Sector Resilience During the COVID-19 Market Crash

A Data Analytics Project

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Tools: Python (pandas, NumPy, matplotlib) | Financial Time-Series Data Analysis

Github Repository: https://github.com/ItayF213/sector-resilience-covid

Research Question & Motivation

Motivation & Context

- The COVID-19 pandemic triggered an unprecedented equity market shock
- U.S. equity market sectors responded very differently in terms of losses and recovery
- Understanding sector resilience helps evaluate risk during extreme market events

Research Question

How did U.S. equity market sectors differ in resilience during and after the COVID-19 market crash?

Data & Scope

Data Source & Coverage

- Daily adjusted closing prices for U.S. sector ETFs
- Sector ETFs used as proxies for S&P 500 sector-level performance
- Data retrieved using the *yfinance* Python library

Analysis Period

- Market peak: February 19, 2020
- Market bottom: March 23, 2020
- Recovery tracked through December 31, 2020

Methodology

Approach

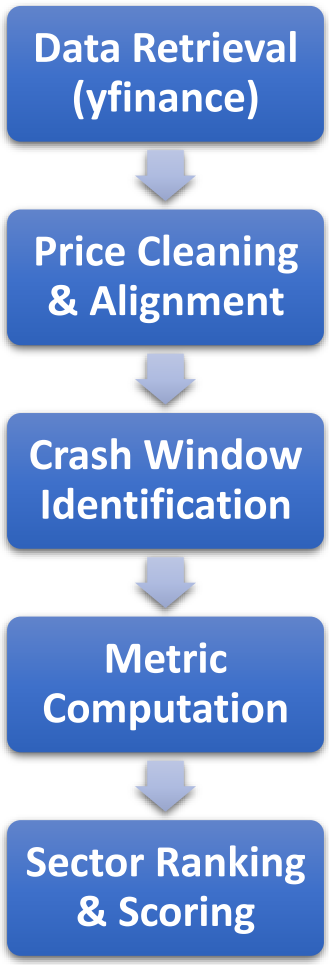
- Identified the COVID-19 market crash using peak and trough dates
- Analyzed sector performance during the crash and recovery phases
- Standardized sector comparisons using percentage-based metrics

Resilience Metrics

- Maximum drawdown during the crash period
- Time required to recover to pre-crash peak levels
- Total return from market peak through December 31, 2020

End-to-End Analytical Pipeline

- Automated retrieval of daily adjusted prices for U.S. sector ETFs
- Standardized preprocessing to ensure consistent time alignment across all sectors
- Metric-driven evaluation of sector resilience across multiple dimensions



Resilience Metrics: Definitions

Maximum Drawdown (Crash Severity)

- Measures the largest peak-to-trough decline during the COVID-19 market crash.

Maximum Drawdown =

$$\frac{\boldsymbol{Lowest\ Price\ - Peak\ Price}}{\boldsymbol{Peak\ Price}}$$

Recovery Speed

- Measures how quickly a sector recovered to its pre-crash price level.

Recover Days =

# of days required to return to Feb 19, 2020 price level

Post-Crash Total Return

- Measures performance after the crash through the end of 2020.

Total Return =

$$\frac{\boldsymbol{Price\ on\ Dec\ 31, 2020\ - Peak\ Price}}{\boldsymbol{Peak\ Price}}$$

Implementation Snapshot (Python)

 # Download and clean price data

```
raw = yf.download(tickers, start = “2018-01-01”,
end = “2023-12- 31”, auto_adjust=False,
progress=False)

prices = raw["Adj Close"].copy()

prices_clean = prices.dropna()
```

 # Compute returns and cumulative performance

```
returns = prices_clean.pct_change().dropna()

cum = (1 + returns).cumprod()
```

 # Define COVID crash window

```
crash = cum.loc[covid_start:covid_bottom]

peak = crash.cummax()

drawdown = crash / peak – 1
```

 # Key resilience metrics

```
max_dd = drawdown.min()

total_return = (covid_period.iloc[-1] /
covid_period.iloc[0] - 1)
```

- End-to-end Python workflow using pandas and yfinance
- Metrics computed directly from adjusted price data
- Fully automated and reproducible across all sectors

Key Results: Sector Resilience Analysis

Key Findings

- Technology (XLK) and Consumer Discretionary (XLY) exhibited the strongest resilience, combining smaller drawdowns with faster recovery and strong post-crash returns
- Energy (XLE) experienced the largest drawdown and slowest recovery, resulting in the weakest overall resilience score
- Defensive sectors such as Consumer Staples (XLP) limited downside risk but exhibited slower recovery
- Sector resilience varied significantly, highlighting the importance of sector-level risk analysis during systemic shocks

	Max Drawdown (Crash) %	Total Return (Feb19-Dec31 2020) %	Recovery Days (to Feb19 level)	Overall Score (lower=better)
XLK	-31.2	28.1	78	7
XLY	-33.9	22.9	77	8
XLC	-30.1	18.2	109	10
XLV	-27.9	10.9	114	11
XLP	-24.3	7.5	142	13
XLB	-36.3	22.3	116	15
XLI	-41.6	7.4	231	23
XLU	-35.6	-7.5	500	25
XLF	-42.8	-2.8	289	26
XLRE	-38.8	-8.3	374	27
XLE	-56.3	-26.3	666	33