

Effective Machine Learning Estimates of Stock Market Returns using Taylor-Rule Inputs

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Abstract

We apply a machine learning approach to estimate 1-year-ahead U.S. excess stock market returns over the 1964-2024 period using inflation and output gap variables as inputs in a Taylor-rule framework. Utilizing a 60-month rolling training window, our Support Vector Regression (SVR) estimates account for about 40% of the variation in realized excess returns. Subsample analysis confirms significant explanatory power across different monetary-policy environments. Our results suggest that SVR effectively detects the dynamically complex interrelationships between the Federal Reserve's policy targets and future equity returns.

Keywords: Support Vector Regression, Machine Learning, Monetary Policy, Stock Market Returns, Taylor-Rule Variables

1. Introduction

This paper applies a Support Vector Regression (SVR) machine-learning model to estimate 1-year-ahead excess stock market returns using as input variables the current output gap and lagged inflation, which Taylor (1993) proposed as key determinants of monetary policy.¹ Traditional models using these “Taylor-rule” variables have struggled to achieve much out-of-sample explanatory power, especially over long periods marked by shifting policy regimes and structural changes (Goyal et al., 2024). Kelly et. al (2024) have shown that machine learning techniques combining Taylor-rule variables with a kitchen sink of other inputs typically demonstrate very poor out-of-sample forecasting performance.

The dynamically complex interrelationships among inflation, the output gap, monetary policy, and economic activity (Coibion & Gorodnichenko, 2012), along with their intricate association with stock market prices and returns (Pflueger & Rinaldi, 2022), may explain why simple univariate and other models using isolated Taylor-rule variables fail to successfully capture the relationships that drive excess returns. For instance, the Federal Reserve tends to adjust monetary policy to changes in the output gap and inflation only gradually over time (Stein & Sundaram, 2018), with real effects occurring after uncertain delays (Romer & Romer, 2004). Moreover, the relative emphasis on these variables has shifted across policy regimes (Clarida et al. 2000).

To address these limitations, we employ a nonlinear SVR framework² to explore whether significant relationships between ex-ante Taylor-rule inputs and ex-post excess stock returns can be identified even under shifting monetary-policy regimes. SVR’s ability

¹Taylor (1993) suggested that the Federal Reserve set short-term interest rates as a linear function of inflation and the output gap. However, policy has often deviated from this rule, for example, during Volcker’s period of money-supply targeting or when Greenspan and Bernanke maintained rates below Taylor-rule levels (Hoover Institution, 2023). Hence, these variables act only as proxies for the Fed’s policy setting rather than reflecting a fixed rule.

²Kelly & Xiu (2023) and others demonstrate the potential of machine-learning methods to capture nonlinear patterns in economic and financial data that standard approaches often miss. However, prior SVR applications to stock market prices have generally relied on daily data using past equity prices as the only inputs (Chhajer et al., 2022).

to map predictors into higher-dimensional feature spaces (Kecman, 2005) allows it to capture complex, nonlinear dependencies (Caballero & Simsek, 2023). Our results show that the SVR model explains roughly 40% of the out-of-sample variation in 1-year-ahead excess stock returns over the last six decades.

The model’s explanatory power remains significant across four distinct monetary-policy subperiods, including: (i) the 1964-1978 pre-Full Employment and Balanced Growth Act era, before employment targeting became a formal policy objective; (ii) the 1983-1987 late-Volcker period, when monetary policy gradually shifted away from strict money-supply targets; (iii) the 1984-2024 post-Act era emphasizing the dual mandates of employment and price stability; and (iv) the 2002-2024 inflation-targeting period, during which the Fed increasingly emphasized keeping inflation close to its 2 percent target. Explanatory power is lowest during the late-Volcker years, consistent with reduced model performance when monetary policy remained less directly linked to the Taylor-rule inputs.

Finally, our findings are robust to alternative machine-learning algorithms, training-window lengths, additional macro-financial variables, and first-differenced Taylor-rule inputs. Across specifications and subperiods, the SVR framework consistently delivers strong and statistically significant out-of-sample explanatory performance.

2. Data

We employ monthly U.S. data spanning 1959/1-2024/12. The dependent variable is the 1-year-ahead excess S&P500 return over the 1-year U.S. Treasury bill yield. The explanatory (input) variables are the 12-month CPI inflation and the output gap, measured as the percentage deviation of actual from potential GDP. Data are obtained from Bloomberg, the Bureau of Labor Statistics, and the Federal Reserve. Summary statistics are reported in Appendix Table A.1.

3. Analytical Framework

We apply a Support Vector Regression (SVR) model (Smola and Schölkopf, 2004) to estimate 1-year-ahead excess stock returns using Taylor-rule input variables - inflation and the output gap - as well as in robustness extensions including unemployment, first-differenced inputs, and additional macro-financial predictors. The SVR estimates a nonlinear function $f(X)_t$ by solving

$$\min_{w, b, \xi_t, \xi_t^*} \frac{1}{2} \|w^2\| + C \sum_t (\xi_t + \xi_t^*) \quad (1)$$

subject to:

$$\begin{aligned} y_t - (w' \phi(X_t) + b) &\leq \varepsilon + \xi_t \\ (w' \phi(X_t) + b) - y_t &\leq \varepsilon + \xi_t^* \\ \xi_t, \xi_t^* &\geq 0 \end{aligned}$$

where w is the weight vector, b is the intercept, and $\phi(\cdot)$ denotes a nonlinear mapping from the input space to a higher-dimensional feature space. The regularization parameter $C > 0$ controls the trade-off between model smoothness and tolerance for deviations exceeding ε ; $\varepsilon > 0$ defines the width of the ε -insensitive loss tube, and the slack variables ξ_t, ξ_t^* measure errors beyond that threshold. The term $\frac{1}{2}\|w\|^2$ ensures smoothness and prevents overfitting.

To capture nonlinearity, we use a SVR with a Radial Basis Function (RBF) kernel, so that the estimated value for the 1-year ahead S&P500 excess return is

$$\hat{y}_{t+1} = \sum_{i=1}^n (\alpha_i - \alpha_i^*) \exp(-\gamma \|x_i - x_t\|^2) + b, \quad (2)$$

where, the parameters C , ε , and γ control regularization, tolerance, and flexibility, respectively. α_i, α_i^* are dual coefficients obtained from ε -SVR optimization (as explained in Appendix A.2), x_i is predictor vector for i^{th} training observation, x_t is predictor vector at time t , and b is the bias term. The study utilizes the SVR parameters $C = 1$, $\gamma = 0.5$, and $\varepsilon = 0.1$, consistent with standard applied settings (Smola & Schölkopf, (2004); Wu & Wang, (2023)). Estimation uses a 60-month rolling training window and estimation accuracy is evaluated using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and McCracken's (2007) F-test. Full model details and robustness analyses appear in the Appendix.

4. Results

Table 1 reports the explanatory performance of the SVR model across the full sample and major monetary-policy subperiods. For the full out-of-sample interval (1964-2024), using a 1959-1963 training window for the first estimation, the SVR model yields an RMSE of 12.61% and an MSE of 159.07%. The corresponding F-statistic of 481.73 indicates that the model's ex-ante estimation accuracy differs significantly from the ex-post mean benchmark at the 0.001 level over this six-decade interval. The out of sample R^2_{oos}

of 0.4008 implies that the SVR estimates reduce squared residual variance by over 40% relative to the ex-post variance of 265.35%. These results suggest that a nonlinear SVR model using only the two core Taylor-rule inputs, lagged inflation and the output gap, accounts for a significant portion of the variation in 1-year-ahead excess stock market returns. Figure 1 illustrates the strong association between the actual and estimated 1-year-ahead excess stock returns, consistent with the high out-of-sample R^2_{OOS} reported in Table 1.

The model’s explanatory power remains robust across distinct monetary-policy regimes. The lowest estimation errors (MSE=102.89%) occur in the 1964-1978 pre-Act subperiod, which exhibits the highest R^2_{OOS} of roughly 50%. Explanatory accuracy declines moderately (to about 30%) in the 1984-2024 post-Act era, when the Federal Reserve formally targeted full employment, and remains similar during the 2002-2024 inflation-targeting era. In contrast, during the 1983-1987 late-Volcker years, the SVR model produces the weakest performance, with an R^2_{OOS} of about 7%. This decline in accuracy is consistent with the model’s reduced explanatory power during a transitional phase when monetary policy shifted away from monetary-aggregate targeting toward interest-rate smoothing.

Overall, the results indicate that the dynamic SVR model maintains significant explanatory power across distinct monetary-policy regimes. Its performance weakens when monetary policy is less focused on the Taylor-rule variables. These findings suggest that, although machine learning methods can adapt to fluctuating macro-financial conditions, their relative explanatory strength is sensitive to shifts in the policy framework and to changes in the relevance of included inputs. The late-Volcker period thus illustrates how shifts in policy focus can alter the strength of relationships relating inflation, the output gap, and asset returns. Nonetheless, even during that regime, the SVR model continues to produce statistically significant estimates of future returns.

Robustness checks using alternative machine-learning methods confirm the consistency of these findings. As reported in Table 2, Random Forest, XGBoost, and Neural Network models (described in Appendix A.2) produce mean-squared errors significantly smaller than the 1964-2024 benchmark variance. Appendix Tables A.2-A.4 show that,

except for the late-Volcker era, these alternative models generally maintain strong explanatory accuracy across subperiods. Furthermore, Appendix Tables A.5-A.9 provide additional evidence of robustness to alternative model specifications. The findings provide some evidence that shorter, rolling windows better capture time-varying relationships between macroeconomic conditions and asset returns (Tables A.5 and A.6). Including unemployment as a third input (Table A.7) improves explanatory power, particularly before 1979, consistent with monetary and fiscal policy historically responding to labor-market conditions alongside inflation and the output gap. Adding more macro-financial inputs (Table A.8) yields some improvement in estimation accuracy over the most recent subperiod. However, using first-differenced Taylor-rule variables (Table A.9) reduces explanatory performance relative to the baseline model. Overall, 37 of 41 F-tests across samples and specifications reject the null of no explanatory power.³

5. Conclusion

This study shows that an SVR model using only lagged inflation and the output gap as inputs can ex-ante explain a large and statistically significant portion of the 1-year-ahead U.S. excess stock returns over the 1964-2024 period. The results are robust across alternative machine learning methods, training-window lengths, and input specifications. The model maintains substantial explanatory power across distinct monetary-policy regimes, with only a modest decline during the late-Volcker period, when policy focus shifted away from monetary-aggregate targeting toward interest-rate smoothing.

Robustness checks in Table 2 show that alternative methods, Random Forest, XGBoost, and Neural Networks, also yield mean-squared errors significantly below the benchmark variance. Extended results in Appendix Tables A.2-A.9 confirm that the SVR estimates remain strong when different training windows, additional variables (including unemployment), and first-differenced Taylor-rule inputs are used. Overall, significant explanatory power is found in 37 of 41 F-tests across models and subperiods.

³For comparison, we also estimated (i) an in-sample OLS regression of future annual excess returns on the inflation rate and output gap and (ii) a 60-month rolling OLS forecast using monthly data, mirroring the overlapping look-ahead horizon of the main SVR model. Both linear benchmarks produced R^2 and R^2_{OOS} values below 0.20 for the 1964-2024 interval (see Appendix Tables A.10-A.11), confirming that the linear specifications exhibit significantly weaker explanatory power and highlighting the importance of capturing nonlinearities in the Taylor-rule variables.

The evidence indicates that future excess stock market returns are closely related to the current inflation rate and output gap, two key variables that shape monetary policy decisions and investors' expectations about real activity and profitability. This finding suggests that the ex-ante explanatory power of the bivariate SVR model for estimating future returns reflects the transmission of macroeconomic conditions into asset prices. Accordingly, the results provide new evidence that macro-financial interactions integrated in monetary-policy frameworks help account for medium-term variations in equity risk premia.

Table 1
Stock Market Estimation Accuracy of the SVR Model^{a,b}

Estimation Out-of-Sample Period ^c	Initial Training Window	R ² _{oos}	MAE	RMSE	MSE	F-statistic
1964-2024	1959-1963	40.08%	9.29%	12.61%	159.07%**	481.73
1964-1978	1959-1963	49.82%	7.67%	10.14%	102.89%**	166.76
1983-1987	1987-1982	6.99%	11.24%	14.94%	224.24%*	3.61
1984-2024	1979-1983	28.03%	10.01%	13.67%	186.97%**	109.95
2002-2024	1997-2001	24.17%	10.46%	14.25%	203.03%**	85.45

* and ** indicate that the model's MSE is significantly smaller than the out-of-sample variance at the 0.10 and 0.001 level, respectively.

^a The model uses the output gap and inflation as explanatory variables.

^b Regularization parameter=1; Smoothing parameter=0.5; error-fitting parameter=0.1

^c The indicated out-of-sample period begins 60 months after the initial in-sample training window.

Table 2
Stock Market Estimation Accuracy across Machine Learning Methods

Model ^a	R ² _{OOS}	MAE	RMSE	MSE	F-statistic
Random Forest ^b	48.05%	9.22%	12.18%	148.50**	567.33
XGBoost ^c	23.86%	10.55%	14.21%	202.05**	225.28
Neural Network ^d	7.10%	12.04%	15.71%	246.51**	55.10

** indicates that the model's MSE is significantly smaller than the out-of-sample variance at the 0.001 level.

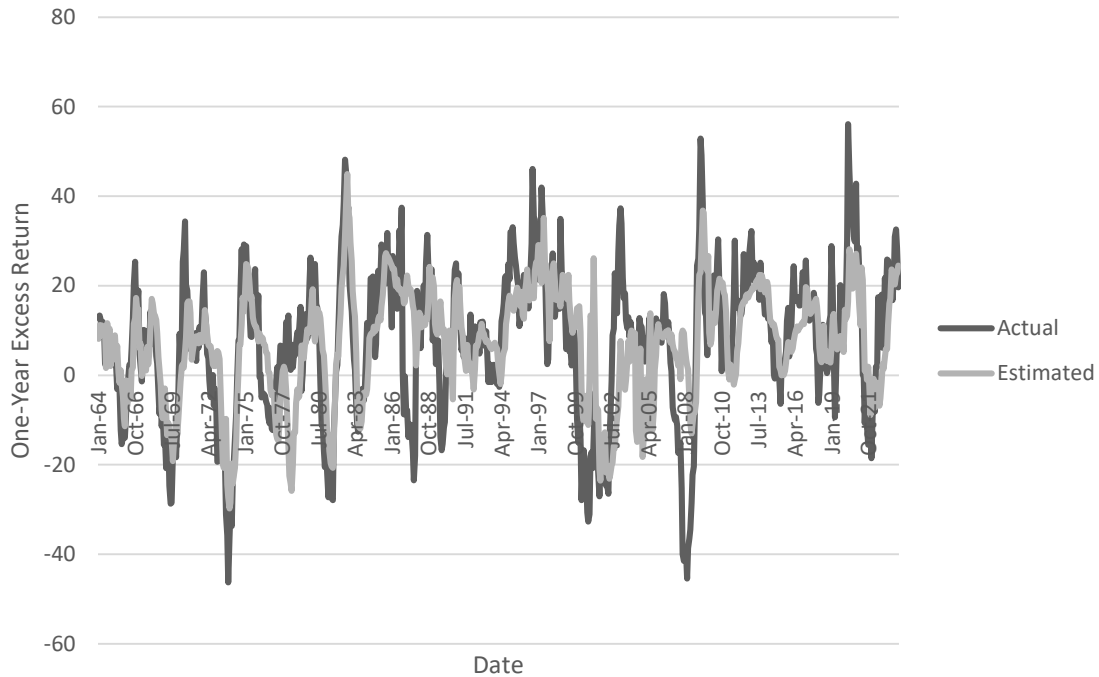
^a The model uses the output gap and inflation as explanatory variables. The 1964-2024 out-of-sample period begins 60 months after the initial in-sample training window (1959-1963).

^b 500 trees; minimum split size=5.

^c Learning rate = 0.3; training instance = 0.8; maximum depth=4; maximum iterations=100.

^d Two neurons; one hidden layer; sigmoid activation function.

Figure 1
Actual and SVR -Estimated 1-Year Excess Stock Return, 1964-2024



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Online Appendix for:
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A.1 Descriptive Statistics

Table A.1 provides summary statistics for the main variables used in the analysis over the 1964-2024 sample period. The dependent variable is the one-year-ahead excess S&P 500 return, defined as the future 1-year total return on the S&P 500 index minus the 1-year U.S. Treasury bill yield, measured ex-ante using information available at time t . The explanatory variables are the 12-month CPI inflation rate and the output gap, measured as the percentage deviation of actual from potential GDP.

Table A.1
Descriptive Statistics of Main Variables
(1964-2024)

Variables^a	Mean	Standard deviation	Skewness	Kurtosis	Range
Inflation	3.73%	2.81%	1.53	2.47	-2.10% to 14.76%
Output Gap	-0.85%	2.37%	0.16	0.65	-10.42% to 5.70%
1-year Excess Return	7.22%	16.11%	-0.43	0.37	-46.25% to 56.17%

Notes: The sample covers monthly U.S. data from January 1964 to December 2024.

^aThe output gap and inflation are the inputs to the estimation process and the future excess return is the output variable being estimated.

A.2 Machine Learning Methods Employed in Robustness Checks

Four different machine-learning methods are employed to assess the robustness of the baseline SVR explanatory results.⁴ These include the Support Vector Regression (SVR) model used in the main analysis, as well as three alternative approaches: Random Forest, XGBoost, and Neural Network. The robustness tests beyond the SVR framework also

⁴Machine learning procedures offer tools for capturing nonlinear and higher dimensional relationships (Kelly et. al, 2024). Recent asset pricing research has incorporated such methods, with studies such as by Gu et. al (2020), Giglio et. al (2022), and Kelly & Xiu (2023) showing their potential to capture some nonlinear patterns in economic/financial data that standard approaches may fail to detect.

include, different training-window lengths, additional input variables, and first-differenced Taylor-rule predictors.

As with the main testing, the explanatory power of the results is evaluated using the R^2_{OOS} , MAE, RMSE, and MSE, with the McCracken (2007) F-statistic testing for a positive difference between the out-of-sample variance ($VARIANCE_{out-of-sample}$) and the model's mean squared residual (MSE_{model}). The F-statistic is computed as

$$F = N[\{VARIANCE_{out-of-sample} - MSE_{model}\} / MSE_{model}], \quad (A-1)$$

where N equals the number of observations minus 12 overlapping periods in the explained variable (i.e., in the 1-year future excess return on the S&P500). The R^2_{OOS} is calculated as

$$R^2_{OOS} = 1 - (MSE_{model} / VARIANCE_{out-of-sample}). \quad (A-2)$$

A.3 Description of Machine Learning Procedures

This subsection describes the procedures utilized in each of the four machine-learning methods applied in this study to estimate excess stock returns. Each of the four methods enables detection of complex non-linearities in the relationships among variables. They are thus hypothesized to be appropriate for estimating the convoluted interrelationships between existing economic/financial variables and future stock market returns.

a) Support Vector Regression (SVR)

The SVR model employs a radial basis function (RBF) kernel within an ε -SVR optimization process. The ε -SVR optimization is the process of finding the optimal SVR model using an ε -insensitive tube where the objective is to minimize prediction errors while keeping the model simple. Any data point falling within the ε -insensitive tube is considered acceptable while any point outside the tube is penalized. The tradeoff between model flatness and error tolerance is controlled by a regularization parameter (C) where a higher regularization parameter value reduces tolerance for errors but may result in overfitting, while a lower regularization parameter value increases tolerance for errors and produces a smoother function (Smola & Scholkopf, 2004). In RBF, the parameter γ controls the influence of each training observation where a lower value makes the model smoother

while a larger value makes the model more flexible but may result in overfitting. Epsilon defines the width of the ε -insensitive tube and indicates how much error is ignored when fitting the model. The SVR estimates are obtained using $C = 1$, $\gamma = 0.5$ and $\varepsilon = 0.1$, where γ equals to the reciprocal of number of input variables.

b) Random Forest

A Random Forest is a machine learning algorithm that builds an ensemble of decision trees on different samples of the data. Each tree produces an individual estimate, and the final output is obtained by averaging across trees. Random Forests can handle complex, nonlinear and high dimensional data and are robust to outliers and noisy data (Ho, 2025). The Random Forest estimates in this study are based on 500 trees with a minimum node size of 5 for splitting.

c) XGBoost

XGBoost (eXtreme Gradient Boosting) is an advanced machine learning algorithm that implements gradient boosting. XGBoost is an ensemble of sequential decision trees where a new tree is trained to correct the residual errors of the previous ones. The algorithm keeps adding trees until additional iterations no longer improve the model's accuracy (Deka and Weiner, 2024). The XGBoost estimates are calculated using a learning rate of 0.3, a maximum tree depth of 4, a subsample ratio of training instance of 0.8, and maximum boosting iterations of 100. The learning rate controls the rate at which the model weights are updated, maximum depth specifies the maximum number of allowed splits in a tree, while subsample ratio indicates the percentage of randomly selected training instances used to train each new tree.

d) Neural Network

A neural network consists of an input layer which represents the input variables and an output layer which represents the outcome variable. It has one or multiple hidden layers which receive inputs from the input layer and transforms them using an activation function before passing them as inputs to the output layer. A neural network can handle complex and nonlinear patterns in the data (Vrbka, J. 2021). In this study, the neural network consists of one-hidden layer with two neurons and a sigmoid activation function with 1000 maximum training iterations.

Tables A.2, A.3, and A.4 report the robustness results for Random Forest, XGBoost, and Neural Network estimations, respectively. None of the alternative methods exhibit meaningful explanatory power for the 1983-1987 subsample. Except for this interval and the weaker Neural Network performance during 2002-2024, all three methods yield MSEs significantly below the out-of-sample variance for both the full sample and other subperiods. These results support the difficulty of explaining stock market variations with Taylor-rule inputs during periods when monetary policy emphasized monetary aggregates, such as the Volcker era. The weaker performance of the Neural Network during 2002-2024 may reflect challenges in estimating relationships when policy focus shifts toward a single target or when monetary policy deviates from Taylor-rule benchmarks.

Table A.2
Stock Market Ex-Ante Estimation Accuracy with Random Forest^a

Estimation Out-of-Sample Period^b	Initial Training Window	R²_{oos}	MAE	RMSE	MSE	F-statistic
1964-2024	1959-1963	44.04%	9.22%	12.19%	148.50%**	567.33
1964-1978	1959-1963	51.81%	7.52%	9.94%	98.79%**	180.65
1983-1987	1978-1982	-1.63%	12.72%	15.65%	245.03%	N/A
1984-2024	1979-1983	34.31%	9.83%	13.05%	170.33%**	125.35
2002-2024	1997-2001	35.19%	9.69%	13.16%	173.10%**	131.45

* and ** indicate an MSE for the SVR estimate that is significantly less than the out-of-sample variance at the 0.10 and 0.001 level, respectively.

^a The Random Forest estimation is calculated using 500 trees and a minimal node size to split of 5.

^b The indicated out-of-sample period is 60 months after the initial date of the in-sample rolling training window using the output gap and inflation as inputs.

Table A.3
Stock Market Ex-Ante Estimation Accuracy with XGBoost^a

Estimation Out-of-Sample Period^b	Initial Training Window	R²_{oos}	MAE	RMSE	MSE	F-statistic
1964-2024	1959-1963	23.86%	10.55%	14.21%	202.05%**	225.28
1964-1978	1959-1963	29.42%	8.77%	12.03%	144.71%**	70.02
1983-1987	1978-1982	-48.93%	14.84%	18.96%	359.96%	N/A
1984-2024	1979-1983	15.94%	11.21%	15.10%	228.17%**	32.73
2002-2024	1997-2001	18.40%	10.98%	14.76%	217.97%**	50.05

* and ** indicate an MSE for the SVR estimate that is significantly different less than the out-of-sample variance at the 0.10 and 0.001 level, respectively.

^a The XGBoost estimate is calculated using a learning rate of 0.3, a maximum depth of 4, a subsample ratio of training instance of 0.8, and maximum boosting iterations of 100.

^b The indicated out-of-sample period is 60 months after the initial date of the in-sample rolling training window using the output gap and inflation as inputs.

Table A.4
Stock Market Ex-Ante Estimation Accuracy with Neural Network^a

Estimation Out-of-Sample Period^b	Initial Training Window	R²_{oos}	MAE	RMSE	MSE	F-statistic
1964-2024	1959-1963	7.10%	12.04%	15.70%	246.51%**	55.10
1964-1978	1959-1963	19.91%	10.43%	12.81%	164.21%**	41.75
1983-1987	1978-1982	-46.31%	15.67%	18.78%	352.74%	N/A
1984-2024	1979-1983	3.44%	11.97%	15.82%	250.37%*	8.55
2002-2024	1997-2001	-6.83%	12.56%	16.89%	285.34%	N/A

* and ** indicate an MSE for the SVR estimate that is significantly less than the out-of-sample variance at the 0.10 and 0.001 level, respectively.

^a The neural network estimate is calculated using one-hidden layer with two neurons, a sigmoid activation function with 1000 maximum iterations.

^b The indicated out-of-sample period is 60 months after the initial date of the in-sample rolling training window using the output gap and inflation as inputs.

A.4 Extended Robustness Testing Results

This section summarizes the estimation results using different training windows, and extended sets of explanatory variables. It also examines models based on first-differenced Taylor-rule inputs. The results of these robustness tests are shown in Tables A.5-9.

As shown in Table A.5, the lowest MSE of 126.29% over the entire sample is produced by the SVR model with two inputs and a 30-month training window, consistent with the dynamic nature of the relationship between monetary policy and subsequent excess stock market returns. Table A.6 further supports that using a 120-month window increases MSE relative to the 60-month benchmark, suggesting that shorter training intervals better capture evolving relationships.⁵ Nonetheless, explanatory strength remains significant across all training windows.

⁵ In a separate exercise using only the 1959-1963 period to train the SVR model, we found (results not shown) that a static SVR with the two Taylor-rule inputs produced an MSE greater than the variance of stock market excess returns over the full 1964-2024 sample. This indicates that dynamic interrelationships between predictors and returns require rolling estimation rather than fixed parameters.

Table A.7 reports SVR results incorporating unemployment as a third input. The lowest MSE (70.18%) occurs during the 1964-1978 subperiod, indicating that roughly two-thirds of the variation in excess returns was explained ex-ante, prior to the formal inclusion of full employment in the Fed’s mandate. Over the full sample, the three-variable specification also yields a low MSE (127.00%).

We also estimate SVR models using eight macro-financial inputs expected to affect monetary policy, economic growth, risk premiums, and equity returns. These include the Baker et al. (2016) economic policy uncertainty index, the inflation rate, the output gap, the unemployment rate, the stock market volatility (VIX), the corporate yields (BAA), the International Continental Exchange (ICE) U.S. dollar index, and the refiners’ crude oil acquisition costs. The sample with complete data for all eight variables spans the 1997-2024 period.⁶ Table A.8 shows that the eight-variable model achieves an MSE of 126.31% for the 2002-2024 horizon, which was the lowest for any of the estimation procedures for that subperiod. Adding U.S. capital flows as a ninth input raises the MSE to 141.94%, implying that this variable adds little explanatory power for U.S. stock returns.

Ho et al. (2018) indicate that international capital flows can significantly affect equity markets, particularly in emerging economies such as China, by transmitting external financial conditions into domestic asset prices. Motivated by this evidence, we add a comparable U.S. capital flow measure as a ninth input to the SVR specification.⁷ As shown in the second line of Table A.8, including this variable increases the MSE to 141.94% over the 2002-2024 interval, indicating that capital flow data contribute little additional explanatory power.

In a further robustness test, we re-estimate the SVR using first differences of the Taylor-rule variables:

$$\Delta\pi_t = \pi_t - \pi_{t-1}, \quad \Delta g_t = g_t - g_{t-1}. \quad (\text{A-3})$$

⁶The uncertainty, oil price, and unemployment data are obtained from www.policyuncertainty.com, https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=R1300___3&f=M, and the Bureau of Labor Statistics, respectively. Data on the other variables are obtained from Bloomberg.

⁷Capital-flow data for the U.S. is available from the U.S. Treasury International Capital (TIC) system, which capture cross-border investment movements for the U.S.

where π_t denotes last-year's CPI inflation reported in period t , and g_t is the output gap reported in period t . This transformation addresses problems of persistence and regime changes in the underlying macroeconomic series (Auerbach & Gorodnichenko, 2012). As shown in Table A.9, differencing produces higher MSEs than the baseline model, indicating that levels of inflation and output gap, not their changes, better capture macro-financial relationships related to excess stock returns.

The results from these additional tests support the findings from Table 1 indicating that the two Taylor-rule inputs have long been useful for explaining stock market returns when utilizing machine learning methods that detect complex, nonlinear relationships in the data. Except for the three alternative machine learning methods over the 1983-1987 interval and the Neural Network model over the 2002-2024 subsample, all of the machine learning procedures demonstrated significant explanatory power using fundamental variables. Across a total of 41 estimation intervals and 10 procedures, 37 (34) show statistically significant explanatory power at the 0.10 (0.001) level, with six R^2_{OOS} values indicating that over half of the subsequent variation in stock market returns was explained ex-ante. These results are consistent with the hypothesis that stock market returns are driven by nonlinear relationships between Taylor-rule variables and asset valuations, transmitted through future monetary and fiscal policy interactions that influence economic activity and corporate profitability.

The overall findings are consistent with empirical evidence from prior studies. Gertler and Karadi (2015) and Miranda-Agrippino and Ricco (2021) show that higher (lower) values of the Taylor-rule variables are associated with tighter (looser) monetary policy. Eraker et al. (2016) find that tighter policy negatively affects long-term growth and corporate profits. A similar inverse relationship between contractionary policy and stock market performance is reported by Thorbecke (1997) and Murphy et al. (2025). Earlier evidence from Fama and Schwert (1977), Sharpe (2002), and Bhamra et al. (2023) also indicates a negative association between inflation and stock returns, while Cooper and Priestly (2009) find that equity returns move inversely with the output gap. Kekre and Lenel (2022) have shown that unexpected monetary policy actions can influence the real economy and asset prices through a risk-premium channel.

Table A.5
SVR Stock Market Ex-Ante Estimation Accuracy with 30 months Training Window^{a,b}

Estimation Out-of-Sample Period	Initial Training Window	R²_{oos}	MAE	RMSE	MSE	F-statistic
7/1961-1/2024	1/1959-6/1961	52.15%	8.13%	11.24%	126.29%**	805.38
7/1961-12/1978	1/1959-6/1961	61.30%	6.88%	9.14%	83.62%**	313.57
7/1980-12/1987	1/1978-6/1980	43.76%	10.49%	13.98%	195.33%**	77.04
7/1981-1/2024	1/1979-6/1981	46.24%	8.61%	12.02%	144.59%**	428.36
7/1999-1/2024	1/1997-6/1999	48.72%	8.97%	12.62%	159.18%**	258.37

* and ** indicate an MSE for the SVR estimate that is significantly less than the out-of-sample variance at the 0.10 and 0.001 level, respectively.

^a Regularization parameter=1; Smoothing parameter=0.5; error-fitting parameter=0.1

^b Output gap and inflation are used as inputs. The shorter training window enables a longer out-of-sample period for each interval compared to the 60-month training window.

Table A.6
SVR Stock Market Ex-Ante Estimation Accuracy with 120 months Training Window^{a,b}

Estimation Out-of-Sample Period	Initial Training Window	R²_{oos}	MAE	RMSE	MSE	F-statistic
1/1969-1/2024	1/1959-12/1968	28.95%	10.77%	14.11%	199.26%**	264.03
1/1969-12/1978	1/1959-12/1968	26.77%	10.60%	13.82%	191.12%**	39.49
1/1989-1/2024	1/1979-12/1988	26.19%	10.49%	13.97%	195.29%**	109.31
1/2007-1/2024	1/1997-12/2006	36.64%	10.16%	13.79%	190.24%**	111.03

* and ** indicate an MSE for the SVR estimate that is significantly less than the out-of-sample variance at the 0.10 and 0.001 level, respectively.

^a Regularization parameter=1; Smoothing parameter=0.5; error-fitting parameter=0.1

^b Output gap and inflation are used as inputs. The shorter training window enables a shorter out-of-sample period for each interval compared to the 60-month training window. It is not possible to utilize a 120-month training window for the 1978-87 Volcker-era subperiod (due to insufficient observations).

Table A.7
SVR Stock Market Ex-Ante Estimation Accuracy with 3 Inputs^a

Estimation Out-of-Sample Period^b	Initial Training Window	R²_{oos}	MAE	RMSE	MSE	F-statistic
1964-2024	1959-1963	52.14%	8.31%	11.27%	127.00%**	785.43
1964-1978	1959-1963	65.77%	6.65%	8.38%	70.18%**	322.79
1983-1987	1978-1982	15.24%	11.31%	14.29%	204.36%*	8.63
1984-2024	1979-1983	41.45%	8.94%	12.32%	151.80%**	169.95
2002-2024	1997-2001	37.18%	9.13%	12.95%	167.81%**	143.92

* and ** indicate an MSE for the SVR estimate that is significantly less than the out-of-sample variance at the 0.10 and 0.001 level, respectively.

^a Regularization parameter=1; Smoothing parameter=0.33; error-fitting parameter=0.1

^b The indicated out-of-sample period is 60 months after the initial date of the in-sample rolling training window using the output gap, inflation, and the unemployment rate as inputs.

Table A.8
SVR Stock Market Ex-Ante Estimation Accuracy with 8 & 9 Inputs^a

Estimation Out-of-Sample Period^b	Initial Training Window	R²_{oos}	MAE	RMSE	MSE	F-statistic
2002-2024 (8 inputs) ^c	1997-2001	52.71%	8.25%	11.24%	126.31%**	277.94
2002-2024 (9 inputs) ^d	1997-2001	46.86%	8.79%	11.91%	141.94%**	218.97

* and ** indicate an MSE for the SVR estimate that is significantly less than the out-of-sample variance at the 0.10 and 0.001 level, respectively.

^a The 8 SVR inputs are the economic policy uncertainty index, inflation, output gap, unemployment, VIX, BAA yield, US dollar index, and oil prices. The SVR results with 9 inputs also have capital flows. Data does not exist for all these inputs for any subperiod except the final one.

^b The indicated out-of-sample period is 60 months after the initial date of the in-sample rolling training window.

^c Regularization parameter=1; Smoothing parameter=0.125; error-fitting parameter=0.1.

^d Regularization parameter=1; Smoothing parameter=0.11; error-fitting parameter=0.1.

Table A.9
SVR Stock Market Ex-Ante Estimation Accuracy with 2 First Differenced Inputs^{a,b}

Estimation Out-of-Sample Period^c	Initial Training Window	R²_{oos}	MAE	RMSE	MSE	F-statistic
1964-2024	1959-1963	10.74%	11.82%	15.39%	236.84%**	86.79
1964-1978	1959-1963	3.07%	11.18%	14.10%	198.72%*	5.33
1983-1987	1978-1982	20.21%	10.86%	13.87%	192.37%**	12.16
1984-2024	1979-1983	6.14%	11.79%	15.60%	243.37%**	15.70
2002-2024	1997-2001	0.80%	11.96%	16.28%	264.95%*	2.15

* and ** indicate an MSE for the SVR estimate that is significantly less than the out-of-sample variance at the 0.10 and 0.001 level, respectively.

^a Regularization parameter=1; Smoothing parameter=0.5; error-fitting parameter=0.1

^b The first differenced inputs are computed as the difference between the current period input value less the prior month's value

^c The indicated out-of-sample period is 60 months after the initial date of the in-sample rolling training window.

A.5 Comparative OLS Results

In order to evaluate the linear relationship of future annual excess stock market returns with the current output gap and inflation rate, an in-sample Ordinary Least Squares (OLS) bivariate regression is run over the 1964-2024 interval. The results shown in Table A.10 indicate significantly negative parameter estimates for both regressors at the 0.001 level, with an $R^2 = 0.15$.⁸ These findings are consistent with a hypothesis of higher (lower) inflation and economic capacity utilization inducing Fed tightening (loosening) and causing a negative (positive) stock market reaction.

A further test is conducted using the two ex-ante Taylor inputs with a rolling 60-month parameter estimation window (that is analogous to the baseline SVR estimation of future excess returns using the two ex-ante Taylor-rule inputs). This linear ex-ante OLS estimation of future excess stock returns results in an R^2_{OOS} of 0.17 as shown in Table A.11.⁹ The latter result indicates explanatory power that is far below that demonstrated by SVR, which

⁸These results are also consistent with the interpretation that equity valuations anticipate future monetary tightening (loosening) in response to higher (lower) inflation and real activity.

⁹ Interestingly, the rolling OLS model's out-of-sample slightly exceeds the in-sample. This pattern, though unusual, can arise when relationships between predictors and returns evolve dynamically over time. As discussed by Hirshleifer et al. (2023), such cases often reflect time-varying macro-financial relations rather than model overfitting. The finding thus reinforces the evidence that the association between stock returns and Taylor-rule variables is not static but changes with monetary-policy regimes and market expectations.

detects nonlinear associations between variables and therefore has a much higher R^2_{OOS} of over 0.40.

Table A.10
In-Sample OLS Regression Results (1964–2024)

Variable	Coefficient	Std. Error	t-stat	p-value	95% Confidence Interval
Inflation (t–1)	–1.041	0.197	–5.29	0.000	[–1.428, –0.654]
Output Gap	–2.297	0.232	–9.91	0.000	[–2.752, –1.842]
Constant	9.131	0.984	9.28	0.000	[7.198, 11.063]
Statistic	Value				
Observations	721				
R ²	0.1528				
Adjusted R ²	0.1504				
Root MSE	15.015				
F(2,718)	64.73 (p < 0.001)				

Dependent variable: 1-year-ahead excess S&P500 return

Table A.11
Rolling OLS (60-Month) Out-of-Sample Results

Statistic	Value
R ² _{oos}	0.1704
RMSE	14.664
MAE	11.527
MSE	214.97
F-statistic	5.12 (p < 0.05)

Notes: The rolling OLS estimation uses a 60-month training window and monthly data from 1964–2024. Each estimate corresponds to a 1-year-ahead excess S&P500 return.

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