

NYU Stern School of Business

Robo-Advisors and Systematic Trading Project

**Can Short-Term Technical and Volatility Features Predict Which Trend
Strategy Will Be Dominant Next, and Under What Measurable Market
Conditions?**

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Table of Contents

1. Executive Summary
2. Phase 1: Strategy Structure Evaluation
3. Feature Engineering & Inputs
4. Machine Learning-Based Trend Classification
5. Strategy Comparison and Performance
6. Strategy Dominance Modeling
7. Monthly Switching with Confidence Threshold
8. Feature Dynamics Around Strategy Crossovers
9. Limitations and Future Work
10. Conclusion & Contributions

1. Executive Summary

This project began with a core hypothesis: **Can short-term volatility signals be used to adjust market exposure dynamically and improve Sharpe ratios?** Building from this question, we developed a systematic trading research framework that combines volatility-aware allocation, trend detection, and machine learning based strategy selection.

Our approach integrates widely used technical and volatility indicators such as RSI, MACD, moving average crossovers, realized volatility, and VIX. We evaluated six strategies from passive Buy & Hold to ML-enhanced and volatility-scaled models to identify which approaches perform best under different market regimes.

A Random Forest classifier was trained to predict daily strategy dominance based on current market features. To make this actionable, we implemented a monthly switching framework with a confidence threshold, ensuring lower trading friction and more stable performance.

Key insights:

- Volatility-aware scaling significantly improved risk-adjusted returns in-sample, especially in the Dynamic TCVS strategy.
- Out-of-sample results confirmed that no single strategy dominates consistently, and market conditions strongly influence performance.
- Strategy crossovers were explainable through shifts in features like RSI, trend strength, and implied volatility.
- Monthly switching provided a conservative yet effective way to adapt across regimes, minimizing drawdowns without overfitting.

This project aims to contribute a practical, data-driven approach to understanding and quantifying the market conditions under which each strategy tends to thrive, identifying the factors behind return crossovers between strategies, and enabling dynamic strategy rotation grounded in explainable market signals and supported by backtesting.

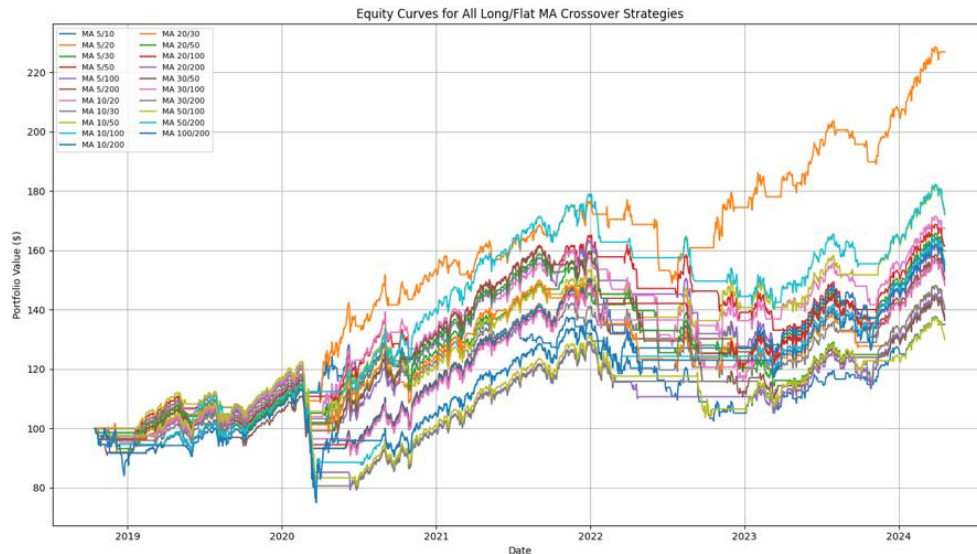
2. Phase 1: Identifying the Best Strategy Structure

The first phase of our project focused on evaluating which core trading structure delivers the most consistent and risk-efficient performance under varied market conditions. Rather than assuming one universal approach, we systematically tested three high-level strategy families — **Long-Flat**, **Long-Short**, and **Short-Only**, across 21 moving average crossover pairs drawn from popular window lengths (5, 10, 20, 30, 50, 100, 200). Each strategy was benchmarked using metrics such as annual return, Sharpe ratio, drawdown, and time in market. This analysis helped us identify not only which approach was most robust, but also which specific MA pairs generated the strongest signal-to-noise ratio for trend identification. The Long-Flat strategy using an **MA(5/20) crossover** emerged as the most effective, combining strong returns with relatively low volatility and moderate market exposure, making it a strong candidate for downstream modeling and switching frameworks.

Long-Flat Strategy (Top 5 by Sharpe Ratio)

MA (Fast/Slow)	Annual Return	Sharpe Ratio	Max Drawdown	Time in Market	Final Value (\$100)
5 / 20	16.06%	1.299	28.16%	66.67%	\$226.87
10 / 50	10.35%	0.846	20.06%	69.41%	\$171.92
10 / 100	10.42%	0.838	38.69%	72.29%	\$172.45
10 / 20	9.83%	0.787	32.02%	67.53%	\$167.48
5 / 50	9.11%	0.770	33.65%	69.41%	\$161.50

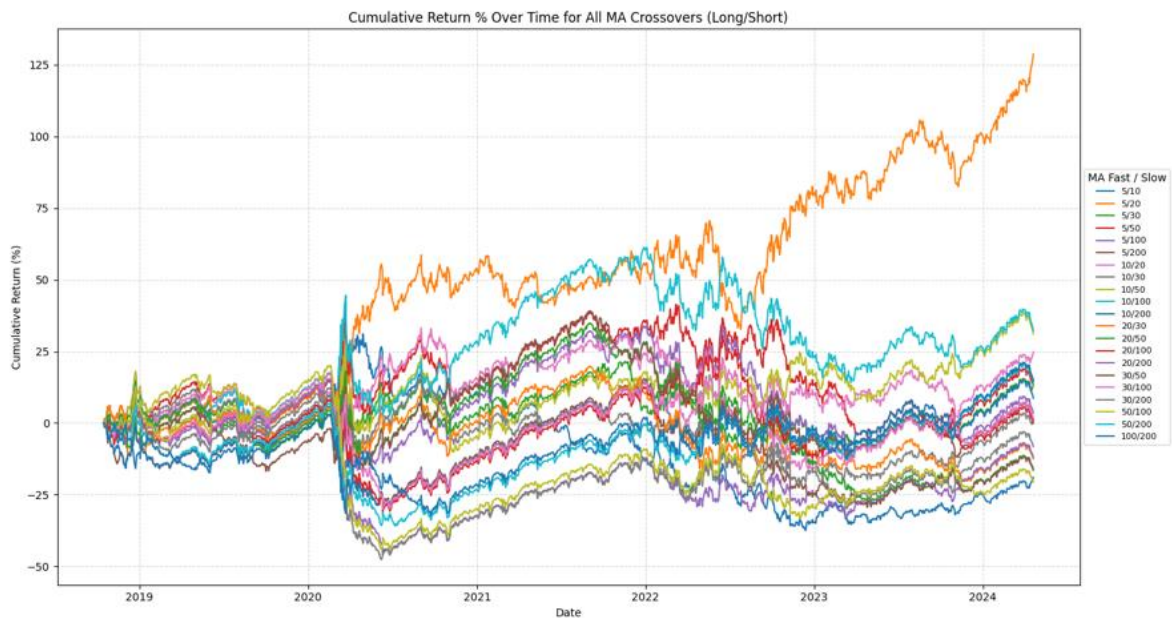
The MA(5/20) crossover had the best Sharpe ratio and return-to-risk profile with moderate exposure, making it the optimal trend signal.



Long-Short Strategy (Top 5 by Sharpe Ratio)

MA (Fast/Slow)	Annual Return	Sharpe Ratio	Max Drawdown	Long %	Short %	Final Value
5 / 20	16.23%	0.784	37.77%	66.67%	33.33%	\$228.73
10 / 100	5.21%	0.252	47.11%	72.29%	27.71%	\$132.25
10 / 50	5.04%	0.243	36.98%	69.41%	30.59%	\$131.08
10 / 20	4.11%	0.198	33.41%	67.53%	32.47%	\$124.81
5 / 50	2.58%	0.124	46.34%	69.41%	30.59%	\$115.04

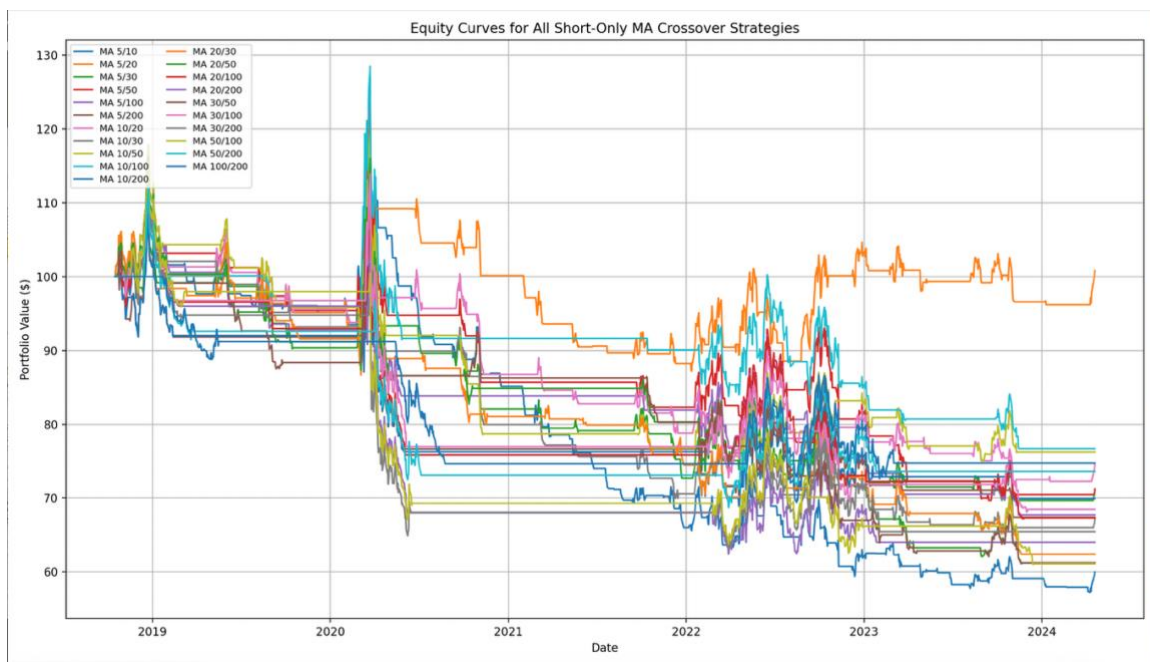
Although 5/20 again performed best within this group, the Sharpe ratios and drawdowns were worse than Long-Flat, reflecting higher risk from short exposure.



Short-Only Strategy (All Underperformed)

MA (Fast/Slow)	Annual Return	Sharpe Ratio	Max Drawdown	Time in Short	Final Value
5 / 20	0.15%	0.009	36.45%	33.33%	\$100.82
10 / 100	-4.71%	-0.284	51.82%	27.71%	\$76.69
10 / 50	-4.81%	-0.288	44.99%	30.59%	\$76.24

All short-only strategies yielded negative or negligible returns with high drawdowns, confirming they are unsuitable as standalone strategies in the S&P 500 context. **(This also explains why we discussed in class that making money while shorting is hard.)**



3. Feature Engineering & Inputs

To build both rule-based and machine learning–driven strategies, we first engineered a set of features designed to capture key aspects of market behavior, including trend strength, momentum shifts, volatility regimes, and recent return patterns. These features were computed from historical price and volatility data of the S&P 500 ETF (SPY), along with implied volatility from the VIX index.

The feature set is summarized below:

Feature	Description
SPY_Close, SPY_High, SPY_Low	Daily closing, high, and low prices of the SPY ETF
VIX_Close	Implied market volatility (VIX index), a proxy for market fear or uncertainty
ATR	5-day Average True Range — a measure of recent price range volatility
MA5, MA20	5-day and 20-day moving averages, used to identify short-term trend direction
RSI	14-day Relative Strength Index — a momentum oscillator
MACD	Difference between MACD line and signal line — used to capture momentum shifts
Realized_Volatility	10-day rolling standard deviation of returns, scaled to annualized values
Trend_5_20	Binary indicator: 1 if MA5 > MA20 (uptrend), else 0
High_Vol	Binary indicator: 1 if VIX is above its 70th percentile (high volatility regime)
Trend_HighVol_Interaction	Interaction term between trend and high volatility flags (Trend_5_20 × High_Vol)
Return_1d, Return_5d, Return_10d	Percentage returns over 1-day, 5-day, and 10-day periods
Trend	Categorical label: “Up” if SPY > MA5, else “Down”
Volatility_Regime	Categorical label: “High” or “Normal,” based on VIX quantile thresholds

These features provided the foundation for both our rule-based logic (e.g., MA crossovers, volatility scaling) and our machine learning classifier.

To move beyond static allocation, we trained a **Random Forest classifier** to predict daily market trends (Up/Down) using these features. This model was used to determine strategy exposure in ML-based and hybrid strategies, forming the backbone of our adaptive strategy selection framework.

Feature computation was implemented in a modular pipeline (feature_engineering.py) using the `ta` library and custom logic.

4. Machine Learning-Based Trend Classification

To move beyond static rule-based strategies, we incorporated a supervised machine learning model designed to predict the next-day market trend using a curated set of technical and volatility indicators. This model plays a key role in enabling dynamic exposure control and strategy selection.

The target variable was defined as a binary label:

- Target = 1 if the SPY ETF closes higher the next day
- Target = 0 otherwise

The full machine learning pipeline was implemented in `model_training.py` and structured as follows:

1. Data Loading and Feature Preparation

The dataset is loaded with engineered features already computed. The target is derived by forward-shifting next-day returns to align with today's feature values.

2. Train-Test Split

A chronological 80/20 split is used to ensure a realistic, time-consistent separation between the training and evaluation sets. This approach avoids data leakage from future market information.

3. Model Selection and Training

We selected a `RandomForestClassifier` for its robustness, interpretability, and ability to handle noisy, correlated features. The model was constrained to a maximum depth of 5 to reduce overfitting and trained with a fixed random seed for reproducibility.

4. Threshold Evaluation and Tuning

In addition to the default 0.5 probability threshold, we tested a range of thresholds between 0.1 and 0.9. A threshold of **0.3** was found to offer a better balance between precision and recall, especially valuable in switching strategies where higher recall is preferred to avoid missing trend reversals.

5. Model Persistence

The trained model is saved using `joblib` for reuse in downstream applications, particularly in the monthly strategy switching logic.

Key Evaluation Insights

- The default threshold (0.5) yielded a balanced classifier but conservative trade signals.
- Lowering the threshold to 0.3 improved the model's sensitivity to upward movements, which is more effective in an allocation context where responsiveness is critical.
- The model demonstrated strong performance during volatile periods, supporting its role as a signal generator in dynamic strategy frameworks.

5. Strategy Comparison and Performance

Having identified a reliable trend signal (MA 5/20) in Phase 1 and engineered a rich feature set, we expanded our exploration to assess how different strategy frameworks perform across varying market regimes. The goal was to understand whether dynamic exposure control, based on predicted trends and volatility, could improve risk-adjusted returns over passive or static rule-based strategies.

We implemented and benchmarked six strategies of increasing complexity and adaptability:

1. Buy & Hold Strategy

A passive benchmark that remains fully invested in the market at all times. It serves as a baseline to evaluate whether tactical exposure adjustments add measurable value.

2. MA 5/20 Crossover Strategy

A classic trend-following strategy that enters a long position when the 5-day moving average crosses above the 20-day moving average. While simple and interpretable, it lacks adaptability to volatility or shifting market regimes.

3. ML-Based Strategy

This approach leverages a Random Forest classifier to predict the next-day market trend (up or down) using a curated set of short-term technical and volatility features. The model is trained on indicators such as RSI, MACD, realized volatility, and VIX, along with trend and return-based signals. The strategy takes a long position when the model forecasts a positive price movement and remains flat otherwise. By replacing static rule-based logic with data-driven trend forecasting, this strategy represents a meaningful shift toward adaptive and probabilistic decision-making in systematic trading.

4. Vol-Scaled ML Strategy

A risk-sensitive adaptation of the ML-based strategy. It scales down position size (to 40%) when volatility is high, thereby aiming to reduce drawdowns and enhance Sharpe ratio. This tests whether exposure adjustment based on volatility can enhance performance.

5. Dynamic TCVS (Trend-Conditioned Volatility Scaling)

This strategy integrates both predicted trend and volatility regime to dynamically adjust exposure. For example, in bullish and volatile conditions, it may increase exposure to 1.5x. In turbulent or uncertain phases, it de-risks accordingly. It is the most sophisticated and responsive strategy in the set.

6. Mean Reversion Strategy

Built on the hypothesis that prices tend to revert during volatile downturns, this strategy increases exposure (up to 1.5x) when markets are oversold and volatility is high, and reduces risk during upward trends. It is designed to capitalize on snap-back opportunities.

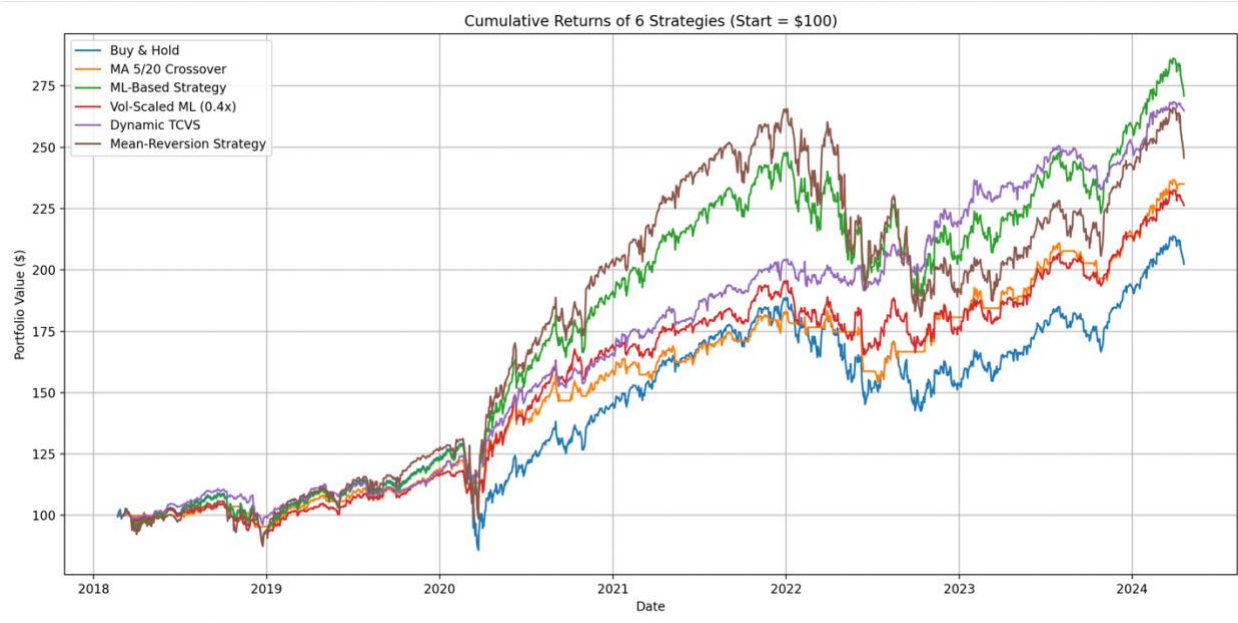
Performance Summary

Strategy	Final Value	Annual Return	Volatility	Sharpe Ratio	Max Drawdown	% Leveraged
Buy & Hold	\$202.36	12.14%	20.04%	0.606	46.21%	0.0%
MA Crossover	\$235.00	14.90%	11.88%	1.255	29.17%	0.0%
ML-Based	\$270.92	17.59%	19.28%	0.912	58.60%	0.0%
Vol-Scaled ML	\$226.33	14.20%	13.92%	1.020	30.08%	0.0%
Dynamic TCVS	\$264.84	17.16%	10.53%	1.630	17.96%	18.36%
Mean Reversion	\$245.64	15.73%	23.99%	0.656	84.76%	23.65%

Key Insights

- **Buy & Hold** consistently underperformed all active strategies in both returns and Sharpe ratio, reaffirming the benefits of dynamic allocation.
- **MA Crossover** offered strong risk-adjusted returns (Sharpe 1.255) with much lower drawdown than Buy & Hold, demonstrating the value of simple trend-following logic.
- **ML-Based Strategy** delivered the highest raw returns (\$270.92), but also experienced the largest drawdown (58.6%), highlighting its sensitivity to market volatility in the absence of scaling.
- **Vol-Scaled ML** showed a better balance between return and risk, validating the benefit of volatility-aware exposure control.
- **Dynamic TCVS** was the most balanced performer, achieving the highest Sharpe ratio (1.63) and the lowest drawdown (17.96%). It demonstrated the power of combining predicted trends and volatility signals.
- **Mean Reversion**, while delivering strong returns, suffered from extreme drawdowns (84.76%), making it unsuitable as a core strategy in trending markets.

The cumulative return chart on the next page illustrates how each strategy evolved over time. While Buy & Hold delivered steady but limited growth, more adaptive strategies such as ML-Based, Vol-Scaled ML, and Dynamic TCVS outperformed, especially during regime shifts and volatile phases by controlling drawdowns and capitalizing on regime-specific strengths.



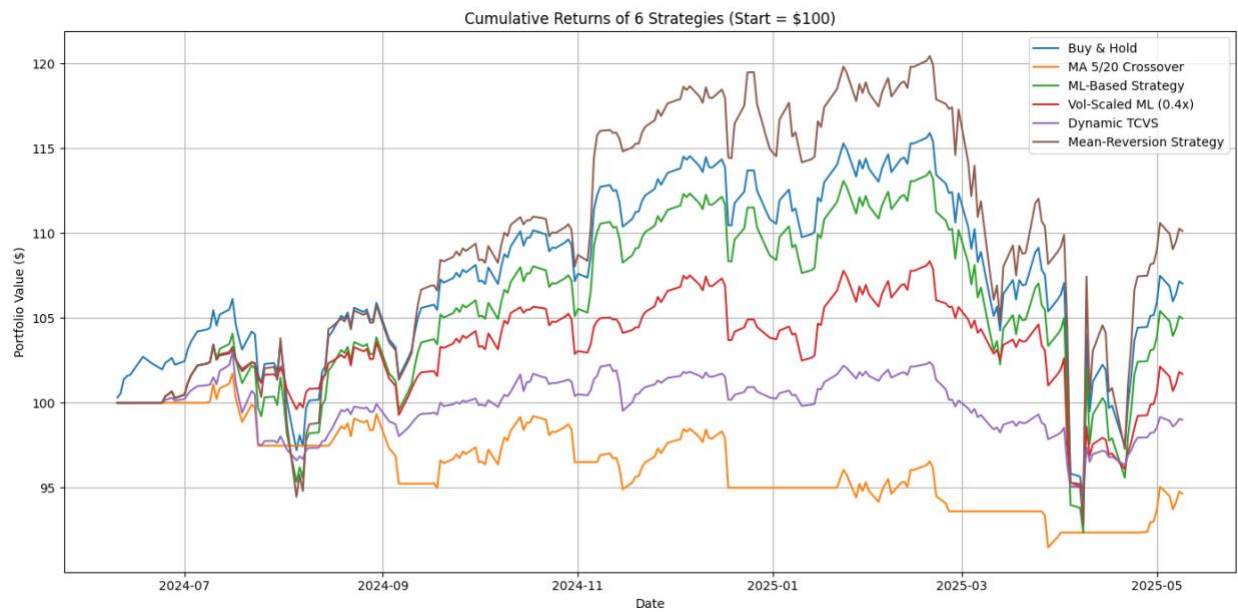
5.1 Out-of-Sample Strategy Performance

To evaluate the robustness and generalizability of each strategy, we tested all six models on an out-of-sample period (2024–2025) that was **excluded from training and parameter tuning**. Each strategy began with a baseline of \$100, and performance was measured using the same set of risk-return metrics as before.

Strategy	Final Value	Annual Return	Volatility	Sharpe Ratio	Max Drawdown	% Leveraged
Buy & Hold	\$107.02	7.76%	20.8%	0.373	21.74%	0.0%
MA Crossover	\$98.74	-1.39%	9.19%	-0.151	10.69%	0.0%
ML-Based	\$107.02	7.76%	20.8%	0.373	21.74%	0.0%
Vol-Scaled ML	\$109.65	10.67%	13.19%	0.809	14.79%	0.0%
Dynamic TCVS	\$97.96	-2.24%	9.69%	-0.231	10.66%	17.75%
Mean Reversion	\$111.62	12.86%	27.39%	0.470	29.04%	26.84%

- **Vol-Scaled ML** was the most balanced performer out-of-sample, offering strong returns with a Sharpe ratio of **0.81** and moderate volatility.
- **Mean Reversion** achieved the highest absolute return (12.86%), but came with high volatility and a max drawdown of nearly **30%**, making it riskier for capital preservation.

- **Dynamic TCVS**, despite being the top in-sample performer, **underperformed in the out-of-sample window**, suggesting some degree of overfitting to past volatility-trend dynamics.
- **MA Crossover**, while simple and robust in-sample, **failed to generalize**, posting a negative return and low Sharpe ratio despite low drawdown.
- **ML-Based** performed identically to Buy & Hold in this window, indicating its sensitivity to unpredictable conditions when not scaled.



These results reaffirm that **no single strategy performs best at all times**, reinforcing the need for adaptive strategy rotation, particularly in volatile or shifting market conditions.

6. Strategy Dominance Modeling

To enable adaptive allocation in changing market conditions, we developed a machine learning–based model that predicts which trading strategy is likely to dominate next, based on short-term technical and volatility features. The process involved three key stages: daily dominance labeling, feature alignment, and classification using a Random Forest model.

Strategy Labeling

We first labeled each day in the dataset with the strategy that delivered the highest return, using returns data from four adaptive strategies:

- ML-Based Strategy
- Volatility-Scaled ML (Conservative Strategy)
- Dynamic TCVS
- Mean Reversion

Static baselines like Buy & Hold and MA Crossover were excluded, as they do not vary dynamically.

Each trading day was tagged with the Best_Strategy using the `.idxmax()` function across strategy return columns. This labeled dataset was then merged with the corresponding market features (e.g., RSI, MACD, VIX), creating a supervised learning dataset for multi-class classification.

Predictive Model and Features

We trained a Random Forest Classifier using 10 features selected for their predictive power:

- RSI, MACD
- Realized Volatility, VIX Close
- Return_1d, Return_5d, Return_10d
- Trend_5_20 (moving average crossover signal)
- High_Vol (binary volatility regime)
- Trend_HighVol_Interaction

This model learned to map current market conditions to the most likely winning strategy.

The trained model was later applied to both in-sample and out-of-sample periods. Alongside each prediction, we also saved the model’s confidence score (i.e., the predicted class probability), which became critical for filtering low-confidence signals during monthly switching.

Dominance Frequency Distribution

In the in-sample period (2018–2023), the model revealed the following dominance distribution:

Strategy	Days Selected	% of Time Dominant
Dynamic TCVS	93	40.26%
ML-Based Strategy	88	38.10%
Mean Reversion	45	19.48%
Vol-Scaled ML	5	2.16%

The dominance was highly concentrated: Dynamic TCVS and ML-Based together covered over 78% of the in-sample period. This observation later influenced our simplification efforts—narrowing focus to the top two strategies when designing switching frameworks.

Strategy Regime Profiles

To interpret when each strategy tends to dominate, we analyzed feature distributions (mean, 25th/50th/75th percentiles) on days where a given strategy was labeled dominant. The table below summarizes average market conditions favoring each strategy:

Feature	Mean Reversion	Dynamic TCVS	ML-Based Strategy	Vol-Scaled ML
RSI	47.9	53.5	61.3	56.3
MACD	-0.79	-0.15	0.51	0.07
Realized Volatility	0.25	0.16	0.14	0.15
VIX Close	23.2	20.6	19.3	18.8
Trend 5 20	0.095	0.66	0.85	0.91
High Vol	0.397	0.326	0.251	0.23
Return 10d	-0.013	-0.001	0.021	0.009

Interpretation:

- Mean Reversion thrives in volatile, oversold conditions with weak or negative trend.
- Dynamic TCVS prefers moderately trending conditions with elevated but manageable volatility.
- ML Strategy dominates during low-volatility, momentum-driven uptrends.
- Vol-Scaled ML was rarely dominant, but aligned with quiet, steadily rising environments.

This modeling framework enabled us to quantify which market conditions favor which strategies, and to use this understanding for forward-looking predictions. Rather than reacting to past performance, the strategy dominance classifier allows us to proactively rotate capital into the strategy most likely to succeed next, given present conditions.

This serves as the backbone for the monthly switching logic, discussed in the next section.

7. Monthly Switching with Confidence Threshold

While the strategy dominance model showed promise in identifying the best-performing strategy for each day, implementing **daily switching** in practice is highly impractical. Frequent allocation shifts across fundamentally different strategies introduce significant friction, including:

- Higher transaction costs
- Increased operational complexity
- Reduced model stability
- Difficulty in reconciling performance across different execution engines (e.g., ML vs. mean reversion logic)

To address these limitations, we designed a **monthly switching framework** that balances predictive adaptability with real-world usability. The goal was to retain the benefits of the dominance model while minimizing unnecessary rebalancing and false signals.

Switching Framework Design


The core design follows two guiding principles:

1. Monthly Frequency

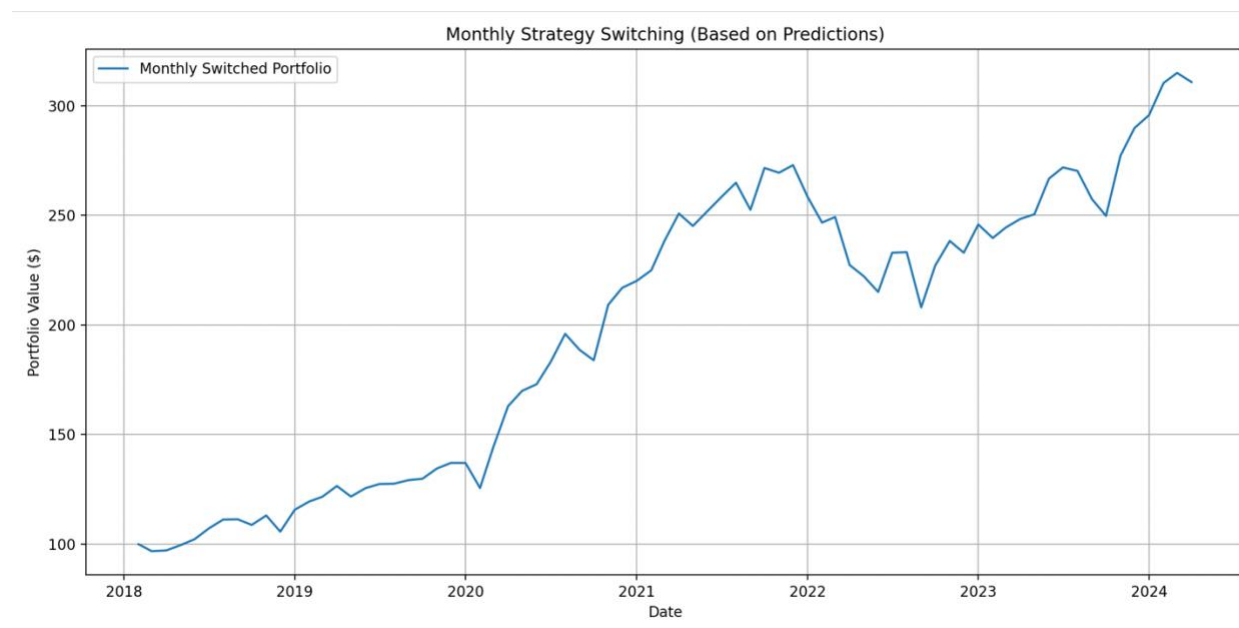
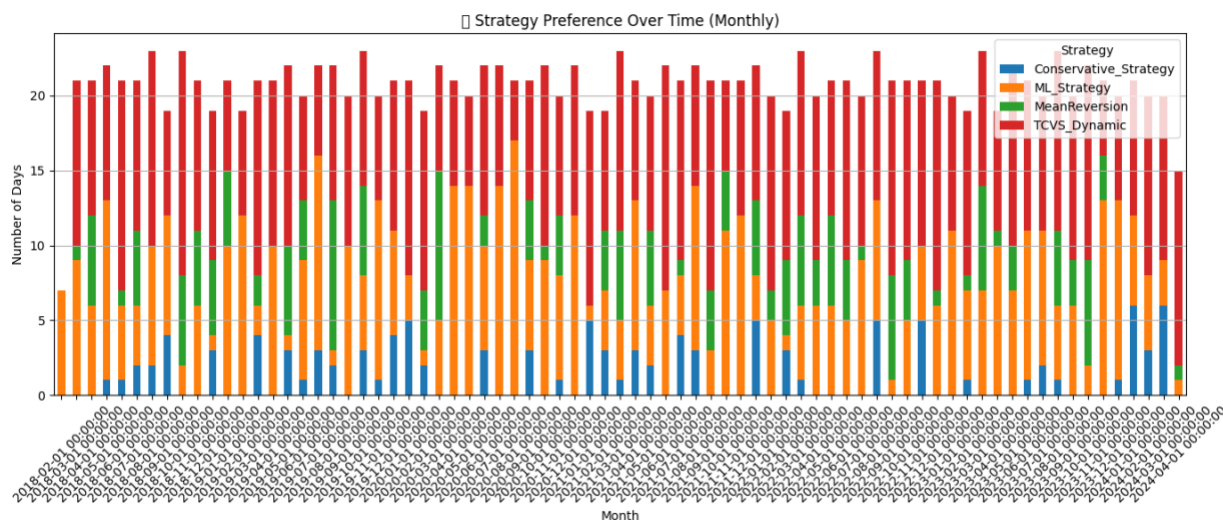
Instead of switching daily, the strategy is updated only once per month, specifically on the first trading day of each month. This cadence aligns better with typical portfolio management cycles and reduces transaction load.

2. Confidence Filtering

We introduced a probability threshold to filter low-confidence predictions. Using the classifier's output probabilities, the strategy is only switched when the model's predicted confidence exceeds a set threshold (e.g., 60%). If no strategy exceeds the threshold, the previous month's strategy is retained.

Strategy	Final Value (\$100)	Annual Return	Volatility	Sharpe Ratio	Max Drawdown
Buy & Hold	\$202.36	12.14%	20.04%	0.606	46.21%
MA Crossover (5/20)	\$235.00	14.90%	11.88%	1.255	29.17%
ML-Based	\$270.92	17.59%	19.28%	0.912	58.60%
Vol-Scaled ML (0.4x)	\$226.33	14.20%	13.92%	1.020	30.08%
Dynamic TCVS	\$264.84	17.16%	10.53%	1.630	17.96%
Mean-Reversion	\$245.64	15.73%	23.99%	0.656	84.76%
 Monthly Switching	\$310.75	19.89%	17.13%	1.161	23.77%

This approach creates a more stable allocation process that switches only when **statistical conviction is high**.



7.1 Out-of-Sample Evaluation

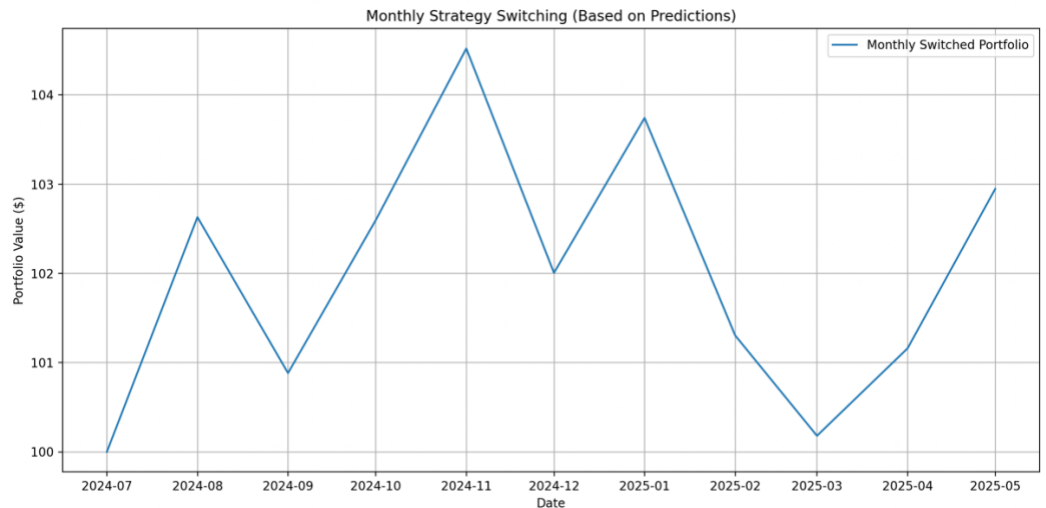
We tested the monthly switching framework on unseen data from 2024–2025. Each month, the classifier predicted the dominant strategy using the most recent market features, and applied the switching logic described above.

Strategy	Final Value	Annual Return	Volatility	Sharpe Ratio	Max Drawdown
Monthly Switching (OOS)	\$102.95	3.22%	6.81%	0.473	4.15%
Buy & Hold	\$104.64	6.00%	22.02%	0.273	21.25%
MA Crossover (5/20)	\$96.56	-4.40%	8.80%	-0.501	8.02%
ML-Based	\$106.88	8.94%	21.30%	0.420	21.71%
Vol-Scaled ML	\$106.41	8.32%	13.82%	0.602	14.35%
Dynamic TCVS	\$100.16	0.20%	9.21%	0.022	10.03%
Mean Reversion	\$110.60	13.83%	28.20%	0.491	28.77%

Observations

- **Monthly Switching** significantly reduced volatility and drawdown while maintaining competitive returns.
- It achieved the **lowest max drawdown (4.15%)** and a respectable Sharpe ratio, despite the conservative switching cadence.
- **Mean Reversion** produced the highest raw return, but at the cost of excessive volatility and drawdown, reinforcing the risk of standalone aggressive strategies.
- Other static strategies either underperformed (MA Crossover) or showed high sensitivity to regime shifts (Dynamic TCVS).

This monthly switching logic offers a practical compromise between adaptability and stability. By switching only when the model has sufficient confidence and doing so on a monthly basis, the framework remains responsive to market regime shifts while avoiding overfitting and excessive turnover.



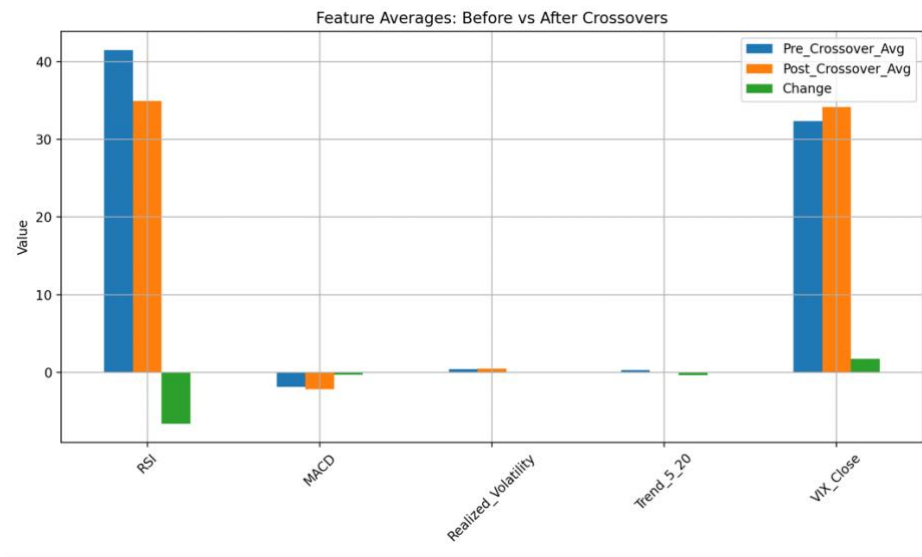
8. Feature Dynamics Around Strategy Crossovers

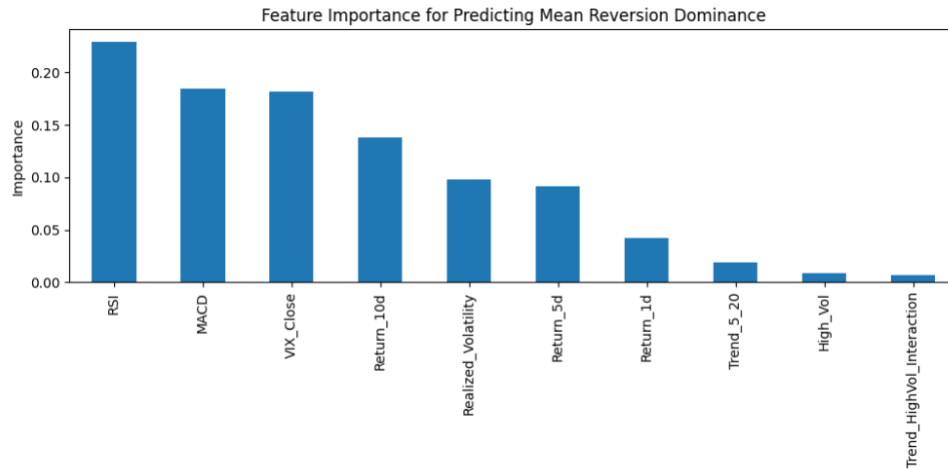
To deepen our understanding of when one strategy begins to outperform another, we analyzed the feature behavior surrounding return crossover points, specifically when Mean Reversion and Dynamic TCVS switch leadership.

A crossover is defined as the point at which the cumulative return of one strategy overtakes the other. For each crossover event, we examined a 5-day window before and after the crossover to compute the average values of key market features.

The chart below illustrates the average feature values before and after crossover events, along with the net change:

Feature	Change (Before → After)	Interpretation
RSI	↓ (~6 points)	Crossovers tend to follow a cooling-off in overbought conditions, often a precursor to mean reversion.
MACD	Slight ↑	Indicates emerging momentum after the reversal point, suggesting trend recovery.
Realized Volatility	↑ (mild)	Volatility tends to rise slightly post-crossover, justifying adaptive scaling.
Trend_5_20	↓	The short-term trend weakens after crossovers, pointing to potential regime shifts.
VIX Close	↑	A slight increase in market stress post-crossover, which aligns with TCVS engagement logic.





These results confirm that **return crossovers are not random**, they are often **preceded by measurable shifts in technical and volatility indicators**. This lends further support to our regime-aware allocation framework, reinforcing the importance of monitoring feature deltas to anticipate strategy transitions.

9. Limitations and Future Work

While the project demonstrates a promising framework for dynamic strategy rotation, several limitations were observed:

Key Limitations

- **Daily vs. Monthly Misalignment:** The model was trained on **daily strategy labels** but used for **monthly switching**, which may reduce accuracy. The first day of the month may not always reflect the full regime.
- **Short Out-of-Sample Window:** Testing was limited to ~1 year (2024–2025), restricting generalizability across market cycles.
- **Static Thresholds:** Switching was triggered by a fixed confidence threshold (e.g., 60%). This may miss subtle but valid signals under uncertain conditions.
- **Narrow Crossover Analysis:** Crossover behavior was only analyzed over a 5-day window. A longer or multi-horizon view (e.g., 10–15 days) may capture more robust trends.
- **Single-Asset Focus:** The model was tested only on SPY. Broader application across other ETFs or sectors could improve resilience.

Future Work

- **Train Models at Monthly Frequency:** Re-train classifiers using **monthly strategy labels** and aggregated features to better align with switching logic.
- **Multi-Horizon Crossover Profiling:** Analyze crossovers over 5, 10, and 15-day windows to distinguish short-term noise from lasting shifts.
- **Probabilistic Allocation:** Instead of switching to one strategy, allocate capital proportionally based on model confidence.
- **Add Macro and Sentiment Features:** Incorporate interest rates, economic indicators, or news sentiment (e.g., FinBERT) for early regime detection.
- **Use Regime Filters:** Classify the current market (e.g., trending vs. volatile) before applying strategy predictions — improving precision.
- **Improve Backtesting Realism:** Add transaction costs, slippage, and latency for more practical performance estimates.

10. Conclusion & Contributions

This project began with a simple but important question: *can short-term volatility and technical signals help us choose the right trading strategy at the right time?* Over the course of this work, I explored how different market regimes affect the performance of a variety of strategies from traditional moving average crossovers to machine learning based trend prediction and how volatility scaling can make these approaches more robust.

One of the key insights was that **long-only strategies tend to outperform**, but their performance and risk profile improve significantly when combined with dynamic exposure techniques. Strategies like **Dynamic TCVS** and **Vol-Scaled ML** showed that adjusting position sizes during volatile phases improves Sharpe ratios and reduces drawdowns. Meanwhile, **machine learning models**, trained on features such as RSI, MACD, volatility, and short-term returns, proved effective in anticipating market direction and selecting the most suitable strategy under varying conditions.

As the project progressed, I focused on understanding **which strategies flourish under what kinds of market behavior**. Mean Reversion performed well in high-volatility, oversold environments with weak trends. ML-based models performed best during smooth, momentum-driven bull markets. Dynamic TCVS emerged as the most balanced, adapting effectively to changes in both trend and volatility. Exact parameters are in the report; there were a few indications, but they can definitely be improved with a bit more study on different timelines.

I also studied **return crossovers** between strategies, particularly between Mean Reversion and TCVS, and observed that measurable shifts in features like RSI, MACD, VIX, and volatility tend to precede these transitions. This suggested that regime shifts are not random and can be detected through interpretable indicators.

As requested, I've saved all key datasets including strategy returns, labeled dominant strategies, and feature matrices in time series **CSV format** within the results/ folder of the GitHub project repository. This ensures the work is reproducible and traceable.

Due to space constraints, I was unable to include all visuals such as confusion matrices, classification reports, and heatmaps within this report. These are available in the images section of the project. My goal was to present the work in a coherent, story-like structure capturing how volatility and trend signals can be used not just to explain markets, but to navigate them more intelligently.

This work provides a strong foundation for regime-aware allocation and opens up several directions for future development, from multi-horizon crossover profiling to macro-integrated switching logic.