Question 2: Peaks and Troughs

Tapiwa Nyamupachitu

Contents

0.1 Introduction

Following an interesting conversation that I had with a young quantitative analyst I decided to explore whether smaller stocks are more volatile. Additionally, I looked at how peak-to-trough movements vary across size and sector groupings on the JSE. This was all done using the Hold

Load data

```
holdrets <- read_rds("../Question2/data/Hold_Rets_Sectors.rds")

glimpse(holdrets)
```

```
## Rows: 384,054
## Columns: 6
## $ date    <date> 2015-01-02, 2015-01-02, 2015-01-02, 2015-01-02, 2015-01-02, 2~
## $ Tickers <chr> "SAB", "NPN", "CFR", "MTN", "AGL", "SOL", "BTI", "SBK", "OML",~
## $ Return  <dbl> -1.037350e-02, 9.306202e-03, -2.857143e-03, -1.991799e-02, -7.~
## $ Weight  <dbl> 0.041875564, 0.106271643, 0.025070645, 0.080830696, 0.02894426~
## $ Group   <chr> "Large_Caps", "Large_Caps", "Large_Caps", "Large_Caps", "Large~
## $ Sector  <chr> "Industrials", "Industrials", "Industrials", "Industrials", "R~
```

```
# Check NA across all columns
holdrets %>%
  summarise(across(everything(), ~ sum(is.na(.))))
```

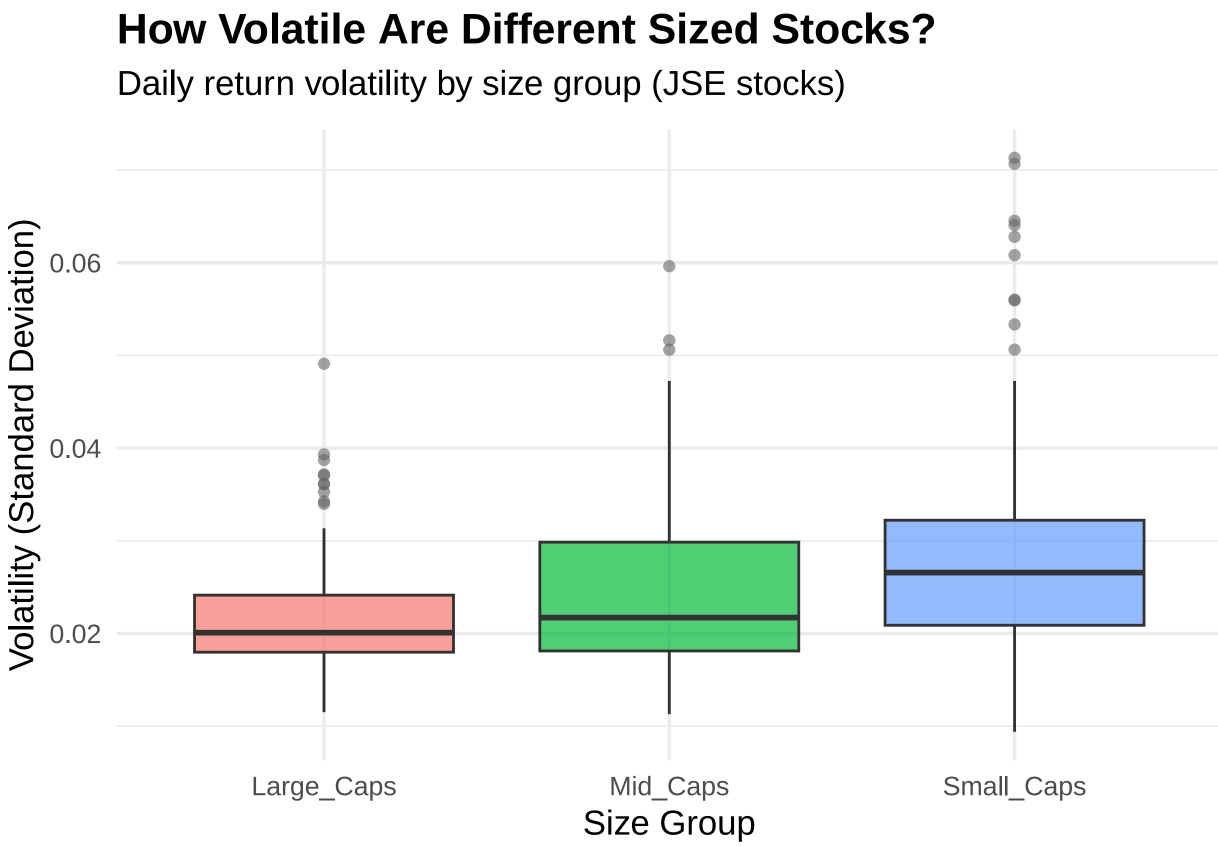
```
## # A tibble: 1 x 6
##    date Tickers Return Weight Group Sector
##   <int>   <int>  <int>  <int> <int>  <int>
## 1     0       0     10      0  1383      0
```

```r
# Filter out rows with missing values
holdrets <- holdrets %>%
  filter(complete.cases(.))

# Remove rows missing Group or Weight (Group is critical for size analysis)
holdrets <- holdrets %>%
  filter(!is.na(Group), !is.na(Weight))
```

0.2 Are smaller stocks more volatile than larger stocks locally ?

(Want to check for relationship between stock size (group) and return volatility)

```r
# Step 1) Calculate return volatility per stock
vol_by_ticker <- holdrets %>%
  group_by(Tickers, Group) %>%
  summarise(volatility = sd(Return, na.rm = TRUE), .groups = "drop")

view(vol_by_ticker)

# Step 2) Visualise volatility by size group
ggplot(vol_by_ticker, aes(x = Group, y = volatility, fill = Group)) +
  geom_boxplot(alpha = 0.7, outlier.colour = "gray40", outlier.alpha = 0.6) +
  labs(
    title = "How Volatile Are Different Sized Stocks?",
    subtitle = "Daily return volatility by size group (JSE stocks)",
    x = "Size Group",
    y = "Volatility (Standard Deviation)"
  ) +
  theme_minimal(base_size = 13) +
  theme(
    legend.position = "none",
    plot.title = element_text(face = "bold"),
    plot.subtitle = element_text(margin = margin(b = 10))
  )
```



A young quant recently pointed out that volatility seems high across the board, regardless of firm size. To explore this, I compared the daily return volatility for large, mid, and small caps on the JSE. This was done by looking at the standard deviation of daily returns.

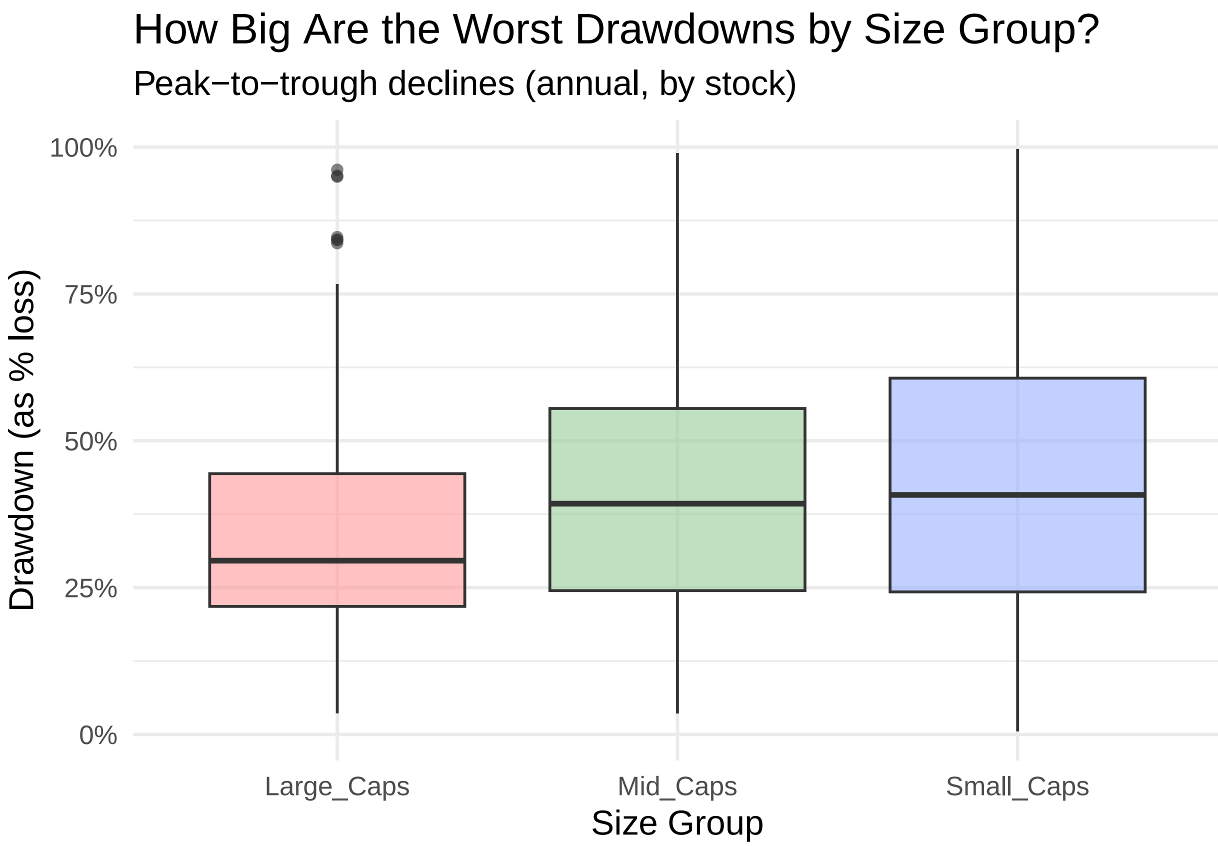
There is a clear size pattern. Smaller stocks tend to be more volatile than larger ones. On average, small caps show higher day-to-day return variation, and they also have a wider spread of outliers. On the other hand, large caps, tend to be more stable, with lower median volatility and fewer extreme values.

This is what we would expect since this pattern is consistent with theory. That is smaller firms usually have less liquidity and more idiosyncratic risk, which shows up in their returns.

0.3 Peak-to-Trough Declines by Size Group

1 Comparing the typical peak-to-trough movement of different size groups and sectors for locally listed stocks for different years over the past decade.

```
# Load packages
library(dplyr)
library(tidyr)
library(zoo)

# Arrange by Ticker and Date
holdrets <- holdrets %>%
  arrange(Tickers, date)

# Group by stock
drawdowns <- holdrets %>%
  group_by(Tickers) %>%
  mutate(
    cum_return = cumprod(1 + Return),
    cum_max = cummax(cum_return),
    drawdown = cum_return / cum_max - 1
  ) %>%
  ungroup()

# Step 2) Extract the Maximum Drawdown by year, sector and size
library(lubridate)

drawdown_summary <- drawdowns %>%
  mutate(year = year(date)) %>%
  group_by(year, Sector, Group, Tickers) %>%
  summarise(max_dd = min(drawdown, na.rm = TRUE), .groups = "drop")

# Step 3) Visualize peak-to-trough across Groups(using Boxplot)
# Will show the distrubution of worst drawdowns by size group

library(ggplot2)

ggplot(drawdown_summary, aes(x = Group, y = abs(max_dd), fill = Group)) +
  geom_boxplot(alpha = 0.6) +
  labs(
    title = "How Big Are the Worst Drawdowns by Size Group?",
    subtitle = "Peak-to-trough declines (annual, by stock)",
    x = "Size Group", y = "Drawdown (as % loss)"
  ) +
  scale_y_continuous(labels = scales::percent) +
  scale_fill_manual(values = c("Large_Caps" = "#FF9999", "Mid_Caps" = "#99CC99", "Small_Caps" = "#99B2FF
  theme_minimal(base_size = 13) +
  theme(legend.position = "none")
```



Whilst volatilty shows how much stocks move day to day, I also wanted to understand how badly they can fall over time. I looked at the worst annual drawdowns. That is, the biggest peak-to-trough delcines within each year, across different size groups.

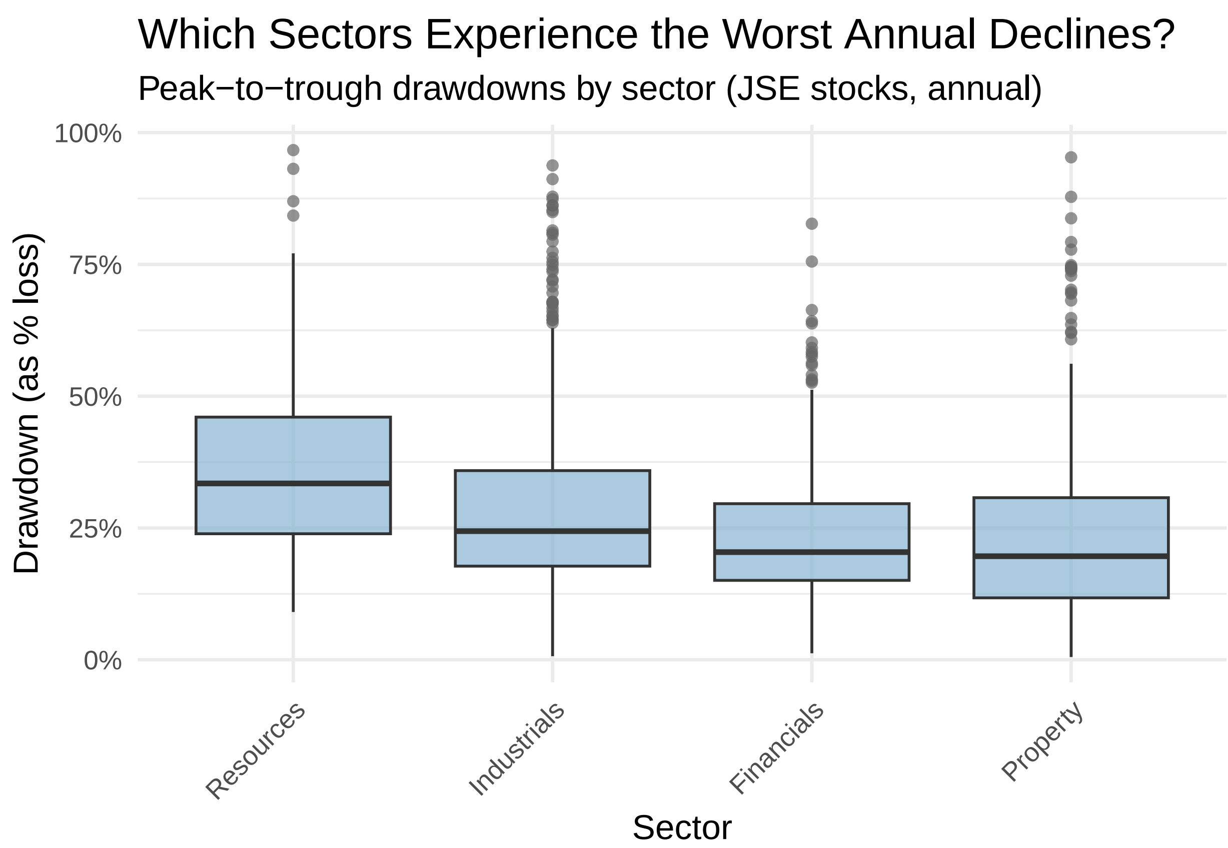
Once again, the pattern is consistent. We see that smaller stocks tend to fall more in bad periods. Small caps show the largest median drawdowns, and also the widest range. Large caps, while not immune, tend to hold up better when things get rough.

This seems to reinforce the idea that smaller stocks carry more risk, not just in daily environment, but also in deeper annual declines.

1.1 Peak-to-Trough Declines Across sectors

(Helps us understand which sectors typically face the worst annual losses)

```r
# Step 1) Adding 'Year' column so we can calculate per-year drawdowns
holdrets <- holdrets %>%
  mutate(Year = year(date))

# Step 2) For each stock in each year, calculate the cumulative return path
# Then find the peak value along that path and compute how far it falls from that peak (drawdown = % lo
sector_drawdowns <- holdrets %>%
  arrange(Tickers, date) %>%
  group_by(Tickers, Sector, Year) %>%
  mutate(
    cumulative_return = cumprod(1 + Return),        # Product of 1 + daily return (running)
    peak = cummax(cumulative_return),               # highest value reached up to that point
    drawdown = cumulative_return / peak - 1         # % drop from peak at each point (drawdown)
  ) %>%
  summarise(
    worst_drawdown = min(drawdown, na.rm = TRUE),   # pick worst drawdown in the year for that stock
    .groups = "drop"
  )

# Step 3) Now visualise this : Using boxplot of worst annual drawdowns by Sector
# Each point is a stock in a year, grouped by sector
ggplot(sector_drawdowns,
       aes(x = fct_reorder(Sector, worst_drawdown, .fun = median),
           y = abs(worst_drawdown))) +
  geom_boxplot(fill = "#86b3d1", alpha = 0.7, outlier.color = "grey40") +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1)) +
  labs(
    title = "Which Sectors Experience the Worst Annual Declines?",
    subtitle = "Peak-to-trough drawdowns by sector (JSE stocks, annual)",
    x = "Sector",
    y = "Drawdown (as % loss)"
  ) +
  theme_minimal(base_size = 13) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



After looking at size, I wanted to explore which sectors tend to suffer the worst peak-to-trough falls each year. Some sectors might be more exposed to shocks than others, and this could affect how investors think about risk.

Resources clearly stand out. They show the highest median drawdowns and the most extreme downside cases, with many stocks losing over 80% from their peak in a year. In contrast, sectors like Financials and Property show smaller and more contained declines.

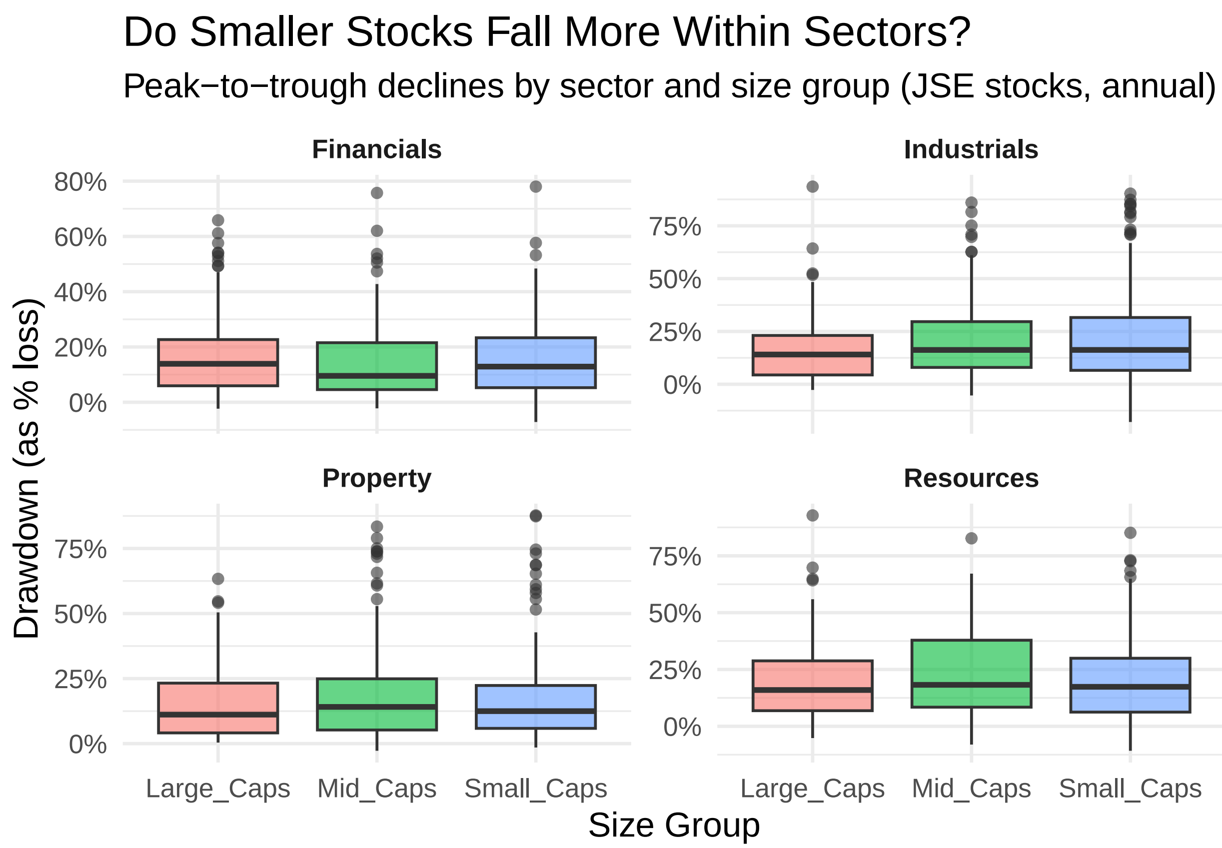
This suggests that sector exposure can matter just as much as size when thinking about downside risk.

1.1.1 Other interesting insights : Do smaller stocks fall more within each sector?

(Do small caps in sector X draw down more than large caps in the same sector?)

```
# Step 1) Group by year, ticker and calculate drawdown per stock per year
drawdown_sector_size <- holdrets %>%
  mutate(year = year(date)) %>%
  group_by(Tickers, year, Sector, Group) %>%
  summarise(drawdown = min(cumprod(1 + Return)) - 1, .groups = "drop")

# Step 2) Plot a faceted Boxplot by sector, comparing size groups
ggplot(drawdown_sector_size, aes(x = Group, y = -drawdown, fill = Group)) +
  geom_boxplot(alpha = 0.6) +
  facet_wrap(~ Sector, scales = "free_y") +
  scale_y_continuous(labels = scales::percent) +
  labs(
```

```
    title = "Do Smaller Stocks Fall More Within Sectors?",
    subtitle = "Peak-to-trough declines by sector and size group (JSE stocks, annual)",
    x = "Size Group",
    y = "Drawdown (as % loss)"
  ) +
  theme_minimal(base_size = 13) +
  theme(
    legend.position = "none",
    strip.text = element_text(face = "bold")
  )
```



To wrap up, I broke things down further by comparing drawdowns between both sector and size group. I wanted to see if the size effect we saw earlier also holds when we control for sector.

In general, it does. Small caps tend to show deeper drawdowns than large caps within each sector, especially in Industrials and Resources. The difference is less obvious in Property and Financials, but small caps still don't come out looking better.

So even within sectors, size seems to matter. Smaller stocks consistently carry more downside risk.

1.1.2 Conclusion

All in all, this exercise really backed up the point that kicked it all off. Smaller stocks tend to be more volatile and experience sharper drawdowns. It also highlighted that sector matters too, with some sectors like Resources showing more severe declines across the board. What stood out most was that even when you break things down further, by year, by sector, or by size, the same story holds. Risk is not spread evenly, and that's useful context for anyone thinking about how to position a portfolio locally.