Is It A Good Idea to Invest in Consumer Staples During Economic Crisis?

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1 Introduction

Economic crises have recurred regularly over the past two centuries, with many individuals experiencing at least one major downturn in their lifetime. A common explanation for this phenomenon is the debt cycle, which arises from patterns of credit expansion and contraction at both personal and institutional levels. Given this historical precedent, another economic downturn appears not only possible but likely in the foreseeable future.

While such crises are inevitable, investors still seek strategies to preserve wealth and mitigate losses. One commonly proposed approach is to invest in Consumer Staples—companies that produce essential goods such as food, beverages, and household items. Demand for these goods is typically price-inelastic and less sensitive to macroeconomic fluctuations, suggesting that firms in this sector may exhibit more stable performance across economic cycles.

This perceived stability makes Consumer Staples an intuitively attractive option for defensive investment during turbulent times. However, intuition alone does not suffice in financial decision-making. Thus, a rigorous data-driven investigation is warranted to evaluate their actual performance under stress.

2 Objectives and Research Plan

This project aims to assess whether Consumer Staples constitute a robust defensive investment strategy during economic crises. Specifically, we seek to answer the following questions: (1) Do Consumer Staples outperform other major sectors in terms of return stability or risk-adjusted return during periods of financial turmoil? (2) How does their performance compare under crisis versus normal regimes? (3) Are Consumer Staples returns significantly influenced by macroeconomic indicators such as CPI, unemployment, and interest rates?

To achieve these goals, we employ a comprehensive empirical approach including: (1) Cross-sectional performance comparison across four key S&P 500 sectors; (2) Time-series modeling (ARCH) to identify volatility-based market regimes; (3) Portfolio construction using representative companies from each sector during manually defined crisis periods (2000, 2008, 2020); (4) Regression analysis to examine the sensitivity of Consumer Staples returns to macroeconomic variables.

Our methodology integrates both quantitative modeling and intuitive crisis definitions to provide a robust assessment of the Consumer Staples sector's role in portfolio defense.

3 Data

To evaluate the behavior of Consumer Staples across different market conditions, we compile a comprehensive dataset consisting of both stock-level and macroeconomic data from January 1997 to December 2024. The dataset supports time-series, cross-sectional, and regression analyses. A detailed description of the data can be found in the Appendix.

4 Methods & Theories

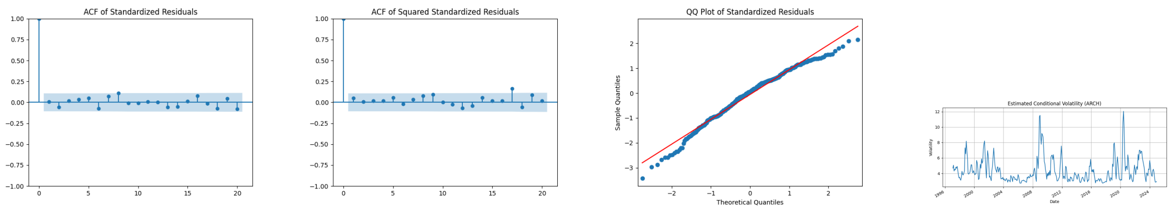
4.1 Time Series Modeling: ARCH-Based Regime Detection

Since economic crises are systemic in nature and affect the market as a whole, we first adopt a time series approach to detect periods of market turbulence. Specifically, we fit an Autoregressive Conditional Heteroskedasticity (ARCH) model to the monthly returns of the S&P 500 index. Model selection is guided by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), both of which favor the ARCH(3) specification. The model is then validated using standard diagnostic tools such as ACF plots, squared residual analysis, and a Lagrange Multiplier test.

To capture volatility clustering and time-varying heteroskedasticity in financial returns, we model the S&P 500 monthly returns using an ARCH(q) process. An ARCH(q) model assumes:

$$r_t = \mu + \epsilon_t, \quad \epsilon_t \sim N(0, h_t), \quad h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2$$

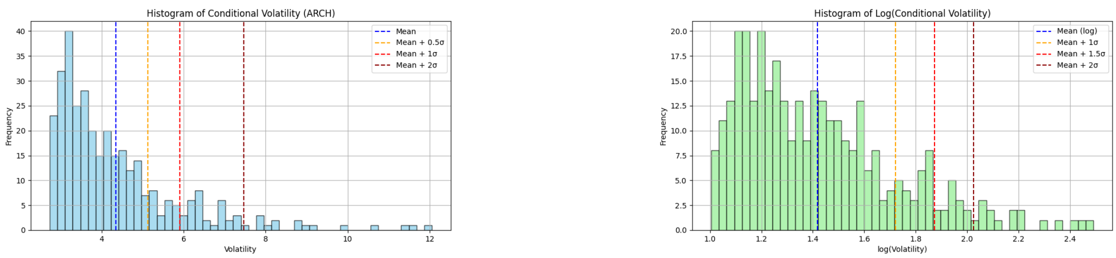
where h_t is the conditional variance at time t, and the parameters $\alpha_0, \alpha_1, \ldots, \alpha_q$ control the dynamics of volatility. We select $q = 3$ based on AIC/BIC criteria, implying that past three periods' squared residuals explain current volatility.



(a) (b) (c) (d)

Figure 1: Model diagnostics: (a) ACF, (b) ACF of squared residuals, (c) QQ plot, (d) Estimated Conditional Volatility. LM test p-value: 0.8258

Given that the model is well-fitted based on diagnostic tests, we proceed to classify market regimes using a volatility threshold defined as $\mu + 0.5\sigma$, where μ and σ denote the mean and standard deviation of monthly volatility, respectively. This threshold is derived from the empirical distribution of volatility, which is notably right-skewed, as illustrated below. Although a log-normal distribution was initially hypothesized, visual inspection suggests this is not an appropriate fit.



(a) Right-skewed Distribution (b) Distribution of log(Volatility)

Figure 2: Histogram of monthly volatility in the S&P 500 index

4.2 Cross-Sectional Comparison: Sector Performance under Different Regimes

Using the regime classification derived from the ARCH model, we conduct a cross-sectional comparison of sector-level performance under crisis and normal conditions. For each sector, we compute the average monthly return and volatility, and calculate the Sharpe ratio using a constant annual risk-free rate of 2% (equivalent to a monthly rate of approximately 0.1652%). x To evaluate sector performance under varying market regimes, we employ the Sharpe Ratio, a widely used metric for risk-adjusted return:

$$\text{Sharpe Ratio} = \frac{\mathbb{E}[R] - R_f}{\sigma_R}$$

where $\mathbb{E}[R]$ is the expected return of the asset or portfolio, R_f is the risk-free rate, and σ_R is the standard deviation of returns. A higher Sharpe Ratio indicates more return per unit of risk.

Sector	Crisis Mean Return	Crisis Volatility	Sharpe ratio	Normal Mean Return	Normal Volatility	Sharpe ratio
Consumer Staples	0.6098%	0.050681	8.773	0.5431%	0.032964	11.464
Consumer Discretionary	1.3965%	0.087843	14.017	0.8348%	0.045600	14.684
Technology	1.3872%	0.104034	11.746	1.1718%	0.063901	15.753
Industrials	0.7393%	0.080683	7.116	0.7182%	0.045253	12.220
S&P 500	0.8%	0.0674	9.418	0.71%	0.0378	14.413

Table 1: Sector-level performance across volatility regimes

Surprisingly, Consumer Staples underperform in terms of the Sharpe ratio during both crisis and normal regimes. This outcome is likely due to our crisis definition based on high volatility, which can occur not only during downturns but also in optimistic markets with rapid price increases. As a result, the observed mean return during crises appears higher than in normal periods, which may distort expectations. Nonetheless, Consumer Staples consistently exhibit lower volatility, supporting their role as a stable option for preserving asset value against inflation.

4.3 Portfolio Construction

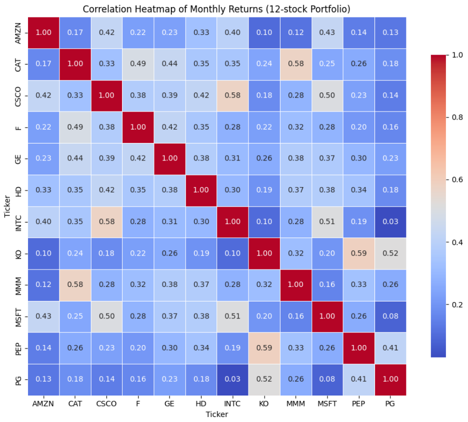
Despite the previous findings, we maintain the belief that investing in Consumer Staples during economic crises remains a viable strategy. To address the volatility-related concerns observed in the regime classification, we adopt a different approach by manually specifying crisis periods—namely the years 2000, 2008, and 2020—based on well-documented historical market downturns.

Within this revised framework, we construct sector-specific portfolios by selecting three representative companies from each sector. The S&P 500 index is used as the benchmark market portfolio for comparison. The observed weak correlations between companies from different sectors justify treating each sector portfolio independently, enabling a fair performance comparison.

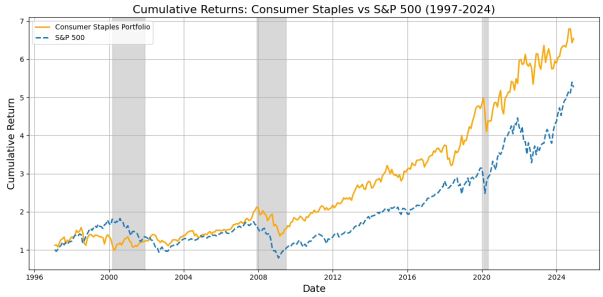
To evaluate sector behavior over time, we compute and plot the 12-month rolling average return and rolling beta (relative to the S&P 500) for each portfolio. During the shaded crisis periods, the Consumer Staples portfolio consistently exhibits lower beta and relatively higher returns. This supports the view that Consumer Staples offer a resilient investment option during economic downturns. See Figure 3.

4.4 Macroeconomic Analysis

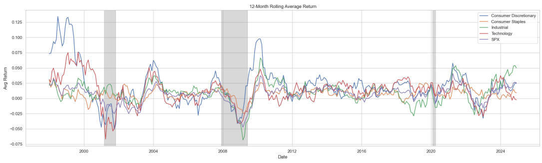
Moreover, Consumer Staples are often regarded as relatively insensitive to fluctuations in the macroeconomic environment. To empirically assess this claim, we characterize the macroeconomic environment using four key indicators: the Consumer Price Index (CPI), Unemployment Rate, Treasury Rate, and the Volatility Index (VIX).



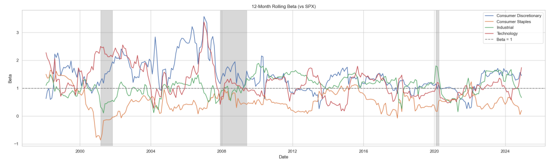
(a) Correlation Heatmap



(b) Sharpe Ratio Consumer Staples vs. SPX



(c) Rolling Average Return



(d) Rolling Beta

Figure 3: Portfolio Construction plots.

After standardizing these variables, we apply an ordinary least squares (OLS) regression to model the monthly returns of the Consumer Staples sector index as a function of these macroeconomic indicators. Since our objective is not to perform statistical inference but rather to observe general relationships, we proceed with OLS estimation without conducting hypothesis tests or diagnostic procedures.

We fit a multiple linear regression model to estimate the relationship between sector returns and macroeconomic indicators:

$$R_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots + \beta_k X_{k,t} + \epsilon_t$$

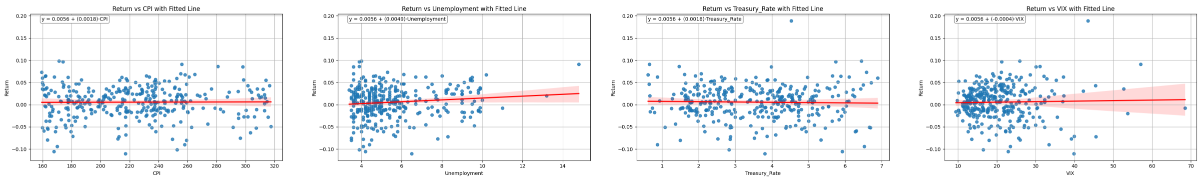
where R_t is the Consumer Staples sector return at time t, $X_{i,t}$ are the standardized macroeconomic variables (CPI, Unemployment, Treasury Rate, VIX), and ϵ_t is the error term. Estimation is conducted using Ordinary Least Squares (OLS), minimizing the residual sum of squares.

Constant	Treasury_rate	CPI	Unemployment	VIX	R^2	Adjusted R^2
0.0056	0.0018	0.0018	0.0049	-0.0004	0.013	0.001

Table 2: Regression results for Consumer Staples monthly return

The resulting model yields a low R^2, indicating a poor fit and suggesting that a linear relationship may not adequately capture the dynamics between Consumer Staples returns and the selected macroeconomic variables. To further investigate, we examine each variable individually by plotting scatter plots of the Consumer Staples sector's monthly return against each standardized macroeconomic indicator.

These visualizations confirm the initial regression result—there is no discernible pattern or strong association between the sector's returns and CPI, Unemployment Rate, Treasury Rate, or VIX. Based on this evidence, we conclude that Consumer Staples returns exhibit weak sensitivity to macroeconomic fluctuations, supporting the common belief in their defensive and stable nature.



(a) Consumer Staples vs. CPI

(b) Consumer Staples vs. Unemployment

(c) Consumer Staples vs. Treasury Rate

(d) Consumer Staples vs. VIX

Figure 4: The Unemployment Rate and VIX tend to remain low, leading to a left-skewed concentration of points in the plots.

5 Conclusion and Future Work

This study set out to evaluate the validity of Consumer Staples as a defensive investment strategy during economic crises. Using both volatility-based regime classification via ARCH modeling and manually defined historical crisis periods, we conducted a comprehensive analysis of the sector's performance relative to other major S&P 500 sectors.

Our findings challenge the common belief that Consumer Staples consistently outperform during downturns. Based on Sharpe ratio comparisons across both crisis and normal regimes, Consumer Staples underperformed relative to Consumer Discretionary and Technology—sectors generally considered more economically sensitive. This outcome may stem from our crisis definition based on heightened volatility, which can also capture optimistic periods of rapid price growth. Nevertheless, the consistently lower volatility of Consumer Staples supports their reputation as a stable asset class aimed at capital preservation rather than excess returns.

To further explore this, we constructed sector-specific portfolios using representative companies. Time-series and cross-sectional analyses—particularly rolling beta and return plots—reinforced the finding that Consumer Staples exhibit lower systematic risk. During manually defined crisis periods, Consumer Staples portfolios displayed relatively higher returns compared to the other three sectors. However, this result may reflect the specific companies selected, and outcomes could vary with alternative portfolio compositions.

In the macroeconomic analysis, regression results and scatter plots revealed weak associations between Consumer Staples returns and key macro indicators such as CPI, unemployment, Treasury rates, and VIX. This supports the common view that Consumer Staples are largely insulated from macroeconomic fluctuations, providing further evidence of their defensive characteristics.

For future work, we plan to use higher-frequency data and expand the number of firms in each sector portfolio to improve robustness. In addition, we aim to test a broader range of asset classes beyond the S&P 500 to assess whether similar defensive behavior holds in other markets or sectors.

In summary, while Consumer Staples may not generate superior returns during crises, their low volatility and macroeconomic insensitivity reaffirm their role as a core component of a diversified, risk-conscious investment strategy.

6 Appendix

6.1 Data Construction

To evaluate the behavior of Consumer Staples across different market conditions, we compile a comprehensive dataset consisting of both stock-level and macroeconomic data from January 1997 to December 2024. The dataset supports time-series, cross-sectional, and regression analyses.

6.1.1 Stock Market Data

We collect historical price data for companies within four major S&P 500 sectors: Consumer Staples, Consumer Discretionary, Technology, and Industrials. At the sector level, we use monthly adjusted closing prices of the S&P 500 sector ETFs as proxies. At the company level, we aim to select three companies that collectively represent the breadth of each sector's industry composition. For the Technology sector, we include Microsoft (software), Intel (hardware), and Cisco Systems (network infrastructure). In the Industrials sector, our selection consists of General Electric (manufacturing and power systems), Caterpillar (construction and mining equipment), and 3M (diversified industrial products). For Consumer Discretionary, we choose Amazon (e-commerce and cloud services), Home Depot (home improvement and housing-related retail), and Ford (automotive). Lastly, for Consumer Staples, we include Procter & Gamble (household products), Coca-Cola, and PepsiCo (beverages and snacks).

To capture stock performance dynamics, we compute two key metrics for each firm and sector:

- **Monthly Log Return**: Computed as the log difference of monthly adjusted closing prices.

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right)$$

  where P_t is the adjusted closing price at month t. Log returns are additive over time and commonly used in financial modeling.

- **Monthly Rate of Change (RoC)**: Calculated as the percentage change relative to the previous month.

$$\mathrm{RoC}_t = \frac{P_t - P_{t-k}}{P_{t-k}} = \frac{P_t}{P_{t-k}} - 1$$

  which measures the percentage change relative to the previous month.

- Missing values due to non-trading months are forward-filled when necessary.

All stock variables are synchronized to monthly frequency and aligned across companies and sectors.

6.1.2 Macroeconomic and Market Data

We retrieve key macroeconomic indicators from official U.S. government and financial databases (primarily FRED and CBOE), covering multiple dimensions of economic activity:

- **Consumer Price Index (CPI)** and **Unemployment Rate**: Available monthly.
- **10-Year Treasury Rate**, **Federal Funds Rate**, and **VIX Index**: Available at daily frequency, aggregated to monthly averages.
- **Real GDP**: Reported quarterly, interpolated to monthly values using linear interpolation.

Each variable is then standardized to zero mean and unit variance prior to regression analysis. The final macroeconomic dataset is merged with stock data by date and covers over two decades of economic cycles and financial shocks.

6.1.3 Final Dataset Overview

The resulting dataset includes:

- Monthly returns and volatility measures at both sector and firm levels;
- Monthly macroeconomic variables aligned for consistent time-series modeling;
- Defined economic crisis periods (2000, 2008, 2020) for crisis regime classification.

This integrated dataset forms the foundation for the analyses in subsequent sections, including volatility modeling, portfolio construction, and regression testing.

6.2 Code Attachment

Click here to access the code file