# Alpha Go Everywhere: Machine Learning and International Stock Returns*

Darwin Choi
CUHK Business School

Wenxi Jiang
CUHK Business School

Chao Zhang
University of Oxford

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**Abstract**

We apply machine learning techniques and use stock characteristics to predict the cross-section of stock returns in 33 international markets. We conduct a stringent test to allay concerns about overfitting: the models are trained with past U.S. data and used to predict international stock returns. With fewer variables (based on past returns, size, volume, and accounting information) as inputs, we arrive at a conclusion similar to that in previous studies predicting U.S. stock returns with hundreds of stock characteristics and macroeconomic variables; complex methods outperform linear models in terms of both predicting returns and generating profits. We achieve even stronger results when the models are trained separately for each market, allowing for country-specific return-characteristic relationships. In most markets, we obtain out-of-sample $R^2$ and Sharpe ratios that are comparable to those in previous studies. Neural network models, which can handle complicated interactions among the predictors, produce the best results among various machine learning methods.

*Darwin Choi, Department of Finance, CUHK Business School, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong, dchoi@cuhk.edu.hk. Wenxi Jiang, Department of Finance, CUHK Business School, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong, wenxijiang@baf.cuhk.edu.hk. Chao Zhang, Department of Statistics, University of Oxford, U.K., chao.zhang@queens.ox.ac.uk. We thank Raymond Kan, Ravi Sastry, and seminar participants at Chinese University of Hong Kong, CUHK Derivatives and Quantitative Investing Conference, Peking University HSBC Business School, and University of Melbourne for helpful comments. Hulai Zhang provided excellent research assistance.

# 1 Introduction

Recent advances in the empirical asset pricing literature adopt machine learning techniques to understand the relationship between stock returns and firm-level and macroeconomic variables (see, for example, Avramov, Cheng, and Metzker, 2019; Chen, Pelger, and Zhu, 2019; Chinco, Clark-Joseph, and Ye, 2019; Gu, Kelly, and Xiu, 2019a, b; Feng, Polson, and Xu, 2018, 2019; Freyberger, Neuhierl, and Weber, 2018; Han et al., 2018). This is partly motivated by the long list of characteristics that seem to predict returns.[1] On the one hand, machine learning significantly improves the explanatory power over traditional linear models as it is designed to handle non-linear relationships and complicated interactions among many different predictors. On the other hand, complex algorithms require the specification of the model configuration (choosing the "hyperparameters") and the estimation of a large number of parameters, making them difficult to interpret economically and prone to overfitting. Although most studies use standard techniques to segregate a part of their observations, usually the most recent periods, as "out-of-sample," they conduct their analyses on only one market—the U.S. In this paper, we apply machine learning methods to predict stock returns in 34 markets around the world. To the extent that international markets are not perfectly correlated with the U.S., we run substantially more out-of-sample tests to provide evidence on the issue of overfitting.

To construct a dataset on a board set of markets and reasonably long sample periods, we cannot use the same number of variables that other U.S. studies are based on; data availability is lower internationally, especially for emerging markets. We trim down the list of explanatory variables to 12, which include the most accessible stock characteristics such as past returns, market capitalization, trading volume, past returns of the industry, and accounting information. Therefore, our tests not only verify the power of machine learning

[1] Harvey, Liu, and Zhu (2016) count that 316 factors have been proposed by 313 papers. McLean and Pontiff (2016) examine 97 characteristics in finance, accounting, and economics journals. Hou, Xue, and Zhang (2018) compile a list of 452 variables. These papers express concerns about false discoveries and replicability. Cochrane (2011) argues that researchers need methods other than cross-sectional regressions and portfolio sorts to address the "zoo of new factors" (see also Kozak, Nagel, and Santosh, 2019).

methods in identifying profitable opportunities and help alleviate concerns about overfitting, but also greatly reduce the number of predictors and improve economic interpretations.

In this paper, we first examine OLS models and their variants: OLS with a Huber loss function that makes it less sensitive to outliers; LASSO, which selects a subset of predictors; and RIDGE, which restricts the magnitude of the regression coefficients. Then we study two classes of non-linear models—decision trees (DTs) and neural network (NN) models. DTs are a non-parametric method for classifications and regressions. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. NN models aggregate and transform input signals into outputs, allowing for multiple layers of transformation and therefore complex interactions among the predictors. In each test, we set aside training and validation periods to train our models and select the hyperparameters, and then use the models to construct forecasts of one-month-ahead stock returns (denominated in U.S. dollars and in excess of the riskfree rate) in the testing period, which does not overlap the other two periods.

In the first set of analysis, we train and validate our models using only past U.S. data and run them on each international market, which is a stringent test to allay overfitting concerns. For example, in the context of an OLS model, the premium associated with each stock characteristic is estimated from past U.S. data, and these estimated characteristic premiums are used to construct the forecasts of international stock returns. Using 94 characteristics, 8 macroeconomic predictors, and 74 industry dummies (i.e., a total number of 920 ($= 94 \times (8+1)+74$) covariates), Gu, Kelly, and Xiu (GKX, 2019a) conclude that non-linear models outperform linear ones in predicting excess returns of U.S. stocks. Even with a smaller set of covariates, in most markets, including the U.S., we arrive at a similar conclusion. While machine learning is still a "black box" and difficult to interpret economically, cross-sectional returns in equity markets worldwide can be predicted reasonably well by widely available firm characteristics; these out-of-sample tests confirm the validity of the previously documented U.S. results. The evidence also suggests that return-characteristic relationships in equity markets worldwide seem not too distinctly different and the U.S. is a representative return structure, which can be learned by complex methods.[2]

Then we train and validate each model separately for each country, allowing more flexibility for the methods to pick up country-specific return-characteristic relationships. GKX show that the highest equal-weighted Sharpe ratio (2.45) and value-weighed Sharpe ratio (1.35) are achieved by a NN model. In most international markets, we find that machine learning methods are able to generate annualized Sharpe ratios that are close to or above 2 (in equal-weighted portfolios) or are above 1 (value-weighted). The outperformance of non-linear models is more prominent in countries where there are more observations, which yield more precise estimates of model parameters. Note that while we do not choose the list of 12 variables based on their potential importance (instead, we choose the ones that are most widely accessible), the majority of these characteristics are shown by GKX to be among the most influential in the cross-section of U.S. stocks. Among the 12 variables, we show that one-month return reversal, firm size, and dollar volume are the most important predictors in the U.S., while in other large international markets some other predictors can dominate.[3]

We illustrate how machine learning can better predict stock returns with an example. Liu, Stambaugh, and Yuan (2019) construct size and value factors in China that dominate factors replicating the U.S.-based Fama and French (1993) procedure. Specifically, they drop the smallest 30% of firms in constructing the size factor because a large portion of the market value of these firms likely reflects the potential shell value in reverse mergers that circumvent tight initial public offerings (IPO) constraints, instead of genuine size-related risk. While

[2]As Rapach, Strauss, and Zhou (2013) argue, the U.S. is a large trading partner for many countries and its stock market is the world's largest and is relevant for other economies. They show that lagged U.S. market returns can predict returns in other markets.

[3]All of our results are similar if we drop dollar volume and turnover from the list of predictors, which expands the sample period for some countries. However, if we further drop one-month return reversal and firm size, two of the strongest explanatory variables in many markets, Sharpe ratios will be greatly reduced. For example, in the U.S., the highest Sharpe ratios obtained by NN models become 0.93 (equal-weighted) and 0.55 (value-weighted), which are not too much higher than those achieved by OLS, 0.80 (equal-weighted) and 0.31 (value-weighted).

our methods, applied internationally, cannot inform us about the institutional frictions in each country, they are more capable of detecting such non-monotonic relationships between returns and characteristics in the data than linear models. Figure 8 shows the estimated relationships between excess returns and firm size in China from a linear OLS model and from a neural network model, respectively. The OLS model fits a straight line to capture the size premium, while the neural network model estimates a negative relationship between size and returns only when size is above a certain threshold (i.e., in situations where the shell value is less relevant). Consequently, we show that the equal-weighted Sharpe ratio in the long-short top- minus bottom-decile portfolio increases from 1.59 in the OLS model to 2.38 in the neural network model.

Our tests compare the out-of-sample $R^2$ (at individual stock and portfolio levels) and long-short portfolio Sharpe ratio of each model in each market. Non-linear models, in particular neural networks, perform well in predicting returns and generating profits. Our evidence confirms that machine learning is powerful and is less likely a result of overfitting, from the perspective of an U.S. investor who decides to invest in each of these markets separately. We also run an additional analysis using all 34 markets together, which corresponds to the case that an U.S. investor invests globally.[4] NN models (with 1 to 5 hidden layers) continue to yield the best predictions among all models.

The remainder of the paper is organized as follows. Section 2 describes the models in this paper. Section 3 outlines the data, experimental design, and evaluation methods in detail. Section 4 presents the results. Section 5 concludes.

## 2 A Brief Introduction to Machine Learning

This section describes the models we use in the paper. Readers who are familiar with machine learning can skip this brief introduction and proceed to Section 3. Generally speaking,

[4]Short selling can be costly or prohibited in some international markets. We ignore any frictions associated with short selling.

machine learning may be divided into two categories, i.e., supervised versus unsupervised learning, depending on the availability of observations for outputs. For supervised learning, a widely accepted definition is that it is a machine learning task intending to "learn" a function that, based on example input-output pairs, best approximates their relationship. However, in unsupervised learning, the primary goal shifts to depict the quantitative relations between input variables due to the absence of outcomes. In this article, we devote supervised learning methods for forecasting stock returns. Generally, the works of supervised learning can be further divided into two groups: classification and regression, in terms of either categorical (such as gender) or continuous (such as a stock price) output variables, respectively.

From a simplified point of view, there are three indispensable components in the machine learning framework for developing models. First, given the input values, we can suppose $Y$ arose from a functional $f(X|\boldsymbol{\theta})$, alternatively stated, $Y = f(X|\boldsymbol{\theta}) + \epsilon$ where the random error $\epsilon$ has $E(\epsilon) = 0$ and is independent of $X$. In our case, we denote the actual and the predicted return of the $i$-th instrument in the $t$-th month as $r_{i,t}$ and $\hat{r}_{i,t}$ (i.e. $\hat{f}(x_{i,t-1})$), respectively. Furthermore, an objective (or loss) function $\mathcal{L}(Y, f(X|\boldsymbol{\theta}))$ is required for estimating model parameters, such as mean squared error (MSE), the most common one. In some scenarios, researchers also supplement the loss function with an additional roughness penalty $\phi(\boldsymbol{\theta})$ in order to suffice the stricter criterion on model complexity or smoothness while potentially sacrificing their partial accuracy. In other words, the ultimate objective function would be $\mathcal{L}(\boldsymbol{\theta}) = \underbrace{\mathcal{L}(Y, f(X|\boldsymbol{\theta}))}_{\text{Loss Function}} + \underbrace{\phi(\boldsymbol{\theta})}_{\text{Penalty}}$. The last component (the computational algorithm) requires more mathematical details, which is for efficiently solving its optimal problem $\min \mathcal{L}(Y, f(X|\boldsymbol{\theta}))$ to seek a useful approximation $\hat{f}(X)$, such as the stochastic gradient descent method for neural networks. In the following content, we emphasize more the construction methods of models rather than their corresponding optimization approaches.

## 2.1 Linear Models

Having seen the model structure, we now consider some linear methods: OLS-3, OLS-3 with Huber loss, OLS, OLS with Huber loss, LASSO, and RIDGE, in which OLS represents ordinary least squares, i.e. linear models with MSE loss, and '-3' means this model is merely fed with three classical predictors: size, momentum, and book to market. Following the basic framework, these models have the same construction way: $f(X|\boldsymbol{\theta}) = X\boldsymbol{\theta}$ but different objective functions, therefore subtle but significant properties. Consequently, each model has its specific situations where it can work best. Particularly, LASSO and RIDGE are able to reduce model complexity and prevent over-fitting that is an inevitable problem for simple linear models with highly correlated data. But RIDGE regression shrinks the coefficients while LASSO selects features. We also use elastic net model (ENET), which linearly combines the loss penalty terms of LASSO and RIDGE. Even though the linear model has been the mainstream in academia and industry for a long past period for the sake of simplicity, strong assumptions are imposed on its structure and might lead to underestimating highly complicated patterns.

| | Loss | Pernalty |
|---|---|---|
| OLS | MSE | None |
| OLS+H | Huber | None |
| LASSO | MSE | $\lambda * \|\boldsymbol{\theta}\|_1$ |
| RIDGE | MSE | $\lambda * \|\boldsymbol{\theta}\|_2$ |
| ENET | MSE | $\lambda_1 * \|\boldsymbol{\theta}\|_1 + \lambda_2 * \|\boldsymbol{\theta}\|_2$ |

Here, $\lambda, \lambda_1, \lambda_2 \geq 0$ determines the amount of penalty. Huber loss (its definition as following) restricts the influences of residuals ($v_{i,t} = r_{i,t} - \hat{r}_{i,t}$) lying beyond a certain scale $\xi$.

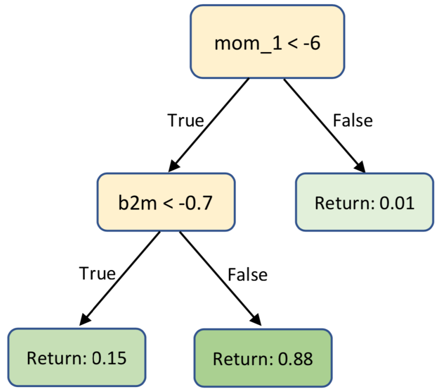
$$\text{Huber Loss} = \begin{cases} v_{i,t}^2, & \text{if } |v_{i,t}| \leq \xi \\ 2\xi|v_{i,t}| - \xi^2, & \text{if } |v_{i,t}| > \xi. \end{cases}$$

## 2.2 Tree Models and Ensemble Models

Tree-Based Models are popular and powerful machine learning methods with intuitive interpretability because of their usage of tree-like models for inferring decision rules from the data (in spite of categorical or continuous values). Analogous to an actual tree, a Tree-Based Model also has three essential constituents: nodes, branches, and leaves, which represent features, rules as well as outcomes, respectively. Figure 1 and the following formula illustrates how a Tree Model makes the decision and its corresponding prediction function. It first splits the space into two parts according to a threshold value of reversal momentum, which is chosen to achieve the best fit, then recursively partitions those sub-spaces into binary components until a certain stopping rule is applied, and finally estimates their responses by averaging $Y$ values in each region.

Ensemble learning is a big family of methods in the machine learning field and aims to combine the outputs of many "weak" or "base" classifiers (that are only slightly better than random guessing), such as a single tree, to produce a powerful "committee." Taken into account the complexity and huge amount of our data, we adopt two ensemble tree models in this paper, Random Forest (RF) and Gradient Boosting Regression Tree (GBRT), which advance the ability of tree models' robustness and increase their structural flexibility. Among them, Bagging and Boosting are the two most representative methods and their differences are clearly illustrated in Figure 2. Generally, the motivation of Bagging is to exploit independence and reduce the error rate by averaging prediction results from a number of base learners, while Boosting seeks a base model at each step that can best fit current residuals and then assigns different weights to previous models and examples. So Bagging algorithm can be conducted in parallel, whereas Boosting belongs to sequential ensemble methods.

**Figure 1.** Regression Tree




$$f = 0.15 \times \mathbf{1}_{\{mom\_1<-6\}}\mathbf{1}_{\{b2m<-0.7\}} + 0.88 \times \mathbf{1}_{\{mom\_1<-6\}}\mathbf{1}_{\{b2m\geq-0.7\}} + 0.01 \times \mathbf{1}_{\{mom\_1\geq-6\}}.$$

**Figure 2.** Ensemble Learning

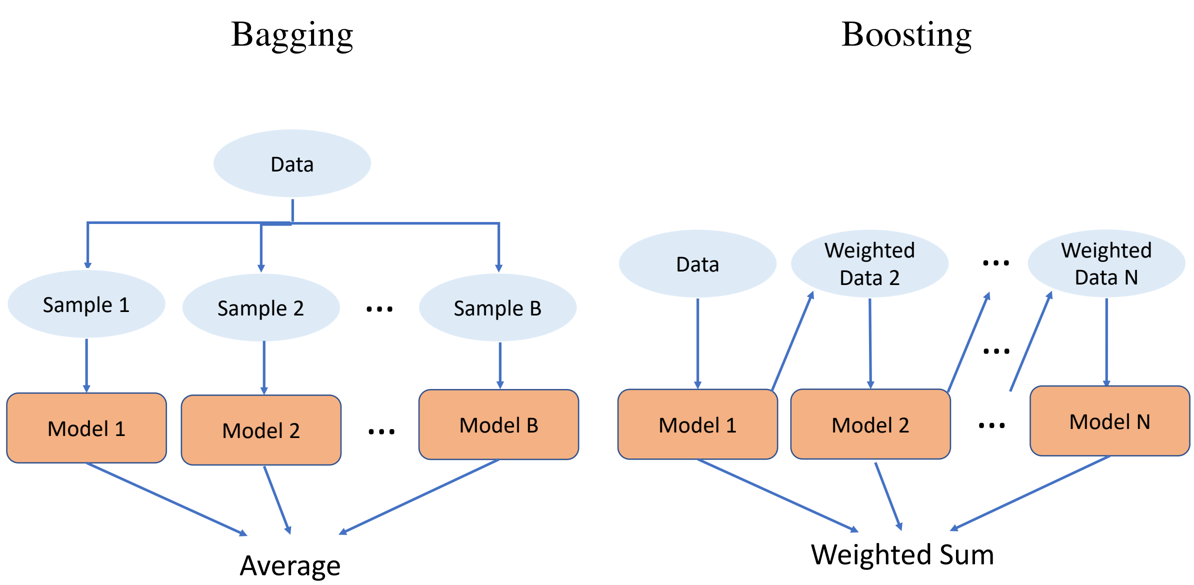
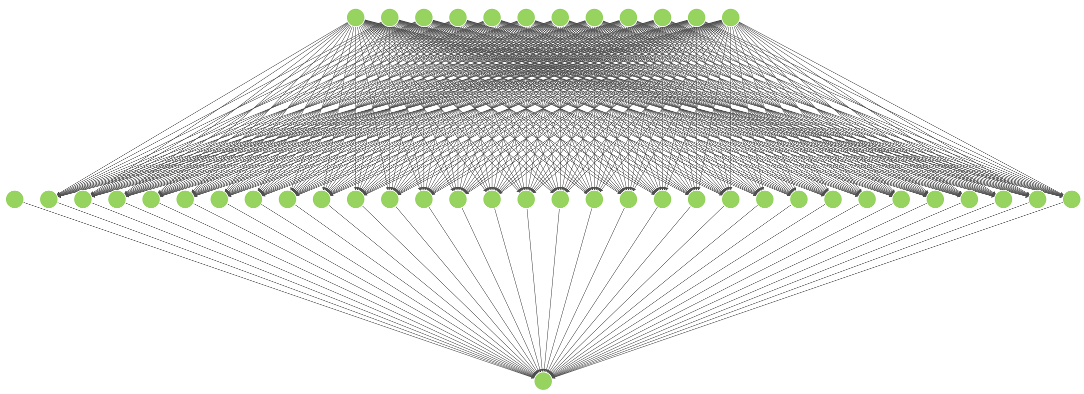


**Figure 3.** Neural Network




## 2.3 Neural Networks (NN)

In this section, we introduce a compelling deep learning method, Neural Network, having extensive applications in many fields. For better explanatory powers, we merely explore the most widely used "vanilla" neural net, i.e. the feed-forward neural network with single or multiple hidden layers rather than customized neural networks for diverse datasets, like ResNet for visual object recognition database. Figure 3 provides a schematic of a feed-forward neural network with a single hidden layer, where green circles denote the input features, hidden units, and output variables, from top to bottom, respectively. Arrows symbolize the forward phase where the activations are propagated from the one layer to the next.[5] In the example, there are 12 predictors in the input layer, 33 hidden units (including bias) and 1 dimentional target, so the total number of parameters to be estimated

[5]In fact, another vital phase for NN is called backward propagation, where the error between the actual and the predicted value is propagated backward from the output layer to the input layer in order to modify the weights. Although recently major breakthroughs of many machine learning techniques are made, there still exist some undesirable properties of NNs, such as concerns of overfitting and "black-box."

is $(1+12) \times 32+(32+1) = 449$ (13 parameters (including bias) for each hidden neuron plus 33 weights to link the activation functions to the output). The main point of a neural network is to combine the input signals in a linear way, then send to the next layer after feeding these aggregated features to a nonlinear activation function $\sigma$, such as sigmoid, and finally approximate the targets. It is worth noting that the neural network degrades to a linear model when $\sigma$ is the identity function. Following the recent machine learning literature, we use the rectified linear unit (ReLU) as the activation function:

$$ReLU(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{otherwise.} \end{cases}$$

More complicated NN models add one or more hidden layers between the input and output layers. We use up to five hidden layers in our estimation, denoted NN1–NN5. Hidden layers increase the model complexity and the number of parameters.

**Batch Normalization** is a critical technique for training deep neural networks by normalizing the inputs or activations to a layer for each mini-batch. According to relevant theoretical analysis, Batch normalization can significantly reduce the shift amount caused by the hidden units, denoted internal covariance shift, further to accelerate the training process (Ioffe and Szegedy, 2015). Specifically speaking, to enhance the stability of neural net, Batch Normalization first adjusts each layer's inputs by subtracting the batch mean and dividing by the batch standard deviation, and then adds trainable parameters to reconstruct the representation power of the network.

# 3 Methods

## 3.1 Data

We obtain data on stock returns, trading volume, market capitalization, and industry information from DataStream, while accounting ratios (book-to-market and sale-to-price) are available from Factset. For the U.S. and China, we supplement the data with CRSP and CSMAR, respectively, because of better coverage. We download data for as many countries as possible and require each market to have at least 100 stocks for at least 3 years. As a result, 34 markets, including the U.S., are in the final sample. Our data range from 2.2 million stock-month observations in the U.S. to around 7,400 in Russia. Table 1 provides the details.

Following the previous literature, we construct the 12 stock characteristics, listed in Table 2, as our baseline experiment. In the robustness tests, we drop turnover rate and dollar volume and only use 10 stock characteristics. This is because trading volume information is not available for some markets until recent years. By doing so, we can extend our sample period of major developed markets to early 1990s. Before we input all features in the model, we normalize them to zero mean and unit standard deviation by month and country.

## 3.2 Model Estimation

The model is set to predict stock's next month return in U.S. Dollars in excess of riskfree rate.[6] To train each model, we separate the sample of each market into 3 non-overlapping parts, while maintaining their chronological order. Training data, which consist of the first 50% of the periods, are used for estimating the model subject to a set of hyperparameter values. Validation data, accounting for around 30%, are deployed to construct forecasts and calculate objective functions based on the estimated model from the training samples.

[6]The riskfree rate is the one-month U.S. Treasury bill return, available from Kenneth French's website. The results are similar if we use returns in the local currency instead of U.S. Dollars.

During this process, we iteratively search for hyperparameters that optimize the objective functions. Finally, testing data are the remaining 20%; they are "out-of-sample" in order to provide objective assessments of the models' performance after determining hyperparameters and normal parameters for the models.

Due to limited computational resources, as noted by Gu, Kelly, and Xiu (GKX, 2019a), models get retrained annually instead of monthly. Also, when we predict the returns in the next calendar year, the training data expands by one year whereas validation samples are maintained with the same size. For example, as shown in Table 1, when predicting the cross-sectional stock returns in 1987 in the U.S., we set the training and validation samples as [1957, 1974] and [1975, 1986], respectively. When we predict the cross-sectional returns in 1988, the training and validation samples are [1957, 1975] and [1976, 1987], respectively.

## 3.3 Post-estimation Evaluation

We use Sharpe ratio and out-of-sample $R^2$ to evaluate the overall performance of machine learning models, and rely on relative importance analysis and sensitivity plot to interpret the estimated models.

**Sharpe Ratio.** We calculate an annualized Sharpe Ratio of long-short portfolio returns. We sort stocks into deciles based on the prediction of models, and then we long the decile with the highest predicted return and short the decile with the lowest. Within each decile, we consider both equal weight and value weight by stocks' market capitalization. We rebalance the portfolio every month. As a widely used measure of return predictability, Sharpe ratio can quantify the profitability when one exploits machine learning models for trading and easily compare with other portfolio or trading strategies, such as market portfolio or momentum.[7]

**Out-of-sample $R^2$.** To evaluate the predictability of each model, we report the out-of-sample $R^2$ ($R^2_{oos}$) based on Equation (1), which examines the model's forecast error and

[7] The Sharpe ratios are computed in the same manner as GKX. Kan, Wang, and Zheng (2019) note that high Sharpe ratios are rarely delivered by professional fund managers. They show that out-of-sample Sharpe ratios should be lower after taking into account the estimation risk of mean and co-variance of returns.

measures how the model's prediction fits the actual data. We first calculate the $R^2_{oos}$ for individual stocks. Since individual stock returns are known to be difficult to predict, $R^2_{oos}$ tends to be low and noisy. Second, we sort stocks into deciles based on model prediction, construct equal- and value-weighted portfolios, and report Portfolio $R^2_{oos}$.

$$R^2_{oos} = 1 - \frac{\sum_{(i,t)\in\text{Test}} (r_{i,t} - \hat{r}_{i,t})^2}{\sum_{(i,t)\in\text{Test}} r^2_{i,t}} \tag{1}$$

**Relative Importance of Predictors.** To identify significant predictors, we adopt the approach in Dimopoulos, Bourret, and Lek (1995) that the relative contribution of each input variable can be measured by computing the Sum of the Squares of the partial Derivatives (SSD). For calculate the contribution of $j$-th input variable, we have

$$\text{SSD}_j = \sum_k \left( \left. \frac{\partial \hat{f}}{\partial x_j} \right|_{x=x^k} \right)^2 \tag{2}$$

where $x^k$ means the $k$-th observation. Then, we normalize all variables' SSD to sum of one, i.e., $\frac{\text{SSD}_j}{\sum_i \text{SSD}_i}$.[8]

**Sensitivity Plots.** After the important variables have been identified, of particular interest is to understand the nature of the dependence of the approximation $\hat{f}(x)$ on their high-dimensional input variables. However, the graphical drawings of $\hat{f}(x)$ can hardly provide a comprehensive summary. Therefore, we adopt an alternative approach that is to focus on the partial relations (defined in Equation (3)) between two input variables and responses (which is the expected return here).

$$\hat{f}_{j|i}(x_j | x_i = q) = \hat{f}(x_j, x_i = q, x_k = \bar{x}_k, k \neq i, j) \tag{3}$$

[8] An alternative way to measure an input variable's importance is to calculate the decline in $R^2$ when one sets all values of the input variable to zero. This is the approach used in GKX and Kelly, Pruitt, and Su (2017). A negative VI value implies the increment of this input variable would lead to a decrease in output and vice-versa. The drawback of this measure is that it is hard to compare negative relative importance, especially across various markets.

where $q$ can be various quantile values for $x_i$. That is, we take account for a certain effect of $i$-th variable on $\hat{f}(x)$ while ignoring the effects of other variables (fixing them at mean values), and then emphasize the effect of $j$-th input variable on $\hat{f}(x)$. Even though such plot cannot offer an entire description of the approximation, it nonetheless can give shed some lights on the economic mechanism we are interested in. This tool can also help alleviate the "black box" criticism on machine learning methods

# 4 Results

## 4.1 Predicting U.S. stock returns with 12 predictors

We first focus on the U.S. stock market and train the various machine learning models with the 12 stock characteristics (listed in Table 2) to predict the cross section of monthly future return. Our main purpose is to compare the performance of our models with those in GKX, who use more than 900 features as inputs. Besides the reduced list of predictors as inputs, our method differs from GKX in (1) the choice of hyperparameter and (2) the way of variable standardization. We pick different hyperparameters in some models to better suit our experiments with much fewer inputs. For standardization, we normalize all variables by month to zero mean and unit standard deviation, while GKX rank-transform variables onto the range of $[-1, +1]$. Standardization is applied to achieve accelerated algorithm convergence rate, especially for NN models. For some machine learning models, the objective function may not work properly when inputs have various ranges, and standardization can effectively avoid this problem.

Table 3 reports the results. We consider three metrics for evaluating model performance: out-of-sample $R^2$ ($R^2_{oos}$, in percent), and Sharpe ratios (SR) of the long-short portfolio returns (value- and equal-weighted). The OLS-3+H model in GKX produces an $R^2$ of 0.16% and value-weighted (equal-weighted) SR of 0.61 (0.83), while in our experiment, $R^2$ is 0.25% and value-weighted (equal-weighted) SR is 0.44 (0.68). The minor difference is plausibly from the choice of hyperparameter in Huber loss and the way of standardization. If we use the same hyperparameters of GKX and standardization method, the results are very similar.

For the linear machine learning model, e.g., ENET, we obtain higher $R^2_{oos}$ but close SR compared to GKX's results, and the case for tree models, RF and GBRT, is similar. The best performing model is NN, consistent with the findings of GKX. In GKX, NN4 has the highest equal-weighted (value-weighted) Sharpe Ratio 2.45 (1.35). Our results are close: we obtain 2.44 (1.00) in NN4, respectively, and our equal-weighted (value-weighted) Sharpe ratio is the highest with NN2 (NN5) and reaches 2.69 (1.39). The lower SR of value-weighted returns than equal-weighted is consistent with the finding in Avramov, Cheng, and Metzker (2019) and GKX. This is not surprising as the literature has shown that larger stocks are subject to less limit to arbitrage and more difficult to forecast abnormal returns.

We also analyze the relative importance of the 12 characteristics in each model; see Figure 4. In NN models, the strongest predictor is stock size (*logsize*), followed by trading volume (*logdolvol*) and reversal (*mom*_1). This finding is also consistent with GKX. The relative importance of each predictor varies in different models.

Overall, our models with only 12 inputs can generate comparable predicability power that shown in GKX. This suggests that the additional features used in GKX provide little extra information. It is worth noting that, for both our paper and GKX, the good performance of machine learning models is achieved after heavily tuning hyperparameters. The result is sensitive to the choice of hyperparameters, which naturally raises the concern of overfitting. Next, we address this issue by running out of sample tests with international stock data.

## 4.2 Predicting international stock returns with the U.S.-trained models

We train and validate the machine learning models using the U.S. data for each year and then apply it to another stock market in the corresponding year. We apply the U.S.-trained model to each of the 33 markets individually. Panel A of Table 4 reports equal-and value-weighted Sharpe ratio for long-short portfolio returns. Here we list the markets based on the descending order of the number of observations. We highlight the cell with the highest Sharpe ratio in color. Starting with the equal-weighted case in the left, for 24 out of 33 markets, or 70%, one of the NN models generates the highest Sharpe ratio. This is more true for markets with more observations. For value-weighted SR, only in 3 markets NN model does not appear to be the most powerful one. In terms of economic magnitude, equal-weighted SR in 17 markets is above 1.5 and 25 markets above 1, and 14 markets have a value-weighted SR greater than one and 26 larger than 0.75. Compared with the market portfolio, the best machine learning model performs better in 31 (29) markets based on equal- (value-) weighted SR.

Panels B and C report the results of out-of-sample $R^2$ and portfolio $R^2$, and the patterns are quite similar. For the majority of the markets, machine learning models, particularly NNs, outperform traditional models. For example, in 19 out of 33, one the NN models achieves the highest $R^2_{oos}$, while OLS-3 stands out in nine markets. As pointed out by Fama and French 2002, OLS-3 is a useful performance benchmark for international markets.

Overall, this result does not only allay the concern of overfitting, but also suggest that machine learning models, especially NNs, capture the common component of return-characteristic relationships in equity markets worldwide. This finding is not surprising in the sense that the previous literature shows most phenomena in the U.S. market can extend to international markets (e.g., Asness, Moskowitz, and Pedersen (2013), Fama and French (2002)), suggesting that the U.S. is a representative return structure.

## 4.3 Predicting international stock with country-specific models

Now we let each market to train and validate its own model and see whether the return predictability can be further improved. The result in the previous subsection suggests that machine learning models can better capture the true return-characteristic relationship. If there is any country-specific component in the return-characteristic relationship due to some institutional friction or investor culture in the local market, by allowing to train the model by each market should presumably achieve stronger the return predictability.

We follow the same procedure that we use for the U.S. market to split the samples, as described in Section 3.2. Panel A of Table 5 summarizes the models' performances in the respect of equal- and value-weighted Sharpe ratios. The countries are sorted in a descending order on the number of available observations. 27 out of the 33 international markets plus the U.S., NNs (from 1 to 5 layers) produce higher equal-weighted SR than other models. In the remaining 7 markets, machine learning methods (LASSO, RIDGE, and Random Forest) dominate in 4 of them. For value-weighted SR, the results are generally aligned.

More importantly, the equal- or value-weighted SRs appear to be higher than those reported in Table 4 in approximately 70% of the markets in our sample. The number of markets with the equal-weighted SR portfolios above 2 (1.5) increases from 12 (18) to 21 (15). For value-weighted SR, 21 markets reach 1, while only 15 do with the U.S.-trained model. This indicates that it is useful by allowing the return-characteristic relationship to be country-specific. In Section 5, by analyzing the cases in China and Japan, we provide more insights on this point.

Panels B and C of Table 5 present similar (though slightly weaker) patterns in out-of-sample $R^2$, and equal- and value-weighted portfolio $R^2$, respectively. For $R^2_{oos}$ of individual stocks, one of the NNs obtains the highest in 25 markets, and the number increases to 28 if we consider both types of non-linear models, i.e., DT and NN. For equal-weighted (value-weighted) portfolio $R^2$, NNs outperform other models in 25 (22) markets.

Last but not least, we pool all stocks in our global sample together to train the machine learning models and predict expected returns. The results are reported in Table 6. The results again show that NN models perform the best. The global equal-weighted (value-weighted) long-short portfolio based on NNs yields a Sharpe ratio of 3.81 (1.66), while the Sharpe ratio of the market portfolio is 0.71 (0.51).

## 4.4 Robustness test: using 10 predictors

We drop two characteristics, i.e., turnover rate and trading volume, which are not available for some markets until the recent years. By doing so, we can extend the sample period for those countries back to early 1990s, particularly for several important developed markets, including Japan, Germany, and Australia, and the number of markets increases to 41. The enlarged sample size can further enhance the validity of our tests.

Similar to the previous analysis, we first train the models with the U.S. data and apply them directly to other markets. Results are reported in Table 7. First, for the U.S., the equal (value) weighted Sharpe remain at a high level and equals 2.61 (1.25) for NN models, even after dropping the two important characteristics. Second, for international markets, our previous findings still hold: NNs perform the best in most markets. In terms of SR (both for equal-weighted and value-weighted), there are around 70% markets obtaining the highest SR through NN. Also, the equal- and value-weighted Sharpe ratios are lower but still quite comparable to those in Table 4. The arithmetic average value of equal- and value-weighted Sharpe ratios in Table 7 are 1.53 and 0.83, respectively, while in Table 4 they are 1.74 and 1.01. The patterns based on $R^2_{oos}$ are generally aligned according to the results in Panels B and C,

In Table 8, we allow the models to be trained by each market. Out the of 41 markets in this sample, there are 13 (21) markets where the best machine learning model generates equal-weighted SR above 2 (1.5), increasing from 11 (20) in Table 7. For value-weighted SR, 20 markets reach 1, while only 10 do with the U.S.-trained model. In 39 markets, the best performing model is NN or DT, in terms of individual stock $R^2_{oos}$.

Based on the model estimations of Table 8, we further analyze the relative importance of the 10 characteristics for each market's best performing NN model; results are shown in Figure 5 for the top 15 markets based on the number of observations. There are some common similarities in the return-characteristic relationship across international equity markets. For example, size appears to be the strongest predictor for about two thirds of the markets.

Also, some market-specific features show up. For example, book-to-market ratio appears to be important for China and Germany, but not so for Hong Kong, Australia, and Italy.

# 5 Discussion

Machine learning techniques, especially neural network (NN) models, offer little economic insight and are often referred to as "black boxes." In this section we discuss two specific examples to illustrate the power of machine learning in the context of international financial markets. As mentioned in the Introduction, NN works well in China because it is able to capture non-linear relationships generated by institutional frictions. Liu, Stambaugh, and Yuan (2019) drop the smallest 30% of firms in constructing the size factor in China, pointing out that the value of these firms incorporates the possibility of reverse mergers (in which small public firms will be acquired by private firms to circumvent IPO constraints and go public). Our NN4 model (the best model in terms of Sharpe ratio and $R^2$ for China), as shown in Figure 8, fits a return-size relationship in 2014 that is consistent with Liu, Stambaugh, and Yuan's (2019) argument. The graph reveals two distinct patterns: for small firms, excess return increases with size, especially for the highest turnover (most liquid) group, possibility reflecting the higher valuation bid up by potential acquirers; for large firms, which are unlikely to be reverse merger targets, we see the usual negative return-size relationship. In contrast, the OLS model fits a downward sloping line to approximate the size premium for all firms, and is unable to take into account the IPO constraints at all.[9] (While we do not see an increase in the variable importance of size in Figure 6, Table 5 shows that NN4 is able to generate a higher equal-weighted Sharpe ratio than OLS, suggesting that the former can better predict the returns of small stocks.)

Although momentum ($mom\_6$) is generally a strong predictor in many countries and previous studies document the profitability of momentum strategies internationally (e.g.,

[9] We pick the year 2014 because IPO regulations are tightest in 2011–2015, according to a KPMG report. Other years in this period show similar patterns.

Rouwenhorst, 1998), Japan is a well-known exception. Asness, Moskowitz, and Pedersen (2013), Fama and French (2012), and Griffin, Ji, and Martin (2003) do not find significantly positive returns in buying past winners and selling past losers, while Chou, Wei, and Chung (2007) report a negative return. Chui, Titman, and Wei (2010) attribute the weak momentum profits in Japan to cultural differences. They argue that individualism is positively related to momentum profits in different countries, and Japanese are typically not individualistic. Figure 9 shows that our OLS estimate is consistent with the prior literature: return decreases weakly with $mom\_6$. However, our NN1 model (the best model for Japan) is able to fit a complex, non-linear relationship. Regardless of the real cause (which machine learning algorithms cannot identify), the NN1 model can make better use of $mom\_6$ in forming cross-sectional returns predictions. This is reflected in the increased variable importance of $mom\_6$ in Figure 7: from 0.03 in the OLS model to 0.1 in all NN models. Overall, despite the lack of economic interpretations, machine learning methods are more capable of learning complex relationships from the data. This is particularly important for international financial markets, where different institutional frictions are present in different countries.

# 6 Conclusion

In recent years, there has been an increasing interest in applying machine learning techniques to financial data. We construct a dataset of 34 international markets and document common machine learning models' performances in predicting the cross-section of stock returns. In the U.S. market, even with only 12 characteristics, the predictive power and profitability of complex machine learning models are comparable to those documented in previous studies using hundreds of variables. More importantly, training our models using U.S. data and applying them on international stocks—a stringent test to address potential overfitting issues—still concludes that machine learning methods outperform linear models. For most of the 34 markets, neural network (NN) models outperform other models, possibly because of the nonlinear and complex interactions among the predictors. We achieve even stronger Sharpe ratios and out-of-sample $R^2$ if we train the models seperately for each country, so that the models can pick up country-specific return-characteristic relationships. Our overall results help alleviate concerns about the overfitting problem of machine learning models by providing out-of-sample evidence and greatly reducing the number of predictors. Future research can provide more economic insights.

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**Table 1. List of Countries/Regions**

This table lists the name of markets in our sample, along with the sample periods and the number of observations, in the case when 12 or 10 stock characteristics are used as model inputs.

| | **12 Variables** | | | | **10 Variables** | | | |
|---|---|---|---|---|---|---|---|---|
| Country | Train | Valid | Test | # Obs | Train | Valid | Test | # Obs |
| USA | [1957, 1974] | [1975, 1986] | [1987, 2017] | 2199969 | [1957, 1974] | [1975, 1986] | [1987, 2017] | 2201817 |
| China | [1999, 2004] | [2005, 2007] | [2008, 2017] | 375468 | [1999, 2004] | [2005, 2007] | [2008, 2017] | 375468 |
| Japan | [2008, 2010] | [2011, 2012] | [2013, 2017] | 357837 | [1988, 1996] | [1997, 2002] | [2003, 2017] | 896143 |
| India | [2007, 2010] | [2011, 2012] | [2013, 2017] | 256474 | [1994, 2000] | [2001, 2005] | [2006, 2017] | 308226 |
| Korea | [1998, 2003] | [2004, 2007] | [2008, 2017] | 229795 | [1994, 2000] | [2001, 2005] | [2006, 2017] | 242790 |
| Hong_Kong | [1997, 2003] | [2004, 2007] | [2008, 2017] | 193475 | [1993, 2000] | [2001, 2005] | [2006, 2017] | 205168 |
| France | [1996, 2002] | [2003, 2006] | [2007, 2017] | 116473 | [1988, 1996] | [1997, 2002] | [2003, 2017] | 171902 |
| Taiwan | [2007, 2010] | [2011, 2012] | [2013, 2017] | 95494 | [1996, 2002] | [2003, 2006] | [2007, 2017] | 150183 |
| Australia | [2008, 2010] | [2011, 2012] | [2013, 2017] | 78841 | [1989, 1997] | [1998, 2003] | [2004, 2017] | 159156 |
| United_Kingdom | [2005, 2008] | [2009, 2011] | [2012, 2017] | 73485 | [1989, 1997] | [1998, 2003] | [2004, 2017] | 123453 |
| Thailand | [1997, 2003] | [2004, 2007] | [2008, 2017] | 64724 | [1999, 2004] | [2005, 2007] | [2008, 2017] | 62963 |
| Singapore | [2007, 2010] | [2011, 2012] | [2013, 2017] | 53684 | [1995, 2001] | [2002, 2006] | [2007, 2017] | 85268 |
| South_Africa | [1996, 2002] | [2003, 2006] | [2007, 2017] | 50703 | [1994, 2000] | [2001, 2005] | [2006, 2017] | 53199 |
| Sweden | [2001, 2005] | [2006, 2009] | [2010, 2017] | 49887 | [1996, 2002] | [2003, 2006] | [2007, 2017] | 66300 |
| Poland | [2006, 2009] | [2010, 2011] | [2012, 2017] | 44316 | [2004, 2007] | [2008, 2010] | [2011, 2017] | 48544 |
| Turkey | [2001, 2005] | [2006, 2009] | [2010, 2017] | 43817 | [2000, 2005] | [2006, 2008] | [2009, 2017] | 46003 |
| Italy | [2001, 2005] | [2006, 2009] | [2010, 2017] | 40907 | [1988, 1996] | [1997, 2002] | [2003, 2017] | 66453 |
| Vietnam | [2010, 2012] | [2013, 2013] | [2014, 2017] | 39418 | [2009, 2011] | [2012, 2013] | [2014, 2017] | 40814 |
| Switzerland | [1998, 2003] | [2004, 2007] | [2008, 2017] | 39316 | [1993, 2000] | [2001, 2005] | [2006, 2017] | 52296 |
| Israel | [2006, 2009] | [2010, 2011] | [2012, 2017] | 38526 | [2004, 2007] | [2008, 2010] | [2011, 2017] | 41587 |
| Indonesia | [2001, 2005] | [2006, 2009] | [2010, 2017] | 31001 | [2000, 2005] | [2006, 2008] | [2009, 2017] | 43450 |
| Greece | [2003, 2007] | [2008, 2010] | [2011, 2017] | 30804 | [1997, 2003] | [2004, 2007] | [2008, 2017] | 44120 |
| Philippines | [2005, 2008] | [2009, 2011] | [2012, 2017] | 19939 | [2006, 2009] | [2010, 2011] | [2012, 2017] | 18940 |
| Denmark | [2004, 2007] | [2008, 2010] | [2011, 2017] | 19810 | [1993, 2000] | [2001, 2005] | [2006, 2017] | 36742 |
| Finland | [2001, 2005] | [2006, 2009] | [2010, 2017] | 19727 | [2000, 2005] | [2006, 2008] | [2009, 2017] | 22791 |
| Sri_Lanka | [2009, 2011] | [2012, 2013] | [2014, 2017] | 19458 | [2008, 2010] | [2011, 2012] | [2013, 2017] | 20415 |
| Norway | [2007, 2010] | [2011, 2012] | [2013, 2017] | 18488 | [1998, 2003] | [2004, 2007] | [2008, 2017] | 32875 |
| Saudi_Arabia | [2010, 2012] | [2013, 2013] | [2014, 2017] | 13157 | [2009, 2011] | [2012, 2013] | [2014, 2017] | 14371 |
| Jordan | [2009, 2011] | [2012, 2013] | [2014, 2017] | 12699 | [2008, 2010] | [2011, 2012] | [2013, 2017] | 13944 |
| Chile | [2006, 2009] | [2010, 2011] | [2012, 2017] | 12466 | [2006, 2009] | [2010, 2011] | [2012, 2017] | 12637 |
| Belgium | [2008, 2010] | [2011, 2012] | [2013, 2017] | 12073 | [2000, 2005] | [2006, 2008] | [2009, 2017] | 22412 |
| Kuwait | [2009, 2011] | [2012, 2013] | [2014, 2017] | 10865 | [2012, 2013] | [2014, 2014] | [2015, 2017] | 7553 |
| Spain | [2010, 2012] | [2013, 2013] | [2014, 2017] | 9446 | [1997, 2003] | [2004, 2007] | [2008, 2017] | 27264 |
| Russia | [2009, 2011] | [2012, 2013] | [2014, 2017] | 7411 | [2009, 2011] | [2012, 2013] | [2014, 2017] | 7449 |
| Germany | | | | | [1988, 1996] | [1997, 2002] | [2003, 2017] | 167993 |
| Malaysia | | | | | [1992, 1999] | [2000, 2004] | [2005, 2017] | 156505 |
| Canada | | | | | [1998, 2003] | [2004, 2007] | [2008, 2017] | 80466 |
| Netherlands | | | | | [1992, 1999] | [2000, 2004] | [2005, 2017] | 34182 |
| Pakistan | | | | | [2007, 2010] | [2011, 2012] | [2013, 2017] | 18267 |
| Egypt | | | | | [2009, 2011] | [2012, 2013] | [2014, 2017] | 11483 |
| Brazil | | | | | [2000, 2001] | [2002, 2002] | [2003, 2005] | 7636 |

**Table 2. List of Stock Characteristics**

| Acronym | |
|---|---|
| mom_1 | 1-month reversal |
| logsize | Log market capitalization |
| mom_12 | 12-month momentum |
| mom_6 | 6-month momentum |
| chmom_6 | Change in mom_6 |
| MAXRET | Maximum daily return |
| indmom_a_12 | Industry 12-month equal-weighted momentum |
| retvol | Return volatility (standard deviation) of daily return |
| logdolvol | Log Dollar trading volume |
| sp | Sales to price |
| turn | Share turnover |
| b2m | Book to market |

**Table 3. Performance of Machine Learning Portfolios: U.S. Market**

In the table, we report the performance of prediction-sorted portfolios over the testing period in the US. All stocks are sorted into deciles based on their predicted returns for the next month. We report monthly out-of-sample R-squared ($R^2_{oos}$), annualized Sharpe ratio of value-weighted long-short portfolio returns (VW SR), and Sharpe ratio of equal-weighted long-short portfolio returns (EV SR). The predictions are based on OLS using only size, book-to-market, and momentum (OLS-3), OLS-3 with Huber loss (OLS-3+H), OLS with all variables (Linear), LASSO, RIDGE, elastic net (ENET), random forest (RF), gradient boosted regression trees with Huber loss (GBRT+H), and neural networks with one to five layers (NN1–NN5). Rows labeled as "GKX" quote the results from Gu, Kelly, and Xu (2019a), while rows of CJZ report our own results using 12 stock characteristics. The model that generates the highest $R^2_{oos}$ or SR is highlighted in color.

| | | OLS-3 | OLS-3+H | LINEAR | LASSO | RIDGE | ENET | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $R^2_{oos}$ | GKX | | 0.16 | | | | 0.11 | 0.33 | 0.34 | 0.33 | 0.39 | 0.40 | 0.39 | 0.36 |
| | CJZ | 0.29 | 0.25 | 0.42 | 0.45 | 0.42 | 0.45 | 0.83 | 0.64 | 0.75 | 0.81 | 0.79 | 0.73 | 0.71 |
| EW SR | GKX | | 0.83 | | | | 1.33 | 1.48 | 1.73 | 2.13 | 2.33 | 2.36 | 2.45 | 2.15 |
| | CJZ | 0.81 | 0.68 | 1.55 | 1.44 | 1.55 | 1.53 | 2.29 | 2.20 | 2.56 | 2.69 | 2.60 | 2.44 | 2.59 |
| VW SR | GKX | | 0.61 | | | | 0.39 | 0.98 | 0.81 | 1.17 | 1.16 | 1.20 | 1.35 | 1.15 |
| | CJZ | 0.40 | 0.44 | 0.33 | 0.30 | 0.33 | 0.39 | 1.03 | 0.49 | 0.94 | 1.07 | 1.06 | 1.00 | 1.39 |

**Table 4. Performance of International Portfolios based on Predictions of US-estimated Machine Learning Models**

In the table, we report the performance of prediction-sorted portfolios over the testing period in international markets. All stocks are sorted into deciles based on their predicted returns for the next month. Predictions are based on machine learning models estimated with US stock market data in the same month of the 12 stock characteristics (listed in Table 2). We report the annualized Sharpe ratio of value- and equal-weighted long-short portfolio returns in Panel A, out-of-sample R-squared of individual stocks in Panel B, and out-of-sample R-squared of the ten sorted portfolios (value- and equal-weighted) in Panel C. Models include OLS using only size, book-to-market, and momentum (OLS-3), OLS with all variables (Linear), LASSO, RIDGE, random forest (RF), gradient boosted regression trees with Huber loss (GBRT+H), and neural networks with one to five layers (NN1–NN5). The model that generates the highest $R^2_{oos}$ or SR for each market is highlighted in color. Markets are sorted in a descending order on the number of observations. In Panel A, we also report the Sharpe ratio of the market portfolio.

Panel A: Equal- and value-weighted Sharpe ratio

| | Equal-Weighted | | | | | | | | | | | | Value-Weighted | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | Market | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | Market | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 |
| USA | 0.58 | 0.81 | 1.55 | 1.44 | 1.55 | 2.29 | 2.20 | 2.56 | 2.69 | 2.60 | 2.44 | 2.59 | 0.53 | 0.40 | 0.33 | 0.30 | 0.33 | 1.03 | 0.49 | 0.94 | 1.07 | 1.06 | 1.00 | 1.39 |
| China | 0.53 | 0.62 | 0.91 | 1.01 | 0.91 | 1.08 | 1.18 | 1.08 | 1.26 | 1.15 | 1.04 | 1.04 | 0.38 | 0.39 | 0.51 | 0.74 | 0.52 | 0.83 | 0.92 | 0.81 | 0.97 | 1.06 | 1.00 | 0.75 |
| Japan | 0.65 | 0.41 | 0.60 | 0.55 | 0.60 | 1.19 | 1.17 | 1.55 | 1.41 | 1.53 | 1.47 | 1.53 | 0.34 | 0.06 | 0.25 | 0.33 | 0.25 | 0.50 | 0.74 | 0.57 | 0.46 | 0.68 | 0.73 | 0.76 |
| India | 0.70 | 0.88 | 0.68 | 0.44 | 0.67 | 1.95 | 1.45 | 1.97 | 2.19 | 2.03 | 1.91 | 1.78 | 0.54 | 0.50 | -0.05 | -0.31 | -0.05 | 0.20 | 0.45 | 0.35 | 0.25 | 0.21 | 0.41 | 0.19 |
| Korea | 0.58 | 1.15 | 1.16 | 1.03 | 1.17 | 1.88 | 1.76 | 2.02 | 2.13 | 2.10 | 2.12 | 1.81 | 0.34 | 0.13 | 0.36 | 0.39 | 0.37 | 1.00 | 0.81 | 0.75 | 0.96 | 0.85 | 1.08 | 0.87 |
| Hong_Kong | 0.44 | 0.68 | 0.65 | 0.57 | 0.65 | 2.00 | 1.49 | 2.20 | 1.95 | 2.15 | 2.05 | 2.02 | 0.31 | 0.27 | 0.19 | 0.12 | 0.18 | 0.44 | 0.12 | 1.08 | 1.25 | 1.17 | 0.81 | 0.70 |
| France | 0.73 | 1.08 | 1.67 | 1.91 | 1.68 | 2.51 | 2.14 | 2.46 | 2.49 | 2.62 | 2.58 | 2.49 | 0.45 | 0.86 | 0.49 | 0.53 | 0.49 | 0.44 | 0.51 | 0.86 | 0.87 | 0.88 | 0.78 | 0.83 |
| Taiwan | 0.62 | 0.30 | -0.12 | -0.17 | -0.12 | 0.42 | 0.52 | 0.60 | 0.62 | 0.14 | 1.12 | 0.09 | 0.63 | -0.17 | -0.48 | -0.48 | -0.48 | -0.14 | 0.03 | 0.14 | 0.28 | -0.15 | 0.57 | -0.15 |
| Australia | 0.64 | 1.03 | 2.42 | 1.99 | 2.42 | 3.96 | 3.75 | 3.97 | 4.14 | 4.08 | 3.89 | 4.09 | 0.51 | 0.57 | 0.31 | -0.40 | 0.31 | 0.68 | 0.52 | 1.74 | 1.53 | 1.60 | 1.29 | 1.50 |
| United_Kingdom | 0.42 | 0.40 | 0.43 | 0.17 | 0.42 | 1.33 | 1.20 | 1.66 | 1.56 | 1.33 | 1.43 | 1.29 | 0.48 | 0.52 | 0.08 | -0.26 | 0.08 | 0.62 | 0.13 | 0.67 | 0.46 | 0.39 | 0.64 | 0.74 |
| Thailand | 0.74 | 0.73 | 0.36 | 0.09 | 0.37 | 0.96 | 0.63 | 1.26 | 1.33 | 1.04 | 1.25 | 1.24 | 0.38 | 0.51 | -0.22 | -0.51 | -0.22 | 0.18 | 0.08 | 0.48 | 0.44 | 0.29 | 0.42 | 0.56 |
| Singapore | 0.35 | 0.75 | 2.44 | 2.80 | 2.43 | 3.09 | 3.30 | 3.17 | 3.41 | 3.21 | 3.30 | 3.20 | 0.37 | 0.51 | 0.44 | 0.05 | 0.44 | 0.82 | 0.77 | 1.44 | 1.36 | 1.50 | 1.56 | 1.13 |
| South_Africa | 1.08 | 1.17 | 2.81 | 2.53 | 2.82 | 2.67 | 2.51 | 2.72 | 2.92 | 2.97 | 2.90 | 2.91 | 0.71 | 0.60 | 0.58 | 0.59 | 0.58 | 1.41 | 0.82 | 0.98 | 1.20 | 1.53 | 1.39 | 1.25 |
| Sweden | 0.54 | 0.69 | 1.12 | 1.12 | 1.08 | 1.71 | 1.49 | 1.70 | 1.68 | 1.55 | 1.57 | 1.53 | 0.37 | 0.55 | 0.09 | 0.32 | 0.07 | 0.97 | 0.70 | 0.79 | 0.79 | 0.96 | 0.55 | 0.89 |
| Poland | 0.29 | 0.88 | 0.63 | 0.60 | 0.63 | 1.67 | 1.47 | 2.10 | 1.89 | 1.84 | 1.82 | 1.88 | 0.33 | 0.33 | -0.16 | -0.13 | -0.16 | 0.79 | 0.57 | 0.79 | 0.72 | 0.80 | 0.89 | 0.80 |
| Turkey | 0.82 | 0.16 | 0.06 | -0.06 | 0.07 | 0.51 | 0.36 | 0.87 | 0.61 | 0.59 | 0.39 | 0.47 | 0.67 | -0.10 | -0.03 | -0.01 | -0.03 | 0.18 | 0.12 | 0.31 | 0.38 | 0.48 | 0.26 | 0.21 |
| Italy | 0.04 | 0.38 | 0.10 | 0.10 | 0.10 | 0.98 | 0.90 | 0.91 | 0.88 | 0.83 | 0.63 | 0.65 | 0.08 | 0.37 | 0.02 | 0.06 | 0.04 | 0.70 | 0.40 | 0.50 | 0.79 | 0.65 | 0.52 | 0.46 |
| Vietnam | 0.74 | 0.85 | 1.54 | 1.51 | 1.54 | 2.33 | 2.15 | 2.50 | 2.93 | 2.43 | 3.17 | 2.63 | 0.59 | 0.09 | 0.25 | -0.13 | 0.25 | 0.66 | 0.27 | 0.85 | 1.02 | 1.31 | 1.17 | 1.52 |
| Switzerland | 0.53 | 0.75 | 0.53 | 0.31 | 0.53 | 0.90 | 0.76 | 0.84 | 0.85 | 0.88 | 0.89 | 0.74 | 0.28 | 0.79 | 0.35 | 0.25 | 0.34 | 0.68 | 0.60 | 0.52 | 0.57 | 0.45 | 0.80 | 0.54 |
| Israel | 0.38 | 0.38 | 0.88 | 0.62 | 0.88 | 0.79 | 0.71 | 0.93 | 0.82 | 1.06 | 0.98 | 0.95 | 0.37 | 0.57 | 0.74 | 0.52 | 0.74 | 0.62 | 0.53 | 1.15 | 0.91 | 1.18 | 0.95 | 1.12 |
| Indonesia | 0.98 | 0.67 | 0.08 | -0.23 | 0.09 | 0.49 | 0.09 | 0.43 | 0.18 | 0.22 | 0.38 | 0.24 | 0.93 | 0.54 | 0.29 | 0.13 | 0.32 | 0.75 | 0.43 | 0.85 | 0.43 | 0.22 | 0.83 | 0.48 |
| Greece | 0.34 | 0.46 | 2.00 | 2.08 | 2.00 | 2.48 | 2.59 | 2.98 | 2.68 | 2.60 | 2.84 | 2.61 | -0.02 | -0.15 | 0.19 | 0.59 | 0.19 | 0.71 | 0.68 | 1.12 | 0.88 | 0.97 | 1.32 | 1.12 |
| Philippines | 1.12 | 0.75 | 1.20 | 1.26 | 1.20 | 1.64 | 1.39 | 1.48 | 1.55 | 1.48 | 1.55 | 1.61 | 0.88 | 0.07 | 0.41 | 0.30 | 0.40 | 0.57 | 0.46 | 1.02 | 0.83 | 0.89 | 0.93 | 1.19 |
| Denmark | 0.54 | 0.33 | 0.84 | 0.87 | 0.84 | 1.44 | 1.45 | 1.58 | 1.47 | 1.66 | 1.70 | 1.70 | 0.76 | 0.51 | 0.04 | 0.08 | 0.04 | 0.77 | 0.41 | 1.08 | 0.76 | 0.93 | 0.85 | 0.78 |
| Finland | 0.52 | 0.84 | 0.81 | 0.56 | 0.81 | 1.08 | 1.15 | 0.87 | 0.91 | 0.97 | 0.96 | 0.88 | 0.12 | 0.40 | 0.02 | 0.08 | 0.02 | 0.46 | 0.18 | 0.63 | 0.61 | 0.24 | 0.46 | 0.81 |
| Sri_Lanka | 0.96 | 0.27 | 1.28 | 2.14 | 1.29 | 2.16 | 2.29 | 1.87 | 2.27 | 1.82 | 2.07 | 2.11 | 1.04 | -0.14 | 0.54 | 0.70 | 0.54 | 1.46 | 1.43 | 0.94 | 1.57 | 1.64 | 1.51 | 1.72 |
| Norway | 0.05 | 0.41 | 0.37 | 0.28 | 0.38 | 0.96 | 0.72 | 1.07 | 1.20 | 1.30 | 1.28 | 1.00 | 0.25 | 0.32 | -0.13 | -0.09 | -0.12 | 0.54 | 0.50 | 0.89 | 0.46 | 0.79 | 0.86 | 0.67 |
| Saudi_Arabia | 0.26 | 0.25 | -0.05 | 0.26 | -0.07 | 1.20 | 0.72 | 0.62 | 0.79 | 0.81 | 0.67 | 0.50 | 0.36 | 0.06 | 0.08 | 0.24 | 0.06 | 0.70 | 0.46 | 0.54 | 0.62 | 0.62 | 0.39 | 0.27 |
| Jordan | 0.38 | 0.37 | -0.10 | -0.22 | -0.10 | 0.97 | 0.57 | 1.16 | 1.40 | 0.95 | 1.47 | 1.13 | -0.04 | -0.33 | -0.24 | 0.00 | -0.24 | 0.77 | 0.29 | 0.41 | 0.79 | 0.41 | 0.85 | 0.86 |
| Chile | 0.85 | 0.86 | 0.21 | -0.25 | 0.23 | 0.46 | 0.30 | 0.36 | 0.41 | 0.24 | 0.11 | 0.25 | 0.65 | 0.52 | 0.21 | -0.06 | 0.21 | 0.38 | 0.15 | 0.73 | 0.76 | 0.34 | 0.52 | 0.48 |
| Belgium | 0.59 | 0.46 | 0.07 | -0.07 | 0.07 | 0.67 | 0.75 | 0.81 | 0.55 | 0.76 | 0.71 | 0.61 | 0.41 | 0.54 | -0.29 | -0.50 | -0.29 | 0.13 | -0.12 | 0.55 | 0.27 | 0.28 | 0.53 | 0.16 |
| Kuwait | 0.29 | 0.50 | 0.70 | 0.74 | 0.71 | 1.15 | 1.19 | 1.55 | 1.78 | 1.46 | 1.87 | 1.58 | 0.21 | 0.41 | 0.37 | 0.07 | 0.37 | 0.73 | 0.93 | 1.25 | 1.28 | 0.99 | 1.18 | 1.07 |
| Spain | 0.33 | 0.48 | 0.24 | -0.32 | 0.25 | 0.43 | 0.36 | 0.65 | 0.52 | 0.41 | 0.59 | 0.11 | 0.37 | 0.44 | 0.29 | -0.15 | 0.30 | 0.47 | 0.75 | 0.74 | 0.90 | 0.45 | 0.66 | 0.12 |
| Russia | 1.22 | 0.28 | 0.77 | 0.74 | 0.76 | 0.73 | 0.79 | 0.70 | 0.84 | 0.46 | 0.75 | 0.84 | 0.90 | 0.23 | 0.26 | 0.38 | 0.26 | 0.66 | 0.57 | 0.57 | 0.53 | 0.73 | 0.80 | 1.11 |

Panel B: Individual stock $R^2_{oos}$

| Country | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| USA | 0.29 | 0.42 | 0.45 | 0.42 | 0.83 | 0.64 | 0.75 | 0.81 | 0.79 | 0.73 | 0.71 |
| China | 0.87 | 0.79 | 0.95 | 0.79 | -98.53 | -5.11 | -0.67 | -0.32 | -0.27 | 0.15 | 0.21 |
| Japan | 0.94 | 0.60 | 0.96 | 0.60 | 0.79 | 0.73 | 0.89 | 0.65 | 0.89 | 0.94 | 0.92 |
| India | 0.71 | 0.42 | 0.58 | 0.42 | 0.56 | 0.66 | 0.70 | 0.81 | 0.84 | 0.81 | 0.80 |
| Korea | 0.61 | 0.44 | 0.59 | 0.44 | 0.56 | 0.48 | 0.56 | 0.69 | 0.64 | 0.63 | 0.60 |
| Hong_Kong | 0.50 | 0.28 | 0.37 | 0.28 | 0.59 | 0.52 | 0.70 | 0.66 | 0.74 | 0.76 | 0.75 |
| France | 0.60 | 0.93 | 0.98 | 0.93 | 1.45 | 1.18 | 1.58 | 1.45 | 1.51 | 1.43 | 1.33 |
| Taiwan | 0.66 | -0.10 | 0.43 | -0.10 | -0.02 | 0.22 | 0.06 | 0.06 | 0.14 | 0.02 | 0.21 |
| Australia | 0.42 | 0.75 | 0.60 | 0.75 | 1.19 | 1.17 | 1.51 | 1.58 | 1.52 | 1.52 | 1.39 |
| United_Kingdom | 0.11 | -0.19 | 0.01 | -0.19 | -3.30 | -0.55 | -0.03 | -0.14 | -0.05 | 0.03 | 0.09 |
| Thailand | 0.83 | 0.20 | 0.50 | 0.20 | 0.75 | 0.61 | 1.02 | 1.05 | 0.99 | 1.05 | 0.84 |
| Singapore | 0.26 | 0.71 | 0.63 | 0.71 | 0.34 | 1.12 | 1.50 | 1.66 | 1.56 | 1.57 | 1.31 |
| South_Africa | 0.92 | 1.60 | 1.47 | 1.60 | 2.96 | 2.23 | 3.09 | 2.77 | 2.78 | 2.31 | 2.41 |
| Sweden | 0.47 | 0.48 | 0.60 | 0.48 | 1.04 | 1.02 | 1.19 | 1.13 | 1.32 | 1.06 | 1.17 |
| Poland | 0.12 | -0.05 | 0.06 | -0.05 | 0.56 | 0.59 | 0.84 | 0.91 | 0.85 | 0.73 | 0.70 |
| Turkey | 0.95 | 0.40 | 0.81 | 0.40 | 0.88 | 0.46 | 0.29 | 0.47 | 0.40 | 0.78 | 0.43 |
| Italy | -0.19 | -0.90 | -0.47 | -0.90 | -0.45 | -0.46 | -0.55 | -0.93 | -0.99 | -1.01 | -0.71 |
| Vietnam | 1.09 | 1.11 | 1.17 | 1.12 | 1.43 | 1.27 | 1.42 | 1.55 | 1.25 | 1.12 | 1.29 |
| Switzerland | 0.59 | -0.36 | 0.11 | -0.36 | -1.74 | -1.37 | -0.99 | -0.98 | -1.11 | -0.70 | -0.38 |
| Israel | 0.55 | 0.43 | 0.57 | 0.43 | -0.74 | 0.15 | 0.07 | 0.10 | 0.08 | 0.43 | 0.43 |
| Indonesia | 0.91 | 0.24 | 0.46 | 0.24 | -1.07 | 0.39 | 0.42 | 0.50 | 0.43 | 0.61 | 0.61 |
| Greece | 0.11 | 0.54 | 0.43 | 0.54 | 0.74 | 0.74 | 1.01 | 1.00 | 0.92 | 1.03 | 0.95 |
| Philippines | 1.03 | 1.12 | 1.17 | 1.12 | -73.34 | 0.63 | 1.19 | 1.57 | 1.54 | 1.45 | 1.59 |
| Denmark | 0.29 | 0.31 | 0.44 | 0.31 | 0.51 | 0.73 | 0.93 | 0.80 | 0.70 | 0.51 | 1.14 |
| Finland | 0.85 | 0.36 | 0.57 | 0.36 | 0.84 | 0.53 | 0.09 | -0.19 | 0.02 | 0.00 | 0.37 |
| Sri_Lanka | 1.06 | 1.30 | 1.43 | 1.30 | 1.44 | 1.62 | 1.55 | 1.79 | 1.58 | 1.70 | 1.59 |
| Norway | 0.07 | -0.22 | -0.11 | -0.22 | -0.04 | 0.23 | 0.15 | 0.10 | 0.28 | 0.36 | 0.31 |
| Saudi_Arabia | 0.08 | -1.42 | 0.05 | -1.41 | 0.20 | 0.03 | -0.24 | -0.35 | -0.21 | -0.42 | -0.34 |
| Jordan | -0.09 | -1.53 | -0.46 | -1.52 | 0.15 | -0.08 | 0.18 | -0.06 | -0.12 | -0.01 | 0.21 |
| Chile | 1.57 | 0.21 | 0.57 | 0.22 | -12.40 | -0.04 | -0.96 | -0.60 | -0.23 | 0.22 | 0.47 |
| Belgium | 0.59 | -0.12 | 0.37 | -0.12 | -5.25 | -0.10 | -0.04 | 0.13 | 0.25 | 0.37 | 0.66 |
| Kuwait | 0.16 | -0.13 | 0.23 | -0.13 | 0.26 | 0.14 | 0.40 | 0.58 | 0.27 | 0.48 | 0.55 |
| Spain | 0.20 | -0.38 | -0.04 | -0.38 | 0.05 | -0.16 | 0.02 | -0.21 | -0.23 | -0.41 | -0.25 |
| Russia | 1.32 | 1.42 | 1.49 | 1.42 | 1.49 | 1.52 | 1.24 | 1.61 | 1.41 | 1.99 | 1.64 |

Panel C: Portfolio $R^2_{oos}$

| | Equal-Weighted | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 |
| USA | 2.90 | 3.41 | 3.55 | 3.41 | 4.58 | 4.12 | 4.85 | 4.63 | 4.65 | 4.59 | 4.55 |
| China | 1.83 | 1.64 | 1.86 | 1.64 | -10.84 | -1.26 | 0.76 | 0.94 | 0.91 | 1.16 | 1.28 |
| Japan | 3.08 | 1.96 | 3.00 | 1.97 | 2.78 | 2.25 | 2.74 | 1.80 | 3.20 | 3.25 | 3.18 |
| India | 2.75 | 2.16 | 2.51 | 2.16 | 2.78 | 2.59 | 2.69 | 3.03 | 3.27 | 3.09 | 3.22 |
| Korea | 2.37 | 2.12 | 2.38 | 2.13 | 2.54 | 1.67 | 2.21 | 2.89 | 3.15 | 2.75 | 2.46 |
| Hong_Kong | 1.55 | 1.01 | 1.11 | 1.01 | 1.68 | 1.46 | 2.21 | 1.92 | 2.13 | 2.19 | 2.23 |
| France | 3.98 | 4.66 | 5.19 | 4.66 | 6.69 | 5.58 | 6.95 | 6.44 | 6.58 | 6.25 | 6.39 |
| Taiwan | 1.96 | -0.18 | 1.07 | -0.17 | 1.54 | 1.03 | 0.68 | 0.96 | 0.84 | 0.59 | 0.62 |
| Australia | 3.00 | 5.68 | 4.76 | 5.69 | 6.94 | 7.19 | 9.15 | 9.26 | 8.69 | 8.66 | 8.18 |
| United_Kingdom | 1.30 | -1.32 | 0.09 | -1.33 | -0.14 | 0.34 | 0.64 | -0.23 | 0.23 | 0.24 | 0.69 |
| Thailand | 2.51 | 1.40 | 1.76 | 1.40 | 2.30 | 1.61 | 3.09 | 3.22 | 2.80 | 2.90 | 2.60 |
| Singapore | 1.39 | 2.93 | 2.63 | 2.93 | 2.97 | 3.42 | 3.96 | 4.50 | 3.91 | 4.20 | 3.44 |
| South_Africa | 3.48 | 8.69 | 7.79 | 8.70 | 10.73 | 9.54 | 11.42 | 10.31 | 10.37 | 9.05 | 9.77 |
| Sweden | 2.40 | 2.22 | 2.68 | 2.23 | 3.76 | 3.40 | 4.01 | 3.44 | 4.33 | 2.97 | 3.73 |
| Poland | 1.10 | -0.58 | 0.14 | -0.58 | 1.43 | 1.23 | 1.88 | 1.94 | 1.84 | 1.65 | 1.79 |
| Turkey | 2.47 | 1.44 | 2.17 | 1.45 | 2.30 | 1.28 | 1.04 | 1.59 | 1.50 | 2.34 | 1.37 |
| Italy | -0.79 | -3.22 | -1.94 | -3.22 | -0.89 | -1.83 | -1.84 | -2.73 | -2.41 | -3.26 | -1.90 |
| Vietnam | 4.22 | 4.10 | 4.33 | 4.11 | 5.23 | 4.72 | 5.31 | 5.64 | 4.61 | 3.95 | 4.35 |
| Switzerland | 2.17 | -0.66 | 0.48 | -0.65 | -0.86 | -2.32 | -0.55 | -1.16 | -0.98 | -0.72 | 0.12 |
| Israel | 1.12 | 2.14 | 2.24 | 2.14 | 0.55 | 1.12 | 2.62 | 2.23 | 2.97 | 3.05 | 2.84 |
| Indonesia | 3.25 | 1.59 | 2.10 | 1.60 | 2.15 | 1.61 | 1.93 | 1.84 | 1.83 | 2.31 | 2.41 |
| Greece | 1.02 | 2.97 | 2.17 | 2.98 | 2.68 | 3.06 | 3.67 | 3.52 | 3.12 | 3.49 | 3.48 |
| Philippines | 4.50 | 4.38 | 4.56 | 4.38 | -24.88 | 4.71 | 4.82 | 5.37 | 5.08 | 4.70 | 5.66 |
| Denmark | 1.40 | 0.71 | 1.72 | 0.71 | 2.62 | 3.29 | 3.16 | 2.30 | 2.73 | 1.77 | 4.09 |
| Finland | 2.01 | 1.02 | 1.55 | 1.02 | 2.48 | 1.72 | 1.26 | 0.74 | 1.77 | 0.81 | 1.91 |
| Sri_Lanka | 3.51 | 3.93 | 4.51 | 3.93 | 4.79 | 4.59 | 4.08 | 5.59 | 3.96 | 4.61 | 4.36 |
| Norway | -0.19 | -2.01 | -1.22 | -2.00 | 1.02 | 0.42 | 1.06 | 0.72 | 1.38 | 1.26 | 0.74 |
| Saudi_Arabia | 0.31 | -2.57 | 0.07 | -2.58 | 0.52 | 0.01 | -0.31 | -0.44 | 0.41 | -0.58 | -0.47 |
| Jordan | -0.33 | -8.68 | -2.09 | -8.65 | 0.81 | -0.70 | 1.81 | 0.70 | -0.67 | 0.71 | 1.02 |
| Chile | 4.63 | 0.35 | 1.49 | 0.36 | -1.27 | 1.29 | -0.09 | 0.42 | 1.63 | 1.46 | 2.32 |
| Belgium | 2.21 | -1.18 | 0.77 | -1.19 | -1.66 | 0.93 | 1.18 | 0.65 | 1.86 | 1.78 | 1.74 |
| Kuwait | 0.51 | -0.19 | 0.73 | -0.17 | 0.58 | 0.37 | 1.73 | 1.98 | 1.62 | 1.42 | 1.47 |
| Spain | 0.62 | -2.22 | -0.69 | -2.25 | 0.00 | -0.76 | -0.60 | -1.66 | -1.17 | -1.58 | -1.17 |
| Russia | 3.94 | 3.75 | 3.77 | 3.76 | 4.21 | 3.88 | 3.23 | 4.12 | 3.59 | 5.11 | 4.60 |

| | Value-Weighted | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 |
| USA | 2.63 | 0.97 | 1.42 | 0.98 | 3.23 | 0.71 | 3.03 | 3.18 | 3.44 | 2.89 | 2.95 |
| China | 1.32 | 1.02 | 1.37 | 1.02 | 1.35 | 0.85 | 0.76 | 0.76 | 0.77 | 0.94 | 0.86 |
| Japan | 0.95 | -0.10 | 1.21 | -0.11 | 0.64 | 0.42 | 0.45 | -0.77 | 1.20 | 1.27 | 0.82 |
| India | 2.19 | 0.21 | 0.79 | 0.21 | 1.69 | 1.50 | 1.18 | 0.88 | 1.27 | 1.65 | 1.33 |
| Korea | 1.41 | 0.46 | 0.90 | 0.46 | 1.03 | -0.17 | 0.82 | 1.28 | 1.55 | 2.00 | 1.38 |
| Hong_Kong | 0.81 | -0.10 | 0.06 | -0.11 | 0.54 | -0.50 | 1.36 | 1.07 | 0.92 | 1.01 | 1.11 |
| France | 3.55 | 1.98 | 2.07 | 1.99 | 2.08 | 0.85 | 3.02 | 2.55 | 2.83 | 2.22 | 1.81 |
| Taiwan | 1.31 | -1.74 | -0.12 | -1.73 | 0.89 | 0.17 | 0.25 | 0.25 | 0.64 | 0.55 | 0.16 |
| Australia | 2.30 | -0.58 | 0.16 | -0.59 | 1.78 | 0.80 | 3.73 | 2.36 | 3.14 | 3.65 | 3.51 |
| United_Kingdom | 2.49 | -0.85 | -0.73 | -0.87 | 1.50 | 0.42 | 1.45 | 0.09 | 1.05 | 0.86 | 0.61 |
| Thailand | 1.63 | -0.30 | 0.13 | -0.31 | 1.10 | 0.04 | 1.45 | 1.44 | 1.18 | 1.45 | 1.08 |
| Singapore | 1.42 | -0.54 | 0.22 | -0.56 | 1.31 | 0.93 | 1.98 | 1.91 | 1.61 | 2.05 | 0.35 |
| South_Africa | 3.03 | 2.55 | 3.07 | 2.55 | 3.96 | 2.09 | 3.87 | 3.60 | 4.19 | 3.33 | 3.51 |
| Sweden | 2.67 | 0.58 | 1.24 | 0.57 | 2.18 | 2.19 | 1.49 | 1.48 | 2.45 | 1.05 | 1.36 |
| Poland | 0.88 | -2.28 | -0.66 | -2.29 | 0.81 | 0.10 | 0.61 | 0.48 | 0.96 | 1.14 | 0.47 |
| Turkey | 1.75 | 1.02 | 1.62 | 1.01 | 1.52 | 0.88 | 0.68 | 1.32 | 1.26 | 1.81 | 1.06 |
| Italy | 0.05 | -2.16 | -1.43 | -2.12 | -0.38 | -1.59 | -0.80 | -0.99 | -0.81 | -1.67 | -0.81 |
| Vietnam | 2.96 | -0.19 | 1.14 | -0.19 | 2.12 | 1.38 | 1.92 | 2.97 | 3.44 | 2.12 | 2.78 |
| Switzerland | 2.83 | 0.56 | 0.62 | 0.49 | 0.62 | -0.86 | 0.19 | 0.77 | 0.43 | 0.44 | -0.12 |
| Israel | 1.73 | 1.93 | 2.03 | 1.92 | 0.90 | 1.29 | 3.87 | 2.59 | 3.69 | 3.27 | 3.10 |
| Indonesia | 3.07 | 2.02 | 1.98 | 2.06 | 2.31 | 2.09 | 2.52 | 1.87 | 1.66 | 2.67 | 2.42 |
| Greece | -0.89 | -0.68 | 0.12 | -0.66 | 0.33 | -0.01 | 0.52 | 0.30 | 0.32 | 0.85 | 0.23 |
| Philippines | 2.67 | 2.03 | 2.29 | 2.03 | 2.41 | 2.38 | 3.09 | 3.42 | 3.31 | 3.16 | 4.51 |
| Denmark | 2.66 | 0.42 | 1.31 | 0.41 | 1.83 | 1.64 | 2.67 | 2.57 | 2.22 | 1.07 | 2.52 |
| Finland | 1.62 | -0.12 | 0.78 | -0.12 | 1.26 | -0.01 | 1.30 | 0.75 | 0.76 | 0.23 | 1.45 |
| Sri_Lanka | 3.10 | 2.66 | 4.07 | 2.65 | 4.38 | 4.15 | 2.77 | 4.96 | 3.85 | 4.19 | 3.82 |
| Norway | 0.95 | -2.27 | -0.30 | -2.29 | 0.69 | 0.55 | 1.74 | 0.75 | 1.19 | 1.32 | 0.62 |
| Saudi_Arabia | 0.60 | -2.88 | 0.39 | -2.81 | 0.76 | 0.00 | -0.30 | -0.33 | 0.53 | -1.50 | -0.08 |
| Jordan | -1.70 | -9.35 | -2.17 | -9.46 | -0.23 | -2.09 | -0.27 | -0.93 | -1.09 | 0.41 | 0.53 |
| Chile | 3.99 | 0.49 | 0.96 | 0.47 | 2.04 | 0.59 | 1.94 | 1.88 | 2.44 | 2.27 | 3.14 |
| Belgium | 2.73 | -2.90 | -1.26 | -2.91 | 0.39 | -0.76 | 0.94 | 0.48 | 0.89 | 0.53 | 0.02 |
| Kuwait | -0.46 | -2.04 | -0.45 | -2.02 | 0.20 | -0.22 | 1.75 | 2.21 | 1.30 | 1.30 | 1.59 |
| Spain | 1.55 | 0.13 | 0.89 | 0.07 | 1.58 | 1.92 | 1.00 | 2.08 | 1.45 | 1.28 | 0.46 |
| Russia | 2.76 | 2.13 | 2.94 | 2.12 | 3.32 | 2.81 | 2.53 | 3.64 | 4.18 | 4.76 | 4.36 |

**Table 5. Performance of International Portfolios based on Predictions of Country-Specific Machine Learning Models**

In the table, we report the performance of prediction-sorted portfolios over the testing period in international markets. All stocks are sorted into deciles based on their predicted returns for the next month. Predictions are based on machine learning models estimated with each market's own data of the 12 stock characteristics (listed in Table 2). We report the annualized Sharpe ratio of value- and equal-weighted long-short portfolio returns in Panel A, out-of-sample R-squared of individual stocks in Panel B, and out-of-sample R-squared of the ten sorted portfolios (value- and equal-weighted) in Panel C. Models include OLS using only size, book-to-market, and momentum (OLS-3), OLS with all variables (Linear), LASSO, RIDGE, random forest (RF), gradient boosted regression trees with Huber loss (GBRT+H), and neural networks with one to five layers (NN1–NN5). The model that generates the highest $R^2_{oos}$ or SR for each market is highlighted in color. Markets are sorted in a descending order on the number of observations. In Panel A, we also report the Sharpe ratio of the market portfolio.

Panel A: Equal- and value-weighted Sharpe ratio

| | Equal-Weighted | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | Market | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown |
| USA | 0.58 | 0.81 | 1.55 | 1.44 | 1.55 | 2.29 | 2.20 | 2.56 | 2.69 | 2.60 | 2.44 | 2.59 | = |
| China | 0.47 | 0.92 | 1.59 | 1.85 | 1.60 | 0.81 | 1.23 | 1.03 | 0.91 | 2.10 | 2.38 | 2.28 | + |
| Japan | 1.56 | 0.97 | 1.15 | 0.52 | 1.13 | -0.12 | 0.51 | 0.04 | 0.74 | 0.98 | 0.10 | 0.99 | - |
| India | 1.33 | 0.66 | 0.66 | 0.80 | 0.67 | 0.91 | 1.14 | 3.24 | 3.15 | 3.22 | 2.79 | 2.24 | + |
| Korea | 0.67 | 1.76 | 2.78 | 2.47 | 2.75 | 2.96 | 3.01 | 3.33 | 3.26 | 3.49 | 3.48 | 3.13 | + |
| Hong_Kong | 0.51 | 1.02 | 1.35 | 1.40 | 1.36 | 2.49 | 2.09 | 3.56 | 3.35 | 3.35 | 3.14 | 3.21 | + |
| France | 0.49 | 1.07 | 3.05 | 2.78 | 2.92 | 1.69 | 1.77 | 3.19 | 3.29 | 3.35 | 3.26 | 3.36 | + |
| Taiwan | 0.90 | -0.18 | 0.92 | 0.60 | 0.92 | 0.83 | -0.67 | 0.43 | 0.72 | 1.07 | 0.49 | 1.47 | + |
| Australia | 0.86 | 1.43 | 1.68 | 1.82 | 1.54 | 1.37 | 1.83 | 2.28 | 2.63 | 3.02 | 1.05 | 2.79 | - |
| United_Kingdom | 0.91 | -0.31 | 1.18 | 0.33 | 0.77 | 0.22 | 0.28 | 1.31 | 0.33 | 0.23 | 0.92 | 1.82 | + |
| Thailand | 0.97 | 1.11 | 1.40 | 1.00 | 1.43 | 2.08 | 1.77 | 2.30 | 2.27 | 2.33 | 2.39 | 2.04 | + |
| Singapore | 0.53 | 0.78 | 2.50 | 1.91 | 2.62 | 2.38 | 3.37 | 3.79 | 3.67 | 3.53 | 4.05 | 3.91 | + |
| South_Africa | 0.99 | 1.14 | 2.12 | 1.79 | 2.02 | 1.88 | 1.81 | 2.02 | 2.15 | 2.24 | 2.31 | 2.26 | - |
| Sweden | 0.92 | 1.29 | 1.29 | 1.02 | 1.27 | 2.26 | 1.26 | 2.22 | 1.75 | 2.11 | 1.75 | 1.10 | + |
| Poland | 0.49 | 0.50 | 0.86 | 0.80 | 0.91 | 1.17 | 0.55 | 1.55 | 1.34 | 1.45 | 1.40 | 0.76 | - |
| Turkey | 0.81 | -0.18 | 0.68 | 0.32 | 0.64 | 0.70 | 0.59 | 0.68 | -0.23 | 0.16 | 0.47 | 0.23 | - |
| Italy | 0.32 | 0.75 | 1.00 | 0.91 | 0.95 | 1.23 | 1.12 | 0.92 | 1.12 | 0.94 | 1.37 | 1.06 | + |
| Vietnam | 1.84 | 1.17 | 2.07 | 1.91 | 1.98 | 1.82 | 2.13 | 3.64 | 3.59 | 3.62 | 3.34 | 2.97 | + |
| Switzerland | 0.55 | 0.51 | 1.06 | 0.76 | 0.98 | 0.47 | 0.83 | 0.19 | 0.80 | 0.66 | 0.69 | 0.84 | + |
| Israel | 1.01 | 0.87 | 0.50 | 0.59 | 0.38 | -0.35 | -0.02 | 0.99 | 0.30 | 0.67 | 0.43 | 0.15 | - |
| Indonesia | 1.26 | 0.98 | 0.93 | 0.78 | 1.02 | 0.85 | 0.41 | 1.05 | 0.79 | 0.61 | 1.24 | 1.07 | + |
| Greece | 0.83 | 0.43 | 1.43 | 1.44 | 1.47 | 0.95 | 0.88 | 2.35 | 2.51 | 1.20 | 2.84 | 1.97 | - |
| Philippines | 1.21 | 0.66 | 1.40 | 1.31 | 1.59 | 1.14 | 1.16 | 1.70 | 2.10 | 1.20 | 1.84 | 1.73 | + |
| Denmark | 0.92 | 1.31 | 1.34 | 1.45 | 1.36 | 1.08 | 1.00 | 1.26 | 1.52 | 1.46 | 1.09 | 0.96 | - |
| Finland | 0.53 | 1.43 | 1.49 | 1.23 | 1.52 | 1.16 | 0.95 | 0.57 | 0.44 | 0.87 | 1.10 | 1.18 | + |
| Sri_Lanka | 0.60 | 0.06 | 2.54 | 2.98 | 2.45 | 2.17 | 1.56 | 2.13 | 1.91 | 2.28 | 2.65 | 2.34 | + |
| Norway | 0.65 | 1.36 | 1.46 | 1.04 | 1.61 | 1.23 | 1.15 | 0.48 | 0.93 | 1.25 | 1.34 | 1.75 | + |
| Saudi_Arabia | -0.10 | 0.16 | -0.03 | -0.09 | 0.23 | 0.61 | 0.29 | 0.36 | -0.13 | 0.86 | 0.12 | 0.39 | - |
| Jordan | 0.52 | 0.43 | 0.43 | 1.14 | 0.81 | 0.82 | 0.50 | 0.94 | 1.24 | 1.17 | 0.49 | 0.57 | - |
| Chile | 0.82 | 0.57 | 0.05 | 0.04 | -0.10 | 0.36 | 0.21 | -0.04 | 0.30 | -0.65 | -0.21 | 0.41 | - |
| Belgium | 1.45 | 0.23 | -0.06 | -0.06 | 0.00 | -0.19 | -0.05 | -0.12 | 0.62 | -0.39 | 1.15 | 0.02 | + |
| Kuwait | -0.13 | 0.40 | 1.03 | 0.63 | 1.21 | 1.08 | 0.93 | 1.60 | 1.06 | 1.92 | 1.82 | 0.39 | + |
| Spain | 0.51 | 0.86 | 0.97 | 0.35 | 0.83 | 0.81 | 0.77 | 0.96 | 1.92 | 0.56 | 0.83 | 0.45 | + |
| Russia | 1.89 | 0.66 | 0.41 | 0.14 | 0.53 | 0.43 | 0.08 | 0.39 | 0.42 | 0.51 | 0.90 | 0.69 | + |

| | Value-Weighted | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | Market | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown |
| USA | 0.53 | 0.40 | 0.33 | 0.30 | 0.33 | 1.03 | 0.49 | 0.94 | 1.07 | 1.06 | 1.00 | 1.39 | = |
| China | 0.19 | 0.82 | 1.11 | 1.54 | 1.11 | 0.49 | 0.05 | -0.03 | 0.47 | 1.02 | 1.21 | 1.04 | + |
| Japan | 1.11 | 0.79 | 0.42 | -0.11 | 0.47 | -0.19 | 0.21 | -0.43 | -0.42 | 0.18 | -0.06 | 0.08 | + |
| India | 1.04 | -0.08 | -0.15 | 0.10 | -0.12 | 0.54 | 0.49 | 1.05 | 1.66 | 1.55 | 1.45 | 1.02 | + |
| Korea | 0.31 | 0.60 | 1.16 | 1.11 | 1.16 | 1.55 | 0.91 | 1.50 | 1.20 | 1.97 | 1.86 | 1.34 | + |
| Hong_Kong | 0.40 | 0.24 | 0.33 | 0.72 | 0.35 | 0.23 | 0.35 | 1.58 | 1.28 | 1.10 | 1.41 | 1.71 | + |
| France | 0.35 | 0.61 | 0.63 | 0.70 | 0.60 | 0.11 | 0.41 | 0.77 | 1.00 | 0.93 | 0.79 | 0.88 | + |
| Taiwan | 0.60 | 0.14 | 0.55 | 0.25 | 0.56 | 0.49 | -0.52 | 0.79 | 0.82 | 0.36 | 0.03 | 1.11 | + |
| Australia | 0.94 | 0.51 | -0.22 | -0.14 | -0.23 | -0.08 | -0.03 | 0.23 | -0.20 | 0.58 | 0.47 | 0.41 | - |
| United_Kingdom | 0.89 | -0.62 | 0.07 | 0.35 | 0.11 | 0.06 | -0.49 | -0.13 | -0.23 | -0.31 | 0.27 | 1.25 | + |
| Thailand | 0.68 | 0.98 | 0.96 | 1.01 | 0.95 | 0.86 | 0.80 | 0.97 | 1.06 | 1.00 | 1.20 | 0.91 | + |
| Singapore | 0.57 | -0.03 | 0.37 | -0.04 | 0.43 | 0.64 | 0.24 | 1.51 | 1.46 | 1.25 | 1.23 | 1.04 | - |
| South_Africa | 0.71 | 0.51 | 0.89 | 0.47 | 0.82 | 0.87 | 1.14 | 1.07 | 1.24 | 1.54 | 1.37 | 1.55 | + |
| Sweden | 0.94 | 0.59 | 0.02 | -0.02 | 0.06 | 0.42 | 0.08 | -0.19 | 0.55 | 1.02 | 0.57 | 0.63 | + |
| Poland | 0.69 | -0.34 | 0.71 | 0.96 | 0.69 | 0.27 | 0.41 | 0.73 | 0.54 | 0.48 | 1.08 | 0.68 | + |
| Turkey | 0.77 | 0.02 | 0.25 | 0.23 | 0.34 | 0.01 | 0.14 | 0.29 | 0.13 | 0.19 | -0.02 | -0.22 | - |
| Italy | 0.33 | 0.45 | 0.18 | 0.75 | 0.48 | 0.50 | 0.10 | 0.53 | 0.53 | 0.32 | 0.88 | 0.73 | + |
| Vietnam | 1.02 | 0.67 | 0.25 | 0.63 | 0.14 | 0.19 | 0.11 | 0.64 | 1.13 | 1.70 | 1.54 | 1.65 | + |
| Switzerland | 0.47 | 0.14 | 0.59 | 0.20 | 0.36 | 0.21 | 0.36 | 0.36 | 0.23 | 0.68 | 0.08 | 0.02 | - |
| Israel | 1.06 | 0.46 | -0.26 | 0.02 | -0.34 | -0.08 | -0.13 | -0.35 | 0.26 | 0.11 | 0.05 | 0.52 | - |
| Indonesia | 1.02 | 0.81 | 0.30 | -0.01 | 0.42 | 0.74 | 0.40 | 1.13 | 0.57 | 0.02 | 0.63 | 0.81 | + |
| Greece | -0.08 | 0.32 | 0.64 | 0.57 | 0.61 | 0.14 | -0.29 | 0.46 | 0.64 | 0.74 | 1.22 | 0.72 | - |
| Philippines | 0.97 | 0.55 | 1.15 | 0.51 | 1.00 | -0.04 | 0.29 | 0.51 | 0.30 | 0.42 | 0.41 | 0.54 | - |
| Denmark | 1.00 | 0.60 | 0.51 | 0.89 | 0.48 | 0.53 | 1.01 | 0.65 | 0.84 | 0.10 | 0.73 | 0.65 | - |
| Finland | 0.45 | 0.24 | 0.37 | 0.72 | 0.33 | 0.94 | 0.85 | 0.17 | 0.84 | -0.04 | -0.11 | 0.52 | + |
| Sri_Lanka | 0.53 | 0.10 | 1.47 | 2.12 | 1.59 | 0.66 | 0.07 | 1.17 | 1.52 | 1.92 | 1.87 | 1.87 | + |
| Norway | 0.80 | 0.26 | 0.77 | 0.86 | 0.95 | 0.59 | 0.49 | 0.14 | 0.45 | 1.33 | 0.88 | 0.98 | + |
| Saudi_Arabia | 0.05 | -0.12 | -0.41 | -1.22 | -0.42 | -0.53 | -0.12 | 0.73 | -0.88 | 0.65 | 0.41 | -0.05 | + |
| Jordan | -0.17 | 0.09 | 0.43 | 0.54 | 1.03 | 0.26 | -0.06 | 0.36 | 1.31 | 1.14 | 1.15 | 1.61 | + |
| Chile | 0.43 | 0.20 | 0.28 | -0.04 | 0.03 | -0.07 | 0.25 | 0.04 | 0.46 | -0.02 | -0.13 | 0.15 | - |
| Belgium | 0.87 | -0.27 | -0.52 | 0.64 | -0.13 | -0.26 | -0.53 | -0.97 | 0.98 | -0.64 | 0.35 | 0.88 | + |
| Kuwait | -0.07 | -0.04 | 0.14 | -0.28 | 0.25 | 0.35 | 0.38 | 0.42 | -0.28 | 0.98 | 0.93 | -0.11 | - |
| Spain | 0.48 | 0.57 | -0.14 | -0.07 | 0.52 | 1.05 | 0.67 | 0.71 | 1.05 | 0.85 | 0.21 | 0.86 | + |
| Russia | 0.91 | 0.24 | 0.32 | 0.46 | 0.52 | 0.16 | -0.31 | 0.76 | 0.23 | 0.30 | 0.94 | 0.80 | - |

Panel B: Individual stock $R^2_{oos}$

| Country | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| USA | 0.29 | 0.42 | 0.45 | 0.42 | 0.83 | 0.64 | 0.75 | 0.81 | 0.79 | 0.73 | 0.71 | = |
| China | 0.66 | 0.89 | 0.87 | 0.89 | 0.51 | -0.75 | 0.60 | 0.58 | 0.68 | 0.68 | 0.82 | - |
| Japan | 1.38 | 1.25 | 1.34 | 1.25 | 1.37 | 0.79 | 1.17 | 1.31 | 1.30 | 1.26 | 1.51 | + |
| India | 1.14 | 1.08 | 1.11 | 1.08 | 1.04 | 0.92 | 1.54 | 1.60 | 1.44 | 1.44 | 1.30 | + |
| Korea | 0.71 | 0.89 | 0.94 | 0.90 | 0.82 | 0.66 | 0.98 | 0.94 | 0.97 | 1.08 | 1.09 | + |
| Hong_Kong | 0.42 | 0.50 | 0.51 | 0.50 | 0.62 | 0.39 | 0.43 | 0.63 | 0.62 | 0.86 | 0.52 | + |
| France | 0.24 | 0.72 | 0.68 | 0.73 | -0.44 | -1.29 | 1.05 | 0.91 | 1.06 | 1.13 | 0.78 | - |
| Taiwan | 1.17 | 0.98 | 1.26 | 1.01 | 1.22 | -0.30 | 1.49 | 1.33 | 1.47 | 1.50 | 1.39 | + |
| Australia | 0.48 | 0.30 | 0.57 | 0.32 | 1.33 | 0.86 | 1.38 | 1.40 | 1.43 | 1.35 | 1.26 | - |
| United_Kingdom | -0.93 | -0.98 | -0.89 | -0.96 | -1.02 | -1.46 | -0.89 | -1.00 | -0.81 | -0.66 | -0.88 | - |
| Thailand | 1.05 | 1.00 | 1.00 | 1.05 | 1.16 | 0.87 | 1.36 | 1.23 | 1.42 | 1.41 | 1.28 | + |
| Singapore | -0.03 | 0.25 | 0.19 | 0.31 | 1.15 | 0.54 | 2.09 | 1.94 | 2.03 | 2.09 | 1.36 | + |
| South_Africa | 0.73 | 1.18 | 1.29 | 1.21 | 2.84 | 1.33 | 2.93 | 3.11 | 3.47 | 3.56 | 3.13 | + |
| Sweden | 0.12 | 0.15 | 0.17 | 0.18 | 0.49 | 0.52 | 0.36 | 0.36 | 0.43 | 0.36 | 0.10 | - |
| Poland | 0.16 | 0.30 | 0.38 | 0.33 | 0.50 | -0.67 | 0.64 | 0.59 | 0.60 | 0.35 | 0.35 | - |
| Turkey | 0.03 | 0.03 | 0.17 | 0.07 | 0.10 | -0.44 | 0.05 | 0.16 | 0.04 | 0.07 | 0.16 | - |
| Italy | -0.94 | -0.86 | -0.94 | -0.86 | -1.41 | -6.39 | -0.97 | -1.11 | -1.06 | -1.04 | -1.06 | - |
| Vietnam | 0.99 | 1.06 | 1.21 | 1.09 | 0.99 | 0.12 | 1.61 | 1.39 | 1.74 | 1.44 | 1.26 | + |
| Switzerland | 0.24 | 0.22 | 0.44 | 0.28 | 0.12 | -1.42 | 0.49 | 0.37 | 0.40 | 0.40 | 0.31 | - |
| Israel | 1.02 | 0.63 | 1.05 | 0.95 | 0.73 | -0.17 | 1.21 | 1.21 | 1.21 | 1.19 | 1.02 | + |
| Indonesia | 0.72 | 0.50 | 0.63 | 0.61 | 0.49 | -0.20 | 0.73 | 0.60 | 0.54 | 0.66 | 0.60 | - |
| Greece | -0.09 | 0.24 | 0.22 | 0.24 | 0.53 | 0.38 | 0.88 | 0.89 | 0.71 | 0.48 | -0.01 | - |
| Philippines | -0.14 | -0.22 | 0.08 | -0.01 | -0.63 | -6.68 | 0.66 | 0.49 | 0.56 | 0.34 | 0.08 | - |
| Denmark | -0.46 | -0.56 | -0.56 | -0.55 | -0.21 | -0.50 | -0.71 | -0.54 | -0.63 | -0.52 | -0.56 | - |
| Finland | 0.69 | 0.62 | 0.50 | 0.65 | 0.67 | 0.36 | 0.28 | 0.11 | 0.18 | 0.42 | 0.37 | - |
| Sri_Lanka | -3.57 | -3.36 | -2.82 | -3.12 | -3.87 | -5.01 | -3.21 | -2.01 | -3.32 | -3.33 | -3.51 | - |
| Norway | 0.57 | 0.56 | 0.51 | 0.54 | 0.31 | 0.02 | 0.31 | 0.38 | 0.43 | 0.40 | 0.26 | + |
| Saudi_Arabia | -1.17 | -1.65 | -1.15 | -1.44 | -1.24 | -1.84 | -0.42 | -0.89 | -0.66 | -0.94 | -1.00 | - |
| Jordan | -0.26 | -1.28 | -0.22 | -0.90 | -0.29 | -2.32 | -0.25 | -0.44 | -0.17 | -0.13 | -0.33 | - |
| Chile | 0.22 | -0.17 | 0.17 | -0.12 | 0.04 | -0.53 | -0.14 | 0.25 | -0.05 | 0.00 | -0.30 | - |
| Belgium | 0.86 | 0.00 | 0.61 | 0.46 | -1.06 | -6.36 | 0.55 | 0.24 | 0.89 | 0.68 | 0.56 | + |
| Kuwait | 0.63 | 0.60 | 0.45 | 0.77 | 0.44 | -0.82 | 0.62 | 0.56 | 0.77 | 0.62 | 0.67 | + |
| Spain | 0.19 | -0.07 | -0.09 | -0.04 | 0.03 | -3.11 | 0.02 | 0.02 | 0.02 | -0.08 | -0.17 | - |
| Russia | -0.11 | -1.45 | -0.05 | -0.80 | -0.61 | -1.70 | 0.02 | 0.17 | 0.27 | 0.06 | -0.04 | - |

## Panel C: Portfolio $R^2_{oos}$

| | Equal-Weighted | | | | | | | | | | | | Value-Weighted | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown |
| USA | 2.90 | 3.41 | 3.55 | 3.41 | 4.58 | 4.12 | 4.85 | 4.63 | 4.65 | 4.59 | 4.55 | = | 2.63 | 0.97 | 1.42 | 0.98 | 3.23 | 0.71 | 3.03 | 3.18 | 3.44 | 2.89 | 2.95 | = |
| China | 1.16 | 1.51 | 1.52 | 1.51 | 0.95 | -1.56 | 1.01 | 0.94 | 1.32 | 1.39 | 1.47 | - | 1.27 | 1.67 | 1.36 | 1.67 | -0.75 | -4.25 | -0.32 | 0.35 | 0.86 | 0.67 | 0.72 | + |
| Japan | 7.67 | 7.40 | 8.05 | 7.40 | 7.93 | 7.61 | 7.48 | 8.33 | 8.74 | 7.73 | 9.67 | + | 6.89 | 3.90 | 6.38 | 4.00 | 5.35 | 4.45 | 5.24 | 5.87 | 4.49 | 4.86 | 8.17 | + |
| India | 7.32 | 7.85 | 7.66 | 7.87 | 7.50 | 6.75 | 10.08 | 9.18 | 9.97 | 9.84 | 8.84 | + | 3.82 | 4.46 | 6.40 | 4.52 | 4.70 | 2.91 | 6.98 | 5.79 | 7.30 | 6.50 | 4.56 | + |
| Korea | 4.61 | 5.60 | 5.73 | 5.60 | 4.24 | 2.96 | 5.77 | 5.61 | 5.48 | 6.19 | 6.27 | + | 2.01 | 1.40 | 1.79 | 1.39 | 0.03 | -3.09 | 1.99 | 1.75 | 2.32 | 3.09 | 3.45 | + |
| Hong_Kong | 1.67 | 2.22 | 2.23 | 2.23 | 2.87 | 2.60 | 1.62 | 2.77 | 1.34 | 3.52 | 1.44 | + | 0.96 | 1.01 | 1.40 | 1.11 | -0.18 | -0.51 | 1.05 | 1.35 | 1.08 | 2.65 | 3.27 | + |
| France | 1.05 | 2.68 | 2.98 | 2.78 | 0.72 | -0.61 | 3.78 | 2.85 | 3.54 | 3.89 | 3.28 | - | 0.54 | -1.68 | -0.37 | -1.61 | -3.14 | -8.55 | 0.68 | 0.39 | 0.97 | 0.66 | 0.58 | - |
| Taiwan | 4.94 | 6.40 | 7.33 | 6.51 | 7.18 | -0.04 | 9.06 | 8.29 | 8.48 | 8.56 | 8.32 | + | 2.75 | 3.66 | 3.56 | 3.62 | 4.44 | -0.54 | 8.07 | 9.02 | 8.83 | 6.72 | 5.64 | + |
| Australia | 4.92 | 1.22 | 5.53 | 1.20 | 6.64 | 4.46 | 7.20 | 3.62 | 8.62 | 8.56 | 2.02 | - | 0.89 | -11.05 | -3.22 | -9.89 | 0.23 | -6.92 | -1.44 | -1.81 | 1.21 | 1.95 | 0.08 | - |
| United_Kingdom | -11.86 | -13.69 | -13.58 | -13.48 | -10.31 | -13.96 | -12.31 | -8.49 | -16.70 | -9.37 | -8.70 | - | -7.28 | -12.28 | -13.04 | -11.07 | -8.07 | -13.12 | -7.59 | -6.11 | -9.02 | -4.19 | -7.99 | - |
| Thailand | 4.48 | 4.31 | 4.28 | 4.56 | 4.32 | 4.06 | 5.25 | 5.04 | 5.89 | 5.76 | 5.23 | + | 4.03 | 3.42 | 4.56 | 4.12 | 2.08 | 1.19 | 4.52 | 3.49 | 3.15 | 3.63 | 3.50 | + |
| Singapore | 1.23 | 3.42 | 2.81 | 4.18 | 3.50 | 2.81 | 11.24 | 11.96 | 11.74 | 12.18 | 8.07 | + | -2.01 | -9.34 | -5.34 | -8.41 | -5.15 | -13.37 | 2.77 | 4.41 | 1.98 | 2.61 | 1.66 | + |
| South_Africa | 6.16 | 9.28 | 7.46 | 8.97 | 11.41 | 8.98 | 10.41 | 14.00 | 14.58 | 15.18 | 12.58 | + | 4.12 | 2.94 | 1.04 | 2.78 | 3.16 | 2.33 | 6.23 | 5.15 | 10.04 | 10.05 | 7.99 | + |
| Sweden | 1.09 | 0.90 | 1.30 | 1.17 | 3.21 | 2.75 | 0.94 | 1.11 | 0.42 | 1.13 | 0.16 | - | 2.94 | 0.23 | 0.39 | 0.57 | -0.29 | -2.48 | 1.30 | 0.65 | 3.47 | 2.00 | 1.52 | + |
| Poland | 0.96 | 1.09 | 3.46 | 1.85 | 1.07 | -9.21 | 4.60 | 5.32 | 5.77 | 2.99 | 3.25 | + | -1.37 | 3.14 | 3.46 | 3.09 | 0.94 | -4.77 | 3.25 | 3.39 | 4.26 | 3.35 | 3.47 | + |
| Turkey | -0.37 | -0.25 | 0.51 | -0.09 | 0.18 | -1.50 | -0.34 | 0.32 | -0.07 | 0.05 | -1.18 | - | -1.34 | -0.76 | 0.12 | -0.25 | -4.04 | -5.76 | -2.97 | -1.71 | -2.24 | -1.81 | -2.77 | - |
| Italy | -2.88 | -2.89 | -3.13 | -2.95 | -5.42 | -22.33 | -3.91 | -4.51 | -3.83 | -3.56 | -3.12 | - | -1.43 | -2.30 | -1.55 | -1.98 | -3.63 | -17.66 | -2.38 | -3.47 | -2.36 | -1.97 | -2.44 | - |
| Vietnam | 6.92 | 8.00 | 8.17 | 8.13 | 7.21 | 1.05 | 9.78 | 14.89 | 13.71 | 10.11 | 10.93 | + | 3.95 | 2.84 | 5.89 | 3.22 | 3.12 | -2.24 | 5.06 | 6.67 | 6.83 | 7.74 | 8.89 | + |
| Switzerland | 1.36 | 1.25 | 1.81 | 1.40 | 1.44 | -0.55 | 1.92 | 1.59 | 2.30 | 1.47 | 1.35 | + | 0.66 | -0.16 | 1.28 | -0.11 | 0.60 | 0.73 | 2.28 | 1.53 | 0.89 | 1.82 | 0.82 | - |
| Israel | 5.25 | 1.03 | 7.66 | 3.82 | 4.39 | 0.92 | 6.57 | 6.53 | 6.07 | 6.38 | 8.06 | + | 7.70 | -2.14 | 6.32 | 1.24 | 4.75 | 0.94 | 4.79 | 4.89 | 3.29 | 5.04 | 5.43 | + |
| Indonesia | 8.33 | 7.06 | 9.56 | 7.90 | 8.46 | 7.39 | 8.49 | 8.42 | 7.15 | 8.27 | 8.06 | + | 1.74 | 0.88 | 5.84 | 1.01 | 4.87 | 4.52 | 3.89 | 3.77 | 5.14 | 3.94 | 3.07 | + |
| Greece | -0.02 | 2.15 | 1.74 | 2.12 | 3.94 | 4.37 | 0.95 | 4.45 | 1.38 | 2.44 | -1.14 | + | -0.75 | -0.90 | -0.48 | -0.88 | -1.93 | -1.34 | -1.41 | -0.53 | -0.45 | -0.99 | -1.37 | - |
| Philippines | -0.44 | -1.71 | 0.20 | -0.69 | 0.48 | -7.56 | 1.57 | 0.83 | 1.60 | 5.18 | -1.25 | - | -1.92 | -0.66 | -5.75 | -2.03 | -14.68 | -47.77 | -4.43 | -6.10 | -5.82 | -4.49 | -1.46 | - |
| Denmark | -2.68 | -3.25 | -3.17 | -3.10 | -3.23 | -5.77 | -0.68 | -3.07 | -1.66 | -3.15 | -4.23 | - | -1.24 | -2.18 | -0.96 | -1.77 | -2.57 | -4.41 | 0.28 | -1.40 | -0.77 | -0.66 | -2.29 | - |
| Finland | 1.26 | 1.19 | 0.80 | 1.35 | -0.20 | -0.69 | -0.27 | -1.05 | -0.90 | 0.29 | 0.39 | - | 0.49 | 0.92 | 0.24 | 1.00 | 0.22 | 0.03 | 0.29 | -0.19 | 0.93 | 0.84 | 0.43 | - |
| Sri_Lanka | -14.90 | -12.95 | -11.16 | -12.44 | -12.72 | -18.44 | -8.54 | -9.83 | -9.24 | -13.81 | -18.43 | - | -18.32 | -22.32 | -15.09 | -18.66 | -25.58 | -39.07 | -15.48 | -24.59 | -23.59 | -21.53 | -28.50 | - |
| Norway | 3.26 | 4.03 | 3.68 | 4.05 | 3.75 | 3.88 | 5.76 | 3.67 | 1.92 | 5.93 | 1.92 | + | 1.15 | 1.78 | 2.07 | 1.92 | 1.58 | -0.22 | 1.22 | 1.30 | 2.82 | 2.55 | 0.99 | + |
| Saudi_Arabia | -2.16 | -3.01 | -2.20 | -2.63 | -2.30 | -3.50 | -1.32 | -2.41 | -1.26 | -1.97 | -1.86 | - | -1.78 | -3.89 | -2.31 | -3.33 | -2.85 | -3.12 | -2.07 | -2.69 | -4.82 | -1.52 | -5.06 | - |
| Jordan | -2.10 | -8.68 | -2.30 | -5.38 | -2.46 | -5.30 | -2.46 | 0.35 | -1.67 | -1.55 | -3.52 | - | -2.33 | -3.36 | -1.47 | -0.04 | -1.82 | -15.24 | -2.26 | -4.24 | 0.09 | -0.10 | -2.56 | - |
| Chile | -0.24 | -1.15 | -0.59 | -1.13 | -1.60 | -4.92 | -1.29 | -2.33 | -1.26 | -1.88 | -2.04 | - | -1.40 | -3.17 | -0.69 | -3.65 | -5.19 | -7.77 | -5.54 | -1.74 | -4.30 | -4.42 | -3.00 | - |
| Belgium | 3.60 | 0.17 | 4.93 | 2.20 | -4.51 | -16.82 | 0.95 | 0.42 | 4.11 | 2.45 | 2.04 | + | 3.00 | -1.91 | 3.30 | 0.45 | -3.93 | -22.57 | 0.68 | 0.07 | 2.68 | 1.17 | 0.10 | + |
| Kuwait | 0.98 | 1.20 | 0.96 | 1.68 | 0.79 | -0.99 | 0.93 | 2.45 | 1.63 | 1.29 | 1.84 | + | 0.66 | -0.99 | 1.11 | 0.13 | -1.05 | -4.19 | 1.64 | 0.95 | 2.74 | 1.07 | 3.10 | + |
| Spain | 0.41 | -0.66 | -0.65 | -0.37 | -0.50 | -2.87 | -0.18 | -0.10 | -0.21 | 0.33 | 0.29 | - | -0.45 | -4.72 | -0.90 | -2.81 | -1.20 | -3.36 | -0.96 | -1.49 | -0.72 | -0.66 | -1.73 | - |
| Russia | 0.78 | -3.80 | 1.49 | -2.06 | -0.65 | -2.18 | 1.03 | 0.92 | 2.20 | 1.23 | 0.28 | - | -5.76 | -3.17 | -5.74 | -2.98 | -3.19 | -3.72 | -3.72 | -1.48 | -7.47 | -2.50 | -0.98 | - |

**Table 6.** Performance of International Portfolios: Pooled All Stocks

In the table, we report the performance of prediction-sorted portfolios of international stocks. All stocks are pooled together and sorted into deciles based on their predicted returns for the next month. Predictions are based on the machine learning models estimated with the data of the 12 stock characteristics (listed in Table 2) of all stocks globally. We report the annualized Sharpe ratio of value- and equal-weighted long-short portfolio returns (VW and EW SR, respectively), out-of-sample R-squared of individual stocks, and out-of-sample R-squared of the ten sorted portfolios (value- and equal-weighted). Models include OLS using only size, book-to-market, and momentum (OLS-3), OLS with all variables (Linear), LASSO, RIDGE, random forest (RF), gradient boosted regression trees with Huber loss (GBRT+H), and neural networks with one to five layers (NN1–NN5). The model that generates the highest $R^2_{oos}$ or SR for each market is highlighted in color.

| | Market | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VW SR | 0.51 | 0.51 | 0.52 | 0.42 | 0.51 | 1.22 | 0.60 | 1.10 | 1.25 | 1.39 | 1.48 | 1.66 |
| EW SR | 0.71 | 1.19 | 2.06 | 1.97 | 2.05 | 3.18 | 3.03 | 3.48 | 3.81 | 3.57 | 3.61 | 3.42 |
| $R^2_{oos}$ | | 0.47 | 0.47 | 0.53 | 0.47 | -1.82 | 0.65 | 0.62 | 0.62 | 0.65 | 0.59 | 0.76 |
| VW Portfolio $R^2_{oos}$ | | 3.14 | 1.06 | 1.52 | 1.05 | 3.29 | 0.22 | 2.56 | 2.81 | 3.59 | 3.00 | 3.19 |
| EW Portfolio $R^2_{oos}$ | | 4.51 | 5.06 | 5.15 | 5.07 | 6.37 | 5.90 | 6.42 | 6.68 | 6.61 | 5.98 | 6.86 |

**Table 7. Performance of International Portfolios based on Predictions of US-estimated Models: Using 10 Predictors**

In the table, we report the performance of prediction-sorted portfolios over the testing period in international markets. All stocks are sorted into deciles based on their predicted returns for the next month. Predictions are based on machine learning models estimated with US stock market data in the same month of the 10 stock characteristics (listed in Table 2). We report the annualized Sharpe ratio of value- and equal-weighted long-short portfolio returns in Panel A, out-of-sample R-squared of individual stocks in Panel B, and out-of-sample R-squared of the ten sorted portfolios (value- and equal-weighted) in Panel C. Models include OLS using only size, book-to-market, and momentum (OLS-3), OLS with all variables (Linear), LASSO, RIDGE, random forest (RF), gradient boosted regression trees with Huber loss (GBRT+H), and neural networks with one to five layers (NN1–NN5). The model that generates the highest $R^2_{oos}$ or SR for each market is highlighted in color. Markets are sorted in a descending order on the number of observations. In Panel A, we also report the Sharpe ratio of the market portfolio.

Panel A: Equal- and value-weighted Sharpe ratio

| | Equal-Weighted | | | | | | | | | | | | Value-Weighted | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | Market | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | Market | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 |
| USA | 0.58 | 0.81 | 1.55 | 1.43 | 1.55 | 2.30 | 2.17 | 2.61 | 2.57 | 2.58 | 2.52 | 2.35 | 0.53 | 0.41 | 0.31 | 0.30 | 0.31 | 0.77 | 0.36 | 0.88 | 0.98 | 1.25 | 1.07 | 1.09 |
| Japan | 0.21 | 0.34 | 1.43 | 1.39 | 1.43 | 2.05 | 1.99 | 2.42 | 2.48 | 2.41 | 2.36 | 2.44 | 0.02 | 0.21 | 0.72 | 0.80 | 0.72 | 0.89 | 0.95 | 0.71 | 0.96 | 0.95 | 0.94 | 0.86 |
| China | 0.53 | 0.62 | 1.14 | 1.01 | 1.14 | 1.03 | 1.12 | 1.37 | 1.42 | 1.24 | 1.21 | 1.41 | 0.38 | 0.40 | 0.70 | 0.74 | 0.70 | 0.75 | 0.83 | 1.26 | 1.28 | 0.87 | 0.75 | 1.17 |
| India | 0.67 | 0.91 | 1.30 | 1.20 | 1.31 | 1.92 | 1.78 | 2.10 | 2.06 | 2.08 | 1.97 | 2.12 | 0.50 | 0.72 | 0.16 | 0.01 | 0.17 | 0.60 | 0.53 | 0.31 | 0.57 | 0.45 | 0.45 | 0.45 |
| Korea | 0.41 | 0.92 | 1.41 | 1.13 | 1.41 | 1.70 | 1.65 | 2.26 | 2.24 | 2.08 | 2.17 | 2.29 | 0.18 | 0.02 | 0.50 | 0.40 | 0.51 | 0.92 | 0.83 | 0.96 | 0.79 | 0.70 | 0.82 | 1.02 |
| Hong_Kong | 0.51 | 0.69 | 0.55 | 0.43 | 0.55 | 1.53 | 1.29 | 1.44 | 1.65 | 1.52 | 1.56 | 1.60 | 0.44 | 0.21 | 0.08 | 0.03 | 0.08 | 0.41 | 0.20 | 0.71 | 0.57 | 0.53 | 0.50 | 0.50 |
| France | 0.66 | 1.02 | 1.83 | 1.80 | 1.83 | 2.14 | 1.94 | 2.08 | 2.36 | 2.24 | 2.28 | 2.27 | 0.46 | 0.70 | 0.71 | 0.59 | 0.71 | 0.72 | 0.61 | 1.17 | 1.16 | 1.21 | 1.22 | 1.17 |
| Germany | 0.49 | 0.97 | 1.33 | 1.22 | 1.33 | 1.80 | 1.74 | 1.86 | 1.76 | 1.78 | 1.82 | 1.69 | 0.42 | 0.66 | 0.51 | 0.42 | 0.51 | 0.71 | 0.61 | 0.86 | 0.90 | 0.76 | 0.74 | 0.75 |
| Australia | 0.61 | 1.33 | 1.77 | 1.64 | 1.77 | 2.33 | 2.31 | 2.64 | 2.73 | 2.58 | 2.54 | 2.54 | 0.54 | 0.89 | 0.46 | 0.07 | 0.46 | 0.71 | 0.55 | 1.12 | 1.11 | 1.01 | 1.09 | 1.05 |
| Malaysia | 0.36 | 0.46 | 1.13 | 1.25 | 1.13 | 2.13 | 1.98 | 2.31 | 2.41 | 2.28 | 2.20 | 2.23 | 0.35 | 0.28 | 0.28 | 0.09 | 0.27 | 0.90 | 0.62 | 1.10 | 0.68 | 1.10 | 0.76 | 0.84 |
| Taiwan | 0.38 | 0.56 | 0.38 | 0.17 | 0.38 | 0.70 | 0.65 | 0.87 | 0.85 | 0.84 | 0.70 | 0.81 | 0.31 | 0.21 | 0.18 | -0.04 | 0.18 | 0.16 | 0.17 | 0.39 | 0.41 | 0.37 | 0.21 | 0.48 |
| United_Kingdom | 0.37 | 0.62 | 0.26 | 0.18 | 0.27 | 0.50 | 0.57 | 0.83 | 0.65 | 0.70 | 0.63 | 0.51 | 0.40 | 0.41 | 0.32 | 0.10 | 0.32 | 0.10 | 0.28 | 0.34 | 0.47 | 0.41 | 0.47 | 0.40 |
| Singapore | 0.26 | 0.53 | 1.37 | 1.34 | 1.37 | 1.80 | 1.75 | 1.94 | 2.01 | 2.09 | 2.23 | 2.04 | 0.32 | 0.24 | -0.03 | 0.03 | -0.03 | 0.57 | 0.43 | 0.68 | 0.67 | 0.65 | 0.73 | 0.53 |
| Canada | 0.75 | 1.02 | 0.83 | 0.62 | 0.83 | 1.33 | 1.20 | 1.19 | 1.30 | 1.27 | 1.27 | 1.17 | 0.60 | 0.59 | 0.23 | 0.15 | 0.23 | 0.56 | 0.54 | 0.80 | 0.76 | 0.71 | 0.76 | 0.56 |
| Italy | 0.21 | 0.29 | 0.34 | 0.25 | 0.34 | 1.07 | 0.92 | 1.06 | 1.00 | 0.98 | 1.04 | 0.94 | 0.25 | 0.34 | -0.09 | -0.12 | -0.08 | 0.55 | 0.48 | 0.60 | 0.76 | 0.57 | 0.75 | 0.65 |
| Sweden | 0.57 | 0.66 | 0.88 | 0.89 | 0.88 | 1.56 | 1.42 | 1.72 | 1.74 | 1.70 | 1.69 | 1.69 | 0.55 | 0.41 | 0.22 | 0.17 | 0.22 | 0.55 | 0.54 | 0.52 | 0.64 | 0.62 | 0.46 | 0.51 |
| Thailand | 0.87 | 0.68 | 0.19 | -0.03 | 0.19 | 0.73 | 0.58 | 1.01 | 1.11 | 1.02 | 1.09 | 0.93 | 0.54 | 0.44 | -0.16 | -0.63 | -0.16 | 0.08 | -0.04 | 0.21 | 0.21 | -0.07 | 0.53 | -0.01 |
| Switzerland | 0.65 | 0.71 | 0.67 | 0.53 | 0.67 | 1.08 | 0.92 | 0.98 | 1.06 | 1.10 | 1.16 | 1.09 | 0.50 | 0.78 | 0.40 | 0.24 | 0.40 | 0.65 | 0.47 | 0.50 | 0.46 | 0.60 | 0.57 | 0.59 |
| South_Africa | 1.12 | 1.41 | 2.50 | 2.42 | 2.51 | 2.44 | 2.34 | 2.69 | 2.71 | 2.77 | 2.87 | 2.81 | 0.73 | 0.52 | 0.57 | 0.61 | 0.57 | 1.14 | 0.79 | 0.99 | 1.11 | 1.26 | 1.33 | 1.09 |
| Poland | 0.51 | 1.07 | 0.34 | 0.45 | 0.34 | 1.08 | 1.11 | 1.34 | 1.36 | 1.42 | 1.51 | 1.45 | 0.49 | 0.47 | -0.24 | -0.11 | -0.20 | 0.41 | 0.53 | 0.95 | 0.79 | 0.85 | 0.66 | 0.66 |
| Turkey | 0.66 | 0.11 | 0.21 | -0.03 | 0.21 | 0.38 | 0.48 | 0.48 | 0.63 | 0.70 | 0.66 | 0.58 | 0.51 | -0.14 | 0.05 | -0.01 | 0.05 | 0.32 | 0.09 | 0.06 | 0.54 | 0.52 | 0.37 | 0.22 |
| Greece | 0.41 | 0.56 | 1.41 | 1.49 | 1.40 | 1.72 | 1.89 | 1.90 | 1.92 | 1.80 | 1.80 | 2.10 | 0.11 | 0.08 | 0.39 | 0.60 | 0.39 | 0.55 | 0.77 | 0.67 | 0.26 | 0.37 | 0.29 | 1.02 |
| Indonesia | 0.93 | 0.90 | 0.79 | 0.73 | 0.80 | 1.82 | 1.38 | 1.46 | 1.45 | 1.45 | 1.59 | 1.62 | 0.73 | 0.59 | 0.42 | 0.36 | 0.43 | 0.90 | 0.69 | 0.91 | 0.46 | 0.54 | 0.61 | 0.79 |
| Vietnam | 0.94 | 0.88 | 0.86 | 1.01 | 0.86 | 1.61 | 1.16 | 1.45 | 1.65 | 1.59 | 1.84 | 1.63 | 0.73 | 0.12 | 0.31 | -0.05 | 0.31 | 0.57 | 0.19 | 0.71 | 0.56 | 0.36 | 0.36 | 0.41 |
| Israel | 0.66 | 0.95 | 0.90 | 0.95 | 0.91 | 0.80 | 0.79 | 0.96 | 1.06 | 1.02 | 1.29 | 1.13 | 0.19 | 0.77 | 0.39 | 0.01 | 0.40 | 0.55 | 0.44 | 1.11 | 1.03 | 1.03 | 1.08 | 0.90 |
| Denmark | 0.61 | 0.81 | 1.03 | 0.99 | 1.02 | 1.39 | 1.32 | 1.39 | 1.53 | 1.48 | 1.55 | 1.49 | 0.73 | 0.63 | 0.36 | 0.36 | 0.36 | 0.64 | 0.31 | 0.74 | 0.80 | 0.55 | 0.70 | 0.92 |
| Netherlands | 0.47 | 0.45 | 0.07 | 0.11 | 0.06 | 0.46 | 0.49 | 0.54 | 0.59 | 0.44 | 0.39 | 0.47 | 0.51 | 0.17 | 0.03 | -0.10 | 0.03 | -0.04 | -0.07 | 0.09 | 0.26 | 0.04 | 0.20 | 0.22 |
| Norway | 0.31 | 0.48 | 0.31 | 0.34 | 0.33 | 0.58 | 0.74 | 0.89 | 1.00 | 1.00 | 0.92 | 0.81 | 0.40 | 0.39 | 0.13 | 0.11 | 0.14 | 0.53 | 0.47 | 0.83 | 0.87 | 0.62 | 0.68 | 0.52 |
| Spain | 0.49 | 0.80 | 0.61 | 0.27 | 0.61 | 0.70 | 0.82 | 0.83 | 0.84 | 0.93 | 0.77 | 0.78 | 0.37 | 0.42 | 0.23 | 0.19 | 0.23 | 0.58 | 0.74 | 0.71 | 0.50 | 0.49 | 0.62 | 0.48 |
| Belgium | 0.56 | 0.76 | 0.52 | 0.42 | 0.52 | 0.76 | 0.87 | 0.95 | 0.95 | 0.86 | 1.03 | 0.93 | 0.39 | 0.66 | 0.09 | -0.26 | 0.09 | -0.19 | -0.07 | 0.24 | 0.34 | 0.29 | 0.41 | 0.36 |
| Finland | 0.43 | 0.76 | 0.55 | 0.33 | 0.55 | 1.18 | 0.99 | 0.79 | 0.83 | 0.94 | 0.72 | 0.83 | 0.05 | 0.38 | -0.12 | -0.17 | -0.12 | 0.42 | 0.24 | 0.38 | 0.32 | 0.44 | 0.26 | 0.34 |
| Sri_Lanka | 0.82 | 0.27 | 1.38 | 1.81 | 1.38 | 1.67 | 1.94 | 1.58 | 1.54 | 1.57 | 1.90 | 2.04 | 0.74 | -0.08 | 0.52 | 0.71 | 0.52 | 0.87 | 1.15 | 0.70 | 0.77 | 0.88 | 0.98 | 1.19 |
| Philippines | 1.18 | 0.85 | 1.41 | 1.38 | 1.41 | 1.60 | 1.34 | 1.46 | 1.79 | 1.91 | 1.76 | 1.87 | 0.87 | 0.17 | 0.09 | 0.38 | 0.09 | 0.34 | 0.47 | 0.44 | 0.86 | 0.90 | 0.89 | 0.75 |
| Pakistan | 1.17 | 0.98 | 0.60 | 0.28 | 0.59 | 1.10 | 1.12 | 1.20 | 1.25 | 1.16 | 1.28 | 1.20 | 1.00 | 0.59 | 0.58 | 0.01 | 0.58 | 0.71 | 0.73 | 0.97 | 0.89 | 0.67 | 0.81 | 1.00 |
| Saudi_Arabia | 0.38 | 0.07 | 0.06 | 0.32 | 0.06 | 0.71 | 0.63 | 0.83 | 0.86 | 0.78 | 0.47 | 0.93 | 0.50 | -0.24 | 0.07 | 0.03 | 0.07 | 0.26 | 0.21 | 0.39 | 0.37 | 0.36 | -0.01 | 0.22 |
| Jordan | 0.19 | 0.27 | -0.09 | -0.29 | -0.09 | 0.66 | 0.22 | 0.66 | 0.77 | 0.70 | 0.96 | 0.80 | -0.12 | -0.33 | -0.16 | -0.15 | -0.15 | 0.54 | 0.06 | 0.54 | 0.38 | 0.55 | 0.58 | 0.68 |
| Egypt | 0.65 | 0.15 | -0.05 | -0.09 | -0.05 | 0.43 | 0.42 | 0.28 | 0.29 | 0.34 | 0.36 | 0.12 | 0.62 | 0.06 | -0.06 | -0.13 | -0.06 | 0.04 | 0.40 | 0.33 | 0.13 | 0.30 | 0.14 | 0.03 |
| Chile | 0.86 | 0.91 | 0.09 | -0.30 | 0.09 | 0.33 | 0.36 | 0.48 | 0.28 | 0.38 | 0.38 | 0.31 | 0.65 | 0.50 | 0.06 | -0.10 | 0.06 | 0.36 | 0.18 | 0.46 | 0.30 | 0.69 | 0.52 | 0.22 |
| Brazil | 0.80 | 0.27 | 0.14 | 0.09 | 0.14 | 0.92 | 0.75 | 0.21 | 0.32 | 0.46 | 0.78 | 0.39 | 0.87 | 0.31 | 0.21 | 0.27 | 0.21 | 0.79 | 0.64 | 0.26 | 0.50 | 0.62 | 0.92 | 0.51 |
| Kuwait | 0.38 | 0.76 | 0.95 | 0.86 | 0.95 | 0.88 | 0.95 | 1.14 | 1.37 | 1.31 | 1.62 | 1.79 | 0.10 | 0.76 | 0.67 | 0.17 | 0.67 | 0.09 | 0.69 | 0.23 | 0.80 | 0.74 | 0.73 | 1.00 |
| Russia | 1.22 | 0.24 | 0.77 | 0.83 | 0.76 | 0.73 | 0.78 | 0.70 | 0.76 | 0.80 | 0.84 | 0.86 | 0.90 | 0.16 | 0.32 | 0.40 | 0.32 | 0.79 | 0.44 | 0.61 | 0.64 | 0.84 | 0.94 | 0.71 |

Panel B: Individual stock $R^2_{oos}$

| Country | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| USA | 0.29 | 0.41 | 0.45 | 0.41 | 0.79 | 0.68 | 0.71 | 0.77 | 0.76 | 0.76 | 0.68 |
| Japan | 0.04 | 0.04 | 0.24 | 0.04 | 0.21 | -0.25 | 0.20 | 0.06 | 0.01 | 0.07 | 0.37 |
| China | 0.87 | 0.88 | 0.95 | 0.88 | -68.70 | -6.87 | -2.04 | -0.52 | 0.16 | 0.27 | 0.79 |
| India | 0.73 | 0.49 | 0.60 | 0.49 | -0.41 | 0.69 | 0.78 | 0.82 | 0.82 | 0.83 | 0.84 |
| Korea | 0.58 | 0.56 | 0.58 | 0.57 | 0.58 | 0.52 | 0.62 | 0.57 | 0.45 | 0.62 | 0.73 |
| Hong_Kong | 0.53 | 0.30 | 0.37 | 0.30 | 0.58 | 0.55 | 0.57 | 0.55 | 0.58 | 0.62 | 0.64 |
| France | 0.50 | 0.84 | 0.87 | 0.84 | 1.18 | 1.14 | 1.13 | 1.19 | 1.19 | 1.22 | 1.15 |
| Germany | 0.22 | 0.24 | 0.27 | 0.24 | 0.19 | 0.28 | 0.53 | 0.55 | 0.59 | 0.58 | 0.60 |
| Australia | 0.45 | 0.64 | 0.59 | 0.65 | 1.10 | 0.78 | 1.41 | 1.40 | 1.45 | 1.42 | 1.17 |
| Malaysia | 0.40 | 0.50 | 0.59 | 0.50 | 0.64 | 0.58 | 0.90 | 0.86 | 0.82 | 0.99 | 0.76 |
| Taiwan | 0.59 | 0.09 | 0.35 | 0.09 | 0.12 | 0.03 | 0.15 | -0.09 | 0.16 | 0.28 | 0.64 |
| United_Kingdom | 0.05 | -0.36 | -0.16 | -0.36 | -2.32 | -0.99 | -0.34 | -0.35 | -0.29 | -0.16 | 0.01 |
| Singapore | 0.40 | 0.78 | 0.71 | 0.78 | 0.86 | 1.09 | 1.57 | 1.52 | 1.62 | 1.63 | 1.35 |
| Canada | 0.70 | 0.49 | 0.61 | 0.49 | 0.64 | 0.72 | 0.67 | 0.74 | 0.89 | 0.99 | 1.07 |
| Italy | -0.03 | -0.57 | -0.26 | -0.56 | -0.08 | -0.40 | -0.39 | -0.67 | -0.72 | -0.60 | -0.18 |
| Sweden | 0.39 | 0.40 | 0.49 | 0.40 | 0.86 | 0.34 | 0.94 | 0.99 | 0.95 | 0.95 | 0.94 |
| Thailand | 0.93 | 0.21 | 0.53 | 0.21 | 0.84 | 0.68 | 0.72 | 0.64 | 0.62 | 0.69 | 0.90 |
| Switzerland | 0.66 | -0.18 | 0.22 | -0.18 | -1.68 | -1.11 | -1.81 | -0.96 | -0.66 | -0.39 | 0.21 |
| South_Africa | 0.95 | 1.58 | 1.48 | 1.58 | 3.06 | 2.49 | 2.97 | 2.73 | 2.50 | 2.48 | 2.12 |
| Poland | 0.19 | -0.01 | 0.10 | -0.01 | 0.57 | 0.59 | 0.76 | 0.64 | 0.69 | 0.70 | 0.58 |
| Turkey | 0.83 | 0.44 | 0.71 | 0.44 | 0.75 | 0.49 | 0.28 | 0.30 | 0.31 | 0.38 | 0.61 |
| Greece | 0.27 | 0.46 | 0.41 | 0.46 | 0.67 | 0.74 | 0.80 | 0.83 | 0.76 | 0.83 | 0.59 |
| Indonesia | 0.90 | 0.64 | 0.71 | 0.64 | -1.84 | 0.84 | 0.73 | 0.76 | 0.85 | 0.79 | 0.97 |
| Vietnam | 1.15 | 1.22 | 1.20 | 1.23 | 1.35 | 1.25 | 1.17 | 1.28 | 1.48 | 1.26 | 1.53 |
| Israel | 0.61 | 0.50 | 0.64 | 0.50 | -2.21 | 0.17 | -0.98 | -0.36 | 0.00 | 0.15 | 0.49 |
| Denmark | 0.51 | 0.37 | 0.51 | 0.37 | 0.18 | 0.24 | 0.39 | 0.56 | 0.57 | 0.59 | 0.67 |
| Netherlands | 0.34 | -0.48 | -0.08 | -0.47 | -1.51 | -1.04 | -1.60 | -1.05 | -0.81 | -0.93 | -0.16 |
| Norway | 0.22 | -0.06 | 0.03 | -0.06 | -0.03 | 0.14 | -0.13 | -0.15 | 0.01 | -0.01 | 0.24 |
| Spain | 0.53 | 0.04 | 0.25 | 0.04 | -0.17 | -0.35 | -0.29 | -0.12 | -0.05 | -0.25 | 0.22 |
| Belgium | 0.55 | 0.01 | 0.38 | 0.01 | -2.34 | -0.47 | -0.97 | -0.25 | -0.03 | 0.02 | 0.41 |
| Finland | 0.62 | 0.00 | 0.25 | 0.01 | 0.24 | 0.24 | -0.77 | -0.52 | -0.55 | -0.56 | 0.05 |
| Sri_Lanka | 0.95 | 1.34 | 1.32 | 1.34 | 1.11 | 1.43 | 0.98 | 1.18 | 1.17 | 1.32 | 1.32 |
| Philippines | 1.08 | 1.23 | 1.24 | 1.23 | -87.72 | -3.11 | 0.36 | 0.80 | 1.18 | 1.11 | 1.34 |
| Pakistan | 1.75 | 1.32 | 1.46 | 1.33 | 1.79 | 1.63 | 1.19 | 1.38 | 1.53 | 1.46 | 1.63 |
| Saudi_Arabia | 0.25 | -0.33 | 0.26 | -0.33 | 0.26 | 0.18 | 0.24 | -0.36 | -0.80 | -0.67 | -0.13 |
| Jordan | -0.26 | -1.26 | -0.71 | -1.25 | -0.23 | -0.34 | -0.59 | -0.76 | -0.89 | -0.71 | -0.32 |
| Egypt | 1.04 | 0.52 | 0.89 | 0.53 | 0.95 | 0.71 | 0.45 | 0.34 | 0.51 | 0.26 | 0.63 |
| Chile | 1.56 | 0.25 | 0.55 | 0.25 | -3.36 | -1.34 | -1.45 | -0.52 | -0.44 | -0.39 | 0.57 |
| Brazil | 1.04 | 1.09 | 1.13 | 1.09 | 1.82 | 1.18 | 1.18 | 1.18 | 1.16 | 1.17 | 1.24 |
| Kuwait | 0.41 | 0.25 | 0.47 | 0.25 | 0.29 | 0.22 | 0.39 | 0.19 | 0.38 | 0.42 | 0.79 |
| Russia | 1.31 | 1.43 | 1.52 | 1.43 | 1.47 | 1.45 | 1.35 | 1.40 | 1.46 | 1.50 | 1.52 |

Panel C: Portfolio $R^2_{oos}$

| | Equal-Weighted | | | | | | | | | | | Value-Weighted | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 |
| USA | 2.90 | 3.32 | 3.54 | 3.32 | 4.54 | 4.02 | 4.16 | 4.24 | 4.30 | 4.48 | 4.22 | 2.63 | 0.89 | 1.41 | 0.88 | 2.68 | 0.87 | 2.69 | 2.99 | 3.46 | 3.40 | 3.25 |
| Japan | -0.04 | 0.39 | 0.81 | 0.40 | 0.86 | -0.13 | 0.71 | 0.60 | 0.77 | 0.56 | 1.24 | -0.72 | -0.84 | -0.21 | -0.85 | -0.14 | -1.23 | -0.76 | -0.45 | -0.03 | -0.42 | 0.28 |
| China | 1.83 | 1.82 | 1.86 | 1.82 | -7.53 | 0.13 | 0.33 | 1.06 | 1.77 | 1.54 | 2.07 | 1.33 | 1.28 | 1.37 | 1.28 | 1.39 | 1.15 | 0.72 | 0.90 | 1.41 | 1.05 | 1.45 |
| India | 2.32 | 2.23 | 2.28 | 2.23 | 2.34 | 2.56 | 2.78 | 2.78 | 2.65 | 2.82 | 2.54 | 2.08 | 0.46 | 0.80 | 0.46 | 1.48 | 1.22 | 0.95 | 1.20 | 1.28 | 1.40 | 1.26 |
| Korea | 1.48 | 1.83 | 1.70 | 1.83 | 1.82 | 1.63 | 2.01 | 2.23 | 2.05 | 2.16 | 2.01 | 0.58 | 0.42 | 0.30 | 0.43 | 0.57 | 0.47 | 0.91 | 0.16 | 0.61 | 0.84 | 0.69 |
| Hong_Kong | 1.91 | 1.15 | 1.25 | 1.16 | 1.83 | 1.73 | 1.74 | 1.75 | 1.83 | 2.15 | 1.91 | 1.27 | 0.02 | 0.31 | 0.01 | 0.88 | 0.66 | 1.04 | 0.52 | 0.65 | 1.16 | 0.78 |
| France | 3.37 | 4.13 | 4.36 | 4.15 | 5.24 | 4.92 | 4.65 | 4.87 | 5.19 | 5.24 | 5.17 | 2.86 | 1.99 | 1.68 | 1.99 | 1.89 | 1.24 | 2.87 | 2.36 | 2.88 | 2.82 | 2.53 |
| Germany | 1.94 | 1.59 | 2.04 | 1.59 | 3.22 | 2.55 | 3.00 | 2.58 | 3.27 | 2.99 | 3.24 | 3.11 | 1.00 | 1.23 | 1.00 | 1.55 | 1.00 | 2.10 | 2.24 | 1.78 | 1.47 | 1.53 |
| Australia | 3.82 | 4.10 | 3.96 | 4.11 | 4.88 | 4.25 | 7.00 | 6.92 | 6.99 | 7.07 | 5.96 | 4.45 | 0.47 | 0.79 | 0.47 | 1.19 | 1.04 | 3.11 | 2.39 | 3.07 | 2.96 | 2.33 |
| Malaysia | 1.11 | 1.14 | 1.32 | 1.14 | 1.43 | 1.22 | 1.92 | 1.74 | 1.60 | 2.16 | 1.34 | 1.00 | 0.17 | 0.49 | 0.18 | 1.03 | 0.49 | 1.73 | 0.89 | 0.87 | 1.47 | 0.65 |
| Taiwan | 1.23 | 0.07 | 0.58 | 0.08 | 0.84 | -0.11 | 0.33 | 0.13 | 0.55 | 0.51 | 1.39 | 0.86 | -0.50 | 0.02 | -0.49 | 0.38 | -0.64 | 0.06 | 0.05 | 0.29 | 0.18 | 1.16 |
| United_Kingdom | 1.39 | -1.58 | -0.45 | -1.57 | -1.48 | -1.34 | -0.07 | -0.92 | -0.75 | -0.16 | 0.34 | 2.12 | -0.07 | 0.34 | -0.06 | 0.25 | 0.22 | 0.73 | 1.08 | 0.84 | 0.93 | 1.01 |
| Singapore | 0.72 | 1.11 | 1.07 | 1.11 | 1.23 | 1.19 | 2.14 | 2.03 | 2.03 | 2.18 | 1.75 | 0.51 | -0.60 | -0.04 | -0.60 | 0.30 | -0.32 | 0.60 | 0.28 | 0.18 | 0.54 | 0.25 |
| Canada | 2.95 | 1.64 | 1.86 | 1.63 | 3.25 | 2.22 | 3.08 | 3.20 | 3.06 | 3.61 | 3.18 | 2.09 | -0.44 | 0.29 | -0.44 | 1.37 | 0.82 | 2.20 | 2.16 | 2.03 | 2.07 | 1.58 |
| Italy | 0.05 | -1.53 | -0.73 | -1.52 | 0.12 | -0.72 | -0.49 | -1.06 | -0.88 | -0.57 | -0.07 | 0.92 | -1.02 | -0.51 | -1.01 | 0.34 | -0.03 | 0.25 | 0.01 | -0.11 | 0.41 | 0.38 |
| Sweden | 2.44 | 1.96 | 2.37 | 1.96 | 3.63 | 3.13 | 3.49 | 3.89 | 3.61 | 3.69 | 3.66 | 2.67 | 1.15 | 1.53 | 1.15 | 1.97 | 1.47 | 1.44 | 2.15 | 1.92 | 1.79 | 1.59 |
| Thailand | 3.33 | 1.57 | 2.17 | 1.58 | 2.98 | 2.32 | 2.44 | 2.52 | 2.48 | 2.94 | 2.85 | 2.05 | -0.33 | 0.29 | -0.33 | 1.23 | 0.37 | 1.01 | 0.73 | 0.75 | 1.75 | 1.11 |
| Switzerland | 2.93 | 0.39 | 1.60 | 0.39 | 0.15 | -0.85 | -0.90 | 0.50 | 1.39 | 1.89 | 2.47 | 3.52 | 0.94 | 1.33 | 0.94 | 1.37 | -0.10 | 1.24 | 1.44 | 2.11 | 1.75 | 2.00 |
| South_Africa | 5.77 | 8.23 | 7.65 | 8.24 | 9.83 | 10.01 | 10.66 | 9.54 | 9.27 | 9.43 | 8.43 | 3.97 | 2.82 | 3.26 | 2.82 | 3.73 | 3.15 | 3.89 | 3.61 | 4.03 | 3.87 | 3.38 |
| Poland | 2.24 | 0.02 | 0.66 | 0.03 | 1.50 | 1.08 | 1.68 | 1.49 | 2.37 | 1.96 | 2.12 | 1.86 | -1.36 | -0.11 | -1.29 | 0.92 | 0.36 | 2.11 | 1.20 | 2.39 | 1.59 | 1.61 |
| Turkey | 1.88 | 1.25 | 1.62 | 1.25 | 1.77 | 1.32 | 1.04 | 1.31 | 1.42 | 1.29 | 1.52 | 1.22 | 0.85 | 1.16 | 0.85 | 1.24 | 0.76 | 0.78 | 1.22 | 1.31 | 1.07 | 1.12 |
| Greece | 1.34 | 2.02 | 1.72 | 2.02 | 2.16 | 2.36 | 2.50 | 2.38 | 2.16 | 2.47 | 1.76 | 0.24 | 0.34 | 0.63 | 0.33 | 0.73 | 0.67 | 0.95 | 0.18 | 0.53 | 0.57 | 0.46 |
| Indonesia | 3.70 | 3.14 | 3.29 | 3.14 | 3.56 | 3.84 | 3.83 | 3.73 | 3.96 | 3.63 | 3.97 | 2.85 | 1.88 | 1.88 | 1.87 | 2.09 | 2.28 | 2.32 | 1.80 | 1.91 | 1.95 | 2.26 |
| Vietnam | 3.79 | 3.62 | 3.59 | 3.62 | 3.69 | 3.55 | 3.57 | 3.69 | 4.31 | 3.46 | 4.03 | 2.95 | 1.51 | 1.74 | 1.53 | 1.81 | 1.55 | 2.03 | 1.73 | 2.26 | 1.14 | 2.46 |
| Israel | 3.04 | 2.95 | 3.36 | 2.96 | 1.63 | 2.43 | 1.50 | 2.04 | 3.13 | 3.38 | 3.38 | 3.65 | 1.35 | 1.34 | 1.36 | 2.17 | 1.41 | 3.48 | 2.54 | 2.95 | 2.81 | 2.61 |
| Denmark | 2.61 | 1.42 | 2.25 | 1.42 | 2.69 | 2.04 | 2.35 | 3.22 | 3.32 | 3.29 | 3.26 | 3.15 | 1.44 | 1.69 | 1.45 | 2.41 | 0.96 | 2.03 | 2.18 | 2.22 | 2.23 | 2.27 |
| Netherlands | 1.73 | -1.05 | 0.34 | -1.04 | -0.70 | -0.67 | -1.30 | -0.39 | -0.05 | -0.80 | 1.00 | 1.91 | -0.24 | 0.30 | -0.21 | 0.74 | -0.24 | 0.42 | 0.66 | 0.24 | 0.43 | 0.78 |
| Norway | 0.86 | -0.37 | 0.07 | -0.36 | 0.76 | 0.81 | 0.70 | 0.82 | 1.33 | 0.91 | 1.45 | 1.67 | -0.07 | 0.55 | -0.07 | 1.10 | 0.72 | 1.44 | 1.33 | 1.46 | 1.03 | 0.98 |
| Spain | 1.71 | -0.13 | 0.65 | -0.13 | 0.62 | -0.19 | -0.14 | 0.09 | 0.63 | -0.06 | 0.91 | 1.48 | -0.11 | 0.77 | -0.12 | 1.39 | 0.56 | 1.22 | 1.29 | 0.95 | 1.01 | 0.81 |
| Belgium | 2.29 | -0.33 | 1.13 | -0.32 | -0.76 | 0.23 | -0.31 | 0.72 | 1.37 | 1.26 | 1.82 | 2.55 | -1.89 | -1.00 | -1.93 | -0.55 | -1.40 | -1.07 | -0.04 | -0.22 | -0.47 | 0.09 |
| Finland | 1.50 | -0.14 | 0.54 | -0.14 | 1.76 | 1.07 | 0.35 | 0.79 | 1.09 | 0.35 | 1.40 | 1.17 | -0.50 | -0.24 | -0.49 | 0.49 | -0.36 | 1.11 | 0.84 | 1.02 | 0.36 | 0.68 |
| Sri_Lanka | 2.72 | 3.63 | 3.57 | 3.62 | 3.70 | 3.46 | 3.11 | 3.21 | 3.23 | 3.86 | 3.56 | 2.12 | 2.70 | 2.77 | 2.71 | 2.66 | 2.78 | 2.72 | 2.29 | 2.82 | 3.00 | 3.05 |
| Philippines | 4.95 | 5.07 | 5.03 | 5.07 | -34.61 | 2.24 | 5.62 | 5.43 | 5.90 | 5.32 | 5.45 | 3.03 | 1.60 | 2.51 | 1.56 | 2.85 | 2.33 | 2.72 | 3.21 | 3.72 | 2.96 | 3.42 |
| Pakistan | 5.42 | 4.31 | 4.67 | 4.32 | 5.53 | 5.00 | 4.79 | 5.12 | 5.74 | 5.25 | 5.23 | 4.21 | 3.06 | 2.96 | 3.06 | 3.93 | 3.73 | 3.98 | 3.63 | 3.88 | 3.79 | 4.09 |
| Saudi_Arabia | 0.84 | -0.39 | 0.70 | -0.39 | 0.92 | 0.51 | 0.97 | 0.43 | 0.06 | -0.22 | 0.43 | 0.79 | -0.40 | 0.81 | -0.38 | 0.78 | 0.46 | 0.61 | 0.60 | 0.31 | -0.53 | 0.18 |
| Jordan | -0.97 | -5.51 | -3.15 | -5.54 | -0.97 | -2.17 | -2.92 | -3.22 | -3.00 | -1.75 | -1.08 | -1.35 | -4.67 | -2.40 | -4.71 | -0.90 | -1.85 | -1.55 | -1.69 | -0.82 | -0.96 | -1.00 |
| Egypt | 2.32 | 1.23 | 1.95 | 1.23 | 2.25 | 1.77 | 1.64 | 1.46 | 2.08 | 1.25 | 1.44 | 2.66 | 0.98 | 1.90 | 0.97 | 2.02 | 1.72 | 1.96 | 1.54 | 2.16 | 1.12 | 1.05 |
| Chile | 4.74 | 0.54 | 1.45 | 0.55 | 0.70 | 1.43 | 0.17 | 0.95 | 1.81 | 1.36 | 2.90 | 4.01 | -0.12 | 0.94 | -0.10 | 0.19 | 0.86 | 2.64 | 1.53 | 3.48 | 2.09 | 2.43 |
| Brazil | 1.99 | 1.55 | 1.65 | 1.55 | 2.58 | 2.34 | 2.14 | 2.19 | 2.71 | 2.61 | 2.54 | 1.62 | 1.23 | 1.55 | 1.24 | 1.81 | 1.70 | 1.31 | 1.40 | 1.63 | 1.77 | 2.03 |
| Kuwait | 1.34 | 0.98 | 1.39 | 0.99 | 0.85 | 0.38 | 2.14 | 1.29 | 1.52 | 1.86 | 2.38 | 0.28 | -1.51 | -1.39 | -1.50 | -0.81 | -0.24 | 0.36 | 0.78 | 0.72 | 0.33 | 1.15 |
| Russia | 3.95 | 3.95 | 3.89 | 3.93 | 3.98 | 3.82 | 3.45 | 3.64 | 3.97 | 3.89 | 3.80 | 2.70 | 1.99 | 3.00 | 1.98 | 3.00 | 2.72 | 3.10 | 2.82 | 3.40 | 3.34 | 3.02 |

**Table 8. Performance of International Portfolios based on Predictions of Country-Specific Models: Using 10 Predictors**

In the table, we report the performance of prediction-sorted portfolios over the testing period in international markets. All stocks are sorted into deciles based on their predicted returns for the next month. Predictions are based on machine learning models estimated with each market's own data of the 10 stock characteristics (listed in Table 2). We report the annualized Sharpe ratio of value- and equal-weighted long-short portfolio returns in Panel A, out-of-sample R-squared of individual stocks in Panel B, and out-of-sample R-squared of the ten sorted portfolios (value- and equal-weighted) in Panel C. Models include OLS using only size, book-to-market, and momentum (OLS-3), OLS with all variables (Linear), LASSO, RIDGE, random forest (RF), gradient boosted regression trees with Huber loss (GBRT+H), and neural networks with one to five layers (NN1–NN5). The model that generates the highest $R^2_{oos}$ or SR for each market is highlighted in color. Markets are sorted in a descending order on the number of observations. In Panel A, we also report the Sharpe ratio of the market portfolio.

## Panel A: Equal- and value-weighted Sharpe ratio

**Equal-Weighted**

| Country | Market | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| USA | 0.58 | 0.81 | 1.55 | 1.43 | 1.55 | 2.30 | 2.17 | 2.61 | 2.57 | 2.58 | 2.52 | 2.35 | = |
| Japan | 0.77 | 0.78 | 0.71 | 0.31 | 0.72 | 1.07 | 0.60 | 1.53 | 1.47 | 1.28 | 1.17 | 1.10 | - |
| China | 0.47 | 0.92 | 1.27 | 1.28 | 1.27 | 1.75 | 1.44 | 0.97 | 1.60 | 1.94 | 1.69 | 1.68 | + |
| India | 0.67 | 1.02 | 0.71 | 0.94 | 0.70 | 1.10 | 1.09 | 1.16 | 1.99 | 1.58 | 1.75 | 1.29 | - |
| Korea | 0.65 | 1.81 | 2.64 | 2.36 | 2.63 | 2.32 | 2.86 | 2.06 | 2.39 | 2.96 | 3.25 | 3.59 | + |
| Hong_Kong | 0.67 | 1.20 | 1.19 | 1.14 | 1.17 | 1.69 | 1.73 | 1.61 | 2.21 | 2.18 | 1.88 | 2.15 | + |
| France | 0.85 | 1.05 | 2.91 | 2.80 | 2.92 | 2.55 | 2.50 | 3.24 | 3.21 | 3.20 | 3.01 | 3.04 | + |
| Germany | 0.94 | 0.81 | 1.37 | 0.94 | 1.36 | 1.61 | 0.96 | 1.78 | 1.58 | 1.82 | 1.56 | 1.09 | - |
| Australia | 0.62 | 1.39 | 2.84 | 2.46 | 2.84 | 2.64 | 2.04 | 3.11 | 3.57 | 3.15 | 3.38 | 3.23 | + |
| Malaysia | 0.64 | 0.56 | 1.61 | 1.85 | 1.62 | 1.52 | 1.48 | 0.79 | 2.27 | 2.42 | 2.33 | 1.61 | + |
| Taiwan | 0.48 | 0.51 | 0.33 | 0.51 | 0.36 | -0.01 | 0.04 | 0.51 | 0.62 | 0.96 | 0.00 | -0.02 | + |
| United_Kingdom | 0.28 | 1.14 | 1.07 | 0.99 | 1.14 | 1.56 | 0.46 | 1.39 | 1.46 | 1.65 | 1.74 | 1.59 | + |
| Singapore | 0.31 | 1.05 | 2.34 | 2.29 | 2.37 | 2.39 | 2.25 | 2.47 | 3.14 | 3.11 | 2.97 | 3.16 | + |
| Canada | 0.61 | 0.95 | 0.92 | 0.58 | 0.86 | 0.87 | 0.39 | 1.31 | 1.65 | 1.20 | 1.18 | 0.88 | + |
| Italy | 0.25 | 0.82 | 0.92 | 1.02 | 0.89 | 0.81 | 0.44 | 0.71 | 0.88 | 0.61 | 0.36 | 0.37 | - |
| Sweden | 0.43 | 1.04 | 1.51 | 1.32 | 1.52 | 2.11 | 1.91 | 1.51 | 2.42 | 2.70 | 2.83 | 2.03 | + |
| Thailand | 0.97 | 1.08 | 1.48 | 1.24 | 1.43 | 1.90 | 1.23 | 1.31 | 2.22 | 2.04 | 2.55 | 1.56 | + |
| Switzerland | 0.57 | 0.66 | 1.16 | 0.76 | 1.19 | 1.04 | 0.95 | 0.42 | 1.16 | 1.21 | 0.76 | 0.37 | + |
| South_Africa | 1.21 | 1.28 | 2.32 | 2.21 | 2.32 | 2.04 | 2.05 | 2.38 | 2.42 | 2.59 | 2.66 | 2.53 | - |
| Poland | 0.12 | 0.67 | 0.64 | 0.04 | 0.62 | 0.99 | 1.08 | 0.51 | 0.36 | -0.05 | 0.47 | 0.06 | - |
| Turkey | 1.20 | 0.16 | 0.48 | 0.07 | 0.53 | 0.83 | 1.05 | 0.13 | 0.40 | 0.93 | 0.72 | 0.79 | + |
| Greece | 0.27 | 1.13 | 1.11 | 0.99 | 1.14 | 0.83 | 0.65 | 0.81 | 0.77 | 0.90 | 1.23 | 0.99 | - |
| Indonesia | 1.70 | 0.91 | 1.31 | 1.27 | 1.37 | 1.76 | 1.87 | 0.45 | 1.32 | 1.93 | 2.22 | 1.50 | + |
| Vietnam | 1.85 | 1.32 | 2.02 | 2.21 | 1.90 | 3.00 | 2.08 | 0.82 | 2.30 | 3.45 | 3.74 | 3.32 | + |
| Israel | 0.70 | 1.24 | 0.62 | 0.58 | 0.65 | 0.23 | 0.60 | -0.46 | 1.13 | 0.71 | 0.73 | 0.45 | - |
| Denmark | 0.15 | 0.93 | 1.37 | 1.21 | 1.52 | 1.39 | 1.11 | 1.67 | 1.54 | 1.35 | 1.12 | 0.82 | + |
| Netherlands | 0.49 | 0.63 | 0.77 | 0.78 | 0.74 | 0.68 | 0.39 | 0.65 | 0.98 | 0.53 | 0.64 | 0.70 | + |
| Norway | 0.13 | 1.18 | 1.23 | 1.18 | 1.25 | 0.83 | 0.89 | 1.16 | 0.75 | 0.92 | 1.04 | 0.70 | + |
| Spain | 0.10 | 0.51 | 0.60 | 0.59 | 0.62 | 0.29 | 0.32 | 0.42 | 0.44 | -0.06 | 0.05 | -0.41 | - |
| Belgium | 1.29 | 0.26 | 0.27 | 0.05 | 0.31 | 0.55 | -0.08 | 0.14 | 0.73 | 0.15 | 0.07 | 0.22 | - |
| Finland | 0.94 | 1.11 | 1.05 | 0.68 | 0.98 | 0.77 | 1.11 | 0.76 | 0.29 | 0.60 | 0.72 | -0.29 | - |
| Sri_Lanka | 0.56 | 0.13 | 2.86 | 2.30 | 2.36 | 1.69 | 1.70 | 0.39 | 1.64 | 1.90 | 1.87 | 1.70 | + |
| Philippines | 1.21 | 0.47 | 1.31 | 1.18 | 1.64 | 1.61 | 0.22 | 1.24 | 1.48 | 1.18 | 1.55 | 1.41 | - |
| Pakistan | 1.65 | 1.18 | 1.10 | 0.79 | 1.10 | 0.56 | 0.33 | 0.30 | 1.23 | 0.93 | 1.06 | -0.42 | - |
| Saudi_Arabia | -0.10 | -0.29 | -0.37 | -0.02 | -0.35 | 0.49 | 0.55 | -0.29 | -0.19 | -0.25 | 0.15 | 0.52 | - |
| Jordan | 0.90 | 0.87 | 1.05 | 0.43 | 0.66 | 0.64 | 0.85 | 0.97 | 0.88 | 1.14 | 0.81 | 0.84 | + |
| Egypt | 0.69 | -0.09 | -0.05 | 0.00 | 0.10 | -0.12 | -0.60 | 0.69 | -0.41 | 0.55 | -0.21 | -0.47 | + |
| Chile | 0.83 | 0.51 | 0.27 | 0.03 | 0.25 | 0.51 | 0.24 | 0.03 | 0.24 | 0.19 | 0.53 | 0.12 | - |
| Brazil | 2.62 | -0.67 | -0.23 | 0.07 | -0.52 | -0.26 | -0.34 | 1.35 | 1.24 | 0.53 | 1.03 | 0.68 | + |
| Kuwait | 0.10 | 0.50 | 0.59 | -0.64 | 0.86 | 0.74 | 0.28 | 0.09 | -0.30 | 0.74 | 0.59 | 0.52 | - |
| Russia | 1.89 | 0.62 | 0.47 | 0.18 | 0.44 | -0.31 | -0.22 | 1.26 | -0.01 | 0.32 | 1.12 | -0.30 | + |

**Value-Weighted**

| Country | Market | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| USA | 0.53 | 0.41 | 0.31 | 0.30 | 0.31 | 0.77 | 0.36 | 0.88 | 0.98 | 1.25 | 1.07 | 1.09 | = |
| Japan | 0.49 | 0.49 | 0.59 | 0.22 | 0.60 | 0.65 | 0.56 | 0.51 | 0.83 | 0.74 | 0.65 | 0.70 | - |
| China | 0.19 | 0.82 | 0.89 | 0.86 | 0.89 | 1.59 | 0.93 | 0.68 | 0.89 | 0.79 | 1.21 | 1.22 | + |
| India | 0.57 | 0.40 | 0.06 | 0.23 | 0.04 | 0.47 | -0.06 | 0.34 | 0.40 | 0.39 | 0.42 | -0.12 | - |
| Korea | 0.41 | 0.91 | 1.13 | 0.92 | 1.12 | 1.13 | 0.80 | 1.13 | 0.90 | 0.93 | 1.71 | 1.88 | + |
| Hong_Kong | 0.56 | 0.38 | 0.58 | 0.77 | 0.53 | 0.86 | 0.37 | 0.55 | 1.33 | 1.01 | 0.92 | 0.97 | + |
| France | 0.67 | 0.58 | 0.77 | 0.81 | 0.77 | 0.56 | 0.58 | 0.71 | 0.71 | 0.98 | 0.92 | 0.67 | - |
| Germany | 0.68 | 0.58 | 0.28 | 0.45 | 0.29 | 0.50 | 0.20 | 0.46 | 0.71 | 0.84 | 1.14 | 0.91 | + |
| Australia | 0.72 | 0.76 | 1.07 | 1.02 | 1.09 | 1.58 | 0.68 | 1.24 | 1.57 | 1.34 | 1.18 | 1.04 | + |
| Malaysia | 0.74 | 0.25 | 0.19 | 0.24 | 0.18 | 0.03 | 0.15 | 0.33 | 0.96 | 1.02 | 0.65 | 0.33 | - |
| Taiwan | 0.38 | -0.13 | -0.06 | 0.05 | -0.03 | -0.19 | -0.45 | -0.01 | 0.14 | 0.53 | 0.13 | -0.65 | + |
| United_Kingdom | 0.59 | 0.33 | 0.47 | 0.26 | 0.51 | 1.05 | 0.08 | 0.89 | 0.81 | 0.60 | 0.94 | 0.66 | + |
| Singapore | 0.28 | 0.15 | 0.21 | 0.30 | 0.25 | 0.81 | 0.63 | 0.79 | 1.38 | 1.21 | 1.60 | 1.42 | + |
| Canada | 0.35 | 0.52 | 0.57 | 0.46 | 0.52 | -0.28 | 0.06 | 0.48 | 0.60 | 0.56 | 0.72 | 0.05 | - |
| Italy | 0.32 | 0.55 | 0.47 | 0.62 | 0.35 | 0.37 | 0.03 | 0.42 | 0.57 | 0.38 | 0.27 | 0.39 | - |
| Sweden | 0.46 | 0.24 | 0.10 | 0.29 | 0.21 | 0.39 | 0.03 | 0.73 | 0.56 | 0.26 | 0.08 | 0.35 | + |
| Thailand | 0.68 | 0.74 | 0.78 | 0.93 | 0.73 | 0.28 | 0.15 | 0.82 | 0.78 | 0.68 | 1.02 | 0.87 | + |
| Switzerland | 0.35 | 0.27 | 0.71 | -0.01 | 0.64 | 0.47 | 0.54 | 0.02 | 0.44 | 0.51 | 0.30 | 0.18 | - |
| South_Africa | 0.88 | 0.24 | 0.74 | 0.47 | 0.70 | 0.31 | 0.33 | 1.29 | 0.71 | 1.30 | 1.35 | 0.60 | + |
| Poland | 0.42 | 0.26 | 0.86 | 0.47 | 1.12 | 0.60 | 0.72 | 0.13 | 0.52 | -0.29 | 0.82 | 0.57 | + |
| Turkey | 0.98 | 0.16 | 0.35 | -0.28 | 0.40 | 0.35 | 0.63 | 0.05 | -0.14 | 0.60 | 0.49 | 0.20 | + |
| Greece | -0.30 | 0.51 | 0.39 | 0.40 | 0.35 | 0.30 | 0.18 | 0.18 | 0.01 | 0.17 | 0.34 | 0.79 | - |
| Indonesia | 1.29 | 0.24 | 0.44 | 0.54 | 0.54 | 0.43 | 0.59 | 0.15 | 0.81 | 0.64 | 0.50 | 0.54 | - |
| Vietnam | 1.01 | 0.56 | 0.57 | 0.38 | 0.60 | 0.28 | 0.29 | 0.35 | 0.77 | 1.18 | 1.21 | 1.79 | + |
| Israel | -0.09 | 1.29 | 0.84 | 0.94 | 0.69 | 0.13 | 0.18 | 0.78 | 0.45 | 1.48 | 0.84 | 0.67 | + |
| Denmark | 0.65 | 0.23 | 0.37 | 0.55 | 0.55 | 0.46 | 0.47 | 0.25 | 0.71 | 0.79 | 0.52 | 0.37 | - |
| Netherlands | 0.55 | 0.41 | 0.40 | 0.01 | 0.29 | 0.07 | -0.25 | 0.06 | 0.38 | 0.27 | 0.07 | 0.52 | + |
| Norway | 0.41 | 0.70 | 0.67 | 0.72 | 0.70 | 0.70 | 0.21 | 0.43 | 0.62 | 0.68 | 0.76 | 0.59 | - |
| Spain | 0.22 | 0.39 | 0.03 | -0.07 | 0.08 | -0.04 | 0.07 | -0.06 | -0.04 | -0.08 | -0.23 | -0.33 | - |
| Belgium | 1.17 | -0.27 | 0.10 | -0.22 | 0.08 | 0.31 | 0.02 | -0.27 | 0.81 | 0.03 | 0.10 | -0.06 | + |
| Finland | 0.70 | 0.36 | -0.06 | 0.02 | -0.13 | 0.65 | 1.10 | 0.76 | 0.36 | 0.36 | 0.37 | -0.19 | + |
| Sri_Lanka | 0.66 | -0.03 | 1.94 | 2.15 | 1.43 | 0.95 | 0.20 | 0.22 | 1.51 | 1.10 | 1.35 | 0.91 | + |
| Philippines | 0.89 | 0.21 | 0.75 | 0.39 | 1.02 | 0.64 | 0.02 | 0.99 | 0.65 | 0.78 | 0.35 | 0.53 | + |
| Pakistan | 1.17 | 0.87 | 1.20 | 0.66 | 1.11 | 1.04 | 0.79 | 0.67 | 0.60 | 0.52 | 0.77 | 0.15 | + |
| Saudi_Arabia | 0.05 | -0.11 | -0.05 | 0.49 | 0.00 | 0.25 | 0.28 | -0.36 | -0.75 | -0.86 | 0.07 | 1.04 | + |
| Jordan | -0.05 | 0.09 | 1.04 | 0.78 | 0.81 | 0.16 | -0.12 | -0.07 | 0.22 | 0.05 | 0.46 | 0.05 | + |
| Egypt | 0.72 | -0.03 | 0.24 | 0.00 | 0.32 | -0.26 | -0.02 | 0.45 | -0.35 | -0.03 | -0.94 | -0.19 | + |
| Chile | 0.65 | 0.25 | 0.43 | 0.05 | 0.63 | 0.25 | 0.77 | 0.31 | 0.17 | -0.31 | 0.00 | -0.14 | + |
| Brazil | 1.92 | -0.71 | -0.09 | 0.36 | -0.25 | -0.18 | -0.17 | 0.54 | 0.99 | 0.29 | 0.54 | 0.54 | + |
| Kuwait | 0.01 | 0.24 | -0.01 | -0.42 | 0.29 | -0.55 | -0.75 | -0.61 | -0.46 | 0.17 | 0.12 | 0.43 | - |
| Russia | 0.91 | -0.04 | 0.02 | 0.10 | 0.03 | -0.29 | -0.76 | 0.25 | -0.32 | 0.32 | 0.89 | -0.61 | - |

Panel B: Individual stock $R^2_{oos}$

| Country | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| USA | 0.29 | 0.41 | 0.45 | 0.41 | 0.79 | 0.68 | 0.71 | 0.77 | 0.76 | 0.76 | 0.68 | = |
| Japan | -0.19 | -0.47 | -0.31 | -0.47 | -0.18 | -0.48 | -0.19 | -0.80 | -0.49 | -0.59 | -0.39 | - |
| China | 0.66 | 0.75 | 0.76 | 0.75 | 0.59 | 0.28 | 0.76 | 0.68 | 0.33 | 0.50 | 0.69 | - |
| India | 0.18 | -0.02 | 0.23 | 0.01 | 0.35 | 0.08 | 0.19 | -0.04 | 0.26 | 0.21 | 0.22 | - |
| Korea | 0.64 | 0.78 | 0.84 | 0.79 | 0.80 | 0.61 | 0.80 | 0.68 | 0.82 | 0.96 | 1.02 | + |
| Hong_Kong | 0.91 | 0.88 | 0.84 | 0.88 | 1.03 | 1.12 | 0.71 | 0.96 | 0.90 | 0.94 | 1.14 | + |
| France | 0.50 | 1.01 | 0.97 | 1.01 | 0.81 | 0.66 | 1.29 | 1.39 | 1.36 | 1.21 | 0.95 | + |
| Germany | 0.14 | 0.16 | 0.18 | 0.16 | 0.51 | 0.32 | 0.65 | 0.32 | 0.22 | 0.04 | 0.12 | + |
| Australia | 0.32 | 0.59 | 0.52 | 0.59 | 0.80 | 0.55 | 0.91 | 1.11 | 1.08 | 1.06 | 0.97 | - |
| Malaysia | 0.19 | 0.35 | 0.47 | 0.36 | 0.51 | 0.19 | 0.41 | 0.73 | 0.83 | 0.44 | 0.57 | - |
| Taiwan | 0.06 | -0.20 | 0.06 | -0.18 | 0.05 | -0.23 | 0.25 | -0.09 | -0.38 | 0.04 | -0.21 | - |
| United_Kingdom | -0.14 | -0.16 | -0.16 | -0.15 | -0.17 | -0.32 | -0.02 | -0.06 | -0.20 | 0.11 | -0.09 | + |
| Singapore | 0.68 | 1.09 | 1.00 | 1.09 | 1.21 | 0.99 | 1.24 | 1.68 | 1.52 | 1.61 | 1.50 | + |
| Canada | 0.39 | 0.34 | 0.35 | 0.35 | 0.43 | 0.39 | 0.34 | 0.69 | 0.46 | 0.50 | 0.56 | - |
| Italy | 0.07 | 0.06 | 0.09 | 0.06 | -0.15 | -0.56 | 0.13 | -0.03 | -0.52 | -0.06 | 0.32 | + |
| Sweden | 0.16 | 0.31 | 0.27 | 0.32 | 0.63 | 0.67 | 0.43 | 0.69 | 0.53 | 0.52 | 0.32 | - |
| Thailand | 1.03 | 1.08 | 1.01 | 1.10 | 0.92 | 0.77 | 0.66 | 1.44 | 1.16 | 1.21 | 0.89 | + |
| Switzerland | 1.05 | 1.15 | 1.17 | 1.17 | 1.33 | 1.21 | 1.00 | 1.21 | 0.85 | 1.40 | 1.37 | + |
| South_Africa | 0.88 | 1.44 | 1.62 | 1.45 | 2.73 | 1.02 | 3.08 | 3.19 | 2.59 | 2.89 | 3.03 | + |
| Poland | -1.06 | -1.36 | -0.99 | -1.28 | -0.93 | -1.88 | -0.90 | -0.76 | -0.99 | -1.03 | -1.10 | - |
| Turkey | 2.88 | 2.95 | 2.86 | 2.94 | 3.40 | 2.79 | 2.77 | 3.08 | 2.59 | 2.87 | 2.72 | + |
| Greece | -0.57 | -0.51 | -0.57 | -0.50 | -1.13 | -0.50 | -0.81 | -0.44 | -0.90 | -0.75 | -1.00 | - |
| Indonesia | 1.46 | 1.49 | 1.48 | 1.49 | 1.33 | 1.32 | 1.40 | 1.38 | 1.49 | 1.45 | 1.58 | + |
| Vietnam | 0.10 | 0.15 | 0.15 | 0.15 | 0.32 | 0.39 | 0.01 | -0.12 | -0.28 | 0.08 | -0.61 | - |
| Israel | 0.35 | 0.15 | 0.25 | 0.21 | -0.10 | -0.92 | 0.33 | 0.08 | -0.09 | 0.09 | 0.40 | - |
| Denmark | -0.21 | -0.09 | -0.10 | -0.08 | -0.07 | -0.25 | 0.26 | -0.11 | -0.05 | -0.38 | -0.18 | - |
| Netherlands | 0.63 | 0.71 | 0.78 | 0.72 | 0.90 | 0.92 | 0.88 | 0.95 | 0.71 | 1.23 | 0.54 | + |
| Norway | 0.15 | -0.03 | 0.10 | 0.11 | -49.70 | - 244.97 | 0.14 | -0.35 | 0.12 | -0.13 | 0.24 | = |
| Spain | -0.89 | -0.91 | -0.93 | -0.91 | -1.33 | -1.58 | -0.98 | -0.98 | -1.13 | -0.59 | -1.41 | - |
| Belgium | 0.39 | 0.13 | 0.22 | 0.21 | -0.89 | -2.76 | 0.54 | 0.60 | 0.26 | 0.65 | 0.60 | + |
| Finland | 1.49 | 1.36 | 1.40 | 1.44 | 1.46 | 1.39 | 1.26 | 1.12 | 1.65 | 1.33 | 1.58 | + |
| Sri_Lanka | -6.68 | -6.57 | -5.82 | -6.20 | -6.18 | -6.44 | -5.23 | -7.11 | -6.25 | -6.31 | -6.29 | - |
| Philippines | -0.24 | -0.30 | -0.31 | -0.12 | -2.01 | -12.28 | 0.03 | 0.23 | 0.42 | 0.12 | 0.10 | - |
| Pakistan | 3.42 | 3.20 | 3.33 | 3.26 | 2.65 | 2.06 | 3.01 | 3.11 | 3.69 | 3.13 | 3.10 | + |
| Saudi_Arabia | -2.28 | -2.65 | -2.15 | -2.40 | -2.23 | -3.22 | -2.17 | -2.47 | -2.41 | -3.12 | -2.89 | - |
| Jordan | -0.76 | -0.86 | -0.76 | -0.78 | -0.89 | -2.04 | -0.97 | -0.95 | -0.46 | -1.25 | -1.33 | - |
| Egypt | 1.60 | 1.51 | 1.85 | 1.61 | 0.08 | -8.15 | 1.60 | 1.43 | 2.93 | 2.71 | 2.59 | + |
| Chile | 0.27 | 0.00 | 0.17 | 0.03 | 0.04 | -0.84 | -0.84 | -0.27 | -0.70 | -0.90 | -0.68 | - |
| Brazil | 0.80 | -0.03 | 1.36 | 0.17 | 0.83 | -2.89 | 3.21 | 4.44 | 3.74 | 6.20 | 3.60 | + |
| Kuwait | -2.32 | -2.67 | -1.64 | -1.96 | -1.84 | -2.88 | -1.72 | -1.77 | -1.77 | -1.55 | -1.21 | - |
| Russia | -0.23 | -1.74 | -0.15 | -1.05 | -0.45 | -2.14 | -1.11 | -0.24 | 0.09 | -0.93 | 0.00 | - |

## Panel C: Portfolio $R^2_{oos}$

| | Equal-Weighted | | | | | | | | | | | | Value-Weighted | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown | OLS-3 | LINEAR | LASSO | RIDGE | RF | GBRT+H | NN1 | NN2 | NN3 | NN4 | NN5 | UpDown |
| USA | 2.90 | 3.32 | 3.54 | 3.32 | 4.54 | 4.02 | 4.16 | 4.24 | 4.30 | 4.48 | 4.22 | = | 2.63 | 0.89 | 1.41 | 0.88 | 2.68 | 0.87 | 2.69 | 2.99 | 3.46 | 3.40 | 3.25 | = |
| Japan | -1.06 | -2.20 | -1.61 | -2.19 | -1.13 | -2.39 | -1.26 | -3.91 | -2.44 | -2.91 | -1.95 | - | -0.50 | -0.95 | -1.33 | -0.93 | -0.62 | -2.00 | -1.24 | -2.56 | -1.66 | -1.92 | -1.37 | - |
| China | 1.16 | 1.28 | 1.31 | 1.28 | 1.94 | 0.36 | 1.31 | 1.13 | 0.34 | 0.70 | 1.18 | - | 1.27 | 1.43 | 1.24 | 1.43 | 1.21 | -1.06 | 0.99 | 0.36 | -0.60 | -0.06 | 1.06 | - |
| India | 1.34 | 0.54 | 1.33 | 0.66 | 1.99 | 1.65 | 1.10 | 0.35 | 1.33 | 1.09 | 1.07 | - | -0.53 | -2.04 | -0.05 | -1.96 | 0.46 | -1.04 | -0.30 | -0.50 | 0.28 | 0.78 | -1.56 | - |
| Korea | 4.05 | 4.62 | 4.94 | 4.71 | 3.99 | 3.18 | 4.77 | 3.78 | 4.57 | 5.31 | 5.84 | + | 2.44 | 1.20 | 2.32 | 1.27 | 1.92 | -1.44 | 1.04 | 0.91 | 1.29 | 2.41 | 3.00 | + |
| Hong_Kong | 4.39 | 4.41 | 3.95 | 4.37 | 4.50 | 4.80 | 3.27 | 4.83 | 4.58 | 4.73 | 5.27 | + | 3.31 | 3.00 | 3.38 | 2.96 | 2.81 | 2.90 | 2.64 | 3.93 | 3.00 | 3.26 | 4.13 | + |
| France | 3.81 | 5.68 | 5.65 | 5.70 | 4.65 | 4.22 | 5.84 | 6.70 | 6.35 | 5.94 | 5.30 | + | 2.94 | 1.79 | 2.17 | 1.79 | 1.25 | 1.13 | 1.66 | 1.80 | 1.78 | 1.83 | 1.44 | + |
| Germany | 1.01 | 1.25 | 1.34 | 1.24 | 3.07 | 2.43 | 4.04 | 1.62 | 1.20 | 0.19 | 0.96 | + | 0.85 | 0.41 | 0.60 | 0.46 | 0.88 | 1.28 | 1.07 | 0.88 | 0.44 | 0.66 | 0.78 | - |
| Australia | 3.31 | 5.56 | 4.83 | 5.54 | 5.21 | 5.02 | 6.61 | 7.82 | 7.18 | 7.63 | 7.23 | + | 3.93 | 4.47 | 4.96 | 4.52 | 2.28 | 2.33 | 4.56 | 5.73 | 4.32 | 4.19 | 4.01 | + |
| Malaysia | 1.03 | 1.99 | 2.46 | 2.03 | 1.59 | 1.64 | 2.65 | 4.38 | 4.58 | 2.35 | 3.16 | + | 0.82 | 0.10 | 0.94 | 0.19 | -0.62 | -1.15 | 2.24 | 1.94 | 2.98 | 0.71 | 2.58 | + |
| Taiwan | 0.13 | -0.57 | 0.12 | -0.49 | -0.08 | -0.31 | 0.71 | -0.36 | -1.17 | 0.16 | -0.68 | - | -0.70 | -1.47 | 0.07 | -1.40 | -0.94 | -2.76 | -0.25 | -0.86 | -2.00 | -0.81 | -1.47 | - |
| United_Kingdom | 0.01 | 0.05 | -0.49 | 0.17 | 0.47 | -0.81 | 0.16 | 0.28 | -0.55 | 1.66 | -0.06 | + | 0.58 | 0.73 | 0.04 | 1.06 | 0.74 | -3.55 | 0.53 | 1.99 | 0.75 | 1.94 | 0.81 | - |
| Singapore | 2.63 | 3.21 | 2.97 | 3.26 | 3.95 | 2.74 | 3.60 | 4.73 | 4.53 | 4.82 | 4.72 | + | 2.20 | 0.47 | 0.91 | 0.56 | 1.40 | 0.59 | 1.91 | 3.07 | 1.85 | 2.99 | 3.54 | + |
| Canada | 1.59 | 0.98 | 0.95 | 1.00 | 2.53 | 2.24 | 1.73 | 3.75 | 1.85 | 1.92 | 2.73 | + | -1.06 | -1.26 | -0.68 | -1.06 | -0.05 | 1.13 | -0.39 | 1.62 | -1.35 | -1.00 | -0.04 | - |
| Italy | 0.38 | 0.19 | 0.34 | 0.19 | -0.31 | -0.84 | 0.45 | 0.01 | -1.82 | -0.08 | 1.37 | + | 0.06 | 0.00 | 0.18 | -0.10 | -0.49 | -0.73 | 0.34 | 0.10 | -1.41 | -0.01 | 1.25 | + |
| Sweden | 1.45 | 2.04 | 1.93 | 2.06 | 2.82 | 3.52 | 2.08 | 3.59 | 2.82 | 3.45 | 2.24 | - | 1.88 | 1.08 | 0.65 | 1.25 | 1.04 | 0.55 | 0.99 | 1.58 | -0.05 | 0.84 | 2.15 | - |
| Thailand | 4.36 | 4.52 | 4.29 | 4.55 | -0.70 | -4.27 | 2.51 | 6.12 | 4.79 | 4.98 | 3.30 | + | 3.81 | 3.93 | 4.54 | 3.96 | -5.78 | -5.67 | -1.17 | 1.35 | 1.25 | 1.97 | 1.97 | + |
| Switzerland | 4.62 | 4.98 | 5.05 | 5.10 | 5.13 | 5.72 | 4.48 | 5.64 | 3.87 | 5.81 | 6.02 | + | 2.66 | 2.37 | 2.34 | 2.40 | 2.01 | 3.92 | 2.59 | 2.93 | 2.22 | 3.43 | 3.86 | + |
| South_Africa | 7.35 | 9.28 | 9.29 | 9.44 | 12.86 | 6.71 | 11.94 | 10.99 | 9.92 | 11.00 | 12.09 | + | 4.52 | 1.68 | 2.22 | 1.93 | 2.97 | -4.29 | 4.83 | 4.26 | 4.44 | 6.15 | 3.90 | + |
| Poland | -10.91 | -12.79 | -11.43 | -12.09 | -11.79 | -17.15 | -11.06 | -9.89 | -11.48 | -11.15 | -11.56 | - | -9.45 | -8.59 | -8.55 | -7.09 | -7.15 | -9.51 | -7.30 | -5.20 | -9.09 | -7.65 | -7.24 | - |
| Turkey | 11.94 | 12.22 | 12.71 | 12.27 | 14.94 | 13.78 | 12.11 | 13.70 | 11.82 | 13.17 | 13.12 | + | 10.56 | 10.62 | 10.34 | 10.69 | 8.60 | 8.02 | 7.10 | 9.52 | 9.37 | 10.25 | 9.13 | + |
| Greece | -0.98 | -0.61 | -0.95 | -0.59 | 0.43 | -0.83 | -1.96 | -0.44 | -2.80 | -1.94 | -2.92 | - | -2.21 | -2.38 | -2.57 | -2.33 | -9.35 | -1.58 | -2.58 | -1.85 | -2.75 | -2.48 | -2.33 | - |
| Indonesia | 11.04 | 11.47 | 12.53 | 11.46 | 11.40 | 11.50 | 11.30 | 13.32 | 13.12 | 10.66 | 12.22 | + | 7.10 | 7.02 | 9.50 | 6.73 | 3.68 | 3.31 | 5.87 | 12.17 | 8.98 | 3.95 | 5.80 | + |
| Vietnam | -0.46 | -0.37 | -0.03 | -0.31 | -0.21 | 0.14 | -1.01 | -2.33 | -3.65 | -0.94 | -6.05 | - | 0.21 | -1.13 | -0.35 | -0.72 | 0.90 | 0.50 | -0.43 | 1.79 | 0.45 | 0.91 | 0.50 | - |
| Israel | 2.20 | 0.82 | 2.02 | 1.11 | 0.89 | -1.39 | 1.89 | 0.95 | -1.06 | 0.10 | 2.43 | - | 3.72 | 1.94 | 2.33 | 1.55 | 0.07 | -2.11 | 1.13 | 0.98 | 1.19 | 1.80 | 2.72 | + |
| Denmark | -0.57 | -0.28 | -0.30 | -0.13 | -0.15 | -0.25 | 1.40 | -0.08 | 0.32 | -1.29 | -0.26 | - | 1.44 | 1.07 | 1.15 | 1.21 | 0.71 | 0.70 | 1.94 | 1.73 | 1.53 | 1.13 | 1.39 | - |
| Netherlands | 2.31 | 2.47 | 2.54 | 2.48 | 2.96 | 3.48 | 2.83 | 3.54 | 2.32 | 4.21 | 2.37 | + | 1.06 | 1.48 | 1.08 | 1.24 | 1.80 | 1.95 | 1.42 | 1.82 | 1.95 | 3.51 | 2.02 | + |
| Norway | 0.61 | 0.39 | 0.34 | 0.70 | -231.98 | -1196.01 | 0.77 | -1.77 | 0.95 | -0.75 | 1.18 | - | -0.22 | 0.00 | -0.09 | 0.02 | -164.60 | -946.92 | 0.61 | -0.60 | 1.42 | 0.17 | 1.16 | - |
| Spain | -2.98 | -3.13 | -3.33 | -3.09 | -4.29 | -5.35 | -3.49 | -3.19 | -4.09 | -2.19 | -5.42 | - | -1.59 | -2.09 | -2.80 | -1.87 | -2.47 | -2.39 | -2.75 | -2.05 | -2.92 | -0.88 | -3.86 | - |
| Belgium | 1.88 | 0.85 | 1.58 | 1.25 | -12.02 | -5.73 | 2.45 | 2.69 | 1.39 | 2.95 | 3.20 | + | -0.15 | 0.25 | 0.63 | 0.42 | -9.32 | -4.42 | 1.43 | 1.43 | 0.44 | 2.15 | 1.58 | - |
| Finland | 4.09 | 3.72 | 3.85 | 3.87 | 3.81 | 3.35 | 4.58 | 4.07 | 5.72 | 4.58 | 5.69 | + | 2.69 | 1.97 | 2.87 | 2.00 | 2.63 | 2.83 | 4.11 | 3.60 | 4.66 | 2.99 | 4.43 | + |
| Sri_Lanka | -24.44 | -23.90 | -22.68 | -22.68 | -23.19 | -23.38 | -20.15 | -26.82 | -23.04 | -24.19 | -23.17 | - | -28.59 | -22.21 | -23.27 | -19.24 | -28.18 | -33.84 | -23.55 | -31.52 | -29.17 | -27.75 | -26.97 | - |
| Philippines | -1.03 | -1.48 | -1.61 | -0.48 | 0.18 | -15.45 | -1.08 | 0.20 | 2.74 | -0.98 | -0.69 | - | -2.53 | -2.62 | -8.44 | -2.17 | -26.18 | -48.18 | -11.29 | 0.00 | -0.53 | -3.37 | -2.99 | - |
| Pakistan | 11.54 | 11.10 | 11.54 | 11.23 | 11.09 | 11.26 | 10.75 | 11.67 | 13.38 | 10.91 | 12.29 | + | 9.01 | 9.12 | 8.75 | 9.02 | 4.95 | 7.94 | 6.19 | 10.27 | 10.21 | 7.21 | 11.68 | + |
| Saudi_Arabia | -4.52 | -5.21 | -4.51 | -4.79 | -4.49 | -5.76 | -4.47 | -5.14 | -5.10 | -6.42 | -6.03 | - | -4.23 | -5.51 | -4.67 | -4.90 | -4.27 | -4.66 | -3.81 | -4.62 | -6.51 | -6.51 | -6.81 | - |
| Jordan | -5.54 | -5.26 | -5.18 | -5.31 | -4.63 | -3.21 | -6.60 | -9.42 | -3.55 | -10.41 | -11.16 | - | -4.84 | -3.94 | -2.59 | -3.91 | -2.13 | -8.86 | -4.36 | -8.71 | -2.50 | -5.15 | -7.12 | - |
| Egypt | 3.89 | 3.62 | 5.40 | 3.86 | 2.96 | -3.17 | 4.01 | 3.67 | 8.01 | 7.25 | 7.01 | + | 3.56 | 3.29 | 5.40 | 3.42 | 2.34 | 1.45 | 3.23 | 3.16 | 7.93 | 6.45 | 6.98 | + |
| Chile | -0.16 | -0.51 | -0.47 | -0.46 | -1.52 | -5.09 | -2.90 | -0.98 | -3.12 | -4.23 | -3.90 | - | -0.87 | -2.58 | -0.12 | -1.94 | -5.55 | -7.67 | -3.91 | -5.44 | -3.32 | -5.52 | -3.10 | - |
| Brazil | 1.28 | 0.30 | 0.22 | 0.56 | 1.45 | 0.48 | 10.19 | 18.38 | 11.72 | 20.99 | 14.74 | + | 1.03 | 0.44 | -0.02 | 1.01 | 1.12 | 0.64 | 7.34 | 15.78 | 8.53 | 14.70 | 13.20 | + |
| Kuwait | -7.53 | -8.92 | -7.25 | -6.78 | -6.45 | -10.25 | -6.20 | -7.81 | -6.57 | -5.35 | -4.93 | - | -9.41 | -13.56 | -6.98 | -9.32 | -12.05 | -20.11 | -12.25 | -7.96 | -9.48 | -5.33 | -12.51 | - |
| Russia | 0.00 | -4.77 | 0.93 | -3.90 | -0.93 | -4.94 | -3.18 | 0.62 | 2.22 | -2.36 | 2.33 | - | -3.73 | -8.78 | -9.53 | -8.81 | -6.50 | -4.62 | -7.26 | -1.16 | -17.08 | -5.48 | 3.39 | - |

**Figure 4. Relative Importance by Model in US**

Variable importance for the 12 stock characteristics (listed in Table 2) in each model in the US market. Rows correspond to individual models, and color gradients within each column indicate the most influential (dark blue) to least influential (red) variables. Variable importances within each model are normalized to sum to one.

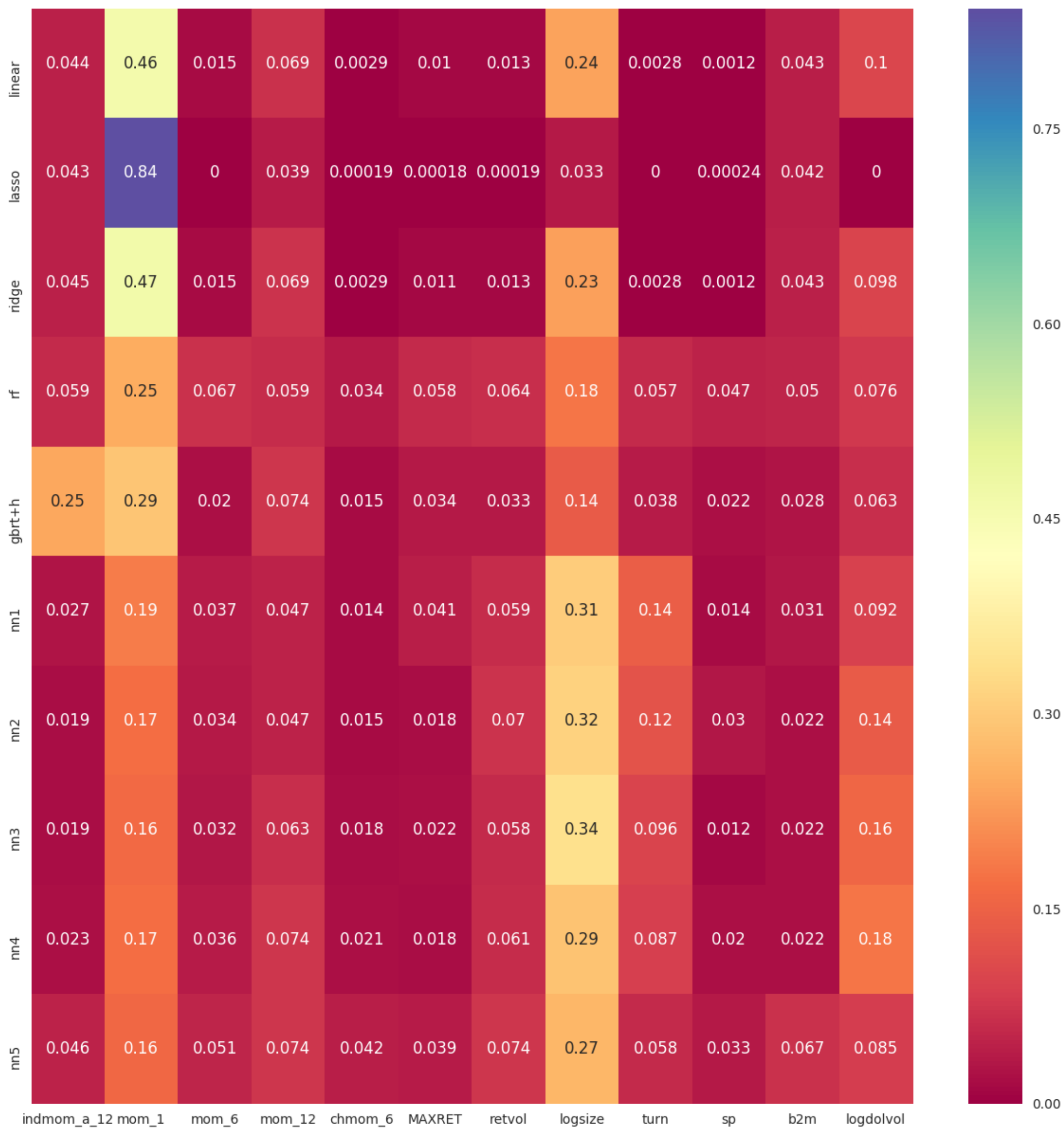

**Figure 5. Relative Importance: International Markets**

Variable importance for the 10 stock characteristics (listed in Table 2) in the best performing NN model (based on $R^2_{oos}$) in each market. Rows correspond to each market, and color gradients within each column indicate the most influential (dark blue) to least influential (red) variables. Variable importances within each model are normalized to sum to one. The figure lists the top 15 market based on the number of observations.

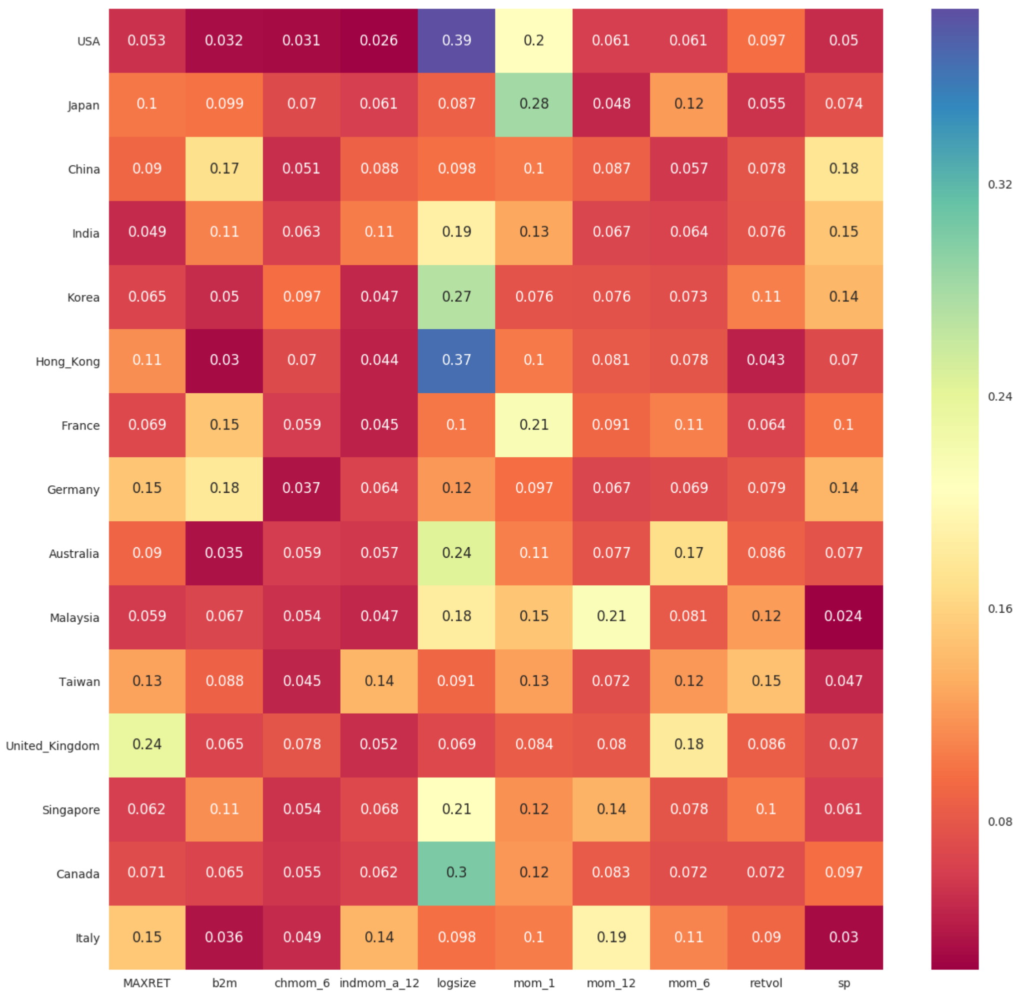

**Figure 6. Relative Importance by Model in China**

Variable importance for the 12 stock characteristics (listed in Table 2) in each model in China. Rows correspond to individual models, and color gradients within each column indicate the most influential (dark blue) to least influential (red) variables. Variable importances within each model are normalized to sum to one.

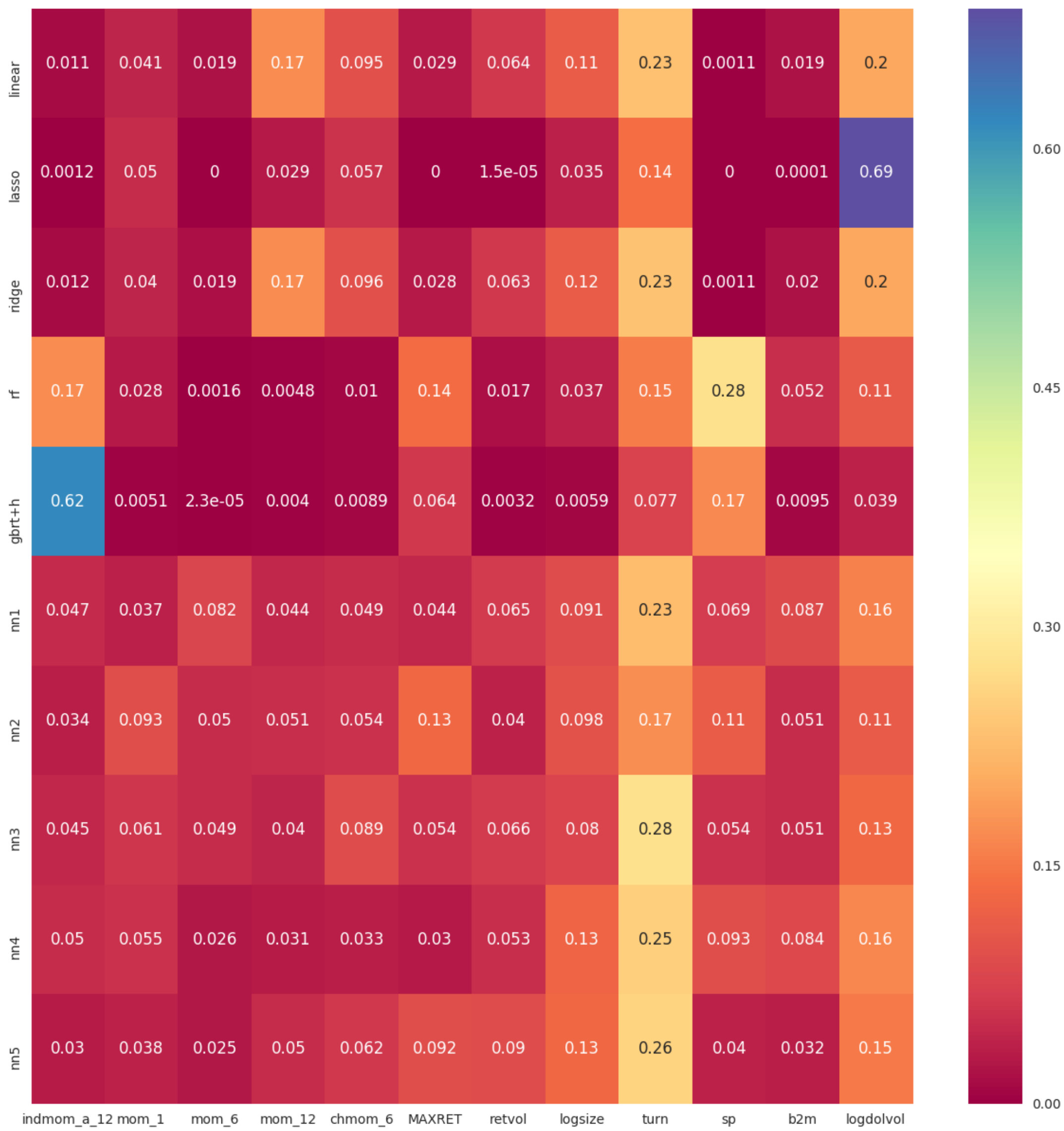

**Figure 7. Relative Importance by Model in Japan**

Variable importance for the 10 stock characteristics (listed in Table 2) in each model in Japan. Rows correspond to individual models, and color gradients within each column indicate the most influential (dark blue) to least influential (red) variables. Variable importances within each model are normalized to sum to one.

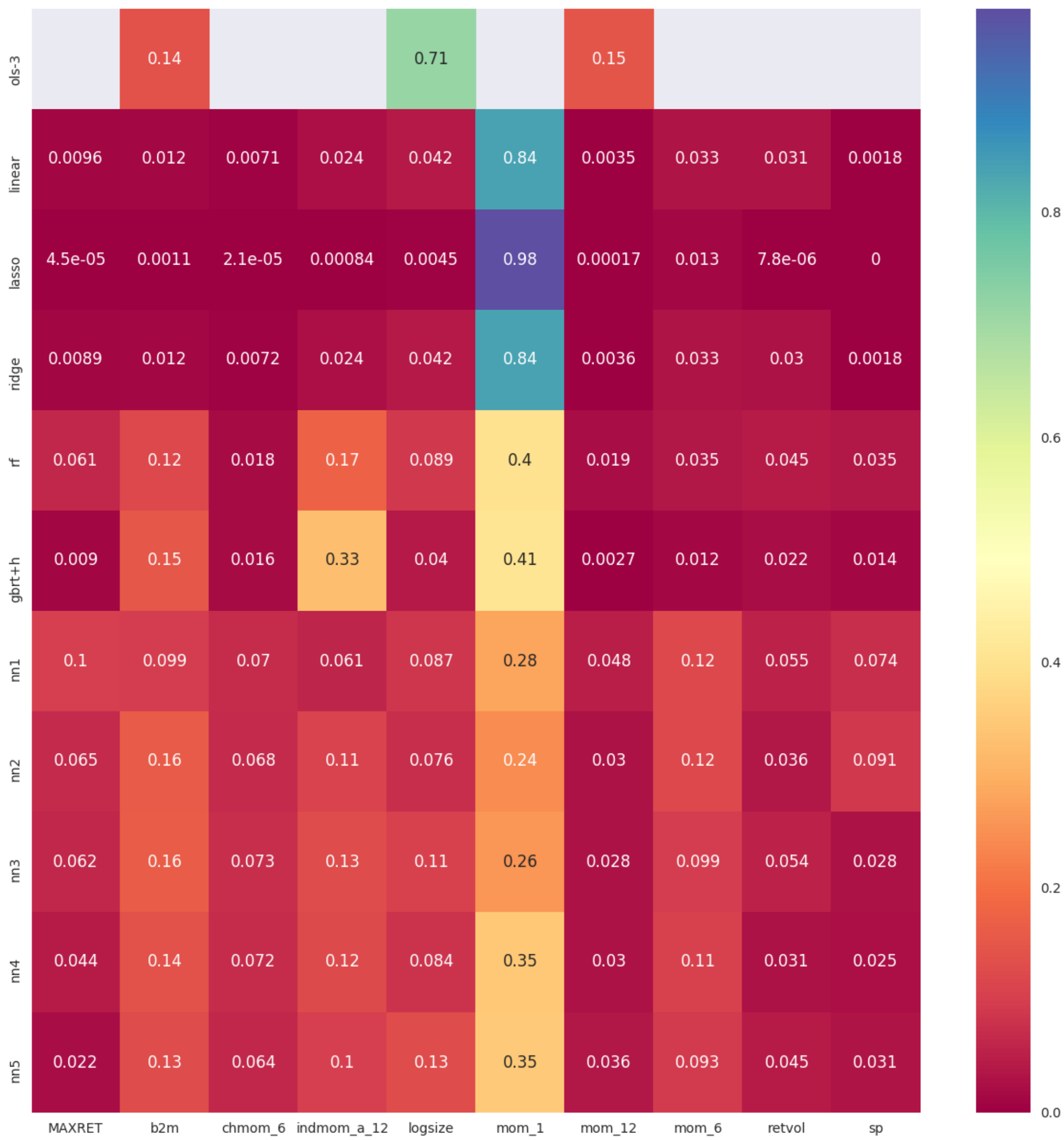

**Figure 8.** Expected Returns and Characteristic Interactions in China

Sensitivity of expected monthly returns (vertical axis, in unit) to interactions effects for size (*logsize*) with turnover (*turn*) in linear model (left panel) and NN4 model (right panel) (holding all other covariates fixed at their mean values). Models are estimated using the 12 stock characteristics (listed in Table 2) in China in 2014.

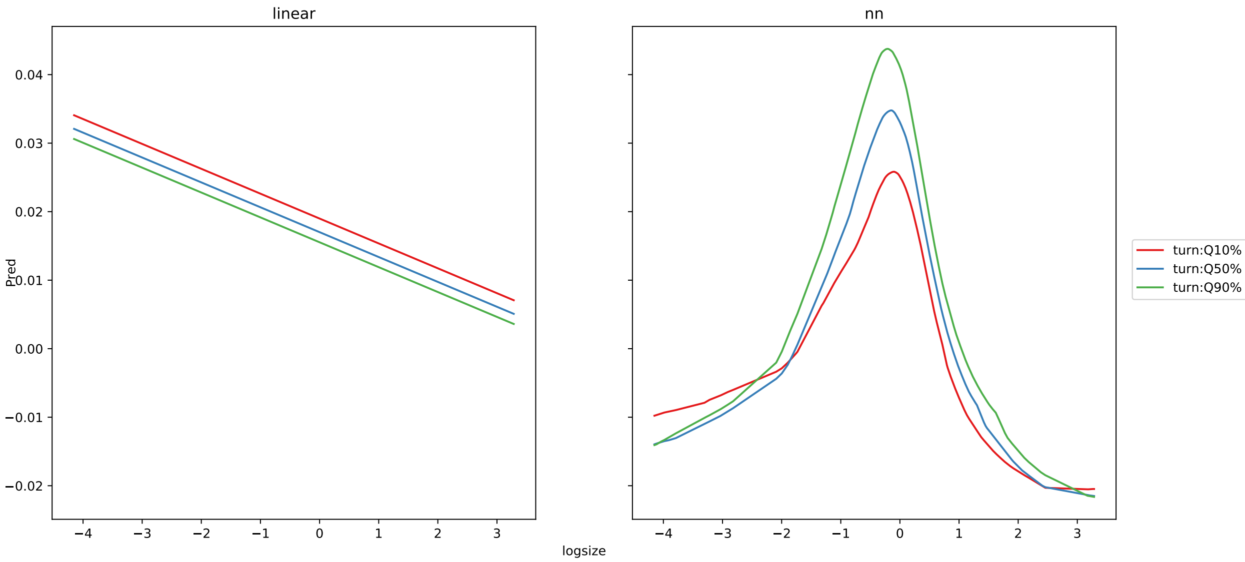

**Figure 9.** Expected Returns and Characteristic Interactions in Japan

Sensitivity of expected monthly returns (vertical axis, in unit) to interactions effects for momentum ($mom\_6$) with size ($logsize$) in linear model (left panel) and NN1 model (right panel) (holding all other covariates fixed at their mean values). Models are estimated using the 10 stock characteristics (listed in Table 2) in Japan in 2014.