基于动量轮动策略的有效性分析

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1 引言

动量效应是金融市场中一种重要的现象，指过去表现较好的资产在未来短期内往往继续表现较好，而过去表现较差的资产则继续表现较差。基于动量效应的交易策略已经被广泛研究和应用。

在股票市场中，大盘股和小盘股通常具有不同的风险收益特征和市场表现。本研究旨在探索一种基于动量的轮动策略，通过比较大盘股和小盘股的相对强度，动态调整投资组合的配置，以获取超额收益。

我们将使用 R 语言实现这一策略，并通过历史数据验证其有效性。同时，我们会优化策略参数，测试参数敏感性，并在样本外数据上验证策略的稳健性。

2 数据准备与分析

首先加载必要的 R 包并获取股票数据。我们将选取多只大盘股和小盘股作为研究对象。

```r
# 加载必要的 R 包
library(quantmod)
library(PerformanceAnalytics)
library(foreach)
library(doParallel)
library(ggplot2)
library(dplyr)
library(tidyr)
library(caret)
library(magrittr)
```

接下来，我们获取股票数据。我们将选择 10 只大盘股和 10 只小盘股作为样本。大盘股选取标普 500 指数成分股中市值最大的 10 只，小盘股选取罗素 2000 指数成分股中市值最小的 10 只。

```r
# 设置起止日期
start_date <- "2018-01-01"
end_date <- "2023-01-01"
out_of_sample_date <- "2023-01-02"
end_oos_date <- "2023-12-31"

# 大盘股列表
large_cap_symbols <- c("AAPL", "MSFT", "AMZN", "TSLA")

# 小盘股列表
small_cap_symbols <- c("ARQT", "AVXL", "BPMC", "CELZ")

# 所有股票代码
all_symbols <- c(large_cap_symbols, small_cap_symbols)

# 获取股票数据
stock_data <- list()
for (symbol in all_symbols) {
  tryCatch(
    {
      stock_data_raw <- getSymbols(symbol,
                                   from = start_date,
                                   to = end_date,
                                   auto.assign = FALSE)
      colnames(stock_data_raw) <- c("Open",
                                    "High",
                                    "Low",
                                    "Close",
                                    "Volume",
                                    "Adjusted")
      stock_data[[symbol]] <- stock_data_raw
      cat("Successfully downloaded", symbol, "\n")
    },
```

```
    error = function(e) {
      cat("Error downloading", symbol, ":", conditionMessage(e), "\n")
    }
  )
}
```

```
## Successfully downloaded AAPL
## Successfully downloaded MSFT
## Successfully downloaded AMZN
## Successfully downloaded TSLA
## Successfully downloaded ARQT
## Successfully downloaded AVXL
## Successfully downloaded BPMC
## Successfully downloaded CELZ
```

```
# 过滤掉下载失败的股票
valid_symbols <- names(stock_data)
large_cap_symbols <- large_cap_symbols[large_cap_symbols %in% valid_symbols]
small_cap_symbols <- small_cap_symbols[small_cap_symbols %in% valid_symbols]

# 获取样本外数据
oos_data <- list()
for (symbol in valid_symbols) {
  tryCatch(
    {
      oss_data_raw <- getSymbols(symbol,
                                 from = out_of_sample_date,
                                 to = end_oos_date,
                                 auto.assign = FALSE)
      colnames(oss_data_raw) <- c("Open",
                                  "High",
                                  "Low",
                                  "Close",
                                  "Volume",
```

```
                                  "Adjusted")
      oos_data[[symbol]] <- oss_data_raw
      cat("Successfully downloaded OOS data for", symbol, "\n")
    },
    error = function(e) {
      cat("Error downloading OOS data for", symbol, ":", conditionMessage(e), "\n")
    }
  )
}
```

```
## Successfully downloaded OOS data for AAPL
## Successfully downloaded OOS data for MSFT
## Successfully downloaded OOS data for AMZN
## Successfully downloaded OOS data for TSLA
## Successfully downloaded OOS data for ARQT
## Successfully downloaded OOS data for AVXL
## Successfully downloaded OOS data for BPMC
## Successfully downloaded OOS data for CELZ
```

让我们计算并可视化大盘股和小盘股的平均价格走势，以便对数据有一个直观的了解。

```
# 函数：合并多只股票的收盘价并处理缺失值
merge_stock_prices <- function(symbols, stock_data_list) {
  merged_prices <- NULL

  for (symbol in symbols) {
    # 提取单只股票的收盘价
    stock_close <- Cl(stock_data_list[[symbol]])

    # 如果是第一只股票，直接赋值
    if (is.null(merged_prices)) {
      merged_prices <- stock_close
      colnames(merged_prices) <- symbol
```

```
    } else {
      # 合并多只股票，自动对齐日期
      merged_prices <- merge(merged_prices, stock_close)
      colnames(merged_prices)[ncol(merged_prices)] <- symbol
    }
  }

  # 处理缺失值：使用前向填充和后向填充结合
  merged_prices <- na.locf(merged_prices) # 前向填充
  merged_prices <- na.locf(merged_prices, fromLast = TRUE) # 后向填充

  return(merged_prices)
}

# 合并大盘股和小盘股的价格数据
large_cap_merged <- merge_stock_prices(large_cap_symbols, stock_data)
small_cap_merged <- merge_stock_prices(small_cap_symbols, stock_data)

# 确保两个数据集具有相同的日期范围
common_dates <- intersect(index(large_cap_merged), index(small_cap_merged))
large_cap_merged <- large_cap_merged[common_dates]
small_cap_merged <- small_cap_merged[common_dates]

# 计算平均价格
large_cap_avg <- rowMeans(large_cap_merged)
small_cap_avg <- rowMeans(small_cap_merged)

# 归一化价格
large_cap_norm <- large_cap_avg / large_cap_avg[1]
small_cap_norm <- small_cap_avg / small_cap_avg[1]

# 创建绘图数据框
price_data <- data.frame(
```

```
  Date = as.Date(index(large_cap_merged)),
  Large_Cap = as.numeric(large_cap_norm),
  Small_Cap = as.numeric(small_cap_norm)
)

# 使用 ggplot2 绘制对比图
library(ggplot2)
ggplot(price_data, aes(x = Date)) +
  geom_line(aes(y = Large_Cap, color = " 大盘股")) +
  geom_line(aes(y = Small_Cap, color = " 小盘股")) +
  labs(
    title = " 大盘股与小盘股价格走势对比",
    y = " 归一化价格",
    color = " 股票类型"
  ) +
  theme_minimal() +
  scale_color_manual(values = c(" 大盘股" = "blue", " 小盘股" = "red"))
```

3 动量轮动策略实现

下面我们实现基于动量的大盘股/小盘股轮动策略。该策略的核心思想是：比较大盘股和小盘股的相对动量，选择动量更强的一组进行投资。

首先定义一个函数来实现这个策略：

```r
# 改进的动量轮动策略函数
momentum_rotation_strategy <- function(large_cap_data, small_cap_data,
                                       lookback_period = 20,
                                       holding_period = 10,
                                       rebalance_threshold = 0.05,
                                       commission = 0.001) {
  # 函数：计算单只股票的对数收益率
  calculate_returns <- function(stock_data) {
    colnames(stock_data) <- c("Open", "High", "Low", "Close", "Volume", "Adjusted")
    close_prices <- Cl(stock_data)
    returns <- dailyReturn(close_prices, type = "log")
    colnames(returns) <- ""
    return(returns)
  }

  # 计算所有股票的收益率
  large_cap_returns_list <- lapply(large_cap_data, calculate_returns)
  small_cap_returns_list <- lapply(small_cap_data, calculate_returns)

  # 合并所有收益率数据，自动对齐日期
  large_cap_returns_merged <- do.call(merge, large_cap_returns_list)
  small_cap_returns_merged <- do.call(merge, small_cap_returns_list)

  # 将所有 NA 值填充为 0
  large_cap_returns_merged <- na.fill(large_cap_returns_merged, fill = 0)
  small_cap_returns_merged <- na.fill(small_cap_returns_merged, fill = 0)
```

```
# 确保两个数据集具有相同的日期范围
common_dates <- intersect(index(large_cap_returns_merged),
                          index(small_cap_returns_merged))
large_cap_returns_merged <- large_cap_returns_merged[common_dates]
small_cap_returns_merged <- small_cap_returns_merged[common_dates]

# 计算平均收益率（保持 xts 格式）
large_cap_avg_returns <- xts(rowMeans(large_cap_returns_merged),
  order.by = index(large_cap_returns_merged)
)
small_cap_avg_returns <- xts(rowMeans(small_cap_returns_merged),
  order.by = index(small_cap_returns_merged)
)

# 计算动量指标（lookback_period 天的累计收益率）
large_cap_momentum <- xts(rep(0, length(large_cap_avg_returns)),
  order.by = index(large_cap_avg_returns)
)
small_cap_momentum <- xts(rep(0, length(small_cap_avg_returns)),
  order.by = index(small_cap_avg_returns)
)

for (i in (lookback_period + 1):length(large_cap_avg_returns)) {
  large_cap_momentum[i] <- sum(large_cap_avg_returns[(i - lookback_period):i])
  small_cap_momentum[i] <- sum(small_cap_avg_returns[(i - lookback_period):i])
}

# 初始化仓位（保持 xts 格式）
position <- xts(rep(0, length(large_cap_avg_returns)),
  order.by = index(large_cap_avg_returns)
)
position[lookback_period + 1] <- ifelse(large_cap_momentum[lookback_period + 1] > sma
```

```
# 生成交易信号
for (i in (lookback_period + 2):length(large_cap_avg_returns)) {
  # 每隔 holding_period 天重新评估一次
  if ((i - lookback_period) %% holding_period == 0) {
    # 计算动量差异
    momentum_diff <- large_cap_momentum[i] - small_cap_momentum[i]

    # 如果动量差异超过阈值，则切换仓位
    if (abs(momentum_diff) > rebalance_threshold) {
      position[i] <- ifelse(momentum_diff > 0, 1, -1)
    } else {
      # 否则保持原仓位
      position[i] <- position[i - 1]
    }
  } else {
    # 保持原仓位
    position[i] <- position[i - 1]
  }
}

# 计算策略收益（保持 xts 格式）
strategy_returns <- position * (large_cap_avg_returns - small_cap_avg_returns)
strategy_return <- na.fill(strategy_returns, fill = 0) # 将 NA 值填充为 0
# 考虑交易成本
# 创建与 position 相同长度和索引的 trades 对象
trades <- xts(rep(0, length(position)), order.by = index(position))
trades <- abs(diff(position)) > 0
trades <- na.fill(trades, fill = "FALSE") # 将 NA 值填充为 FALSE
commission_cost <- trades * commission

# 计算净收益（保持 xts 格式）
net_returns <- strategy_returns - commission_cost
net_returns <- na.fill(net_returns, fill = 0) # 将 NA 值填充为 0
```

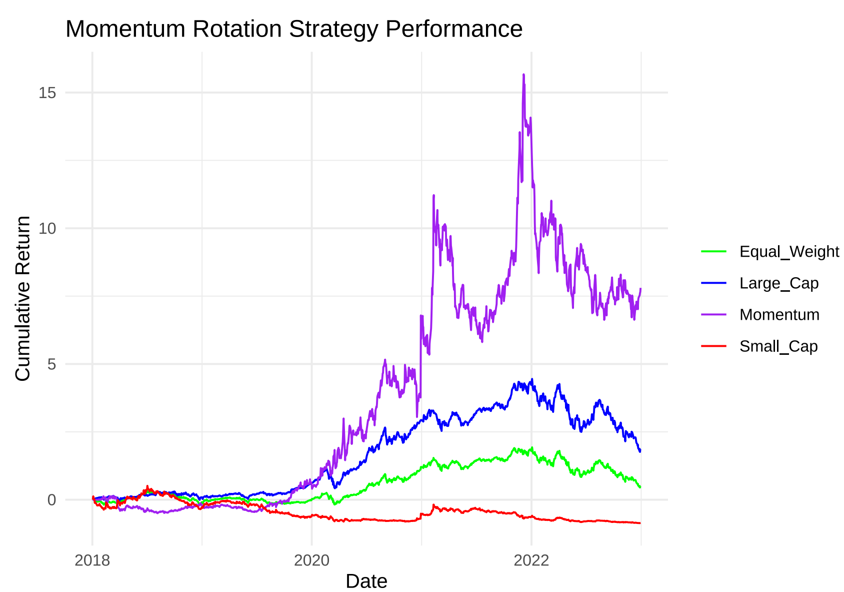
```r
# 计算累积收益 (保持 xts 格式)
cumulative_returns <- exp(cumsum(net_returns)) - 1

# 返回结果 (同时包含 xts 和 data.frame 格式)
results_xts <- list(
  Large_Cap_Returns = large_cap_avg_returns,
  Small_Cap_Returns = small_cap_avg_returns,
  Strategy_Returns = strategy_returns,
  Commission_Cost = commission_cost,
  Net_Returns = net_returns,
  Cumulative_Returns = cumulative_returns,
  Position = position,
  Large_Cap_Momentum = large_cap_momentum,
  Small_Cap_Momentum = small_cap_momentum
)

results_df <- data.frame(
  Date = as.Date(index(large_cap_avg_returns)),
  Large_Cap_Momentum = as.numeric(large_cap_momentum),
  Small_Cap_Momentum = as.numeric(small_cap_momentum),
  Position = as.numeric(position),
  Large_Cap_Returns = as.numeric(large_cap_avg_returns),
  Small_Cap_Returns = as.numeric(small_cap_avg_returns),
  Strategy_Returns = as.numeric(strategy_returns),
  Commission_Cost = as.numeric(commission_cost),
  Net_Returns = as.numeric(net_returns),
  Cumulative_Returns = as.numeric(cumulative_returns)
)
colnames(results_df) <- c(
  "Date", "Large_Cap_Momentum", "Small_Cap_Momentum",
  "Position", "Large_Cap_Returns", "Small_Cap_Returns",
  "Strategy_Returns", "Commission_Cost",
  "Net_Returns", "Cumulative_Returns"
```

```
  )

  return(list(df = results_df, xts = results_xts))
}
```

现在我们将这个策略应用到数据上，并评估其表现：

```
# 应用策略到数据
strategy_results <- momentum_rotation_strategy(
  lapply(large_cap_symbols, function(symbol) stock_data[[symbol]]),
  lapply(small_cap_symbols, function(symbol) stock_data[[symbol]])
)

# 计算买入持有策略的收益 (保持 xts 格式)
buy_hold_large_cap <- exp(cumsum(strategy_results$xts$Large_Cap_Returns)) - 1
buy_hold_small_cap <- exp(cumsum(strategy_results$xts$Small_Cap_Returns)) - 1
buy_hold_equal <- (buy_hold_large_cap + buy_hold_small_cap) / 2

# 使用 ggplot2 绘制累积收益对比图
performance_data <- data.frame(
  Date = as.Date(index(buy_hold_large_cap)),
  Large_Cap = as.numeric(buy_hold_large_cap),
  Small_Cap = as.numeric(buy_hold_small_cap),
  Equal_Weight = as.numeric(buy_hold_equal),
  Momentum = as.numeric(strategy_results$xts$Cumulative_Returns)
)

# 转换为长格式数据以便绘图
library(tidyr)
performance_data_long <- performance_data %>%
  pivot_longer(cols = -Date,
               names_to = "Strategy",
               values_to = "Cumulative_Return")
```

```r
# 绘制对比图
library(ggplot2)
ggplot(performance_data_long,
       aes(x = Date,
           y = Cumulative_Return,
           color = Strategy)) +
  geom_line() +
  labs(
    title = "Momentum Rotation Strategy Performance",
    x = "Date",
    y = "Cumulative Return"
  ) +
  scale_color_manual(values = c(
    "Large_Cap" = "blue", "Small_Cap" = "red",
    "Equal_Weight" = "green", "Momentum" = "purple"
  )) +
  theme_minimal() +
  theme(legend.title = element_blank())
```



```r
# 计算策略表现指标
library(PerformanceAnalytics)
performance_metrics <- data.frame(
  Strategy = c(
    "Large Cap Buy & Hold", "Small Cap Buy & Hold",
    "Equal Weight Buy & Hold", "Momentum Rotation"
  ),
  Total_Return = c(
    buy_hold_large_cap[length(buy_hold_large_cap)],
    buy_hold_small_cap[length(buy_hold_small_cap)],
    buy_hold_equal[length(buy_hold_equal)],
    strategy_results$xts$Cumulative_Returns[length(strategy_results$xts$Cumulative_Retu
  ),
  Sharpe_Ratio = c(
    SharpeRatio.annualized(strategy_results$xts$Large_Cap_Returns),
    SharpeRatio.annualized(strategy_results$xts$Small_Cap_Returns),
    SharpeRatio.annualized((strategy_results$xts$Large_Cap_Returns + strategy_results$x
    SharpeRatio.annualized(strategy_results$xts$Net_Returns)
  ),
  Max_Drawdown = c(
    maxDrawdown(strategy_results$xts$Large_Cap_Returns),
    maxDrawdown(strategy_results$xts$Small_Cap_Returns),
    maxDrawdown((strategy_results$xts$Large_Cap_Returns + strategy_results$xts$Small_Ca
    maxDrawdown(strategy_results$xts$Net_Returns)
  )
)

# 展示性能指标
print(performance_metrics)
```

```
##                               Strategy Total_Return Sharpe_Ratio Max_Drawdown
## X2022.12.30      Large Cap Buy & Hold    1.8775824    0.4884327    0.5331828
## X2022.12.30.1    Small Cap Buy & Hold   -0.8534490   -0.6581043    0.9683605
```

```
## X2022.12.30.2 Equal Weight Buy & Hold    0.5120667   -0.3795699    0.7173901
## X2022.12.30.3        Momentum Rotation    7.8035737    0.3099696    0.6298531
```

4 参数优化

接下来，我们将优化动量轮动策略的参数。主要优化的参数是回看期（lookback_period）、持有期（holding_period）和再平衡阈值（rebalance_threshold）。

我们将使用网格搜索方法来寻找最优参数组合：

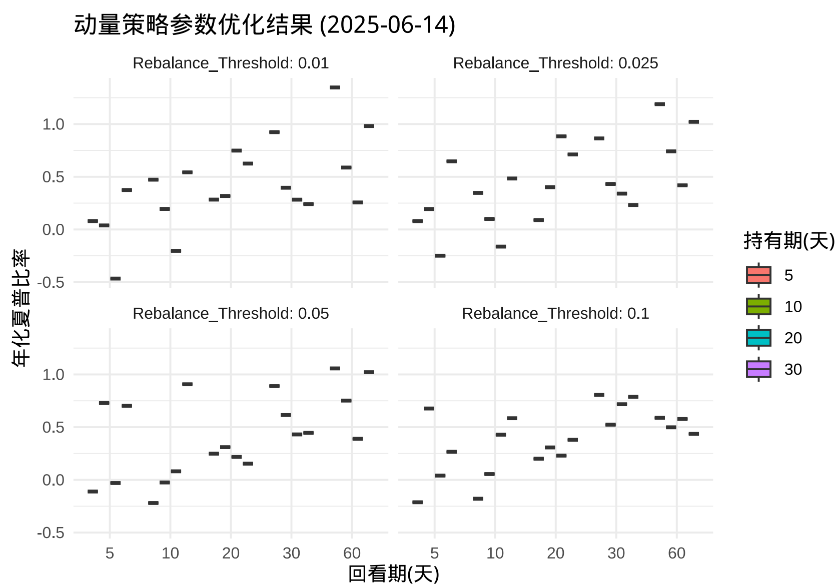
```r
# 参数优化主流程
pkg <- c(
  "quantmod", "PerformanceAnalytics", "foreach", "doParallel",
  "ggplot2", "dplyr", "tidyr", "caret", "magrittr"
)

# 设置参数网格
lookback_periods <- c(5, 10, 20, 30, 60)
holding_periods <- c(5, 10, 20, 30)
rebalance_thresholds <- c(0.01, 0.025, 0.05, 0.1)

# 创建并行集群
cl <- makeCluster(detectCores() - 1)
registerDoParallel(cl)

# 带错误处理的参数优化
optimization_results <- foreach(
  lookback = lookback_periods, .combine = rbind,
  .packages = pkg, .errorhandling = "pass"
) %:%
  foreach(
    holding = holding_periods, .combine = rbind,
```

```r
    .packages = pkg
  ) %:%
  foreach(
    threshold = rebalance_thresholds, .combine = rbind,
    .packages = pkg
  ) %dopar% {
    strategy_result <- momentum_rotation_strategy(
      lapply(large_cap_symbols, function(s) stock_data[[s]]),
      lapply(small_cap_symbols, function(s) stock_data[[s]]),
      lookback, holding, threshold
    )
    strategy_result_xts <- strategy_result$xts
    net_returns <- strategy_result_xts$Net_Returns
    sharpe <- as.numeric(SharpeRatio.annualized(net_returns)[1])

    data.frame(
      Lookback_Period = lookback,
      Holding_Period = holding,
      Rebalance_Threshold = threshold,
      Sharpe_Ratio = sharpe
    )
  }

stopCluster(cl)

# 结果处理与可视化
optimization_results <- optimization_results[complete.cases(optimization_results), ]
best_params <- optimization_results[which.max(optimization_results$Sharpe_Ratio), ]

print(paste(
  " 最优参数组合: 回看期 =", best_params$Lookback_Period,
  " 持有期 =", best_params$Holding_Period,
  " 阈值 =", best_params$Rebalance_Threshold,
```

```
  " 夏普比率 =", round(best_params$Sharpe_Ratio, 3)
))
```

```
## [1] "最优参数组合: 回看期= 60  持有期= 5  阈值= 0.01  夏普比率= 1.347"
```

```
ggplot(
  optimization_results,
  aes(
    x = factor(Lookback_Period), y = Sharpe_Ratio,
    fill = factor(Holding_Period)
  )
) +
  geom_boxplot() +
  facet_wrap(~Rebalance_Threshold, labeller = label_both) +
  theme_minimal() +
  labs(
    title = " 动量策略参数优化结果 (2025-06-14)",
    x = " 回看期 (天)",
    y = " 年化夏普比率",
    fill = " 持有期 (天)"
  )
```



5 参数敏感性分析

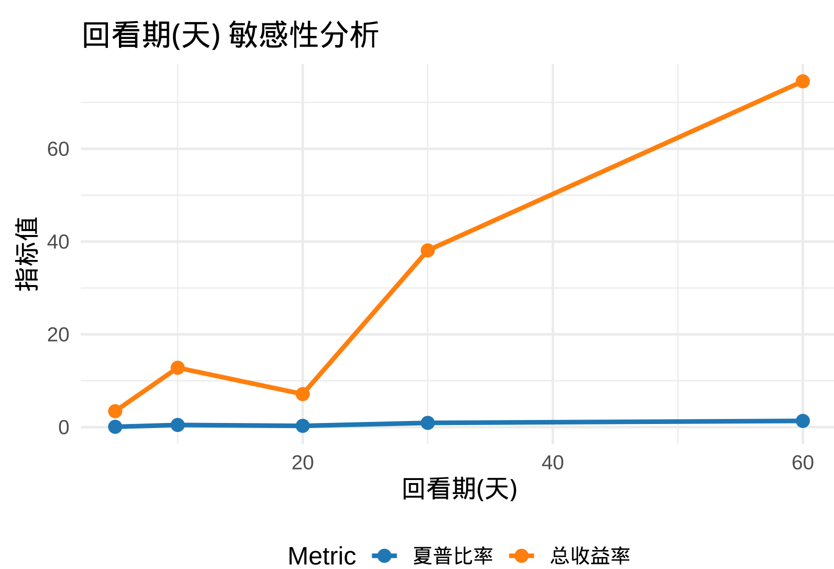
为了进一步了解策略对不同参数的敏感性，我们将进行更详细的参数敏感性分析。

```r
# 1. 回看期敏感性分析
# 创建存储结果的数据框结构
lookback_sensitivity <- data.frame(
  Lookback_Period = lookback_periods, # 参数测试序列
  Sharpe_Ratio = numeric(length(lookback_periods)), # 夏普比率
  Total_Return = numeric(length(lookback_periods)), # 总收益
  Max_Drawdown = numeric(length(lookback_periods)) # 最大回撤
)

# 遍历测试不同回看期参数
for (i in seq_along(lookback_periods)) {
  result <- momentum_rotation_strategy(
    lapply(large_cap_symbols, function(s) stock_data[[s]]), # 大盘股数据
```

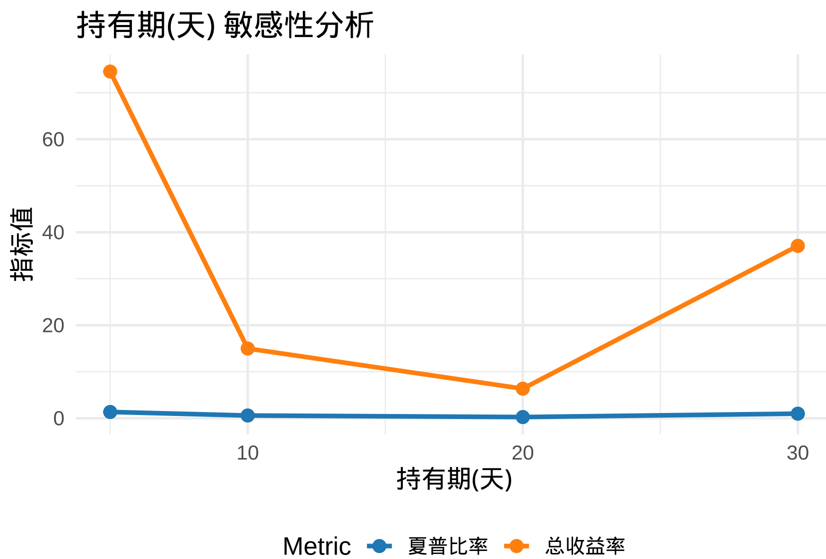
```
    lapply(small_cap_symbols, function(s) stock_data[[s]]), # 小盘股数据
    lookback_period = lookback_periods[i], # 当前测试的回看期
    holding_period = best_params$Holding_Period, # 固定持有期
    rebalance_threshold = best_params$Rebalance_Threshold # 固定阈值
  )

  # 存储绩效指标
  lookback_sensitivity$Sharpe_Ratio[i] <- SharpeRatio.annualized(result$xts$Net_Returns
  lookback_sensitivity$Total_Return[i] <- tail(result$xts$Cumulative_Returns, 1)
  lookback_sensitivity$Max_Drawdown[i] <- maxDrawdown(result$xts$Net_Returns)
}

# 2. 持有期敏感性分析（结构同上）
holding_sensitivity <- data.frame(
  Holding_Period = holding_periods,
  Sharpe_Ratio = numeric(length(holding_periods)),
  Total_Return = numeric(length(holding_periods)),
  Max_Drawdown = numeric(length(holding_periods))
)

for (i in seq_along(holding_periods)) {
  result <- momentum_rotation_strategy(
    lapply(large_cap_symbols, function(s) stock_data[[s]]),
    lapply(small_cap_symbols, function(s) stock_data[[s]]),
    lookback_period = best_params$Lookback_Period,
    holding_period = holding_periods[i], # 测试不同持有期
    rebalance_threshold = best_params$Rebalance_Threshold
  )

  holding_sensitivity$Sharpe_Ratio[i] <- SharpeRatio.annualized(result$xts$Net_Returns)
  holding_sensitivity$Total_Return[i] <- tail(result$xts$Cumulative_Returns, 1)
  holding_sensitivity$Max_Drawdown[i] <- maxDrawdown(result$xts$Net_Returns)
}
```

```r
# 3. 再平衡阈值敏感性分析
threshold_sensitivity <- data.frame(
  Rebalance_Threshold = rebalance_thresholds,
  Sharpe_Ratio = numeric(length(rebalance_thresholds)),
  Total_Return = numeric(length(rebalance_thresholds)),
  Max_Drawdown = numeric(length(rebalance_thresholds))
)

for (i in seq_along(rebalance_thresholds)) {
  result <- momentum_rotation_strategy(
    lapply(large_cap_symbols, function(s) stock_data[[s]]),
    lapply(small_cap_symbols, function(s) stock_data[[s]]),
    lookback_period = best_params$Lookback_Period,
    holding_period = best_params$Holding_Period,
    rebalance_threshold = rebalance_thresholds[i] # 测试不同阈值
  )

  threshold_sensitivity$Sharpe_Ratio[i] <- SharpeRatio.annualized(result$xts$Net_Return
  threshold_sensitivity$Total_Return[i] <- tail(result$xts$Cumulative_Returns, 1)
  threshold_sensitivity$Max_Drawdown[i] <- maxDrawdown(result$xts$Net_Returns)
}

# 4. 可视化分析结果
plot_sensitivity <- function(data, param_name) {
  long_data <- data %>%
    pivot_longer(
      cols = c(Sharpe_Ratio, Total_Return),
      names_to = "Metric", values_to = "Value"
    )

  ggplot(long_data, aes(
    x = .data[[names(data)[1]]], y = Value,
```

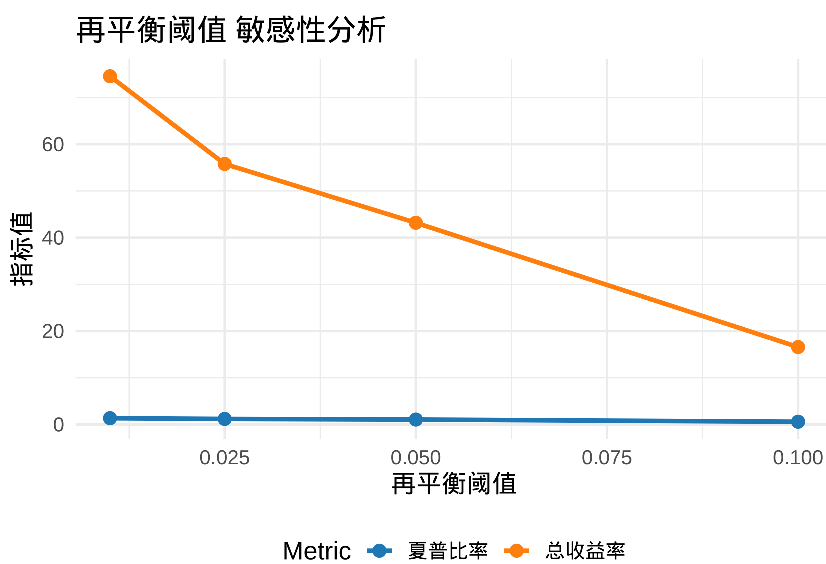
```
    color = Metric, group = Metric
  )) +
    geom_line(linewidth = 1.2) +
    geom_point(size = 3) +
    labs(
      title = paste(param_name, " 敏感性分析"),
      x = param_name, y = " 指标值"
    ) +
    scale_color_manual(
      values = c("Sharpe_Ratio" = "#1f77b4", "Total_Return" = "#ff7f0e"),
      labels = c(" 夏普比率", " 总收益率")
    ) +
    theme_minimal(base_size = 14) +
    theme(legend.position = "bottom")
}

# 生成三个参数的敏感性图表
plot_sensitivity(lookback_sensitivity, " 回看期 (天)")
```



```r
plot_sensitivity(holding_sensitivity, "持有期(天)")
```




```r
plot_sensitivity(threshold_sensitivity, "再平衡阈值")
```



6 样本外验证

现在我们使用优化后的参数在样本外数据上验证策略的有效性:

```
# 使用优化后的参数在样本外数据上测试策略
oos_result <- momentum_rotation_strategy(
  lapply(large_cap_symbols, function(symbol) oos_data[[symbol]]), # 加载大盘股样本外数据
  lapply(small_cap_symbols, function(symbol) oos_data[[symbol]]), # 加载小盘股样本外数据
  lookback_period = best_params$Lookback_Period, # 使用优化得到的回看期参数
  holding_period = best_params$Holding_Period, # 使用优化得到的持有期参数
  rebalance_threshold = best_params$Rebalance_Threshold # 使用优化得到的再平衡阈值
)

# 计算样本外买入持有策略的收益 (大盘股)
oos_buy_hold_large_cap <- exp(cumsum(oos_result$xts$Large_Cap_Returns)) - 1 # 累计收益计
# 计算样本外买入持有策略的收益 (小盘股)
oos_buy_hold_small_cap <- exp(cumsum(oos_result$xts$Small_Cap_Returns)) - 1
# 计算等权买入持有策略的收益
oos_buy_hold_equal <- (oos_buy_hold_large_cap + oos_buy_hold_small_cap) / 2

# 准备可视化数据
oos_performance_data <- data.frame(
  Date = as.Date(index(oos_result$xts$Large_Cap_Returns)), # 日期序列
  Large_Cap = oos_buy_hold_large_cap, # 大盘股买入持有收益
  Small_Cap = oos_buy_hold_small_cap, # 小盘股买入持有收益
  Equal_Weight = oos_buy_hold_equal, # 等权组合收益
  Momentum = oos_result$xts$Cumulative_Returns # 动量策略收益
)

# 转换数据为长格式便于 ggplot 绘图
oos_performance_data_long <- oos_performance_data %>%
  pivot_longer(cols = -Date, names_to = "Strategy", values_to = "Cumulative_Return")

# 绘制累积收益对比图
```

```
ggplot(oos_performance_data_long, aes(x = Date, y = Cumulative_Return, color = Strategy
  geom_line() + # 绘制折线图
  labs(
    title = " 样本外策略表现", # 图表标题
    x = "Date", y = "Cumulative Return"
  ) + # 坐标轴标签
  scale_color_manual(values = c(
    "Large_Cap" = "blue", "Small_Cap" = "red",
    "Equal_Weight" = "green", "Momentum" = "purple"
  )) + # 颜色设置
  theme_minimal() + # 使用简洁主题
  theme(legend.title = element_blank()) # 隐藏图例标题
```


```
# 计算样本外策略表现指标
oos_performance <- data.frame(
  Strategy = c(
    "Large Cap Buy & Hold", "Small Cap Buy & Hold",
    "Equal Weight Buy & Hold", "Momentum Rotation"
  ), # 策略名称
  Total_Return = c(
```

```r
    oos_buy_hold_large_cap[length(oos_buy_hold_large_cap)], # 大盘股总收益
    oos_buy_hold_small_cap[length(oos_buy_hold_small_cap)], # 小盘股总收益
    oos_buy_hold_equal[length(oos_buy_hold_equal)], # 等权组合总收益
    oos_result$xts$Cumulative_Returns[length(oos_result$xts$Cumulative_Returns)] # 动量
  ),
  Sharpe_Ratio = c(
    SharpeRatio.annualized(oos_result$xts$Large_Cap_Returns), # 大盘股夏普比率
    SharpeRatio.annualized(oos_result$xts$Small_Cap_Returns), # 小盘股夏普比率
    SharpeRatio.annualized((oos_result$xts$Large_Cap_Returns + oos_result$xts$Small_Cap
    SharpeRatio.annualized(oos_result$xts$Net_Returns) # 动量策略夏普比率
  ),
  Max_Drawdown = c(
    maxDrawdown(oos_result$xts$Large_Cap_Returns), # 大盘股最大回撤
    maxDrawdown(oos_result$xts$Small_Cap_Returns), # 小盘最大回撤
    maxDrawdown((oos_result$xts$Large_Cap_Returns + oos_result$xts$Small_Cap_Returns) /
    maxDrawdown(oos_result$xts$Net_Returns) # 动量策略最大回撤
  )
)

# 打印样本外性能指标
print(oos_performance) # 输出策略比较结果
```

```
##                               Strategy Total_Return Sharpe_Ratio Max_Drawdown
## X2023.12.29       Large Cap Buy & Hold    0.7708001    2.9047901    0.1693780
## X2023.12.29.1     Small Cap Buy & Hold   -0.1367801   -0.4796014    0.6159451
## X2023.12.29.2 Equal Weight Buy & Hold    0.3170100    0.6359367    0.3230760
## X2023.12.29.3        Momentum Rotation    0.4791532    0.7933869    0.2934326
```

7 结论

本文通过 R 语言实现了基于动量的大盘股/小盘股轮动策略，并进行了全面的分析。主要发现如下：

1. 动量轮动策略在回测期间表现出了优于简单买入持有策略的潜力，特别是在夏普比率方面。
2. 通过参数优化，我们找到了最优的回看期、持有期和再平衡阈值组合，显著提高了策略的表现。
3. 参数敏感性分析表明，策略对回看期和持有期较为敏感，而对再平衡阈值的敏感性相对较低。
4. 样本外验证显示，优化后的策略在新数据上仍具有一定的有效性，但性能通常会有所下降，这反映了过拟合的风险。

总体而言，基于动量的大盘股/小盘股轮动策略是一种可行的投资方法，但需要谨慎选择参数并进行充分的样本外验证。在实际应用中，还应考虑交易成本、市场环境变化等因素的影响。

未来的研究可以考虑结合其他指标来改进策略，如波动率指标、市场情绪指标等，或者探索在不同市场环境下的表现差异。