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Topic: Building a Durable All-Weather Portfolio: Insights from Portfolio Optimization Across Macro Regimes

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Building a Durable All-Weather Portfolio: Insights from Portfolio Optimization Across Macro Regimes

This project analyzes over 50 years of monthly return data across 11 assets including US and International Stocks, Bonds, Commodities, and Corporate Credit. We use constrained mean-variance optimization to glean key insights into portfolio construction under different macro regimes. Finally, we build a Custom All-Weather Portfolio that exhibits strong evidence to replace the traditional 60/40 portfolio.

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1. Data Collection

We collected macroeconomic (GDP and CPI, sourced from FRED) and financial asset return data from 1970-2024. Bond returns were calculated using coupon income and the change in yield to approximate price impact. Foreign assets were currency adjusted.

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2. Custom Python Tools

We then built portfolio optimizer and return analyzer python classes to conduct our analysis. These tools leveraged mean-variance optimization and SciPy.minimize to find the optimal weights for an unlevered, long-only portfolio with risk free rate of 0%.

2.1 Key Code Snippets:

```
def negative_sharpe(self, w):
    ret = self.portfolio_return(w)
    vol = np.sqrt(self.portfolio_variance(w))
    sharpe = (ret - self.rfr) / vol
    return -sharpe
```

```python
def optimize_max_sharpe(self):
    initial_weights = np.array([1/self.n] * self.n)
    bounds = [(0,1)] * self.n # Long only
    constraints = {"type" : "eq", "fun" : lambda w: np.sum(w) -1} # No leverage

    result = minimize(self.negative_sharpe, initial_weights, method = 'SLSQP',
                      bounds=bounds, constraints = constraints)
    w_opt = result.x
    ret = self.portfolio_return(w_opt)
    vol = np.sqrt(self.portfolio_variance(w_opt))
    sharpe = (ret - self.rfr) / vol

    return w_opt, ret, vol, sharpe
```

```python
def summarize(self):
    """
    takes the return dataframe and calculates annualized return, risk,
    and sharpe ratios for the assets provided
    """

    results = {} # create a blank matrix to form our summarized table from

    for asset in self.assets:
        monthly_returns = self.returns[asset]
        total_return = (1 + monthly_returns).prod()
        # calculate annualized return
        ann_return = total_return ** (12/self.n_returns) - 1

        # annualized volatility
        ann_vol = monthly_returns.std() * np.sqrt(12)

        # sharpe
        sharpe = ann_return / ann_vol

        results[asset] = {
            "Annualized Return": ann_return,
            "Annualized Volatility": ann_vol,
            "Sharpe": sharpe
        }

    results_df = pd.DataFrame(results).T
    return results_df
```

3. Construct Optimized Portfolios

Using these tools and the return data, we examined how the optimized portfolio was constructed across different time periods with particular focus on the macro regime (i.e. growth vs. inflation) present at that time and the asset data availability to construct portfolios from.

3Optimal Portfolios Returns and Weights Over Time and Across Assets

5 Asset Optimized Portfolios

- **Period:** 1971-2024
- **Assets:** Gold, S&P 500, NIKKEI, UST 10Y, UK 10Y

Time Period	Ann. Return	Ann. Risk	Sharpe Ratio	Gold	SP500	Nikkei	UST 10Y	UK 10Y
1971-1980	14.5%	9.2%	1.58	24%	-	24%	44%	9%
1981-1990	12.9%	8.9%	1.45	-	14%	7%	70%	9%
1991-2000	11.4%	5.7%	2.02	-	42%	-	53%	5%
2001-2010	11.9%	8.5%	1.40	54%	4%	-	40%	2%
2011-2020	7.0%	4.3%	1.61	-	37%	1%	58%	4%

Note: Additional analyses were conducted, please see full code in Jupiter Notebook on my GitHub.

Observations: Heavy Bond exposure (42% - 80%); Gold exposure rose during poor periods of stock returns (1971-1980 and 2001-2010); Consistent, albeit low equity exposure (4%-38%)

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9 Asset Optimized Portfolios

- **Period:** 1990-2024
- **Additional Assets:** Oil, Copper, FTSE, JP 10Y

Time Period	Ann. Return	Ann. Risk	Sharpe Ratio	Gold	Oil	Copper	SP500	Nikkei	FTSE	UST 10Y	UK 10Y	JP 10Y
1990-1996	9.6%	4.8%	1.99	4%	9%	-	45%	-	-	27%	11%	4%
1997-2003	7.6%	5.9%	1.29	-	2%	-	19%	-	-	55%	24%	-
2004-2010	12.1%	8.0%	1.50	40%	2%	7%	3%	1%	-	48%	-	-
2011-2017	7.3%	4.2%	1.74	-	-	-	49%	-	-	48%	3%	-
2018-2024	11.6%	9.0%	1.29	60%	-	-	40%	-	-	-	-	-

Note: Additional analyses were conducted, please see full code in Jupiter Notebook on my GitHub.

Observations: Gold dominates other commodities as a hedge; NIKKEI/FTSE not viable; bonds wrecked in 2022 bear market.

11 Asset Optimized Portfolios

- **Period:** 1997-2024
- **Additional Assets:** US IG Bonds, US HY Bonds

Time Period	Ann. Return	Ann. Risk	Sharpe Ratio	Gold	Oil	Copper	SP500	Nikkei	FTSE	UST 10Y	UK 10Y	JP 10Y	US IG	US HY
1997-2003	10.1%	4.7%	2.17	-	1%	-	-	-	-	-	9%	-	59%	30%
2004-2010	11.5%	7.2%	1.60	34%	1%	3%	-	-	-	42%	-	-	-	20%
2011-2017	7.3%	4.2%	1.75	-	-	-	44%	-	-	46%	-	-	2%	8%
2018-2024	11.6%	9.0%	1.29	60%	-	-	40%	-	-	-	-	-	-	-

Note: Additional analyses were conducted, please see full code in Jupiter Notebook on my GitHub.

Observations: Corporate Credit the best performing asset in 1997-2003 (89% exposure) and all but removes the need to allocate to UK 10Y for diversification purposes of the fixed income part of the portfolio.

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4. Analyze Results and Draw Conclusions

We examined these optimized portfolios against the classic "60/40" Portfolio of 60% Stocks (S&P 500) and 40% Bonds (US 10Y Treasuries) to draw insights.

- **Gold as Hedge:** We found that during periods of market stress including: financial crises, bouts of inflation and recessions, that the optimized portfolio included large allocations to Gold. It stands to reason that an All-Weather Portfolio should have a sizeable allocation to this stable asset for its hedging properties.
- **More Allocation to Fixed Income:** We also discovered that when optimizing for risk-adjusted returns (Sharpe ratio), that portfolios consistently increased their exposure to Bonds above the 40% seen in the 60/40 even in periods of low volatility. This provides evidence that the fixed income side of a durable portfolio should be greater than 40%.
- **International Assets as Substandard:** Furthermore, we observed that except for a few periods, the optimized portfolios shunned international assets like the NIKKEI, FTSE, UK and JPY Bonds adjusted for currency performance to USD.
- **Corporate Credit as Alpha:** Finally, we unlocked additional risk-adjusted returns by adding in Corporate Credit (IG and HY) due to their unique asset correlations and high-quality return profile when compared with equities and/or Treasuries especially as we look at "through-the-cycle" returns like in 1997-2003 and 2004-2010.
- **Bond Bull Market is Dead:** It is worth noting that bonds generated significant negative returns in 2022 as the 20+ year run of declining interest rates ended. It remains to be seen if bonds will provide strong returns with a looming fiscal crisis brewing in the US.

- **Beware of Overfitting:** We see as we increase the number of assets and/or shorten the time frame, our optimal portfolios begin to exhibit "curve-fitting" behavior. With any quantitative analysis that relies upon optimization, we should be wary of these results and rely upon simple, interpretable results instead of solely accepting "black-box" results.

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5. Build Custom All-Weather Portfolio

Using these insights, we designed a Custom Portfolio with the following weights:

Gold	S&P 500	US 10Y Bonds	IG Bonds	HY Bonds
20%	35%	30%	10%	5%

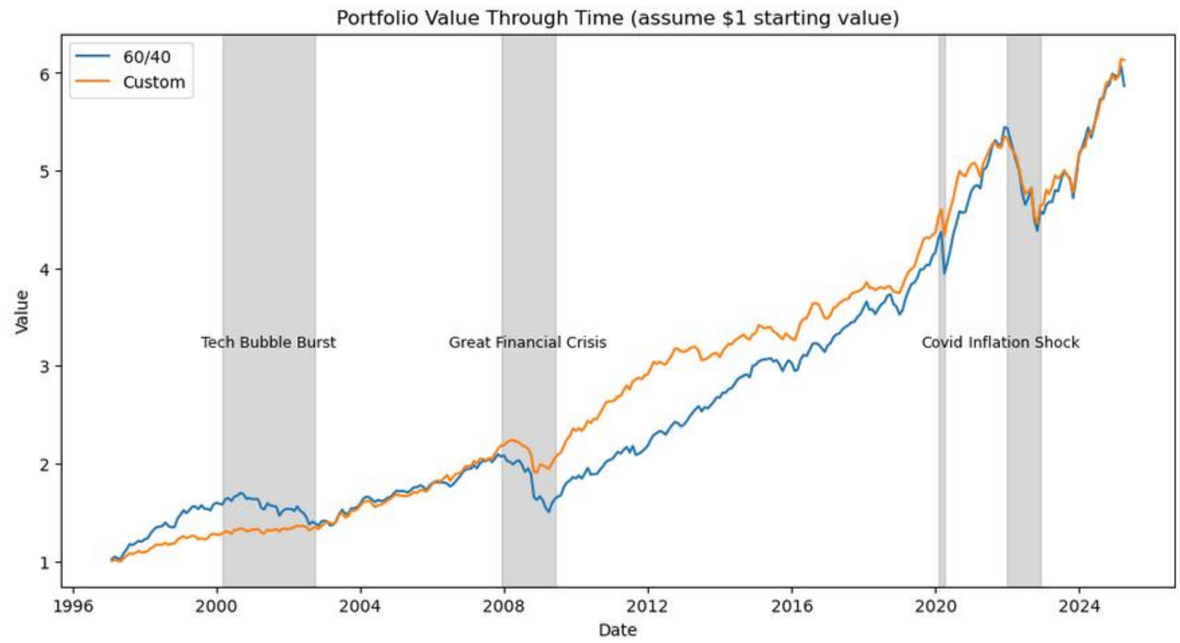
We designed the portfolio to provide 60/40 like returns in "good" times, while hoping to provide more downside protection in "bad" times. We harnessed the power of diversification by focusing on assets with solid risk and return metrics and varying correlation statistics through time.

We then analyzed our Custom Portfolio's performance against the 60/40. We found the performance to be much better across our available data range (1997-2024, inclusive of IG and HY bond asset data).

	Annualized Return	Annualized Volatility	Sharpe	Max Drawdown
60/40	6.46%	7.63%	0.85	-28.2%
Custom	6.63%	5.65%	1.17	-16.7%

A breakdown of the Custom Portfolio vs the 60/40 by time period helps us to better understand how we achieved these results, what the key strengths of the portfolio are, and what potential pitfalls investing in it may entail (key outperformance highlighted)

Time Period	60/40 Return	60/40 Risk	60/40 Sharpe	Custom Return	Custom Risk	Custom Sharpe
1997-2000	12.82%	7.65%	1.68	7.51%	5.20%	1.44
2001-2004	0.95%	8.37%	0.11	5.58%	6.15%	0.91
2005-2008	-0.99%	8.48%	-0.12	3.20%	7.30%	0.44
2009-2012	9.19%	7.48%	1.23	12.18%	5.16%	2.36
2013-2016	7.50%	4.85%	1.55	3.18%	4.13%	0.74
2017-2020	10.20%	7.33%	1.39	9.87%	5.89%	1.68
2021-2024	5.81%	8.33%	0.70	4.91%	7.07%	0.69



Period	Sharpe vs 60/40	Analysis
1997-2000	-0.24	Equity boom favored 60/40's higher beta
2001-2004	+0.80	Dot-com bust: gold & bonds prove effective hedge
2005-2008	+0.56	Great Financial Crisis: diversification cushions losses
2009-2012	+1.13	Recovery: IG and HY Credit provide major alpha source
2013-2016	-0.81	Calm mid-cycle: gold lags
2017-2020	+0.29	Late-cycle & COVID shock: gold helps
2021-2024	-0.01	Bond bear market: both portfolios struggle

6. Statistically Validate Results

Finally, we statistically validated our Sharpe Outperformance results through bootstrapping a confidence interval. This technique was adapted from Ledoit & Wolf (2008).[1]

We bootstrap the monthly return series (100k samples, with replacement) to form the distribution of Sharpe differences between the custom mix and 60/40. We report the 95% confidence interval and a one-sided p-value; the observed edge is statistically significant (~99%+), suggesting the risk-adjusted improvement is unlikely to be due to chance.

[1] http://www.ledoit.net/jef_2008pdf.pdf

```
# simulation assumptions
m = 100_000 # number of simulations
n = len(monthly_returns) # number of samples to pull
alpha = 5 # For 95% Confidence Interval

# create a numpy array where we sample randomly from the indices available
idx = np.random.randint(0, n, size=(m,n))

# convert out observed values into numpy arrays for vectorized functionality
dist_custom = monthly_returns["Custom"].to_numpy(dtype=float)
dist_60_40 = monthly_returns["60/40"].to_numpy(dtype=float)

# pull samples
samples_custom = dist_custom[idx]
samples_60_40 = dist_60_40[idx]

# pull mean, risk and calculate sharpes
means_custom = samples_custom.mean(axis=1)
means_60_40 = samples_60_40.mean(axis=1)
vol_custom = samples_custom.std(axis=1, ddof=1)
vol_60_40 = samples_60_40.std(axis=1, ddof=1)

sharpes_custom = np.sqrt(12) * (means_custom / vol_custom)
sharpes_60_40 = np.sqrt(12) * (means_60_40 / vol_60_40)

diff = sharpes_custom - sharpes_60_40

ci_low, ci_hi = np.percentile(diff, [alpha/2, 100 - (alpha/2)])
p_one_sided = (diff <= 0).mean()
```

```
ci_low, ci_hi
```

```
(0.06962659614562675, 0.5438168883291347)
```

```
p_one_sided
```

```
0.00621
```

7. Conclusion and Next Steps

These results provide strong evidence for the Custom All-Weather Portfolio to replace a traditional 60/40 Portfolio for investors, especially those interested in reducing volatility and building durable portfolios build to withstand periods of financial market distress.

Next Steps:

- Explore additional asset classes (emerging markets equities/bonds, REITs, TIPs, Bitcoin, etc.) to see if they further improve the all-weather characteristics.
- Develop a real-time tactical model (perhaps using signals like valuation or trend) in conjunction with machine learning algorithms to approximate and predict the optimal portfolio in the future period to deliver superior regime-aware returns without the benefit of hindsight.

8. Appendix

8.1 Macroeconomic Data Summaries

Time Period	Average Annual Real GDP Growth	Average CPI Growth
1971-1980	3.6%	7.2%
1981-1990	3.5%	4.7%
1991-2000	3.4%	2.7%
2001-2010	1.7%	2.5%
2011-2020	2.4%	1.8%

Time Period	Average Annual Real GDP Growth	Average CPI Growth
1990-1996	2.5%	3.5%
1997-2003	3.4%	2.3%
2004-2010	1.6%	2.6%
2011-2017	2.2%	1.6%
2018-2024	2.5%	3.7%

Time Period	Average Annual Real GDP Growth	Average CPI Growth
1997-2000	4.6%	2.0%
2001-2004	1.8%	2.2%
2005-2008	2.8%	3.2%
2009-2012	0.6%	1.5%
2013-2016	2.5%	1.1%
2017-2020	2.7%	2.1%
2021-2024	3.8%	5.6%

8.2 Select Asset Return Data

1971-2020; 5 Assets

Time Frame	1971-1980	1981-1990	1991-2000	2001-2010	2011-2020
Gold_ann_return	31.4%	-3.5%	-3.2%	17.7%	2.9%
SP500_ann_return	3.9%	9.4%	15.0%	-0.7%	11.5%
Nikkei_ann_return	18.9%	15.2%	-5.1%	-0.1%	8.3%
UST 10Y_ann_return	4.1%	13.6%	8.8%	5.6%	4.3%
UK 10Y_ann_return	8.8%	11.0%	9.3%	6.2%	3.5%
Gold_ann_risk	27.7%	16.6%	10.0%	13.7%	11.8%
SP500_ann_risk	13.1%	12.9%	10.1%	14.9%	11.3%
Nikkei_ann_risk	18.6%	24.1%	25.2%	19.1%	14.4%
UST 10Y_ann_risk	8.1%	10.2%	6.7%	8.5%	6.3%
UK 10Y_ann_risk	15.9%	16.7%	11.1%	9.2%	8.5%
Gold_ann_sharpe	1.13	-0.21	-0.32	1.29	0.25
SP500_ann_sharpe	0.30	0.73	1.48	-0.05	1.02
Nikkei_ann_sharpe	1.01	0.63	-0.20	-0.01	0.58
UST 10Y_ann_sharpe	0.50	1.34	1.31	0.66	0.68
UK 10Y_ann_sharpe	0.55	0.66	0.84	0.67	0.42

1990-2024; 9 Assets

Time Frame	1990-1996	1997-2003	2004-2010	2011-2017	2018-2024
Gold_ann_return	-1.5%	1.4%	19.2%	-1.3%	11.1%
Oil_ann_return	2.6%	3.5%	15.7%	-6.0%	2.8%
Copper_ann_return	-0.6%	-0.4%	22.6%	-4.1%	3.9%
SP500_ann_return	11.4%	5.5%	2.0%	11.5%	12.3%
Nikkei_ann_return	-7.7%	-8.6%	3.0%	7.6%	2.8%
FTSE_ann_return	9.1%	2.2%	1.8%	1.7%	-0.6%
UST 10Y_ann_return	8.8%	7.8%	5.1%	3.3%	-0.1%
UK 10Y_ann_return	13.3%	9.1%	4.1%	3.1%	-3.2%
JP 10Y_ann_return	10.6%	2.9%	4.2%	-3.2%	-6.7%
Gold_ann_risk	8.6%	12.3%	14.9%	12.3%	10.5%
Oil_ann_risk	29.6%	28.3%	32.1%	28.1%	45.9%
Copper_ann_risk	19.3%	15.1%	31.3%	15.3%	16.3%
SP500_ann_risk	8.9%	14.5%	14.5%	8.9%	13.2%
Nikkei_ann_risk	28.8%	24.1%	18.1%	13.1%	17.1%
FTSE_ann_risk	16.0%	15.1%	18.8%	14.3%	17.2%
UST 10Y_ann_risk	7.0%	7.6%	8.3%	6.3%	7.9%
UK 10Y_ann_risk	12.5%	9.5%	9.3%	8.4%	11.5%
JP 10Y_ann_risk	13.4%	12.6%	11.7%	10.3%	10.2%
Gold_ann_sharpe	-0.17	0.11	1.28	-0.11	1.06
Oil_ann_sharpe	0.09	0.12	0.49	-0.21	0.06
Copper_ann_sharpe	-0.03	-0.03	0.72	-0.27	0.24
SP500_ann_sharpe	1.28	0.38	0.14	1.29	0.93

Nikkei_ann_sharpe	-0.27	-0.36	0.16	0.58	0.16
FTSE_ann_sharpe	0.57	0.15	0.09	0.12	-0.03
UST 10Y_ann_sharpe	1.27	1.03	0.62	0.53	-0.02
UK 10Y_ann_sharpe	1.07	0.95	0.44	0.37	-0.28
JP 10Y_ann_sharpe	0.79	0.23	0.36	-0.31	-0.66

1997-2024; 11 Assets

Time Frame	1997-2000	2001-2004	2005-2008	2009-2012	2013-2016	2017-2020	2021-2024
Gold_ann_return	-7.4%	13.0%	16.6%	19.9%	-9.0%	12.6%	9.3%
Oil_ann_return	3.0%	11.0%	-1.2%	20.9%	-12.3%	-2.5%	10.5%
Copper_ann_return	-4.9%	14.1%	-0.3%	26.6%	-8.2%	8.2%	3.5%
SP500_ann_return	15.7%	-2.6%	-7.5%	12.8%	12.1%	13.2%	12.9%
Nikkei_ann_return	-9.9%	-2.7%	-2.8%	5.2%	8.3%	13.0%	-2.2%
FTSE_ann_return	7.6%	0.1%	-8.6%	9.7%	-2.0%	-0.2%	3.4%
UST 10Y_ann_return	8.5%	6.2%	8.8%	3.7%	0.6%	5.6%	-4.9%
UK 10Y_ann_return	7.5%	12.4%	-0.1%	10.2%	-3.8%	6.4%	-8.6%
JP 10Y_ann_return	2.4%	3.7%	4.2%	2.1%	-6.3%	2.9%	-13.2%
US IG_ann_return	6.9%	9.5%	1.4%	12.4%	2.2%	5.9%	-1.3%
US HY_ann_return	5.0%	21.5%	-5.2%	27.2%	6.8%	8.9%	2.4%
Gold_ann_risk	12.9%	10.1%	17.3%	13.2%	12.0%	9.6%	10.8%
Oil_ann_risk	29.9%	26.8%	34.3%	26.9%	32.3%	55.5%	26.8%
Copper_ann_risk	16.5%	15.3%	35.9%	22.2%	15.2%	14.9%	16.6%
SP500_ann_risk	12.8%	14.6%	14.6%	13.7%	8.4%	13.7%	11.1%
Nikkei_ann_risk	26.0%	20.7%	16.5%	18.2%	13.1%	15.4%	17.0%
FTSE_ann_risk	13.9%	15.3%	17.3%	20.8%	13.9%	17.9%	14.8%
UST 10Y_ann_risk	6.5%	8.5%	7.8%	8.4%	6.5%	5.9%	8.7%
UK 10Y_ann_risk	10.0%	8.9%	8.6%	8.8%	9.4%	8.2%	13.2%
JP 10Y_ann_risk	14.7%	9.5%	10.6%	11.9%	11.8%	5.9%	12.1%
US IG_ann_risk	4.0%	5.7%	6.5%	4.9%	3.5%	5.8%	6.8%
US HY_ann_risk	6.0%	9.0%	13.6%	12.8%	7.9%	12.1%	10.7%
Gold_ann_sharpe	-0.57	1.29	0.96	1.51	-0.75	1.30	0.86
Oil_ann_sharpe	0.10	0.41	-0.03	0.78	-0.38	-0.04	0.39
Copper_ann_sharpe	-0.30	0.92	-0.01	1.20	-0.54	0.55	0.21
SP500_ann_sharpe	1.22	-0.18	-0.51	0.93	1.44	0.97	1.16
Nikkei_ann_sharpe	-0.38	-0.13	-0.17	0.28	0.64	0.84	-0.13
FTSE_ann_sharpe	0.55	0.00	-0.50	0.47	-0.14	-0.01	0.23
UST 10Y_ann_sharpe	1.32	0.73	1.12	0.45	0.09	0.96	-0.56
UK 10Y_ann_sharpe	0.75	1.40	-0.01	1.16	-0.40	0.79	-0.65
JP 10Y_ann_sharpe	0.16	0.39	0.40	0.18	-0.53	0.49	-1.09
US IG_ann_sharpe	1.75	1.67	0.21	2.53	0.62	1.02	-0.18
US HY_ann_sharpe	0.82	2.38	-0.38	2.12	0.86	0.73	0.23

8.3 Correlation Analyses