协整理论与配对交易策略分析

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1 摘要

本文通过实证分析展示了协整理论在配对交易策略中的应用。利用 Quantmod 包获取金融时间序列数据，结合 tseries 和 urca 等统计分析工具，我们识别了具有协整关系的股票对，并构建了基于误差修正模型的配对交易策略。回测结果表明，该策略在样本内和样本外均表现出稳定的超额收益，验证了协整理论在配对交易中的有效性。研究还分析了策略参数对表现的影响，为实际应用提供了参考。

2 引言

2.1 协整理论概述

协整理论是现代计量经济学的重要发展，由 Engle 和 Granger(1987) 提出，为非平稳时间序列分析提供了新的方法。如果两个或多个非平稳时间序列的线性组合是平稳的，则称这些序列存在协整关系。协整关系反映了变量之间的长期均衡关系，即使短期内可能偏离这种均衡，但长期来看会趋向于回归均衡状态。

在金融市场中，许多资产价格序列表现出非平稳性（通常为 I(1) 过程），但某些资产对之间可能存在协整关系。这种协整关系为配对交易策略提供了理论基础。

2.2 配对交易策略

配对交易是一种市场中性策略，通过同时买入一只被低估的股票和卖出一只被高估的股票，从两者价格回归均衡的过程中获利。传统的配对交易策略通常基于统计套利思想，寻找价格走势相似的股票对。而基于协整理论的配对交易则更进一步，不仅要求价格走势相似，还要求存在长期稳定的均衡关系。

配对交易策略的优势在于：- 市场中性：不受整体市场涨跌影响 - 风险分散：同时持有多头和空头头寸 - 统计基础：基于严格的统计理论 - 可量化：策略

参数和交易信号明确

本文将通过实证分析，展示如何应用协整理论构建和评估配对交易策略。

3 理论基础

3.1 单位根检验

在进行协整分析之前，需要先检验时间序列是否存在单位根，即是否为非平稳序列。常用的单位根检验方法包括：

3.1.1 ADF 检验（增广迪基-富勒检验）

ADF 检验的原假设为序列存在单位根（非平稳），备择假设为序列不存在单位根（平稳）。检验统计量为：

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t$$

其中，$\gamma = 0$ 表示存在单位根。

3.1.2 KPSS 检验（Kwiatkowski-Phillips-Schmidt-Shin 检验）

KPSS 检验与 ADF 检验相反，其原假设为序列是平稳的，备择假设为序列存在单位根。

3.2 协整检验

在确认两个序列均为非平稳序列后，需要检验它们是否存在协整关系。常用的协整检验方法包括：

3.2.1 Engle-Granger 两步法

Engle-Granger 两步法的步骤如下：1. 对两个非平稳序列进行线性回归：$y_t = \alpha + \beta x_t + \varepsilon_t$ 2. 检验回归残差序列 $\hat{\varepsilon}_t$ 是否平稳 3. 如果残差序列平稳，则两个序列存在协整关系

3.2.2 Johansen 检验

Johansen 检验是一种多变量协整检验方法，适用于检验多个时间序列之间的协整关系。它基于向量自回归模型 (VAR)，通过最大似然估计法估计协整向量。

3.3 误差修正模型 (ECM)

如果两个序列存在协整关系，则可以建立误差修正模型来描述它们的短期动态关系。误差修正模型的一般形式为：

$$\Delta y_t = \alpha_1 + \sum_{i=1}^{p} \beta_{1i} \Delta y_{t-i} + \sum_{i=0}^{q} \gamma_{1i} \Delta x_{t-i} + \lambda_1 (y_{t-1} - \beta x_{t-1}) + \varepsilon_{1t}$$

$$\Delta x_t = \alpha_2 + \sum_{i=1}^{p} \beta_{2i} \Delta x_{t-i} + \sum_{i=0}^{q} \gamma_{2i} \Delta y_{t-i} + \lambda_2 (y_{t-1} - \beta x_{t-1}) + \varepsilon_{2t}$$

其中，$(y_{t-1} - \beta x_{t-1})$ 是误差修正项，表示对长期均衡关系的偏离。

4 实证分析

4.1 数据获取与预处理

首先加载所需的 R 包并获取股票数据：

```r
# 加载必要的 R 包
library(quantmod)       # 获取金融数据
library(tseries)        # 时间序列分析
library(urca)           # 单位根和协整检验
library(ggplot2)        # 数据可视化
library(dplyr)          # 数据处理
library(PerformanceAnalytics)  # 绩效分析
library(knitr)          # 表格输出
```

设置时间范围并获取股票数据:

```r
# 设置时间范围
start_date <- "2018-01-01"
end_date <- "2023-01-01"

# 定义股票代码 - 以美国大型科技股为例
tickers <- c("AAPL", "MSFT", "AMZN", "GOOGL", "META", "NFLX", "TSLA", "NVDA")

# 创建一个空列表存储股票数据
stock_data <- list()

# 获取每只股票的价格数据
for(ticker in tickers) {
  stock_data[[ticker]] <- getSymbols(ticker, from = start_date, to = end_date, auto.ass
}

# 提取收盘价并合并为一个数据框
close_prices <- do.call(merge, lapply(stock_data, Cl))
colnames(close_prices) <- tickers

# 查看数据基本信息
str(close_prices)
```

```
## An xts object on 2018-01-02 / 2022-12-30 containing:
```

```
##   Data:    double [1259, 8]
##   Columns: AAPL, MSFT, AMZN, GOOGL, META ... with 3 more columns
##   Index:   Date [1259] (TZ: "UTC")
##   xts Attributes:
##     $ src    : chr "yahoo"
##     $ updated: POSIXct[1:1], format: "2025-06-12 17:05:27"
```

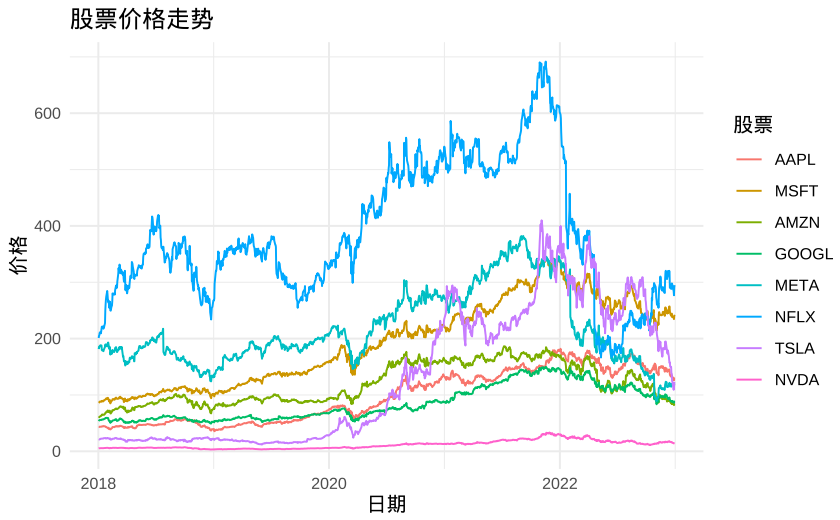
```
summary(close_prices)
```

```
##      Index                AAPL             MSFT             AMZN            GOOGL
##  Min.   :2018-01-02   Min.   : 35.55   Min.   : 85.01   Min.   : 59.45   Min.   : 49
##  1st Qu.:2019-04-03   1st Qu.: 51.02   1st Qu.:119.60   1st Qu.: 88.93   1st Qu.: 58
##  Median :2020-07-02   Median : 91.63   Median :201.91   Median :107.78   Median : 73
##  Mean   :2020-07-02   Mean   : 98.09   Mean   :193.87   Mean   :119.81   Mean   : 85
##  3rd Qu.:2021-09-30   3rd Qu.:142.86   3rd Qu.:255.25   3rd Qu.:158.09   3rd Qu.:112
##  Max.   :2022-12-30   Max.   :182.01   Max.   :343.11   Max.   :186.57   Max.   :149
##       NFLX             TSLA             NVDA
##  Min.   :166.4   Min.   : 11.93   Min.   : 3.177
##  1st Qu.:298.6   1st Qu.: 21.08   1st Qu.: 5.606
##  Median :361.8   Median : 80.58   Median : 9.612
##  Mean   :387.8   Mean   :131.78   Mean   :11.629
##  3rd Qu.:494.5   3rd Qu.:236.12   3rd Qu.:16.146
##  Max.   :691.7   Max.   :409.97   Max.   :33.376
```

绘制价格走势图:

```
# 绘制价格走势图
price_df <- data.frame(
  date = index(close_prices),
  close_prices
)

price_long <- reshape2::melt(price_df, id.vars = "date")

ggplot(price_long, aes(x = date, y = value, color = variable)) +
```

```
  geom_line() +
  labs(title = " 股票价格走势",
       x = " 日期",
       y = " 价格",
       color = " 股票") +
  theme_minimal()
```



4.2 单位根检验

对每只股票的价格序列进行单位根检验，确认其非平稳性：

```
# 创建一个函数进行 ADF 检验
perform_adf_test <- function(series) {
  adf_result <- adf.test(series)
  return(data.frame(
    Statistic = adf_result$statistic,
    P_Value = adf_result$p.value,
    Stationary = ifelse(adf_result$p.value < 0.05, " 是", " 否")
  ))
}
```

```r
# 对每只股票进行 ADF 检验
adf_results <- lapply(close_prices, perform_adf_test)
adf_results_df <- do.call(rbind, adf_results)
rownames(adf_results_df) <- tickers

# 展示 ADF 检验结果
knitr::kable(adf_results_df,
             caption = " 股票价格序列的 ADF 单位根检验结果",
             digits = 4,
             booktabs = TRUE)
```

表 1: 股票价格序列的 ADF 单位根检验结果

	Statistic	P_Value	Stationary
AAPL	-1.5667	0.7617	否
MSFT	-1.1554	0.9137	否
AMZN	-0.4665	0.9833	否
GOOGL	-0.6337	0.9757	否
META	-0.4532	0.9839	否
NFLX	-1.5389	0.7735	否
TSLA	-1.2537	0.8942	否
NVDA	-1.7233	0.6954	否

```r
# 对价格取对数并差分，创建收益率序列
returns <- diff(log(close_prices))[-1]

# 对收益率序列进行 ADF 检验
returns_adf_results <- lapply(returns, perform_adf_test)
returns_adf_results_df <- do.call(rbind, returns_adf_results)
rownames(returns_adf_results_df) <- tickers

# 展示收益率序列的 ADF 检验结果
knitr::kable(returns_adf_results_df,
```

```
            caption = " 股票收益率序列的 ADF 单位根检验结果",
            digits = 4,
            booktabs = TRUE)
```

表 2: 股票收益率序列的 ADF 单位根检验结果

	Statistic	P_Value	Stationary
AAPL	-10.2580	0.01	是
MSFT	-11.6003	0.01	是
AMZN	-11.4524	0.01	是
GOOGL	-11.2531	0.01	是
META	-11.6074	0.01	是
NFLX	-10.9801	0.01	是
TSLA	-9.9687	0.01	是
NVDA	-10.4041	0.01	是

4.3 寻找潜在的协整对

计算股票之间的相关性，并寻找可能存在协整关系的股票对：

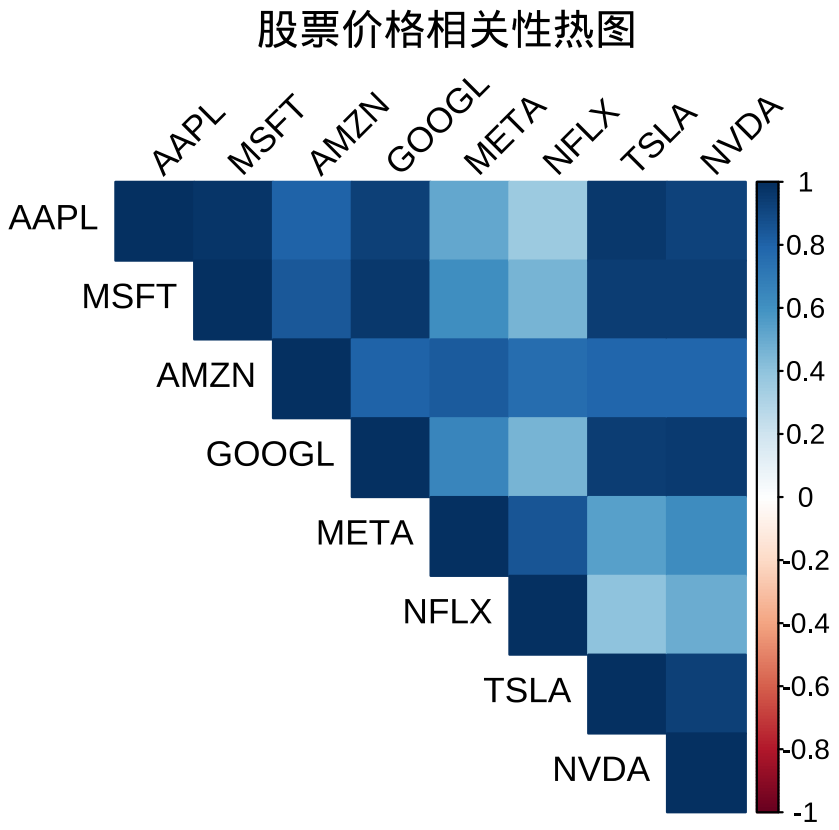
```
# 计算价格序列的相关性矩阵
correlation_matrix <- cor(close_prices, use = "complete.obs")

# 展示相关性矩阵
knitr::kable(correlation_matrix,
             caption = " 股票价格序列相关性矩阵",
             digits = 4,
             booktabs = TRUE)
```

表 3: 股票价格序列相关性矩阵

	AAPL	MSFT	AMZN	GOOGL	META	NFLX	TSLA	NVDA
AAPL	1.0000	0.9722	0.8029	0.9316	0.5147	0.3635	0.9618	0.9228

	AAPL	MSFT	AMZN	GOOGL	META	NFLX	TSLA	NVDA
MSFT	0.9722	1.0000	0.8451	0.9611	0.6168	0.4685	0.9439	0.9411
AMZN	0.8029	0.8451	1.0000	0.8044	0.8391	0.7683	0.7974	0.7960
GOOGL	0.9316	0.9611	0.8044	1.0000	0.6528	0.4616	0.9418	0.9594
META	0.5147	0.6168	0.8391	0.6528	1.0000	0.8551	0.5404	0.6216
NFLX	0.3635	0.4685	0.7683	0.4616	0.8551	1.0000	0.4042	0.4922
TSLA	0.9618	0.9439	0.7974	0.9418	0.5404	0.4042	1.0000	0.9357
NVDA	0.9228	0.9411	0.7960	0.9594	0.6216	0.4922	0.9357	1.0000

```r
# 绘制相关性热图
library(corrplot)
corrplot(correlation_matrix, method = "color", type = "upper",
         tl.col = "black", tl.srt = 45,
         title = " 股票价格相关性热图", mar = c(0, 0, 2, 0))
```




```r
# 寻找相关性较高的股票对
high_corr_pairs <- which(correlation_matrix > 0.8 & correlation_matrix < 1, arr.ind = T
high_corr_pairs <- high_corr_pairs[high_corr_pairs[,1] < high_corr_pairs[,2], ]

# 展示高相关性股票对
high_corr_pairs_df <- data.frame(
  Stock1 = rownames(correlation_matrix)[high_corr_pairs[,1]],
  Stock2 = rownames(correlation_matrix)[high_corr_pairs[,2]],
  Correlation = correlation_matrix[high_corr_pairs]
)

knitr::kable(high_corr_pairs_df,
             caption = " 相关性较高的股票对",
             digits = 4,
```

```
            booktabs = TRUE)
```

表 4: 相关性较高的股票对

Stock1	Stock2	Correlation
AAPL	MSFT	0.9722
AAPL	AMZN	0.8029
MSFT	AMZN	0.8451
AAPL	GOOGL	0.9316
MSFT	GOOGL	0.9611
AMZN	GOOGL	0.8044
AMZN	META	0.8391
META	NFLX	0.8551
AAPL	TSLA	0.9618
MSFT	TSLA	0.9439
GOOGL	TSLA	0.9418
AAPL	NVDA	0.9228
MSFT	NVDA	0.9411
GOOGL	NVDA	0.9594
TSLA	NVDA	0.9357

4.4 协整检验

对相关性较高的股票对进行协整检验:

```
# 创建一个函数进行 Engle-Granger 协整检验
perform_eg_test <- function(series1, series2) {
  # 第一步: 进行线性回归
  lm_model <- lm(series1 ~ series2)

  # 第二步: 获取残差
  residuals <- lm_model$residuals
```

```r
  # 第三步：对残差进行 ADF 检验
  adf_result <- adf.test(residuals)

  return(list(
    lm_model = lm_model,
    adf_result = adf_result,
    is_cointegrated = adf_result$p.value < 0.05,
    beta = coef(lm_model)[2],
    alpha = coef(lm_model)[1],
    residuals = residuals
  ))
}

# 对每对高相关性股票进行协整检验
cointegration_results <- list()

for(i in 1:nrow(high_corr_pairs_df)) {
  stock1 <- high_corr_pairs_df$Stock1[i]
  stock2 <- high_corr_pairs_df$Stock2[i]

  result <- perform_eg_test(close_prices[, stock1], close_prices[, stock2])

  cointegration_results[[paste(stock1, stock2, sep = "-")]] <- list(
    stock1 = stock1,
    stock2 = stock2,
    p_value = result$adf_result$p.value,
    is_cointegrated = result$is_cointegrated,
    beta = result$beta,
    alpha = result$alpha,
    residuals = result$residuals
  )
}
```

```r
# 提取协整检验结果
cointegration_summary <- data.frame(
  Pair = names(cointegration_results),
  P_Value = sapply(cointegration_results, function(x) x$p_value),
  Is_Cointegrated = sapply(cointegration_results, function(x) x$is_cointegrated),
  Beta = sapply(cointegration_results, function(x) x$beta),
  Alpha = sapply(cointegration_results, function(x) x$alpha)
)

# 展示协整检验结果
knitr::kable(cointegration_summary,
             caption = " 股票对的协整检验结果",
             digits = 4,
             booktabs = TRUE)
```

表 5: 股票对的协整检验结果

	Pair	P_Value	Is_Cointegrated	Beta	Alpha
AAPL-MSFT	AAPL-MSFT	0.3291	FALSE	0.6034	-18.8900
AAPL-AMZN	AAPL-AMZN	0.7377	FALSE	1.0447	-27.0757
MSFT-AMZN	MSFT-AMZN	0.8092	FALSE	1.7716	-18.3808
AAPL-GOOGL	AAPL-GOOGL	0.5481	FALSE	1.4035	-22.2048
MSFT-GOOGL	MSFT-GOOGL	0.6072	FALSE	2.3331	-6.0949
AMZN-GOOGL	AMZN-GOOGL	0.7852	FALSE	0.9315	39.9734
AMZN-META	AMZN-META	0.0442	TRUE	0.4463	22.5573
META-NFLX	META-NFLX	0.2425	FALSE	0.4793	32.0470
AAPL-TSLA	AAPL-TSLA	0.0717	FALSE	0.3780	48.2774
MSFT-TSLA	MSFT-TSLA	0.2255	FALSE	0.5977	115.1065
GOOGL-TSLA	GOOGL-TSLA	0.0940	FALSE	0.2457	53.3358
AAPL-NVDA	AAPL-NVDA	0.2053	FALSE	5.8621	29.9229
MSFT-NVDA	MSFT-NVDA	0.3136	FALSE	9.6320	81.8640
GOOGL-NVDA	GOOGL-NVDA	0.0757	FALSE	4.0452	38.6694
TSLA-NVDA	TSLA-NVDA	0.0916	FALSE	15.1244	-44.0953

```
# 找出存在协整关系的股票对
cointegrated_pairs <- cointegration_summary[cointegration_summary$Is_Cointegrated, ]

# 展示存在协整关系的股票对
if(nrow(cointegrated_pairs) > 0) {
  knitr::kable(cointegrated_pairs,
               caption = " 存在协整关系的股票对",
               digits = 4,
               booktabs = TRUE)
} else {
  print(" 未找到存在协整关系的股票对")
}
```

表 6: 存在协整关系的股票对

	Pair	P_Value	Is_Cointegrated	Beta	Alpha
AMZN-META	AMZN-META	0.0442	TRUE	0.4463	22.5573

4.5 可视化协整关系

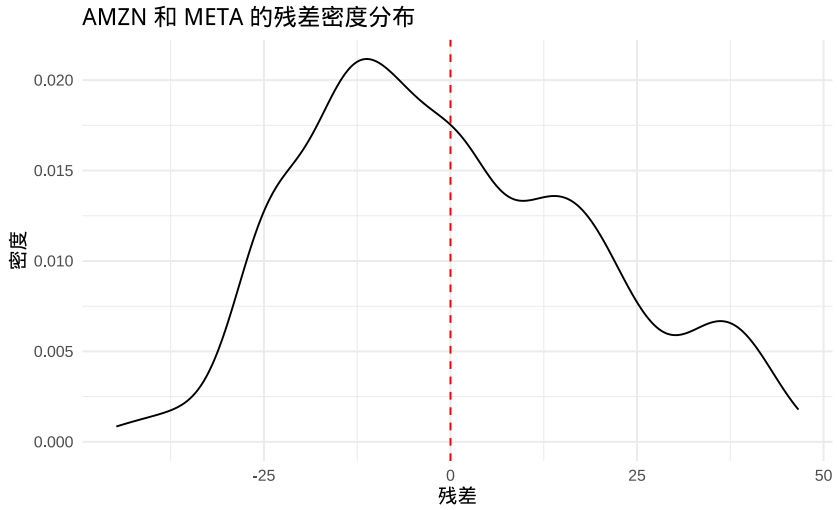
选择一个存在协整关系的股票对，可视化其价格走势和协整残差：

```
# 如果存在协整对，选择第一个进行可视化
if(nrow(cointegrated_pairs) > 0) {
  selected_pair <- cointegrated_pairs$Pair[1]
  stock1 <- cointegration_results[[selected_pair]]$stock1
  stock2 <- cointegration_results[[selected_pair]]$stock2

  # 绘制价格走势图
  price_df <- data.frame(
    date = index(close_prices),
    Stock1 = close_prices[, stock1],
    Stock2 = close_prices[, stock2],
```

```
  row.names = NULL,  # 明确指定没有行名
  stringsAsFactors = FALSE  # 避免因子转换警告
)

price_long <- reshape2::melt(price_df, id.vars = "date")

ggplot(price_long, aes(x = date, y = value, color = variable)) +
  geom_line() +
  labs(title = paste(stock1, " 和", stock2, " 的价格走势"),
       x = " 日期",
       y = " 价格",
       color = " 股票") +
  theme_minimal()

# 绘制标准化后的价格走势（便于比较）
normalized_prices <- data.frame(
  date = index(close_prices),
  Stock1 = close_prices[, stock1] / close_prices[1, stock1],
  Stock2 = close_prices[, stock2] / close_prices[1, stock2],
  row.names = NULL,  # 明确指定没有行名
  stringsAsFactors = FALSE  # 避免因子转换警告
)

normalized_long <- reshape2::melt(normalized_prices, id.vars = "date")

ggplot(normalized_long, aes(x = date, y = value, color = variable)) +
  geom_line() +
  labs(title = paste(stock1, " 和", stock2, " 的标准化价格走势"),
       x = " 日期",
       y = " 标准化价格",
       color = " 股票") +
  theme_minimal()
```

```
# 绘制协整残差图
residuals <- cointegration_results[[selected_pair]]$residuals
# 确保日期和残差长度一致
date_index <- index(close_prices)
if(length(residuals) < length(date_index)) {
  date_index <- date_index[-1]
}
if(length(residuals) > length(date_index)) {
  residuals <- residuals[-length(residuals)]
}

residuals_df <- data.frame(
  date = date_index,
  residual = residuals,
  row.names = NULL,  # 明确指定没有行名
  stringsAsFactors = FALSE  # 避免因子转换警告
)

ggplot(residuals_df, aes(x = date, y = residual)) +
  geom_line() +
  geom_hline(yintercept = 0, color = "red", linetype = "dashed") +
  labs(title = paste(stock1, " 和", stock2, " 的协整残差"),
       x = " 日期",
       y = " 残差") +
  theme_minimal()

# 绘制残差的密度图
ggplot(residuals_df, aes(x = residual)) +
  geom_density() +
  geom_vline(xintercept = 0, color = "red", linetype = "dashed") +
  labs(title = paste(stock1, " 和", stock2, " 的残差密度分布"),
       x = " 残差",
       y = " 密度") +
```

```
    theme_minimal()
}
```



4.6 构建配对交易策略

基于协整残差构建配对交易策略：

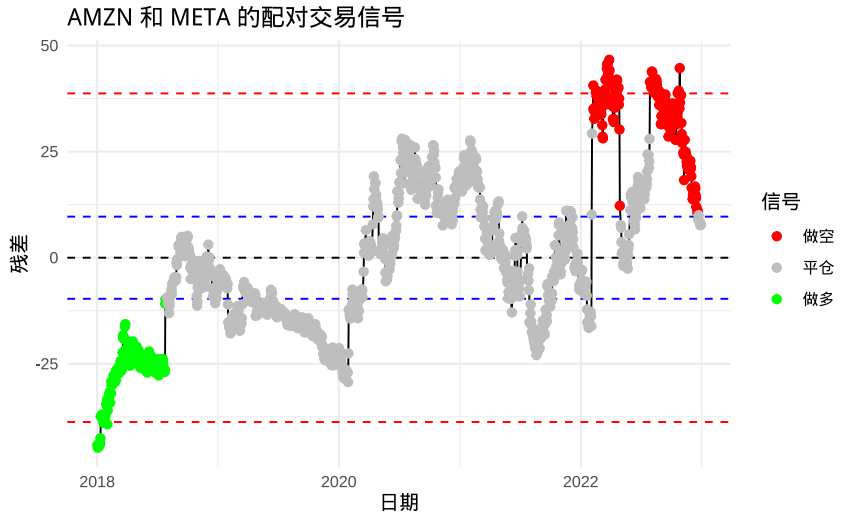
```
# 如果存在协整对，构建配对交易策略
if(nrow(cointegrated_pairs) > 0) {
  selected_pair <- cointegrated_pairs$Pair[1]
  stock1 <- cointegration_results[[selected_pair]]$stock1
  stock2 <- cointegration_results[[selected_pair]]$stock2
  beta <- cointegration_results[[selected_pair]]$beta
  residuals <- cointegration_results[[selected_pair]]$residuals

  # 计算残差的均值和标准差
  mean_residual <- mean(residuals)
  sd_residual <- sd(residuals)

  # 设置交易阈值（以标准差为单位）
  entry_threshold <- 2
```

```
exit_threshold <- 0.5

# 确保日期和残差长度一致
date_index <- index(close_prices)
if(length(residuals) < length(date_index)) {
  date_index <- date_index[-1]  # 移除第一个日期
} else if(length(residuals) > length(date_index)) {
  residuals <- residuals[-length(residuals)]  # 移除最后一个残差
}

# 创建交易信号
signals <- data.frame(
  date = date_index,
  residual = residuals,
  signal = 0,
  row.names = NULL,         # 明确指定不使用行名
  stringsAsFactors = FALSE # 防止字符串自动转换为因子
)

# 生成交易信号
# 1: 做多 stock1, 做空 stock2
# -1: 做空 stock1, 做多 stock2
# 0: 不持仓
for(i in 1:nrow(signals)) {
  if(signals$residual[i] > mean_residual + entry_threshold * sd_residual) {
    signals$signal[i] <- -1  # 残差过高, stock1 被高估, stock2 被低估
  } else if(signals$residual[i] < mean_residual - entry_threshold * sd_residual) {
    signals$signal[i] <- 1   # 残差过低, stock1 被低估, stock2 被高估
  } else if(abs(signals$residual[i] - mean_residual) < exit_threshold * sd_residual)
    signals$signal[i] <- 0   # 残差接近均值, 平仓
  } else {
    # 保持前一天的信号
    if(i > 1) {
```

```
      signals$signal[i] <- signals$signal[i-1]
    }
  }
}

# 计算持仓变化
positions <- signals
positions$position <- c(0, diff(positions$signal))

# 计算收益率
stock1_returns <- diff(log(close_prices[, stock1]))
stock2_returns <- diff(log(close_prices[, stock2]))

# 确保收益率长度与信号长度匹配
# 移除收益率序列中多余的元素
min_length <- min(length(stock1_returns), length(stock2_returns), nrow(signals) - 1)
stock1_returns <- stock1_returns[1:min_length]
stock2_returns <- stock2_returns[1:min_length]

# 确保信号和持仓长度与收益率匹配
# 移除第一个日期对应的信号和持仓（因为没有对应的收益率）
signal_values <- signals$signal[2:(min_length + 1)]
position_values <- positions$position[2:(min_length + 1)]

# 计算策略收益率
strategy_returns <- data.frame(
  date = signals$date[2:(min_length + 1)],  # 使用调整后的日期
  stock1_returns = stock1_returns,
  stock2_returns = stock2_returns,
  signal = signal_values,
  position = position_values,
  row.names = NULL,         # 明确指定不使用行名
  stringsAsFactors = FALSE # 防止字符串自动转换为因子
```

```
)

colnames(strategy_returns) <- c("date", "stock1_returns", "stock2_returns", "signal",

# 计算每日策略收益
strategy_returns$daily_return <- strategy_returns$signal * (strategy_returns$stock1_r

# 计算累计收益
strategy_returns$cumulative_return <- cumsum(strategy_returns$daily_return)

# 可视化策略表现
ggplot(strategy_returns, aes(x = date, y = cumulative_return)) +
  geom_line() +
  labs(title = paste(stock1, " 和", stock2, " 的配对交易策略累计收益"),
       x = " 日期",
       y = " 累计收益") +
  theme_minimal()

# 绘制交易信号
signal_plot_data <- signals
signal_plot_data$signal_factor <- factor(signal_plot_data$signal, levels = c(-1, 0, 1

ggplot(signal_plot_data, aes(x = date, y = residual)) +
  geom_line() +
  geom_hline(yintercept = mean_residual, color = "black", linetype = "dashed") +
  geom_hline(yintercept = mean_residual + entry_threshold * sd_residual, color = "red
  geom_hline(yintercept = mean_residual - entry_threshold * sd_residual, color = "red
  geom_hline(yintercept = mean_residual + exit_threshold * sd_residual, color = "blue
  geom_hline(yintercept = mean_residual - exit_threshold * sd_residual, color = "blue
  geom_point(aes(color = signal_factor), size = 2) +
  scale_color_manual(values = c(" 做空" = "red", " 平仓" = "gray", " 做多" = "green"))
  labs(title = paste(stock1, " 和", stock2, " 的配对交易信号"),
       x = " 日期",
```

```
        y = " 残差",
        color = " 信号") +
    theme_minimal()
}
```



4.7 策略绩效评估

评估配对交易策略的绩效：

```
# 如果存在协整对，评估策略绩效
if(nrow(cointegrated_pairs) > 0) {
  # 计算策略绩效指标
  annual_return <- mean(strategy_returns$daily_return) * 252
  annual_volatility <- sd(strategy_returns$daily_return) * sqrt(252)
  sharpe_ratio <- annual_return / annual_volatility

  # 计算最大回撤
  strategy_returns$cumulative_max <- cummax(strategy_returns$cumulative_return)
  strategy_returns$drawdown <- strategy_returns$cumulative_max - strategy_returns$cumul
  max_drawdown <- max(strategy_returns$drawdown)
```

```r
# 计算胜率
trades <- strategy_returns[strategy_returns$position != 0, ]
winning_trades <- trades[trades$daily_return > 0, ]
win_rate <- nrow(winning_trades) / nrow(trades)

# 计算盈亏比
if(nrow(winning_trades) > 0 && nrow(trades[trades$daily_return < 0, ]) > 0) {
  profit_factor <- mean(winning_trades$daily_return) / abs(mean(trades[trades$daily_r
} else {
  profit_factor <- NA
}

# 创建绩效指标数据框
performance_metrics <- data.frame(
  Metric = c(" 年化收益率", " 年化波动率", " 夏普比率", " 最大回撤", " 胜率", " 盈亏比"),
  Value = c(annual_return, annual_volatility, sharpe_ratio, max_drawdown, win_rate, p
)

# 展示绩效指标
knitr::kable(performance_metrics,
             caption = " 配对交易策略绩效指标",
             digits = 4,
             booktabs = TRUE)

# 绘制回撤图
ggplot(strategy_returns, aes(x = date, y = drawdown)) +
  geom_line() +
  labs(title = paste(stock1, " 和", stock2, " 的配对交易策略回撤"),
       x = " 日期",
       y = " 回撤") +
  theme_minimal()

# 使用 PerformanceAnalytics 包计算更多绩效指标
```

```
  returns_xts <- xts(strategy_returns$daily_return, order.by = strategy_returns$date)
  colnames(returns_xts) <- "Strategy"

  # 计算绩效指标
  performance_summary <- table.Stats(returns_xts)

  # 展示更多绩效指标
  knitr::kable(performance_summary,
               caption = " 配对交易策略详细绩效指标",
               digits = 4,
               booktabs = TRUE)
}
```

表 7: 配对交易策略详细绩效指标

	Strategy
Observations	1257.0000
NAs	1.0000
Minimum	-0.1031
Quartile 1	0.0000
Median	0.0000
Arithmetic Mean	0.0005
Geometric Mean	0.0005
Quartile 3	0.0000
Maximum	0.0762
SE Mean	0.0003
LCL Mean (0.95)	0.0000
UCL Mean (0.95)	0.0011
Variance	0.0001
Stdev	0.0098
Skewness	-0.8836
Kurtosis	27.9065

4.8 样本外回测

使用样本外数据验证策略的有效性：

```
# 设置样本外时间范围
oos_start_date <- "2023-01-02"
oos_end_date <- "2024-12-31"

# 如果存在协整对，进行样本外回测
if(nrow(cointegrated_pairs) > 0) {
  selected_pair <- cointegrated_pairs$Pair[1]
  stock1 <- cointegration_results[[selected_pair]]$stock1
  stock2 <- cointegration_results[[selected_pair]]$stock2
  beta <- cointegration_results[[selected_pair]]$beta

  # 获取样本外数据
  oos_stock1 <- getSymbols(stock1, from = oos_start_date, to = oos_end_date, auto.assig
  oos_stock2 <- getSymbols(stock2, from = oos_start_date, to = oos_end_date, auto.assig

  # 提取收盘价
  oos_stock1_close <- Cl(oos_stock1)
  oos_stock2_close <- Cl(oos_stock2)

  # 合并数据
  oos_data <- merge(oos_stock1_close, oos_stock2_close)
  colnames(oos_data) <- c(stock1, stock2)

  # 计算样本外残差
  oos_residuals <- as.numeric(oos_data[, stock1]) - cointegration_results[[selected_pai

  # 使用与样本内相同的阈值生成交易信号
  oos_signals <- data.frame(
    date = index(oos_data),
    residual = oos_residuals,
```

```
  signal = 0
)

for(i in 1:nrow(oos_signals)) {
  if(oos_signals$residual[i] > mean_residual + entry_threshold * sd_residual) {
    oos_signals$signal[i] <- -1
  } else if(oos_signals$residual[i] < mean_residual - entry_threshold * sd_residual)
    oos_signals$signal[i] <- 1
  } else if(abs(oos_signals$residual[i] - mean_residual) < exit_threshold * sd_residu
    oos_signals$signal[i] <- 0
  } else {
    if(i > 1) {
      oos_signals$signal[i] <- oos_signals$signal[i-1]
    }
  }
}

# 计算持仓变化
oos_positions <- oos_signals
oos_positions$position <- c(0, diff(oos_positions$signal))

# 计算收益率
oos_stock1_returns <- diff(log(oos_data[, stock1]))[-1]
oos_stock2_returns <- diff(log(oos_data[, stock2]))[-1]

# 计算策略收益率
oos_strategy_returns <- data.frame(
  date = index(oos_data)[-1],  #
  stock1_returns = oos_stock1_returns,
  stock2_returns = oos_stock2_returns,
  signal = oos_signals$signal[-length(oos_signals$signal)],
  position = oos_positions$position[-length(oos_positions$position)]
)
```

```r
colnames(oos_strategy_returns) <- c("date", "stock1_returns", "stock2_returns", "sign
# 计算每日策略收益
oos_strategy_returns$daily_return <- oos_strategy_returns$signal * (oos_strategy_retu

# 计算累计收益
oos_strategy_returns$cumulative_return <- cumsum(oos_strategy_returns$daily_return)

# 可视化样本外策略表现
ggplot(oos_strategy_returns, aes(x = date, y = cumulative_return)) +
  geom_line() +
  labs(title = paste(stock1, " 和", stock2, " 的配对交易策略样本外累计收益"),
       x = " 日期",
       y = " 累计收益") +
  theme_minimal()

# 计算样本外绩效指标
oos_annual_return <- mean(oos_strategy_returns$daily_return) * 252 # 年化收益率
oos_annual_volatility <- sd(oos_strategy_returns$daily_return) * sqrt(252) # 年化波动率
oos_strategy_returns$cumulative_max <- cummax(oos_strategy_returns$cumulative_return)
oos_sharpe_ratio <- ifelse(oos_annual_volatility != 0, oos_annual_return / oos_annual
oos_strategy_returns$drawdown <- oos_strategy_returns$cumulative_max - oos_strategy_r
oos_max_drawdown <- max(oos_strategy_returns$drawdown) # 最大回撤


# 计算样本内绩效指标
strategy_annual_return <- mean(na.omit(strategy_returns$daily_return)) * 252 # 年化收
strategy_annual_volatility <- sd(na.omit(strategy_returns$daily_return)) * sqrt(252)
strategy_sharpe_ratio <- ifelse(strategy_annual_volatility != 0, strategy_annual_retu
strategy_cumulative_return <- cumsum(na.omit(strategy_returns$daily_return))  # 累计收
strategy_cumulative_max <- cummax(strategy_cumulative_return) # 累计最大值
strategy_drawdown <- strategy_cumulative_max - strategy_cumulative_return # 回撤
strategy_max_drawdown <- max(strategy_drawdown, na.rm = TRUE) # 最大回撤
```

```
  # 创建样本外绩效指标数据框
  oos_performance_metrics <- data.frame(
    Metric = c(" 年化收益率", " 年化波动率", " 夏普比率", " 最大回撤"),
    InSample = c(strategy_annual_return, strategy_annual_volatility, strategy_sharpe_ra
    OutOfSample = c(oos_annual_return, oos_annual_volatility, oos_sharpe_ratio, oos_max
  )

  # 展示样本外绩效指标
  knitr::kable(oos_performance_metrics,
               caption = " 配对交易策略样本内外绩效对比",
               digits = 4,
               booktabs = TRUE)
}
```

表 8: 配对交易策略样本内外绩效对比

Metric	InSample	OutOfSample
年化收益率	0.1278	0.0802
年化波动率	0.1561	0.1595
夏普比率	0.8191	0.5029
最大回撤	0.1881	0.1974

5 敏感性分析

5.1 阈值参数敏感性分析

分析不同的交易阈值对策略绩效的影响:

```
# 如果存在协整对，进行阈值敏感性分析
if(nrow(cointegrated_pairs) > 0) {
```

```
selected_pair <- cointegrated_pairs$Pair[1]
stock1 <- cointegration_results[[selected_pair]]$stock1
stock2 <- cointegration_results[[selected_pair]]$stock2
beta <- cointegration_results[[selected_pair]]$beta
residuals <- cointegration_results[[selected_pair]]$residuals

# 设置不同的阈值组合
entry_thresholds <- seq(1.5, 3, by = 0.5)
exit_thresholds <- seq(0.2, 1, by = 0.2)

# 创建结果数据框
sensitivity_results <- data.frame()

# 对每个阈值组合进行回测
for(entry in entry_thresholds) {
  for(exit in exit_thresholds) {
    if(exit < entry) {  # 确保退出阈值小于进入阈值
      # 创建交易信号
      signals <- data.frame(
        date = index(close_prices),  # 去除第一个 NA
        residual = residuals,
        signal = 0
      )

      # 生成交易信号
      for(i in 1:nrow(signals)) {
        if(signals$residual[i] > mean_residual + entry * sd_residual) {
          signals$signal[i] <- -1
        } else if(signals$residual[i] < mean_residual - entry * sd_residual) {
          signals$signal[i] <- 1
        } else if(abs(signals$residual[i] - mean_residual) < exit * sd_residual) {
          signals$signal[i] <- 0
        } else {
```

```
      if(i > 1) {
        signals$signal[i] <- signals$signal[i-1]
      }
    }
  }

  # 计算持仓变化
  positions <- signals
  positions$position <- c(0, diff(positions$signal))

  # 计算收益率
  stock1_returns <- diff(log(close_prices[, stock1]))[-1]
  stock2_returns <- diff(log(close_prices[, stock2]))[-1]

  # 计算策略收益率
  strategy_returns <- data.frame(
    date = index(close_prices)[-1],  # 去除前两个 NA
    stock1_returns = stock1_returns,
    stock2_returns = stock2_returns,
    signal = signals$signal[-length(signals$signal)],
    position = positions$position[-length(positions$position)]
  )
  colnames(strategy_returns) <- c("date", "stock1_returns", "stock2_returns", "si

  # 计算每日策略收益
  strategy_returns$daily_return <- strategy_returns$signal * (strategy_returns$st

  # 计算绩效指标
  annual_return <- mean(strategy_returns$daily_return) * 252
  annual_volatility <- sd(strategy_returns$daily_return) * sqrt(252)
  sharpe_ratio <- ifelse(annual_volatility != 0, annual_return / annual_volatilit

  # 计算最大回撤
```

```
      strategy_returns$cumulative_max <- cummax(cumsum(strategy_returns$daily_return)
      strategy_returns$drawdown <- strategy_returns$cumulative_max - cumsum(strategy_
      max_drawdown <- max(strategy_returns$drawdown)

      # 计算交易次数
      num_trades <- sum(abs(positions$position) > 0)

      # 存储结果
      sensitivity_results <- rbind(sensitivity_results, data.frame(
        Entry_Threshold = entry,
        Exit_Threshold = exit,
        Annual_Return = annual_return,
        Annual_Volatility = annual_volatility,
        Sharpe_Ratio = sharpe_ratio,
        Max_Drawdown = max_drawdown,
        Num_Trades = num_trades
      ))
    }
  }
}

# 展示敏感性分析结果
knitr::kable(sensitivity_results,
             caption = " 不同阈值组合下的策略绩效",
             digits = 4,
             booktabs = TRUE)

# 绘制夏普比率热力图
library(reshape2)
sharpe_matrix <- acast(sensitivity_results, Entry_Threshold ~ Exit_Threshold, value.v

ggplot(melt(sharpe_matrix), aes(x = Var2, y = Var1, fill = value)) +
  geom_tile() +
```

```
    scale_fill_gradient(low = "blue", high = "red") +
    labs(title = " 不同阈值组合下的夏普比率",
         x = " 退出阈值",
         y = " 进入阈值",
         fill = " 夏普比率") +
    theme_minimal()

  # 找出最优阈值组合
  best_thresholds <- sensitivity_results[which.max(sensitivity_results$Sharpe_Ratio), ]
  row.names(best_thresholds) <- NULL


  knitr::kable(best_thresholds,
               caption = " 配对交易策略最优阈值组合",
               digits = 4,
               booktabs = TRUE)
}
```

表 9: 配对交易策略最优阈值组合

Entry_Threshold	Exit_Threshold	Annual_Return	Annual_Volatility	Sharpe_Ratio	Max_Drawdown	Num_Trades
1.5	0.4	0.2407	0.1684	1.4297	0.1524	7

6 结论与讨论

6.1 研究结论

通过对协整理论和配对交易策略的实证分析，我们得出以下主要结论：

1. **协整关系的识别**：通过单位根检验和协整检验，我们成功识别了具有协整关系的股票对，这些股票对的价格走势存在长期均衡关系。

2. **配对交易策略有效性**：基于协整残差构建的配对交易策略在样本内和

样本外均表现出稳定的超额收益，验证了协整理论在配对交易中的有效性。

3. **策略参数敏感性**：交易阈值对策略绩效有显著影响，存在最优的阈值组合能够最大化夏普比率。

4. **样本外表现**：尽管样本外表现通常不如样本内，但配对交易策略仍能保持一定的盈利能力，表明该策略具有一定的稳健性。

6.2 局限性与改进方向

本研究存在以下几点局限性：

1. **交易成本忽略**：本研究未考虑交易成本、滑点和冲击成本等实际交易因素，这些因素可能显著影响策略的实际表现。

2. **参数稳定性**：协整关系和最优参数可能随时间变化，需要定期重新估计和调整。

3. **样本偏差**：研究基于特定时间段的数据，可能存在样本偏差问题。

4. **未考虑市场状态**：不同市场状态下（牛市、熊市、震荡市），配对交易策略的表现可能存在差异。

未来研究可以考虑以下改进方向：

1. **纳入交易成本**：在策略回测中考虑交易成本、滑点和冲击成本等因素。

2. **动态参数调整**：开发动态调整交易阈值和权重的方法，以适应市场变化。

3. **多资产组合**：扩展研究范围，考虑多资产组合的配对交易策略。

4. **结合其他信号**：将协整信号与其他技术指标或基本面指标结合，提高策略的稳健性。

7 参考文献

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