILLAGE SPRMKT.'A'	0.72%	Consumer Staples	0.120
ESCALADE	0.40%	Consumer Discretionary	0.122
ICAHN ENTERPRISES	4.21%	Industrials	0.127
CSP	0.54%	Technology	0.129
EASTERN	4.57%	Basic Materials	0.129
FRP HOLDINGS	1.00%	Real Estate	0.132
SIMMONS 1ST.T.'A'	2.26%	Finance	0.132
EVERGY	6.40%	Utilities	0.135
TAYLOR DEVICES	0.38%	Industrials	0.140
WESBANCO	2.48%	Finance	0.150
CVB FINICIAL	1.36%	Finance	0.151
UNITED FIRE GROUP	1.23%	Finance	0.152
ASTRONICS	0.21%	Industrials	0.155
COMMUNITY TRUST BANCORP	1.66%	Finance	0.157
DORCHESTER MINERALS	1.31%	Energy	0.161
NEWTEKONE	0.25%	Finance	0.163
ALLIANT ENERGY (XSC)	7.85%	Utilities	0.163

Company	Weight	Sector	Beta
FARMER BROTHERS	2.28%	Consumer Staples	0.169
CITY HLDG.	0.15%	Finance	0.172
SUPERIOR GROUP OF COMPANIES	4.90%	Consumer Discretionary	0.174
BIOLIFE SOLUTIONS	0.09%	Healthcare	0.179
NORTHEAST BANK	2.49%	Finance	0.182
PERMA-PIPE INTL.HDG.	0.35%	Basic Materials	0.183
ROCKY MNT.CHOCO.FAC.	0.69%	Consumer Staples	0.190

Appendix A2: Portfolio weight allocations per month of the ML portfolio during the 2000 testing period.

January	Weight	Sector	February	Weight	Sector
ALLIENT	0.83%	Industrials	ALLIENT	0.97%	Industrials
BIOLIFE SOLUTIONS	0.83%	Healthcare	BIOLIFE SOLUTIONS	0.93%	Healthcare
TRANSCAT	1.64%	Industrials	TRANSCAT	1.87%	Industrials
COGNEX	0.09%	Industrials	COGNEX	0.38%	Industrials
FREQUENCY ELECTRONICS	1.97%	Industrials	FREQUENCY ELECTRONICS	2.22%	Industrials
LATTICE SEMICONDUCTOR	-0.73%	Technology	LATTICE SEMICONDUCTOR	-0.53%	Technology
TERADYNE (XSC)	-1.00%	Technology	TERADYNE (XSC)	-0.94%	Technology
SEMTECH ELECTRONIC ARTS	0.26%	Technology	SEMTECH ELECTRONIC ARTS	0.27%	Technology
ANALOG DEVICES	-1.11%	Consumer Discretionary	ANALOG DEVICES	-0.98%	Consumer Discretionary
HOST HOTELS & RESORTS REIT	-0.58%	Technology	HOST HOTELS & RESORTS REIT	-0.47%	Technology
SEI INVESTMENTS	2.06%	Real Estate	SEI INVESTMENTS	2.59%	Real Estate
PAYCHEX	4.81%	Finance	PAYCHEX	5.26%	Finance
LAM RESEARCH	2.71%	Industrials	LAM RESEARCH	2.74%	Industrials
DENTSPLY SIRONA	-0.83%	Technology	DENTSPLY SIRONA	-0.84%	Technology
ADOBE (NAS)	6.15%	Healthcare	ADOBE (NAS)	6.62%	Healthcare
WENDY'S CLASS A	-0.22%	Technology	WENDY'S CLASS A	-0.37%	Technology
INTEL	1.86%	Consumer Discretionary	INTEL	2.06%	Consumer Discretionary
KLA	2.10%	Technology	KLA	2.23%	Technology
FIFTH THIRD BANCORP	-0.27%	Technology	FIFTH THIRD BANCORP	-0.52%	Technology
ERICSSON 'B' ADR 1:1	10.03%	Finance	ERICSSON 'B' ADR 1:1	10.14%	Finance
ZIONS BANCORP.	-0.75%	Telecommunication	ZIONS BANCORP.	-0.78%	Telecommunication
KULICKE & SOFFA INDS.	9.51%	Finance	KULICKE & SOFFA INDS.	9.30%	Finance
TEXAS INSTRUMENTS	-0.85%	Technology	TEXAS INSTRUMENTS	-0.79%	Technology
REPLIGEN	0.91%	Technology	REPLIGEN	0.96%	Technology
VOXX INTERNATIONAL 'A'	0.55%	Healthcare	VOXX INTERNATIONAL 'A'	0.53%	Healthcare
	0.62%	Consumer Discretionary		0.62%	Consumer Discretionary

LEONARDO DRS	0.69%	Industrials	LEONARDO DRS	0.64%	Industrials
COMCAST A	0.20%	Telecommunication	COMCAST A	-0.16%	Telecommunication
CADIZ	0.92%	Utilities	CADIZ	0.94%	Utilities
CALAMP	0.88%	Telecommunication	CALAMP	0.84%	Telecommunication
MICRON TECHNOLOGY	-0.28%	Technology	MICRON TECHNOLOGY	-0.20%	Technology
1ST SOURCE	11.82%	Finance	1ST SOURCE	11.87%	Finance
PLEXUS	1.72%	Technology	PLEXUS	1.70%	Technology
COHU	2.23%	Technology	COHU	2.05%	Technology
PTC	-1.81%	Technology	PTC	-1.98%	Technology
NATIONAL WSTN.LF.GP.'A'	4.11%	Finance	NATIONAL WSTN.LF.GP.'A'	4.13%	Finance
VODAFONE GP.SPN.ADR 1:10	6.88%	Telecommunication	VODAFONE GP.SPN.ADR 1:10	6.56%	Telecommunication
AVIS BUDGET GROUP	-0.18%	Consumer Discretionary	AVIS BUDGET GROUP	-0.30%	Consumer Discretionary
US GOLD	1.18%	Basic Materials	US GOLD	1.17%	Basic Materials
JOHNSON OUTDOORS 'A'	4.86%	Consumer Discretionary	JOHNSON OUTDOORS 'A'	4.63%	Consumer Discretionary
NEONODE	0.37%	Technology	NEONODE	0.40%	Technology
DOMINARI HOLDINGS	0.84%	Healthcare	DOMINARI HOLDINGS	0.81%	Healthcare
GT BIOPHARMA	0.27%	Healthcare	GT BIOPHARMA	0.30%	Healthcare
ABEONA	0.51%	Healthcare	ABEONA	0.43%	Healthcare
THERAPEUTICS THERMOGENESIS HOLDINGS	0.61%	Healthcare	THERAPEUTICS THERMOGENESIS HOLDINGS	0.61%	Healthcare
AUTOMATIC DATA PROC.	11.22%	Industrials	AUTOMATIC DATA PROC.	10.63%	Industrials
PHOTRONIC	-2.40%	Technology	PHOTRONIC	-2.56%	Technology
MICROSOFT	3.23%	Technology	MICROSOFT	2.98%	Technology
SKYWORKS SOLUTIONS	0.70%	Technology	SKYWORKS SOLUTIONS	0.68%	Technology
FIRST CTZN.BCSH.A	10.80%	Finance	FIRST CTZN.BCSH.A	10.34%	Finance
March	Weight	Sector	April	Weight	Sector
ALLIENT	0.77%	Industrials	ALLIENT	1.02%	Industrials
BIOLIFE SOLUTIONS	0.82%	Healthcare	BIOLIFE SOLUTIONS	1.01%	Healthcare
TRANSCAT	1.55%	Industrials	TRANSCAT	2.09%	Industrials
COGNEX	0.12%	Industrials	COGNEX	0.64%	Industrials
FREQUENCY ELECTRONICS	2.03%	Industrials	FREQUENCY ELECTRONICS	2.44%	Industrials

LATTICE SEMICONDUCTOR	-0.75%	Technology	LATTICE SEMICONDUCTOR	-0.48%	Technology
TERADYNE (XSC)	-1.21%	Technology	TERADYNE (XSC)	-0.58%	Technology
SEMTECH ELECTRONIC ARTS	0.25%	Technology	SEMTECH ELECTRONIC ARTS	0.31%	Technology
ANALOG DEVICES	-1.26%	Consumer Discretionary	ANALOG DEVICES	-0.92%	Consumer Discretionary
HOST HOTELS & RESORTS REIT	-0.45%	Technology	HOST HOTELS & RESORTS REIT	-0.47%	Technology
SEI INVESTMENTS	2.29%	Real Estate	SEI INVESTMENTS	3.15%	Real Estate
PAYCHEX	4.97%	Finance	PAYCHEX	5.63%	Finance
LAM RESEARCH	2.44%	Industrials	LAM RESEARCH	3.12%	Industrials
DENTSPLY SIRONA	-0.86%	Technology	DENTSPLY SIRONA	-0.91%	Technology
ADOBE (NAS)	6.66%	Healthcare	ADOBE (NAS)	7.21%	Healthcare
WENDY'S CLASS A	-0.35%	Technology	WENDY'S CLASS A	-0.33%	Technology
INTEL	2.15%	Consumer Discretionary	INTEL	2.35%	Consumer Discretionary
KLA FIFTH THIRD	2.32%	Technology	KLA FIFTH THIRD	2.69%	Technology
BANCORP	-0.48%	Technology	BANCORP	-0.63%	Technology
ERICSSON 'B' ADR 1:1	9.88%	Finance	ERICSSON 'B' ADR 1:1	9.63%	Finance
ZIONS BANCORP.	-0.77%	Telecommunication	ZIONS BANCORP.	-0.86%	Telecommunication
KULICKE & SOFFA INDS.	9.24%	Finance	KULICKE & SOFFA INDS.	7.86%	Finance
TEXAS INSTRUMENTS	-0.73%	Technology	TEXAS INSTRUMENTS	-0.76%	Technology
REPLIGEN	0.72%	Technology	REPLIGEN	0.43%	Technology
VOXX INTERNATIONAL 'A'	0.49%	Healthcare	VOXX INTERNATIONAL 'A'	0.52%	Healthcare
LEONARDO DRS	0.66%	Consumer Discretionary	LEONARDO DRS	0.82%	Consumer Discretionary
CADIZ	0.58%	Industrials	CADIZ	0.54%	Industrials
COMCAST A	0.97%	Utilities	COMCAST A	1.00%	Utilities
CALAMP	-0.05%	Telecommunication	CALAMP	-0.08%	Telecommunication
MICRON TECHNOLOGY	0.82%	Telecommunication	MICRON TECHNOLOGY	0.82%	Telecommunication
1ST SOURCE	-0.10%	Technology	1ST SOURCE	-0.20%	Technology
PLEXUS	12.04%	Finance	PLEXUS	11.75%	Finance
	1.80%	Technology		1.77%	Technology

COHU	2.18%	Technology	COHU	2.07%	Technology
PTC	-1.92%	Technology	PTC	-2.11%	Technology
NATIONAL	4.27%	Finance	NATIONAL	4.25%	Finance
WSTN.LF.GP.'A'			WSTN.LF.GP.'A'		
VODAFONE	6.69%	Telecommunic	VODAFONE	6.65%	Telecommunic
GP.SPN.ADR		ation	GP.SPN.ADR		ation
1:10			1:10		
AVIS BUDGET	-0.29%	Consumer	AVIS BUDGET	-0.40%	Consumer
GROUP		Discretionary	GROUP		Discretionary
US GOLD	1.25%	Basic Materials	US GOLD	1.21%	Basic Materials
JOHNSON	4.85%	Consumer	JOHNSON	4.57%	Consumer
OUTDOORS 'A'		Discretionary	OUTDOORS 'A'		Discretionary
NEONODE	0.43%	Technology	NEONODE	0.39%	Technology
DOMINARI	0.87%	Healthcare	DOMINARI	0.84%	Healthcare
HOLDINGS			HOLDINGS		
GT BIOPHARMA	0.29%	Healthcare	GT BIOPHARMA	0.24%	Healthcare
ABEONA	0.54%	Healthcare	ABEONA	0.53%	Healthcare
THERAPEUTICS			THERAPEUTICS		
THERMOGENESI	0.69%	Healthcare	THERMOGENESI	0.64%	Healthcare
S HOLDINGS			S HOLDINGS		
AUTOMATIC	11.19%	Industrials	AUTOMATIC	9.66%	Industrials
DATA PROC.			DATA PROC.		
PHOTRONIC	-2.42%	Technology	PHOTRONIC	-2.82%	Technology
MICROSOFT	3.41%	Technology	MICROSOFT	2.83%	Technology
SKYWORKS	0.80%	Technology	SKYWORKS	0.65%	Technology
SOLUTIONS			SOLUTIONS		
FIRST	10.60%	Finance	FIRST	10.20%	Finance
CTZN.BCSH.A			CTZN.BCSH.A		
May	Weight	Sector	June	Weight	Sector
AMGEN	0.94%	Healthcare	AMGEN	-0.80%	Healthcare
APPLE	0.50%	Technology	APPLE	-1.03%	Technology
ASTEC	0.32%	Industrials	ASTEC	0.57%	Industrials
INDUSTRIES			INDUSTRIES		
ASTRONICS	1.23%	Industrials	ASTRONICS	-0.17%	Industrials
AXOGEN	0.55%	Healthcare	AXOGEN	0.08%	Healthcare
BALCHEM	-0.20%	Basic Materials	BALCHEM	0.36%	Basic Materials
CVB FINCIAL	-1.66%	Finance	CVB FINCIAL	4.57%	Finance
DIODES	-0.09%	Technology	DIODES	0.08%	Technology
DMC GLOBAL	0.88%	Energy	DMC GLOBAL	0.09%	Energy
ESCALADE	-0.08%	Consumer	ESCALADE	0.47%	Consumer
		Discretionary			Discretionary
FASTEL	-0.64%	Consumer	FASTEL	-2.21%	Consumer
		Discretionary			Discretionary
GENTEX	-2.62%	Consumer	GENTEX	-0.71%	Consumer
		Discretionary			Discretionary
HASBRO	-5.21%	Consumer	HASBRO	-2.82%	Consumer
		Discretionary			Discretionary

JACK HENRY AND ASSOCIATES	-3.59%	Industrials	JACK HENRY AND ASSOCIATES	0.02%	Industrials
LSI INDUSTRIES	0.24%	Industrials	LSI INDUSTRIES	-0.24%	Industrials
LIFEWAY FOODS	-5.83%	Consumer Staples	LIFEWAY FOODS	0.07%	Consumer Staples
LIGHT WONDER	-2.56%	Consumer Discretionary	LIGHT WONDER	-0.40%	Consumer Discretionary
MARTEN TRANSPORT	-0.80%	Industrials	MARTEN TRANSPORT	0.78%	Industrials
MERCER INTL. MONSTER BEVERAGE	-0.43%	Basic Materials	MERCER INTL. MONSTER BEVERAGE	-0.91%	Basic Materials
NAPCO SECURITY TECHS.	-	Consumer Staples	NAPCO SECURITY TECHS.	0.38%	Consumer Staples
NEOGEN	13.49%	Industrials	NEOGEN	0.56%	Industrials
NORTHERN TRUST	0.45%	Industrials	NORTHERN TRUST	0.40%	Healthcare
PAM	0.02%	Healthcare	PAM	-0.28%	Finance
TRANSPORTATION SVS.	-0.07%	Finance	TRANSPORTATION SVS.	0.32%	Industrials
PATRICK INDUSTRIES	-1.74%	Industrials	PATRICK INDUSTRIES	0.32%	Industrials
RESEARCH FRONTIERS	-4.38%	Industrials	RESEARCH FRONTIERS	-0.19%	Industrials
ROSS STORES	-0.35%	Technology	ROSS STORES	-0.08%	Technology
ROYAL GOLD	0.01%	Consumer Discretionary	ROYAL GOLD	-0.87%	Consumer Discretionary
SKYWEST	7.35%	Basic Materials	SKYWEST	0.29%	Basic Materials
SUNOPTA (NAS)	1.72%	Consumer Discretionary	SUNOPTA (NAS)	-0.75%	Consumer Discretionary
T ROWE PRICE GROUP	-0.52%	Consumer Staples	T ROWE PRICE GROUP	0.07%	Consumer Staples
COOPER COS.	2.49%	Finance	COOPER COS.	-2.30%	Finance
TWIN DISC	43.73%	Healthcare	TWIN DISC	-0.63%	Healthcare
US ENERGY	13.41%	Industrials	US ENERGY	9.17%	Industrials
VIATRIS	-1.83%	Energy	VIATRIS	0.37%	Energy
WAFD	5.21%	Healthcare	WAFD	-1.27%	Healthcare
XOMA	3.84%	Finance	XOMA	-2.54%	Finance
WESTERN DIGITAL	7.38%	Healthcare	WESTERN DIGITAL	-0.56%	Healthcare
DATA I/O	3.24%	Technology	DATA I/O	1.38%	Technology
HEALTHCARE SERVICES GROUP	9.71%	Technology	HEALTHCARE SERVICES GROUP	2.59%	Technology
	20.14%	Healthcare		6.42%	Healthcare

G-III APPAREL GROUP	4.80%	Consumer Discretionary	G-III APPAREL GROUP	0.50%	Consumer Discretionary
SUPERIOR GROUP OF COMPANIES	-0.50%	Consumer Discretionary	SUPERIOR GROUP OF COMPANIES	34.47%	Consumer Discretionary
SLM	0.33%	Finance	SLM	20.15%	Finance
MIDDLEBY	0.06%	Industrials	MIDDLEBY	3.71%	Industrials
DONEGAL GP.'B'	1.67%	Finance	DONEGAL GP.'B'	9.10%	Finance
DESTINATION XL GROUP	0.81%	Consumer Discretionary	DESTINATION XL GROUP	2.40%	Consumer Discretionary
SHYFT GROUP	8.76%	Industrials	SHYFT GROUP	6.51%	Industrials
UNITED GUARDIAN	1.91%	Basic Materials	UNITED GUARDIAN	5.04%	Basic Materials
PERMA-PIPE	2.43%	Basic Materials	PERMA-PIPE	2.91%	Basic Materials
INTL.HDG.			INTL.HDG.		
HAWKINS	2.47%	Basic Materials	HAWKINS	4.94%	Basic Materials
July	Weight	Sector	August	Weight	Sector
ALLIENT	0.69%	Industrials	ALLIENT	0.62%	Industrials
BIOLIFE SOLUTIONS	0.85%	Healthcare	BIOLIFE SOLUTIONS	0.79%	Healthcare
TRANSCAT	1.65%	Industrials	TRANSCAT	1.56%	Industrials
COGNEX	0.24%	Industrials	COGNEX	0.14%	Industrials
FREQUENCY ELECTRONICS	1.91%	Industrials	FREQUENCY ELECTRONICS	1.87%	Industrials
LATTICE SEMICONDUCTOR	-1.04%	Technology	LATTICE SEMICONDUCTOR	-1.20%	Technology
TERADYNE (XSC)	-1.11%	Technology	TERADYNE (XSC)	-1.28%	Technology
SEMTECH	0.19%	Technology	SEMTECH	0.13%	Technology
ELECTRONIC ARTS	-1.34%	Consumer Discretionary	ELECTRONIC ARTS	-1.33%	Consumer Discretionary
ANALOG DEVICES	-0.75%	Technology	ANALOG DEVICES	-0.85%	Technology
HOST HOTELS & RESORTS REIT	3.28%	Real Estate	HOST HOTELS & RESORTS REIT	3.09%	Real Estate
SEI INVESTMENTS	4.53%	Finance	SEI INVESTMENTS	4.02%	Finance
PAYCHEX	2.34%	Industrials	PAYCHEX	2.27%	Industrials
LAM RESEARCH	-1.20%	Technology	LAM RESEARCH	-1.16%	Technology
DENTSPLY SIRONA	7.36%	Healthcare	DENTSPLY SIRONA	7.41%	Healthcare
ADOBE (NAS)	-0.82%	Technology	ADOBE (NAS)	-0.96%	Technology
WENDY'S CLASS A	2.64%	Consumer Discretionary	WENDY'S CLASS A	2.62%	Consumer Discretionary
INTEL	2.29%	Technology	INTEL	2.12%	Technology

KLA	-0.70%	Technology	KLA	-0.69%	Technology
FIFTH THIRD	8.49%	Finance	FIFTH THIRD	8.16%	Finance
BANCORP			BANCORP		
ERICSSON 'B'	-0.96%	Telecommunic	ERICSSON 'B'	-1.04%	Telecommunic
ADR 1:1		ation	ADR 1:1		ation
ZIONS	8.44%	Finance	ZIONS	8.68%	Finance
BANCORP.			BANCORP.		
KULICKE &	-0.73%	Technology	KULICKE &	-0.67%	Technology
SOFFA INDS.			SOFFA INDS.		
TEXAS	0.55%	Technology	TEXAS	0.70%	Technology
INSTRUMENTS			INSTRUMENTS		
REPLIGEN	0.45%	Healthcare	REPLIGEN	0.46%	Healthcare
VOXX	0.76%	Consumer	VOXX	0.76%	Consumer
INTERNATIONA		Discretionary	INTERNATIONA		Discretionary
L 'A'			L 'A'		
LEONARDO DRS	0.43%	Industrials	LEONARDO DRS	0.44%	Industrials
CADIZ	1.01%	Utilities	COMCAST A	0.47%	Telecommunic
			CADIZ	0.97%	Utilities
COMCAST A	0.38%	Telecommunic			
		ation			
CALAMP	0.74%	Telecommunic	CALAMP	0.66%	Telecommunic
		ation			ation
MICRON	0.30%	Technology	MICRON	0.46%	Technology
TECHNOLOGY			TECHNOLOGY		
1ST SOURCE	12.04%	Finance	1ST SOURCE	12.28%	Finance
PLEXUS	1.72%	Technology	PLEXUS	1.74%	Technology
COHU	2.18%	Technology	COHU	2.18%	Technology
PTC	-1.87%	Technology	PTC	-1.83%	Technology
NATIONAL	4.99%	Finance	NATIONAL	5.11%	Finance
WSTN.LF.GP.'A'			WSTN.LF.GP.'A'		
VODAFONE	6.02%	Telecommunic	AVIS BUDGET	0.18%	Consumer
GP.SPN.ADR		ation	GROUP		Discretionary
1:10					
AVIS BUDGET	0.03%	Consumer	VODAFONE	6.13%	Telecommunic
GROUP		Discretionary	GP.SPN.ADR		ation
			1:10		
US GOLD	1.21%	Basic Materials	US GOLD	1.09%	Basic Materials
JOHNSON	5.10%	Consumer	JOHNSON	5.03%	Consumer
OUTDOORS 'A'		Discretionary	OUTDOORS 'A'		Discretionary
NEONODE	0.31%	Technology	NEONODE	0.27%	Technology
DOMINARI	0.87%	Healthcare	DOMINARI	0.90%	Healthcare
HOLDINGS			HOLDINGS		
GT BIOPHARMA	0.21%	Healthcare	GT BIOPHARMA	0.23%	Healthcare
ABEONA	0.59%	Healthcare	ABEONA	0.57%	Healthcare
THERAPEUTICS			THERAPEUTICS		
THERMOGENESI	0.85%	Healthcare	THERMOGENESI	0.88%	Healthcare
S HOLDINGS			S HOLDINGS		

AUTOMATIC DATA PROC.	11.53%	Industrials	AUTOMATIC DATA PROC.	12.04%	Industrials
PHOTRONIC	-2.30%	Technology	PHOTRONIC	-2.17%	Technology
MICROSOFT	3.94%	Technology	MICROSOFT	4.24%	Technology
SKYWORKS SOLUTIONS	0.43%	Technology	SKYWORKS SOLUTIONS	0.43%	Technology
FIRST CTZN.BCSH.A	11.26%	Finance	FIRST CTZN.BCSH.A	11.52%	Finance
September	Weight	Sector	October	Weight	Sector
AMGEN	0.82%	Healthcare	AMGEN	0.83%	Healthcare
APPLE	-0.14%	Technology	APPLE	-0.15%	Technology
ASTEC INDUSTRIES	0.96%	Industrials	ASTEC INDUSTRIES	1.16%	Industrials
ASTRONICS	0.19%	Industrials	ASTRONICS	0.23%	Industrials
AXOGEN	0.52%	Healthcare	AXOGEN	0.55%	Healthcare
BALCHEM	1.27%	Basic Materials	BALCHEM	1.34%	Basic Materials
CVB FINCIAL	6.80%	Finance	CVB FINCIAL	7.09%	Finance
DIODES	0.28%	Technology	DIODES	0.26%	Technology
DMC GLOBAL	0.39%	Energy	DMC GLOBAL	0.43%	Energy
ESCALADE	1.34%	Consumer Discretionary	ESCALADE	1.36%	Consumer Discretionary
FASTEL	-0.28%	Consumer Discretionary	FASTEL	-0.28%	Consumer Discretionary
GENTEX	-0.25%	Consumer Discretionary	GENTEX	-0.25%	Consumer Discretionary
HASBRO	0.88%	Consumer Discretionary	HASBRO	0.90%	Consumer Discretionary
JACK HENRY AND ASSOCIATES	0.83%	Industrials	JACK HENRY AND ASSOCIATES	0.81%	Industrials
LSI INDUSTRIES	1.34%	Industrials	LSI INDUSTRIES	1.51%	Industrials
LIFEWAY FOODS	0.22%	Consumer Staples	LIFEWAY FOODS	0.25%	Consumer Staples
LIGHT WONDER	-0.09%	Consumer Discretionary	LIGHT WONDER	-0.06%	Consumer Discretionary
MARTEN TRANSPORT	1.90%	Industrials	MARTEN TRANSPORT	1.91%	Industrials
MERCER INTL.	0.59%	Basic Materials	MERCER INTL.	0.58%	Basic Materials
MONSTER BEVERAGE	0.58%	Consumer Staples	MONSTER BEVERAGE	0.60%	Consumer Staples
NAPCO SECURITY	1.07%	Industrials	NAPCO SECURITY	1.17%	Industrials
TECHS.			TECHS.		
NEOGEN	1.01%	Healthcare	NEOGEN	1.04%	Healthcare
NORTHERN TRUST	2.12%	Finance	NORTHERN TRUST	2.66%	Finance

PAM	0.36%	Industrials	PAM	0.34%	Industrials
TRANSPORTATI ON SVS.			TRANSPORTATI ON SVS.		
PATRICK	0.77%	Industrials	PATRICK	0.88%	Industrials
INDUSTRIES			INDUSTRIES		
RESEARCH	0.22%	Technology	RESEARCH	0.38%	Technology
FRONTIERS			FRONTIERS		
ROSS STORES	0.22%	Consumer Discretionary	ROSS STORES	0.42%	Consumer Discretionary
ROYAL GOLD	0.36%	Basic Materials	ROYAL GOLD	0.35%	Basic Materials
SKYWEST	-0.27%	Consumer Discretionary	SKYWEST	-0.27%	Consumer Discretionary
SUNOPTA (NAS)	0.10%	Consumer Staples	SUNOPTA (NAS)	0.11%	Consumer Staples
T ROWE PRICE GROUP	-1.40%	Finance	T ROWE PRICE GROUP	-1.38%	Finance
COOPER COS.	-0.09%	Healthcare	COOPER COS.	-0.08%	Healthcare
TWIN DISC	17.26%	Industrials	TWIN DISC	17.73%	Industrials
US ENERGY	0.60%	Energy	US ENERGY	0.67%	Energy
VIATRIS	0.64%	Healthcare	VIATRIS	0.89%	Healthcare
WAFD	2.29%	Finance	WAFD	2.52%	Finance
XOMA	-0.47%	Healthcare	XOMA	-0.45%	Healthcare
WESTERN DIGITAL	0.19%	Technology	WESTERN DIGITAL	0.21%	Technology
DATA I/O	1.69%	Technology	DATA I/O	1.75%	Technology
HEALTHCARE SERVICES GROUP	3.89%	Healthcare	HEALTHCARE SERVICES GROUP	3.76%	Healthcare
G-III APPAREL GROUP	0.14%	Consumer Discretionary	G-III APPAREL GROUP	0.14%	Consumer Discretionary
SUPERIOR GROUP OF COMPANIES	20.81%	Consumer Discretionary	SUPERIOR GROUP OF COMPANIES	19.44%	Consumer Discretionary
SLM	10.33%	Finance	SLM	9.97%	Finance
MIDDLEBY	2.02%	Industrials	MIDDLEBY	1.87%	Industrials
DONEGAL GP.'B'	5.31%	Finance	DONEGAL GP.'B'	5.00%	Finance
DESTINATION XL GROUP	1.11%	Consumer Discretionary	DESTINATION XL GROUP	1.08%	Consumer Discretionary
SHYFT GROUP	3.40%	Industrials	SHYFT GROUP	2.88%	Industrials
UNITED GUARDIAN	3.03%	Basic Materials	UNITED GUARDIAN	2.78%	Basic Materials
PERMA-PIPE	1.98%	Basic Materials	PERMA-PIPE	2.07%	Basic Materials
INTL.HDG. HAWKINS	3.15%	Basic Materials	INTL.HDG. HAWKINS	3.02%	Basic Materials
November	Weight	Sector	December	Weight	Sector

AMGEN	-0.13%	Healthcare	PATRICK INDUSTRIES	0.55%	Industrials
APPLE	-0.82%	Technology	AMGEN	0.31%	Healthcare
ASTEC INDUSTRIES	0.90%	Industrials	APPLE	-0.49%	Technology
ASTRONICS	-0.11%	Industrials	ASTEC INDUSTRIES	0.99%	Industrials
AXOGEN	0.22%	Healthcare	ASTRONICS	0.11%	Industrials
BALCHEM	0.55%	Basic Materials	AXOGEN	0.34%	Healthcare
CVB FINCIAL	5.09%	Finance	BALCHEM	0.88%	Basic Materials
DIODES	-0.12%	Technology	CVB FINCIAL	6.04%	Finance
DMC GLOBAL	-0.07%	Energy	DIODES	-0.01%	Technology
ESCALADE	0.79%	Consumer Discretionary	DMC GLOBAL	0.09%	Energy
FASTEL	-1.22%	Consumer Discretionary	ESCALADE	1.03%	Consumer Discretionary
GENTEX	-0.54%	Consumer Discretionary	FASTEL	-0.70%	Consumer Discretionary
HASBRO	-1.63%	Consumer Discretionary	GENTEX	-0.53%	Consumer Discretionary
JACK HENRY AND ASSOCIATES	0.69%	Industrials	HASBRO	-0.60%	Consumer Discretionary
LSI INDUSTRIES	0.62%	Industrials	JACK HENRY AND ASSOCIATES	0.76%	Industrials
LIFEWAY FOODS	0.09%	Consumer Staples	LSI INDUSTRIES	1.01%	Industrials
LIGHT WONDER	-0.43%	Consumer Discretionary	LIFEWAY FOODS	0.12%	Consumer Staples
MARTEN TRANSPORT	0.97%	Industrials	LIGHT WONDER	-0.26%	Consumer Discretionary
MERCER INTL.	-0.57%	Basic Materials	MARTEN TRANSPORT	1.45%	Industrials
MONSTER BEVERAGE	0.43%	Consumer Staples	MERCER INTL.	-0.04%	Basic Materials
NAPCO SECURITY TECHS.	0.83%	Industrials	MONSTER BEVERAGE	0.48%	Consumer Staples
NEOGEN	0.60%	Healthcare	NAPCO SECURITY TECHS.	1.02%	Industrials
NORTHERN TRUST	0.09%	Finance	NEOGEN	0.80%	Healthcare
PAM TRANSPORTATION SVS.	0.29%	Industrials	NORTHERN TRUST	1.36%	Finance

PATRICK INDUSTRIES	0.15%	Industrials	PAM TRANSPORTATION SVS.	0.33%	Industrials
RESEARCH FRONTIERS	0.18%	Technology	RESEARCH FRONTIERS	0.28%	Technology
ROSS STORES	-0.39%	Consumer Discretionary	ROSS STORES	0.05%	Consumer Discretionary
ROYAL GOLD	0.25%	Basic Materials	ROYAL GOLD	0.27%	Basic Materials
SKYWEST	-0.64%	Consumer Discretionary	SKYWEST	-0.48%	Consumer Discretionary
SUNOPTA (NAS)	-0.06%	Consumer Staples	SUNOPTA (NAS)	-0.01%	Consumer Staples
T ROWE PRICE GROUP	-2.15%	Finance	T ROWE PRICE GROUP	-1.72%	Finance
COOPER COS.	-0.46%	Healthcare	COOPER COS.	-0.32%	Healthcare
TWIN DISC	10.34%	Industrials	TWIN DISC	13.62%	Industrials
US ENERGY	0.42%	Energy	US ENERGY	0.55%	Energy
VIATRIS	-0.02%	Healthcare	VIATRIS	0.49%	Healthcare
WAFD	-0.80%	Finance	WAFD	0.87%	Finance
XOMA	-0.62%	Healthcare	XOMA	-0.58%	Healthcare
WESTERN DIGITAL	1.04%	Technology	WESTERN DIGITAL	0.54%	Technology
DATA I/O	2.43%	Technology	DATA I/O	2.09%	Technology
HEALTHCARE SERVICES GROUP	6.00%	Healthcare	HEALTHCARE SERVICES GROUP	5.14%	Healthcare
G-III APPAREL GROUP	0.51%	Consumer Discretionary	G-III APPAREL GROUP	0.36%	Consumer Discretionary
SUPERIOR GROUP OF COMPANIES	28.86%	Consumer Discretionary	SUPERIOR GROUP OF COMPANIES	24.22%	Consumer Discretionary
SLM	17.93%	Finance	SLM	14.45%	Finance
MIDDLEBY	3.03%	Industrials	MIDDLEBY	2.58%	Industrials
DONEGAL GP.'B'	7.80%	Finance	DONEGAL GP.'B'	6.36%	Finance
DESTINATION XL GROUP	2.16%	Consumer Discretionary	DESTINATION XL GROUP	1.75%	Consumer Discretionary
SHYFT GROUP	4.83%	Industrials	SHYFT GROUP	3.77%	Industrials
UNITED GUARDIAN	4.72%	Basic Materials	UNITED GUARDIAN	3.85%	Basic Materials
PERMA-PIPE	3.17%	Basic Materials	PERMA-PIPE	2.71%	Basic Materials
INTL.HDG.			INTL.HDG.		
HAWKINS	4.84%	Basic Materials	HAWKINS	4.12%	Basic Materials

Appendix A3: ML results of all the companies in the dataset from the 2000 testing period. For the total row, percentages (including R²) are averaged, and the other columns are medians of the scores.

Company	Accuracy(%)	R²	RMSE	MAE	MAPE(%)	SMAPE(%)
<i>Total</i>	<i>44.11</i>	<i>0.45</i>	<i>1.28</i>	<i>1.11</i>	<i>10.82</i>	<i>28.14</i>
1ST SOURCE	66.67	0.75	0.70	0.55	3.65	12.79
ABEONA THERAPEUTICS	50.00	0.87	4.66E+03	3.42E+03	9.68	53.09
ADOBE (NAS)	67	0.68	3.69	3.30	10.99	36.46
ADVANCED MICRO DEVICES	91.67	0.67	5.68	4.89	15.58	51.59
AGILYSYS	41.67	0.80	0.75	0.60	4.27	16.91
ALICO	50	0.11	0.45	0.34	2.06	3.19
ALLIANT ENERGY (XSC)	58.33	0.00	1.46	1.41	9.58	13.35
ALLIENT	75.00	0.00	2.41	2.02	46.27	88.68
AMER.ELEC.PWR.	58	0.25	4.17	3.74	10.05	20.11
AMER.SOFTWARE CL.A	66.67	0.54	3.14	2.10	26.35	73.30
AMER.WOODMARK	58.33	0.82	0.52	0.42	4.62	16.78
AMERISERV FINL.	50.00	0.25	0.60	0.54	12.56	19.73
AMGEN	0.00	0.00	8.23	7.85	11.90	18.64
AMTECH SYS.	66.67	0.65	2.63	1.81	20.13	63.73
ANALOG DEVICES	83.33	0.87	5.51	4.38	6.04	32.75
ANIXA BIOSCIENCES	83.33	0.65	9.54	7.47	16.58	54.07
APA	58.33	0.37	3.26	2.93	12.12	29.62
APOGEE ENTERPRISES	41.67	0.00	2.43	2.38	54.01	54.14
APPLE	0.00	0.86	0.11	0.09	18.49	51.50
APPLIED MATS.	83.33	0.96	2.01	1.54	4.16	41.34
ARK RESTAURANTS	33.33	0.55	0.56	0.46	6.57	14.51
ARROW FINANCIAL	41.67	0.84	0.25	0.22	3.04	10.87
ASCENT INDUSTRIES	41.67	0.60	0.65	0.57	8.74	19.19
ASTEC INDUSTRIES	0.00	0.96	1.33	1.03	4.90	50.98
ASTRONICS	0.00	0.66	0.06	0.04	4.64	13.68
ASTRONOVA	66.67	0.00	0.73	0.54	16.17	18.09
ATLANTIC AMERICAN	50.00	0.59	0.22	0.18	7.75	16.58
ATRION	41.67	0.00	1.52	1.40	11.36	16.14
AUTODESK	66.67	0.85	0.83	0.62	7.26	33.34
AUTOMATIC DATA PROC.	41.67	0.07	5.18	4.99	11.23	21.58
AVIS BUDGET GROUP	41.67	0.96	1.01	0.79	4.67	34.17
AVNET	66.67	0.79	2.28	1.93	6.28	24.57
AXOGEN	0.00	0.12	0.64	0.44	15.57	25.43
BAKER HUGHES A	75.00	0.04	3.67	3.44	14.68	29.99
BALCHEM	16.67	0.01	0.33	0.29	12.82	25.51
BASSETT FRTR.INDS.	58.33	0.73	0.67	0.49	3.95	11.83
BIOLIFE SOLUTIONS	33.33	0.66	4.94	3.68	16.52	58.49
BIO-TECHNE	50.00	0.75	1.33	1.13	9.78	34.37
BRIDGFORD FOODS	50.00	0.13	1.51	1.29	10.73	22.97
CSP	50.00	0.23	1.21	0.85	22.09	40.28
CADENCE DESIGN SYS.	41.67	0.63	1.99	1.74	7.77	22.90

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
CADIZ	50.00	0.56	25.19	23.60	10.31	27.15
CALAMP	58.33	0.90	77.50	60.51	8.59	54.33
CAPITAL SOUTHWEST	58.33	0.33	0.25	0.20	3.94	7.58
CASEY'S GENERAL STORES	50.00	0.51	0.91	0.80	6.85	16.27
CELLDEX THERAPEUTICS	58.33	0.82	182.16	148.44	10.04	44.35
CINCINNATI FINL.	66.67	0.00	3.80	3.63	11.00	20.25
CINTAS	33.33	0.61	4.16	3.77	9.04	26.19
CIRRUS LOGIC	58.33	0.67	5.33	4.35	16.83	50.87
CITY HLDG.	83.33	0.85	1.20	1.03	14.05	42.40
COCA COLA	58.33	0.48	4.14	3.85	8.44	21.24
CONSOLIDATED						
COCA COLA EUROPACIFIC	50.00	0.50	1.51	1.24	8.09	19.71
PARTNERS						
COGNEX	75.00	0.91	0.89	0.73	6.47	43.40
COHU	75.00	0.91	4.03	3.25	10.63	64.89
COMCAST A	41.67	0.45	1.02	0.91	6.99	16.44
COMMERCE BCSH.	41.67	0.73	0.57	0.44	3.99	12.88
COMTECH TELECOM.	41.67	0.79	0.58	0.48	6.76	27.15
CRACKER BARREL OLD	41.67	0.59	2.30	1.86	12.06	35.45
CTRY. STORE						
CSX	33.33	0.00	0.47	0.45	35.38	38.46
CVB FINANCIAL	16.67	0.43	0.28	0.25	4.94	10.88
DATA I/O	58.33	0.00	2.12	2.00	47.19	81.55
DENTSPLY SIRONA	58.33	0.00	1.78	1.66	15.36	26.14
DESTINATION XL GROUP	33.33	0.00	0.50	0.39	19.03	33.80
DIGI INTERNATIONAL	50.00	0.85	0.90	0.80	11.42	34.64
DIODES	0.00	0.78	0.69	0.56	9.47	39.15
DISTRIBUTION SOLUTIONS	58.33	0.00	0.96	0.87	6.99	9.83
GROUP						
DLH HOLDINGS	25.00	0.60	2.98	2.26	12.21	33.33
DMC GLOBAL	8.33	0.00	0.30	0.26	44.87	44.10
DOMINARI HOLDINGS	75.00	0.84	2.00E+05	1.70E+05	9.84	39.25
DONEGAL GP.'B'	66.67	0.01	0.86	0.64	10.30	18.42
DORCHESTER MINERALS	33.33	0.08	2.14	1.81	13.11	28.49
DYNATRONICS	33.33	0.00	5.55	4.84	17.00	33.35
SCRIPPS E W 'A'	33.33	0.00	0.70	0.65	11.76	17.68
EASTERN	50.00	0.58	0.49	0.40	4.12	10.07
ELECTRONIC ARTS	41.67	0.75	1.75	1.42	6.59	25.73
ERICSSON 'B' ADR 1:1	83.33	0.78	7.03	6.26	9.00	35.01
ESCALADE	8.33	0.00	0.46	0.42	13.54	26.81
EVERGY	41.67	0.39	2.24	1.83	9.23	20.32
EXELON	50.00	0.21	3.01	2.67	14.72	28.99
FASTENAL	0.00	0.00	0.60	0.54	15.05	25.87
FIFTH THIRD BANCORP	33.33	0.41	4.69	4.44	9.61	21.65
FIRST CTZN.BCSH.A	50.00	0.00	6.94	6.73	10.23	16.33
FIRST FINL.BANC.	41.67	0.77	0.55	0.44	2.68	8.81

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
FIRST MERCHANTS	41.67	0.18	1.27	1.13	5.72	11.34
FLEXSTEEL INDS.	50.00	0.51	0.58	0.50	4.06	8.38
FONAR	75.00	0.62	8.83	7.61	12.53	34.52
FOSTER (LB)	66.67	0.00	0.67	0.58	17.32	24.37
FRANKLIN ELECTRIC	50.00	0.00	0.61	0.59	6.96	9.48
FREQUENCY ELECTRONICS	41.67	0.48	4.40	3.87	17.99	46.01
FRP HOLDINGS	50.00	0.00	0.56	0.50	22.91	27.54
FULTON FINANCIAL	58.33	0.00	1.49	1.36	12.68	23.12
GEN DIGITAL	66.67	0.94	0.22	0.16	4.11	33.35
GENTEX	0.00	0.93	0.35	0.27	3.83	28.07
G-III APPAREL GROUP	50.00	0.35	0.34	0.28	14.66	36.56
GOODYEAR TIRE & RUB.	58.33	0.87	1.30	1.02	4.33	21.41
GREAT STHN.BANCORP	41.67	0.83	0.47	0.38	4.07	16.32
GT BIOPHARMA	50.00	0.93	1.57E+07	9.70E+06	11.18	87.18
HASBRO	0.00	0.90	0.87	0.73	5.09	26.56
HAWKINS	25.00	0.27	0.10	0.07	1.83	3.41
HEALTHCARE SERVICES GROUP	50.00	0.00	0.41	0.38	38.44	41.48
HEARTLAND EXPRESS	41.67	0.12	0.58	0.48	10.28	20.65
HELEN OF TROY	58.33	0.38	0.72	0.65	11.12	20.28
HERON THERAPEUTICS	58.33	0.72	34.99	30.80	10.46	36.15
HINGHAM INSTN.FOR SVG.	33.33	0.57	0.75	0.68	4.78	12.57
HONEYWELL INTL.	75.00	0.87	2.72	2.17	4.62	25.21
HOST HOTELS & RESORTS REIT	58.33	0.00	1.30	1.23	12.03	18.83
HUNTINGTON BCSH.	50.00	0.87	0.68	0.53	3.13	14.97
HURCO COMPANIES	58.33	0.00	0.50	0.41	9.98	15.36
ICAD	33.33	0.72	2.09	1.60	11.58	43.05
IMMUCELL	50.00	0.69	0.66	0.47	12.23	41.88
INDEPENDENT BANK MASS.	41.67	0.54	0.73	0.59	4.82	12.08
INDEPENDENT BANK	58.33	0.49	8.16	7.74	10.66	25.56
INGLES MARKETS 'A'	33.33	0.57	0.40	0.32	3.18	6.80
INTEL	66.67	0.89	4.07	3.55	6.32	34.28
INTER PARFUMS	41.67	0.00	0.41	0.37	10.15	16.88
INTERDIGITAL	66.67	0.94	2.52	1.36	8.08	67.83
INTERFACE	41.67	0.36	1.55	1.41	26.75	39.56
INTERGROUP	58.33	0.00	2.31	2.22	16.87	24.78
INVESTORS TITLE	33.33	0.86	0.77	0.55	4.27	17.28
ITERIS	50.00	0.94	0.98	0.72	4.88	38.18
HUNT JB TRANSPORT SVS.	58.33	0.32	0.33	0.27	7.17	14.55
J & J SNACK FOODS	25.00	0.45	0.81	0.69	9.47	17.44
JACK HENRY AND ASSOCIATES	0.00	0.36	3.74	3.48	15.68	36.28
JOHNSON OUTDOORS 'A'	41.67	0.34	0.76	0.61	8.11	17.31
KELLY SERVICES 'A'	50.00	0.00	1.20	1.02	4.22	6.74

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
KEWAUNEE SCIENTIFIC	58.33	0.00	1.43	1.31	10.77	17.58
KEY-TRONIC	58.33	0.59	0.47	0.38	10.85	22.60
KLA	66.67	0.89	4.48	3.60	7.93	46.73
KOSS	66.67	0.77	0.49	0.36	6.96	28.35
KULICKE & SOFFA INDS.	50.00	0.95	2.24	1.70	6.41	61.43
LSI INDUSTRIES	0.00	0.82	0.50	0.42	4.12	15.60
LAKELAND INDS.	41.67	0.00	0.74	0.62	16.21	29.49
LAM RESEARCH	75.00	0.93	3.10	2.38	6.76	55.30
LANCASTER COLONY	41.67	0.92	0.94	0.73	2.81	16.10
LATTICE SEMICONDUCTOR	58.33	0.82	2.66	2.23	7.29	32.79
LEE ENTERPRISES	41.67	0.30	22.51	21.70	8.47	18.56
LEONARDO DRS	58.33	0.82	4.40	2.92	9.12	50.09
LIFEWAY FOODS	8.33	0.74	0.08	0.07	4.59	13.46
LIGHT WONDER	0.00	0.41	0.47	0.42	10.54	24.84
MARTEN TRANSPORT	0.00	0.00	0.12	0.10	9.29	14.54
MATTEL	33.33	0.65	0.80	0.66	5.38	14.02
MCGRATH RENTCORP	33.33	0.48	0.44	0.35	4.11	9.09
MERCER INTL.	0.00	0.00	2.28	2.16	26.45	40.80
MESA LABORATORIES	33.33	0.00	0.96	0.84	15.52	27.81
MGE ENERGY	25.00	0.28	0.81	0.66	4.85	10.18
MGP INGREDIENTS	58.33	0.00	0.57	0.49	11.18	18.12
MICRON TECHNOLOGY	58.33	0.83	8.64	7.48	12.68	54.95
MICROSOFT	50.00	0.82	3.65	3.30	8.39	32.83
MIDDLEBY	50.00	0.00	0.12	0.11	10.33	16.85
MIDDLESEX WATER	33.33	0.78	0.34	0.25	1.67	5.75
MILLERKNOLL	66.67	0.26	3.01	2.82	10.39	22.31
MITEK SYSTEMS	58.33	0.95	0.78	0.60	15.33	93.59
MONSTER BEVERAGE	16.67	0.00	0.01	0.00	8.21	10.96
NAPCO SECURITY TECHS.	0.00	0.00	0.03	0.03	7.74	11.26
NATIONAL WSTN.LF.GP.'A'	41.67	0.00	9.07	8.80	11.48	19.15
NATURAL ALTS.INTL.	41.67	0.00	0.65	0.60	32.59	38.15
NATURES SUNSHINE PRODUCTS	75.00	0.38	0.66	0.52	6.30	14.02
NEOGEN	8.33	0.00	0.09	0.08	12.76	19.08
NEONODE	50.00	0.92	2.03E+03	1.65E+03	9.34	65.45
NEWELL BRANDS (XSC)	50.00	0.73	1.50	1.33	5.68	16.80
NEWTEKONE	50.00	0.00	12.63	11.55	36.63	63.79
NORDSON	50.00	0.26	1.57	1.36	10.07	21.86
NORTHERN TRUST	0.00	0.34	9.08	8.68	11.99	27.07
OLD NATIONAL BANCORP	58.33	0.00	2.14	2.06	8.91	13.90
ORASURE TECHS.	41.67	0.00	3.50	3.20	27.99	46.87
OTTER TAIL	50.00	0.00	2.24	1.95	8.62	14.60
PAM TRANSPORTATION SVS.	0.00	0.12	0.18	0.17	6.79	13.36
PACCAR	50.00	0.16	0.33	0.27	4.56	8.55
PARAMOUNT GLOBAL A	41.67	0.05	5.20	4.87	10.13	19.05

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
PARK OHIO HOLDINGS	66.67	0.82	0.66	0.48	7.11	23.19
PATRICK INDUSTRIES	8.33	0.68	0.42	0.38	13.17	27.70
PAYCHEX	50.00	0.59	5.62	5.27	12.83	34.68
PEPSICO	33.33	0.10	4.98	4.80	11.53	22.92
PERMA-PIPE INTL.HDG.	75.00	0.41	0.41	0.32	9.52	16.25
PHOTRONIC	58.33	0.82	2.78	2.29	7.89	33.70
PINEAPPLE ENERGY	58.33	0.56	4.63	4.11	11.52	31.54
PLEXUS	75.00	0.72	8.55	7.48	15.44	53.90
POPULAR	25.00	0.54	7.86	7.35	6.35	15.91
POTLATCHDELTIC	41.67	0.46	2.36	2.19	7.15	16.77
POWELL INDUSTRIES	50.00	0.00	1.90	1.69	17.28	28.34
PSYCHEMEDICS	33.33	0.00	2.10	2.04	10.29	14.29
PTC	41.67	0.95	3.26	2.01	5.25	46.50
RCM TECHS.	41.67	0.95	0.87	0.74	13.79	69.10
REGIS	33.33	0.27	29.84	28.35	9.64	20.63
REPLIGEN	58.33	0.33	2.05	1.61	21.44	47.82
RESEARCH FRONTIERS	0.00	0.16	5.03	4.55	19.03	38.03
RICHARDSON ELECTRONICS	58.33	0.00	2.99	2.71	19.85	40.37
ROSS STORES	0.00	0.68	0.20	0.15	6.74	21.71
ROYAL GOLD	8.33	0.82	0.21	0.16	4.72	19.18
SEACOAST BKG.OF FLA.	25.00	0.00	2.45	2.39	5.99	8.92
SEI INVESTMENTS	41.67	0.85	2.21	1.77	11.28	52.71
SELECTIVE IN.GP.	41.67	0.17	0.88	0.75	7.91	15.35
SEMTECH	91.67	0.94	2.33	1.81	5.29	37.69
SENECA FOODS	41.67	0.07	1.01	0.90	7.12	13.43
SKYWEST	0.00	0.66	2.57	2.38	11.01	33.64
SKYWORKS SOLUTIONS	66.67	0.72	5.93	4.89	10.48	36.80
SLM	16.67	0.79	0.53	0.38	6.98	26.86
STAAR SURGICAL	66.67	0.08	1.83	1.71	12.50	23.97
SUNOPTA (NAS)	8.33	0.38	0.23	0.20	12.68	30.04
SUPERIOR GROUP OF COMPANIES	25.00	0.23	0.32	0.28	6.74	10.62
T ROWE PRICE GROUP	0.00	0.13	1.99	1.84	8.96	18.04
TSR	58.33	0.93	0.46	0.35	2.98	20.33
TERADYNE (XSC)	75.00	0.95	5.28	4.06	6.08	54.97
TEXAS INSTRUMENTS	75.00	0.81	6.25	5.35	8.19	34.74
COOPER COS.	0.00	0.00	0.42	0.40	9.45	15.62
DIXIE GP.'A'	50.00	0.27	1.03	0.89	24.23	36.45
ODP	41.67	0.88	7.98	5.85	5.87	32.67
SHYFT GROUP	25.00	0.00	0.42	0.30	26.40	28.81
THERMOGENESIS HOLDINGS	50.00	0.83	8.63E+03	6.53E+03	7.77	35.86
TRANSCAT	75.00	0.43	0.48	0.39	18.53	31.32
TRUSTCO BANK NY	41.67	0.00	2.98	2.66	5.65	10.17
TRUSTMARK	33.33	0.00	1.48	1.41	7.47	11.74

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
TWIN DISC	0.00	0.00	0.80	0.76	18.43	27.38
US ENERGY	0.00	0.76	15.61	12.38	7.42	28.48
US.LIME & MINERALS	66.67	0.50	0.60	0.47	7.12	14.43
US GOLD	66.67	0.79	2.14E+03	1.84E+03	11.37	41.57
UMB FINANCIAL	50.00	0.00	0.65	0.57	3.35	5.16
UNITED BANKSHARES	41.67	0.38	1.07	0.93	4.60	9.86
UNITED FIRE GROUP	41.67	0.54	0.50	0.40	4.46	9.10
UNITED GUARDIAN	41.67	0.00	0.81	0.77	16.74	24.65
UTAH MEDICAL PRODUCTS	66.67	0.00	0.76	0.71	9.73	13.95
VALLEY NATIONAL	33.33	0.00	1.20	1.08	8.64	15.01
VALUE LINE	41.67	0.00	3.63	3.55	9.93	13.64
VAXART	66.67	0.84	44.16	33.65	7.67	37.63
VIATRIS	0.00	0.09	1.42	1.29	10.85	21.78
VILLAGE SPRMKT.'A'	58.33	0.27	0.12	0.09	2.72	4.65
VIRCO MANUFACTURING	50.00	0.90	0.28	0.20	2.35	13.23
VODAFONE GP.SPN.ADR	50.00	0.76	4.58	4.05	7.50	26.13
1:10						
VOXX INTERNATIONAL 'A'	66.67	0.96	3.23	2.23	7.43	77.80
WD-40	33.33	0.00	1.25	1.14	5.67	9.35
WAFD	0.00	0.67	1.04	0.78	5.88	17.73
WALGREENS BOOTS	33.33	0.69	3.29	2.99	8.78	25.88
ALLIANCE						
WENDY'S CLASS A	41.67	0.00	0.70	0.60	9.11	17.07
WERNER ENTERPRISES	58.33	0.65	0.60	0.43	5.41	14.60
WESBANCO	33.33	0.54	0.80	0.67	2.94	6.55
WESTAMERICA BANCORP.	41.67	0.66	2.68	2.44	8.07	22.69
WESTERN DIGITAL	50.00	0.28	1.03	0.88	16.04	34.29
WSFS FINANCIAL	50.00	0.67	0.13	0.11	2.93	7.12
XCEL ENERGY	58.33	0.45	2.52	2.34	9.84	23.23
XEROX HOLDINGS	75.00	0.90	6.06	5.24	11.49	60.60
XOMA	0.00	0.89	319.03	243.10	9.79	63.09
ZIONS BANCORP.	41.67	0.01	6.09	5.86	11.96	22.36

Appendix B: Results from the 2010 testing period.

Appendix B1: Minimum variance portfolio weight allocations during the 2010 testing period.

Companies	Weight	Sector	Beta
MIND CTI	0.00%	Technology	-0.402
LISATA THERAPEUTICS	1.00%	Healthcare	-0.307
WETOUGH TECHNOLOGY	3.15%	Finance	-0.275
ASURE SOFTWARE	0.00%	Technology	-0.247
URBAN ONE 'A'	0.30%	Consumer Discretionary	-0.242
TECHPRECISION	1.97%	Basic Materials	-0.229
AEMETIS	1.91%	Energy	-0.200
QURATE RETAIL SERIES B	0.15%	Consumer Discretionary	-0.190
NVE	2.26%	Technology	-0.188
LENDINGTREE	3.80%	Finance	-0.187
NETSCOUT SYSTEMS	0.00%	Technology	-0.186
ARK RESTAURANTS	0.30%	Consumer Discretionary	-0.185
CONN'S	0.71%	Consumer Discretionary	-0.181
CREATIVE REALITIES	2.41%	Technology	-0.181
HUB GROUP 'A'	0.00%	Industrials	-0.180
374WATER	1.52%	Industrials	-0.180
VALLEY NATIONAL	0.88%	Finance	-0.172
ELECTRONIC ARTS	0.00%	Consumer Discretionary	-0.168
METHANEX (S)	0.10%	Industrials	-0.158
UNITED FIRE GROUP	7.11%	Finance	-0.158
ANDERSONS	1.64%	Consumer Staples	-0.158
ENTERPRISE BANCORP	6.65%	Finance	-0.156
HOST HOTELS & RESORTS REIT	2.24%	Real Estate	-0.156
GEOSPACE TECHNOLOGIES	0.00%	Energy	-0.154
FASTENAL	0.00%	Consumer Discretionary	-0.153
ANGIODYMICS	1.68%	Healthcare	-0.147
XCEL BRANDS	0.00%	Consumer Discretionary	-0.146
BIG 5 SPTG.GOODS	0.00%	Consumer Discretionary	-0.144
CHILDRENS PLACE	0.97%	Consumer Discretionary	-0.144
FORTRESS BIOTECH	5.49%	Healthcare	-0.143
ADTRAN HOLDINGS	2.27%	Telecommunication	-0.142
NBT BANCORP	0.48%	Finance	-0.142
DMC GLOBAL	1.08%	Energy	-0.141
GALAPAGOS N V SPN.ADR 1:1	2.32%	Healthcare	-0.139
REGIS	2.09%	Consumer Discretionary	-0.137
FRP HOLDINGS	2.90%	Real Estate	-0.135
DALLASNEWS SERIES A	1.26%	Consumer Discretionary	-0.135
MARTIN MIDSTREAM PTNS.	0.22%	Energy	-0.135
CADIZ	10.65%	Utilities	-0.134
AMERICA S CAR MART	9.44%	Consumer Discretionary	-0.134
ZEBRA TECHNOLOGIES 'A'	3.01%	Industrials	-0.133
BANCORP	7.04%	Finance	-0.133
LARGO (NAS)	1.75%	Energy	-0.132

Companies	Weight	Sector	Beta
PATTERSON UTI ENERGY	0.00%	Energy	-0.130
EDESA BIOTECH	1.16%	Healthcare	-0.128
RADWARE	2.05%	Technology	-0.126
NXP SEMICONDUCTORS	0.51%	Technology	-0.126
PALISADE BIO	0.77%	Healthcare	-0.125
TWIN DISC	0.92%	Industrials	-0.124
COLLIERS INTL.GP. (NAS)	3.87%	Real Estate	-0.124

Appendix B2: Portfolio weight allocations per month of the ML portfolio during the 2010 testing period.

January	Weight	Sector	February	Weight	Sector
AMARIN ADR 1:1	1.66%	Healthcare	AMARIN ADR 1:1	3.06%	Healthcare
GILAT	1.95%	Telecommunicati on	GILAT	3.86%	Telecommunicati on
SAPIENS INTL.	2.95%	Technology	SAPIENS INTL.	3.85%	Technology
USIO	0.50%	Industrials	USIO	0.75%	Industrials
SIRIUS XM HOLDINGS	-0.25%	Consumer Discretionary	SIRIUS XM HOLDINGS	0.21%	Consumer Discretionary
SWK HOLDINGS	0.37%	Finance	SWK HOLDINGS	0.92%	Finance
PARK OHIO HOLDINGS	-1.41%	Industrials	PARK OHIO HOLDINGS	-1.01%	Industrials
SUNOPTA (NAS)	2.56%	Consumer Staples	SUNOPTA (NAS)	2.76%	Consumer Staples
SOCKET MOBILE	1.12%	Industrials	SOCKET MOBILE	1.34%	Industrials
VIAVI SOLUTIONS	-1.50%	Telecommunicati on	VIAVI SOLUTIONS	-0.73%	Telecommunicati on
CIVISTA BANCSHARES	17.07%	Finance	CIVISTA BANCSHARES	17.63%	Finance
PURE CYCLE	1.32%	Utilities	PURE CYCLE	1.44%	Utilities
PERMA-FIX ENV.SVS.	6.46%	Utilities	PERMA-FIX ENV.SVS.	6.50%	Utilities
HARMONIC	-1.98%	Telecommunicati on	HARMONIC	-1.83%	Telecommunicati on
KULICKE & SOFFA INDS.	-3.05%	Technology	KULICKE & SOFFA INDS.	-2.83%	Technology
ARROWHEAD PHARMS.	0.15%	Healthcare	ARROWHEAD PHARMS.	0.17%	Healthcare
CENTRAL GDN.& PET	4.37%	Consumer Discretionary	CENTRAL GDN.& PET	4.17%	Consumer Discretionary
IDENTIVE	3.75%	Technology	IDENTIVE	3.77%	Technology
NETSOL TECHS.	0.82%	Technology	NETSOL TECHS.	0.72%	Technology
SCRIPPS E W 'A'	6.43%	Consumer Discretionary	SCRIPPS E W 'A'	6.30%	Consumer Discretionary
EXTREME NETWORKS	-1.11%	Telecommunicati on	EXTREME NETWORKS	-1.34%	Telecommunicati on
AVID BIOSERVICES	-0.17%	Healthcare	AVID BIOSERVICES	0.04%	Healthcare
VERU	3.89%	Consumer Staples	VERU	3.75%	Consumer Staples
EMCORE	-1.76%	Technology	EMCORE	-1.67%	Technology
DAWSON GEOPHYSICAL	1.00%	Energy	DAWSON GEOPHYSICAL	1.02%	Energy
RAMBUS	0.49%	Technology	RAMBUS	0.33%	Technology
TOWER	2.18%	Technology	TOWER	1.68%	Technology
HOLOGIC	3.48%	Healthcare	HOLOGIC	3.52%	Healthcare
DMC GLOBAL	0.10%	Energy	DMC GLOBAL	0.17%	Energy
STEEL CONNECT	-2.27%	Technology	STEEL CONNECT	-2.36%	Technology

LAKELAND FINANCIAL	13.22%	Finance	LAKELAND FINANCIAL	13.02%	Finance
GREAT ELM GROUP	-0.22%	Finance	GREAT ELM GROUP	-0.70%	Finance
AMNEAL PHARMACEUTICALS A	6.44%	Healthcare	AMNEAL PHARMACEUTICALS A	5.83%	Healthcare
ENCORE CAP.GP.	0.74%	Finance	ENCORE CAP.GP.	0.67%	Finance
COGNEX	4.76%	Industrials	COGNEX	4.34%	Industrials
DXP ENTS.	1.28%	Industrials	DXP ENTS.	1.25%	Industrials
CLEARONE	4.73%	Telecommunication	CLEARONE	4.38%	Telecommunication
ASTROTECH	1.56%	Industrials	ASTROTECH	1.31%	Industrials
ARCA BIOPHARMA	1.36%	Healthcare	SOLUNA HOLDINGS	1.40%	Technology
SOLUNA HOLDINGS	1.55%	Technology	SILICOM	0.16%	Technology
SILICOM	0.37%	Technology	ARCA BIOPHARMA	1.40%	Healthcare
ATN INTERNATIONAL	10.87%	Telecommunication	KOPIN	-1.94%	Technology
KOPIN	-1.65%	Technology	TG THERAPEUTICS	0.23%	Healthcare
TG THERAPEUTICS	0.24%	Healthcare	ATN INTERNATIONAL	9.55%	Telecommunication
TRIMBLE	2.34%	Industrials	TRIMBLE	1.62%	Industrials
AKAMAI TECHS.	-0.86%	Technology	AKAMAI TECHS.	-1.08%	Technology
COGNIZANT TECH.SLTN.'A'	1.17%	Technology	COGNIZANT TECH.SLTN.'A'	0.82%	Technology
AUTODESK	5.62%	Technology	AUTODESK	4.84%	Technology
CENTURY ALUMINUM	-3.32%	Basic Materials	CENTURY ALUMINUM	-3.65%	Basic Materials
CASI PHARMACEUTICALS	0.63%	Healthcare	CASI PHARMACEUTICALS	0.37%	Healthcare
March	Weight	Sector	April	Weight	Sector
LATTICE SEMICONDUCTOR	-1.36%	Technology	AMARIN ADR 1:1	2.89%	Healthcare
MAGIC SFTW.ENTS. (NAS)	2.21%	Technology	GILAT	3.53%	Telecommunication
METHANEX (NAS)	1.40%	Basic Materials	SAPIENS INTL.	3.77%	Technology
MITEK SYSTEMS	-0.20%	Technology	USIO	0.81%	Industrials
MKS INSTRUMENTS	1.35%	Industrials	SIRIUS XM HOLDINGS	0.21%	Consumer Discretionary
MONSTER BEVERAGE	1.32%	Consumer Staples	SWK HOLDINGS	0.73%	Finance
NATURAL ALTS.INTL.	3.06%	Consumer Staples	PARK OHIO HOLDINGS	-0.95%	Industrials

NATURAL HEALTH TRENDS	0.10%	Consumer Staples	SUNOPTA (NAS)	2.73%	Consumer Staples
NEOGENOMICS	0.45%	Healthcare	SOCKET MOBILE	1.67%	Industrials
NEONODE	0.19%	Technology	VIAVI SOLUTIONS	-0.83%	Telecommunication
NICHOLAS FINANCIAL	3.40%	Finance	CIVISTA	16.82%	Finance
NORTECH SYSTEMS	2.14%	Technology	BANCSHARES		
NORTHWEST BANCSHARES	4.20%	Finance	PURE CYCLE	1.57%	Utilities
NVIDIA	-0.86%	Technology	PERMA-FIX	6.56%	Utilities
OPKO HEALTH	0.17%	Healthcare	ENV.SVS.		
PAC.PREMIER BANC.	1.05%	Finance	HARMONIC	-1.85%	Telecommunication
PENN	0.22%	Consumer Discretionary	KULICKE & SOFFA INDS.	-2.90%	Technology
ENTERTAINMENT			ARROWHEAD	0.17%	Healthcare
PEOPLES	9.58%	Finance	PHARMS.		
BANC.OF NOCA.			CENTRAL GDN.& PET	3.84%	Consumer Discretionary
PEPSICO	27.76%	Consumer Staples	IDENTIVE	3.73%	Technology
PETMED EXPRESS	1.04%	Consumer Staples	NETSOL TECHS.	0.89%	Technology
PHOTRONIC	-1.29%	Technology	SCRIPPS E W 'A'	5.87%	Consumer Discretionary
PROPHASE LABS	1.96%	Consumer Staples	EXTREME NETWORKS	-1.36%	Telecommunication
QCR HDG.	9.61%	Finance	AVID	0.32%	Healthcare
RADCOM	0.18%	Telecommunication	BIOSERVICES		
RADNET	0.14%	Healthcare	VERU	3.85%	Consumer Staples
RESEARCH FRONTIERS	0.10%	Technology	EMCORE	-1.49%	Technology
ROYAL GOLD	3.12%	Basic Materials	DAWSON	1.22%	Energy
RUSH	1.04%	Consumer Discretionary	GEOPHYSICAL		
ENTERPRISES 'B'			RAMBUS	0.42%	Technology
SAVARA	0.09%	Healthcare	TOWER	1.88%	Technology
SBA COMMS.	-0.34%	Real Estate	HOLOGIC	3.61%	Healthcare
SCTY.NAT.FINL.'A'	1.66%	Finance	DMC GLOBAL	0.20%	Energy
SIFY			STEEL CONNECT	-2.47%	Technology
TECHNOLOGIES			LAKELAND	12.81%	Finance
ADR 1:1			FINANCIAL		
SMITH WESSON	-0.03%	Consumer Discretionary	GREAT ELM	-0.60%	Finance
BRANDS			GROUP		
SMITH MIDLAND	1.37%	Industrials	AMNEAL	5.68%	Healthcare
			PHARMACEUTICA		
			LS A		
			ENCORE CAP.GP.	0.57%	Finance

SPAR GROUP	0.46%	Consumer Discretionary	COGNEX	4.80%	Industrials
STERICYCLE	6.46%	Utilities	DXP ENTS.	1.30%	Industrials
STEVEN MADDEN	1.06%	Consumer Discretionary	CLEARONE	4.63%	Telecommunication
STREAMLINE HEALTH SLTN.	0.66%	Technology	ASTROTECH	1.29%	Industrials
TAITRON COMPONENTS	1.36%	Industrials	ARCA	0.96%	Healthcare
TANDY LEATHER FACTORY	5.15%	Consumer Discretionary	BIOPHARMA		
TAYLOR DEVICES	1.52%	Industrials	SILICOM	0.24%	Technology
TRANSACT TECHNOLOGIES	1.13%	Technology	TG THERAPEUTICS	0.24%	Healthcare
TUCOWS 'A'	1.24%	Technology	SOLUNA HOLDINGS	1.41%	Technology
US.LIME & MINERALS	2.68%	Industrials	KOPIN	-1.97%	Technology
UNITED BANKSHARES	-0.73%	Finance	ATN INTERNATIONAL	10.01%	Telecommunication
UPBOUND GROUP	2.11%	Consumer Discretionary	TRIMBLE	1.66%	Industrials
VIRTRA	0.33%	Industrials	AKAMAI TECHS.	-1.09%	Technology
WESBANCO	-0.03%	Finance	COGNIZANT TECH.SLTN.'A'	0.97%	Technology
WESTERN DIGITAL	-0.39%	Technology	AUTODESK	5.01%	Technology
INOTIV	2.21%	Healthcare	CENTURY ALUMINUM	-3.80%	Basic Materials
			CASI PHARMACEUTICALS	0.43%	Healthcare
May	Weight	Sector	June	Weight	Sector
AMARIN ADR 1:1	3.00%	Healthcare	LATTICE SEMICONDUCTOR	-1.68%	Technology
GILAT	3.88%	Telecommunication	MAGIC SFTW.ENTS. (NAS)	2.06%	Technology
SAPIENS INTL.	3.95%	Technology	METHANEX (NAS)	1.70%	Basic Materials
USIO	0.85%	Industrials	MITEK SYSTEMS	-0.22%	Technology
SIRIUS XM HOLDINGS	0.29%	Consumer Discretionary	MKS INSTRUMENTS	1.46%	Industrials
SWK HOLDINGS	1.03%	Finance	MONSTER BEVERAGE	1.33%	Consumer Staples
PARK OHIO HOLDINGS	-1.03%	Industrials	NATURAL ALTS.INTL.	3.02%	Consumer Staples
SUNOPTA (NAS)	2.84%	Consumer Staples	NATURAL HEALTH TRENDS	0.07%	Consumer Staples
SOCKET MOBILE	1.87%	Industrials	NEOGENOMICS	0.45%	Healthcare
VIAVI SOLUTIONS	-1.24%	Telecommunication	NEONODE	0.17%	Technology

CIVISTA BANCSHARES	16.32%	Finance	NICHOLAS FINANCIAL	3.42%	Finance
PURE CYCLE	1.56%	Utilities	NORTECH SYSTEMS	2.28%	Technology
PERMA-FIX ENV.SVS.	6.39%	Utilities	NORTHWEST BANCSHARES	4.68%	Finance
HARMONIC	-1.74%	Telecommunicati on	NVIDIA	-0.58%	Technology
KULICKE & SOFFA INDS.	-2.98%	Technology	OPKO HEALTH	0.11%	Healthcare
ARROWHEAD PHARMS.	0.14%	Healthcare	PAC.PREMIER BANC.	1.01%	Finance
CENTRAL GDN.& PET	3.86%	Consumer Discretionary	PENN ENTERTAINMENT	-0.11%	Consumer Discretionary
IDENTIVE	3.56%	Technology	PEOPLES BANC.OF NOCA.	9.70%	Finance
NETSOL TECHS.	0.90%	Technology	PEPSICO	28.84%	Consumer Staples
SCRIPPS E W 'A'	5.49%	Consumer Discretionary	PETMED EXPRESS	1.26%	Consumer Staples
EXTREME NETWORKS	-1.09%	Telecommunicati on	PHOTRONIC	-1.58%	Technology
AVID BIOSERVICES	0.58%	Healthcare	PROPHASE LABS	1.86%	Consumer Staples
VERU	3.83%	Consumer Staples	QCR HDG.	9.42%	Finance
EMCORE	-1.18%	Technology	RADCOM	0.26%	Telecommunicati on
DAWSON GEOPHYSICAL	1.21%	Energy	RADNET	-0.07%	Healthcare
RAMBUS	0.54%	Technology	RESEARCH FRONTIERS	-0.05%	Technology
TOWER	2.02%	Technology	ROYAL GOLD	2.84%	Basic Materials
HOLOGIC	3.95%	Healthcare	RUSH	0.63%	Consumer Discretionary
DMC GLOBAL	0.21%	Energy	ENTERPRISES 'B' SAVARA	0.09%	Healthcare
STEEL CONNECT	-2.61%	Technology	SBA COMMS.	-0.38%	Real Estate
LAKELAND FINANCIAL	12.38%	Finance	SCTY.NAT.FINL.'A'	1.54%	Finance
GREAT ELM GROUP	-0.78%	Finance	SIFY TECHNOLOGIES	0.04%	Telecommunicati on
AMNEAL PHARMACEUTICA LS A	5.49%	Healthcare	ADR 1:1 SMITH WESSON BRANDS	0.05%	Consumer Discretionary
ENCORE CAP.GP. COGNEX	0.54%	Finance	SMITH MIDLAND	1.40%	Industrials
	4.41%	Industrials	SPAR GROUP	0.43%	Consumer Discretionary
DXP ENTS.	1.36%	Industrials	STERICYCLE	6.36%	Utilities
CLEARONE	4.91%	Telecommunicati on	STEVEN MADDEN	1.21%	Consumer Discretionary

ARCA	1.03%	Healthcare	STREAMLINE	0.65%	Technology
BIOPHARMA			HEALTH SLTN.		
ASTROTECH	1.24%	Industrials	TAITRON	1.43%	Industrials
			COMPONENTS		
SILICOM	0.39%	Technology	TANDY LEATHER	5.27%	Consumer
			FACTORY		Discretionary
TG	0.28%	Healthcare	TAYLOR DEVICES	1.55%	Industrials
THERAPEUTICS					
KOPIN	-2.13%	Technology	TRANSACT	1.19%	Technology
			TECHNOLOGIES		
ATN	10.08%	Telecommunicati	TUCOWS 'A'	1.24%	Technology
INTERNATIONAL		on			
TRIMBLE	1.36%	Industrials	US.LIME &	2.52%	Industrials
			MINERALS		
SOLUNA	1.35%	Technology	UNITED	-1.31%	Finance
HOLDINGS			BANKSHARES		
AKAMAI TECHS.	-0.74%	Technology	UPBOUND	1.94%	Consumer
			GROUP		Discretionary
COGNIZANT	1.04%	Technology	VIRTRA	0.41%	Industrials
TECH.SLTN.'A'					
AUTODESK	4.72%	Technology	WESBANCO	-0.21%	Finance
CENTURY	-3.93%	Basic Materials	WESTERN	-0.43%	Technology
ALUMINUM			DIGITAL		
CASI	0.60%	Healthcare	INOTIV	2.71%	Healthcare
PHARMACEUTICA					
LS					
July	Weight	Sector	August	Weight	Sector
AMARIN ADR 1:1	2.11%	Healthcare	LATTICE	-1.98%	Technology
			SEMICONDUCTO		
GILAT	2.65%	Telecommunicati	R		
		on	MAGIC	2.04%	Technology
SAPIENS INTL.	3.49%	Technology	SFTW.ENTS.		
USIO	0.76%	Industrials	(NAS)		
SIRIUS XM	-0.06%	Consumer	METHANEX (NAS)	1.85%	Basic Materials
HOLDINGS		Discretionary	MITEK SYSTEMS	-0.26%	Technology
SWK HOLDINGS	0.86%	Finance	MKS	1.58%	Industrials
			INSTRUMENTS		
PARK OHIO	-1.46%	Industrials	MONSTER	1.29%	Consumer
HOLDINGS			BEVERAGE		Staples
SUNOPTA (NAS)	3.07%	Consumer	NATURAL	3.13%	Consumer
		Staples	ALTS.INTL.		Staples
SOCKET MOBILE	1.94%	Industrials	NATURAL HEALTH	0.03%	Consumer
VIAVI SOLUTIONS	-1.96%	Telecommunicati	TRENDS		Staples
		on	NEOGENOMICS	0.45%	Healthcare
CIVISTA	15.86%	Finance	NEONODE	0.19%	Technology
BANCSHARES					
PURE CYCLE	1.74%	Utilities	NICHOLAS	3.55%	Finance
			FINANCIAL		
			NORTECH	2.54%	Technology
			SYSTEMS		

PERMA-FIX ENV.SVS. HARMONIC	5.99% -1.75%	Utilities Telecommunicati on	NORTHWEST BANCSHARES NVIDIA	5.03% -0.50%	Finance Technology
KULICKE & SOFFA INDS. ARROWHEAD PHARMS.	-3.32% 0.13%	Technology Healthcare	OPKO HEALTH PAC.PREMIER BANC.	0.15% 1.00%	Healthcare Finance
CENTRAL GDN.& PET IDENTIVE	3.73% 3.85%	Consumer Discretionary Technology	PENN ENTERTAINMENT PEOPLES	-0.18% 9.30%	Consumer Discretionary Finance
NETSOL TECHS.	0.92%	Technology	BANC.OF NOCA. PEPSICO	30.02%	Consumer Staples
SCRIPPS E W 'A'	4.96%	Consumer Discretionary	PETMED EXPRESS	1.34%	Consumer Staples
EXTREME NETWORKS AVID BIOSERVICES	-0.97% 0.72%	Telecommunicati on Healthcare	PHOTRONIC PROPHASE LABS	-1.60% 1.60%	Technology Consumer Staples
VERU	3.99%	Consumer Staples	QCR HDG.	9.48%	Finance
EMCORE	-1.29%	Technology	RADCOM	0.21%	Telecommunicati on
DAWSON GEOPHYSICAL RAMBUS	1.28% 0.76%	Energy Technology	RADNET RESEARCH FRONTIERS	-0.10% 0.18%	Healthcare Technology
TOWER HOLOGIC	2.29% 4.07%	Technology Healthcare	ROYAL GOLD RUSH ENTERPRISES 'B'	2.84% 0.56%	Basic Materials Consumer Discretionary
DMC GLOBAL STEEL CONNECT LAKELAND FINANCIAL	-0.01% -2.63% 13.83%	Energy Technology Finance	SAVARA SBA COMMS. SCTY.NAT.FINL.'A'	0.41% -0.48% 1.50%	Healthcare Real Estate Finance
ARCA BIOPHARMA	1.07%	Healthcare	SIFY TECHNOLOGIES ADR 1:1	0.04%	Telecommunicati on
GREAT ELM GROUP AMNEAL PHARMACEUTICA LS A	-0.57% 5.47%	Finance Healthcare	SMITH WESSON BRANDS SMITH MIDLAND	-0.06% 1.48%	Consumer Discretionary Industrials
ENCORE CAP.GP.	0.97%	Finance	SPAR GROUP	0.40%	Consumer Discretionary
COGNEX DXP ENTS.	4.32% 1.54%	Industrials Industrials	STERICYCLE STEVEN MADDEN	6.12% 1.27%	Utilities Consumer Discretionary
CLEARONE	5.33%	Telecommunicati on	STREAMLINE HEALTH SLTN.	0.58%	Technology

ASTROTECH	1.23%	Industrials	TAITRON COMPONENTS	1.38%	Industrials
SILICOM	0.63%	Technology	TANDY LEATHER FACTORY	5.25%	Consumer Discretionary
TG THERAPEUTICS	0.32%	Healthcare	TAYLOR DEVICES	1.53%	Industrials
SOLUNA HOLDINGS	1.38%	Technology	TRANSACT TECHNOLOGIES	1.25%	Technology
KOPIN	-2.04%	Technology	TUCOWS 'A'	1.38%	Technology
ATN INTERNATIONAL	10.15%	Telecommunication	US.LIME & MINERALS	2.39%	Industrials
TRIMBLE	1.98%	Industrials	UNITED BANKSHARES	-1.49%	Finance
AKAMAI TECHS.	-0.49%	Technology	UPBOUND GROUP	1.67%	Consumer Discretionary
COGNIZANT TECH.SLTN.'A'	1.32%	Technology	VIRTRA	0.48%	Industrials
AUTODESK	5.08%	Technology	WESBANCO	-0.63%	Finance
CENTURY ALUMINUM	-3.95%	Basic Materials	WESTERN DIGITAL	-0.47%	Technology
CASI PHARMACEUTICALS	0.72%	Healthcare	INOTIV	2.23%	Healthcare
September	Weight	Sector	October	Weight	Sector
LIGHTPATH TECHS.	-6.95%	Industrials	AMARIN ADR 1:1	3.04%	Healthcare
8X8	0.03%	Telecommunication	GILAT	3.87%	Telecommunication
AIR T	3.15%	Industrials	SAPIENS INTL.	3.99%	Technology
AMAZON.COM	-1.42%	Consumer Discretionary	USIO	0.88%	Industrials
AMERICA S CAR MART	3.47%	Consumer Discretionary	SIRIUS XM HOLDINGS	0.24%	Consumer Discretionary
APPLE	3.81%	Technology	SWK HOLDINGS	1.46%	Finance
APPLIED MATS.	7.37%	Technology	PARK OHIO HOLDINGS	-1.40%	Industrials
APTOSE BIOSCIENCES (NAS)	0.72%	Healthcare	SUNOPTA (NAS)	3.34%	Consumer Staples
ART'S-WAY MANUFACTURING	1.63%	Industrials	SOCKET MOBILE	2.11%	Industrials
ASTRONICS	3.21%	Industrials	VIAVI SOLUTIONS	-1.79%	Telecommunication
ATLANTICUS HOLDINGS	-2.55%	Industrials	CIVISTA BANCSHARES	16.11%	Finance
ATRION	7.99%	Healthcare	PURE CYCLE	1.92%	Utilities
AXT	0.62%	Technology	PERMA-FIX ENV.SVS.	6.26%	Utilities
AZENTA	-6.25%	Healthcare	HARMONIC	-1.77%	Telecommunication

BAKER HUGHES A	3.14%	Energy	KULICKE & SOFFA INDS.	-3.31%	Technology
BEL FUSE 'A'	6.62%	Telecommunication	ARROWHEAD PHARMS.	0.13%	Healthcare
BEL FUSE 'B'	-7.66%	Telecommunication	CENTRAL GDN.& PET IDENTIVE	3.66%	Consumer Discretionary Technology
BIO-KEY INTL.	1.80%	Industrials	NETSOL TECHS.	3.95%	Technology
CHARLES AND COLVARD CTZN.& NTHN.	1.11%	Consumer Discretionary	SCRIPPS E W 'A'	0.89%	Technology
COMTECH TELECOM.	9.49%	Finance	EXTREME NETWORKS	4.41%	Consumer Discretionary Telecommunication
CONSUMER PRTF.SVS. COPART	4.18%	Telecommunication	AVID BIOSERVICES	-1.16%	Healthcare
DENNY'S	0.38%	Finance	VERU	0.59%	Healthcare
DESCARTES SYS.GP. (NAS)	9.08%	Consumer Discretionary	EMCORE	4.15%	Consumer Staples Technology
DORMAN PRODUCTS	-0.19%	Consumer Discretionary	DAWSON GEOPHYSICAL	-1.03%	Technology
EBAY	2.85%	Technology	RAMBUS	1.29%	Energy
EDUCATIONAL DEV.	-0.24%	Consumer Discretionary	TOWER	0.75%	Technology
ENGLOBAL	2.96%	Consumer Discretionary	HOLOGIC	2.11%	Technology
EURO TECH HOLDINGS	10.10%	Consumer Discretionary	DMC GLOBAL	4.11%	Healthcare
FIRST BUSEY 'A'	-0.38%	Industrials	STEEL CONNECT	0.16%	Energy
FULL HOUSE RESORTS	0.49%	Industrials	LAKELAND FINANCIAL	-2.77%	Technology
GOLDEN OCEAN GROUP	4.08%	Finance	GREAT ELM GROUP	13.67%	Finance
HERITAGE COMMERCE	1.64%	Consumer Discretionary	AMNEAL PHARMACEUTICALS A	-0.81%	Finance
HUB GROUP 'A'	0.99%	Industrials	ENCORE CAP.GP.	5.28%	Healthcare
HUDSON TECHNOLOGIES	0.15%	Finance	COGNEX	0.98%	Finance
ICU MEDICAL	0.57%	Industrials	DXP ENTS.	3.49%	Industrials
IMUNON	1.61%	Industrials	CLEARONE	1.30%	Industrials
INNODATA	10.85%	Healthcare	ASTROTECH	5.27%	Telecommunication
INTERLINK ELECTRONICS	2.64%	Healthcare	ARCA BIOPHARMA	1.08%	Industrials
ITERIS	1.00%	Technology	SILICOM	0.96%	Healthcare
	1.45%	Industrials	TG THERAPEUTICS	0.57%	Technology
	0.89%	Industrials		0.29%	Healthcare

HUNT JB	4.28%	Industrials	SOLUNA	1.07%	Technology
TRANSPORT SVS.			HOLDINGS		
LSI INDUSTRIES	-1.79%	Industrials	KOPIN	-2.24%	Technology
LATTICE	-4.92%	Technology	ATN	9.13%	Telecommunicati
SEMICONDUCTO			INTERNATIONAL		on
R			TRIMBLE	1.95%	Industrials
MAGIC	3.70%	Technology	AKAMAI TECHS.	-0.61%	Technology
SFTW.ENTS.			COGNIZANT	1.76%	Technology
(NAS)			TECH.SLTN.'A'		
METHANEX (NAS)	4.12%	Basic Materials	AUTODESK	4.26%	Technology
MITEK SYSTEMS	0.07%	Technology	CENTURY	-4.22%	Basic Materials
			ALUMINUM		
MKS	0.14%	Industrials	CASI	0.62%	Healthcare
INSTRUMENTS			PHARMACEUTICA		
MONSTER	2.74%	Consumer	LS		
BEVERAGE		Staples			
NATURAL	7.23%	Consumer			
ALTS.INTL.		Staples			
November	Weight	Sector	December	Weight	Sector
AMARIN ADR 1:1	2.85%	Healthcare	AMARIN ADR 1:1	3.29%	Healthcare
GILAT	3.74%	Telecommunicati	GILAT	4.66%	Telecommunicati
		on			on
SAPIENS INTL.	3.99%	Technology	SAPIENS INTL.	4.30%	Technology
USIO	0.86%	Industrials	USIO	0.96%	Industrials
SIRIUS XM	0.21%	Consumer	SIRIUS XM	0.41%	Consumer
HOLDINGS		Discretionary	HOLDINGS		Discretionary
SWK HOLDINGS	1.43%	Finance	SWK HOLDINGS	1.68%	Finance
PARK OHIO	-1.44%	Industrials	PARK OHIO	-1.20%	Industrials
HOLDINGS			HOLDINGS		
SUNOPTA (NAS)	3.40%	Consumer	SUNOPTA (NAS)	3.66%	Consumer
		Staples			Staples
SOCKET MOBILE	2.09%	Industrials	SOCKET MOBILE	2.05%	Industrials
VIAVI SOLUTIONS	-1.98%	Telecommunicati	VIAVI SOLUTIONS	-1.75%	Telecommunicati
		on			on
CIVISTA	15.73%	Finance	CIVISTA	15.73%	Finance
BANCSHARES			BANCSHARES		
PURE CYCLE	1.82%	Utilities	PURE CYCLE	1.99%	Utilities
PERMA-FIX	6.36%	Utilities	PERMA-FIX	6.57%	Utilities
ENV.SVS.			ENV.SVS.		
HARMONIC	-1.72%	Telecommunicati	HARMONIC	-1.79%	Telecommunicati
		on			on
KULICKE & SOFFA	-3.24%	Technology	KULICKE & SOFFA	-3.24%	Technology
INDS.			INDS.		
ARROWHEAD	0.13%	Healthcare	ARROWHEAD	0.12%	Healthcare
PHARMS.			PHARMS.		
CENTRAL GDN.&	3.70%	Consumer	CENTRAL GDN.&	3.55%	Consumer
PET		Discretionary	PET		Discretionary
IDENTIVE	3.88%	Technology	IDENTIVE	3.85%	Technology
NETSOL TECHS.	1.03%	Technology	NETSOL TECHS.	0.95%	Technology

SCRIPPS E W 'A'	4.28%	Consumer Discretionary	SCRIPPS E W 'A'	4.09%	Consumer Discretionary
EXTREME NETWORKS	-1.33%	Telecommunication	EXTREME NETWORKS	-1.47%	Telecommunication
AVID BIOSERVICES	0.66%	Healthcare	AVID BIOSERVICES	0.73%	Healthcare
VERU	4.31%	Consumer Staples	VERU	4.05%	Consumer Staples
EMCORE	-1.01%	Technology	EMCORE	-0.98%	Technology
DAWSON	1.40%	Energy	DAWSON	1.41%	Energy
GEOPHYSICAL			GEOPHYSICAL		
RAMBUS	0.77%	Technology	RAMBUS	0.75%	Technology
TOWER	2.13%	Technology	TOWER	2.02%	Technology
HOLOGIC	4.29%	Healthcare	HOLOGIC	4.54%	Healthcare
DMC GLOBAL	0.32%	Energy	DMC GLOBAL	0.28%	Energy
STEEL CONNECT	-2.69%	Technology	STEEL CONNECT	-2.84%	Technology
LAKELAND	13.41%	Finance	LAKELAND	13.10%	Finance
FINANCIAL			FINANCIAL		
GREAT ELM GROUP	-0.81%	Finance	GREAT ELM GROUP	-0.82%	Finance
AMNEAL	5.26%	Healthcare	AMNEAL	5.02%	Healthcare
PHARMACEUTICALS A			PHARMACEUTICALS A		
ENCORE CAP.GP.	0.92%	Finance	ENCORE CAP.GP.	0.78%	Finance
COGNEX	3.61%	Industrials	COGNEX	4.09%	Industrials
DXP ENTS.	1.27%	Industrials	DXP ENTS.	1.12%	Industrials
CLEARONE	5.36%	Telecommunication	CLEARONE	5.15%	Telecommunication
ASTROTECH	1.13%	Industrials	ASTROTECH	1.08%	Industrials
ARCA	1.00%	Healthcare	SOLUNA HOLDINGS	1.00%	Technology
BIOPHARMA			ARCA	1.01%	Healthcare
SILICOM	0.58%	Technology	BIOPHARMA		
TG	0.30%	Healthcare	SILICOM	0.56%	Technology
THERAPEUTICS			TG	0.27%	Healthcare
KOPIN	-2.33%	Technology	THERAPEUTICS		
ATN	9.27%	Telecommunication	TRIMBLE	2.22%	Industrials
INTERNATIONAL			AKAMAI TECHS.	-0.65%	Technology
SOLUNA	1.09%	Technology	COGNIZANT	1.51%	Technology
HOLDINGS			TECH.SLTN.'A'		
TRIMBLE	2.07%	Industrials	AUTODESK	3.89%	Technology
AKAMAI TECHS.	-0.63%	Technology	CENTURY	-4.52%	Basic Materials
COGNIZANT	1.79%	Technology	ALUMINUM		
TECH.SLTN.'A'			CASI	0.59%	Healthcare
AUTODESK	4.47%	Technology	PHARMACEUTICALS		
CENTURY	-4.41%	Basic Materials			
ALUMINUM					
CASI	0.68%	Healthcare			
PHARMACEUTICALS					

Appendix B3: ML results of all the companies in the dataset from the 2010 testing period. For the total row, percentages (including R²) are averaged, and the other columns are medians of the scores.

Company	Accuracy(%)	R²	RMSE	MAE	MAPE(%)	SMAPE(%)
<i>Total</i>	49.34	0.02	2.70	2.34	30.76	34.24
1-800-FLOWERS.COM 'A'	50.00	0.00	0.58	0.48	24.17	27.57
1ST SOURCE	66.67	0.33	1.14	0.89	5.82	10.73
8X8	0.00	0.00	0.96	0.78	41.03	70.39
AAON	83.33	0.00	0.54	0.45	9.34	14.68
ABEO THERAPEUTICS	41.67	0.00	1.18E+03	1.08E+03	37.56	39.32
ACHIEVE LIFE SCIENCES	66.67	0.00	3.56E+04	3.48E+04	102.38	85.91
ACI WORLDWIDE	50.00	0.00	1.09	0.86	11.74	16.94
ADOBE (S)	66.67	0.00	9.40	8.57	28.75	31.88
ADTRAN HOLDINGS	58.33	0.00	6.42	5.25	16.78	26.10
ADVANCED MICRO DEVICES	66.67	0.00	3.04	2.83	37.87	40.21
ADVANCED ENERGY INDS.	50.00	0.00	3.12	2.53	19.31	21.44
AEHR TEST SYS.	50.00	0.00	0.74	0.57	27.29	41.47
AETHLON MED.	25.00	0.00	584.08	488.85	24.82	26.11
AGILYSYS	41.67	0.00	3.54	3.07	48.99	46.34
AINOS	25.00	0.00	139.26	128.37	137.35	92.47
AIR T	0.00	0.00	3.20	3.07	43.42	73.05
AKAMAI TECHS.	41.67	0.00	15.10	12.82	28.56	46.79
ALICO	66.67	0.00	6.54	6.01	25.20	28.50
ALKERMES	41.67	0.00	3.20	2.79	21.42	32.43
ALLIANCE RSO.PTNS.L P UT LP.	50.00	0.00	4.46	3.47	12.62	18.92
ALLIANT ENERGY (XSC)	58.33	0.00	1.37	1.14	6.60	9.34
ALLIENT	83.33	0.00	1.14	1.00	33.09	54.49
ALTO INGREDIENTS	33.33	0.00	89.34	67.91	50.71	96.21
AMARIN ADR 1:1	58.33	0.00	2.03	1.44	44.64	80.37
AMAZON.COM	0.00	0.00	4.79	4.68	66.70	131.04
AMDOCS	66.67	0.00	3.13	2.38	8.63	10.80
AMEDISYS	75.00	0.00	18.33	15.67	52.44	47.76
AMER.ELEC.PWR.	41.67	0.00	3.90	2.99	8.84	10.71
AMER.SOFTWARE CL.A	58.33	0.00	0.89	0.73	13.43	17.49
AMERICAN SUPERCONDUCTOR	58.33	0.00	122.49	114.66	38.33	40.54
AMER.WOODMARK	58.33	0.28	2.20	1.76	9.53	15.43
AMERICA S CAR MART	0.00	0.00	10.87	10.74	42.80	71.25
AMERIS BANCORP	75.00	0.00	2.66	2.56	26.31	39.84
AMERISERV FINL.	58.33	0.00	0.23	0.18	10.54	13.67
AMGEN	41.67	0.00	6.98	5.72	10.48	12.68
AMKOR TECH.	58.33	0.00	1.27	1.11	18.04	21.51
AMNEAL	58.33	0.00	2.93	2.55	13.71	20.93
PHARMACEUTICALS A						
AMTECH SYS.	33.33	0.02	4.90	3.92	28.36	38.15

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
ALOG DEVICES	75.00	0.00	4.21	3.50	11.98	17.03
ANDERSONS	50.00	0.00	4.54	3.89	16.29	25.07
ANI PHARMACEUTICALS	50.00	0.03	8.31	6.64	10.78	14.84
ANIKA THERAPEUTICS	41.67	0.00	2.84	2.74	44.77	46.91
ANIXA BIOSCIENCES	50.00	0.00	8.92	8.32	128.47	93.40
ANSYS	75.00	0.00	3.12	2.47	5.72	10.03
APA	75.00	0.00	12.86	9.83	10.46	14.12
APOGEE ENTERPRISES	66.67	0.00	2.86	2.50	22.29	24.08
APPLE	0.00	0.00	5.45	5.28	56.13	102.54
APPLIED MATS.	0.00	0.00	3.87	3.76	30.56	34.17
APTOSE BIOSCIENCES (S)	8.33	0.00	3.33E+03	2.84E+03	52.21	96.89
APYX MEDICAL	58.33	0.00	4.43	3.93	139.88	91.83
ARCA BIOPHARMA	41.67	0.00	1.01E+03	862.46	28.86	45.42
ARCBEST	58.33	0.00	10.84	10.23	43.01	44.84
ARCH CAP.GP.	33.33	0.07	0.66	0.56	6.41	9.43
ARK RESTAURANTS	41.67	0.00	1.99	1.81	13.05	15.82
ARROW FINCIAL	41.67	0.00	1.22	0.95	5.54	9.43
ARROWHEAD PHARMS.	41.67	0.00	5.08	4.27	38.19	66.52
ART'S-WAY MANUFACTURING	0.00	0.00	3.94	3.38	48.13	85.65
ARTESIAN RES.'A'	33.33	0.00	2.23	1.95	10.79	13.18
ASCENT INDUSTRIES	58.33	0.39	0.72	0.56	6.01	11.73
ASML HLDG.ADR 1:1	50.00	0.00	5.70	4.75	15.19	18.57
ASPEN TECHNOLOGY	58.33	0.02	1.11	0.94	8.40	13.89
ASSERTIO HOLDINGS	50.00	0.05	3.76	2.91	17.90	25.73
ASTEC INDUSTRIES	58.33	0.07	2.45	2.00	6.79	11.05
ASTRAZENECA ADR 2:1	25.00	0.00	2.66	2.20	9.07	10.66
ASTRONICS	0.00	0.00	3.17	2.83	54.93	103.11
ASTRONOVA	58.33	0.00	0.62	0.51	7.07	8.96
ASTROTECH	58.33	0.00	131.56	120.83	49.48	52.82
ASURE SOFTWARE	75.00	0.00	1.01	1.00	61.85	61.13
ATLANTIC AMERICAN	58.33	0.00	0.31	0.25	14.59	22.41
ATLANTICUS HOLDINGS	0.00	0.00	3.68	3.53	80.23	70.80
ATN INTERTIOL	33.33	0.00	16.06	14.12	34.12	36.18
ATRION	0.00	0.00	124.27	123.66	82.15	181.98
AUDIOCODES (S)	58.33	0.00	1.41	1.08	25.56	40.80
AUTODESK	58.33	0.00	4.75	3.89	12.05	18.34
AUTOMATIC DATA PROC.	58.33	0.00	4.18	3.62	9.82	12.66
AVADEL	25.00	0.00	1.01	0.85	11.75	13.52
PHARMACEUTICALS						
AVID BIOSERVICES	66.67	0.00	7.20	6.10	48.79	46.73
AVIS BUDGET GROUP	50.00	0.00	2.85	2.53	22.85	27.06
AVNET	66.67	0.00	4.99	4.42	16.36	20.13
AWARE	58.33	0.00	0.39	0.33	13.80	16.95
AXT	0.00	0.00	3.69	3.15	54.90	102.67
AZENTA	0.00	0.00	3.71	3.54	46.13	47.44

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
BAKER HUGHES A	0.00	0.00	7.14	6.35	18.89	27.83
BALCHEM	58.33	0.00	4.04	3.24	11.78	17.23
BALLARD PWR.SYS. (S)	50.00	0.00	0.64	0.54	31.36	32.71
BANCFIRST	58.33	0.00	1.41	1.12	5.48	8.66
BANK OF MARIN BANCORP	50.00	0.00	0.92	0.70	4.30	7.05
BANK OZK	58.33	0.00	1.25	1.11	11.91	17.92
BANNER	58.33	0.02	9.28	7.30	38.39	45.31
BARRETT BUS.SVS.	58.33	0.00	1.49	1.25	8.52	12.81
BASSETT FRTR.INDS.	58.33	0.00	1.61	1.46	29.22	45.80
BEL FUSE 'A'	0.00	0.00	3.79	3.30	17.55	20.49
BEL FUSE 'B'	0.00	0.00	3.77	3.10	16.08	18.62
BGC GROUP A	66.67	0.00	0.95	0.77	18.76	28.89
BIOCRYST PHARMS.	41.67	0.00	1.27	1.08	19.37	22.42
BIOGEN	50.00	0.00	5.58	4.90	9.42	11.83
BIO-KEY INTL.	8.33	0.00	268.95	244.29	43.85	44.35
BIOLASE	50.00	0.00	8.86E+03	7.58E+03	54.24	48.67
BIOMARIN PHARM.	66.67	0.00	3.11	2.55	10.91	15.43
BIO-TECHNE	33.33	0.00	3.50	3.27	21.29	24.75
BJ'S RESTAURANTS	58.33	0.00	7.67	6.02	20.43	31.73
BOK FINL.	75.00	0.00	3.52	2.98	6.19	9.70
BOOKING HOLDINGS	58.33	0.00	85.96	66.76	21.75	31.34
B O S BETTER ONLINE SOLUTIONS	41.67	0.00	2.30	1.97	36.55	39.37
BRIDGFORD FOODS	58.33	0.00	2.80	2.53	19.07	28.20
BROOKLINE BANCORP	66.67	0.00	0.88	0.74	7.60	10.12
CSG SYS.INTL.	75.00	0.00	1.69	1.39	7.12	9.71
CSP	41.67	0.05	0.19	0.16	7.93	11.06
C&F FINL.	83.33	0.00	1.36	1.05	5.51	8.95
CH ROBINSON WWD.	58.33	0.10	7.38	6.74	10.81	14.71
CADENCE DESIGN SYS.	50.00	0.00	0.88	0.73	10.09	14.81
CADIZ	83.33	0.00	1.49	1.23	10.01	14.86
CALAMP	41.67	0.00	14.43	12.48	21.86	24.35
CAL MAINE FOODS	41.67	0.00	2.45	2.15	13.83	16.30
CAMDEN T.	58.33	0.00	2.49	1.88	9.22	13.65
CANTALOUPE	41.67	0.00	0.44	0.37	36.51	49.17
CANTERBURY PARK HOLDING	91.67	0.20	1.20	0.76	7.99	14.90
CAP.CITY BK.GP.	58.33	0.00	2.01	1.81	14.17	18.11
CAPITAL SOUTHWEST	75.00	0.00	0.78	0.66	7.56	11.67
CAPITOL FED.FINL.	50.00	0.00	2.67	2.07	17.37	19.98
CARVER BANCORP	33.33	0.00	58.44	44.14	98.15	61.24
CASELLA WST.SYS.'A'	66.67	0.15	0.63	0.46	9.45	13.78
CASEY'S GENERAL STORES	41.67	0.00	4.77	3.93	10.29	16.43
CASI PHARMACEUTICALS	50.00	0.00	531.66	480.83	121.41	84.59
CASS INFO.SYS.	50.00	0.01	1.47	1.22	5.77	9.12
CATHAY GEN.BANCORP	75.00	0.00	4.41	4.05	32.86	52.32

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
CELLDEX THERAPEUTICS	66.67	0.00	18.76	16.06	21.68	27.18
CENTRAL GDN.& PET	66.67	0.00	1.50	1.32	17.10	20.12
CENTURY ALUMINUM	58.33	0.00	5.56	5.00	43.85	44.06
CENTURY CASINOS	58.33	0.00	0.47	0.42	18.82	21.97
CERUS	41.67	0.00	1.14	1.00	32.21	52.41
CF BANKSHARES	50.00	0.00	14.66	11.98	46.49	43.38
CHARLES AND COLVARD	0.00	0.00	1.64	1.56	84.12	71.82
CHECK POINT SFTW.TECHS.	58.33	0.06	4.38	3.52	10.09	14.78
CHEESECAKE FACTORY	58.33	0.00	3.73	2.95	10.51	17.09
CHILDRENS PLACE	41.67	0.00	10.27	9.13	19.50	30.24
CHI TURAL RES.	66.67	0.00	10.04	8.31	15.75	20.82
CHURCHILL DOWNS	58.33	0.00	0.62	0.47	8.07	11.60
CINCINTI FINL.	66.67	0.00	1.72	1.38	4.90	8.10
CINTAS	33.33	0.00	2.06	1.64	6.28	8.36
CIRRUS LOGIC	66.67	0.00	6.97	5.79	37.47	65.91
CISCO SYSTEMS	58.33	0.00	3.40	2.64	12.17	13.99
CTZN.& NTHN.	0.00	0.00	7.14	6.92	59.73	58.47
CITY HLDG.	66.67	0.00	3.37	2.83	9.22	12.70
CIVISTA BANCSHARES	33.33	0.00	0.70	0.57	13.40	17.38
CLARUS	66.67	0.00	1.55	1.30	19.76	31.52
CLEARFIELD	41.67	0.00	0.93	0.84	29.34	45.70
CLEARONE	50.00	0.00	0.11	0.09	7.59	11.32
CLIMB GLOBAL SOLUTIONS	58.33	0.00	1.30	1.06	10.49	16.69
CNB FINL.	66.67	0.00	3.35	2.89	22.08	24.48
COCA COLA	50.00	0.00	6.28	5.38	10.36	12.86
CONSOLIDATED COCA COLA EUROPACIFIC PARTNERS	58.33	0.00	3.01	2.40	12.36	18.99
CODORUS VLY.BANC.	58.33	0.00	1.48	1.28	23.15	36.55
COGNEX	58.33	0.00	1.15	0.80	12.93	20.27
COGNIZANT TECH.SLTN.'A'	50.00	0.00	6.52	5.32	17.52	26.62
COHU	66.67	0.00	1.80	1.52	11.59	16.05
COLLIERS INTL.GP. (S)	66.67	0.00	2.20	1.74	12.12	18.68
COLONY BANKCORP	50.00	0.00	1.45	1.17	20.32	28.52
COLUMBIA BKG.SYS.	50.00	0.00	2.63	2.12	10.38	16.00
COLUMBIA SPORTSWEAR	66.67	0.00	5.56	4.94	18.45	27.83
COLUMBUS MCKINNON NY	58.33	0.00	2.08	1.73	10.34	15.76
COMCAST A	58.33	0.00	1.04	0.90	9.49	13.99
COMMERCE BCSH.	66.67	0.00	2.32	1.94	10.09	12.51
COMMUNITY TRUST BANCORP	75.00	0.02	1.55	1.27	5.11	8.83
COMTECH TELECOM.	0.00	0.00	15.26	14.69	48.63	84.82
CONNECTONE BANCORP	50.00	0.00	2.05	1.86	24.17	27.49
CONSOLIDATED WT.	41.67	0.00	3.23	2.64	26.22	27.72

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
CONSUMER PRTF.SVS.	8.33	0.00	1.17	1.09	112.12	85.80
COPART	0.00	0.00	0.32	0.31	13.91	19.58
CORVEL	75.00	0.00	2.67	2.21	11.02	15.63
COSTAR GP.	58.33	0.01	0.51	0.44	10.16	14.61
COSTCO WHOLESALE	58.33	0.00	5.21	4.07	6.95	10.93
COVENT LOGISTICS GROUP A	50.00	0.00	3.40	3.03	39.80	68.41
CRA INTL.	75.00	0.00	7.47	6.68	33.32	35.49
CRACKER BARREL OLD CTRY. STORE	75.00	0.00	10.82	9.89	19.73	29.83
CREATIVE MEDIA AND COMMUNITY TRUST	58.33	0.00	2.28	1.71	4.67	8.96
CREDIT ACCEP.	41.67	0.00	10.70	8.40	14.87	22.63
CRESUD SACIFYA SPN.ADR 1:10	33.33	0.00	2.13	1.86	16.25	21.24
CREXENDO	50.00	0.00	3.04	2.74	64.22	59.07
CSX	66.67	0.22	0.54	0.43	7.25	11.80
CVB FINCIAL	66.67	0.00	1.20	1.05	12.07	15.02
CVD EQUIPMENT	75.00	0.06	1.62	1.30	26.78	36.21
DAKTRONICS	58.33	0.15	2.20	1.82	19.00	25.57
DATA I/O	50.00	0.00	0.72	0.59	11.49	15.93
DAWSON GEOPHYSICAL	50.00	0.00	1.32	1.01	13.52	15.22
DENNY'S	0.00	0.00	0.88	0.72	21.83	33.46
DENTSPLY SIRO	33.33	0.00	5.63	4.96	15.67	18.58
DESCARTES SYS.GP. (S)	0.00	0.00	2.41	2.37	38.33	62.10
DESTITION XL GROUP	58.33	0.00	1.52	1.37	34.20	55.38
DESWELL INDS.	66.67	0.00	0.78	0.66	18.96	22.53
DIA.HILL INV.GP.	58.33	0.04	8.28	7.07	10.94	15.15
DIGI INTERTIOL	58.33	0.00	1.23	0.99	10.90	13.93
DIME COMMUNITY BANCSHARES	41.67	0.00	2.77	2.25	9.78	11.25
DIODES	66.67	0.00	3.44	2.94	15.99	21.38
DISTRIBUTION SOLUTIONS GROUP	66.67	0.00	2.67	2.43	31.34	36.17
DIVERSIFIED HEALTHCARE	33.33	0.00	2.67	2.11	10.33	12.19
DLH HOLDINGS	58.33	0.00	0.26	0.24	38.75	41.64
DMC GLOBAL	66.67	0.00	5.79	5.44	34.25	37.71
DOLLAR TREE	66.67	0.00	5.56	4.60	19.46	30.42
DOMIRI HOLDINGS	41.67	0.00	1.00E+05	7.17E+04	34.65	30.03
DORCHESTER MINERALS	66.67	0.00	3.06	2.54	9.75	15.52
DORMAN PRODUCTS	0.00	0.00	7.39	6.27	46.06	81.31
DXP ENTS.	41.67	0.00	4.71	3.76	20.02	31.92
DYTRONICS	50.00	0.00	4.70	4.31	21.42	25.28
SCRIPPS E W 'A'	66.67	0.00	1.26	1.00	12.15	19.39
EAGLE BANC.	75.00	0.01	0.92	0.79	7.01	12.15
EAST WEST BANCORP	66.67	0.01	1.24	1.00	5.81	9.30

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
EASTERN	41.67	0.05	1.93	1.71	11.87	15.88
EBAY	0.00	0.00	4.41	4.20	39.70	65.34
EDAP TMS SPN.ADR 1:1	33.33	0.16	0.81	0.61	20.49	28.72
EDUCATIOL DEV.	0.00	0.00	0.38	0.34	10.89	15.24
EGAIN	33.33	0.00	0.21	0.18	18.90	23.94
ELBIT SYSTEMS (S)	41.67	0.00	15.36	13.16	25.13	27.88
ELECTRO-SENSORS	50.00	0.00	0.35	0.29	7.53	9.69
ELECTRONIC ARTS	50.00	0.00	4.19	3.76	23.41	26.75
ELTEK	66.67	0.22	0.77	0.58	9.21	15.17
EMCORE	58.33	0.00	9.05	7.34	15.59	23.48
ENCORE CAP.GP.	75.00	0.00	2.19	1.77	8.76	14.69
ENCORE WIRE	66.67	0.00	2.60	2.13	10.62	14.69
ENERGY FOCUS	33.33	0.00	219.00	189.79	40.94	69.80
ENGLOBAL	0.00	0.00	4.54	3.82	18.76	21.57
EPLUS	50.00	0.12	0.60	0.45	8.97	14.17
ERICSSON 'B' ADR 1:1	41.67	0.00	1.03	0.85	7.79	11.23
ERIE INDEMNITY 'A'	58.33	0.00	11.51	8.97	16.47	26.04
ESCALADE	66.67	0.00	2.18	1.89	39.84	68.83
ETER THERAPEUTICS	50.00	0.00	164.43	124.68	14.41	18.18
EURO TECH HOLDINGS	0.00	0.00	0.36	0.32	18.59	22.91
EURONET WWD.	41.67	0.00	7.57	6.88	43.74	44.66
EVERGY	58.33	0.00	1.60	1.28	5.57	8.28
EXELON	33.33	0.00	7.50	6.75	22.95	26.20
EXPONENT	50.00	0.10	0.79	0.68	8.62	12.03
EXTREME NETWORKS	58.33	0.00	0.84	0.80	26.62	40.50
EZCORP 'A' NON VTG.	66.67	0.00	3.38	2.59	11.55	16.99
F5	66.67	0.00	36.84	27.72	27.78	46.69
FARMER BROTHERS	66.67	0.00	4.19	3.83	23.04	26.28
FARMERS T.BANC	16.67	0.00	0.49	0.40	10.39	12.28
FARO TECHS.	66.67	0.26	3.29	2.84	12.35	18.77
FASTEL	41.67	0.00	1.31	1.14	8.84	13.77
FIFTH THIRD BANCORP	58.33	0.00	2.49	2.31	17.64	25.83
FINCIAL INSTITUTIONS	75.00	0.00	4.44	3.96	22.57	35.47
FIRST BANCORP	66.67	0.00	1.53	1.25	9.01	12.33
FIRST BANCORP.1	66.67	0.00	1.56	1.28	9.24	12.49
FIRST BUSEY 'A'	0.00	0.00	5.68	5.53	43.08	45.54
FIRST CTZN.BCSH.A	66.67	0.00	23.84	20.60	10.66	15.55
FIRST COMMUNITY BANKSHARES	75.00	0.05	1.46	1.14	7.87	13.85
FIRST FINL.BKSH.	66.67	0.00	1.58	1.44	17.54	20.70
FIRST FINL.BANC.	83.33	0.00	1.80	1.42	8.08	12.56
FIRST FINCIAL	50.00	0.00	4.72	4.19	14.86	18.80
FIRST MERCHANTS	75.00	0.00	1.75	1.58	19.32	29.39
FIRST OF LONG ISLAND	58.33	0.00	1.20	1.04	9.39	12.39
FIRST UTD.	33.33	0.00	1.75	1.42	34.33	35.32
FIRST US BANCSHARES	58.33	0.00	7.13	6.45	62.42	57.88

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
FIRSTCASH HOLDINGS	50.00	0.06	3.22	2.64	10.50	14.84
FLEX	58.33	0.00	0.90	0.77	16.83	19.84
FLEXSTEEL INDS.	50.00	0.00	3.84	3.21	21.78	34.00
FLUSHING FINCIAL	75.00	0.04	0.95	0.80	6.19	11.06
FOR	41.67	0.00	0.34	0.29	20.90	23.24
FORMULA SYS.1985 ADR 1:1	33.33	0.00	2.00	1.59	10.94	15.72
FORRESTER RESEARCH	66.67	0.00	4.09	3.57	11.01	16.65
FORWARD INDUSTRIES	58.33	0.00	1.34	1.16	31.24	51.15
FOSSIL GROUP	58.33	0.00	14.94	10.27	18.42	29.19
FOSTER (LB)	75.00	0.08	3.49	2.79	9.58	14.63
FORWARD AIR	66.67	0.00	1.92	1.61	5.97	10.00
FRANKLIN ELECTRIC	58.33	0.00	2.48	2.05	11.94	17.29
FREQUENCY ELECTRONICS	50.00	0.00	0.75	0.64	12.36	16.75
FRP HOLDINGS	58.33	0.00	3.31	3.13	32.12	35.34
FUEL TECH	33.33	0.00	1.85	1.64	25.82	28.37
FUELCELL ENERGY	50.00	0.00	252.85	225.17	110.78	80.27
FULL HOUSE RESORTS	0.00	0.00	1.09	1.08	35.16	55.90
FULTON FINCIAL	58.33	0.00	0.72	0.57	5.89	9.10
G.WILLI-FOOD INTL.	58.33	0.00	0.71	0.57	9.44	11.77
GAIA 'A'	66.67	0.00	1.59	1.42	20.94	24.10
GEN DIGITAL	33.33	0.00	2.30	2.07	23.61	26.71
GESYS	58.33	0.00	0.57	0.41	24.66	36.15
GENTEX	75.00	0.23	1.22	0.76	6.75	11.88
GENTHERM	58.33	0.00	1.62	1.42	14.17	19.56
GEOSPACE TECHNOLOGIES	58.33	0.00	7.18	4.68	14.63	22.33
GEOVAX LABS	33.33	0.00	2.44E+09	2.32E+09	351.55	141.26
GERMAN AMERICAN BANCORP	75.00	0.00	0.94	0.74	7.11	10.45
GERON	58.33	0.00	0.73	0.59	11.95	13.58
GIBRALTAR INDS.	58.33	0.00	6.91	6.48	61.55	58.22
G-III APPAREL GROUP	66.67	0.00	2.51	2.04	14.65	23.35
GILAT	50.00	0.00	1.12	0.99	18.01	25.68
GILEAD SCIENCES	41.67	0.00	4.56	3.94	21.61	23.72
GLOBAL SELF STORAGE	33.33	0.00	0.32	0.28	7.39	9.98
GOLDEN ENTERTAINMENT	50.00	0.00	1.41	1.22	32.28	33.91
GOLDEN OCEAN GROUP	0.00	0.00	60.99	59.61	64.07	123.55
GOOD TIMES REST. PF.SHS.	50.00	0.00	0.96	0.75	35.51	33.32
GOODYEAR TIRE & RUB.	50.00	0.00	4.20	3.81	34.01	36.32
GREAT ELM GROUP	58.33	0.00	8.91	8.16	30.30	47.59
GREAT STHN.BANCORP	91.67	0.00	1.41	1.17	5.31	9.00
GSE SYSTEMS	66.67	0.00	16.68	13.77	36.31	37.28
GT BIOPHARMA	33.33	0.00	2.34E+06	2.14E+06	45.26	44.40
GULF ISLAND FABRICATION	66.67	0.00	4.08	3.40	18.45	24.54
HACKETT GROUP	41.67	0.00	0.58	0.42	11.82	18.65

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
HAIN CELESTIAL GP.	58.33	0.00	2.30	1.87	16.21	25.45
HANCOCK WHITNEY	58.33	0.00	12.99	11.63	35.16	37.33
HANMI FINICIAL	58.33	0.00	5.80	4.07	25.82	38.43
HARMONIC	66.67	0.00	0.70	0.57	8.76	11.75
HARTE-HANKS	66.67	0.18	10.77	8.17	6.55	12.32
HASBRO	66.67	0.00	7.75	6.67	15.38	23.73
HAWAIIAN HOLDINGS	66.67	0.00	1.15	0.91	15.31	19.25
HAWKINS	58.33	0.00	4.92	3.70	21.25	34.45
HEALTHCARE SERVICES GROUP	50.00	0.00	1.58	1.18	8.37	11.40
HEARTLAND EXPRESS	66.67	0.00	1.58	1.31	8.62	11.04
HEARTLAND FINL.USA	58.33	0.00	1.63	1.32	7.86	13.36
HEIDRICK & STGL.INTL.	41.67	0.00	11.08	10.25	46.48	47.01
HELEN OF TROY	58.33	0.00	1.88	1.60	6.42	9.31
HENRY SCHEIN	58.33	0.00	1.16	0.93	4.16	7.03
HERITAGE COMMERCE	0.00	0.00	5.12	5.09	134.01	103.79
HERITAGE FINICIAL	41.67	0.00	0.96	0.77	5.38	7.53
HERON THERAPEUTICS	58.33	0.00	11.71	10.93	78.57	68.18
HIBBETT	66.67	0.00	4.07	2.89	9.92	15.90
HIGHWAY HOLDINGS	66.67	0.00	0.58	0.40	14.03	22.77
HMN FINICIAL	50.00	0.00	1.11	0.96	23.15	28.22
HOLOGIC	66.67	0.00	1.70	1.34	8.06	11.83
HONEYWELL INTL.	75.00	0.00	3.73	3.19	7.38	11.34
HOPE BANCORP	50.00	0.00	3.43	3.25	41.25	43.12
HORIZON BANCORP	75.00	0.00	0.84	0.73	16.24	24.60
HOST HOTELS & RESORTS REIT	66.67	0.00	2.07	1.82	12.20	18.43
HUB GROUP 'A'	0.00	0.00	13.78	13.70	90.77	216.92
HUDSON TECHNOLOGIES	0.00	0.00	0.81	0.72	34.41	55.77
HUNTINGTON BCSH.	66.67	0.00	1.73	1.63	27.81	43.02
HURCO COMPANIES	75.00	0.00	2.32	1.95	10.57	15.11
ICU MEDICAL	0.00	0.00	7.95	7.74	21.69	31.90
IAC	66.67	0.00	0.81	0.65	11.42	17.19
ICAD	25.00	0.00	1.30	1.01	12.10	14.28
ICAHN ENTERPRISES	58.33	0.00	6.41	5.58	15.33	17.08
ICON	50.00	0.00	3.39	2.91	11.80	15.25
IDENTIVE	33.33	0.00	7.36	6.77	39.14	41.27
IDEXX LABORATORIES	58.33	0.30	1.95	1.59	5.24	10.08
IMMERSION	41.67	0.07	0.56	0.46	8.67	13.50
IMMUCELL	50.00	0.00	0.89	0.79	24.25	26.97
IMUNON	8.33	0.00	3.24E+03	3.17E+03	98.97	255.67
INCYTE	50.00	0.00	3.91	3.37	23.50	36.61
INDEPENDENT BANK MASS.	50.00	0.00	2.14	1.74	6.94	11.93
INDEPENDENT BANK	66.67	0.00	6.25	5.41	268.83	108.11
INGLES MARKETS 'A'	58.33	0.21	1.64	1.30	7.84	12.48

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
INNODATA	8.33	0.00	1.01	0.89	25.30	31.55
INNOSPEC	58.33	0.00	4.39	3.03	18.62	29.62
INOTIV	41.67	0.00	0.34	0.22	20.47	25.61
INOVIO	50.00	0.00	7.96	6.95	13.06	15.21
PHARMACEUTICALS						
INSIGHT ENTS.	58.33	0.00	2.30	1.86	12.53	19.12
INTEGRA LFSC.HDG.	66.67	0.23	1.41	1.17	6.26	10.49
INTEL	58.33	0.00	2.21	1.92	9.45	11.93
INTELLICHECK	41.67	0.00	8.22	7.47	63.48	58.53
INTER PARFUMS	75.00	0.00	3.53	3.02	17.63	27.33
INTERDIGITAL	58.33	0.18	3.86	3.13	10.93	16.16
INTERFACE	50.00	0.00	4.21	3.69	27.86	44.61
INTERLINK ELECTRONICS	8.33	0.00	2.39	2.39	608.24	195.76
INTEVAC	75.00	0.00	2.06	1.77	14.09	20.00
INTERTIOL BCSH.	75.00	0.00	3.21	2.87	15.60	18.58
INTRUSION	33.33	0.00	8.63	7.82	44.81	79.51
INTUIT	50.00	0.00	7.95	6.13	14.30	22.29
INVESTORS TITLE	33.33	0.00	2.94	2.47	7.79	9.03
IONIS PHARMACEUTICALS	58.33	0.00	2.51	2.28	24.81	27.92
IRIDEX	58.33	0.00	0.50	0.40	10.48	17.16
ITERIS	0.00	0.00	0.39	0.36	24.86	28.22
ITRON	41.67	0.00	11.99	9.89	16.49	19.35
HUNT JB TRANSPORT SVS.	0.00	0.00	29.38	29.30	83.15	185.77
J & J SCK FOODS	75.00	0.43	2.18	1.81	4.21	8.87
JACK HENRY AND ASSOCIATES	58.33	0.18	1.76	1.42	5.76	9.67
JACK IN THE BOX	58.33	0.00	1.78	1.44	6.53	9.30
JAKKS PACIFIC	58.33	0.00	28.44	22.17	13.51	20.87
JANONE	33.33	0.00	3.09	2.55	16.18	25.91
JOHN B SANFILIPPO & SON	58.33	0.00	2.65	2.11	15.73	17.96
JOHNSON OUTDOORS 'A'	66.67	0.00	2.59	2.27	18.00	26.67
KVH INDUSTRIES	33.33	0.00	1.68	1.40	10.75	12.62
KAZIA THERAPEUTICS ADS 1:10	58.33	0.00	14.07	12.84	303.48	127.69
KELLY SERVICES 'A'	66.67	0.00	3.02	2.48	15.13	23.88
KEWAUNEE SCIENTIFIC	58.33	0.00	3.12	2.70	22.98	26.11
KEY-TRONIC	66.67	0.00	1.78	1.69	30.42	47.62
KFORCE	66.67	0.00	1.46	1.24	8.80	12.66
KLA	66.67	0.00	6.43	5.87	23.50	27.18
KOPIN	66.67	0.00	0.91	0.82	23.20	26.09
KOSS	41.67	0.00	0.75	0.58	11.76	13.53
KRATOS DEF&SCTY.SLTN.	58.33	0.00	5.90	5.72	48.41	83.88
KULICKE & SOFFA INDS.	50.00	0.00	1.31	1.07	14.81	23.00
LSI INDUSTRIES	0.00	0.00	5.63	5.47	88.21	77.00
LAKELAND BANCORP	75.00	0.00	2.27	2.05	25.24	39.32
LAKELAND FINICIAL	58.33	0.29	0.77	0.66	5.00	9.89

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
LAKELAND INDS.	50.00	0.00	1.08	0.95	10.17	14.65
LAM RESEARCH	58.33	0.12	4.46	3.71	9.60	14.54
LAMAR ADVERTISING 'A'	66.67	0.00	4.00	3.27	10.99	15.34
LANCASTER COLONY	58.33	0.00	4.25	3.32	6.15	10.06
LANDSTAR SYSTEM	50.00	0.00	3.78	3.05	7.87	10.73
LATTICE SEMICONDUCTOR	0.00	0.00	1.38	1.08	31.46	31.41
LEE ENTERPRISES	66.67	0.00	8.17	6.68	21.55	29.03
LENDWAY	33.33	0.00	8.05	6.53	14.40	22.23
LEORDO DRS	25.00	0.00	0.56	0.46	9.78	10.36
LESAKA TECHNOLOGIES	50.00	0.00	7.77	7.07	53.56	52.22
LIFECORE BIOMEDICAL	50.00	0.00	1.19	1.06	17.58	20.41
LIFETIME BRANDS	41.67	0.00	5.70	5.14	36.75	62.61
LIFEWAY FOODS	50.00	0.00	2.58	2.23	21.88	24.85
LIGAND PHARMS.'B'	58.33	0.00	1.06	0.87	14.87	16.83
LIGHT WONDER	66.67	0.00	4.78	3.95	41.48	40.46
LIGHTPATH TECHS.	33.33	0.00	2.34	2.30	100.06	259.38
LINCOLN ELECTRIC HDG.	58.33	0.02	2.30	1.73	6.51	11.02
LINDE (NYS)	58.33	0.00	7.29	5.40	6.64	9.85
LISATA THERAPEUTICS	58.33	0.00	680.86	519.21	17.24	23.13
LITTELFUSE	50.00	0.00	6.74	5.64	13.70	20.21
LIVANOVA	41.67	0.08	3.88	3.26	14.07	19.50
LIVE VENTURES	50.00	0.00	11.99	11.40	108.02	84.63
LOGITECH INTL. (S)	58.33	0.00	2.56	2.05	13.23	17.31
MACATAWA BANK	58.33	0.00	0.63	0.55	33.14	38.28
MAGIC SFTW.ENTS. (S)	0.00	0.00	1.83	1.13	30.18	51.15
MANHATTAN ASSOCS.	66.67	0.34	0.54	0.43	6.42	11.31
MANHATTAN BRIDGE CAPITAL	41.67	0.00	0.45	0.43	31.41	49.20
MANTECH	66.67	0.00	9.91	8.52	38.27	38.74
MARINE PETROLEUM TRUST	58.33	0.00	3.21	2.32	11.69	17.16
MARKER THERAPEUTICS	58.33	0.00	1.12E+04	1.10E+04	487.43	172.86
MARRIOTT INTL.'A'	66.67	0.00	4.98	4.19	12.51	19.55
MARTEN TRANSPORT	66.67	0.00	0.62	0.52	9.09	14.25
MATRIX SERVICE	75.00	0.00	1.80	1.57	16.17	19.27
MATTEL	58.33	0.00	1.63	1.35	5.88	9.64
MATTHEWS INTL.'A'	50.00	0.00	7.72	7.11	21.64	25.02
MCGRATH RENTCORP	58.33	0.22	1.93	1.60	6.73	11.07
MEDALLION FINL.	58.33	0.00	1.43	1.26	16.82	19.81
MERCANTILE BANK	66.67	0.00	2.05	1.76	32.04	52.06
MERCER INTL.	83.33	0.00	2.28	2.04	37.40	62.38
MERCURY SYSTEMS	66.67	0.15	2.17	1.51	10.36	16.08
MERIT MEDICAL SYS.	41.67	0.00	4.64	4.41	34.88	38.14
MESA LABORATORIES	50.00	0.00	3.92	3.43	14.34	17.10
METHANEX (S)	0.00	0.00	18.35	18.08	74.19	154.16
MGE ENERGY	58.33	0.00	2.16	1.69	7.03	10.86

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
MGP INGREDIENTS	58.33	0.15	1.06	0.85	10.98	15.70
MICROBOT MEDICAL	58.33	0.00	9.03E+03	8.54E+03	54.21	53.64
MICROCHIP TECH.	58.33	0.00	1.57	1.22	8.64	13.03
MICRON TECHNOLOGY	41.67	0.00	3.48	3.18	39.52	41.39
MICROSOFT	58.33	0.00	7.04	6.46	24.69	28.04
MICROSTRATEGY	66.67	0.00	20.76	18.70	23.01	26.07
MICROVISION	41.67	0.00	9.99	8.72	52.73	49.60
MIDDLEBY	66.67	0.00	4.24	3.29	14.90	22.31
MIDDLESEX WATER	50.00	0.00	1.85	1.55	9.22	11.97
MIDWESTONE FINL.GP.	66.67	0.00	4.61	4.20	29.11	46.71
MILLERKNOLL	58.33	0.00	2.29	1.73	8.36	14.10
MILLICOM INTL.CELU.	33.33	0.00	10.43	8.86	12.35	17.73
MIND TECHNOLOGY	75.00	0.12	10.47	8.25	10.53	14.74
MITEK SYSTEMS	0.00	0.00	1.49	0.85	34.20	64.06
MKS INSTRUMENTS	0.00	0.00	1.73	1.39	6.96	9.06
MORCH CASINO & RESORT	66.67	0.00	1.86	1.68	16.13	24.36
MONRO	75.00	0.00	5.09	3.70	12.23	19.91
MONSTER BEVERAGE	0.00	0.00	2.61	2.58	69.99	140.74
MOTORCAR PARTS OF AM.	41.67	0.00	3.33	2.48	27.64	45.13
MYRIAD GENETICS	33.33	0.00	8.67	7.87	43.71	44.40
PCO SECURITY TECHS.	58.33	0.00	0.16	0.13	12.11	16.43
THANS FAMOUS	50.00	0.00	0.93	0.71	4.57	6.38
TIOL BANKSHARES	66.67	0.00	3.81	3.19	12.72	15.89
TIOL BEVERAGE	75.00	0.00	1.67	1.51	24.81	28.02
TIOL WSTN.LF.GP.'A'	66.67	0.00	25.72	22.34	14.37	16.88
TURAL ALTS.INTL.	16.67	0.00	0.70	0.60	8.28	10.90
TURAL HEALTH TRENDS	16.67	0.00	1.56	1.56	1.04E+03	212.12
TURES SUNSHINE PRODUCTS	58.33	0.16	1.18	0.79	7.80	12.78
NBT BANCORP	66.67	0.07	1.40	1.10	4.90	8.68
NEKTAR THERAPEUTICS	58.33	0.00	3.58	3.21	23.04	35.43
NEOGEN	58.33	0.00	1.52	1.11	13.56	20.98
NEOGENOMICS	0.00	0.00	0.16	0.14	11.64	15.20
NEONODE	0.00	0.00	6.38	5.28	70.29	57.90
NETAPP	58.33	0.00	8.50	7.02	16.09	23.15
NETSCOUT SYSTEMS	58.33	0.02	3.50	2.70	14.77	21.15
NETSOL TECHS.	50.00	0.00	4.14	2.75	20.45	30.90
NEUROCRINE BIOSCIENCES	50.00	0.00	3.13	2.42	38.77	71.82
NEWELL BRANDS (XSC)	50.00	0.00	1.36	1.05	6.44	10.88
NEWTEKONE	58.33	0.00	1.55	1.38	20.09	30.79
NICE SPN.ADR 1:1	58.33	0.00	4.43	3.69	12.61	15.11
NICHOLAS FINCIAL	8.33	0.00	6.18	6.11	70.89	143.53
NN	58.33	0.00	3.09	2.44	31.43	52.73
NORDSON	58.33	0.05	4.51	3.73	10.36	15.16
NORTECH SYSTEMS	0.00	0.00	2.86	2.84	79.20	73.49
NORTHERN TECHS.INTL.	66.67	0.00	1.13	0.80	12.78	20.53

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
NORTHERN TRUST	66.67	0.00	5.46	4.78	9.48	11.68
NORTHRIM BANCORP	66.67	0.00	1.64	1.43	8.58	11.61
NORTHWEST BANCSHARES	0.00	0.00	1.86	1.80	15.53	22.06
NORTHWEST PIPE	66.67	0.00	6.06	5.46	28.04	30.19
NOVANTA	58.33	0.00	4.74	4.26	57.24	111.67
NOVAVAX	58.33	0.00	8.18	7.41	16.21	19.31
NVIDIA	0.00	0.00	0.96	0.76	19.92	29.78
OSI SYSTEMS	41.67	0.00	4.21	3.34	10.58	14.70
OBLONG	41.67	0.00	83.13	71.71	22.44	24.82
OCEANFIRST FINL.	50.00	0.15	0.78	0.58	5.07	9.10
ODYSSEY MARINE EXP.	50.00	0.06	4.39	3.66	20.54	26.37
OLD DOMINION FGT.LINES	66.67	0.23	0.65	0.54	10.15	15.10
OLD TIOL BANCORP	50.00	0.00	2.84	2.59	24.26	27.69
OLD POINT FINCIAL	41.67	0.00	4.35	3.85	32.32	34.62
OLD SECOND BANCORP	50.00	0.00	7.20	6.78	351.81	134.67
OLYMPIC STEEL	41.67	0.00	9.24	8.12	33.17	35.35
ONESPAN	50.00	0.00	1.31	1.02	12.83	19.39
OPEN TEXT (S)	50.00	0.00	0.96	0.79	7.20	9.76
OPKO HEALTH	0.00	0.00	0.89	0.74	29.18	46.32
OPTICAL CABLE	50.00	0.00	0.97	0.92	31.62	34.85
OPTION CARE HEALTH	41.67	0.00	10.88	9.22	43.68	42.38
ORASURE TECHS.	41.67	0.00	0.90	0.75	17.14	20.58
O REILLY AUTOMOTIVE	75.00	0.00	9.30	7.57	14.40	22.80
ORTHOFIX MEDICAL	25.00	0.00	4.29	3.41	11.36	13.44
OTTER TAIL	58.33	0.00	6.37	6.06	29.54	33.09
PAM TRANSPORTATION SVS.	50.00	0.00	0.84	0.69	19.70	30.24
PACCAR	58.33	0.00	5.17	4.28	13.46	19.85
PAC.PREMIER BANC.	0.00	0.00	3.52	3.45	79.77	72.68
PAPA JOHNS INTL.	50.00	0.00	0.84	0.68	5.35	8.08
PARAMOUNT GLOBAL A	58.33	0.16	1.48	1.18	7.62	12.17
PARAMOUNT GLOBAL B	58.33	0.01	1.60	1.27	8.04	12.59
PARK OHIO HOLDINGS	58.33	0.00	8.94	8.15	59.78	113.17
PATHWARD FINCIAL	66.67	0.00	2.73	2.37	32.03	38.46
PATRICK INDUSTRIES	58.33	0.00	0.23	0.19	16.73	22.37
PATRIOT T.BANCORP	33.33	0.00	5.30	4.73	24.04	36.62
PATTERSON COMPANIES	58.33	0.00	1.83	1.56	5.37	8.04
PATTERSON UTI ENERGY	75.00	0.09	2.40	2.00	12.38	17.02
PAYCHEX	66.67	0.00	5.10	4.59	16.48	19.22
PC CONNECTION	58.33	0.00	1.23	1.10	16.57	22.29
PEAPACK-GLADSTONE FINL.	58.33	0.00	1.12	0.91	7.11	10.30
PEGASYSTEMS	41.67	0.00	3.30	2.70	19.25	21.42
PENN ENTERTAINMENT	0.00	0.00	1.74	1.52	22.20	33.53
PENNS WOODS BANC.	41.67	0.00	1.97	1.45	6.95	11.13
PEOPLES BANCORP	66.67	0.00	4.36	3.89	25.78	40.45

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
PEOPLES BANC.OF NOCA.	0.00	0.00	3.74	3.70	77.45	72.10
PEPSICO	0.00	0.00	31.94	31.88	49.48	85.84
PERDOCEO EDUCATION	50.00	0.00	5.23	4.35	19.19	24.59
PERFICIENT	58.33	0.00	1.54	1.21	10.93	18.12
PERMA-FIX ENV.SVS.	58.33	0.00	3.27	2.86	34.31	35.89
PERMA-PIPE INTL.HDG.	50.00	0.20	0.94	0.73	10.00	15.03
PETMED EXPRESS	0.00	0.00	14.83	14.68	79.02	170.63
PHOTRONIC	0.00	0.00	7.26	7.21	147.78	109.15
PINEAPPLE ENERGY	33.33	0.00	4.46	3.68	14.07	17.92
PLAINS ALL AMERICAN	58.33	0.00	2.55	2.05	6.77	9.95
PIPELINE UNITS						
PLEXUS	66.67	0.00	4.25	3.57	11.64	14.98
PLUG POWER	33.33	0.00	4.00	3.81	83.69	73.61
POOL	66.67	0.00	2.47	1.98	8.75	14.32
POPULAR	50.00	0.00	6.31	5.34	18.27	27.60
PORTAGE BIOTECH	33.33	0.00	16.80	15.39	66.13	60.35
POTLATCHDELTIC	41.67	0.00	2.85	2.38	6.87	8.51
POWELL INDUSTRIES	41.67	0.00	3.28	2.57	8.56	11.30
POWER INTEGRATIONS	58.33	0.00	2.66	2.29	13.65	17.29
POWERFLEET	66.67	0.00	0.58	0.46	19.61	22.22
PREFORMED LINE	66.67	0.00	12.11	10.78	31.89	36.23
PRODUCTS						
PREMIER FINCIAL	58.33	0.00	0.73	0.64	12.44	16.39
PRICESMART	66.67	0.00	6.01	4.62	15.79	24.55
PRIMEENERGY RESOURCES	33.33	0.00	16.20	15.15	74.60	67.53
PRO-DEX COLONIAL	25.00	0.00	1.98	1.96	109.21	90.72
PROGRESS SOFTWARE	66.67	0.24	2.42	1.86	8.11	13.57
PROPHASE LABS	0.00	0.00	1.27	1.24	136.29	100.67
PROVIDENT FINL.HDG.	75.00	0.00	2.67	2.35	40.85	70.75
PSYCHEMEDICS	66.67	0.00	1.50	1.31	15.17	21.94
PTC	75.00	0.05	2.05	1.66	8.63	12.78
PURE CYCLE	58.33	0.00	0.71	0.62	23.08	27.51
QCR HDG.	0.00	0.00	2.22	2.10	23.34	26.87
QORVO	50.00	0.14	4.38	3.79	18.24	24.88
QUALCOMM	33.33	0.00	8.99	7.60	19.81	22.99
QUANTUM	58.33	0.00	7.83	6.38	40.86	41.85
QUICKLOGIC	50.00	0.00	31.36	25.80	44.23	77.83
QUIDELORTHO	50.00	0.00	2.51	2.18	17.75	20.63
RCM TECHS.	41.67	0.00	1.57	1.35	33.99	57.46
RADCOM	0.00	0.00	3.31	2.88	69.95	67.97
RADIUS RECYCLING A	66.67	0.06	5.84	4.63	9.82	14.52
RADNET	0.00	0.00	0.52	0.39	14.27	19.67
RADWARE	41.67	0.00	5.49	4.21	28.98	48.76
RAMBUS	50.00	0.00	5.48	4.97	24.85	28.11
RAVE RESTAURANT GROUP	41.67	0.00	0.16	0.13	6.96	10.16
RCI HOSPITALITY HDG.	66.67	0.00	2.73	2.16	21.30	28.89

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
REGENCY CENTERS	58.33	0.00	3.05	2.51	6.57	9.99
REGENERON PHARMS.	66.67	0.31	2.10	1.69	6.59	11.29
REGIS	41.67	0.00	36.98	30.21	8.48	12.18
REPLIGEN	50.00	0.00	0.97	0.92	26.53	30.34
REPUBLIC BANCORP OF KEN. 'A'	50.00	0.19	2.45	1.92	9.39	15.39
RESEARCH FRONTIERS	0.00	0.00	2.29	2.18	62.75	59.81
RF INDUSTRIES	66.67	0.00	0.48	0.36	11.86	18.49
RGC RES.	58.33	0.00	0.84	0.70	6.80	8.54
RICHARDSON ELECTRONICS	75.00	0.00	3.25	3.03	30.89	48.68
RIVERVIEW BANCORP	75.00	0.14	0.36	0.27	11.48	16.63
ROCKWELL MEDICAL	41.67	0.00	21.44	17.39	28.11	30.51
ROCKY BRANDS	75.00	0.00	1.19	0.97	10.94	16.80
ROCKY MNT.CHOCO.FAC.	50.00	0.00	1.63	1.55	16.49	23.67
ROPER TECHNOLOGIES	66.67	0.00	8.47	6.69	10.15	15.67
ROSS STORES	50.00	0.00	2.23	1.93	13.55	20.65
ROYAL GOLD	0.00	0.00	30.41	30.26	62.19	117.90
RUSH ENTERPRISES 'B'	0.00	0.00	1.72	1.36	21.27	32.63
RYAIR SPN.ADR 1:5	50.00	0.00	2.92	2.20	7.61	10.05
S & T BANCORP	75.00	0.19	1.93	1.55	7.59	13.36
SAGA COMMS.'A'	66.67	0.00	6.78	6.13	36.32	60.64
SANDY SPRING BANCORP	75.00	0.00	6.40	6.04	37.64	62.28
SANMI	58.33	0.00	2.72	2.14	14.96	20.86
SAPIENS INTL.	41.67	0.00	0.78	0.68	27.75	44.76
SAREPTA THERAPEUTICS	58.33	0.00	2.18	1.82	17.14	23.99
SAVARA	0.00	0.00	275.63	219.96	82.64	185.74
SB FINICIAL GROUP	58.33	0.00	2.68	2.19	64.21	54.88
SBA COMMS.	0.00	0.00	31.56	31.48	86.48	198.87
SCANSOURCE	50.00	0.00	2.50	1.95	7.19	10.00
SCHOLASTIC	66.67	0.00	6.60	5.97	22.45	25.69
SEACOAST BKG.OF FLA.	58.33	0.00	1.72	1.54	20.96	25.32
SCTY.T.FINL.'A'	0.00	0.00	0.44	0.39	37.33	38.96
SEELOS THERAPEUTICS	83.33	0.00	5.62E+04	5.22E+04	202.97	111.12
SEI INVESTMENTS	58.33	0.00	3.01	2.64	12.24	18.28
SELECTIVE IN.GP.	58.33	0.00	1.41	1.11	7.05	9.93
SEMTECH	58.33	0.24	2.18	1.84	9.72	14.74
SENECA FOODS 'A'	50.00	0.00	4.35	3.69	12.75	17.64
SENSTAR TECHNOLOGIES	41.67	0.00	0.82	0.72	35.18	36.90
SERVICE PROPERTIES TRUST	50.00	0.00	3.47	2.96	13.70	16.79
SHENDOAH TELECOM.	33.33	0.00	1.03	0.93	16.62	19.59
SHOE CARNIVAL	58.33	0.32	0.94	0.79	10.97	17.55
SIEBERT FINICIAL	33.33	0.00	0.34	0.25	13.22	15.12
SIERRA BANCORP	58.33	0.00	3.79	3.57	30.31	47.68

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
SIFY TECHNOLOGIES ADR 1:1	0.00	0.00	2.49	2.47	151.91	110.33
SIGA TECHNOLOGIES	75.00	0.00	3.08	2.05	19.48	31.45
SIGMATRON INTL.	58.33	0.00	0.62	0.52	8.60	11.12
SILICOM	66.67	0.00	4.04	3.04	22.17	33.95
SIMMONS 1ST.T.'A'	50.00	0.00	1.40	1.23	9.03	11.44
SIMULATIONS PLUS	25.00	0.00	1.14	1.04	42.26	71.93
SINCLAIR A	66.67	0.00	2.32	2.07	29.93	47.25
SIRIUS XM HOLDINGS	75.00	0.00	0.61	0.57	51.04	90.58
SKYWEST	58.33	0.00	4.14	3.91	28.10	31.53
SKYWORKS SOLUTIONS	50.00	0.00	4.79	3.42	16.09	24.51
SLEEP NUMBER	66.67	0.00	1.76	1.45	16.65	26.13
SLM	58.33	0.00	0.52	0.43	10.67	13.27
SMITH WESSON BRANDS	0.00	0.00	0.56	0.52	17.37	20.60
SMITH MICRO SOFTWARE	75.00	0.23	65.39	47.87	13.56	21.44
SMITH MIDLAND	8.33	0.00	0.27	0.22	13.73	19.85
SOCKET MOBILE	41.67	0.00	0.53	0.36	15.68	17.16
SOLIGENIX	50.00	0.00	158.96	110.59	19.25	20.72
SOLU HOLDINGS	50.00	0.00	22.29	21.94	128.31	99.40
SOUTHSIDE BANCSHARES	50.00	0.00	0.95	0.83	5.85	9.35
SPAR GROUP	0.00	0.00	0.16	0.14	14.55	20.93
SSR MINING	41.67	0.00	4.39	3.89	21.09	26.43
STAAR SURGICAL	75.00	0.00	1.59	1.38	26.39	42.23
STAGWELL A	75.00	0.00	1.96	1.67	19.56	30.06
STARBUCKS	66.67	0.17	1.30	0.98	7.07	12.59
STEEL CONNECT	66.67	0.00	30.77	27.19	42.26	42.94
STEEL DYMICS	58.33	0.00	3.60	3.21	21.50	24.35
STERICYCLE	0.00	0.00	57.67	57.10	89.84	212.93
STERLING	58.33	0.00	6.49	5.76	42.94	43.39
INFRASTRUCTURE						
STEVEN MADDEN	0.00	0.00	6.35	6.12	56.73	104.24
STOCK YARDS BANCORP	50.00	0.00	0.96	0.79	5.05	7.88
STONEX GROUP	91.67	0.00	2.00	1.38	10.35	16.38
STRATASYS	58.33	0.00	7.93	7.05	25.68	39.95
STRATEGIC EDUCATION	66.67	0.00	51.03	36.90	23.25	25.73
STRATTEC SECURITY	50.00	0.00	6.16	4.29	15.54	24.54
STRATUS PROPERTIES NEW	75.00	0.00	1.81	1.66	20.60	23.97
STREAMLINE HEALTH SLTN.	0.00	0.00	1.08	1.00	71.53	64.12
SUMMIT FINL.GP.	58.33	0.00	0.88	0.71	21.68	24.78
SUNOPTA (S)	66.67	0.00	1.84	1.49	26.69	42.16
SUPERIOR GROUP OF COMPANIES	75.00	0.00	0.41	0.33	6.79	9.02
SURMODICS	33.33	0.00	11.30	10.24	78.56	66.93
SWK HOLDINGS	50.00	0.00	0.48	0.41	4.60	7.83
SYNOPSIS	58.33	0.00	1.93	1.49	6.63	10.41

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
SYPRIS SOLUTIONS	58.33	0.00	0.69	0.54	13.75	21.41
TAT TECHNOLOGIES	58.33	0.00	2.26	1.90	29.26	30.83
T ROWE PRICE GROUP	66.67	0.00	7.36	5.93	11.97	16.59
TSR	50.00	0.00	0.53	0.47	10.28	13.49
TAITRON COMPONENTS	8.33	0.00	0.21	0.19	15.42	19.18
TAKE TWO INTACT.SFTW.	66.67	0.28	0.79	0.62	6.33	11.39
TANDY LEATHER FACTORY	0.00	0.00	0.88	0.79	17.76	25.92
TAYLOR DEVICES	0.00	0.00	0.94	0.80	14.49	20.88
TEX THERAPEUTICS	16.67	0.00	1.13E+06	1.02E+06	58.64	53.72
TERADYNE (XSC)	58.33	0.18	1.09	0.87	8.24	13.28
TETRA TECH	58.33	0.00	7.65	7.30	34.22	37.44
TEXAS INSTRUMENTS	66.67	0.06	2.82	2.50	9.71	14.36
TG THERAPEUTICS	33.33	0.00	99.31	79.53	95.80	65.36
COOPER COS.	50.00	0.12	1.47	1.20	10.99	15.61
DIXIE GP.'A'	58.33	0.00	1.09	0.88	22.06	34.59
ODP	50.00	0.00	17.89	16.17	33.02	35.03
SHYFT GROUP	75.00	0.00	1.56	1.38	28.89	31.19
SINGING MACHINE	33.33	0.04	0.45	0.38	33.87	41.32
THERMOGENESIS HOLDINGS	50.00	0.00	6.28E+03	5.49E+03	26.45	29.50
TIMBERLAND BANCORP	41.67	0.00	0.55	0.42	11.42	13.97
TITAN PHARMS.DE	41.67	0.00	9.56E+03	7.82E+03	27.11	33.99
TOWER	66.67	0.00	5.94	5.43	24.43	37.43
TOWNEBANK	50.00	0.00	2.21	2.02	14.02	20.86
TRACTOR SUPPLY	66.67	0.00	3.57	2.82	15.02	23.60
TRANSACT TECHNOLOGIES	0.00	0.00	1.66	1.51	18.76	27.40
TRANSCAT	58.33	0.00	0.48	0.39	5.41	8.07
TRICO BANCSHARES	66.67	0.00	2.46	1.97	12.07	15.10
TRIMBLE	66.67	0.00	5.39	4.98	31.24	49.03
TRINITY BIOTECH ADR 1:20	75.00	0.00	12.20	10.76	32.60	53.16
TRUSTCO BANK NY	58.33	0.00	4.59	4.04	14.01	17.34
TRUSTMARK	66.67	0.00	2.37	2.03	9.24	11.64
TTEC HOLDINGS	58.33	0.00	5.84	5.22	35.27	37.39
TUCOWS 'A'	16.67	0.00	0.39	0.31	10.68	15.06
TWIN DISC	66.67	0.00	6.05	3.79	19.90	32.86
UFP TECHNOLOGIES	50.00	0.00	3.87	3.53	33.72	54.42
US ENERGY	66.67	0.00	72.35	63.02	21.29	23.95
US GLOBAL INVRS.	50.00	0.00	5.29	4.88	68.28	62.24
US.LIME & MINERALS	0.00	0.00	28.18	28.12	72.20	147.50
US GOLD	50.00	0.00	1.25E+03	1.16E+03	85.59	72.50
UFP INDUSTRIES	66.67	0.00	2.42	2.10	19.84	23.21
ULTRALIFE	83.33	0.15	0.79	0.69	14.58	20.87
UMB FINICIAL	66.67	0.00	4.73	4.07	10.97	13.82
UNITED BANKSHARES	0.00	0.00	19.63	19.50	74.91	156.42
UNITED BANCORP OH.	50.00	0.00	0.78	0.64	7.68	9.04
UNITED FIRE GROUP	58.33	0.25	1.59	1.32	6.69	11.66

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE(%)	SMAPE(%)
UNITED GUARDIAN	25.00	0.00	1.33	1.02	7.74	12.02
UNITED SECURITY BCSH.	41.67	0.00	0.60	0.54	15.28	20.36
UNITED THERAPEUTICS	66.67	0.05	4.43	3.92	7.20	10.41
UNITY BANCORP	58.33	0.00	0.90	0.81	16.31	24.89
UNIVERSAL DISPLAY	50.00	0.00	7.56	5.85	26.93	44.09
UNIVERSAL ELECTRONICS	50.00	0.00	3.92	3.24	16.30	21.01
UNIVERSAL STAINLESS & ALLOY PRODUCTS	58.33	0.00	4.99	3.93	15.48	22.56
UNIVEST FINCIAL	50.00	0.11	1.09	0.87	4.71	8.63
UPBOUND GROUP	0.00	0.00	17.32	17.05	72.31	148.07
URBAN ONE 'A'	58.33	0.00	1.93	1.58	134.46	82.94
URBAN OUTFITTERS	41.67	0.00	4.03	3.54	10.59	13.85
USIO	50.00	0.00	0.31	0.27	40.77	70.97
UTAH MEDICAL PRODUCTS	25.00	0.00	4.95	4.46	16.59	19.57
VSE	66.67	0.00	6.89	6.04	35.60	36.95
VALLEY TIOL	66.67	0.00	1.22	1.03	8.34	10.70
VALUE LINE	58.33	0.00	9.99	8.67	54.79	51.47
VAXART	66.67	0.00	26.01	19.71	5.46	9.11
VEECO INSTRUMENTS	66.67	0.00	6.13	4.74	11.17	17.84
VERICEL	58.33	0.00	18.84	17.64	54.12	54.39
VERISIGN	50.00	0.00	3.83	3.05	10.01	15.41
VERTEX PHARMS.	41.67	0.00	11.78	10.85	30.45	33.64
VERU	58.33	0.00	0.65	0.48	8.15	13.41
VIASAT	50.00	0.07	4.39	3.64	10.21	14.56
VIATRIS	50.00	0.00	1.81	1.47	7.55	11.26
VIAVI SOLUTIONS	58.33	0.00	1.90	1.71	25.49	39.53
VICOR	41.67	0.00	5.32	4.66	31.44	51.19
VILLAGE SPRMKT.'A'	50.00	0.00	2.41	1.89	6.98	11.11
VIRCO MANUFACTURING	33.33	0.00	1.20	1.10	37.27	39.56
VIRTRA	0.00	0.00	0.25	0.20	14.39	20.25
VODAFONE GP.SPN.ADR 1:10	33.33	0.00	2.83	2.16	9.56	12.80
VOXX INTERTIOL 'A'	58.33	0.21	0.67	0.54	7.30	12.10
WD-40	50.00	0.00	2.94	2.40	6.79	10.39
WAFD	50.00	0.00	4.12	3.46	21.65	24.11
WALGREENS BOOTS ALLIANCE	50.00	0.00	6.90	5.90	18.94	21.95
WASHINGTON TST.BANC.	83.33	0.00	2.20	1.90	9.76	14.92
WENDY'S CLASS A	58.33	0.00	0.93	0.85	18.96	22.41
WERNER ENTERPRISES	75.00	0.00	1.19	1.00	5.09	7.66
WESBANCO	0.00	0.00	5.02	4.70	29.67	32.83
WEST BANCORPORATION	75.00	0.00	1.46	1.28	17.95	27.40
WESTAMERICA BANCORP.	50.00	0.00	6.83	5.69	10.64	12.93
WESTERN DIGITAL	0.00	0.00	23.13	22.36	63.47	122.18
WEYCO GROUP	58.33	0.00	2.78	2.45	10.34	12.73
WILHELMI INTERTIOL	50.00	0.00	0.53	0.45	18.11	25.76

Company	Accuracy(%)	R²	RMSE	MAE	MAPE(%)	SMAPE(%)
WILLAMETTE	41.67	0.00	0.27	0.21	5.89	6.95
VLY.VINEYARDS						
WILLIS LEASE FINCE	58.33	0.00	3.70	3.14	28.88	30.53
WINDTREE THERAPEUTICS	58.33	0.00	3.17E+07	3.15E+07	953.21	206.36
WINMARK	50.00	0.00	7.92	6.71	21.03	33.77
WINTRUST FINCIAL	41.67	0.00	3.59	2.76	7.94	11.48
WOODWARD	66.67	0.00	3.70	3.05	9.57	14.15
WORLD ACCEPTANCE	66.67	0.00	4.49	3.58	8.59	11.81
WSFS FINCIAL	75.00	0.00	3.70	3.34	25.13	39.84
XCEL ENERGY	41.67	0.00	1.69	1.30	6.05	8.43
XEROX HOLDINGS	66.67	0.03	2.96	2.47	9.12	13.87
XOMA	33.33	0.00	111.77	96.25	135.94	84.33
YORK WATER	41.67	0.00	1.42	1.10	7.74	11.52
YUNHONG GREEN CTI	41.67	0.00	3.56	3.03	50.49	94.49
ZEBRA TECHNOLOGIES 'A'	58.33	0.11	3.77	3.04	9.69	14.25
ZIFF DAVIS	75.00	0.00	4.45	3.98	18.47	27.27
ZIONS BANCORP.	50.00	0.00	7.08	6.56	29.39	45.90

Appendix C: Results from the 2020 testing period.

Appendix C1: Minimum variance portfolio weight allocations during the 2020 testing period.

Companies	Weight	Sector	Beta
ASTEC INDUSTRIES	0.02%	Industrials	-1.097
SUPER LEAGUE ENTERPRISE	0.00%	Technology	-0.504
INTERNATIONAL MONEY EXPRESS	0.27%	Finance	-0.265
SUPERIOR GROUP OF COMPANIES	0.01%	Consumer Discretionary	-0.222
PAYONEER GLOBAL	0.01%	Industrials	-0.099
VITAL FARMS	0.00%	Consumer Staples	-0.096
MVB FINCIAL	0.06%	Finance	-0.091
XOS	0.23%	Industrials	-0.057
XP A	0.00%	Finance	-0.048
CYCLACEL PHARMS.	0.29%	Healthcare	-0.041
ALDEYRA THERAPEUTICS	1.39%	Healthcare	-0.040
SIL PHARMA	0.05%	Consumer Discretionary	-0.039
KINGSWOOD ACQUISITION A	0.06%	Finance	-0.034
KYMERA THERAPEUTICS ORD	9.29%	Healthcare	-0.003
FLUENT	0.11%	Consumer Discretionary	0.015
FIRST BUSEY 'A'	0.98%	Finance	0.024
BANK FIRST	2.71%	Finance	0.030
GLADSTONE COML.	3.34%	Real Estate	0.032
BANCFIRST	5.65%	Finance	0.033
CATHAY GEN.BANCORP	6.31%	Finance	0.036
PLUM ACQUISITION A	0.67%	Finance	0.038
LAMAR ADVERTISING 'A'	4.66%	Real Estate	0.041
MINERVA NEUROSCIENCES	0.17%	Healthcare	0.053
SUNRISE NEW ENERGY A	0.12%	Technology	0.054
CERTARA	0.38%	Healthcare	0.056
KORNIT DIGITAL	0.37%	Industrials	0.058
PASITHEA THERAPEUTICS	4.69%	Healthcare	0.058
JET AI	4.31%	Technology	0.064
NOODLES 'A'	1.31%	Consumer Discretionary	0.064
CERVOMED	0.97%	Healthcare	0.065
WHOLE EARTH BRANDS A	6.08%	Consumer Staples	0.070
GULF RESOURCES	5.65%	Basic Materials	0.072
STRYVE FOODS A	4.22%	Consumer Staples	0.072
BIO-PATH HOLDINGS	0.24%	Healthcare	0.073
MAGYAR BANCORP	1.57%	Finance	0.073
MAGIC SFTW.ENTS. (NAS)	2.82%	Technology	0.077
YORK WATER	0.60%	Utilities	0.078
PATRIA INVESTMENTS A	1.15%	Finance	0.081
CALUMET SPY.PRDS.PTNS.	4.43%	Basic Materials	0.081
PROKIDNEY A	0.90%	Healthcare	0.083
BARRETT BUS.SVS.	0.00%	Industrials	0.084
DZS	5.63%	Telecommunication	0.085
SOTERA HEALTH COMPANY	5.87%	Healthcare	0.086

Companies	Weight	Sector	Beta
TEYA THERAPEUTICS	1.36%	Healthcare	0.088
COLLIERS INTL.GP. (NAS)	1.15%	Real Estate	0.091
HERITAGE COMMERCE	0.16%	Finance	0.093
KELLY SERVICES 'B'	5.23%	Industrials	0.096
CARPARTS COM	0.00%	Consumer Discretionary	0.101
INTERDIGITAL	4.22%	Telecommunication	0.104
ENERGY FOCUS	0.31%	Industrials	0.104

Appendix C2: Portfolio weight allocations per month of the ML portfolio during the 2020 testing period.

January	Weight	Sector	February	Weight	Sector
OCUPHIRE	1.19%	Healthcare	OCUPHIRE	1.15%	Healthcare
PHARMA			PHARMA		
FUTURE FINTECH GROUP	0.80%	Finance	FUTURE FINTECH GROUP	0.79%	Finance
LIGHTBRIDGE	0.36%	Industrials	LIGHTBRIDGE	0.34%	Industrials
GYRODYNE	9.42%	Real Estate	GYRODYNE	9.42%	Real Estate
CAPRICOR THERAPEUTICS	0.58%	Healthcare	CAPRICOR THERAPEUTICS	0.58%	Healthcare
US GOLD	0.68%	Basic Materials	US GOLD	0.72%	Basic Materials
MICROBOT MEDICAL	-0.01%	Healthcare	MICROBOT MEDICAL	-0.01%	Healthcare
MARKER THERAPEUTICS	0.24%	Healthcare	MARKER THERAPEUTICS	0.27%	Healthcare
RIOT PLATFORMS	0.32%	Finance	RIOT PLATFORMS	0.32%	Finance
ALTIMMUNE	0.23%	Healthcare	ALTIMMUNE	0.22%	Healthcare
CARDIFF ONCOLOGY	0.37%	Healthcare	CARDIFF ONCOLOGY	0.39%	Healthcare
GYRE THERAPEUTICS	0.25%	Healthcare	GYRE THERAPEUTICS	0.25%	Healthcare
TG THERAPEUTICS	-0.05%	Healthcare	TG THERAPEUTICS	-0.06%	Healthcare
PORTAGE BIOTECH	0.00%	Healthcare	PORTAGE BIOTECH	0.00%	Healthcare
LIFEWAY FOODS	2.94%	Consumer Staples	PSYCHEMEDICS	9.36%	Healthcare
PSYCHEMEDICS	9.44%	Healthcare	LIFEWAY FOODS	2.84%	Consumer Staples
BROADWIND	-1.42%	Industrials	BROADWIND	-1.41%	Industrials
CINEVERSE A	0.80%	Consumer Discretionary	CINEVERSE A	0.82%	Consumer Discretionary
ANTELOPE ENTERPRISE HOLDINGS A	0.71%	Industrials	ANTELOPE ENTERPRISE HOLDINGS A	0.68%	Industrials
GNE.TECHS.SPN. ADR 1:30	-0.04%	Healthcare	GNE.TECHS.SPN. ADR 1:30	-0.03%	Healthcare
DIGITAL ALLY	0.78%	Industrials	DIGITAL ALLY	0.85%	Industrials
INNOVIVA	-0.79%	Healthcare	INNOVIVA	-0.80%	Healthcare
ARCA BIOPHARMA	0.71%	Healthcare	ARCA BIOPHARMA	0.71%	Healthcare
HARTE-HANKS	-0.61%	Consumer Discretionary	HARTE-HANKS	-0.61%	Consumer Discretionary
MACATAWA BANK	5.29%	Finance	MACATAWA BANK	5.33%	Finance
IOVANCE BIOTHERAPEUTICS	0.01%	Healthcare	COCRYSTAL PHARMA	0.02%	Healthcare

SANARA MEDTECH	0.66%	Healthcare	IOVANCE BIOTHERAPEUTIC S	0.01%	Healthcare
COCRYSTAL PHARMA	0.02%	Healthcare	SANARA MEDTECH	0.67%	Healthcare
LEXICON PHARMACEUTICA LS	-1.80%	Healthcare	LEXICON PHARMACEUTICA LS	-1.84%	Healthcare
THERMOGENESIS HOLDINGS	0.80%	Healthcare	WATERSTONE FINANCIAL	6.04%	Finance
WATERSTONE FINANCIAL	5.63%	Finance	THERMOGENESIS HOLDINGS	0.82%	Healthcare
INOTIV	2.57%	Healthcare	INOTIV	2.56%	Healthcare
HEALTHSTREAM DISTRIBUTION	2.03%	Healthcare	HEALTHSTREAM DISTRIBUTION	2.07%	Healthcare
SOLUTIONS GROUP	1.10%	Industrials	SOLUTIONS GROUP	1.07%	Industrials
TFS FINANCIAL	27.35%	Finance	TFS FINANCIAL	27.30%	Finance
HUDSON GLOBAL	-1.16%	Industrials	HUDSON GLOBAL	-1.20%	Industrials
CATALYST PHARMACEUTICA L PARTNERS	0.21%	Healthcare	CATALYST PHARMACEUTICA L PARTNERS	0.26%	Healthcare
PERASO	-0.46%	Technology	PERASO	-0.48%	Technology
SURMODICS	1.24%	Healthcare	SURMODICS	1.24%	Healthcare
CADENCE DESIGN SYS.	6.16%	Technology	NEUROMETRIX	2.56%	Healthcare
NEUROMETRIX	2.64%	Healthcare	CADENCE DESIGN SYS.	6.17%	Technology
FLUENT	0.56%	Consumer Discretionary	FLUENT	0.53%	Consumer Discretionary
CAPITAL SOUTHWEST	11.96%	Finance	AETERNA ZENTARIS (NAS)	0.15%	Healthcare
EPLUS	2.14%	Technology	CAPITAL SOUTHWEST	11.87%	Finance
AETERNA ZENTARIS (NAS)	0.15%	Healthcare	EPLUS	2.03%	Technology
MOLECULAR TEMPLATES	-0.46%	Healthcare	MOLECULAR TEMPLATES	-0.49%	Healthcare
THE9 AMERICAN DEPOSITORY SHARES 1:300	0.73%	Consumer Discretionary	THE9 AMERICAN DEPOSITORY SHARES 1:300	0.73%	Consumer Discretionary
WILLDAN GROUP	3.21%	Industrials	WILLDAN GROUP	3.22%	Industrials
PENN ENTERTAINMENT	2.05%	Consumer Discretionary	GLOBUS MARITIME	0.44%	Industrials
GLOBUS MARITIME	0.46%	Industrials	PENN ENTERTAINMENT	2.15%	Consumer Discretionary
March	Weight	Sector	April	Weight	Sector
PROFIRE ENERGY	-0.45%	Energy	OCUPHIRE PHARMA	1.51%	Healthcare

PROPHASE LABS	2.20%	Consumer Staples	FUTURE FINTECH GROUP	1.18%	Finance
QUEST RESOURCE HOLDING	0.41%	Utilities	LIGHTBRIDGE	0.50%	Industrials
REGENCY CENTERS	12.34%	Real Estate	GYRODYNE	12.74%	Real Estate
REPLIGEN	2.24%	Healthcare	CAPRICOR THERAPEUTICS	0.86%	Healthcare
RIGEL PHARMS.	-0.73%	Healthcare	US GOLD	0.32%	Basic Materials
SAVARA	0.21%	Healthcare	MICROBOT MEDICAL	-0.05%	Healthcare
SELLAS LIFE SCIENCES GROUP	0.62%	Healthcare	MARKER THERAPEUTICS	0.23%	Healthcare
SERVICE PROPERTIES TRUST	-4.03%	Real Estate	RIOT PLATFORMS	0.09%	Finance
SIEBERT FINANCIAL	0.78%	Finance	ALTIMMUNE	0.63%	Healthcare
SIFY TECHNOLOGIES ADR 1:1	0.37%	Telecommunication	CARDIFF ONCOLOGY	0.33%	Healthcare
SIRIUS XM HOLDINGS	0.06%	Consumer Discretionary	GYRE THERAPEUTICS	0.21%	Healthcare
SMART POWERR	1.30%	Energy	TG THERAPEUTICS	-0.02%	Healthcare
SOCKET MOBILE	1.91%	Industrials	PORTAGE BIOTECH	0.00%	Healthcare
SOLIGENIX	0.25%	Healthcare	LIFEWAY FOODS	2.80%	Consumer Staples
SONO TEK	2.01%	Industrials	PSYCHEMEDICS	9.89%	Healthcare
SPAR GROUP	-0.74%	Consumer Discretionary	BROADWIND	-1.33%	Industrials
SPOK HOLDINGS	-0.48%	Telecommunication	CINEVERSE A	0.74%	Consumer Discretionary
STAAR SURGICAL	-0.64%	Healthcare	ANTELOPE ENTERPRISE HOLDINGS A	0.70%	Industrials
STEALTH GAS	1.59%	Industrials	GNE.TECHS.SPN. ADR 1:30	0.00%	Healthcare
STERLING INFRASTRUCTURE	-2.53%	Industrials	DIGITAL ALLY	0.88%	Industrials
STREAMLINE HEALTH SLTN.	1.20%	Technology	INNOVIVA	-1.07%	Healthcare
SUNPOWER	-2.62%	Energy	ARCA BIOPHARMA	1.15%	Healthcare
SUNSHINE BIOPHARMA	0.23%	Healthcare	HARTE-HANKS	0.55%	Consumer Discretionary
SYNOPSISYS	16.17%	Technology	MACATAWA BANK	4.62%	Finance

SYPRIS SOLUTIONS	1.31%	Industrials	COCRYSTAL PHARMA	0.02%	Healthcare
TAITRON COMPONENTS	1.62%	Industrials	IOVANCE BIOTHERAPEUTICS	0.00%	Healthcare
TECHPRECISION	1.31%	Basic Materials	SANARA MEDTECH	0.78%	Healthcare
TETRA TECH	0.82%	Industrials	LEXICON PHARMACEUTICALS	-1.41%	Healthcare
DIXIE GP.'A'	1.66%	Consumer Discretionary	THERMOGENESIS HOLDINGS	0.53%	Healthcare
ENSIGN GROUP	5.24%	Healthcare	WATERSTONE FINANCIAL	8.46%	Finance
THERATECHNOLOGIES (NAS)	0.40%	Healthcare	INOTIV	2.84%	Healthcare
TROOPS	0.59%	Technology	HEALTHSTREAM DISTRIBUTION SOLUTIONS GROUP	3.46%	Healthcare
TWIN DISC	-1.12%	Industrials	TFS FINANCIAL	0.28%	Industrials
US GLOBAL INVRS.	1.00%	Finance		27.31%	Finance
UNITED GUARDIAN	9.26%	Basic Materials	HUDSON GLOBAL	-0.37%	Industrials
UNITED SECURITY BCSH.	5.81%	Finance	CATALYST PHARMACEUTICAL PARTNERS	0.12%	Healthcare
UNIVERSAL ELECTRONICS	-0.34%	Consumer Discretionary	PERASO	-0.35%	Technology
UNIVEST FINANCIAL	-0.37%	Finance	SURMODICS	0.69%	Healthcare
URBAN ONE 'A'	-0.88%	Consumer Discretionary	CADENCE DESIGN SYS.	6.36%	Technology
URBAN ONE 'D' NON VTG.	0.62%	Consumer Discretionary	NEUROMETRIX	2.08%	Healthcare
USIO	-0.04%	Industrials	FLUENT	0.35%	Consumer Discretionary
VAXART	0.86%	Healthcare	CAPITAL SOUTHWEST	10.26%	Finance
VERTEX ENERGY	0.04%	Utilities	EPLUS	0.35%	Technology
VIAVI SOLUTIONS	-5.39%	Telecommunication	AETERNA	0.19%	Healthcare
VIRTRA	0.42%	Industrials	ZENTARIS (NAS)		
YORK WATER	8.21%	Utilities	MOLECULAR TEMPLATES	-0.62%	Healthcare
ZW DATA ACTION TECHNOLOGIES	-0.08%	Technology	THE9 AMERICAN DEPOSITORY SHARES 1:300	1.08%	Consumer Discretionary
ZYNEX	1.43%	Healthcare	WILLDAN GROUP	3.05%	Industrials
			PENN ENTERTAINMENT	-3.12%	Consumer Discretionary

ASIA PACIFIC WIRE CABLE	35.93%	Industrials	GLOBUS MARITIME	0.20%	Industrials
May	Weight	Sector	June	Weight	Sector
OCUPHIRE PHARMA	1.80%	Healthcare	OCUPHIRE PHARMA	1.85%	Healthcare
FUTURE FINTECH GROUP	1.25%	Finance	FUTURE FINTECH GROUP	1.34%	Finance
LIGHTBRIDGE	0.44%	Industrials	LIGHTBRIDGE	0.47%	Industrials
GYRODYNE	13.15%	Real Estate	GYRODYNE	13.17%	Real Estate
CAPRICOR THERAPEUTICS	0.32%	Healthcare	CAPRICOR THERAPEUTICS	0.38%	Healthcare
US GOLD	0.45%	Basic Materials	US GOLD	0.44%	Basic Materials
MICROBOT MEDICAL	-0.03%	Healthcare	MICROBOT MEDICAL	-0.04%	Healthcare
MARKER THERAPEUTICS	0.27%	Healthcare	MARKER THERAPEUTICS	0.34%	Healthcare
RIOT PLATFORMS	0.12%	Finance	RIOT PLATFORMS	0.14%	Finance
ALTIMMUNE	0.66%	Healthcare	ALTIMMUNE	0.65%	Healthcare
CARDIFF ONCOLOGY	0.28%	Healthcare	CARDIFF ONCOLOGY	0.26%	Healthcare
GYRE THERAPEUTICS	0.19%	Healthcare	GYRE THERAPEUTICS	0.25%	Healthcare
TG THERAPEUTICS	-0.01%	Healthcare	TG THERAPEUTICS	0.00%	Healthcare
PORTAGE BIOTECH	0.00%	Healthcare	PORTAGE BIOTECH	0.00%	Healthcare
LIFEWAY FOODS	2.94%	Consumer Staples	PSYCHEMEDICS	9.79%	Healthcare
PSYCHEMEDICS	9.75%	Healthcare	LIFEWAY FOODS	3.04%	Consumer Staples
BROADWIND	-1.20%	Industrials	BROADWIND	-1.06%	Industrials
CINEVERSE A	0.91%	Consumer Discretionary	CINEVERSE A	0.53%	Consumer Discretionary
ANTELOPE ENTERPRISE HOLDINGS A	0.77%	Industrials	ANTELOPE ENTERPRISE HOLDINGS A	0.68%	Industrials
GNE.TECHS.SPN. ADR 1:30	-0.13%	Healthcare	GNE.TECHS.SPN. ADR 1:30	-0.02%	Healthcare
DIGITAL ALLY	0.89%	Industrials	DIGITAL ALLY	0.87%	Industrials
INNOVIVA	-0.73%	Healthcare	INNOVIVA	-0.55%	Healthcare
ARCA BIOPHARMA	1.20%	Healthcare	ARCA BIOPHARMA	0.74%	Healthcare
HARTE-HANKS	0.10%	Consumer Discretionary	HARTE-HANKS	0.18%	Consumer Discretionary
MACATAWA BANK	5.29%	Finance	MACATAWA BANK	5.13%	Finance
COCRYSTAL PHARMA	0.02%	Healthcare	COCRYSTAL PHARMA	0.02%	Healthcare
IOVANCE BIOTHERAPEUTIC S	0.00%	Healthcare	IOVANCE BIOTHERAPEUTIC S	0.03%	Healthcare

SANARA MEDTECH	0.72%	Healthcare	SANARA MEDTECH	0.73%	Healthcare
LEXICON PHARMACEUTICALS	-1.50%	Healthcare	LEXICON PHARMACEUTICALS	-1.39%	Healthcare
THERMOGENESIS HOLDINGS	0.76%	Healthcare	THERMOGENESIS HOLDINGS	0.84%	Healthcare
WATERSTONE FINANCIAL	9.39%	Finance	WATERSTONE FINANCIAL	9.44%	Finance
INOTIV	2.89%	Healthcare	INOTIV	2.95%	Healthcare
HEALTHSTREAM	3.74%	Healthcare	HEALTHSTREAM	3.57%	Healthcare
DISTRIBUTION SOLUTIONS GROUP	0.07%	Industrials	DISTRIBUTION SOLUTIONS GROUP	0.13%	Industrials
TFS FINANCIAL	26.86%	Finance	TFS FINANCIAL	24.80%	Finance
HUDSON GLOBAL	0.11%	Industrials	HUDSON GLOBAL	0.38%	Industrials
CATALYST PHARMACEUTICAL PARTNERS	0.09%	Healthcare	CATALYST PHARMACEUTICAL PARTNERS	0.16%	Healthcare
PERASO	-0.22%	Technology	PERASO	-0.22%	Technology
SURMODICS	0.93%	Healthcare	SURMODICS	0.89%	Healthcare
NEUROMETRIX	1.98%	Healthcare	CADENCE DESIGN SYS. NEUROMETRIX	8.07%	Technology
CADENCE DESIGN SYS. FLUENT	6.90%	Technology	FLUENT	2.17%	Healthcare
CAPITAL SOUTHWEST	0.31%	Consumer Discretionary	CAPITAL SOUTHWEST	0.12%	Consumer Discretionary
AETERNA	9.04%	Finance	EPLUS	10.04%	Finance
ZENTARIS (NAS)	0.16%	Healthcare	AETERNA	-0.19%	Technology
EPLUS	-0.25%	Technology	ZENTARIS (NAS)	0.21%	Healthcare
MOLECULAR TEMPLATES	-0.66%	Healthcare	MOLECULAR TEMPLATES	-0.68%	Healthcare
THE9 AMERICAN DEPOSITORY SHARES 1:300	1.06%	Consumer Discretionary	THE9 AMERICAN DEPOSITORY SHARES 1:300	1.11%	Consumer Discretionary
WILLDAN GROUP	2.83%	Industrials	WILLDAN GROUP	2.64%	Industrials
PENN ENTERTAINMENT	-4.11%	Consumer Discretionary	PENN ENTERTAINMENT	-4.56%	Consumer Discretionary
GLOBUS MARITIME	0.18%	Industrials	GLOBUS MARITIME	0.16%	Industrials
July	Weight	Sector	August	Weight	Sector
OCUPHIRE	1.78%	Healthcare	OCUPHIRE	1.75%	Healthcare
PHARMA			PHARMA		
FUTURE FINTECH GROUP	1.31%	Finance	FUTURE FINTECH GROUP	1.33%	Finance
LIGHTBRIDGE	0.31%	Industrials	LIGHTBRIDGE	0.28%	Industrials

GYRODYNE	15.87%	Real Estate	GYRODYNE	16.00%	Real Estate
CAPRICOR THERAPEUTICS	0.39%	Healthcare	CAPRICOR THERAPEUTICS	0.40%	Healthcare
US GOLD	0.51%	Basic Materials	US GOLD	0.51%	Basic Materials
MICROBOT MEDICAL MARKER THERAPEUTICS	-0.03%	Healthcare	MICROBOT MEDICAL MARKER THERAPEUTICS	-0.04%	Healthcare
RIOT PLATFORMS	0.34%	Healthcare	RIOT PLATFORMS	0.30%	Healthcare
ALTIMMUNE	0.12%	Finance	ALTIMMUNE	0.02%	Finance
CARDIFF ONCOLOGY	0.72%	Healthcare	CARDIFF ONCOLOGY	0.70%	Healthcare
GYRE THERAPEUTICS	0.24%	Healthcare	GYRE THERAPEUTICS	0.25%	Healthcare
TG THERAPEUTICS	0.25%	Healthcare	TG THERAPEUTICS	0.28%	Healthcare
PORTAGE BIOTECH	0.00%	Healthcare	PORTAGE BIOTECH	0.01%	Healthcare
PSYCHEMEDICS	0.00%	Healthcare	PSYCHEMEDICS	0.00%	Healthcare
LIFEWAY FOODS	9.72%	Healthcare	LIFEWAY FOODS	9.47%	Healthcare
BROADWIND	3.29%	Consumer Staples	BROADWIND	3.35%	Consumer Staples
CINEVERSE A	-0.92%	Industrials	CINEVERSE A	-0.77%	Industrials
ANTELOPE ENTERPRISE HOLDINGS A	0.32%	Consumer Discretionary	ANTELOPE ENTERPRISE HOLDINGS A	0.32%	Consumer Discretionary
GNE.TECHS.SPN. ADR 1:30	0.81%	Industrials	GNE.TECHS.SPN. ADR 1:30	0.76%	Industrials
DIGITAL ALLY	-0.03%	Healthcare	DIGITAL ALLY	-0.18%	Healthcare
INNOVIVA	0.53%	Industrials	INNOVIVA	0.52%	Industrials
ARCA BIOPHARMA	-0.49%	Healthcare	ARCA BIOPHARMA	-0.30%	Healthcare
HARTE-HANKS	0.70%	Healthcare	HARTE-HANKS	0.70%	Healthcare
MACATAWA BANK	0.11%	Consumer Discretionary	MACATAWA BANK	0.03%	Consumer Discretionary
COCRYSTAL PHARMA	4.70%	Finance	COCRYSTAL PHARMA	4.83%	Finance
IOVANCE BIOTHERAPEUTICS	0.02%	Healthcare	IOVANCE BIOTHERAPEUTICS	0.04%	Healthcare
SANARA MEDTECH	0.04%	Healthcare	SANARA MEDTECH	0.74%	Healthcare
LEXICON PHARMACEUTICALS	0.70%	Healthcare	LEXICON PHARMACEUTICALS	-1.18%	Healthcare
WATERSTONE FINANCIAL	-1.17%	Healthcare	WATERSTONE FINANCIAL	0.02%	Healthcare
	9.20%	Finance	THERMOGENESIS HOLDINGS	0.87%	Healthcare

INOTIV	2.92%	Healthcare	WATERSTONE FINANCIAL	9.98%	Finance
THERMOGENESIS HOLDINGS	0.92%	Healthcare	INOTIV	2.84%	Healthcare
HEALTHSTREAM DISTRIBUTION SOLUTIONS GROUP	3.31%	Healthcare	HEALTHSTREAM DISTRIBUTION SOLUTIONS GROUP	2.99%	Healthcare
TFS FINANCIAL	-0.37%	Industrials	TFS FINANCIAL	-0.42%	Industrials
HUDSON GLOBAL	23.82%	Finance	HUDSON GLOBAL	23.15%	Finance
CATALYST PHARMACEUTICAL PARTNERS	0.53%	Industrials	CATALYST PHARMACEUTICAL PARTNERS	0.71%	Industrials
PERASO	0.23%	Healthcare	PERASO	0.20%	Healthcare
SURMODICS	-0.28%	Technology	SURMODICS	-0.29%	Technology
NEUROMETRIX	0.40%	Healthcare	NEUROMETRIX	0.25%	Healthcare
CADENCE DESIGN SYS.	2.12%	Healthcare	CADENCE DESIGN SYS.	2.10%	Healthcare
FLUENT	8.73%	Technology	FLUENT	9.53%	Technology
CAPITAL SOUTHWEST EPLUS	0.04%	Consumer Discretionary	CAPITAL SOUTHWEST EPLUS	0.01%	Consumer Discretionary
AETERNA ZENTARIS (NAS)	10.04%	Finance	AETERNA ZENTARIS (NAS)	9.92%	Finance
MOLECULAR TEMPLATES	-0.31%	Technology	MOLECULAR TEMPLATES	0.17%	Healthcare
THE9 AMERICAN DEPOSITORY SHARES 1:300	0.14%	Healthcare	THE9 AMERICAN DEPOSITORY SHARES 1:300	-0.64%	Technology
WILLDAN GROUP	-0.70%	Healthcare	WILLDAN GROUP	-0.53%	Healthcare
PENN ENTERTAINMENT	1.22%	Consumer Discretionary	PENN ENTERTAINMENT	0.10%	Industrials
GLOBUS MARITIME	2.35%	Industrials	GLOBUS MARITIME	0.10%	Industrials
			THE9 AMERICAN DEPOSITORY SHARES 1:300	1.20%	Consumer Discretionary
			WILLDAN GROUP	2.22%	Industrials
			PENN ENTERTAINMENT	-4.49%	Consumer Discretionary
September	Weight	Sector	October	Weight	Sector
PROFIRE ENERGY	0.14%	Energy	OCUPHIRE PHARMA	1.73%	Healthcare
PROPHASE LABS	3.69%	Consumer Staples	FUTURE FINTECH GROUP	1.28%	Finance
QUEST RESOURCE HOLDING	0.68%	Utilities	LIGHTBRIDGE	0.26%	Industrials
REGENCY CENTERS	11.29%	Real Estate	GYRODYNE	15.72%	Real Estate
REPLIGEN	2.78%	Healthcare	CAPRICOR THERAPEUTICS	0.46%	Healthcare

RIGEL PHARMS.	-0.81%	Healthcare	US GOLD	0.47%	Basic Materials
SAVARA	0.44%	Healthcare	MICROBOT	-0.04%	Healthcare
SELLAS LIFE SCIENCES GROUP	0.28%	Healthcare	MEDICAL MARKER THERAPEUTICS	0.24%	Healthcare
SERVICE PROPERTIES TRUST	-5.91%	Real Estate	RIOT PLATFORMS	-0.01%	Finance
SIEBERT FINANCIAL SIFY	0.05%	Finance	ALTIMMUNE	0.68%	Healthcare
TECHNOLOGIES ADR 1:1	0.41%	Telecommunication	CARDIFF ONCOLOGY	0.34%	Healthcare
SIRIUS XM HOLDINGS	3.78%	Consumer Discretionary	GYRE THERAPEUTICS	0.25%	Healthcare
SMART POWERR	1.07%	Energy	TG THERAPEUTICS	0.00%	Healthcare
SOCKET MOBILE	1.60%	Industrials	PORTAGE BIOTECH	0.00%	Healthcare
SOLIGENIX	0.39%	Healthcare	PSYCHEMEDICS	8.99%	Healthcare
SONO TEK	3.47%	Industrials	LIFEWAY FOODS	2.71%	Consumer Staples
SPAR GROUP	1.02%	Consumer Discretionary	BROADWIND	-0.57%	Industrials
SPOK HOLDINGS	3.84%	Telecommunication	CINEVERSE A	0.28%	Consumer Discretionary
STAAR SURGICAL	-0.31%	Healthcare	ANTELOPE ENTERPRISE HOLDINGS A	0.63%	Industrials
STEALTH GAS	5.23%	Industrials	GNE.TECHS.SPN. ADR 1:30	-0.21%	Healthcare
STERLING INFRASTRUCTURE	-2.16%	Industrials	DIGITAL ALLY	0.57%	Industrials
STREAMLINE HEALTH SLTN.	1.88%	Technology	INNOVIVA	-0.23%	Healthcare
SUNPOWER	-2.78%	Energy	ARCA BIOPHARMA	0.69%	Healthcare
SUNSHINE BIOPHARMA	0.23%	Healthcare	HARTE-HANKS	0.07%	Consumer Discretionary
SYNOPSIS	20.50%	Technology	MACATAWA BANK	4.47%	Finance
SYPRIS SOLUTIONS	1.27%	Industrials	COCRYSTAL PHARMA	0.03%	Healthcare
TAITRON COMPONENTS	5.04%	Industrials	IOVANCE BIOTHERAPEUTICS	0.04%	Healthcare
TECHPRECISION	1.17%	Basic Materials	SANARA MEDTECH	0.75%	Healthcare

TETRA TECH	2.47%	Industrials	LEXICON PHARMACEUTICALS	-1.09%	Healthcare
DIXIE GP.'A'	1.44%	Consumer Discretionary	THERMOGENESIS HOLDINGS	0.78%	Healthcare
ENSIGN GROUP	1.53%	Healthcare	WATERSTONE FINANCIAL	10.71%	Finance
THERATECHNOLOGIES (NAS)	0.43%	Healthcare	INOTIV	2.95%	Healthcare
TROOPS	0.97%	Technology	HEALTHSTREAM DISTRIBUTION SOLUTIONS GROUP	2.56%	Healthcare
TWIN DISC	-2.39%	Industrials	TFS FINANCIAL	-0.28%	Industrials
US GLOBAL INVRS.	2.13%	Finance	HUDSON GLOBAL	25.31%	Finance
UNITED GUARDIAN	11.11%	Basic Materials	CATALYST PHARMACEUTICAL PARTNERS	1.02%	Industrials
UNITED SECURITY BCSH.	2.68%	Finance	PERASO	0.18%	Healthcare
UNIVERSAL ELECTRONICS	-0.64%	Consumer Discretionary	SURMODICS	-0.30%	Technology
UNIVEST FINANCIAL	3.76%	Finance	CADENCE DESIGN SYS.	0.17%	Healthcare
URBAN ONE 'A'	-0.04%	Consumer Discretionary	FLUENT	9.51%	Technology
URBAN ONE 'D' NON VTG.	0.43%	Consumer Discretionary	NEUROMETRIX	0.06%	Consumer Discretionary
USIO	0.75%	Industrials	CAPITAL SOUTHWEST	2.14%	Healthcare
VAXART	1.74%	Healthcare	AETERNA ZENTARIS (NAS)	9.80%	Finance
VERTEX ENERGY	0.41%	Utilities	EPLUS	0.17%	Healthcare
VIAVI SOLUTIONS	-3.01%	Telecommunications	MOLECULAR TEMPLATES	-1.05%	Technology
VIRTRA	1.51%	Industrials	THE9 AMERICAN DEPOSITORY SHARES 1:300	-0.54%	Healthcare
YORK WATER	6.59%	Utilities	WILLDAN GROUP	1.09%	Consumer Discretionary
ZW DATA ACTION TECHNOLOGIES	0.04%	Technology	PENN ENTERTAINMENT PLUS	1.87%	Industrials
ZYNEX	1.11%	Healthcare	THERAPEUTICS	-4.28%	Consumer Discretionary
ASIA PACIFIC WIRE CABLE	8.75%	Industrials		-0.38%	Healthcare
November	Weight	Sector	December	Weight	Sector
OCUPHIRE PHARMA	1.71%	Healthcare	OCUPHIRE PHARMA	1.80%	Healthcare
FUTURE FINTECH GROUP	1.26%	Finance	FUTURE FINTECH GROUP	1.23%	Finance

LIGHTBRIDGE	0.27%	Industrials	LIGHTBRIDGE	0.22%	Industrials
GYRODYNE	15.63%	Real Estate	GYRODYNE	15.66%	Real Estate
CAPRICOR	0.44%	Healthcare	CAPRICOR	0.44%	Healthcare
THERAPEUTICS			THERAPEUTICS		
US GOLD	0.48%	Basic Materials	US GOLD	0.45%	Basic Materials
MICROBOT	-0.04%	Healthcare	MICROBOT	-0.04%	Healthcare
MEDICAL			MEDICAL		
MARKER	0.22%	Healthcare	MARKER	0.24%	Healthcare
THERAPEUTICS			THERAPEUTICS		
RIOT PLATFORMS	-0.06%	Finance	RIOT PLATFORMS	-0.07%	Finance
ALTIMMUNE	0.70%	Healthcare	ALTIMMUNE	0.78%	Healthcare
CARDIFF	0.30%	Healthcare	CARDIFF	0.36%	Healthcare
ONCOLOGY			ONCOLOGY		
GYRE	0.27%	Healthcare	GYRE	0.28%	Healthcare
THERAPEUTICS			THERAPEUTICS		
TG	0.00%	Healthcare	TG	0.01%	Healthcare
THERAPEUTICS			THERAPEUTICS		
PORTAGE	0.00%	Healthcare	PORTAGE	0.00%	Healthcare
BIOTECH			BIOTECH		
PSYCHEMEDICS	9.04%	Healthcare	PSYCHEMEDICS	8.79%	Healthcare
LIFEWAY FOODS	2.77%	Consumer Staples	LIFEWAY FOODS	2.65%	Consumer Staples
BROADWIND	-0.58%	Industrials	BROADWIND	-0.66%	Industrials
CINEVERSE A	0.26%	Consumer Discretionary	CINEVERSE A	0.21%	Consumer Discretionary
GNE.TECHS.SPN. ADR 1:30	-0.22%	Healthcare	ANTELOPE ENTERPRISE HOLDINGS A	0.70%	Industrials
ANTELOPE ENTERPRISE HOLDINGS A	0.65%	Industrials	GNE.TECHS.SPN. ADR 1:30	-0.22%	Healthcare
DIGITAL ALLY	0.59%	Industrials	DIGITAL ALLY	0.60%	Industrials
INNOVIVA	-0.35%	Healthcare	INNOVIVA	-0.16%	Healthcare
ARCA	0.69%	Healthcare	ARCA	0.69%	Healthcare
BIOPHARMA			BIOPHARMA		
HARTE-HANKS	0.20%	Consumer Discretionary	HARTE-HANKS	0.19%	Consumer Discretionary
MACATAWA BANK	4.90%	Finance	MACATAWA BANK	4.51%	Finance
COCRYSTAL	0.02%	Healthcare	COCRYSTAL	0.03%	Healthcare
PHARMA			PHARMA		
IOVANCE	0.03%	Healthcare	IOVANCE	0.05%	Healthcare
BIOTHERAPEUTICS			BIOTHERAPEUTICS		
SANARA	0.76%	Healthcare	SANARA	0.78%	Healthcare
MEDTECH			MEDTECH		
LEXICON	-1.10%	Healthcare	LEXICON	-1.21%	Healthcare
PHARMACEUTICALS			PHARMACEUTICALS		
WATERSTONE FINANCIAL	10.83%	Finance	WATERSTONE FINANCIAL	10.78%	Finance

THERMOGENESIS HOLDINGS	0.75%	Healthcare	THERMOGENESIS HOLDINGS	0.72%	Healthcare
INOTIV	2.97%	Healthcare	INOTIV	2.99%	Healthcare
HEALTHSTREAM DISTRIBUTION SOLUTIONS GROUP	2.58%	Healthcare	HEALTHSTREAM DISTRIBUTION SOLUTIONS GROUP	2.36%	Healthcare
TFS FINANCIAL	-0.35%	Industrials	TFS FINANCIAL	-0.49%	Industrials
HUDSON GLOBAL	24.29%	Finance	HUDSON GLOBAL	24.25%	Finance
CATALYST PHARMACEUTICAL PARTNERS	1.11%	Industrials	CATALYST PHARMACEUTICAL PARTNERS	1.27%	Industrials
PERASO	0.16%	Healthcare	PERASO	0.14%	Healthcare
SURMODICS	-0.32%	Technology	SURMODICS	-0.33%	Technology
CADENCE DESIGN SYS.	0.16%	Healthcare	CADENCE DESIGN SYS.	0.66%	Healthcare
NEUROMETRIX	9.78%	Technology	NEUROMETRIX	10.36%	Technology
FLUENT	2.14%	Healthcare	FLUENT	2.11%	Healthcare
CAPITAL SOUTHWEST EPLUS	0.04%	Consumer Discretionary	CAPITAL SOUTHWEST EPLUS	0.06%	Consumer Discretionary
MOLECULAR TEMPLATES	9.83%	Finance	MOLECULAR TEMPLATES	9.93%	Finance
GLOBUS MARITIME	-1.05%	Technology	GLOBUS MARITIME	0.15%	Healthcare
AETERNA ZENTARIS (NAS)	-0.58%	Healthcare	AETERNA ZENTARIS (NAS)	-1.21%	Technology
WILLDAN GROUP	0.07%	Industrials	WILLDAN GROUP	-0.54%	Healthcare
THE9 AMERICAN DEPOSITORY SHARES 1:300	0.15%	Healthcare	THE9 AMERICAN DEPOSITORY SHARES 1:300	1.05%	Consumer Discretionary
PENN ENTERTAINMENT	1.81%	Industrials	PENN ENTERTAINMENT	1.72%	Industrials
	1.09%	Consumer Discretionary		0.09%	Industrials
	-4.31%	Consumer Discretionary		-4.36%	Consumer Discretionary

Appendix C3: ML results of all the companies in the dataset from the 2020 testing period. For the total row, percentages (including R²) are averaged, and the other columns are medians of the scores.

Company	Accuracy(%)	R²	RMSE	MAE	MAPE*(%)	SMAPE(%)
<i>Total</i>	55.01	0.06	9.47	8.04	57.88	58.61
1-800-FLOWERS.COM 'A'	83.33	0.10	4.81	3.75	16.01	34.35
1ST SOURCE	75.00	0.00	24.51	22.30	64.31	61.15
8X8	75.00	0.08	4.06	3.47	19.44	26.10
AAON	75.00	0.38	3.11	2.46	6.58	19.07
ABEONA THERAPEUTICS	66.67	0.00	24.05	20.29	45.80	39.03
ACACIA RESH.-ACI.TECHS.	58.33	0.00	0.74	0.59	16.47	33.33
ACADIA PHARMACEUTICALS	50.00	0.00	8.01	6.65	15.29	20.72
ACCELERATE DIAGNOSTICS	33.33	0.00	87.35	74.77	79.18	66.75
ACCURAY	50.00	0.10	0.78	0.71	29.73	39.04
ACHIEVE LIFE SCIENCES	58.33	0.00	160.32	158.94	1.85E+03	262.00
ACI WORLDWIDE	66.67	0.00	11.09	9.99	35.02	38.99
ACNB	50.00	0.00	18.55	16.39	69.65	63.53
ADDUS HOMECARE	41.67	0.00	22.26	19.36	21.56	28.36
ADEIA	0.00	0.00	1.98	1.86	50.36	50.54
ADOBE (NAS)	83.33	0.42	50.22	43.49	10.15	25.38
ADTRAN HOLDINGS	66.67	0.53	1.35	1.10	11.24	24.05
ADVANCED MICRO DEVICES	66.67	0.00	18.89	15.35	20.85	38.77
ADVANCED ENERGY INDS.	66.67	0.00	15.24	12.21	19.97	31.26
AEHR TEST SYS.	75.00	0.00	0.40	0.35	19.21	25.15
AEMETIS	41.67	0.00	1.15	0.76	38.06	71.95
AEROVIRONMENT	66.67	0.52	7.06	5.43	8.13	21.47
AETERNA ZENTARIS (NAS)	66.67	0.00	165.17	155.66	327.25	144.86
AETHLON MED.	0.00	0.00	13.69	12.68	70.07	142.48
AGENUS	41.67	0.00	17.22	13.92	22.89	31.39
AGILYSYS	83.33	0.28	6.33	5.75	25.08	36.40
AGNC INVESTMENT REIT	83.33	0.00	7.04	6.27	45.61	47.46
AIR T	58.33	0.00	11.48	10.06	89.12	74.83
AIR TRANSPORT SVS.GP.	75.00	0.37	3.29	2.68	12.38	26.39
AIRNET TECH.AMER. DEPY. SHS.1:1	66.67	0.00	5.87	5.78	156.74	112.52
AKAMAI TECHS.	75.00	0.00	12.51	10.56	10.34	18.01
ALAUNOS THERAPEUTICS	50.00	0.00	41.89	38.65	92.53	78.62
ALICO	75.00	0.00	10.41	8.70	28.45	32.00
ALIGN TECHNOLOGY	75.00	0.56	66.74	54.99	18.98	36.83
ALKERMES	58.33	0.00	5.28	4.54	26.28	31.63
ALLEGiant TRAVEL	83.33	0.00	70.65	65.12	58.75	56.71
ALLIANCE RSO.PTNS.L P UT LP.	75.00	0.00	6.99	6.49	183.45	114.04
ALLIANT ENERGY (XSC)	66.67	0.00	12.00	9.96	19.22	23.53

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
ALLIENT	66.67	0.00	11.86	11.06	45.89	47.77
ALLOT (NAS)	66.67	0.00	2.07	1.69	15.84	23.84
ALNYLAM	50.00	0.00	19.00	15.82	11.85	18.97
PHARMACEUTICALS						
ALPHABET A	75.00	0.65	5.15	4.34	6.06	19.57
ALPHATEC HOLDINGS	66.67	0.27	2.34	2.07	38.89	50.21
ALTERITY THERAPEUTICS	50.00	0.00	10.12	7.98	55.30	103.84
ADR 1:600						
ALTIMMUNE	58.33	0.00	10.45	7.52	60.43	122.47
ALTISOURCE PRTF.SLTN.	33.33	0.00	11.01	10.11	92.25	76.77
ALTO INGREDIENTS	58.33	0.00	3.67	2.35	60.19	114.45
AMARIN ADR 1:1	58.33	0.00	16.63	15.00	264.54	129.52
AMAZON.COM	83.33	0.00	34.33	30.16	21.02	37.98
AMDOCS	50.00	0.00	20.35	16.74	27.55	31.30
AMEDISYS	75.00	0.27	29.29	24.94	11.32	25.38
AMER.ELEC.PWR.	50.00	0.00	26.40	21.48	25.69	29.26
AMER.SOFTWARE CL.A	83.33	0.00	2.74	2.21	14.19	19.09
AMERICAN	0.00	0.00	5.08	4.07	40.17	49.60
SUPERCONDUCTOR						
AMER.WOODMARK	91.67	0.00	44.86	41.16	58.60	56.07
AMERICAN COASTAL	41.67	0.00	6.60	5.64	90.76	71.64
INSURANCE						
AMERICAN PUBLIC ED.	41.67	0.00	5.43	4.68	16.81	24.63
AMERICA S CAR MART	83.33	0.00	45.69	42.49	50.89	50.95
AMERIS BANCORP	75.00	0.00	22.14	20.25	78.81	69.89
AMERISAFE	66.67	0.00	26.04	22.43	37.26	38.95
AMERISERV FINL.	41.67	0.00	1.47	1.27	43.21	44.50
AMES NAT.	75.00	0.00	12.00	10.63	53.17	52.61
AMGEN	50.00	0.00	54.55	44.54	19.42	24.13
AMICUS THERAPEUTICS	66.67	0.07	4.31	3.18	19.48	37.60
AMKOR TECH.	75.00	0.00	3.72	3.43	30.74	36.48
AMNEAL	50.00	0.00	1.38	1.16	28.70	33.24
PHARMACEUTICALS A						
AMTECH SYS.	66.67	0.00	3.43	3.27	62.49	60.85
ANALOG DEVICES	66.67	0.00	20.62	17.27	14.78	23.88
ANAVEX LIFE SCIS.	0.00	0.00	1.31	1.07	23.15	35.01
ANDERSONS	58.33	0.00	13.39	12.57	73.59	66.94
ANGIODYNAMICS	50.00	0.00	7.57	6.99	66.02	62.21
ANI PHARMACEUTICALS	66.67	0.00	32.36	27.84	91.88	74.30
ANIKA THERAPEUTICS	75.00	0.00	23.33	21.79	60.93	59.30
ANIXA BIOSCIENCES	58.33	0.00	1.38	1.23	54.51	53.09
ANSYS	83.33	0.76	18.35	14.95	5.37	20.27
ANTELOPE ENTERPRISE	58.33	0.00	38.66	38.24	187.36	262.00
HOLDINGS A						
APA	0.00	0.00	9.15	8.62	81.05	68.40
APOGEE ENTERPRISES	66.67	0.00	13.40	11.97	53.19	52.94

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
APPLE	83.33	0.38	17.09	13.77	13.05	31.99
APPLIED DNA SCIENCES	58.33	0.00	75.42	62.16	39.72	71.86
APPLIED MATS.	66.67	0.10	10.13	7.96	13.78	26.06
APTOSE BIOSCIENCES (NAS)	66.67	0.00	399.82	332.56	24.25	25.54
APYX MEDICAL	0.00	0.00	2.94	2.53	40.69	70.25
ARBUTUS BIOPHARMA (NAS)	50.00	0.27	0.80	0.64	33.77	40.91
ARCA BIOPHARMA	50.00	0.00	3.42	2.98	70.88	63.56
ARCBEST	66.67	0.62	4.63	3.86	15.59	33.00
ARCH CAP.GP.	75.00	0.00	16.39	14.59	47.77	48.16
ARK RESTAURANTS	41.67	0.00	13.43	11.98	105.55	83.22
ARQ	0.00	0.00	3.94	3.72	73.52	66.83
ARROW FINANCIAL	66.67	0.00	14.62	13.31	51.97	52.26
ARROWHEAD PHARMS.	50.00	0.00	27.68	25.86	65.20	63.27
ART'S-WAY MANUFACTURING	66.67	0.00	0.32	0.25	10.48	18.83
ARTESIAN RES.'A'	50.00	0.00	7.31	5.99	16.62	20.31
ASCENT INDUSTRIES	50.00	0.00	6.12	5.00	79.61	63.50
ASCENT SOLAR TECHS.	50.00	0.00	6.08E+07	6.02E+07	3.21E+07	262.00
ASIA PACIFIC WIRE CABLE	58.33	0.00	0.40	0.33	26.23	32.38
ASML HLDG.ADR 1:1	66.67	0.67	34.73	28.30	8.04	23.99
ASPEN TECHNOLOGY	50.00	0.00	22.25	19.71	17.67	25.58
ASPIRA WOMENS HEALTH	66.67	0.00	37.60	29.82	54.99	115.84
ASSERTIO HOLDINGS	50.00	0.00	2.49	2.06	87.94	66.49
ASTEC INDUSTRIES	58.33	0.73	4.28	3.14	7.56	24.30
ASTRAZENECA ADR 2:1	50.00	0.00	9.80	7.86	15.30	21.47
ASTRONICS	66.67	0.00	24.84	23.15	243.12	130.64
ASTRONOVA	41.67	0.00	8.84	8.27	106.54	85.97
ASTROTECH	50.00	0.00	22.43	19.74	31.20	31.29
ASURE SOFTWARE	66.67	0.00	2.04	1.80	26.11	30.57
ATA CREATIVITY GLOBAL ADR 1:2	0.00	0.00	0.20	0.15	15.06	18.27
ATLANTIC AMERICAN	0.00	0.00	0.49	0.44	23.15	26.48
ATLANTICUS HOLDINGS	50.00	0.00	4.16	3.16	23.01	35.04
ATN INTERNATIONAL	50.00	0.00	15.80	11.82	23.26	23.89
ATRICURE	66.67	0.00	6.70	5.28	12.55	22.37
ATRION	0.00	0.00	619.76	618.83	95.01	237.10
AUBURN NAT.BANCORP.	58.33	0.00	20.01	15.45	38.00	39.64
AUDIOCODES (NAS)	0.00	0.00	25.26	24.74	83.92	189.72
AUTODESK	83.33	0.67	22.15	18.48	8.21	24.86
AUTOMATIC DATA PROC.	75.00	0.00	46.74	39.07	26.53	31.32
AVADEL PHARMACEUTICALS	50.00	0.00	2.48	2.01	30.16	28.35
AVIAT NETWORKS	66.67	0.13	3.66	2.55	24.15	48.36

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
AVID BIOSERVICES	66.67	0.00	1.75	1.59	25.64	36.43
AVIS BUDGET GROUP	83.33	0.00	9.96	8.72	42.44	44.11
AVNET	58.33	0.00	26.63	25.06	88.14	77.21
AWARE	50.00	0.00	0.65	0.54	19.35	22.62
AXCELIS TECHS.	75.00	0.00	5.02	3.79	16.34	24.12
AXOGEN	58.33	0.00	9.65	9.36	82.54	74.06
AXON ENTERPRISE	58.33	0.49	13.00	10.23	10.79	25.68
AXT	50.00	0.40	1.51	1.04	19.36	35.88
AYRO	50.00	0.00	237.47	234.87	832.14	262.00
AZENTA	58.33	0.59	7.98	6.15	13.77	31.03
B RILEY FINANCIAL	91.67	0.47	4.49	3.90	16.93	30.72
BAIDU ADS 1:8	75.00	0.00	23.88	21.09	17.34	27.12
BAIJIAYUN GROUP A	75.00	0.00	2.18	1.42	28.29	51.30
BAKER HUGHES A	66.67	0.00	15.89	15.08	97.97	82.25
BALCHEM	58.33	0.00	22.41	19.11	19.20	23.71
BALLARD PWR.SYS. (NAS)	0.00	0.00	11.06	10.25	71.58	147.91
BANCFIRST	83.33	0.00	25.08	22.97	54.45	54.19
BANK OF MARIN	66.67	0.00	24.47	22.59	69.10	64.61
BANCORP						
BANK OF THE JAMES FINL. GROUP	41.67	0.00	7.11	6.51	68.11	63.79
BANK OZK	75.00	0.00	11.33	10.45	44.72	47.03
BANKFINANCIAL	58.33	0.00	5.30	4.65	58.71	55.95
BANNER	75.00	0.00	30.22	27.95	74.59	68.10
BARRETT BUS.SVS.	83.33	0.00	51.45	48.42	89.84	77.33
BASSETT FRTR.INDS.	66.67	0.00	8.28	7.67	91.10	74.95
BCB BANCORP	58.33	0.00	6.79	6.01	65.10	60.58
BEACON ROOFING SUPPLY	83.33	0.00	7.08	6.28	25.54	34.12
BEASLEY BROADCAST GROUP A	50.00	0.00	1.48	1.24	76.45	61.66
BEL FUSE 'A'	33.33	0.00	6.56	6.11	59.39	57.32
BEL FUSE 'B'	50.00	0.00	10.40	9.71	90.19	76.79
BGC GROUP A	58.33	0.00	3.81	3.50	119.46	90.74
BIG 5 SPTG.GOODS	0.00	0.00	4.63	3.93	214.77	96.77
BIMI INTERNATIONAL MEDICAL	0.00	0.00	97.04	90.42	72.50	150.14
BIOCRYST PHARMS.	66.67	0.33	1.13	0.87	22.54	35.16
BIOGEN	58.33	0.00	85.88	68.52	25.56	25.63
BIO-KEY INTL.	50.00	0.00	49.67	39.29	36.39	63.48
BIOLASE	0.00	0.00	377.60	295.05	27.08	35.08
BIOLIFE SOLUTIONS	66.67	0.41	7.02	5.09	24.33	46.50
BIOMARIN PHARM.	58.33	0.00	23.41	19.93	22.73	24.63
BIOMERICA	41.67	0.00	3.60	3.00	41.21	77.19
BIO-PATH HOLDINGS	0.00	0.00	95.53	92.77	94.49	234.69

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
BIORESTORATIVE THERAPIES	50.00	0.00	3.80E+03	3.77E+03	2.80E+05	258.27
BIO-TECHNE	75.00	0.56	6.46	5.41	9.01	22.41
BJ'S RESTAURANTS	66.67	0.00	15.67	14.25	65.55	58.06
BLACKBAUD	58.33	0.00	33.62	29.51	52.10	51.85
BLINK CHARGING	0.00	0.00	10.16	7.54	229.68	114.69
BOK FINL.	75.00	0.00	42.30	39.10	69.69	64.85
BOOKING HOLDINGS	66.67	0.00	630.31	580.09	34.12	38.61
B O S BETTER ONLINE SOLUTIONS	66.67	0.00	0.85	0.78	31.56	50.85
BRAINSTORM CELL THERP.	50.00	0.00	5.84	4.47	41.48	75.22
BRIDGELINE DIGITAL	25.00	0.00	18.77	18.56	1.14E+03	262.00
BRIDGFORD FOODS	16.67	0.00	10.58	9.59	54.13	52.59
BROADCOM	66.67	0.36	43.10	36.28	12.24	25.72
BROADWAY FINANCIAL	0.00	0.00	2.62	1.71	11.85	16.36
BROADWIND	83.33	0.00	1.58	1.15	30.37	62.14
BROOKLINE BANCORP	66.67	0.00	8.82	8.02	78.79	69.95
BRUKER	66.67	0.00	14.83	13.06	30.74	35.42
CECO ENV.	0.00	0.00	2.86	2.59	35.74	58.95
CSG SYS.INTL.	50.00	0.00	19.99	17.01	39.91	41.50
CSP	66.67	0.00	2.98	2.57	63.73	58.60
C&F FINL.	50.00	0.00	28.43	25.49	76.28	68.12
CH ROBINSON WWD.	58.33	0.48	8.68	6.87	8.51	22.21
CADENCE DESIGN SYS.	83.33	0.00	26.00	23.43	23.53	40.31
CADIZ	50.00	0.00	3.44	3.06	30.37	30.70
CALAMP	75.00	0.00	70.70	63.54	37.97	41.31
CALAVO GROWERS	41.67	0.00	30.80	27.98	43.43	45.53
CAL MAINE FOODS	50.00	0.00	11.68	9.54	24.48	27.03
CALUMET	58.33	0.00	1.06	0.96	43.62	43.06
SPY.PRDS.PTNS.						
CAMBRIDGE BANC.	75.00	0.00	29.24	26.41	45.79	47.50
CAMDEN NAT.	83.33	0.00	19.31	16.92	51.33	51.46
CAMTEK (NAS)	58.33	0.53	2.51	1.85	12.44	32.34
CANADIAN SOLAR	8.33	0.00	13.81	10.05	30.66	52.06
CANTALOUPE	16.67	0.00	4.85	4.61	59.12	111.47
CANTERBURY PARK HOLDING	50.00	0.00	3.05	2.63	23.19	28.44
CAP.CITY BK.GP.	66.67	0.00	11.84	10.49	50.59	50.93
CAPITAL PRODUCT PARTNERS	50.00	0.00	8.20	7.40	100.17	81.18
CAPITAL SOUTHWEST	66.67	0.00	11.21	10.40	73.36	67.27
CAPITOL FED.FINL.	58.33	0.00	4.36	3.57	33.23	35.18
CAPRICOR THERAPEUTICS	41.67	0.00	2.90	2.31	48.71	95.84
CARDIFF ONCOLOGY	75.00	0.00	8.50	5.46	54.12	117.35
CARPARTS COM	83.33	0.00	7.34	5.80	53.97	115.34

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
CARTER BANKSHARES	66.67	0.00	11.62	10.51	132.30	94.07
CARVER BANCORP	50.00	0.00	2.64	2.07	39.27	75.28
CASELLA WST.SYS.'A'	75.00	0.70	3.15	2.54	4.91	18.92
CASEY'S GENERAL STORES	58.33	0.00	21.88	17.68	10.50	19.92
CASI PHARMACEUTICALS	41.67	0.00	121.29	106.24	55.24	52.78
CASS INFO.SYS.	41.67	0.00	25.52	23.02	58.65	57.14
CASSAVA SCIENCES	0.00	0.00	4.96	4.28	115.16	77.41
CATALYST PHARMACEUTICAL PARTNERS	50.00	0.00	1.11	0.98	26.60	24.31
CATHAY GEN.BANCORP	66.67	0.00	17.73	15.95	62.78	59.65
CAVCO INDUSTRIES	58.33	0.00	48.68	41.20	23.60	28.61
CBAK ENERGY TECHNOLOGY	50.00	0.08	2.02	1.38	108.78	107.47
CELLDEX THERAPEUTICS	25.00	0.00	14.50	12.66	175.47	262.00
CELLECTAR BIOSCIENCES	0.00	0.00	7.37	6.74	49.45	49.74
CELSIUS HOLDINGS	0.00	0.00	5.47	4.05	65.69	139.19
CEMTREX	66.67	0.00	53.84	51.50	132.66	98.69
CENTRAL GDN.& PET	66.67	0.40	2.85	2.41	8.78	21.22
CENTRAL GDN.& PET 'A' NV.	75.00	0.00	3.84	3.36	12.67	24.14
CENTURY ALUMINUM	83.33	0.19	2.03	1.72	31.40	42.87
CENTURY CASINOS	66.67	0.00	3.13	2.88	68.57	58.40
CERAGON NETWORKS	50.00	0.44	0.29	0.23	11.96	22.95
CERUS	75.00	0.06	1.00	0.84	13.99	26.08
CERVOMED	58.33	0.00	233.68	230.51	452.82	262.00
CEVA	83.33	0.00	6.91	6.16	16.86	31.55
CF BANKSHARES	75.00	0.00	3.30	2.79	24.40	31.96
CHAMPIONS ONCOLOGY	33.33	0.08	1.50	1.14	14.92	25.74
CHARLES AND COLVARD	58.33	0.00	8.47	7.90	99.34	82.25
CHARTER COMMS.CL.A	58.33	0.76	33.77	26.81	5.10	19.89
CHECK POINT SFTW.TECHS.	75.00	0.00	17.85	14.70	12.78	21.04
CHEESECAKE FACTORY	75.00	0.00	15.96	14.50	57.72	55.94
CHEMUNG FINL.	58.33	0.00	19.00	17.42	58.56	57.10
CHILDRENS PLACE	41.67	0.00	36.11	32.06	110.82	82.91
CHINA AUTV.SYS.	8.33	0.00	1.50	1.05	38.02	42.07
CHINA JO JO DRUGSTORES	41.67	0.00	247.17	210.84	74.88	58.79
CHINA NATURAL RES.	50.00	0.00	4.62	4.42	80.19	71.61
CHROMADEx	58.33	0.00	0.75	0.61	14.50	22.11
CHURCHILL DOWNS	83.33	0.58	10.78	8.04	14.19	30.29
CIMPRESS	58.33	0.00	59.53	55.02	69.38	64.28
CINCINNATI FINL.	58.33	0.00	42.29	36.61	49.74	49.45
CINEVERSE A	58.33	0.00	11.95	7.96	42.68	56.71
CINTAS	75.00	0.72	27.94	22.10	8.96	25.53

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
CIRRUS LOGIC	58.33	0.00	23.01	19.20	28.79	32.21
CISCO SYSTEMS	66.67	0.00	16.95	14.34	34.38	37.21
CITI TRENDS	75.00	0.17	8.45	7.39	45.93	53.51
CITIZENS CMTY.BANCORP	58.33	0.00	6.33	5.73	76.84	68.67
CTZN.& NTHN.	66.67	0.00	13.03	11.47	62.65	59.13
CITY HLDG.	75.00	0.00	27.55	23.52	37.02	39.13
CIVISTA BANCSHARES	66.67	0.00	8.42	7.42	50.58	49.51
CLARUS	66.67	0.00	3.41	3.16	26.64	33.94
CLEAN ENERGY FUELS	8.33	0.00	1.21	0.67	22.79	28.73
CLEARFIELD	50.00	0.61	3.04	2.54	15.96	35.86
CLEARONE	66.67	0.00	0.20	0.16	17.66	26.99
CLIMB GLOBAL SOLUTIONS	58.33	0.00	4.94	4.02	18.55	35.73
CME GROUP	66.67	0.00	60.92	49.11	28.92	31.22
CNB FINL.	66.67	0.00	17.54	15.91	89.93	76.51
COCA COLA CONSOLIDATED	58.33	0.00	84.72	74.01	30.35	34.51
COCA COLA EUROPACIFIC PARTNERS	66.67	0.00	16.78	14.26	35.31	38.19
COCRYSTAL PHARMA	25.00	0.00	41.97	41.24	334.99	262.00
CODA OCTOPUS GROUP	0.00	0.00	1.66	1.44	23.00	34.96
CODORUS VLY.BANC.	58.33	0.00	24.78	23.82	165.44	113.87
COFFEE HOLDING CO.	50.00	0.00	1.92	1.82	56.29	55.95
COGENT	58.33	0.00	19.18	16.44	24.12	21.45
COMMS.HOLDINGS						
COGNEX	83.33	0.69	5.70	3.97	7.41	23.87
COGNIZANT	58.33	0.65	5.77	4.68	7.85	22.72
TECH.SLTN.'A'						
COHU	66.67	0.00	7.30	6.46	36.92	45.22
COLLIERS INTL.GP. (NAS)	75.00	0.00	29.95	26.85	44.01	46.80
COLONY BANKCORP	66.67	0.00	6.87	6.17	52.23	51.95
COLOR STAR TECHNOLOGY A	75.00	0.00	32.65	29.50	127.37	91.03
COLUMBIA BKG.SYS.	75.00	0.00	19.82	18.19	64.93	61.48
COLUMBIA SPORTSWEAR	66.67	0.00	26.11	23.23	28.95	33.49
COLUMBUS MCKINNON NY	83.33	0.00	12.48	11.74	36.51	40.60
COMCAST A	58.33	0.00	5.90	5.19	12.04	21.25
COMMERCE BCSH.	66.67	0.00	11.65	9.55	19.24	24.59
COML.VEH.GP.	58.33	0.00	2.64	2.21	89.24	70.23
COMMUNITY TRUST BANCORP	66.67	0.00	22.00	19.86	60.63	58.34
COMMUNITY WEST BANCSHARES	58.33	0.00	10.08	9.04	65.98	61.73
COMMVAULT SYSTEMS	58.33	0.00	13.10	11.37	27.39	32.55
COMPUGEN (NAS)	66.67	0.00	7.61	6.88	49.73	90.14

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
COMSCORE	50.00	0.00	61.60	55.37	110.36	85.39
COMSTOCK HOLDING 'A'	0.00	0.00	1.01	0.89	34.53	56.56
COMTECH TELECOM.	0.00	0.00	7.73	7.34	40.25	44.82
CONNECTONE BANCORP	75.00	0.00	15.01	13.96	90.11	77.41
CONN'S	66.67	0.00	6.04	5.85	75.22	65.96
CONSOLIDATED WT.	0.00	0.00	2.86	2.22	14.83	21.41
CONSOLIDATED	83.33	0.00	1.65	1.36	21.79	34.25
COMMS.HDG.						
CONSUMER PRTF.SVS.	75.00	0.05	0.73	0.61	24.11	32.08
COPART	75.00	0.73	2.10	1.74	7.76	23.52
CORCEPT THERAPEUTICS	0.00	0.00	12.03	11.33	69.45	140.45
CORVEL	0.00	0.00	52.87	50.66	63.48	123.15
COSTAR GP.	91.67	0.40	8.47	7.42	9.77	24.20
COSTCO WHOLESALE	58.33	0.33	24.93	18.87	5.80	17.77
COVENANT LOGISTICS	66.67	0.56	2.31	1.85	16.10	31.03
GROUP A						
CPS TECHNOLOGIES	83.33	0.00	0.83	0.69	37.15	63.00
CRA INTL.	66.67	0.00	16.60	14.76	36.30	39.20
CRACKER BARREL OLD	66.67	0.00	62.58	56.71	51.10	51.48
CTRY. STORE						
CREATIVE MEDIA AND	75.00	0.00	5.77	4.92	49.47	48.85
COMMUNITY TRUST						
CREATIVE REALITIES	58.33	0.00	10.59	10.06	266.39	136.10
CREDIT ACCEP.	58.33	0.00	162.19	130.96	39.34	41.81
CRESUD SACIFYA	58.33	0.00	2.95	2.69	87.41	74.86
SPN.ADR 1:10						
CREXENDO	16.67	0.00	3.83	3.50	54.34	99.74
CROCS	75.00	0.17	12.22	10.39	38.18	47.06
CROSS COUNTRY HLTHCR.	58.33	0.00	8.43	8.03	114.55	91.20
CROWN CRAFTS	66.67	0.00	1.60	1.39	26.20	33.08
CRYOPORT	0.00	0.00	28.74	25.33	74.66	159.08
CSX	0.00	0.00	15.06	14.70	58.64	109.28
CUMBERLAND PHARMS.	33.33	0.00	2.38	2.07	63.59	58.99
CURIS	41.67	0.00	42.82	40.81	167.08	119.03
CUTERA	66.67	0.00	21.31	20.07	124.48	93.56
CVB FINANCIAL	50.00	0.00	5.81	4.80	26.15	28.42
CVD EQUIPMENT	50.00	0.00	0.88	0.73	22.26	29.68
CYCLACEL PHARMS.	50.00	0.00	334.95	320.37	462.40	166.40
CYTOKINETICS	83.33	0.00	6.87	5.55	27.04	48.11
CYTOSORBENTS	50.00	0.00	3.60	3.13	36.18	63.84
DAILY JOURNAL	58.33	0.00	68.20	55.70	20.82	27.03
DAKTRONICS	58.33	0.00	2.88	2.54	58.54	56.33
DALLASNEWS SERIES A	66.67	0.00	4.37	3.87	76.51	66.54
DATA I/O	75.00	0.00	1.58	1.49	43.62	45.85
DAWSON GEOPHYSICAL	8.33	0.00	3.44	3.42	247.57	140.45
DELCATH SYS	66.67	0.00	2.13E+08	2.11E+08	1.90E+09	262.00

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
DENNY'S	58.33	0.00	10.90	9.81	95.73	78.32
DENTSPLY SIRONA	66.67	0.00	19.17	17.04	37.82	40.91
DESCARTES SYS.GP. (NAS)	75.00	0.76	3.87	3.03	6.48	22.93
DESTINATION XL GROUP	50.00	0.00	0.97	0.91	266.75	133.16
DESWELL INDS.	0.00	0.00	0.24	0.20	7.85	10.07
DEXCOM	0.00	0.00	76.88	74.92	86.15	198.63
DIA.HILL INV.GP.	66.67	0.00	37.84	34.36	28.59	34.60
DIGI INTERNATIONAL	66.67	0.00	7.26	6.88	54.49	54.58
DIGIMARC	50.00	0.00	16.72	14.42	85.54	74.39
DIGITAL ALLY	75.00	0.10	19.38	14.19	37.87	63.07
DIGITAL TURBINE	0.00	0.00	22.86	16.97	78.91	177.03
DIME COMMUNITY	75.00	0.00	17.82	16.19	78.45	69.97
BANCSHARES						
DIODES	58.33	0.00	14.94	13.38	26.59	33.79
DISTRIBUTION	58.33	0.00	10.31	9.57	52.73	52.77
SOLUTIONS GROUP						
DIVERSIFIED HEALTHCARE	50.00	0.00	5.57	5.10	138.10	98.49
DLH HOLDINGS	0.00	0.00	4.90	4.43	57.88	110.17
DMC GLOBAL	75.00	0.00	17.39	16.14	51.75	52.38
DOLLAR TREE	50.00	0.00	18.39	16.14	17.73	25.61
DOMINARI HOLDINGS	66.67	0.00	96.49	94.92	781.59	202.70
DONEGAL GP.'A'	0.00	0.00	0.67	0.48	3.50	4.43
DORCHESTER MINERALS	66.67	0.00	10.91	9.97	89.14	76.50
DORMAN PRODUCTS	50.00	0.37	10.24	8.60	12.16	26.01
DURECT	50.00	0.00	23.18	22.11	116.20	92.38
DXP ENTS.	66.67	0.00	29.19	27.52	152.79	106.16
DYADIC INTL.	50.00	0.00	1.55	1.21	17.16	28.66
DYNATRONICS	41.67	0.00	3.33	3.05	79.79	70.07
DYNAVAX TECHNOLOGIES	50.00	0.00	2.11	1.83	39.39	43.33
DZS	83.33	0.58	1.90	1.47	20.74	37.29
SCRIPPS E W 'A'	50.00	0.00	6.60	6.19	62.26	59.45
EAGLE BANCORP MNTA.	58.33	0.00	7.05	6.28	35.09	38.78
EAGLE BANC.	58.33	0.00	23.24	21.00	66.19	61.88
EAST WEST BANCORP	75.00	0.00	18.29	16.66	46.06	48.03
EASTERN	58.33	0.00	16.10	14.89	73.08	67.09
EBAY	66.67	0.09	8.26	6.50	13.20	29.93
ECHOSTAR	58.33	0.00	22.53	19.49	73.85	64.94
EDAP TMS SPN.ADR 1:1	0.00	0.00	0.94	0.84	26.10	33.07
EDGIO	33.33	0.00	54.33	45.37	21.57	25.24
EDUCATIONAL DEV.	50.00	0.00	5.14	4.13	35.49	64.59
EGAIN	66.67	0.11	2.88	2.00	16.62	34.46
EHEALTH	33.33	0.00	37.27	31.80	37.57	31.94
ELBIT SYSTEMS (NAS)	58.33	0.00	48.91	38.62	30.72	33.54
ELECTRO-SENSORS	91.67	0.00	0.68	0.56	15.31	22.86
ELECTRONIC ARTS	75.00	0.19	12.21	10.66	8.79	19.07
ELECTROVAYA (NAS)	75.00	0.00	1.97	1.22	37.31	79.55

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
ELTEK	0.00	0.00	1.16	1.00	26.04	28.48
EMCORE	83.33	0.43	5.03	4.15	14.07	27.07
ENCORE CAP.GP.	83.33	0.00	6.33	5.01	15.78	25.87
ENCORE WIRE	75.00	0.00	18.33	16.37	33.23	37.23
ENERGY FOCUS	0.00	0.00	16.50	14.17	54.83	60.20
ENERGY RECOVERY	0.00	0.00	3.93	3.58	37.85	62.45
ENERGY SERVICES OF AMERICA	0.00	0.00	0.26	0.24	28.79	32.00
ENGLOBAL	58.33	0.00	3.61	2.91	36.42	45.05
ENSTAR GROUP	75.00	0.00	67.81	61.12	36.63	40.18
ENTEGRIS	66.67	0.18	13.62	10.70	14.77	31.29
ENTERPRISE BANCORP	50.00	0.00	14.54	12.78	54.90	53.61
ENTER.FINL.SVS.	66.67	0.00	21.74	19.60	64.12	60.67
EPLUS	66.67	0.00	11.76	10.33	28.30	33.27
EQUINIX REIT	58.33	0.00	79.04	63.19	9.05	19.17
ERICSSON 'B' ADR 1:1	0.00	0.00	1.91	1.54	14.64	20.57
ERIE INDEMNITY 'A'	75.00	0.72	15.61	12.26	6.47	22.21
ESCALADE	66.67	0.00	5.69	4.42	27.19	55.39
ESSA BANCORP	58.33	0.00	5.25	4.49	33.39	36.56
ETERNA THERAPEUTICS	58.33	0.00	30.21	26.50	40.14	42.68
EURO TECH HOLDINGS	8.33	0.00	0.34	0.27	23.44	36.55
EURONET WWD.	66.67	0.00	70.94	64.39	64.61	60.79
EUROSEAS	58.33	0.00	2.75	2.61	87.41	203.14
EVERGY	58.33	0.00	20.66	16.27	29.57	31.76
EVOTEC SE SPONSORED ADR 2:1	66.67	0.00	1.79	1.42	10.68	19.72
EXACT SCIS.	66.67	0.29	17.85	13.28	17.32	30.70
EXELIXIS	0.00	0.00	15.31	15.04	69.64	140.39
EXELON	75.00	0.00	9.27	7.80	28.29	32.00
EXLSERVICE HDG.	0.00	0.00	6.65	6.34	45.52	78.24
EXPEDIA GROUP	75.00	0.00	34.09	30.71	37.15	42.32
EXPONENT	83.33	0.00	7.83	6.24	8.29	17.45
EXTREME NETWORKS	75.00	0.00	3.62	3.38	82.72	71.78
EYEPOINT	41.67	0.00	11.01	9.63	166.30	100.69
PHARMACEUTICALS						
EZCORP 'A' NON VTG.	41.67	0.00	2.77	2.49	49.15	49.71
F5	58.33	0.00	31.68	26.03	19.89	27.44
FANHUA 1:20 ADR	41.67	0.00	10.61	8.91	61.24	55.56
FARMER BROTHERS	58.33	0.00	11.03	9.88	180.95	108.25
FARMERS NAT.BANC	66.67	0.00	5.31	4.55	38.46	40.57
FARO TECHS.	66.67	0.68	4.10	3.24	5.99	20.13
FASTENAL	75.00	0.75	2.80	2.33	5.79	20.87
FENNEC PHARMS. (NAS)	0.00	0.00	3.44	3.27	44.49	75.96
FIFTH THIRD BANCORP	66.67	0.00	12.99	11.97	58.30	56.84
FINANCIAL INSTITUTIONS	75.00	0.00	17.80	16.06	90.61	76.64
FIRST BANCORP	58.33	0.00	21.53	19.73	81.27	71.29

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
FIRST BANCORP.1	66.67	0.00	15.42	14.27	64.44	61.50
FIRST BANCSHARES MS	75.00	0.00	15.15	13.61	60.86	58.47
FIRST BANK	58.33	0.00	5.19	4.69	63.66	60.11
FIRST BUSEY 'A'	75.00	0.00	14.31	13.17	72.23	66.60
FIRST BUS.FINL.SVS.	66.67	0.00	14.40	13.14	79.32	70.65
FIRST CAP.	66.67	0.00	18.87	15.85	26.44	30.52
FIRST CTZN.BCSH.A	75.00	0.00	206.06	185.64	47.03	48.95
FIRST COMMUNITY BANKSHARES	58.33	0.00	17.18	15.49	74.07	66.93
FIRST CMTY.	50.00	0.00	11.18	10.17	67.93	63.24
FIRST FINANCIAL NW.	75.00	0.00	8.11	7.38	74.75	67.85
FIRST FINL.BKSH.	75.00	0.00	10.06	8.90	29.66	34.31
FIRST FINL.BANC.	66.67	0.00	12.08	10.76	75.28	67.30
FIRST FINANCIAL	75.00	0.00	16.94	14.95	42.75	44.67
FIRST INTERNET BANCORP	83.33	0.00	8.38	7.20	43.47	46.56
FIRST MERCHANTS	66.67	0.00	19.83	17.76	65.17	61.03
FIRST OF LONG ISLAND	75.00	0.00	13.87	12.80	79.65	71.34
FIRST SAVINGS FINL.GP.	50.00	0.00	8.99	8.18	51.64	51.89
FIRST SOLAR	0.00	0.00	36.22	31.15	45.94	81.83
FIRST UTD.	41.67	0.00	9.97	8.80	66.99	59.81
FIRST US BANCSHARES	66.67	0.00	6.62	6.04	83.89	73.12
FIRSTCASH HOLDINGS	66.67	0.00	28.25	22.69	36.08	36.50
FITLIFE BRANDS	58.33	0.42	0.69	0.53	15.43	30.78
FLEX	75.00	0.00	2.71	2.33	30.91	39.52
FLEXSTEEL INDS.	50.00	0.36	6.22	5.67	40.51	52.96
FLUENT	66.67	0.00	5.34	4.74	38.21	46.13
FLUSHING FINANCIAL	75.00	0.00	12.04	10.96	89.19	76.02
FNCB BANCORP	58.33	0.00	3.69	3.38	55.55	54.78
FONAR	0.00	0.00	16.28	15.94	76.54	162.95
FORMFACTOR	0.00	0.00	20.10	19.04	65.91	129.87
FORMULA SYS.1985 ADR 1:1	91.67	0.45	9.41	7.23	10.59	23.37
FORRESTER RESEARCH	58.33	0.00	10.44	9.25	26.65	31.76
FORTINET	58.33	0.00	3.40	2.78	11.63	19.61
FORWARD INDUSTRIES	66.67	0.00	0.35	0.29	20.26	32.90
FOSSIL GROUP	0.00	0.00	6.39	5.97	132.29	93.80
FOSTER (LB)	75.00	0.00	7.87	7.09	51.91	51.75
FORWARD AIR	83.33	0.00	23.96	22.04	39.34	43.15
FRANKLIN ELECTRIC	91.67	0.00	8.51	7.36	13.13	23.26
FRANKLIN FINL.SVS.	50.00	0.00	17.62	15.45	61.71	58.35
FREEDOM HOLDING	0.00	0.00	23.49	21.61	96.98	246.70
FREIGHTCAR AMERICA	41.67	0.00	1.06	1.00	69.13	64.79
FREQUENCY ELECTRONICS	0.00	0.00	1.19	0.89	10.20	12.12
FRP HOLDINGS	50.00	0.00	7.94	6.77	32.21	35.25

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
FUEL TECH	0.00	0.00	1.13	0.70	62.78	66.06
FUELCELL ENERGY	0.00	0.00	5.77	5.54	258.90	136.26
FULL HOUSE RESORTS	0.00	0.00	0.91	0.82	46.83	48.48
FULTON FINANCIAL	66.67	0.00	7.25	6.34	58.71	55.75
FUTURE FINTECH GROUP	41.67	0.00	6.87	6.10	71.85	147.28
G.WILLI-FOOD INTL.	75.00	0.00	3.80	3.25	18.84	36.16
GAIA 'A'	58.33	0.10	1.33	1.01	10.80	22.61
GALAPAGOS N V SPN.ADR 1:1	33.33	0.00	92.63	70.49	52.27	43.51
GALECTIN THERAPEUTICS	50.00	0.00	0.50	0.41	16.89	23.07
GEN DIGITAL	75.00	0.00	4.76	4.28	20.97	32.74
GENASYS	50.00	0.00	1.37	1.12	21.75	39.85
GNE.TECHS.SPN.ADR 1:30	75.00	0.00	7.25	6.09	35.53	62.47
GENMAB 10 SPONSORED ADR 10:1	0.00	0.00	27.91	27.09	87.28	203.22
GENTEX	83.33	0.00	6.54	5.62	20.66	27.85
GENTHERM	83.33	0.00	8.98	7.47	18.24	29.33
GEOSPACE TECHNOLOGIES	58.33	0.00	10.52	9.65	144.72	101.30
GEOVAX LABS	58.33	0.00	4.22E+07	4.18E+07	5.34E+07	262.00
GERMAN AMERICAN BANCORP	0.00	0.00	11.52	11.18	36.33	58.56
GERON	50.00	0.38	0.26	0.21	13.79	26.00
GIBRALTAR INDS.	66.67	0.68	5.75	4.45	8.94	25.34
GIGAMEDIA	50.00	0.28	0.26	0.20	7.32	19.17
G-III APPAREL GROUP	58.33	0.00	12.21	11.43	92.18	73.97
GILAT	50.00	0.00	3.40	2.83	48.03	43.19
GILEAD SCIENCES	50.00	0.00	15.64	13.06	19.54	18.54
GLADSTONE COML.	58.33	0.00	9.33	8.62	50.73	51.02
GLEN BURNIE BANCORP	58.33	0.00	4.29	3.91	41.63	44.02
GLOBAL SELF STORAGE	58.33	0.00	1.09	0.91	23.15	27.70
GLOBUS MARITIME	25.00	0.00	99.87	88.94	698.23	151.71
GOLAR LNG (NAS)	83.33	0.00	7.45	6.97	86.48	74.92
GOLDEN ENTERTAINMENT	58.33	0.00	12.51	11.82	111.69	85.32
GOLDEN MATRIX GROUP	75.00	0.00	1.81E+06	1.79E+06	1.11E+08	262.00
GOLDEN OCEAN GROUP	58.33	0.00	2.51	2.33	62.40	60.16
GOOD TIMES REST. PF.SHS.	66.67	0.00	0.72	0.68	62.14	58.19
GOODYEAR TIRE & RUB.	75.00	0.00	8.39	7.93	91.04	78.25
GRAND CANYON EDUCATION	66.67	0.00	23.11	18.68	22.09	27.02
GRAVITY ADR 1:1	58.33	0.00	56.34	38.02	37.63	73.06
GREAT ELM GROUP	66.67	0.00	0.58	0.53	22.93	26.43
GREAT LAKES DREDGE & DOCK	58.33	0.00	3.23	2.93	30.90	35.76

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
GREAT STHN.BANCORP	66.67	0.00	28.56	25.67	63.18	59.96
GREEN PLAINS	0.00	0.00	4.42	3.21	46.59	38.45
GREENE COUNTY BANC.	75.00	0.00	5.15	4.46	38.67	40.74
GREENLIGHT CAPITAL A	66.67	0.00	4.77	4.37	62.34	59.94
GRUPO AEROPORTUARIO DEL CENTRO NORTE ADS 1:8	58.33	0.00	26.33	24.06	66.21	61.26
GRUPO FINANCIERO GALICIA CL.B SHS.SPN.ADR 1:10	58.33	0.00	9.32	8.44	98.98	80.10
GSE SYSTEMS	33.33	0.00	13.05	12.40	116.49	92.74
GSI TECHNOLOGY	0.00	0.00	0.98	0.81	11.19	15.66
GT BIOPHARMA	50.00	0.00	1.02E+05	1.01E+05	1.23E+05	261.52
GULF ISLAND FABRICATION	41.67	0.00	2.18	1.94	62.44	58.60
GULF RESOURCES	50.00	0.00	2.01	1.85	38.70	64.40
GYRE THERAPEUTICS	66.67	0.00	6.83	5.76	44.48	45.09
GYRODYNE	58.33	0.00	23.88	23.83	139.66	262.00
H&E EQUIPMENT SERVICES	83.33	0.00	19.60	18.78	97.70	81.39
HACKETT GROUP	58.33	0.00	3.76	3.12	23.54	25.61
HAIN CELESTIAL GP.	41.67	0.31	3.88	3.42	10.93	24.08
HALLADOR ENERGY	50.00	0.00	2.61	2.50	303.27	147.99
HALOZYME THERAPEUTICS	91.67	0.00	8.18	6.46	21.72	40.03
HANCOCK WHITNEY	0.00	0.00	9.57	8.83	39.41	42.87
HANMI FINANCIAL	75.00	0.00	13.23	12.14	123.44	93.24
HARMONIC	66.67	0.00	2.91	2.62	44.87	46.22
HARROW	66.67	0.00	4.25	4.09	75.99	69.95
HARTE-HANKS	50.00	0.00	2.68	2.49	116.28	90.00
HARVARD BIOSCIENCE	83.33	0.40	0.45	0.35	12.68	25.50
HASBRO	50.00	0.00	42.53	38.95	50.16	50.86
HAWAIIAN HOLDINGS	58.33	0.00	16.24	14.79	104.68	83.49
HAWKINS	75.00	0.00	9.47	9.22	42.05	45.57
HAWTHORN BANCSHARES	0.00	0.00	7.28	6.96	39.16	64.48
HAYNES INTL.	58.33	0.00	14.28	12.68	61.43	57.65
HEALTHCARE SERVICES GROUP	75.00	0.00	5.98	4.69	20.20	24.26
HEALTHSTREAM	41.67	0.00	9.35	7.69	36.87	36.72
HEARTLAND EXPRESS	0.00	0.00	1.49	1.22	6.10	8.27
HEARTLAND FINL.USA	66.67	0.00	22.29	19.97	59.44	57.59
HEIDRICK & STGL.INTL.	66.67	0.00	15.53	14.28	63.06	60.36
HELEN OF TROY	83.33	0.15	23.22	18.76	10.65	22.69
HENNESSY ADVISORS	66.67	0.00	2.50	2.13	25.04	28.68
HENRY SCHEIN	75.00	0.00	17.66	15.31	24.94	30.43

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
HERITAGE COMMERCE	58.33	0.00	6.19	5.51	72.96	65.82
HERITAGE FINANCIAL	58.33	0.00	12.68	11.57	56.43	55.55
HERON THERAPEUTICS	58.33	0.00	10.87	9.99	62.65	59.77
HIBBETT	66.67	0.32	9.84	8.66	44.50	55.30
HIGHWAY HOLDINGS	75.00	0.00	0.97	0.75	24.41	41.44
HIMAX TECHNOLOGIES	66.67	0.00	1.24	0.86	18.63	32.93
ADR 1:2						
HINGHAM INSTN.FOR SVG.	75.00	0.00	61.24	57.13	31.48	36.73
HIREQUEST	41.67	0.35	0.86	0.67	8.98	17.92
HMN FINANCIAL	58.33	0.00	5.36	4.78	31.28	30.30
HOLLYSYS ATMTN.TECHS.	50.00	0.00	8.32	7.40	59.76	56.96
HOLOGIC	66.67	0.77	5.39	3.60	7.49	25.68
HOME BANCORP	58.33	0.00	10.51	9.42	36.07	37.53
HONEYWELL INTL.	75.00	0.00	42.72	37.81	23.91	31.58
HOOKER FURNISHINGS	0.00	0.00	7.94	6.56	26.34	39.89
HOPE BANCORP	66.67	0.00	7.57	6.78	76.59	68.45
HORIZON BANCORP	75.00	0.00	11.46	10.77	94.87	80.09
HOST HOTELS & RESORTS REIT	58.33	0.00	9.61	8.84	74.67	67.96
HUB GROUP 'A'	91.67	0.00	3.91	3.48	13.74	20.18
HUDSON GLOBAL	50.00	0.00	4.11	3.63	37.91	40.69
HUDSON TECHNOLOGIES	0.00	0.00	2.28	2.27	240.80	140.22
HUNTINGTON BCSH.	75.00	0.00	6.28	5.72	59.00	57.34
HURCO COMPANIES	33.33	0.00	14.34	13.06	44.51	46.29
HURON CNSL.GP.	50.00	0.00	32.00	28.02	63.19	59.26
ICU MEDICAL	58.33	0.00	36.80	31.08	16.00	18.27
IAC	66.67	0.33	17.32	13.73	18.34	39.91
ICAD	83.33	0.00	2.38	1.83	16.49	28.25
ICAHN ENTERPRISES	58.33	0.00	20.99	17.61	34.95	37.68
ICF INTERNATIONAL	75.00	0.00	35.96	31.64	46.48	47.50
ICON	41.67	0.00	23.01	18.65	10.71	21.41
IDEANOMICS	25.00	0.20	68.09	51.13	47.48	58.45
IDENTIVE	66.67	0.00	1.75	1.60	36.64	42.26
IDEXX LABORATORIES	83.33	0.36	61.74	50.51	13.67	30.97
IES HOLDINGS	58.33	0.60	5.05	4.15	16.12	34.13
ILLUMINA	66.67	0.00	71.84	55.09	17.82	24.71
IMMERSION	58.33	0.24	1.06	0.86	11.59	21.37
IMMUCELL	50.00	0.00	0.71	0.60	11.80	22.52
IMUNON	58.33	0.00	24.16	22.13	172.58	104.79
INCYTE	66.67	0.00	21.71	18.32	21.48	24.81
INDEPENDENT BANK MASS.	58.33	0.00	30.89	26.44	42.15	43.29
INDEPENDENT BANK	75.00	0.00	11.11	10.11	68.79	63.94
INFINERA	66.67	0.00	1.55	1.32	21.81	30.16
INFORMATION SVS.GP.	0.00	0.00	1.22	1.14	51.67	51.54

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
INGLES MARKETS 'A'	66.67	0.00	17.07	14.99	38.46	40.86
INNODATA	50.00	0.00	1.37	0.77	24.35	55.93
INNOSPEC	58.33	0.00	40.08	34.97	47.12	47.88
INNOV.SLTN.& SPT.	58.33	0.31	1.04	0.84	18.40	30.78
INNOVIVA	66.67	0.00	4.46	3.34	29.74	31.12
INOTIV	66.67	0.36	1.04	0.76	14.63	27.26
INOVIO	50.00	0.00	124.55	103.04	64.70	133.20
PHARMACEUTICALS						
INSEEGO	58.33	0.00	26.05	20.57	19.49	33.93
INSIGHT ENTS.	58.33	0.00	29.26	27.51	50.66	51.75
INSMED	50.00	0.61	4.01	3.17	11.42	29.20
INSULET	58.33	0.30	24.07	18.96	9.06	22.40
INTEGRA LFSC.HDG.	41.67	0.00	20.30	17.88	36.30	39.61
INTEL	58.33	0.00	20.25	15.67	31.33	32.09
INTELLICHECK	75.00	0.07	1.77	1.45	24.54	33.05
INTER PARFUMS	75.00	0.00	36.44	32.72	71.40	65.10
INTERACTIVE BROKERS GROUP A	66.67	0.00	6.21	5.41	11.43	20.34
INTERDIGITAL	66.67	0.00	7.80	6.07	10.90	20.38
INTERFACE	50.00	0.00	10.55	9.42	120.60	90.23
INTERGROUP	50.00	0.00	13.46	11.93	40.40	42.86
INTEVAC	66.67	0.00	2.98	2.78	50.25	51.19
INTERNATIONAL BCSH.	83.33	0.00	20.21	18.54	61.78	59.32
INTUIT	83.33	0.77	18.58	15.34	5.28	20.21
INTUITIVE SURGICAL	66.67	0.67	18.86	14.79	7.68	23.45
INVESTORS TITLE	50.00	0.00	47.72	40.97	30.45	35.05
INVO BIOSCIENCE	0.00	0.00	101.41	96.87	79.66	174.74
IONIS PHARMACEUTICALS	58.33	0.00	17.92	14.04	27.35	30.66
IOVANCE	83.33	0.24	5.65	4.62	14.32	25.09
BIOTHERAPEUTICS						
IPG PHOTONICS	66.67	0.74	15.29	12.44	8.26	25.19
IRIDEX	66.67	0.00	0.92	0.81	41.59	42.70
IRIDIUM	91.67	0.12	3.82	3.21	12.29	23.59
COMMUNICATIONS						
IROBOT	75.00	0.00	15.80	13.31	18.30	36.73
ITERIS	0.00	0.00	0.71	0.56	13.50	16.40
ITRON	58.33	0.00	29.82	26.20	39.60	42.59
ITURAN (NAS)	58.33	0.00	12.65	11.10	72.10	65.04
HUNT JB TRANSPORT SVS.	75.00	0.11	15.15	12.02	10.48	22.86
J & J SNACK FOODS	66.67	0.00	73.49	66.08	48.91	49.90
JACK HENRY AND ASSOCIATES	66.67	0.00	26.52	22.64	13.62	17.10
JACK IN THE BOX	75.00	0.00	19.38	16.80	28.84	33.75
JAKKS PACIFIC	50.00	0.00	9.21	8.58	171.16	110.57
JANONE	83.33	0.00	1.15	0.78	17.67	34.18

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
JAZZ PHARMACEUTICALS	41.67	0.00	40.30	36.61	29.42	34.94
JETBLUE AIRWAYS	75.00	0.00	8.74	8.00	70.81	64.39
JEWETT CAMERON	75.00	0.00	1.45	1.28	18.31	28.54
TRADING NEW U\$ (NAS)						
JOHN B SANFILIPPO & SON	58.33	0.00	31.03	26.20	33.35	35.20
JOHNSON OUTDOORS 'A'	58.33	0.22	11.07	8.87	11.92	24.69
KVH INDUSTRIES	66.67	0.00	3.14	2.65	29.66	33.15
KAISER ALUMINUM	75.00	0.00	54.62	48.80	70.75	64.20
KAMADA	50.00	0.00	1.39	1.10	15.68	23.62
KANDI TECHNOLOGIES GROUP	58.33	0.36	2.00	1.48	30.53	49.92
KAZIA THERAPEUTICS ADS 1:10	66.67	0.39	1.81	1.37	27.43	48.53
KEARNY FINANCIAL	66.67	0.00	8.01	7.43	86.45	75.18
KELLY SERVICES 'A'	66.67	0.00	12.10	11.68	70.70	66.54
KENTUCKY FIRST FED.BANC.	41.67	0.00	2.22	1.84	29.06	32.70
KEURIG DR PEPPER	66.67	0.00	4.61	3.66	12.86	20.03
KEWAUNEE SCIENTIFIC	50.00	0.00	5.41	4.93	53.31	53.00
KEY-TRONIC	58.33	0.40	1.50	1.24	20.00	39.84
KINGSTONE COMPANIES	66.67	0.00	3.44	3.19	57.85	56.54
KIRKLAND'S	8.33	0.00	7.38	6.55	462.60	130.15
KLA	66.67	0.59	21.40	15.52	8.80	24.44
KOLIBRI GLOBAL (NAS) ENERGY	50.00	0.00	0.27	0.24	68.58	59.55
KOPIN	0.00	0.00	1.32	1.20	218.69	103.93
KORU MEDICAL SYSTEMS	0.00	0.00	6.91	6.58	83.11	187.07
KOSS	58.33	0.41	0.41	0.34	24.39	37.16
KRATOS DEF&SCTY.SLTN.	75.00	0.61	2.00	1.55	8.82	22.31
KULICKE & SOFFA INDS.	75.00	0.00	8.77	8.00	32.83	37.95
LSI INDUSTRIES	91.67	0.50	0.85	0.58	11.65	24.79
LAKELAND FINANCIAL	66.67	0.00	9.53	8.21	18.47	26.19
LAKELAND INDS.	75.00	0.00	8.36	7.61	38.31	64.24
LAM RESEARCH	83.33	0.67	40.35	29.85	8.85	25.86
LAMAR ADVERTISING 'A'	66.67	0.00	36.24	32.49	49.77	50.40
LANCASTER COLONY	0.00	0.00	128.17	127.37	79.52	173.02
LANDMARK BANCORP	58.33	0.00	5.51	4.49	24.25	29.09
LANDSTAR SYSTEM	66.67	0.21	11.40	9.49	8.05	20.18
LANTRONIX	0.00	0.00	2.28	2.10	51.16	93.21
LARGO (NAS)	66.67	0.00	1.46	1.24	18.31	28.50
LATTICE SEMICONDUCTOR	75.00	0.00	9.29	7.56	24.33	44.07
LCNB	58.33	0.00	6.59	5.86	40.86	43.08
LEE ENTERPRISES	66.67	0.00	6.23	5.52	57.93	55.05
LEMAITRE VASCULAR	83.33	0.00	11.83	10.92	36.85	41.09

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
LENDINGTREE	75.00	0.00	75.82	62.38	23.67	30.59
LENDWAY	66.67	0.00	0.99	0.71	13.60	23.01
LEONARDO DRS	83.33	0.41	1.15	0.89	14.20	31.67
LESAKA TECHNOLOGIES	58.33	0.00	0.88	0.72	21.87	25.68
LEXARIA BIOSCIENCE	66.67	0.00	5.76	4.86	63.14	55.58
LEXICON	58.33	0.00	3.03	2.82	158.28	105.69
PHARMACEUTICALS						
LIBERTY GLOBAL CL.A	58.33	0.00	5.56	4.88	22.99	28.83
LIBERTY GLOBAL SR.C	58.33	0.00	5.12	4.47	21.79	28.11
LIFECORE BIOMEDICAL	58.33	0.00	3.40	2.84	28.97	32.50
LIFEMD	0.00	0.00	4.12	3.01	60.37	126.55
LIFETIME BRANDS	83.33	0.52	2.12	1.68	21.91	41.39
LIFEVANTAGE	0.00	0.00	4.25	3.81	27.49	42.93
LIFEWAY FOODS	50.00	0.00	1.93	1.36	28.58	55.83
LIGAND PHARMS.'B'	75.00	0.00	17.49	13.22	23.17	28.93
LIGHT WONDER	58.33	0.03	10.18	8.37	61.48	61.21
LIGHTBRIDGE	41.67	0.00	7.87	7.75	199.67	262.00
LIGHTPATH TECHS.	75.00	0.00	2.02	1.79	73.11	155.74
LIGHTWAVE LOGIC	66.67	0.00	0.13	0.10	15.52	21.57
LIMONEIRA	75.00	0.00	7.55	6.71	46.74	47.90
LINCOLN EDUCA.SVS.	75.00	0.00	2.08	1.59	29.74	59.71
LINCOLN ELECTRIC HDG.	83.33	0.00	25.17	23.63	26.34	33.65
LINDE (NYS)	75.00	0.28	24.06	19.47	9.06	22.10
LIQUIDITY SERVICES	75.00	0.38	2.49	1.64	23.19	42.48
LISATA THERAPEUTICS	50.00	0.00	50.37	47.91	172.80	114.67
LITTELFUSE	75.00	0.00	42.49	37.81	22.53	32.25
LIVANOVA	75.00	0.00	34.43	30.82	60.70	58.05
LIVE VENTURES	58.33	0.54	1.49	1.22	14.78	33.13
LIVEPERSON	83.33	0.55	9.04	7.43	21.00	39.77
LKQ	66.67	0.00	9.16	8.38	30.28	35.82
LOGITECH INTL. (NAS)	66.67	0.19	15.60	13.02	18.74	37.88
LULULEMON ATHLETICA	75.00	0.30	50.47	42.61	14.07	31.70
LUNA INNOVATIONS	66.67	0.00	1.85	1.56	24.69	30.30
MACATAWA BANK	66.67	0.00	4.54	3.98	53.51	52.81
MADRIGAL	50.00	0.59	11.48	9.25	9.12	24.32
PHARMACEUTICALS						
MAGIC SFTW.ENTS. (NAS)	75.00	0.25	2.08	1.77	14.17	30.44
MAIDEN HOLDINGS	83.33	0.00	0.58	0.45	31.15	52.00
MANHATTAN ASSOCS.	75.00	0.65	9.30	6.87	9.89	25.39
MANHATTAN BRIDGE	0.00	0.00	2.91	2.79	58.02	107.91
CAPITAL						
MANITEX	66.67	0.00	2.27	2.02	45.59	46.99
INTERNATIONAL						
MANNATECH	66.67	0.00	4.59	4.22	30.31	35.36
MANNKIND	0.00	0.00	2.46	2.38	158.09	108.57
MARCHEX 'B'	41.67	0.00	2.68	2.52	140.99	102.06

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
MARINE PETROLEUM TRUST	66.67	0.35	0.58	0.40	17.65	35.10
MARKER THERAPEUTICS	33.33	0.00	23.97	21.97	123.39	92.42
MARKETAXESS HOLDINGS	66.67	0.30	65.53	57.45	12.57	25.55
MARRIOTT INTL.'A'	58.33	0.00	67.15	61.34	63.51	60.51
MARTEN TRANSPORT	58.33	0.00	1.86	1.51	9.67	19.63
MARTIN MIDSTREAM PTNS.	50.00	0.00	2.44	2.24	139.24	96.77
MARVELL TECHNOLOGY	58.33	0.00	8.43	7.33	20.46	37.93
MASIMO	58.33	0.00	43.19	36.57	16.23	29.68
MATRIX SERVICE	0.00	0.00	4.82	4.51	45.07	48.40
MATTEL	0.00	0.00	7.06	6.56	53.25	96.77
MATTHEWS INTL.'A'	0.00	0.00	8.14	7.53	33.11	36.40
MCGRATH RENTCORP	75.00	0.00	28.87	25.60	43.29	45.50
MEDALLION FINL.	0.00	0.00	3.60	3.21	119.60	86.26
MEDICINOVA (NAS)	8.33	0.00	1.41	1.16	24.51	26.44
MEI PHARMA	33.33	0.00	12.00	8.79	20.31	37.07
MELCO RESORTS ENTERTAINMENT ADR 1:3	66.67	0.00	15.59	14.90	88.12	77.82
MERCADOLIBRE	83.33	0.00	402.83	317.54	27.82	53.33
MERCANTILE BANK	83.33	0.00	17.83	16.08	71.86	65.70
MERCER INTL.	0.00	0.00	1.90	1.69	21.25	25.07
MERCURY SYSTEMS	41.67	0.00	13.07	11.10	14.42	17.39
MERIT MEDICAL SYS.	83.33	0.00	8.52	7.77	17.47	30.88
MESA LABORATORIES	75.00	0.00	50.82	41.88	17.00	24.04
MESOBLAST ADR 1:10	0.00	0.00	9.75	7.95	34.23	48.59
METHANEX (NAS)	75.00	0.00	20.66	19.03	95.00	77.47
MGE ENERGY	66.67	0.00	24.81	20.90	31.46	34.59
MGP INGREDIENTS	50.00	0.00	19.60	18.60	50.89	51.94
MICROBOT MEDICAL	41.67	0.00	4.94	4.54	64.42	60.63
MICROCHIP TECH.	66.67	0.00	12.37	11.05	23.00	31.83
MICRON TECHNOLOGY	66.67	0.00	10.47	8.38	17.23	26.19
MICROSOFT	83.33	0.32	18.98	15.60	8.21	21.13
MICROSTRATEGY	75.00	0.37	47.45	30.61	17.48	33.36
MICROVISION	0.00	0.00	1.44	0.93	89.56	90.37
MID PENN BANCORP	41.67	0.00	12.28	11.18	56.12	55.34
MIDDLEBY	91.67	0.00	38.08	33.83	43.46	47.42
MIDDLESEX WATER	66.67	0.00	10.55	8.36	12.73	19.56
MIDWESTONE FINL.GP.	66.67	0.00	18.64	16.95	82.76	72.52
MILLERKNOLL	58.33	0.00	19.74	18.11	69.84	64.12
MILLICOM INTL.CELU.	33.33	0.00	9.22	8.63	35.87	38.15
MIMEDX GROUP	66.67	0.00	3.47	3.27	64.44	60.99
MIND C T I	66.67	0.00	0.71	0.65	30.15	34.53
MIND TECHNOLOGY	58.33	0.00	13.19	12.06	76.53	63.89
MITEK SYSTEMS	0.00	0.00	3.52	2.63	21.65	33.33
MKS INSTRUMENTS	66.67	0.37	13.97	10.25	9.77	23.52

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
MODIVCARE	75.00	0.01	26.28	19.13	18.91	38.72
MOLECULAR TEMPLATES	66.67	0.00	82.41	65.17	40.00	35.27
MONARCH CASINO & RESORT	75.00	0.00	15.36	13.89	39.07	42.03
MONDELEZ	75.00	0.00	9.26	7.70	13.96	19.95
INTERNATIONAL CL.A						
MONOLITHIC PWR.SYS.	58.33	0.17	54.34	44.37	16.85	34.87
MONRO	66.67	0.00	41.47	37.43	77.05	68.62
MONSTER BEVERAGE	75.00	0.57	3.21	2.89	7.91	22.14
MORNINGSTAR	75.00	0.67	15.43	12.01	7.76	22.88
MOTORCAR PARTS OF AM.	58.33	0.00	7.76	7.14	44.40	46.84
MYR GROUP	83.33	0.61	6.33	5.05	14.86	32.85
MYRIAD GENETICS	66.67	0.00	17.28	15.87	112.86	88.63
NAPCO SECURITY TECHS.	66.67	0.00	5.08	4.75	41.67	44.39
NASDAQ	83.33	0.31	3.19	2.58	6.69	18.17
NATHANS FAMOUS	41.67	0.00	26.10	22.23	40.83	41.94
NATIONAL CINEMEDIA	75.00	0.00	48.84	43.58	145.97	99.46
NATIONAL BANKSHARES	50.00	0.00	21.88	19.46	68.85	63.22
NATIONAL BEVERAGE	0.00	0.00	27.44	26.09	80.65	177.85
NATIONAL WSTN.LF.GP.'A'	66.67	0.00	131.99	118.42	60.38	58.06
NATURAL ALTS.INTL.	75.00	0.00	1.38	1.16	16.00	25.54
NATURAL HEALTH TRENDS	0.00	0.00	3.17	3.00	66.32	61.27
NATURES SUNSHINE PRODUCTS	66.67	0.68	1.03	0.82	7.89	23.01
NBT BANCORP	75.00	0.00	15.26	12.96	43.10	43.97
NEKTAR THERAPEUTICS	58.33	0.00	7.52	5.79	31.77	34.55
NEOGEN	58.33	0.00	3.78	3.03	8.54	18.05
NEOGENOMICS	91.67	0.64	4.58	3.48	9.39	26.77
NEONODE	66.67	0.00	4.72	3.83	52.55	104.79
NEPHROS	0.00	0.00	2.15	1.86	22.92	35.00
NETAPP	83.33	0.00	25.95	23.84	52.06	52.74
NETEASE ADR 1:5	75.00	0.00	14.85	13.14	15.72	29.21
NETFLIX	91.67	0.00	85.91	75.03	16.24	29.84
NETGEAR	75.00	0.66	3.15	2.51	9.62	25.46
NETSCOUT SYSTEMS	0.00	0.00	2.14	1.76	7.27	9.33
NETSOL TECHS.	50.00	0.00	0.72	0.63	21.31	26.28
NEUROCRINE BIOSCIENCES	50.00	0.00	26.61	20.44	20.63	25.10
NEUROMETRIX	33.33	0.00	98.58	96.99	618.71	192.00
NEW YORK MORTGAGE TRUST	75.00	0.00	17.36	15.79	155.48	103.58
NEWELL BRANDS (XSC)	66.67	0.00	5.06	4.58	28.80	34.90
NEWTEKONE	66.67	0.00	8.05	7.28	42.50	44.61

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
NEXSTAR MEDIA GROUP	75.00	0.00	45.43	41.38	48.87	49.51
NEXTRIP	58.33	0.00	225.75	214.03	400.05	159.83
NICE SPN.ADR 1:1	83.33	0.00	42.58	39.41	19.26	33.02
NICHOLAS FINANCIAL	58.33	0.00	2.68	2.44	34.01	37.85
NN	58.33	0.00	5.81	5.43	128.62	90.53
NORDSON	66.67	0.53	16.45	12.55	7.55	20.84
NORTECH SYSTEMS	58.33	0.00	2.07	1.97	46.77	49.16
NORTHEAST BANK	83.33	0.00	7.71	7.27	42.70	45.28
NORTHEAST	16.67	0.00	2.05	1.76	27.31	30.11
COMMUNITY BANCORP						
NORTHERN TECHS.INTL.	0.00	0.00	2.46	1.56	14.31	20.87
NORTHERN TRUST	66.67	0.00	28.94	25.20	30.57	33.86
NORTHFIELD BANCORP	66.67	0.00	7.97	7.02	66.11	61.40
DEL.						
NORTHRIM BANCORP	66.67	0.00	13.40	11.93	45.53	46.64
NORTHWEST	66.67	0.00	7.57	6.69	63.14	59.52
BANCSHARES						
NORTHWEST PIPE	58.33	0.00	15.89	14.68	55.59	55.22
NORTHWESTERN ENERGY	75.00	0.00	25.97	21.31	38.91	39.85
GROUP						
NORWOOD FINANCIAL	41.67	0.00	18.12	16.36	63.64	60.49
NOVA	83.33	0.39	8.38	6.86	13.26	30.25
NOVANTA	66.67	0.73	6.96	5.27	5.39	20.62
NOVAVAX	58.33	0.00	81.93	65.14	84.26	197.44
NOVO INTEGRATED	66.67	0.00	24.43	21.68	57.28	108.58
SCIENCES						
NVE	66.67	0.00	27.37	22.72	42.66	43.75
NVIDIA	83.33	0.00	54.81	49.52	47.14	81.50
OSI SYSTEMS	58.33	0.00	37.10	33.78	43.44	45.71
OAK VALLEY BANCORP	50.00	0.00	7.81	6.93	49.43	49.75
OBLONG	75.00	0.00	24.81	15.49	31.41	62.86
OCEANFIRST FINL.	75.00	0.00	11.84	10.58	66.08	61.81
OCUPHIRE PHARMA	75.00	0.00	6.77	6.46	73.36	154.05
ODYSSEY MARINE EXP.	0.00	0.00	1.87	1.40	23.56	37.12
OFFICE PROPERTIES	50.00	0.00	13.98	11.50	50.04	48.63
INCOME						
OHIO VALLEY BANC	41.67	0.00	20.97	18.65	80.72	70.40
OLD DOMINION	83.33	0.00	15.31	13.84	15.89	30.34
FGT.LINES						
OLD NATIONAL BANCORP	83.33	0.00	6.71	5.91	41.57	43.84
OLD POINT FINANCIAL	0.00	0.00	13.02	12.13	65.05	127.40
OLD SECOND BANCORP	66.67	0.00	6.09	5.56	67.03	62.90
OLYMPIC STEEL	50.00	0.00	6.74	6.27	55.51	54.97
OMEGA FLEX	41.67	0.62	18.43	14.27	14.13	32.09
OMEROS	0.00	0.00	2.55	2.07	14.55	20.77
OMNICELL	58.33	0.00	16.18	12.82	17.79	28.48

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
ON SEMICONDUCTOR	83.33	0.00	7.94	7.35	39.54	44.88
ONCOLYTICS BIOTECH (OTC)	58.33	0.00	4.47	4.36	221.36	132.20
ONCTERNAL THERAPEUTICS	50.00	0.00	124.98	121.00	229.96	131.31
ONESPAN	50.00	0.07	4.04	2.98	13.42	25.21
ONTRAK	66.67	0.00	179.72	137.11	48.94	92.50
OPEN TEXT (NAS)	83.33	0.00	8.65	7.05	16.82	22.89
OPKO HEALTH	50.00	0.00	1.69	1.31	34.80	67.54
OPTEX SYSTEMS HDG.	0.00	0.00	1.98	1.97	103.85	88.88
OPTICAL CABLE	33.33	0.00	0.53	0.47	17.55	21.02
OPTIMIZERX	66.67	0.44	4.90	3.74	24.45	47.06
OPTIMUMBANK HOLDINGS	58.33	0.00	14.01	13.85	529.49	188.34
OPTION CARE HEALTH	0.00	0.00	2.45	1.98	16.51	19.25
ORAMED	75.00	0.00	2.34	2.06	64.81	59.56
PHARMACEUTICALS						
ORASURE TECHS.	25.00	0.00	4.14	3.27	25.70	44.27
O REILLY AUTOMOTIVE	58.33	0.00	89.65	78.43	18.69	25.95
ORIGIN AGRITECH	58.33	0.00	3.87	3.19	35.72	68.11
ORION ENERGY SYSTEMS	50.00	0.00	2.54	1.90	27.83	49.09
ORRSTOWN FINL.SVS.	66.67	0.00	11.22	10.21	71.18	65.64
ORTHOFIX MEDICAL	41.67	0.00	20.34	18.32	55.74	54.77
OTTER TAIL	66.67	0.00	28.94	26.03	64.14	60.47
PAM TRANSPORTATION SVS.	50.00	0.00	7.16	6.62	73.34	66.79
PACCAR	66.67	0.00	9.51	8.43	16.25	25.26
PAC.PREMIER BANC.	75.00	0.00	12.51	11.40	51.49	51.95
PALISADE BIO	66.67	0.00	1.17E+06	1.16E+06	3.48E+04	260.38
PALTALK	8.33	0.00	3.94	3.93	372.85	166.06
PAPA JOHNS INTL.	75.00	0.22	11.68	9.03	11.64	25.64
PARAMOUNT GLOBAL A	66.67	0.00	21.63	20.48	76.81	69.11
PARAMOUNT GLOBAL B	75.00	0.00	20.42	19.44	83.22	72.14
PARK OHIO HOLDINGS	0.00	0.00	7.59	7.18	39.24	43.51
PARKE BANCORP	58.33	0.00	11.59	10.45	78.67	69.98
PATHWARD FINANCIAL	75.00	0.00	27.08	25.42	119.74	90.86
PATRICK INDUSTRIES	66.67	0.40	9.36	6.85	17.07	29.30
PATRIOT NAT.BANCORP	58.33	0.00	6.69	6.01	90.62	75.63
PATTERSON COMPANIES	100	0.70	2.60	2.21	9.60	27.31
PATTERSON UTI ENERGY	58.33	0.00	3.79	3.56	103.30	80.83
PAYCHEX	66.67	0.00	18.55	16.17	21.10	28.15
PC CONNECTION	66.67	0.00	14.40	12.55	28.86	32.94
PDF SOLUTIONS	0.00	0.00	6.14	5.50	28.69	44.42
PEAPACK-GLADSTONE FINL.	75.00	0.00	14.13	12.48	70.13	63.67
PEGASYSTEMS	91.67	0.31	17.07	14.60	13.18	30.30

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
PENN ENTERTAINMENT	66.67	0.00	23.28	17.13	40.72	67.71
PENNS WOODS BANC.	66.67	0.00	16.22	14.52	64.67	60.78
PEOPLES BANCORP	58.33	0.00	15.66	13.93	62.70	59.34
PEOPLES BANC.OF NOCA.	66.67	0.00	17.21	15.67	83.91	72.67
PEOPLE FINL.SVS.	58.33	0.00	20.78	18.35	49.66	50.03
PEPSICO	75.00	0.00	23.48	19.40	14.13	19.22
PERASO	83.33	0.00	27.08	23.56	38.02	40.54
PERDOCEO EDUCATION	50.00	0.00	7.29	6.08	48.37	47.62
PERFICIENT	83.33	0.00	13.76	12.61	32.74	37.15
PERION NETWORK	58.33	0.08	1.96	1.79	28.49	36.72
PERMA-FIX ENV.SVS.	50.00	0.00	2.84	2.57	40.61	42.76
PERMA-PIPE INTL.HDG.	33.33	0.00	6.23	5.73	96.73	80.62
PETMED EXPRESS	58.33	0.00	6.62	4.84	14.47	24.72
PHARMACYTE BIOTECH	33.33	0.00	36.30	31.41	198.20	94.99
PHOTRONIC	50.00	0.00	7.14	6.35	58.07	56.00
PILGRIMS PRIDE	58.33	0.00	16.32	14.67	83.18	71.96
PINEAPPLE ENERGY	41.67	0.00	6.51	5.44	51.87	50.28
PINNACLE FINANCIAL	75.00	0.00	32.36	29.85	69.93	64.72
PTNS.						
PIXELWORKS	8.33	0.00	0.87	0.72	26.96	29.75
PLAINS ALL AMERICAN	58.33	0.00	11.14	10.10	135.44	95.88
PIPELINE UNITS						
PLEXUS	66.67	0.00	21.09	19.13	28.00	33.15
PLUG POWER	0.00	0.00	11.89	8.46	65.69	137.03
PLUMAS BANC.QUINCY	50.00	0.00	7.93	6.97	33.47	36.98
CAL.						
PLURI	58.33	0.00	34.80	29.41	41.19	78.76
PLUS THERAPEUTICS	41.67	0.00	323.42	320.18	1.01E+03	217.01
POOL	75.00	0.55	39.85	32.29	10.78	29.76
POPULAR	75.00	0.00	25.01	22.60	57.32	55.86
PORTAGE BIOTECH	66.67	0.00	4.94	4.53	39.21	65.62
POTLATCHDELTIC	0.00	0.00	10.35	9.05	21.10	31.61
POWELL INDUSTRIES	58.33	0.00	29.21	27.20	102.53	84.70
POWER INTEGRATIONS	75.00	0.55	6.13	5.22	9.05	22.18
POWERFLEET	0.00	0.00	1.32	1.13	21.18	26.05
PRA GROUP	75.00	0.12	5.17	3.99	11.51	23.55
PRECIPIO	50.00	0.00	235.11	233.32	830.02	202.58
PREFERRED BANK LOS	83.33	0.00	30.81	27.55	73.60	66.70
ANGELES						
PREFORMED LINE	75.00	0.00	16.84	15.04	28.77	34.06
PRODUCTS						
PREMIER FINANCIAL	75.00	0.00	16.53	15.14	84.68	73.83
PRICESMART	75.00	0.00	12.52	11.06	17.81	27.65
PRIMEENERGY	25.00	0.00	100.46	89.48	139.30	96.82
RESOURCES						
PRIMIS FINANCIAL	50.00	0.00	7.73	6.84	70.67	64.42

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
PRINCIPAL FINL.GP.	58.33	0.00	19.88	17.99	44.53	46.42
PRO-DEX COLONIAL	0.00	0.00	22.10	20.59	86.30	199.39
PROFIRE ENERGY	0.00	0.00	0.68	0.64	79.94	71.23
PROGRESS SOFTWARE	66.67	0.00	9.56	8.05	21.17	25.19
PROPHASE LABS	0.00	0.00	3.71	2.22	40.50	78.14
PROVIDENT FINL.HDG.	66.67	0.00	14.96	13.81	102.65	83.95
PSYCHEMEDICS	58.33	0.00	3.58	3.11	63.54	56.04
PTC	75.00	0.70	8.18	6.53	8.29	24.16
PURE CYCLE	66.67	0.00	5.46	4.75	48.85	49.16
QCR HDG.	83.33	0.00	17.85	16.08	52.05	52.21
QORVO	66.67	0.32	19.03	16.51	15.58	29.24
QUALCOMM	83.33	0.69	14.47	11.36	11.03	30.62
QUANTUM	66.67	0.00	4.92	4.71	105.68	85.76
QUEST RESOURCE HOLDING	0.00	0.00	2.65	2.62	161.03	112.68
QUICKLOGIC	58.33	0.00	4.05	3.62	109.75	84.31
QUIDELORTHO	58.33	0.00	103.81	84.97	41.80	79.54
QURATE RETAIL SERIES A	75.00	0.29	1.59	0.93	17.38	38.90
RCM TECHS.	58.33	0.00	1.77	1.61	108.08	86.02
RADCOM	75.00	0.00	1.45	1.26	15.42	25.30
RADIUS RECYCLING A	83.33	0.00	9.01	8.66	49.04	52.66
RADNET	58.33	0.00	7.36	6.50	43.37	44.63
RADWARE	58.33	0.00	5.44	4.50	18.56	24.62
RAMBUS	58.33	0.01	1.71	1.42	9.85	18.38
RAVE RESTAURANT GROUP	50.00	0.00	1.08	0.98	142.48	97.15
RCI HOSPITALITY HDG.	66.67	0.00	7.59	6.52	48.11	53.50
READING INTL.'A'	58.33	0.00	9.47	8.80	233.22	127.61
RECON TECHNOLOGY A	75.00	0.00	50.13	45.45	204.48	115.91
RED ROBIN GMT.BURGERS	41.67	0.00	22.49	20.37	171.48	106.93
REGENCY CENTERS	0.00	0.00	16.22	13.61	27.23	42.89
REGENERON PHARMS.	50.00	0.00	135.44	113.45	20.17	33.70
REGIS	41.67	0.00	240.61	219.71	141.97	99.00
REPLIGEN	0.00	0.00	124.98	120.42	88.50	208.26
REPUBLIC BANCORP OF KEN. 'A'	58.33	0.00	18.27	16.26	49.85	50.17
RESEARCH FRONTIERS	41.67	0.00	0.97	0.78	25.91	29.39
RES.CONNECTN.	66.67	0.00	8.48	7.91	67.55	64.05
RETAIL OPPOR.INVS.	58.33	0.00	7.76	6.99	65.07	61.07
RF INDUSTRIES	33.33	0.00	4.03	3.71	78.28	70.11
RGC RES.	50.00	0.00	7.64	6.34	26.17	27.22
RIBBON COMMUNICATIONS	66.67	0.32	0.91	0.62	13.61	30.69
RICHARDSON ELECTRONICS	75.00	0.00	2.08	1.88	43.66	45.65

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
RIGEL PHARMS.	0.00	0.00	0.88	0.78	39.22	40.24
RIOT PLATFORMS	75.00	0.00	7.67	7.47	406.15	155.77
RIVERVIEW BANCORP	50.00	0.00	11.45	11.13	219.18	132.73
ROCKWELL MEDICAL	50.00	0.00	17.50	14.00	102.67	72.25
ROCKY BRANDS	58.33	0.00	11.68	11.02	48.21	49.91
ROCKY MNT.CHOCO.FAC.	33.33	0.00	6.81	6.14	167.21	106.31
ROPER TECHNOLOGIES	75.00	0.19	35.69	27.93	7.30	19.00
ROSS STORES	58.33	0.00	41.33	36.28	38.78	41.71
ROYAL GOLD	41.67	0.00	34.05	28.27	25.15	29.78
RUSH ENTERPRISES 'A'	66.67	0.00	4.22	3.91	20.71	31.54
RUSH ENTERPRISES 'B'	75.00	0.00	3.90	3.36	20.26	30.40
RYANAIR SPN.ADR 1:5	58.33	0.00	25.17	22.64	31.28	38.49
S & T BANCORP	58.33	0.00	23.43	20.72	93.51	77.03
SAFETY IN.GP.	58.33	0.00	32.81	27.17	36.66	38.20
SAGA COMMS.'A'	41.67	0.00	12.21	9.80	44.02	42.63
SAIA	75.00	0.51	23.09	16.84	12.80	33.50
SANARA MEDTECH	75.00	0.28	8.91	6.60	29.35	53.49
SANDY SPRING BANCORP	75.00	0.00	23.72	22.39	87.67	76.70
SANGAMO	66.67	0.44	1.70	1.21	11.83	27.28
THERAPEUTICS						
SANMINA	33.33	0.00	13.46	12.28	44.87	46.69
SANOFI 2 ADR 2:1	50.00	0.00	9.71	7.57	15.43	20.66
SAPIENS INTL.	75.00	0.56	2.78	2.08	8.31	22.29
SAREPTA THERAPEUTICS	58.33	0.15	20.00	16.74	12.64	23.32
SAVARA	0.00	0.00	5.59	5.54	325.26	153.55
SB FINANCIAL GROUP	66.67	0.00	5.74	4.86	34.41	37.73
SBA COMMS.	58.33	0.00	40.71	31.39	10.78	18.14
SCANSOURCE	50.00	0.00	19.28	17.55	76.43	68.55
SCHOLASTIC	58.33	0.00	18.76	16.18	66.43	60.32
SEACOAST BKG.OF FLA.	66.67	0.00	12.05	10.82	52.10	52.01
SEAGATE TECHNOLOGY	50.00	0.00	16.27	13.92	27.84	32.00
HOLDINGS						
SEANERGY MARITIME	50.00	0.00	127.10	125.88	1.26E+03	262.00
HDG.						
SCTY.NAT.FINL.'A'	75.00	0.64	0.57	0.48	9.46	23.20
SEELOS THERAPEUTICS	50.00	0.00	2.57E+04	2.55E+04	1.22E+04	257.30
SEI INVESTMENTS	66.67	0.00	20.14	17.10	32.31	35.69
SELECTIVE IN.GP.	91.67	0.00	19.41	16.93	30.75	35.11
SELLAS LIFE SCIENCES	0.00	0.00	6.10	5.99	233.59	134.39
GROUP						
SEMTECH	75.00	0.40	7.50	5.61	12.06	26.18
SENECA FOODS 'A'	41.67	0.00	7.60	6.29	16.75	22.96
SENSTAR TECHNOLOGIES	41.67	0.00	0.63	0.55	24.59	30.89
SERVICE PROPERTIES	0.00	0.00	16.84	15.82	205.83	118.89
TRUST						

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
SEVEN HILLS REALTY TRUST	58.33	0.00	12.29	10.69	112.23	84.73
SHARPLINK GAMING	75.00	0.00	5.57	4.64	18.44	32.36
SHENANDOAH TELECOM.	50.00	0.00	5.59	4.38	14.94	18.35
SHOE CARNIVAL	66.67	0.00	6.31	5.80	42.23	44.92
SHORE BANCSHARES	50.00	0.00	7.83	7.10	66.00	61.84
SIEBERT FINANCIAL	0.00	0.00	3.01	2.39	36.76	63.83
SIERRA BANCORP	66.67	0.00	13.47	12.26	64.36	60.98
SIFY TECHNOLOGIES ADR 1:1	8.33	0.00	0.30	0.25	27.50	29.66
SIGA TECHNOLOGIES	75.00	0.00	1.35	1.23	19.51	32.94
SIGMATRON INTL.	50.00	0.00	1.34	1.22	37.53	41.11
SILICOM	91.67	0.00	4.40	3.33	10.04	20.68
SILICON LABS.	75.00	0.00	31.17	28.06	28.02	33.26
SILICON MOTION TECH.ADR 1:4	58.33	0.00	18.99	16.10	40.31	41.99
SIMMONS 1ST.NAT.'A'	75.00	0.00	12.41	11.17	63.04	59.86
SIMULATIONS PLUS	50.00	0.00	23.68	20.62	36.09	61.52
SINCLAIR A	66.67	0.00	15.86	14.64	74.47	67.53
SINGULARITY FUTURE TECHNOLOGY	50.00	0.00	8.00	6.62	34.84	37.79
SINOVAC BIOTECH	0.00	0.00	1.79	1.57	24.34	27.64
SIRIUS XM HOLDINGS	8.33	0.00	0.70	0.58	10.11	12.63
SKYWEST	50.00	0.00	39.46	36.45	115.44	89.54
SKYWORKS SOLUTIONS	58.33	0.20	18.65	15.40	13.41	25.99
SLEEP NUMBER	91.67	0.33	13.08	11.19	30.39	42.25
SLM	58.33	0.00	2.95	2.59	32.59	38.08
SMART POWERR	0.00	0.00	5.86	5.81	202.14	128.04
SMITH WESSON BRANDS	83.33	0.00	6.36	5.00	32.14	64.24
SMITH MICRO SOFTWARE	66.67	0.00	14.74	13.28	35.02	57.62
SMITH MIDLAND	66.67	0.47	0.89	0.78	13.29	26.52
SOCKET MOBILE	0.00	0.00	0.83	0.77	56.89	54.92
SOHU COM ADR 1:1	41.67	0.43	3.97	3.45	29.00	49.20
SOLIGENIX	0.00	0.00	7.85	5.79	17.33	25.12
SOLUNA HOLDINGS	83.33	0.00	30.62	23.79	75.33	157.47
SONNET BIOTHERAPEUTICS HOLDINGS	50.00	0.00	9.14E+03	8.72E+03	840.63	187.01
SONOMA PHARMACEUTICALS	50.00	0.00	11.76	11.60	178.40	262.00
SONO TEK	0.00	0.00	0.98	0.72	20.25	30.73
SOTHERLY HOTELS	50.00	0.00	5.84	5.45	254.40	132.41
SOUTHERN FIRST BCSH.	66.67	0.00	21.95	19.90	71.52	65.47
SOUTHERN MO.BANCORP	75.00	0.00	15.16	13.33	54.18	53.10
SOUTHSIDE BANCSHARES	66.67	0.00	14.62	12.59	45.01	45.96
SPAR GROUP	8.33	0.00	0.27	0.24	30.38	33.25

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
SPARTANNASH	58.33	0.00	4.14	3.33	17.95	32.49
SPOK HOLDINGS	0.00	0.00	4.32	4.26	42.29	45.34
SSR MINING	58.33	0.00	5.14	4.40	24.69	30.79
STAAR SURGICAL	0.00	0.00	43.62	40.45	77.88	168.47
STABILIS SOLUTIONS	50.00	0.00	2.11	1.95	91.89	75.84
STAGWELL A	75.00	0.00	2.17	2.12	117.43	92.67
STAR BULK CARRIERS	58.33	0.00	7.59	7.27	108.56	88.90
STAR EQUITY HOLDINGS	41.67	0.00	0.77	0.62	21.10	21.84
STARBUCKS	75.00	0.00	21.02	18.61	22.87	29.84
STEALTH GAS	0.00	0.00	0.70	0.65	36.68	39.16
STEEL CONNECT	58.33	0.00	9.32	8.26	141.27	97.40
STEEL DYNAMICS	66.67	0.00	11.47	10.89	39.08	43.16
STERICYCLE	66.67	0.00	11.86	10.47	17.61	26.19
STERLING	0.00	0.00	3.91	3.24	23.41	34.42
INFRASTRUCTURE						
STEVEN MADDEN	66.67	0.00	26.27	24.32	100.68	82.37
STOCK YARDS BANCORP	75.00	0.00	10.89	9.87	27.14	32.78
STONEX GROUP	66.67	0.39	4.27	3.28	10.78	24.14
STRATA SKIN SCIENCES	50.00	0.00	12.55	12.41	912.36	212.69
STRATASYS	58.33	0.00	9.54	8.36	54.77	53.18
STRATEGIC EDUCATION	58.33	0.00	66.93	49.33	49.06	43.10
STRATTEC SECURITY	66.67	0.22	8.55	7.58	37.52	48.83
STRATUS PROPERTIES	41.67	0.00	10.59	9.45	54.59	53.75
NEW						
STREAMLINE HEALTH	0.00	0.00	0.43	0.35	34.58	34.64
SLTN.						
SUMMIT STATE BANK	66.67	0.00	4.44	4.11	44.20	46.50
SUNOPTA (NAS)	66.67	0.00	3.44	2.61	39.07	77.44
SUNPOWER	0.00	0.00	7.17	5.01	49.65	65.12
SUNSHINE BIOPHARMA	0.00	0.00	287.42	209.85	73.22	164.61
SUPER MICRO	75.00	0.05	3.15	2.55	9.78	19.88
COMPUTER						
SUPERCOM (NAS)	41.67	0.00	5.11	3.61	29.97	54.31
SUPERIOR GROUP OF	75.00	0.50	4.46	4.11	30.90	49.58
COMPANIES						
SURMODICS	58.33	0.00	9.50	7.37	19.67	26.58
SYNAPTICS	75.00	0.61	6.28	5.03	7.10	21.11
SYNCHRONOSS	66.67	0.00	22.76	20.19	69.21	62.38
TECHNOLOGIES						
SYNOPSIS	0.00	0.00	159.74	155.40	82.98	186.22
SYPRIS SOLUTIONS	0.00	0.00	0.28	0.24	24.06	31.79
TAT TECHNOLOGIES	66.67	0.00	1.32	1.16	28.60	32.45
T ROWE PRICE GROUP	83.33	0.00	15.26	12.71	9.94	21.06
TSR	58.33	0.21	1.18	0.80	14.26	33.30
TAITRON COMPONENTS	0.00	0.00	0.27	0.20	7.34	10.07
TAKE TWO INTACT.SFTW.	75.00	0.61	15.75	13.28	8.95	24.32

Company	Accuracy(%)	R²	RMSE	MAE	MAPE*(%)	SMAPE(%)
TANDY LEATHER FACTORY	25.00	0.00	3.16	2.81	85.99	73.43
TAOPING	58.33	0.00	41.43	39.88	144.13	105.91
TAYLOR DEVICES	66.67	0.00	1.82	1.57	15.74	17.17
TECHPRECISION	0.00	0.00	2.32	2.23	40.20	66.52
TECHTARGET	66.67	0.35	9.60	6.79	16.74	40.82
TELESAT B VARIABLE VOTING A	58.33	0.00	10.10	9.07	49.44	49.86
TENAX THERAPEUTICS	58.33	0.00	999.00	895.95	46.14	82.73
TERADYNE (XSC)	75.00	0.62	11.17	8.41	10.16	27.93
TERAWULF	66.67	0.00	1.74	1.53	48.18	50.08
TERRITORIAL BANCORP	58.33	0.00	9.62	7.95	35.42	36.00
TETRA TECH	0.00	0.00	65.71	63.93	69.59	140.35
TEXAS CAPITAL BANCSHARES	66.67	0.00	28.33	25.85	79.36	69.54
TEXAS INSTRUMENTS	75.00	0.31	14.62	12.36	9.52	22.43
TEXAS ROADHOUSE	83.33	0.46	8.43	6.74	12.96	27.49
TFS FINANCIAL	75.00	0.00	5.93	5.18	33.38	36.00
TG THERAPEUTICS BANCORP	66.67	0.00	12.38	9.21	36.06	66.55
COOPER COS.	91.67	0.00	5.93	5.52	65.02	60.60
DIXIE GP.'A'	58.33	0.00	17.14	14.41	18.27	23.95
ENSIGN GROUP	8.33	0.00	1.04	0.89	74.07	155.91
ODP	0.00	0.00	38.49	36.62	70.94	145.14
SHYFT GROUP	66.67	0.00	9.91	9.12	41.64	44.51
THE9 AMERICAN DEPOSITORY SHARES 1:300	75.00	0.27	3.65	3.22	19.80	32.58
THERAPEUTICSMD	66.67	0.00	45.48	37.22	100.68	68.72
THERATECHNOLOGIES (NAS)	41.67	0.00	63.82	57.44	86.90	73.96
THERMOGENESIS HOLDINGS	0.00	0.00	3.06	2.73	32.79	35.07
TIMBERLAND BANCORP	41.67	0.00	170.47	139.86	62.92	128.79
TIPTREE	66.67	0.00	15.50	14.32	75.60	68.56
TITAN MACHINERY	58.33	0.00	3.55	3.11	57.52	55.24
TITAN PHARMS.DE	83.33	0.00	4.87	4.48	40.45	46.92
T-MOBILE US	66.67	0.00	151.68	132.96	129.73	87.16
TOWER	91.67	0.00	19.75	17.98	16.81	30.12
TOWNEBANK	66.67	0.00	6.55	5.75	28.86	33.82
TRACTOR SUPPLY	58.33	0.00	11.08	9.71	51.54	51.17
TRANSACT TECHNOLOGIES	75.00	0.37	19.10	16.26	13.04	29.78
TRANSCAT	58.33	0.00	6.68	6.10	119.89	88.66
TRAVELZOO	75.00	0.00	8.25	7.13	24.95	30.35
TRAVERE THERAPEUTICS	66.67	0.00	2.34	2.12	33.36	39.82
	75.00	0.00	4.05	3.46	17.74	31.83

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
TRICO BANCSHARES	58.33	0.00	25.86	24.35	82.16	73.49
TRIMAS	75.00	0.00	12.03	10.98	44.01	46.21
TRIMBLE	83.33	0.76	4.75	3.56	8.55	26.71
TRINITY BIOTECH ADR 1:20	75.00	0.00	7.93	6.45	55.63	103.89
TRIP COM GROUP ADR 1:1	58.33	0.00	9.18	8.37	29.15	33.82
TROOPS	0.00	0.00	0.48	0.46	48.61	50.19
TRUBRIDGE	66.67	0.00	3.49	2.93	11.58	21.10
TRUSTCO BANK NY	75.00	0.00	18.51	16.52	55.77	54.66
TRUSTMARK	66.67	0.00	13.82	12.12	50.33	50.30
TTEC HOLDINGS	83.33	0.56	7.95	5.45	9.79	29.69
TTM TECHNOLOGIES	75.00	0.00	5.79	5.37	45.13	47.08
TUCOWS 'A'	50.00	0.10	8.36	7.10	11.67	23.89
TWIN DISC	0.00	0.00	5.51	5.23	85.60	74.83
UFP TECHNOLOGIES	50.00	0.00	16.52	14.18	33.09	36.48
US ENERGY	58.33	0.00	1.90	1.59	31.19	52.61
US GLOBAL INVRS.	0.00	0.00	1.84	1.50	53.81	104.04
US.LIME & MINERALS	75.00	0.00	15.93	14.20	16.32	25.29
US GOLD	25.00	0.00	16.48	16.13	202.11	262.00
UFP INDUSTRIES	75.00	0.00	12.10	11.05	22.83	30.60
ULTA BEAUTY	66.67	0.00	68.84	58.83	26.65	31.60
ULTRA CLEAN HOLDINGS	58.33	0.04	4.87	4.02	19.73	31.37
ULTRALIFE	58.33	0.00	2.36	1.92	30.01	32.52
UMB FINANCIAL	75.00	0.00	19.64	17.23	32.43	37.18
UNION BANKSHARES	50.00	0.00	22.00	20.16	94.09	78.71
UNITED AIRLINES HOLDINGS	58.33	0.00	58.20	53.63	154.40	104.99
UNITED BANKSHARES	50.00	0.00	16.28	14.63	54.87	54.02
UNITED BANCORP OH.	50.00	0.00	6.42	6.06	52.12	52.84
UNITED COMMUNITY BANKS	66.67	0.00	11.17	9.83	50.01	49.87
UNITED FIRE GROUP	66.67	0.00	25.02	21.45	87.50	72.65
UNITED GUARDIAN	0.00	0.00	2.67	2.44	16.69	19.89
UNITED SECURITY BCSH.	0.00	0.00	3.18	2.91	45.54	46.62
UNITED THERAPEUTICS	75.00	0.00	19.16	15.95	13.68	25.18
UNITY BANCORP	50.00	0.00	10.22	9.19	65.77	61.52
UNIVERSAL DISPLAY	58.33	0.00	63.05	58.70	35.07	40.40
UNIVERSAL ELECTRONICS	0.00	0.00	5.90	5.04	11.51	14.96
UNIVERSAL LOGISTICS HDG.	66.67	0.52	2.34	1.94	12.29	26.39
UNIVERSAL STAINLESS & ALLOY PRODUCTS	50.00	0.00	8.59	7.67	110.03	85.23
UNIVEST FINANCIAL	0.00	0.00	4.28	3.90	22.52	27.06
UPBOUND GROUP	91.67	0.22	5.38	4.45	19.94	31.44
URBAN ONE 'A'	0.00	0.00	6.48	3.67	52.55	88.61

Company	Accuracy(%)	R ²	RMSE	MAE	MAPE*(%)	SMAPE(%)
URBAN ONE 'D' NON VTG.	0.00	0.00	0.81	0.70	68.41	59.39
URBAN OUTFITTERS	66.67	0.00	10.16	9.23	47.50	49.02
USIO	8.33	0.00	0.49	0.42	25.93	29.14
UTAH MEDICAL PRODUCTS	50.00	0.00	35.41	29.94	35.30	37.77
UTSTARCOM HOLDINGS	50.00	0.00	6.65	5.61	106.51	78.25
VSE	58.33	0.00	13.18	12.52	47.56	49.09
VALLEY NATIONAL	75.00	0.00	4.26	3.76	47.82	48.48
VALUE LINE	58.33	0.00	7.59	6.44	23.57	24.30
VANDA	58.33	0.00	5.78	5.19	46.97	47.59
PHARMACEUTICALS						
VAXART	8.33	0.00	10.48	9.94	604.23	144.08
VBI VACCINES (NAS)	58.33	0.00	46.37	35.87	40.33	77.07
VEECO INSTRUMENTS	75.00	0.00	2.64	2.15	17.66	27.22
VERICEL	50.00	0.52	3.30	2.78	18.37	32.93
VERINT SYSTEMS	75.00	0.00	7.89	6.94	28.79	34.05
VERISIGN	75.00	0.00	31.01	26.49	13.04	17.11
VERISK ANALYTICS CL.A	75.00	0.32	15.21	13.17	7.85	20.29
VERTEX ENERGY	8.33	0.00	0.76	0.71	121.65	91.62
VERTEX PHARMS.	58.33	0.00	45.94	36.81	14.90	18.70
VERU	66.67	0.00	1.44	1.05	30.54	34.71
VIASAT	50.00	0.00	44.58	40.20	107.75	85.24
VIATRIS	75.00	0.00	7.97	6.87	42.74	44.40
VIAVI SOLUTIONS	0.00	0.00	7.37	7.25	55.35	100.63
VICOR	75.00	0.00	17.36	15.01	20.70	40.21
VILLAGE SPRMKT.'A'	50.00	0.00	3.99	3.11	13.40	18.34
VIRACTA THERAPEUTICS	58.33	0.00	45.46	43.34	570.02	169.20
VIRCO MANUFACTURING	41.67	0.00	2.09	1.84	79.51	68.93
VIRTRA	8.33	0.00	0.74	0.56	19.43	21.81
VODAFONE GP.SPN.ADR	58.33	0.00	6.06	5.13	33.89	36.69
1:10						
VOXX INTERNATIONAL 'A'	58.33	0.11	3.06	2.04	26.37	49.74
WD-40	58.33	0.07	26.94	21.55	11.07	22.50
WAFD	75.00	0.00	17.60	15.46	63.69	59.64
WALGREENS BOOTS ALLIANCE	50.00	0.00	25.32	21.87	54.99	53.01
WASHINGTON TST.BANC.	66.67	0.00	26.44	24.17	69.09	64.22
WATERSTONE FINANCIAL	83.33	0.00	4.72	4.12	26.38	31.41
WENDY'S CLASS A	33.33	0.00	4.97	4.14	20.93	27.01
WERNER ENTERPRISES	58.33	0.00	6.21	4.86	12.30	18.99
WESBANCO	66.67	0.00	22.27	20.73	88.34	76.32
WEST BANCORPORATION	50.00	0.00	14.63	13.65	76.36	69.70
WESTAMERICA BANCORP.	58.33	0.00	25.66	22.05	38.94	40.64
WESTERN DIGITAL	83.33	0.00	26.75	23.61	56.95	53.81

Company	Accuracy(%)	R²	RMSE	MAE	MAPE*(%)	SMAPE(%)
WESTERN	50.00	0.00	4.28	3.75	64.39	60.11
NENG.BANCORP						
WESTPORT FUEL SYS. (NAS)	83.33	0.00	12.49	11.32	78.20	72.57
WEYCO GROUP	50.00	0.00	12.23	10.75	59.85	56.77
WHERE FOOD COMES FROM	75.00	0.21	1.62	1.33	16.41	24.12
WILLAMETTE VLY.VINEYARDS	58.33	0.00	1.13	0.98	15.90	21.04
WILLDAN GROUP	66.67	0.00	8.81	7.73	29.64	37.06
WILLIS LEASE FINANCE	66.67	0.00	41.98	37.90	165.56	107.01
WILLIS TOWERS WATSON	58.33	0.00	41.93	33.70	16.83	22.69
WINMARK	50.00	0.00	63.68	55.51	34.40	38.26
WINTRUST FINANCIAL	83.33	0.00	33.67	31.22	70.83	65.40
WOODWARD	66.67	0.00	50.98	46.54	59.70	57.53
WORLD ACCEPTANCE	58.33	0.00	21.57	18.60	25.98	36.39
WARNER BROS DISCOVERY SERIES A	58.33	0.00	13.49	12.16	53.79	53.51
WSFS FINANCIAL	83.33	0.00	18.56	17.00	57.85	56.65
WW INTERNATIONAL	66.67	0.00	18.45	16.84	72.11	65.00
WYNN RESORTS	66.67	0.00	73.82	67.56	83.40	72.41
XCEL ENERGY	50.00	0.00	9.75	7.65	11.48	18.25
XEROX HOLDINGS	50.00	0.00	22.00	19.77	105.60	84.32
XOMA	66.67	0.00	7.88	6.40	31.09	39.29
XTL BIOPHARMACEUTICALS	75.00	0.32	0.41	0.29	14.44	34.88
ADR 1:100						
YORK WATER	0.00	0.00	23.63	23.47	51.84	91.81
YUNHONG GREEN CTI	50.00	0.00	1.00	0.84	43.45	77.40
ZEBRA TECHNOLOGIES 'A'	75.00	0.65	31.42	24.76	9.65	25.71
ZIFF DAVIS	66.67	0.00	27.76	23.26	37.48	39.61
ZIONS BANCORP.	66.67	0.00	21.17	19.29	58.14	56.42
ZUMIEZ	58.33	0.00	12.90	12.05	47.11	49.10
ZW DATA ACTION TECHNOLOGIES	0.00	0.00	2.86	2.51	52.72	49.04
ZYNEX	0.00	0.00	13.20	12.56	88.34	207.68