College of Management of Technology

Investments, FIN-405

Portfolio Construction

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1 Introduction

2 The Data

Monthly stock returns from January 1, 1964, to December 31, 2023, for all common stocks traded on the NYSE and AMEX, the *equal-weighted* CRSP market return and 1-month T-bill returns as a risk-free rate were downloaded and then merged in a single CSV file.

3 Betting against Beta strategy (BaB)

(a) In order to compute time-varying market $\beta_{t,n}$, we built rolling covariance matrix between excess stock returns and excess market returns and then divided the estimated covariance by the market variance. See **python file.py**.

(b) We can see the results in **Figure** 1, and 2. The evidence is not consistent with the CAPM, since according to this theory σ_P is the relevant measure of risk for efficiently diversified portfolios and only systematic (non-diversifiable) risk will be rewarded in equilibrium by higher average returns. For both portfolios sorts, the standard deviation is increasing with higher deciles for both portfolios as expected, but on the other hand, higher beta portfolios don't offer a risk-adjusted return that compensates for their higher risk, which is reflected in lower SR for higher beta deciles for both portfolios and deviates from CAPM. This means that for stocks, there is another factor rather than the market risk that affects the expected returns. Higher beta stocks have higher demand because investors want more exposure to risk. This reduces their expected return and therefor overall lower beta stocks have higher sharpe ratios. This is against the CAPM which states that the market is the only source of risk which assets are compensated for.

(c) See **python file.py**.

(d) The required statistics are reported in **Table 1**. As we can see, there is a highly statistically significant alpha which means that this factor is important in explaining the expected returns which is consistent with our previous findings.

4 Momentum Strategy (MoM)

(a) The results can be seen in **Figure** 3 and 4. Both portfolio sorts show returns increasing within higher deciles, but standard deviation moves following a convex pattern which is not consistent with CAPM, yielding to Sharpe Ratio increasing almost linearly. This return-variance trade-off leads to better risk-adjusted returns for both portfolios in higher deciles portfolios and is not consistent with CAPM. To sum up, the increasing sharpe ratio trend with higher deciles shows that the momentum factor affects the expected return. Stock with previous high returns, continue to give higher returns. Again this is against the CAPM which states that the market is the only source of risk.

(b) All the metrics and test-statistics are summarized in **Table 2** and **3**. We see that in both cases the average return is statistically significant which is consistent with our previous findings. For both type of portfolio sorting, long strategy was the best on all metrics and momentum strategy was the worst on all metrics. Portfolios' average return of the momentum strategy is statistically significantly different from zero for both portfolio sorts for all main confidence intervals especially for *equal-weighted* (p-value = 0.0042).

5 Idiosyncratic Volatility Strategy (IV)

(a) We built rolling covariance matrix between excess stock returns and excess market returns as in 3 (a) and then obtained time varying idiosyncratic volatility for each stock as (see **python file.py**):

$$\sigma_{t,n}^{idio} = \sqrt{\sigma_{t,n}^{2(tot)} - \sigma_{t,n}^{2(syst)}} = \sqrt{\sigma_{t,n}^{2(tot)} - \beta_{t,n}^2 \sigma_{t,n}^{2(mkt)}} \tag{1}$$

(b) The results are shown in **Figure** 5 and 6. The evidence is not consistent with the CAPM for both portfolios. The reason is the same as the previous parts. If the CAPM had held, there should be no pattern in the Sharpe ratio of different portfolios made based on idiosyncratic volatility. But here we see assets with lower idiosyncratic volatility have higher Sharpe ratios. This is evidence that stocks get compensated for having low individual risk.

(c) All the metrics and test-statistics are summarized in **Table 4** and **5**. This time we observe that the t-stat of average returns is not significant. This might mean that although we have a pattern on the Sharpe ratios, it is not strong enough to affect assets expected returns.

Comparing our results for *equal-weighted* portfolio with the one of Ang, Hodrick, Xing, and Zhang (2006; **Table** VI page 285)[1], we observe that we both have negative average returns, for a strategy which goes long the high decile portfolios and short the low decile portfolios. However, our return is a very small negative return theirs is very big (around 10 times bigger in magnitude). In addition, our return is not statistically significant while it is significant in their case. This means that in our case, the IV factor doesn't seem to be significantly important in contrast to their results. These main differences could come from the data sample analyzed since their dataset spans from July 1963 to December 2000 instead ours is expanding it until the end of 2023.
Financial markets have evolved significantly between the periods 1963-2000 and 2000-2023. New regulations, technological advancements, changes in market participants, and global economic events could impact the behavior of stock returns and volatilities.
Market volatility and investor behavior have changed over time. The period from 2000-2023 includes significant events such as the dot-com bubble burst, the 2008 financial crisis, and the COVID-19 pandemic, which could have different impacts compared to earlier periods. Ang et al. (2006) also used daily data to calculate volatility, whereas your analysis uses monthly data. Daily data provides a finer resolution, capturing more short-term fluctuations, which can lead to different volatility estimates.
The method for estimating idiosyncratic volatility (e.g., rolling window size, winsorization thresholds) can significantly affect the results. Even small methodological differences can lead to different outcomes.
Ang et al. (2006) used idiosyncratic volatility relative to the Fama-French three-factor model. Our analysis was based on a different model (e.g., CAPM), the residuals and hence the volatility estimates will differ.

6 Optimal Fund Portfolio Return (STRAT)

The results for the three strategies can be seen in **Table** 6. We observe that equally weighted and risk parity portfolios give high Sharpe ratios while MVE portfolio do not.

7 Performance and risk analysis for the Fund strategy

(a) The results of the regression can be seen in **Table** 7. As we can see, the R-squared is approximately 50%, which indicates that these factors explain the strategy. Also, we see that in the Fama-French factors, the *market factor*, the *SMB*, and *CMA* are statistically significant. In the Industries, we have that *Durables*, *Energy*, *Chemistry*, *Telecommunication*, *Utilities*, and *Money* are significant. The α is very small and not significant, which means that the regression explains the returns of the strategy.

(b) In **Figure** 8, we plot the weights for the three industries that are the most relevant drivers of the risk: *Utilities*, *Durables*, and *Money*, since they had the highest t-stat in the regression computed in the previous part. Also, in **Figure** 7, we plot the beta (exposure to market) of the strategy.

(c) In **Table** 10, we see the statistics for the industry hedged portfolio. We see that compared to the unhedged strategy, the mean return and volatility drop. This means that the industry factors explain a lot of risk and return of the strategy.

8 Industry neutral strategy

(a) For this part, we repeat the procedure done in part 3, 4, 5 and 6. At every step where we grouped by *Date* we also group by the *Industry* in order to compute strategy portfolios for each date-industry pair. **Table** 9 indicates the mean, the standard error, the Sharp Ratio and t-statistics of 12 industry separated strategies. Based on the t-statistics we see that most of the strategies are statistically significant for a 5% significance level. The industry that has the highest strategy Sharp Ratio of 0.499716 is Business Equipment. It is also the industry yielding the highest average return and it is exposed to the second lowest volatility.

(b) Computed Industry-Neutral Portfolio yields a much higher mean annualized return, 0.080123 compared to the 0.0051. However, the standard deviation is also higher but the increase in the the mean return offsets the increase in volatility which results in higher Sharp Ratio. This is because when we build the optimal strategy for each of

[1] Panel B: Portfolios Sorted by Idiosyncratic Volatility Relative to FF-3

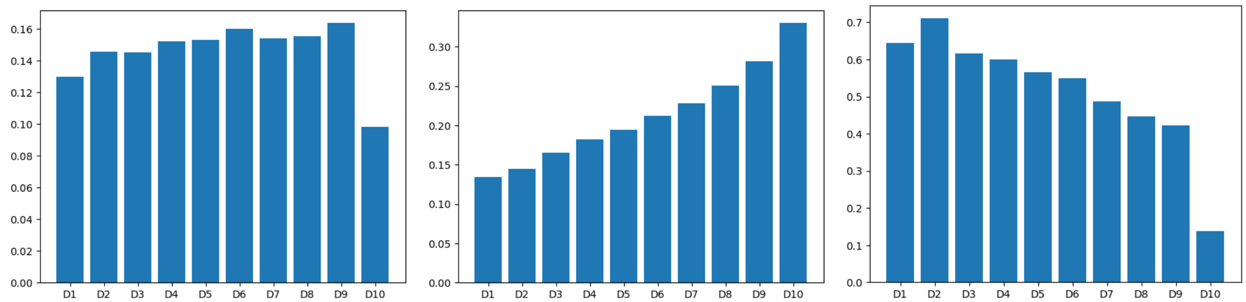
the industries and aggregate these it performs better than a strategy using the aggregated BAB, MOM, and IV strategies.

(c) We see the results of the regression in **Table** 10. Compared to the previous regression, we get a higher R-squared by 0.15. We also get a higher and more significant alpha which indicates that these strategy gives better yield than the previous hedged strategy.

Significant beta coefficients were found for several factors, including Mkt-RF, SMB, and CMA, highlighting their influence on the portfolio returns. R-squared value of 0.489, indicating that 48.9% of the variance in returns is explained by these factors.

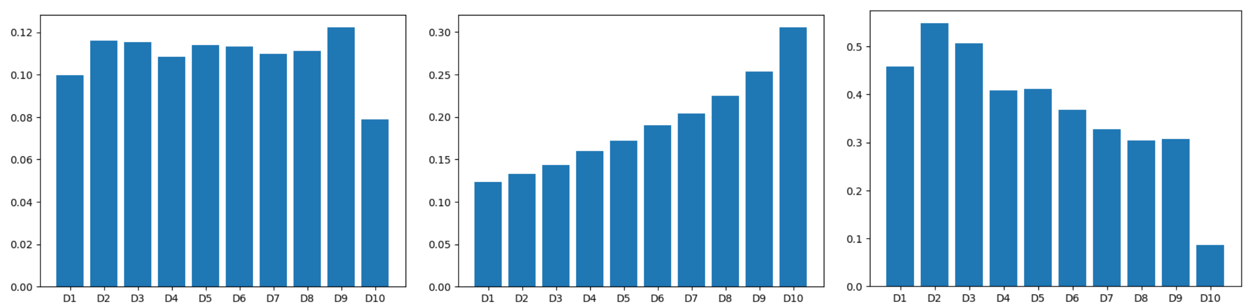
(d) We see the strategy that we just built has positive significant alpha. Hence, It is not consistent with the CAPM because we are regressing on the market portfolio and other factors but we still get significant alpha. If we assume that the factors that we include are all the factors that explain the risk of the asset returns, then this is also not consistent with the APT because since all the factors are tradable, the alpha should not be statistically significant.

9 Figures and Tables



(a) Mean Return (b) Standard Deviation (c) Sharpe Ratio

Figure 1: **BAB Annualized Metrics for Equal-weighted Portfolio Deciles**

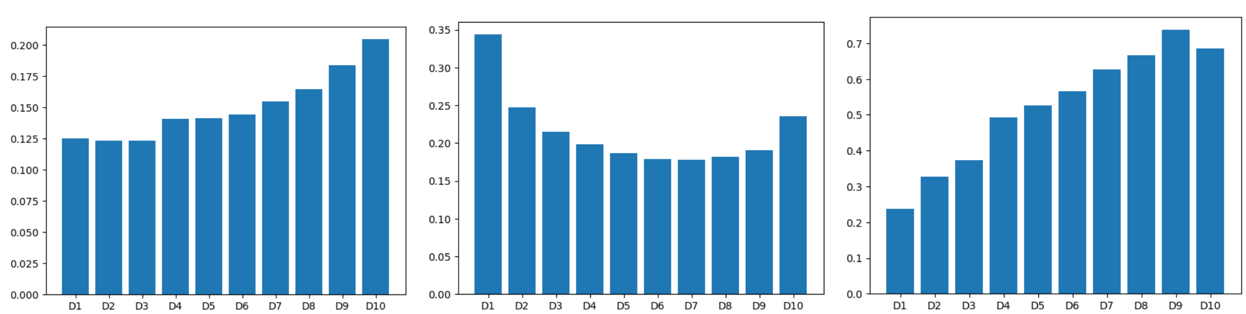


(a) Mean Return (b) Standard Deviation (c) Sharpe Ratio

Figure 2: **BAB Annualized Metrics for Value-Weighted Portfolio Deciles**

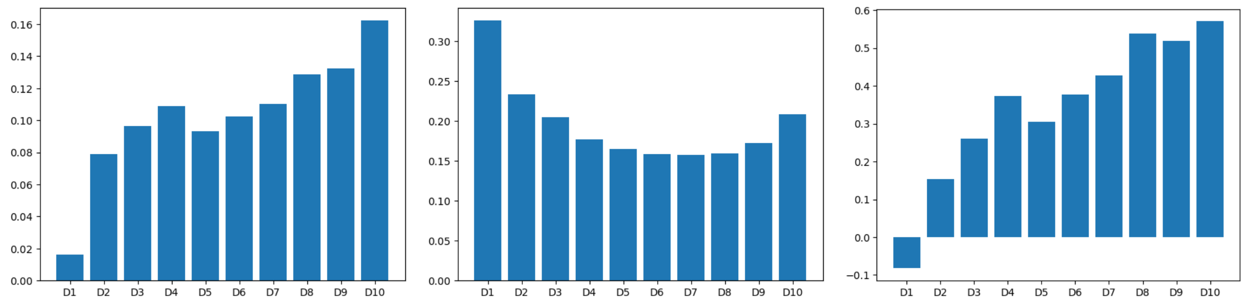
Metric	**Value**	**t-stat**
Annualized Mean Return of BaB factor	0.1147	-
Annualized Standard Deviation of BaB factor	0.1403	-
Sharpe Ratio of BaB factor	0.8175	-
Annualized Alpha of BaB factor	0.0806	5.2635

Table 1: **Summary Statistics of BaB Factor**



(a) Mean Return (b) Standard Deviation (c) Sharpe Ratio

Figure 3: **MOM Annualized Metrics for Equal-Weighted Portfolio Deciles**



(a) Mean Return (b) Standard Deviation (c) Sharpe Ratio

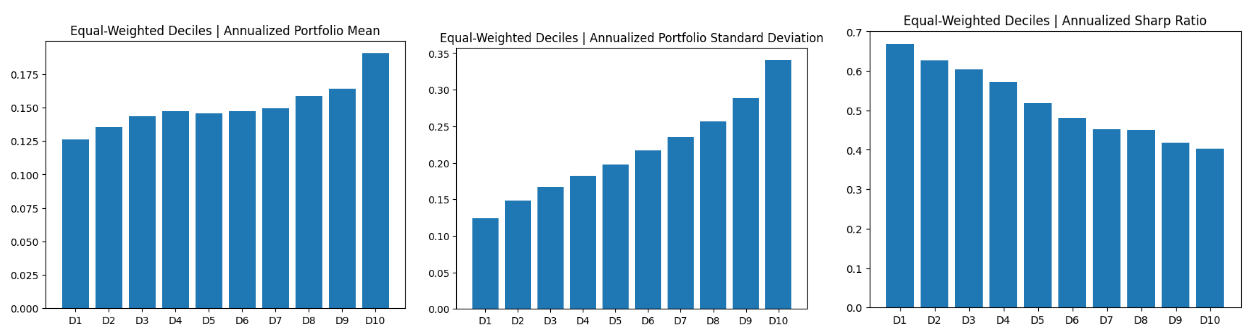
Figure 4: **MOM Annualized Metrics for Value-Weighted Portfolio Deciles**

Metric (Annualized)	**Mean**	**Standard Deviation**	**Sharpe Ratio**	**t-stat**	**p-value**
Long Strategy	0.1829	0.1989	0.704	-	-
Short Strategy	0.1230	0.2616	0.306	-	-
Momentum Strategy	0.0599	0.1612	0.372	-	-
Average Return of Mom $\neq 0$	-	-	-	2.85	0.0042

Table 2: **Summary Statistics for Equal-Weighted Portfolio for MoM**

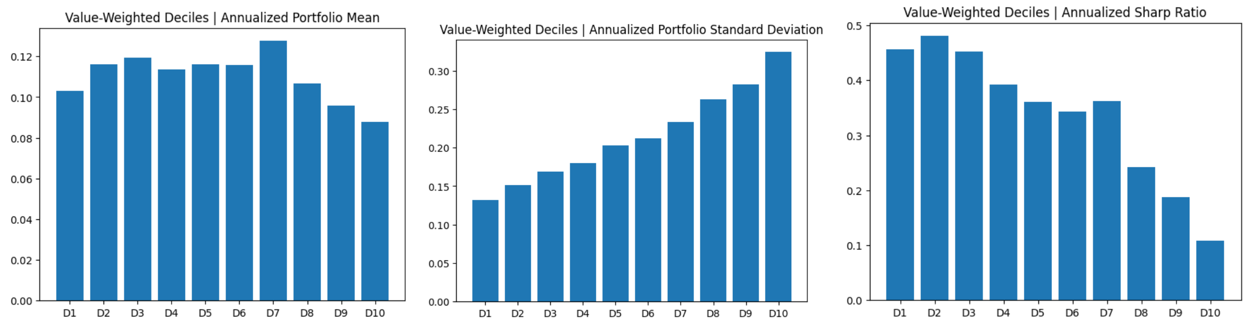
Metric (Annualized)	**Mean**	**Standard Deviation**	**Sharpe Ratio**	**t-stat**	**p-value**
Long Strategy	0.1355	0.1675	0.552	-	-
Short Strategy	0.0818	0.2198	0.176	-	-
Momentum Strategy	0.0537	0.1698	0.316	-	-
Average Return of Mom $\neq 0$	-	-	-	2.43	0.0155

Table 3: **Summary Statistics for Value-Weighted Portfolio for MoM**



(a) (b) (c)

Figure 5: **IV Equal-Weighted Deciles**



(a) (b) (c)

Figure 6: **IV Value-Weighted Deciles**

Metric (Annualized)	**Mean**	**Standard Deviation**	**Sharpe Ratio**	**t-stat**	**p-value**
Long Strategy	0.1641	0.2825	0.429	-	-
Short Strategy	0.1350	0.1422	0.647	-	-
IV Strategy	0.0291	0.1944	0.150	-	-
Average Return of IV $\neq 0$	-	-	-	1.130	0.2588

Table 4: **Summary Statistics for Equal-Weighted Portfolio for IV**

Metric (Annualized)	**Mean**	**Standard Deviation**	**Sharpe Ratio**	**t-stat**	**p-value**
Long Strategy	0.094	0.2644	0.194	-	-
Short Strategy	0.1086	0.1396	0.469	-	-
IV Strategy	-0.01415	0.1844	-0.077	-	-
Average Return of IV $\neq 0$	-	-	-	-0.058	0.5630

Table 5: **Summary Statistics for Value-Weighted Portfolio for IV**

Strategy	**Mean**	**Standard Deviation**	**Sharpe Ratio**
Equally Weighted	0.0978	0.10	0.55
Risk Parity	0.1064	0.10	0.64
Mean-Variance Efficient Portfolio	0.0406	0.10	-0.02

Table 6: **Summary Statistics for 'Optimal' Portfolio for STRAT**

Dep. Variable:	RP	**R-squared:**	0.475
Model:	OLS	**Adj. R-squared:**	0.459
Method:	Least Squares	**F-statistic:**	31.46
No. Observations:	646	**Prob (F-statistic):**	1.67e-75
Df Residuals:	627	**Log-Likelihood:**	1579.8
Df Model:	18	**AIC:**	-3122.
Covariance Type:	nonrobust	**BIC:**	-3037.

	Coef	**STD Error**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	0.0022	0.001	1.508	0.132	-0.001	0.005
Mkt-RF	1.2028	0.168	7.159	0.000	0.873	1.533
SMB	0.3051	0.036	8.431	0.000	0.234	0.376
HML	0.0456	0.054	0.845	0.398	-0.060	0.151
RMW	0.0298	0.053	0.564	0.573	-0.074	0.133
CMA	0.1386	0.066	2.086	0.037	0.008	0.269
No Dur	-0.0482	0.048	-0.996	0.320	-0.143	0.047
Durbl	-0.0806	0.020	-4.614	0.000	-0.119	-0.042
Manuf	-0.0166	0.054	-0.310	0.756	-0.122	0.089
Enrgy	-0.0749	0.023	-3.259	0.001	-0.120	-0.030
Chems	-0.1440	0.045	-3.220	0.001	-0.232	-0.056
BusEq	-0.1294	0.040	-3.265	0.001	-0.207	-0.052
Telcm	-0.1368	0.030	-4.331	0.000	-0.195	-0.079
Utils	0.1365	0.030	4.572	0.000	0.078	0.195
Shops	-0.0183	0.040	-0.455	0.649	-0.097	0.061
Hlth	-0.0327	0.032	-1.019	0.309	-0.096	0.030
Money	-0.2625	0.046	-5.723	0.000	-0.353	-0.172
Other	-0.0234	0.056	-0.421	0.674	-0.133	0.086

Omnibus:	28.992	**Durbin-Watson:**	1.759
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	81.631
Skew:	-0.073	**Prob(JB):**	1.88e-18
Kurtosis:	4.735		

Table 7: **OLS Regression Results**

Strategy	**Mean**	**Standard Deviation**	**Sharpe Ratio**
Industry-Hedged Portfolio	0.0051	0.0212	0.24

Table 8: **Summary Statistics for 'Industry-Hedged' Portfolio for STRAT**

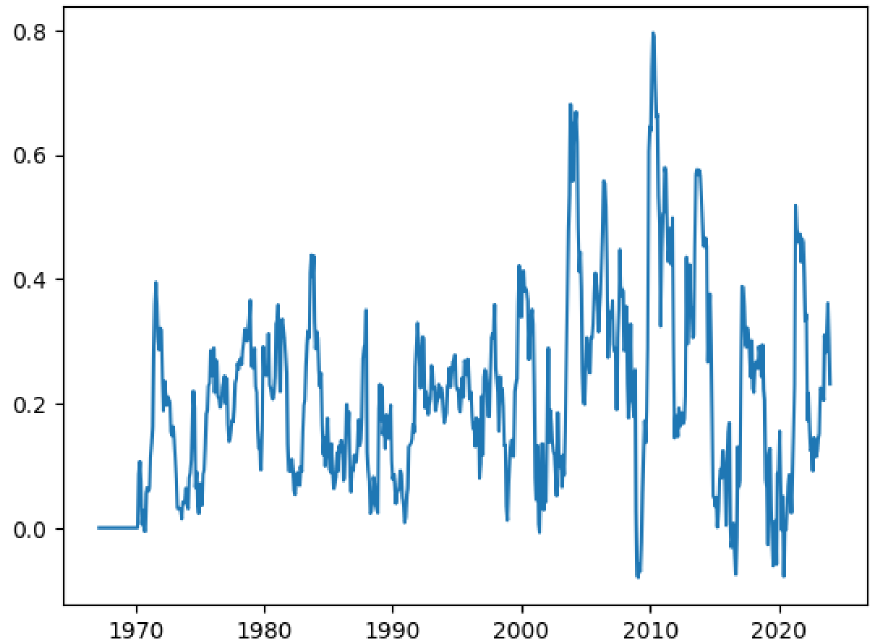


Figure 7: **Daily Beta for the STRAT**

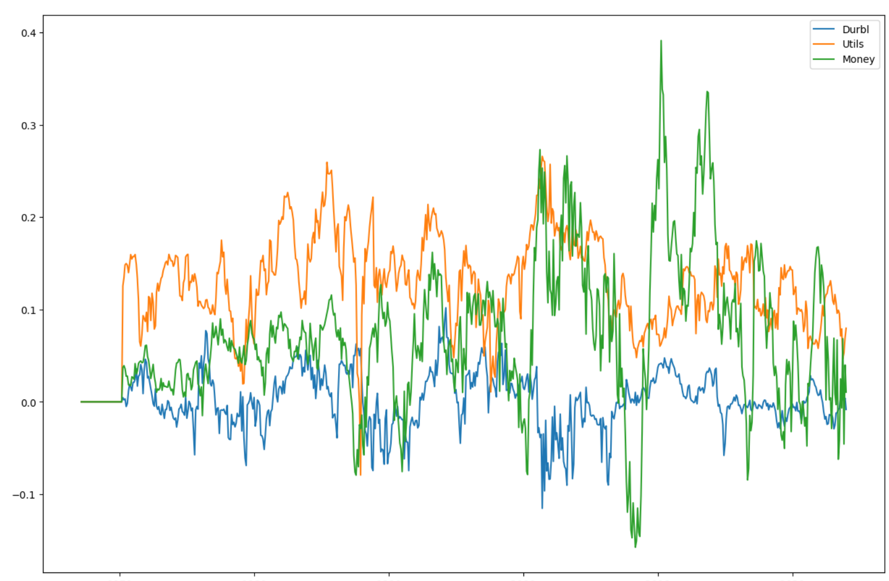


Figure 8: **Exposure of the 3 Industries**

Industry	Mean RP	Std RP	Sharpe Ratio	t-statistic	p-value
BusEq	0.094251	0.075201	0.499716	3.983597	0.000167
Chems	0.087745	0.092345	0.435698	3.400123	0.000764
Durbl	0.071560	0.092056	0.349234	2.410853	0.009123
Enrgy	0.072309	0.108642	0.267204	2.013835	0.062120
Hlth	0.0754301	0.130345	0.250831	2.019846	0.059037
Manuf	0.079285	0.089213	0.401946	3.165234	0.001930
Money	0.080217	0.067064	0.452043	3.765424	0.000323
NoDur	0.079246	0.090532	0.320125	2.540748	0.020155
Other	0.068751	0.089102	0.420127	2.953021	0.002901
Shops	0.082301	0.098723	0.392043	2.590125	0.009230
Telcm	0.102928	0.119201	0.450213	3.002412	0.000912
Utils	0.075429	0.080411	0.271842	1.820346	0.052019
Industry-Neutral	0.080123	0.059762	0.612054	4.500173	0.000018

Table 9: **Summary statistics for all industries**

Dep. Variable:	RP	**R-squared:**	0.489
Model:	OLS	**Adj. R-squared:**	0.455
Method:	Least Squares	**F-statistic:**	30.86
No. Observations:	646	**Prob (F-statistic):**	2.62e-74
Df Residuals:	627	**Log-Likelihood:**	1892.4
Df Model:	18	**AIC:**	-3747.
Covariance Type:	nonrobust	**BIC:**	-3662.

	Coef	**STD Error**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	0.0030	0.001	3.344	0.001	0.001	0.005
No Dur	-0.0295	0.030	-0.990	0.323	-0.088	0.029
Durbl	-0.0556	0.012	-4.593	0.000	-0.079	-0.032
Manuf	-0.0034	0.033	-0.102	0.919	-0.068	0.061
Enrgy	-0.0392	0.014	-2.769	0.006	-0.067	-0.011
Chems	-0.0918	0.028	-3.329	0.001	-0.146	-0.038
BusEq	-0.0889	0.024	-3.636	0.000	-0.137	-0.041
Telcm	-0.0967	0.018	-5.313	0.000	-0.132	-0.061
Utils	0.0396	0.018	2.150	0.032	0.003	0.076
Shops	-0.0189	0.025	-0.761	0.447	-0.068	0.030
Hlth	-0.0081	0.020	-0.407	0.684	-0.047	0.031
Money	-0.1277	0.028	-4.518	0.000	-0.183	-0.072
Other	-0.0249	0.034	-0.725	0.469	-0.092	0.042
Mkt-RF	0.7554	0.104	7.296	0.000	0.552	0.959
SMB	0.2131	0.022	9.553	0.000	0.169	0.257
HML	0.0302	0.033	0.909	0.364	-0.035	0.095
RMW	0.0494	0.033	1.519	0.129	-0.014	0.113
CMA	0.0944	0.041	2.306	0.021	0.014	0.175
RF	-0.3379	0.216	-1.567	0.118	-0.761	0.086

Omnibus:	88.320	**Durbin-Watson:**	1.806
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	528.585
Skew:	-0.419	**Prob(JB):**	1.66e-115
Kurtosis:	7.352		

Table 10: **Summary Statistics for 'Industry-Hedged' Portfolio for STRAT**