

ORIGINAL RESEARCH

An Empirical Study of Volatility Regimes in a Multifactor Equity Portfolio

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Abstract

This paper presents an empirical analysis of a rules-based multifactor equity portfolio and examines how its performance varies across market volatility regimes. The portfolio is constructed from a fixed universe of 50 large-cap U.S. equities and employs a cross-sectional ranking methodology based on valuation, profitability, growth, and risk signals, with momentum used only as a secondary tie-breaker. The strategy is rebalanced monthly and is evaluated relative to the SPDR S&P 500 ETF (SPY) using both gross and net-of-transaction-cost returns. Market volatility regimes are identified using the CBOE Volatility Index (VIX). Low- and high-volatility regimes are defined as the bottom and top terciles of a rolling three-month (63 trading-day) average of daily VIX levels. Portfolio performance is summarized using annualized return, annualized volatility, Sharpe ratio, and information ratio versus SPY. Results indicate pronounced regime dependence: risk-adjusted and benchmark-relative performance is strongest in low-volatility regimes, while elevated-volatility regimes exhibit substantially higher return variability and weaker benchmark-relative outcomes. This analysis is intended as an empirical research note and a methodological prototype rather than a production trading framework.

Keywords: Multifactor Investing; Portfolio Management; Volatility Regimes; Equity Strategies; Quantitative Finance; Econometrics

1. Introduction

Systematic multifactor equity strategies play an important role in both academic asset-pricing research and practical portfolio management. By combining signals related to valuation, profitability, growth, market risk, and balance-sheet leverage, multifactor approaches seek to rank securities on characteristics associated with differences in cross-sectional stock returns while maintaining transparent and rules-based portfolio construction. Research on factor investing has documented associations between value, profitability, investment, and momentum characteristics and stock returns across markets and sample periods (Fama and French 2015; Asness, Moskowitz, and Pedersen 2013; Jegadeesh and Titman 1993).

The realized performance of factor portfolios may nevertheless vary across market environments. Periods of elevated market uncertainty can coincide with larger price fluctuations, changing correlations, and substantial differences in the relative performance of stocks and investment styles. Financial returns also exhibit volatility clustering, meaning that high-volatility observations tend to be followed by further high-volatility observations rather than occurring independently over time (Bollerslev 1986). These

features motivate an examination of whether the behavior of a static multifactor portfolio differs across volatility conditions.

Market volatility is commonly summarized by the CBOE Volatility Index (VIX), an index derived from S&P 500 index-option prices that reflects the market's expectation of near-term volatility. In this paper, the VIX is used as an ex-post classification variable: it divides portfolio-return observations into low-, medium-, and high-volatility regimes. This use of the VIX does not test a real-time volatility-timing strategy, nor does it establish that volatility causes changes in portfolio performance. Instead, it provides a transparent way to compare the portfolio's realized return, risk, and benchmark-relative outcomes across different market-volatility environments.

Prior literature provides reasons to expect that factor behavior can vary during stressed markets. For example, Daniel and Moskowitz (2016) document severe momentum crashes in particular market conditions, while Ang, Chen, and Xing (2006) study the importance of downside risk in equity returns. However, evidence concerning individual factors or momentum crashes does not necessarily imply identical results for a simple long-only multifactor portfolio. The present study therefore evaluates this question empirically within a fixed 50-stock large-cap U.S. equity universe.

This paper examines a rules-based, monthly rebalanced multifactor portfolio constructed from five equally weighted signals: valuation, profitability, revenue growth, realized price volatility, and debt-to-equity. Lower P/E, lower realized volatility, and lower debt-to-equity receive more favorable scores, while higher ROE and revenue growth receive more favorable scores. Twelve-month momentum is calculated from adjusted prices and used only as a secondary sorting criterion when composite scores are tied; it is not included in the portfolio's weighted composite score.

2. Methodology

2.1 Data and Universe

The strategy is evaluated over a fixed universe of 50 large-cap U.S. equities spanning multiple sectors. The complete ticker list is provided in the Appendix. The universe is static over the sample and was selected retrospectively; it is therefore not a point-in-time index-constituent universe.

Daily adjusted closing prices for the equity universe and the SPDR S&P 500 ETF (SPY) benchmark were obtained from Yahoo Finance using the `yfinance` Python package. The sample begins on January 1, 2016, and ends on January 1, 2026. SPY daily returns were aligned to the portfolio-return dates and used to calculate benchmark-relative performance measures.

The use of a fixed retrospective universe may create selection and survivorship bias because firms that delisted, merged, failed, or lacked continuous observations are not represented in the same way as they would be in a point-in-time investable universe. Accordingly, the results describe the selected fixed universe and should not be interpreted as performance for a historically investable large-cap benchmark universe.

2.2 Data Collection

Fundamental variables—trailing price-to-earnings ratio (P/E), return on equity (ROE), revenue growth, and debt-to-equity—were retrieved from Yahoo Finance through the `yfinance` Python package on December 1, 2025.

Yahoo Finance provided historical price data used to calculate price-based signals, but this study did not use a verified point-in-time historical fundamental-data database. The retrieved fundamental values were therefore treated as static cross-sectional snapshot inputs and applied retrospectively in the monthly ranking procedure. They were not matched to the information set known to investors at each historical rebalance date.

This design may introduce look-ahead bias because the snapshot values may reflect financial information that was not publicly available at earlier rebalance dates. The reported results should consequently be interpreted as an exploratory methodological demonstration of portfolio behavior across retrospectively defined VIX regimes, rather than as evidence of a historically implementable investment strategy.

2.3 Factor Construction

At each rebalance date, the algorithm computes price-based factors from historical adjusted prices and combines them with fundamental variables retrieved from Yahoo Finance. Incorporating profitability and balance-sheet quality alongside valuation metrics helps capture cross-sectional return differentials while mitigating exposure to distress risks (Novy-Marx, 2013):

- **Momentum** (tie-breaker only): trailing 12-month total return, computed as $P_t/P_{t-252} - 1$, where P_t is the adjusted close and 252 is the trading-day lookback. Momentum is not included in the weighted composite score; it is used only as a secondary sorting criterion to break ties.
- **Volatility** (risk): annualized standard deviation of daily returns over the prior 252 trading days, i.e., $\sigma_t = \text{Std}(\Delta P/P) \cdot \sqrt{252}$.
- **Value**: trailing price-to-earnings (P/E), where lower values are preferred.
- **Profitability**: return on equity (ROE), where higher values are preferred.
- **Growth**: revenue growth, where higher values are preferred.
- **Leverage Risk**: debt-to-equity ratio, where lower values are preferred.

Here, $P_{i,t}$ is the adjusted closing price of stock i at time t . Momentum is not included in the composite score. It is used only as a pre-specified secondary sorting rule when securities have equal composite scores.

The combination of valuation, profitability, growth, and risk-related characteristics is motivated by multifactor asset-pricing research, although the specific static fundamental-data implementation in this study is subject to the timing limitation described above.

2.4 Winsorization, Standardization, and Scoring

On each rebalance date, all factor inputs (including momentum and the five score components) are win-sorized at the 1st and 99th percentiles across the universe to prevent extreme outliers from distorting cross-sectional rankings (Barroso & Santa-Clara, 2015). Each factor is then standardized using a cross-sectional z-score. For variables where lower values are preferred (P/E, volatility, debt-to-equity), the standardized values are multiplied by -1 so that higher standardized scores represent more favorable characteristics. A composite score is computed as an equal-weighted sum of standardized factors:

$$S_i = \frac{1}{4} (z_{PE,i}^* + z_{ROE,i}^* + z_{RevGrowth,i}^* + z_{D/E,i}^*)$$

2.5 Portfolio Selection, Rebalancing, and Returns

Signals are formed using information available at the final trading day of each calendar month. At each month-end ranking date, all stocks in the fixed universe are ranked in descending order by the composite score S_i . Twelve-month momentum is used only as a secondary descending sort key when composite scores are tied.

The top 30 ranked securities are selected for the long-only portfolio. The selected stocks are equal-weighted, with each receiving a target portfolio weight of $1/30$. The portfolio is held from the first trading day following the ranking date until the next monthly rebalance.

Daily portfolio returns are calculated as the equally weighted mean of the daily returns of the selected constituents. Two return series are reported:

- **Gross returns**: exclude transaction costs.
- **Net returns**: apply a turnover-based transaction cost model as described below in Section 2.6.

2.6 Turnover and Transaction Cost Model

Holdings turnover measures the fraction of positions replaced between two consecutive monthly rebalances:

$$\text{Turnover} = 1 - \frac{|H_t \cap H_{t-1}|}{|H_t|}$$

where H_t is the set of 30 securities held after rebalance t . With a constant 30-stock equal-weighted portfolio, this quantity represents the proportion of portfolio positions that changed at the rebalance. The baseline transaction-cost model assumes a cost of 10 basis points for 100% holdings turnover:

$$\text{Cost} = 0.001 \times \text{Turnover}.$$

This estimated cost is deducted from the first daily return of each new holding period to create the net portfolio-return series. The model is simplified and does not capture bid-ask spreads, market impact, taxes, liquidity constraints, or execution delays.

2.7 Volatility Regimes (VIX)

Daily VIX closing levels were obtained from Yahoo Finance using the ticker `^VIX`. A 63-trading-day rolling average of the VIX was calculated to represent approximately three months of market volatility conditions. Low- and high-volatility thresholds were defined as the 33rd and 67th percentiles, respectively, of the full-sample distribution of this smoothed VIX series.

Each trading day was classified as:

- `low_vol` if smoothed VIX is below or equal to the 33rd percentile,
- `high_vol` if smoothed VIX is above or equal to the 67th percentile,
- `mid` otherwise.

Performance summaries were calculated using net portfolio returns and SPY returns on matching trading dates. Because the VIX thresholds are estimated using the full sample, this is an ex-post descriptive regime classification. It is not a real-time VIX-timing rule, since later VIX observations influence the threshold values used to classify earlier dates.

2.8 Performance Metrics

Let r_t denote daily portfolio returns and b_t denote benchmark returns. Reported statistics include:

- Annualized return: $\left(\prod_{t=1}^T (1 + r_t) \right)^{252/T} - 1$
- Annualized volatility: $\text{Std}(r_t) \cdot \sqrt{252}$
- Sharpe Ratio: $\frac{E[r_t]}{\text{Std}(r_t)} \cdot \sqrt{252}$
- Information ratio vs. SPY: $\frac{E[r_t - b_t]}{\text{Std}(r_t - b_t)} \cdot \sqrt{252}$

3. Data Availability and Reproducibility

Daily adjusted-price data for the fixed 50-stock universe, the SPDR S&P 500 ETF (SPY), and the CBOE Volatility Index (`^VIX`) were retrieved from Yahoo Finance using the `yfinance` Python package. The complete 50-ticker universe, factor definitions, scoring formula, factor directions, portfolio-selection rule, rebalancing schedule, turnover calculation, transaction-cost assumption, VIX-regime definition, and treatment of missing observations are reported in the Appendix.

Fundamental variables—trailing price-to-earnings ratio, return on equity, revenue growth, and debt-to-equity—were retrieved from Yahoo Finance on December 1, 2025. Yahoo Finance fundamental fields were used as static cross-sectional snapshot inputs in the retrospective ranking procedure; the study did not use a verified point-in-time historical fundamental database. Consequently, the fundamental inputs may contain information that was not available at earlier historical rebalance dates, creating possible look-ahead bias.

The implementation produces the gross and net portfolio equity curves, VIX-regime performance summaries, and a holdings-change log. The reported output files are `equity_curves.csv`, `regime_summary.csv`, and `holdings_changes.xlsx`. The analysis should therefore be interpreted as an exploratory empirical prototype of regime-dependent portfolio behavior, rather than evidence of a his-

torically investable trading strategy. The Python implementation and output files used to generate the reported results are included as supplementary material.

4. Results

4.1 Full-Sample Performance (Net of Costs)

Table 1 summarizes full-sample performance for the net portfolio. These values correspond to the code's regime summary for ALL and the printed average turnover. Consistent with empirical factor literature, composite multi-factor portfolios exhibit positive long-term excess returns, though performance varies significantly across macro environments (Carhart, 1997; Fama & French, 2015).

Table 1. Full-sample performance summary (net of transaction costs).

Metric	Value
Annualized Return	0.223
Annualized Volatility	0.171
Sharpe Ratio	1.260
Information Ratio vs SPY	1.115
Average Turnover (per rebalance)	0.024

4.2 Equity Curve

Figure 1 displays the equity curve output (cumulative returns) for the portfolio and benchmark. In the code implementation, the plot includes both gross and net portfolio equity curves alongside SPY.

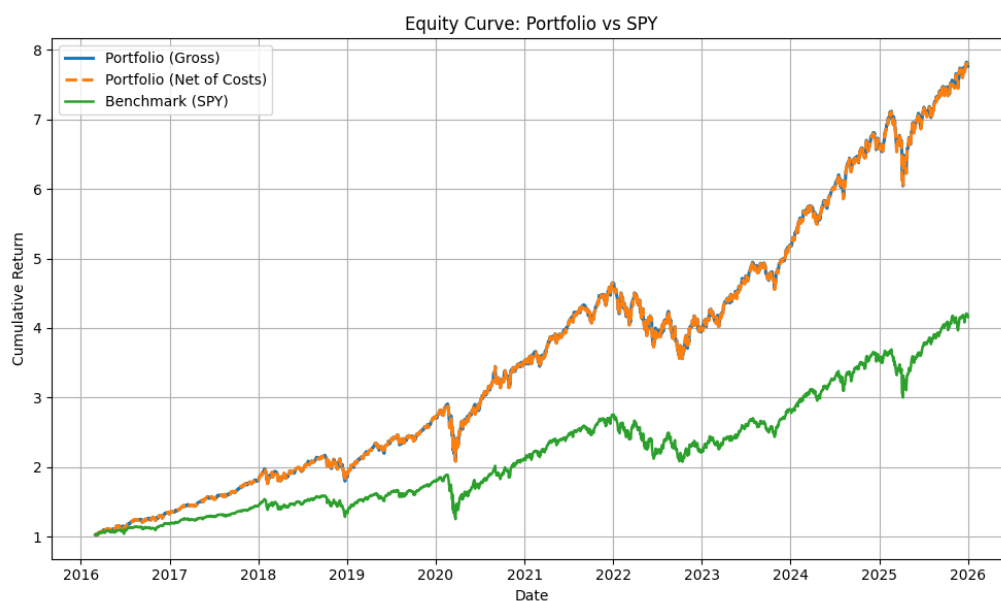


Figure 1. Equity curve of the portfolio versus SPY (the code plots gross and net portfolio curves alongside the benchmark).

4.3 Performance Across Volatility Regimes

Table 2 reports regime-level performance for the net portfolio relative to SPY. Regimes are defined by terciles of the rolling three-month average of daily VIX levels, consistent with the implementation.

Risk-adjusted and benchmark-relative performance is strongest during low-volatility regimes. Although annualized returns remain high during elevated-volatility periods, benchmark-relative and risk-adjusted performance deteriorate substantially, as reflected in lower information and Sharpe ratios. While

Table 2. VIX regime sensitivity (net portfolio vs. SPY).

Volatility Regime	Days	Ann. Return	Ann. Vol.	Sharpe	Info Ratio
ALL	2452	0.223	0.171	1.260	1.115
LOW_VIX	809	0.235	0.117	1.858	2.205
HIGH_VIX	809	0.294	0.232	1.228	0.253

the present analysis does not isolate specific factor effects, this pattern is broadly consistent with prior evidence that cross-sectional investment strategies may experience increased drawdown risk and less stable performance during periods of market stress (Daniel & Moskowitz, 2016; Barroso & Santa-Clara, 2015).

5. Limitations

This study uses retrospective backtesting and does not represent live trading performance. Fundamental variables—P/E, ROE, revenue growth, and debt-to-equity—were retrieved from Yahoo Finance as static snapshot inputs and applied retrospectively across historical rebalance dates. These inputs were not matched to the information available to investors at each portfolio-formation date and may therefore introduce look-ahead bias. This limitation affects the portfolio rankings as well as the resulting full-sample and regime-specific performance measures. Accordingly, the reported results should be interpreted as an exploratory methodological demonstration rather than evidence of historically investable performance.

The portfolio uses a fixed, retrospectively selected universe of 50 large-cap U.S. equities rather than a point-in-time constituent database. This design may introduce selection and survivorship bias because the universe does not systematically represent firms that delisted, failed, merged, or were otherwise absent from the selected sample. Its limited size and large-cap focus also restrict the generalizability of the findings to other equity universes and asset classes.

Transaction costs are modeled as a simple linear function of holdings turnover. This approximation does not capture bid-ask spreads, market impact, taxes, execution delays, or trading required to restore equal weights among continuing holdings. Net returns should therefore be understood as returns after the specified cost assumption, not as a complete estimate of implementable trading costs.

Volatility regimes are defined using the 33rd and 67th percentiles of the full-sample distribution of a 63-trading-day average of VIX levels. Because later observations influence these thresholds, the classifications are suitable for an ex-post descriptive comparison rather than a real-time trading rule. Alternative smoothing windows, thresholds, and sample periods could produce different classifications and performance comparisons.

Finally, the analysis compares realized portfolio outcomes across volatility regimes; it does not establish that volatility causes changes in factor performance. It also does not test whether VIX-based factor tilts, volatility targeting, or defensive cash allocations improve returns or reduce drawdowns. Those approaches require separate evaluation using historically available inputs and an explicitly specified trading rule.

6. Conclusion

This study empirically demonstrates that the risk and return characteristics of a static, rules-based multi-factor equity portfolio vary significantly across VIX-defined volatility regimes. Specifically, the strategy exhibits its strongest risk-adjusted performance during low-volatility regimes, whereas high-volatility regimes introduce elevated return variability and weaker benchmark-relative returns (Ang & Bekaert, 2002; Chow et al., 1999).

While these findings highlight the regime dependence of static factor allocations, this analysis evaluates portfolio performance ex-post across partitioned market environments. It does not directly test the

performance of active timing mechanisms. Therefore, these results suggest promising avenues for future research, specifically testing whether active VIX-based dynamic factor tilts (Daniel & Moskowitz, 2016), volatility-targeted rebalancing (Barroso & Santa-Clara, 2015), or defensive cash allocations can systematically mitigate drawdown risks during high-volatility regimes.

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A. Appendix

50-Ticker Universe

AAPL, MSFT, AMZN, NVDA, GOOGL, META, BRK-B, LLY, JNJ, JPM, V, PG, XOM, UNH, MA, HD, CVX, ABBV, MRK, COST, PEP, KO, BAC, WMT, MCD, CSCO, CRM, ACN, TMO, LIN, ABT, ORCL, AMD, DIS, PFE, PM, INTC, INTU, TXN, AMGN, HON, UNP, LOW, SPGI, IBM, QCOM, GE, CAT, NKE, GS.

Data Handling and Considerations

Missing fundamental observations: When a fundamental metric was unavailable in the downloaded Yahoo Finance snapshot, the missing value was replaced with the median of the available values for that metric across the stock universe. This replacement occurred before winsorization and z-score standardization. The resulting fundamental inputs were applied retrospectively across monthly ranking dates; this procedure did not reconstruct historical fundamental observations or resolve look-ahead bias.

Incomplete price histories and inactive securities: Securities without complete price histories for the specified sample period, January 1, 2016 through January 1, 2026, were excluded before backtest execution. Requiring complete histories may introduce selection and survivorship bias because securities with interrupted or unavailable histories are omitted. The analysis therefore describes a fixed retrospective universe rather than a point-in-time investable universe.

Extreme observations: The five scoring inputs and the momentum tie-breaker were winsorized cross-sectionally at the 1st and 99th percentiles before z-score standardization. Values below the 1st percentile were set to the 1st-percentile value, and values above the 99th percentile were set to the 99th-percentile value. This procedure limits the influence of extreme observations without removing securities from the universe.

Scoring Formula and Composite Rank Calculation

On each monthly rebalance date, cross-sectional factor values are calculated across the 50-stock universe for four fundamental metrics: Price-to-Earnings (x_{PE}), Return on Equity (x_{ROE}), Trailing Revenue Growth ($x_{RevGrowth}$), and Debt-to-Equity ($x_{D/E}$).

Winsorization: Extreme factor values are capped at the 1st and 99th percentiles to eliminate extreme outliers, along with their adverse effects:

$$x_{f,i}^w = \max(x_f^{(0.01)}, \min(x_{f,i}, x_f^{(0.99)}))$$

Standardization (Z-Score): Cross-sectional z-scores are computed for each factor f across all N stocks:

$$z_{f,i} = \frac{x_{f,i}^w - \bar{x}_f}{s_f}$$

Directional Adjustment: Factors where lower values are desirable (P/E and D/E) are inverted by multiplying by -1 :

$$z_{f,i}^* = -z_{f,i} \quad \text{for } f \in \{PE, \text{Volatility}, D/E\}$$

Composite Score: The final composite score S_i for stock i is calculated using an equal-weighted factor model:

$$S_i = \frac{1}{4} (z_{PE,i}^* + z_{ROE,i}^* + z_{RevGrowth,i}^* + z_{D/E,i}^*)$$

Securities are ranked in descending order by S_i . Standardized 12-month momentum is used as a secondary descending sort key for tied composite scores; momentum receives no weight in the composite score.

Portfolio Selection Procedure

Ranking: At the final trading day of each calendar month, all 50 stocks in the fixed universe are ranked in descending order by composite score S_i . When composite scores are tied, stocks are ranked in descending order by their standardized 12-month momentum.

Selection: The top 30 ranked stocks ($N = 30$) are selected for inclusion in the long-only portfolio.

Weighting and Rebalancing: Each selected stock receives an equal target weight of $1/30$, approximately 3.33%. The month-end ranking determines the portfolio for the following month. At the monthly portfolio change, dropped constituents are removed, newly selected constituents are added, and equal target weights are assigned to the selected stocks.

Return Calculation: For each subsequent holding period, daily gross portfolio returns are calculated as the arithmetic mean of the selected constituents' daily returns. Net returns deduct the turnover-based transaction costs described in Section 2.6.

Backtest Implementation Code (Python)

```
import numpy as np
import pandas as pd
import yfinance as yf
import matplotlib.pyplot as plt

TICKERS = """
AAPL MSFT AMZN NVDA GOOGL META BRK-B LLY JNJ JPM V PG XOM UNH MA HD
CVX ABBV MRK COST PEP KO BAC WMT MCD CSCO CRM ACN TMO LIN ABT ORCL
AMD DIS PFE PM INTC INTU TXN AMGN HON UNP LOW SPGI IBM QCOM GE CAT NKE GS
""".split()
START, END, N = "2016-01-01", "2026-01-01", 30

px = yf.download(
    TICKERS + ["SPY", "^VIX"], start=START, end=END,
    auto_adjust=True, progress=False
)["Close"]
px = px.reindex(px["SPY"].dropna().index)
prices = px.reindex(columns=TICKERS).dropna(axis=1)
excluded = sorted(set(TICKERS) - set(prices.columns))
print("Excluded:", excluded, "| Final universe:", len(prices.columns))
if len(prices.columns) < N:
    raise ValueError("Fewer than 30 stocks have complete price histories.")

fields = ["trailingPE", "returnOnEquity", "revenueGrowth", "debtToEquity"]
fund = pd.DataFrame({
    t: {f: yf.Ticker(t).info.get(f, np.nan) for f in fields}
    for t in prices.columns
}).T.apply(pd.to_numeric, errors="coerce").replace(
    [np.inf, -np.inf], np.nan)
fund.to_csv("fundamental_snapshot.csv")
print("Fundamental retrieval date:",
      pd.Timestamp.now(tz="UTC").isoformat())
if fund.isna().all().any():
    raise ValueError(
        "An entire fundamental field is missing; check Yahoo data.")
fund = fund.fillna(fund.median())

returns = prices.pct_change(fill_method=None)
momentum = prices / prices.shift(252) - 1
volatility = returns.rolling(252).std() * np.sqrt(252)
dates = prices.groupby(prices.index.to_period("M")).tail(1).index
```

```

gross, net, log, previous = [], [], [], None
for j, date in enumerate(dates):
    if (volatility.loc[date].isna().any()
        or momentum.loc[date].isna().any()):
        continue
    stop = (dates[j + 1] if j + 1 < len(dates)
            else prices.index[-1])
    raw = fund.copy()
    raw["vol"] = volatility.loc[date]
    raw["mom"] = momentum.loc[date]
    clipped = raw.clip(
        raw.quantile(.01), raw.quantile(.99), axis=1)
    z = ((clipped - clipped.mean())
         / clipped.std().replace(0, np.nan)).fillna(0)
    z[["trailingPE", "debtToEquity", "vol"]] *= -1
    ranked = pd.DataFrame({
        "score": z.drop(columns="mom").mean(axis=1),
        "momentum": z["mom"]})
    picks = ranked.sort_values(
        ["score", "momentum"], ascending=False
    ).head(N).index.tolist()
    period = returns.loc[
        (returns.index > date) & (returns.index <= stop),
        picks]
    if period.empty:
        continue
    turn = (np.nan if previous is None
            else 1 - len(set(picks) & set(previous)) / N)
    g, n = period.mean(axis=1), period.mean(axis=1)
    if previous is not None:
        n.iloc[0] -= .001 * turn
    gross.append(g)
    net.append(n)
    log.append({"rebalance_date": date,
               "turnover": turn,
               "held": ", ".join(picks)})
    previous = picks

if not net:
    raise ValueError(
        "No holding periods remain after the 252-day lookback.")
g, n = pd.concat(gross), pd.concat(net)
b = px["SPY"].pct_change(fill_method=None).reindex(n.index)
v = px["^VIX"].rolling(63).mean().dropna()
lo, hi = v.quantile([.33, .67])
regime = pd.Series("mid", index=v.index)
regime[v <= lo] = "low_vol"
regime[v >= hi] = "high_vol"
data = pd.DataFrame({
    "net": n, "bench": b,
    "regime": regime.reindex(n.index)}).dropna()

def metrics(name, d):
    r, excess = d["net"], d["net"] - d["bench"]
    return {
        "regime": name, "days": len(r),
        "ann_return":
            (1 + r).prod() ** (252 / len(r)) - 1,
        "ann_vol": r.std() * np.sqrt(252),
        "sharpe": r.mean() / r.std() * np.sqrt(252),
        "info_ratio":
            excess.mean() / excess.std() * np.sqrt(252)}

summary = pd.DataFrame([
    metrics(name,
           data if name == "ALL"
           else data[data["regime"] == name])
    for name in ["ALL", "low_vol", "mid", "high_vol"]])
equity = (1 + pd.DataFrame({
    "Gross": g, "Net": n, "SPY": b})).cumprod()
equity.to_csv("equity_curves.csv")

```

```
summary.to_csv("regime_summary.csv", index=False)
pd.DataFrame(log).to_excel(
    "holdings_changes.xlsx", index=False)
print(summary.to_string(index=False))
print("Average turnover:",
      pd.DataFrame(log)["turnover"].mean())
equity.plot(title="Growth of $1",
            ylabel="Portfolio value", figsize=(9, 5))
plt.tight_layout()
plt.savefig("equity_curve.png", dpi=200)
plt.show()
```

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