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碩士論文

Department of Finance

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Master's Thesis

不同總體經濟環境下系統風險分散方法之敏感度分析

Sensitivity Analysis of Systematic Risk Diversification Approaches Under Various Macroeconomic Environments

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摘要

此篇論文旨在討論不同總體經濟環境和經濟循環週期階段下系統風險分散方法之敏感度分析。本篇研究討論量化建模方法以及策略投資風險分散方法之可行性以及其在不同總體環境下的表現。我們採用耦合進行量化多變量建模，並使用50/50動能/價值投資組合作為策略風險分散方法。本研究採用以各種資產種類為標的之美國ETFs作為資產交易之選擇以提供投資人更具有可行性的結果。我們得出結論為量化建模以及策略投資分散方法統計上皆顯著有效，而在經濟擴張期內策略投資分散方法表現優於整體市場，而量化建模方法則整體上更為穩健，對總體經濟環境之敏感性較低。

關鍵字：資產配置、耦合、總體敏感度分析、ETFs

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Abstract

We discuss the efficiency of systematic risk diversification under various macroeconomic environments and economic cycle phases using both quantitative approach and strategic approach. We adapt Copula for quantitative multivariate modeling and combo of 50/50 momentum/value for strategic approach. For more accessible and investable results, we apply the U.S. Exchange-Traded Funds (ETFs) with various assets underlying as asset universe in this study. We conclude that both approaches we proposed are valid and effective and that the strategic approach outperforms the market in the expansion period, while the quantitative approach is overall more robust and less sensitive to macroeconomic environments.

Keywords: asset allocation, Copula, macroeconomic sensitivity analysis, ETFs

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Chapter 1

Introduction

Asset allocation and diversification have been a widely discussed topic. Modern portfolio theory suggests that by holding a diversified portfolio of non-perfectly correlated assets, investors can diversify individual unsystematic risk and hence obtain a maximized expected return under a given level of risk. Later on, CAPM introduces the concept of the market portfolio. The market portfolio is defined as all investable assets in the world, held in proportion to their market values. According to CAPM, the market portfolio is theoretically on the efficient frontier, indicating that it offers the best possible risk-return combination available in the market. However, it is quite challenging for individual investors to directly create a market portfolio to diversify idiosyncratic risk due to the limitations of time-consuming and wealth conditions. Exchange-traded funds (ETFs), which track the performances of broad market indices such as the MSCI index or S&P500, can be an effective approximation of market portfolios for individual investors.

Unlike idiosyncratic risk, which can be eliminated through equity diversification, systematic risks are relatively challenging to offset. It could derived from economic cycles, political factors, or even environmental and social risks such as climate change. It is hard to diversify systematic risk using only equity. Plenty of literature suggests that including various asset types can effectively enhance portfolio return. Niko Canner et al. (1986) [3] provide empirical evidence that asset allocation, rather than individual security

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selection or market timing, accounted for the majority of the variance in portfolio returns.

Plenty of research shows that investing style and strategy explain excess returns as well. Jegadeesh and Titman (1993) [9] establish groundwork in discussing the predictability of future returns from past returns. They provide empirical evidence that buying past winners and selling past losers could yield significant abnormal returns in the stock market. More literature shows the robustness and consistency of the momentum strategy. Tobias J. Moskowitz et al.(2012) [10] extend the momentum strategy into various asset classes, including equity index, currency, commodity, and bond futures. They find persistence in returns in diverse asset classes and their futures contracts. DeBondt and Thaler (1985) [2] provide empirical evidence that under long-term periods (3-5 years), low past returns portfolios yield higher future returns and high past returns portfolios yield lower future returns. Fama and French (1992) [6] introduce three-factor model, which includes ”Value” (high book-to-market ratio) as a significant factor for cross-section asset pricing. Later on, some literature explores the efficiency of momentum and value investing in different asset classes. Claude B. Erb et al. (2006) [5] analyze the role of commodities futures in asset allocation, stating that adding commodities into the portfolio with tactical strategies can have better performances. Houweling, P. and Van Zundert, J. (2017) [7] offer empirical evidence that value and momentum factors can generate statistically significant excess returns in corporate bond markets.

For a more general application, CS Asness (2013) [1] provides comprehensive evidence on return premia of momentum and value strategy globally across various assets, including stock, fixed income, commodities, and currencies. Though most of the previous theories focus on equities, the results show that value and momentum strategies are still quite valid among various countries and asset markets. Moreover, the combination

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of value and momentum strategy can deliver stronger performances.

Various studies have attempted to discuss the relationship between macroeconomic factors and asset return. Chen, Roll, and Ross (1986) [4] offers a general view of how a set of macroeconomic variables exposes systematic influences on stock market returns. The candidates of macroeconomic variables mainly focus on industrial production, inflation, term structure, and consumption. They conclude that stock returns are exposed to innovative economic news and are priced accordingly as well. Antti Ilmanen et al.(2020) [8] provide a comprehensive and integrated viewpoint on how equities and fixed income respond to different economic environments. They also find that investing style diversification can reduce macroeconomic sensitivities and deliver more robust performances across different environments.

Building upon the foundational insights provided by the aforementioned studies, this research seeks to further elucidate the relationships between macroeconomic factors and systematic risk diversification. Plenty of research offers empirical evidence on the benefits of asset allocation, but only a few focus on the comparison between the efficiency of adapting quantitative approach and strategic approach. The innovative aspect of our study lies in the discussion on the performances of asset-risk diversify approach (by Copula) and strategy diversify approach (50/50 momentum/value). We adopt the methodology from Antti Ilmanen et al. (2020) [8] and classify time series macroeconomic factors into ”Up” and ”Down” environments. The objective is to examine the performance of these diversification strategies across upturn and downturn macroeconomic conditions using various asset classes, thereby providing a more comprehensive viewpoint on the diversification of systematic risk.

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In contrast to prior research that usually includes indices directly in the asset universe, this study seeks to provide more accessible outcomes by focusing solely on U.S. ETFs that track these indices. By narrowing our asset universe to these specific ETFs as trading targets, we aim to offer insights that are directly applicable and easily interpretable for investors and practitioners. We select SPY, AGG, and GLD, etc as proxies of equity, fixed-income, and gold markets, which are all actively traded ETFs globally.

We provide details of data selection and portfolio construction in Section 2 and present our empirical results in Section 3. We conclude and provide some potential future work in Section 4.

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Chapter 2

Data and Portfolio Construction

2.1 Macroeconomic Factors

We select *Growth*, *Forward Inflation*, *Real yields*, *Volatility*, and *Unemployment* as our macroeconomic factors. It is important to highlight that we apply macroeconomic leading indicators to provide a more contemporaneous evaluation of the economic landscape instead of using realized data. This approach enables a timelier and more predictive insight into how various macroeconomic conditions impact portfolio performance.

- *Growth*: U.S Monthly Industrial Production

- *Forward Inflation*: Equally weighted of 10-year breakeven rate and 5-year, 5-year forward inflation

- *Real Yields*: Daily differences between 10-year U.S. Treasury yield and 2-year U.S. Treasury yield

- *Volatility*: Daily CBOE Volatility Index (VIX)

- *Unemployment*: U.S Weekly Initial Claims

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Macroeconomic variables data are collected from June 2006 to December 2022 and standardized using Z-scores. Periods with Z-scores above the median are classified as 'Up' environments, indicating higher economic activity, whereas those below the median are defined as 'Down' environments, reflecting lower activity.

Table 2.1: Correlation Matrix of Macroeconomic Indicators

	Industrial Prod.	**Forward Infl.**	**T10Y-2Y**	**Initial Claim**	**Volatility**	**S&P500**
Industrial Prod.	1.0000					
Forward Infl.	0.2101	1.0000				
T10Y-2Y	-0.5731	0.1744	1.0000			
Initial Claim	-0.0171	-0.1973	-0.0648	1.0000		
Volatility	-0.4980	-0.3869	0.1466	0.3191	1.0000	
S&P500	-0.0165	0.1640	0.0189	-0.2023	-0.4375	1.0000

2.2 Asset Universe

To enhance accessibility for a broader spectrum of investors, this study exclusively incorporates U.S. Exchange-Traded Funds (ETFs) to evaluate the performance across equity, fixed-income, and gold markets. The selection includes prominent ETFs such as the SPDR S&P 500 ETF Trust (SPY), iShares Core S&P 500 ETF (IVV), and Invesco QQQ Trust (QQQ) to serve as proxies for the equity market. For fixed-income analysis, a diverse range of ETFs is considered, each tracking distinct maturity profiles of investable U.S. government and corporate bonds. Specifically, the iShares Core U.S. Aggregate Bond ETF (AGG) is utilized to represent the overall bond market, while the iShares 20+ Year Treasury Bond ETF (TLT) serves as a benchmark for the long-term treasury seg-

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ment. Additionally, the Vanguard Short-Term Bond ETF (BSV) is included to capture the median-term treasury market, tracking the Bloomberg U.S. 1–5 Year Government/Credit Float Adjusted Index. Furthermore, the SPDR Bloomberg 1-3 Month T-Bill ETF (BIL) is employed as a proxy for short-term Treasury Bills. The gold market is evaluated using the SPDR Gold Shares (GLD) ETF. The dataset spans monthly observations from July 2007 to December 2022.

2.3 Portfolio Construction

We refer to the two risk diversified portfolio we propose in this study as ”asset risk diversified portfolio” and ”strategy diversified portfolio”

2.3.1 Asset Risk Diversified Portfolio

Due to quantitative and computational limitations, we are not able to include all selected ETFs for estimating the multivariate distribution of various assets. SPY and GLD are included as the primary proxies of equity market and gold market in asset-risk diversified portfolio formation. In terms of fixed income, we have curated two distinct asset universes: the first includes only AGG, while the second encompasses TLT and BIL. Since TLT tracks long-term treasury bonds and BIL tracks 1-3 month T-bill, whereas AGG provides a broader target in fixed income, we want to examine whether the selection of bond maturity will affect portfolio performances.

For the first portfolio, the trading period is in between t, *(t=1:186, 2007/07-2022/12)*.For the second portfolio, trading period is in between t, *(t=1:174, 2008/08-2022/12)* since some ETFs were issued later. We adapt Copula theory for estimating asset risk diversified

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portfolio monthly since Copula has great flexibility in forming joint distributions. Empirical evidence shows that returns on equity, fixed income, and gold market are hardly to be independent. Random variables with inter-correlation are accepted via Copula approach, thereby enabling to provide a straightforward methodology for multivariate density modeling.

We use a Constant Relative Risk Aversion (CRRA) utility function to find the optimization of portfolio weights, which is instrumental in the maximization of expected utility. To estimate the joint probability density functions of ETF log returns, we select daily log returns spanning the previous 12-1 months. A rolling window sampling methodology is employed to continuously update our sample, thereby preventing overfitting and ensuring the robustness of our estimations. This methodological framework allows for dynamic adjustment to the changing market conditions, which is crucial for maintaining the relevance and accuracy of the model.

We provide a brief mathematical introduction to Copula and optimal weight estimation in the following section. By Sklar's theorem, let $\mathbf{X} = (X_1, X_2, \ldots, X_n)$ be a random vector and let $H(x_1, x_2, \ldots, x_n)$ be the multivariate CDF of $\mathbf{X}$. Then there exists a copula C such that

$$H(x_1, x_2, \ldots, x_n) = C(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)),$$

where $F_i(x_i)$ is the marginal CDF of X_i. If the multivariate distribution has a density h, then

$$h(x_1, x_2, \ldots, x_n) = c(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)) \cdot f_1(x_1) \cdot f_2(x_2) \cdots f_n(x_n),$$

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where c is the density of the copula and $f_i(x_i)$ is the marginal PDF of X_i. To obtain optimal weight w_t^* at time t, we find the arg max of the expectation CRRA utility:

$$
\begin{aligned}
w_t^* &= \arg\max \mathbb{E}\left[U(w_{x1,t} \cdot X_{1,t} + w_{x2,t} \cdot X_{2,t} + w_{x3,t} \cdot X_{3,t})\right] \\
&= \arg\max \iiint U(w_{x1,t} \cdot X_{1,t} + w_{x2,t} \cdot X_{2,t} + w_{x3,t} \cdot X_{3,t}) \cdot \hat{c}_t(F_{X1,t}, F_{X2,t}, F_{X3,t}) \\
&\quad \cdot \hat{f}_{X1,t}(x_1) \cdot \hat{f}_{X2,t}(x_2) \cdot \hat{f}_{X3,t}(x_3)\, dx_1\, dx_2\, dx_3
\end{aligned}
$$

where $\hat{c}_t$, $\hat{f}_{X1,t}$, $\hat{f}_{X2,t}$, and $\hat{f}_{X3,t}$ are estimated by daily log returns from the previous 12-1 months.

2.3.2 Strategy Diversified Portfolio

Momentum strategy and value strategy are two of the most applied investing styles. We follow the framework from previous studies and add minor modifications to establish a more suitable trading condition for our asset universe for every trading period *t (t=1:186, 2007/07-2022/12)*.

I. Momentum Measure and Strategy

We follow the methodology proposed by Jegadeesh and Titman (1993) [9] to perform momentum strategy. Our approach involves identifying the ”long target” as the ETF with the highest cumulative return over the past 12-1 months and designating the ”short target” as the ETF with the lowest cumulative return over the same period. Upon meeting predefined trading conditions, we initiate (exit) trades in the market and adjust our portfolio accordingly.

Trading conditions for momentum strategy entail buying the ”long target” if its re-

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turn in month *t-1* is greater than or equal to zero. Conversely, we liquidate our position in the ”short target” if its return in month *t-1* is less than or equal to zero. Ideally, we construct a zero-cost portfolio. If can't, which indicates the ”short target” does not meet its trading condition or there are no positions to short, we invest certain shares in the ”long target” directly.

II. Value Measure and Strategy

For adapting the measure of value, it is not feasible to simply apply Fama and French (1992, 1993) [6] book value of equity to market value of equity, BE/ME, as value measures since the book values of ETFs are challenging to estimate and define. Instead, we follow the value measure methodology proposed by CS Asness (2013) [1] . Value is defined as the negative of the spot returns over the past five years, determined by taking the logarithm of the ratio between the average spot price of the prior five years and the current spot price (5-year reversal).

As shown in Figure 1 (a), the trend of stock price and its 5-year reversal have a positive relationship, showing that using 5-year reversal as an approximation of value measure is reasonable. We consider ETF with low 5-year reversal as ”cheap” target and ETF with high 5-year reversal as ”expensive” target. Similarly, we long cheap target and short expensive target monthly if trading conditions are satisfied.

Trading conditions for value strategy involve buying cheap target if its *month t-1 median* is greater than *month t-3 to t-1 30 percentile* and liquidating the position of expensive target if its *month t-1 median* is less than *month t-3 to t-1 70 percentile*. Similarly, we construct a zero-cost portfolio monthly if possible and invest certain shares in cheap target alternatively if zero-cost portfolio can not performed. These trading conditions are designed to capture the timing of trend reversals.

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III. 50/50 Combo Portfolio

50/50 Combo portfolio is constructed by 0.5× Momentum + 0.5× Value, aiming to provide a strategy diversified portfolio.

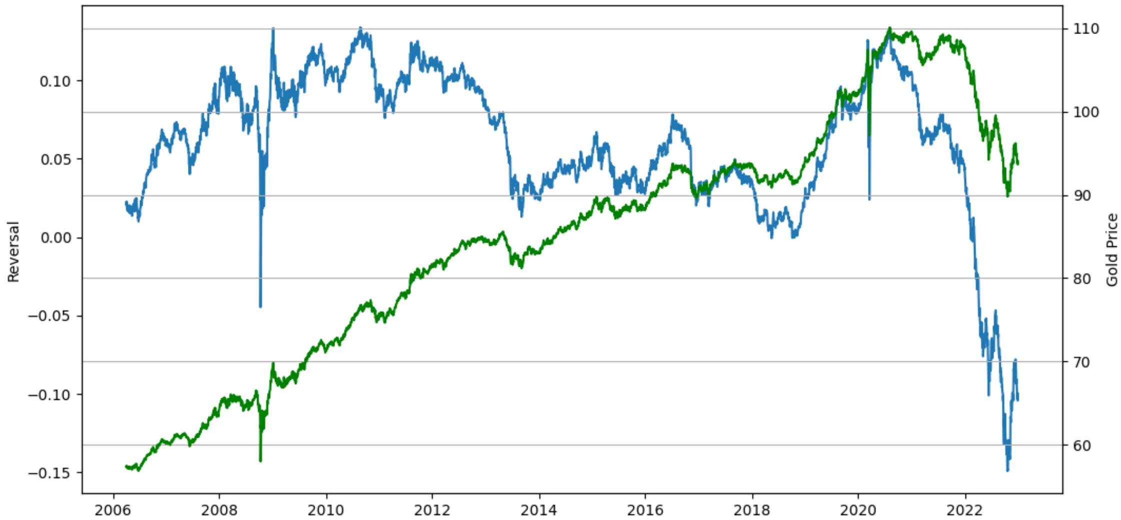

Figure 2.1: 5Y Reversal and Prices. Figure 2.1 (a) displays the positive relationship between 5Y reversal and price trend, indicating using 5Y reversal as value measure is valid.

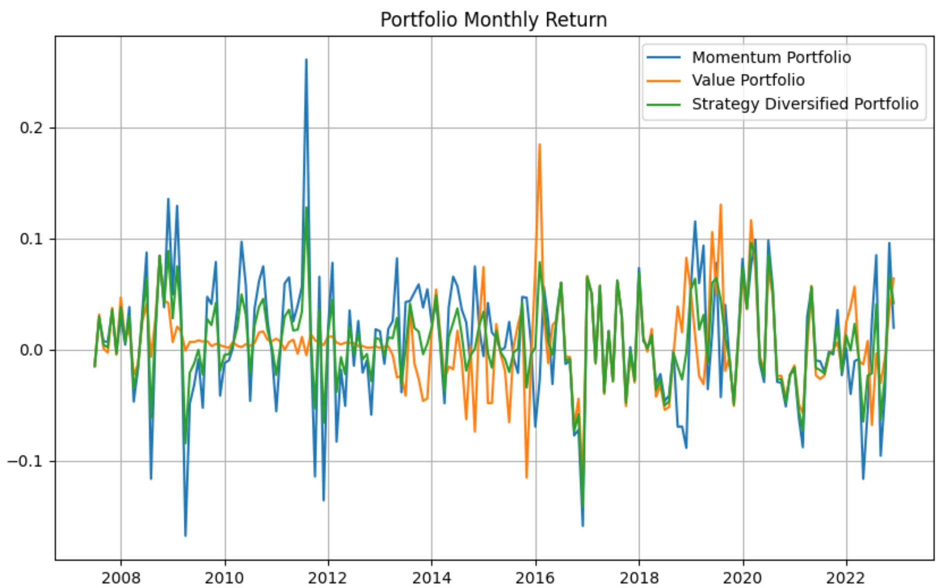

Figure 2.2: Monthly Returns of Strategy Portfolios. Figure 2.2 shows that strategy diversified portfolio (green) inherits excess return and mitigates the loss from both value (orange) and momentum (blue) portfolios, thereby providing better performances.

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Chapter 3

Portfolio Performances

3.1 Performances Comparison of Diversified Portfolios and Benchmark

Table 3.1: Summary statistics of portfolio performances.
Panel A includes SPY, AGG and GLD, from *2007/07 to 2022/12*. Panel B includes SPY, TLT, BIL and GLD, from *2008/07 to 2022/12*. Panel C includes all selected ETFs in section 2-2, from *2007/07 to 2022/12*.

Panel A: Asset risk diversified portfolios with aggregated Bond

Strategy	Mean	Std	Min	Max	Kurtosis	$\frac{\text{Mean}}{\text{Std}}$
Benchmark	0.0060	0.0401	-0.2092	0.1187	7.2761	0.1497
Copula (RRA=1)	0.0087	0.0531	-0.2198	0.1825	2.2313	0.1642
Copula (RRA=2)	0.0101	0.0422	-0.2198	0.1825	5.3584	0.2406
Copula (RRA=3)	0.0106	0.0395	-0.1635	0.1825	3.4447	0.2688
Copula (RRA=5)	0.0113	0.0395	-0.2028	0.1267	5.7717	0.2851

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Table 3.1: Summary statistics of portfolio performances (continued)

Panel B: Asset risk diversified portfolios with long/short term bond

Strategy	Mean	Std	Min	Max	Kurtosis	$\frac{\text{Mean}}{\text{Std}}$
Benchmark	0.0064	0.0418	-0.2092	0.1187	7.7868	0.1541
Copula (RRA=1)	0.0117	0.0599	-0.1326	0.2839	4.9908	0.1958
Copula (RRA=2)	0.0101	0.0585	-0.1326	0.3215	8.9865	0.1725
Copula (RRA=3)	0.0099	0.0467	-0.1326	0.2820	7.8258	0.2117
Copula (RRA=5)	0.0094	0.0437	-0.1326	0.2792	9.1112	0.2140

Panel C: Strategy diversified portfolios

Strategy	Mean	Std	Min	Max	Kurtosis	$\frac{\text{Mean}}{\text{Std}}$
Benchmark	0.0060	0.0401	-0.2092	0.1187	7.2761	0.1497
Momentum	0.0150	0.0663	-0.1960	0.1709	0.3362	0.2258
Value	0.0112	0.0471	-0.1259	0.1789	0.9214	0.2377
Combo 50/50	0.0131	0.0491	-0.1445	0.1405	0.6447	0.2663

We propose the hypothesis that the asset risk diversified portfolio and strategy diversified portfolio have better performances than the benchmark under different macro conditions overall.

As depicted in Table 3.1, the findings suggest that asset-risk diversified portfolios with relative risk aversions (RRA) greater than or equal to 1 exhibit superior performance relative to the benchmark. Specifically, portfolios with higher RRA parameters demonstrate lower volatility and higher returns. These results indicate that investors with higher

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risk aversion preferences may benefit more from asset risk diversification strategies.

The hypothesis test result, provided in Table 3.2, shows that our hypothesis is 10% statistically significant for RRA greater than 1 in the portfolio using aggregated bonds (AGG). As for portfolios including various bond types, though still outperforming the benchmark, the result is not significant. A possible reason might derived from the liquidity risk of ETFs.

Simple momentum portfolio has quite similar results to value strategy portfolios, with a significant level of 1%. Combo 50/50, the strategy diversified portfolio, offsets the downturn and the upturn from both strategies, inheriting excess return and mitigating the loss, as depicted in Figure 2.2. As shown in Table 2 panel C and Table 3, the performance of Combo 50/50 portfolios is statistically significantly superior to the benchmark and simple strategy portfolios.

The result in this section confirms that both asset risk diversified and strategy diversified portfolios yield higher returns with similar risk levels compared to the benchmark, showing that using ETFs as the target of asset allocation is valid. Notably, the strategy diversified approach shows stronger statistical significance and also exhibits lower kurtosis compared to the benchmark, indicating less extreme returns and potentially more robust performance under different risk exposures.

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Table 3.2: t-stat of portfolio performance.
The null hypothesis is $r_p - r_m \leq 0$ and the alternative hypothesis is $r_p - r_m > 0$, where r_p is the return of portfolios and r_m is the return of benchmark.

Portfolio	Aggregate Bond	Long/Short Term Bond	All Selected ETFs
Copula (RRA=1)	0.7818	0.9547	
Copula (RRA=2)	1.2263*	0.6831	
Copula (RRA=3)	1.3481*	0.7141	
Copula (RRA=5)	1.5034*	0.6309	
Momentum			3.0795***
Value			3.2419***
Combo 50/50			3.3314***

3.2 Performances Under Various Macroeconomic Environments

Empirical studies suggest that relative risk aversions (RRA) should be around 1 to 2 for general investors. To provide a more accurate result, we refer Copula (RRA=2) as the asset risk diversified portfolio in the following section. We try to discuss the effectiveness and performances of asset-risk diversified portfolios and strategy diversified portfolio under various macroeconomic risk exposures in the following part.

As illustrated in Figure 3.1, exchange-traded funds (ETFs) with distinct underlying assets exhibit a pronounced preference for specific macroeconomic conditions. For example, GLD, an ETF that tracks gold prices, tends to perform better when real yields are low. Conversely, AGG, which represents aggregated bond indices, shows better performance during periods of low inflation. The disparities in performance between favorable and unfavorable macroeconomic conditions are readily observable, highlighting the significant

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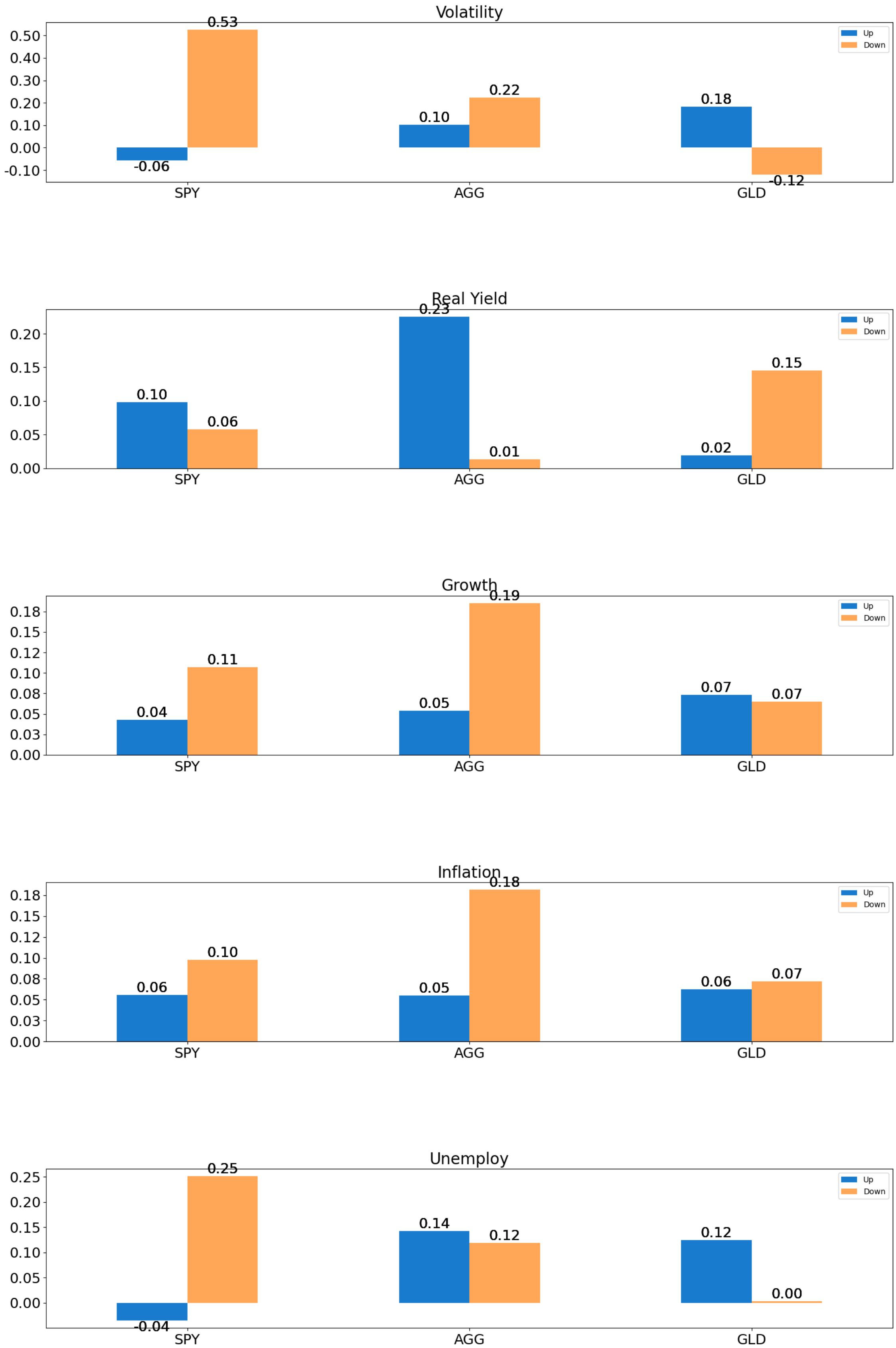

Figure 3.1: ETF Sharpe under various macroeconomic environment

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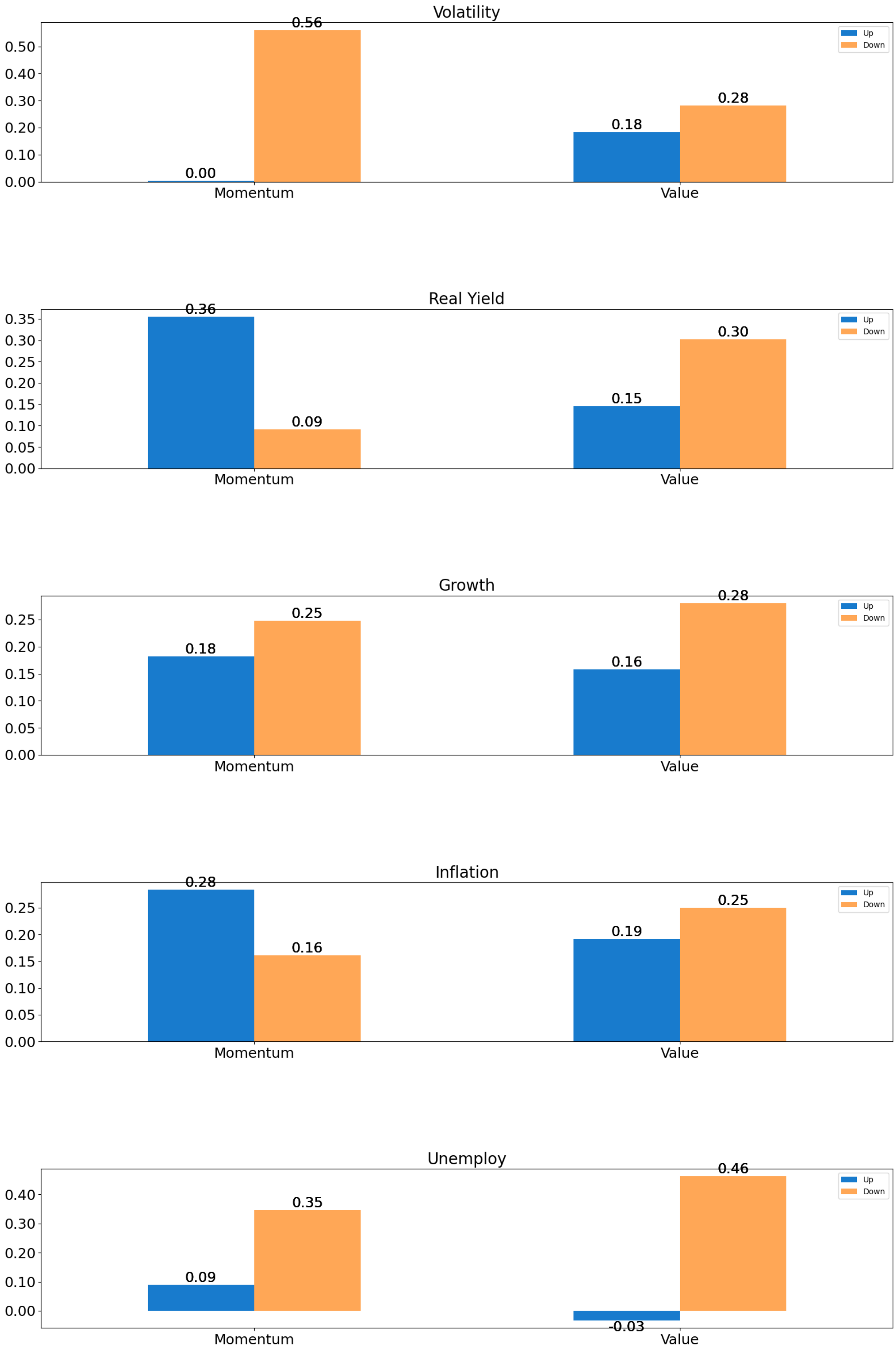

Figure 3.2: Strategy portfolios Sharpe under various macroeconomic environment

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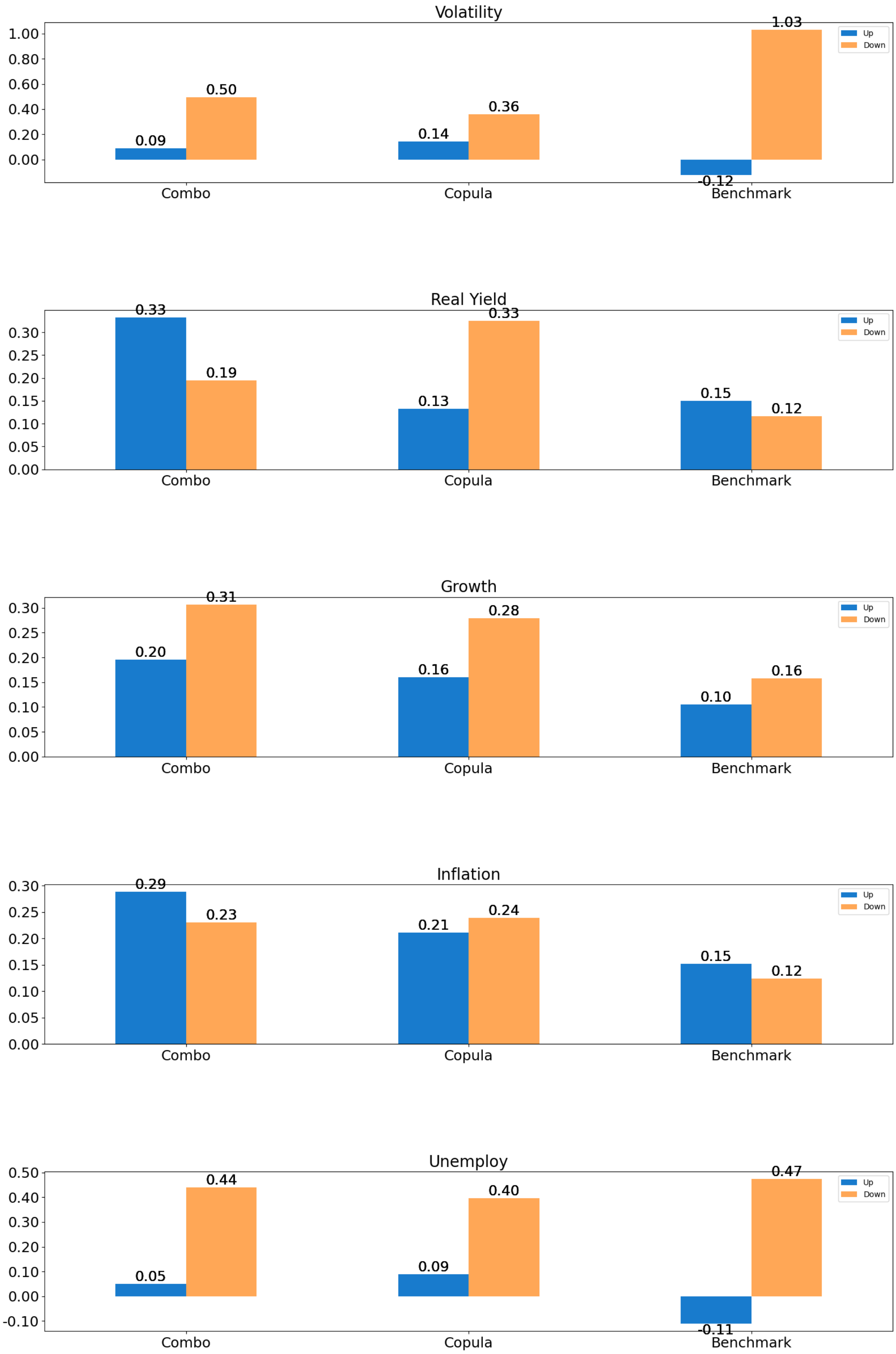

Figure 3.3: Risk diversified portfolios Sharpe under various macroeconomic environment

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impact of economic environments on individual asset behavior.

In the analysis of simple strategy portfolios, the predilection for specific macroeconomic environments is not as distinct as observed in ETFs, as shown in Figure 3.2; nevertheless, there is a noticeable inclination towards periods of high market volatility and high unemployment rates. This tendency can be attributed to the inherent characteristics of VIX as a measure of market sentiment. General investors, who are risk-adverting and seek profits from the mispricing of expected returns, tend to prefer a stable market with trends. Conversely, volatility traders, who exploit mispricing in higher moments, are inclined towards a more volatile and uncertain market environment. Moreover, a higher VIX is usually accompanied by an irrationally pessimistic view of the market, resulting in less trading activity and price deviation in the market.

Regarding the unemployment indicator, recall that we apply the change in the initial claim instead of the US unemployment rate since the former is a leading factor and the latter is a lagging factor. An increase in initial claims generally signals a contraction in market activity, as it suggests that more individuals are losing jobs and, consequently, consumer confidence and spending might diminish. This economic downturn prompts investors to adopt a more conservative behavior, potentially increasing their savings and reducing speculative activities; therefore, impacts the performance of strategy portfolios.

In reviewing risk diversified portfolios, it’s clear that both asset risk diversified and strategy diversified portfolios generally outperform the benchmark across most economic conditions, as shown in Figure 3.3. They show only slightly weaker results during high volatility and high unemployment times. Importantly, both risk diversified portfolios still perform positively during unfavorable environments, even when the benchmark shows a

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negative Sharpe ratio. Between the two, the strategy diversified portfolio tends to slightly outperform the asset-risk diversified portfolio in both positive and negative market conditions.

Overall, the empirical results show the efficacy of both diversification strategies in augmenting portfolio performance, particularly in mitigating risks and stabilizing returns across various macroeconomic uncertainties. These findings suggest that both diversification approaches we proposed can be an effective tool for managing market risks. However, it is important to note that during periods characterized by heightened market fear (High VIX) and high unemployment rates, the risk exposure remains challenging to offset through the use of Exchange-Traded Funds (ETFs).

3.3 Performances Under Economic Cycles

In the following section, we aim to capture the underlying economic activities and evaluate the performance of risk diversified portfolios across different phases of the economic cycle. Unlike Section 3-2, where leading macroeconomic data are applied, we utilize realized data to delineate periods of economic expansion and contraction. The typical duration of an economic cycle spans approximately 6 to 8 years; however, due to data limitations, we are unable to provide a comprehensive analysis adhering to the strict definition of economic cycles. Nevertheless, by examining changes in real GDP growth, we can reasonably categorize our data period into two distinct economic cycles.

During expansion phases, GDP and inflation rates generally exhibit robust growth, while unemployment rates typically reach their lowest levels at the cycle's peak. The periods of expansion identified in the data are from November 2011 to October 2019, which

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is also the longest expansion so far. Conversely, during contraction phases, GDP growth decelerates and inflation remains elevated, accompanied by a rising unemployment rate. Notably, two significant depressions are observed: the economic crisis in 2008 and the COVID-19 pandemic in 2020. As illustrated in Figure 3.4 (a), GDP growth experienced a significant decline during these depression periods. Economic recessions are typically characterized by low inflation and high unemployment rates, posing significant challenges for investors. While entering the recovery phases, GDP growth begins to accelerate, inflation hits the trough and starts to reverse. Market demands drive up the supply side, creating more job opportunities and leading to the decline of the unemployment rate.

As demonstrated in Table 3.3, the strategy diversified portfolio exhibits a substantial outperformance in returns compared to other portfolios during expansion periods, while asset risk diversified portfolio and the S&P 500 demonstrate similar performance levels. This discrepancy could be attributed to an over-optimistic market sentiment during expansion phases, leading to price deviations from fundamental values and resulting in abnormal returns for strategy investing. During contraction periods, though the strategy-diversified approach continues to show effective results relative to the benchmark, the benefits of the asset-risk diversified approach become much more pronounced; it maintains positive performance with a risk level akin to that of the expansion periods, where both the strategy-diversified portfolio and the S&P 500 experience negative Sharpe ratios. In depression periods, both risk-diversified approaches yield defensive outcomes. They incur relatively minor losses (mean=-0.0040, -0.0021) compared to the benchmark S&P 500 (mean=-0.0365). During recovery periods, returns for both risk-diversified portfolios and the benchmark are similar, with the S&P 500 exhibiting a slightly higher Sharpe ratio. This observation is reasonable since equities tend to be more favored than fixed-income

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and gold during the recovery phases.

Both risk-diversified approaches offer substantial diversification benefits during economic downturns while maintaining positive performance in periods of economic upturns. As discussed in Section 3-2, mitigating the risks associated with heightened market volatility and unemployment rates proves to be relatively challenging. Our findings indicate that an asset-risk diversified portfolio delivers superior performance in environments characterized by high market volatility and high unemployment rates, with Sharpe ratios of 0.14 and 0.09, respectively, which is better than strategy diversified portfolio and the benchmark. This outcome underscores its robust risk diversification capabilities across various market conditions and economic phases, corroborating the results presented in this section.

In conclusion, the asset-risk diversified approach exhibits lower sensitivity to macroeconomic conditions, providing stability across different economic scenarios, while the strategy-diversified approach demonstrates the potential for higher returns during flourishing economic phases. This distinction highlights the varying advantages of each approach depending on the prevailing economic environment.

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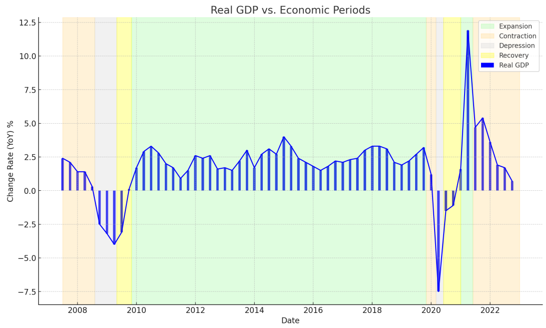
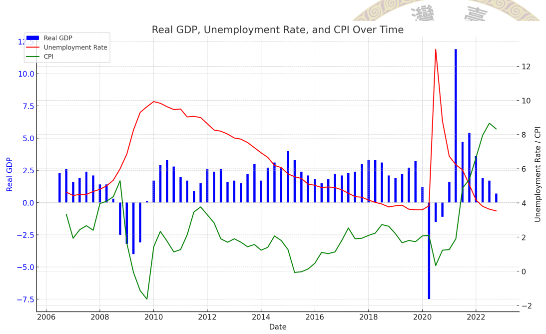
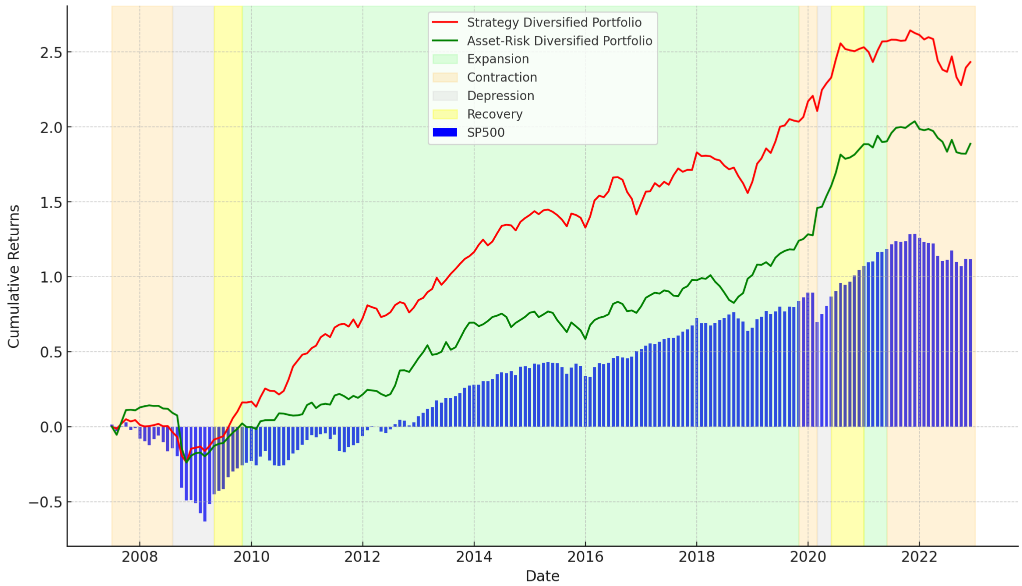


(a) Real GDP vs. Economic Periods



(b) Real GDP, Unemployment Rate (red), and CPI(green)



(c) Cumulative Portfolio Returns vs. Economic Periods

Figure 3.4: Comparison of Different Economic Indicators and Portfolios

expansion:green; contraction:orange; depression:gray; recovery: yellow

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Table 3.3: Portfolio performances across economic cycles.
Combo 50/50 is represented as strategy diversified portfolio and Copula-2 is represented as asset-risk diversified portfolio.

Panel A: Expansion

	Mean	Std	Min	Max	Sharpe	Count
Combo 50/50	0.1593	0.0446	-0.1039	0.1193	0.3474	125
Copula-2	0.0099	0.0343	-0.0674	0.0994	0.2776	125
Benchmark	0.0096	0.0279	-0.1085	0.0639	0.3286	125

Panel B: Contraction

	Mean	Std	Min	Max	Sharpe	Count
Combo 50/50	0.0014	0.0540	-0.1445	0.1171	-0.0001	34
Copula-2	0.0076	0.0390	-0.0826	0.0848	0.1587	34
Benchmark	-0.0027	0.0381	-0.0795	0.0623	-0.1070	34

Panel C: Depression

	Mean	Std	Min	Max	Sharpe	Count
Combo 50/50	-0.0040	0.0755	-0.1253	0.1405	-0.0588	12
Copula-2	-0.0021	0.0956	-0.2198	0.1825	-0.0258	12
Benchmark	-0.0365	0.0978	-0.2092	0.1187	-0.3766	12

Panel D: Recovery

	Mean	Std	Min	Max	Sharpe	Count
Combo 50/50	0.0352	0.0450	-0.3786	0.1192	0.7779	13
Copula-2	0.0358	0.0384	-0.0280	0.1221	0.9294	13
Benchmark	0.0366	0.0246	-0.0115	0.0787	1.4865	13

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3.4 Risk sensitivity

In the last section, we perform regression tests and aim to discuss to what extent can macroeconomic variables affect portfolio returns. Independent variables are returns of the portfolios and dependent variables are macroeconomic factors provided in section 2-1. Instead of forecasting, we focus on the explaining power and sensitivity of macroeconomic factors to the return of different diversification approaches.

As shown in Table 3.4, all models are jointly significant, validating our selection of macroeconomic factors. Except for the constant term, all coefficients display small but statistically significant results across all regressions, suggesting that portfolio returns are influenced by these macroeconomic risk exposures, albeit to a relatively small extent. Among the portfolios, the benchmark, represented by the S&P 500, demonstrates the best fit. It not only has the most statistically significant results but also exhibits the highest adjusted R-squared and the lowest root MSE.

For the risk diversified portfolios, the asset risk diversified approach shows a better fit and more significant results compared to the strategy-diversified approach. Both risk diversified portfolios have lower adjusted R-squared and higher root MSE values compared to the benchmark. These observations suggest that while the risk diversified portfolios proposed in this study are significantly influenced by macroeconomic conditions, the explanatory power of these risk exposures is reduced through diversification. This indicates that the excess returns in the risk-diversified portfolios are relatively less sensitive to macroeconomic conditions compared to the benchmark.

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Table 3.4: Regression Results.
Dependent variables are macroeconomic factors in section 2-1 and the independent variable is the return of the portfolio.

	Strategy Diversified	Asset-risk Diversified	Benchmark
F(5, 180)	8.01	10.31	36.35
Adj R-squared	0.1593	0.201	0.4886
Root MSE	0.0450	0.0377	0.0287
Growth	-0.0045	-0.0035	-0.0054
	(-4.02)	(-3.76)	(-7.55)
Inflation	-0.0026	-0.0017	-0.0008
	(-1.42)	(-1.09)	(-0.72)
Unemployment	-0.00004	0.00022	-0.0001
	(-0.93)	(5.38)	(-3.26)
Volatility	-0.0192	-0.0177	-0.0287
	(-4.34)	(-4.79)	(-10.22)
RealYields	-0.0109	-0.012	-0.0132
	(-2.45)	(-3.22)	(-4.64)
cons	0.4629	0.3609	0.5392
	(4.26)	(3.97)	(7.80)

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Chapter 4

Conclusion and Future Work

We find that using the U.S. Exchange-Traded Funds (ETFs) can effectively diversify systematic risk and that both quantitative approach and strategic approach we proposed are valid. We also observe that risks of market volatility and unemployment are relatively hard to offset via ETFs. Excess returns of strategic approach are more pronounced in expansion periods, and quantitative approach presents more stable performances under different economic phases. In conclusion, strategic approach can benefit investors with possibly higher returns but also valid systematic risk diversification, whereas quantitative approach can provide more robust results and less sensitivity to macroeconomic environments.

Since most of the Exchange-Traded Funds (ETFs) included in this study were initiated between 2000 and 2007, we are unable to provide a long-term analysis or conduct a robust robustness check. Future research could extend the data sample periods back to the 80s by applying market indices. To enhance robustness checks, future studies should consider incorporating transaction costs and the expense ratios of ETFs. Although monetary policy and currency are recognized as essential factors for systematic risk, this study does not include currency and carry trade due to the limited availability and complexity of currency ETFs. Future research could expand the asset universe to include currencies and perform carry trade analyses to further explore their effectiveness.

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