FIN7032
Final Project

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Overview – Low-Beta Value Equity Strategy

The objective of my proposed fund is to achieve low Market Beta Value exposure. We are targeting stocks with low market beta and a higher value exposure. Recently there has been fears of an AI/Chip related bubble, with the Mag 7 making up 35% of the S&P value as of Dec 1st 2025 (Lyle Daly, 2025). Mag 7 stocks share more relation to Growth and Momentum, while they are also playing an oversized role in the Markets total success. My aims for the fund were to target all of the benefits of Value with extra protection from the total market. My fund would likely not be a fantastic long-term investment for someone who is less risk adverse and wanting to maximize gains, but for those who have a more bearish attitude on the near future (1-3 years), or are far more risk adverse.

Methodology

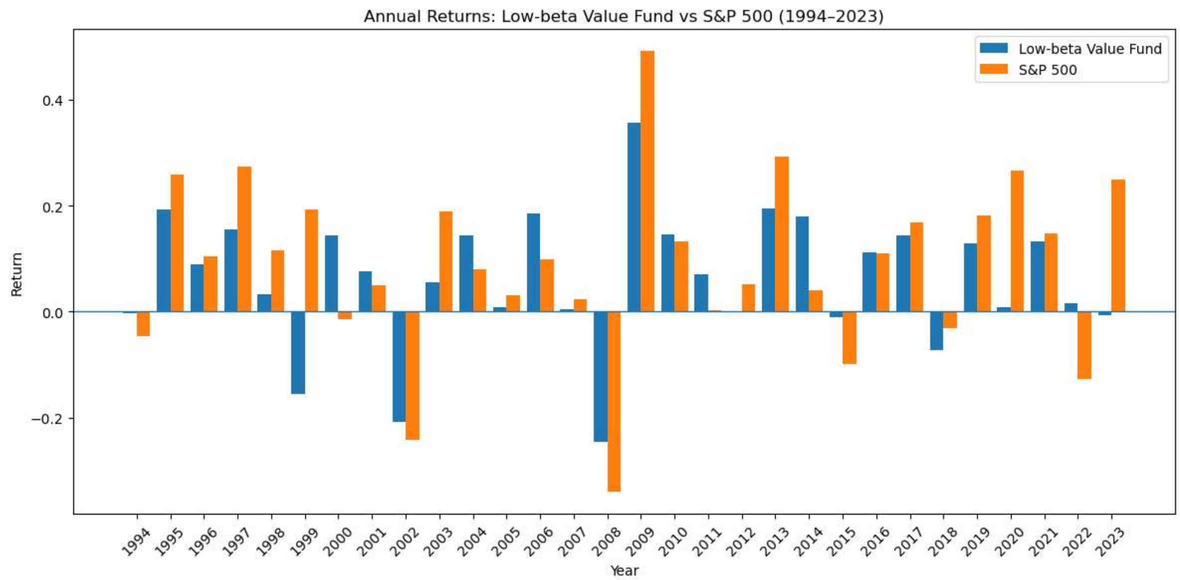
I began the project by pulling in the signals dataset. The most vital pieces in the set being the BM (book-to-market), beta (market factor), and MC (market-cap). Once the dataset is loading, we clean and filter for invest ability. Invest ability meant that the stock had a price > $5, was in the top 1500 stocks in MC, and have an ADV > 10. After which a value factor filter is applied with only the top 30% of BM stocks being included in the fund. Before adding the market beta constraint, we ran the purely value factor long only portfolio as a baseline. Once the baseline was completed, we ran a CAPM model, to observes its relation to the market. Once the baseline was complete I started working on a construct that would only use low market beata stocks. Since a long only portfolio can't achieve a $\beta = 0$ we had to settle for lower beta. Next we create two buckets, one for high beta and one for low beta (bottom 10% historically). Next weights were computed. Our target ideally would have been $\beta = 0$ but reiterating what I said earlier, this can't be done without short positions. So we use a mixed ranking step to reduce the market factor as far as we can. Portfolio beta is a weighted average of the betas in each bucket. Solving the linear equation

$$\beta_{\text{mix}} = a\,\beta_{\text{low}} + (1 - a)\,\beta_{\text{high}}$$

gives the mixture weight a needed to reach the target beta. This allows systematic beta reduction while preserving diversification. Next, we construct the returns of S&P, Baseline, and Low beta strategy and compare. Factor regressions were run at a few points to observe the relationship the factors had between strategies. Lastly, we played with some tables and charts to see how the strategy did and to focus more on the specifics of the portfolio.

Back-testing

The following table shows performance of my strategy alongside the performance of the S&P 500 for that year. My strategy still shared a lot of similarities with the S&P. Both had positive years 23 of the 30 years in the set. My portfolio also outperformed the S&P in 13/30 of the years. Our lower beta did have a desired effect of dulling the pain from bad years, but also by dulling the good years in many cases. The best year for my strategy relative the S&P was 2000 when my strategy returned 15.9% compared to the S&Ps -1.5%. The worst year conveniently was the year before 1999 where low beta returned -15.5% compared to the S&Ps 19.2%.



Next we can look at cumulative performance of the strategy as well a risk adjusted measures compared to its peers. The line graph below shows that while the strategy didn't perform better or as well as the S&P it did a better than the strictly long portfolio we laid out in the beginning. The area that really drew my eye was the most recent years (2020-2024), where we can see a consistent deviation, which is what we would expect to see from the growth/momentum driven returns of the market in recent years. The low-beta strategy did look to iron out some of the steep declines of both the alternative strategies. My strategy did achieve the lowest volatility of the different strategies, but reviewing the Sharpe from the table we can see that the drop in returns may not have been a worthy sacrifice relative to the drop in volatility. The annual average returns came in 2.58 less than the S&P. My end goal of trying to minimize the beta looks to have been successful with a β = 0.42. One stat where my strategy did well was in the max drawdown area. If capital preservation took priority over maximum returns, may strategy me be appealing.

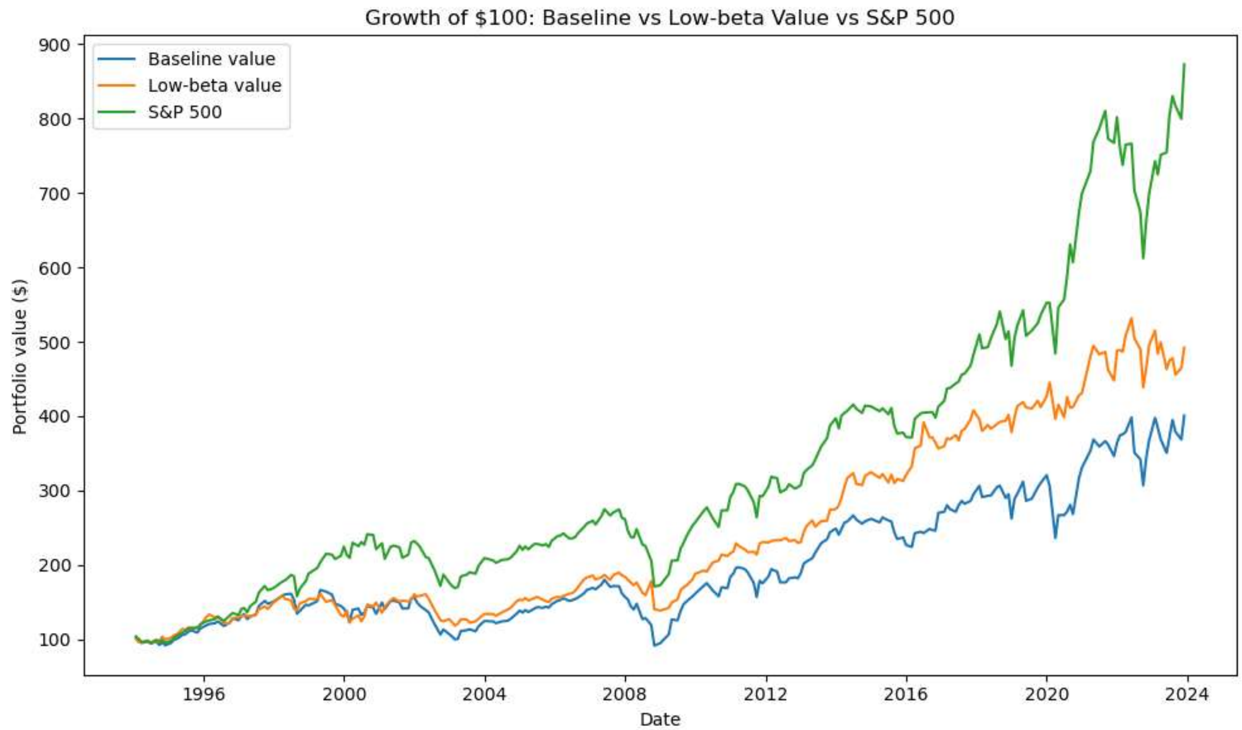
Summary metrics (in % where applicable):

	Low-beta value	Baseline value	S&P 500
Mean monthly (%)	0.717045	0.701571	0.957126
Vol monthly (%)	4.153082	5.505551	4.464438
Sharpe (monthly)	0.125865	0.092169	0.171049

Mean annual (%)	8.952126	8.751425	12.109843
Vol annual (%)	14.386698	19.071789	15.465266
Beta (vs MktRF)	0.424956	1.042888	0.958248
Max drawdown (%)	-26.826938	-49.227104	-37.865574

Annual excess return statistics (Fund - S&P):

Mean annual excess (%)	-2.586204
Vol annual excess (%)	11.952039
Sharpe(annual excess)	-0.216382



When comparing performance over the different lengths in time, the S&P consistently beats my Low-beta fund. We learned in class that value portfolios haven't performed phenomenally in the past few years and my data would agree, even with a low beta constraint. On the upside, it does look like overtime we can see regression to the mean performance. If those speculating that there is a bubble and it pops the 40 year mark may see equal returns.

Compounded average annual return over trailing windows (in %):

	Fund CAGR (%)	S&P CAGR (%)
Last 1 years	-0.702040	24.889434
Last 3 years	4.539684	7.684338
Last 5 years	5.401084	13.295605

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Last 10 years       5.989426      8.191985
Last 30 years       5.456360      7.489537
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Lastly I used the Fama French 3 factor model and regressed it against my fund. While there is alpha (0.0009) it isn't statistically significant. We can see that all 3 factors did show effects with significance. Earlier in my code I ran a CAPM model against the baseline Value strategy and that regression showed a Market Beta of 1.03 with significance. So my goal of dropping beta was achieved. Another stat to observe is the R^2. With the baseline showing 0.75 just from Market factor, my strategy achieved $R^2 =$ 0.37. Meaning that the factor model is explaining less of the variation observed in the data. This suggests that my fund may contribute its performance to other variable that may not be observed here.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 excess   R-squared:                       0.368
Model:                            OLS   Adj. R-squared:                  0.360
Method:                 Least Squares   F-statistic:                     42.64
Date:                Tue, 09 Dec 2025   Prob (F-statistic):           2.63e-22
Time:                        14:43:38   Log-Likelihood:                 508.33
No. Observations:                 255   AIC:                            -1009.
Df Residuals:                     251   BIC:                            -994.5
Df Model:                           3
Covariance Type:                  HAC
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0009      0.002      0.476      0.634      -0.003       0.004
mktrf          0.4971      0.049     10.077      0.000       0.400       0.594
smb           -0.2268      0.069     -3.301      0.001      -0.361      -0.092
hml            0.4085      0.078      5.217      0.000       0.255       0.562
==============================================================================
Omnibus:                       13.658   Durbin-Watson:                   2.261
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               33.786
Skew:                           0.077   Prob(JB):                     4.61e-08
Kurtosis:                       4.776   Cond. No.                         33.9
==============================================================================
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Holdings

My final holdings can be seen below. My top holding was Verizon, which I thought was ironic (my dad is a lineman for them and always talks about insecure his position is). Verizon is a telecommunications company that They had a weight of about 16.43% of the total final portfolio. The next 2 top holding were CVS and Cigna, which are 2 of the largest healthcare companies in the nation. That tracks with our investing theory since healthcare doesn't have very cyclical characteristics. The majority of my top ten were utilities, which also doesn't have cyclical characteristics. I also extended that cell to include the top 20 holdings as an experiment and utilities became even more prevalent. My top 10 account for 70.77% of the portfolio's holdings.

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Top 10 holdings at 2023-12-29
    permno ticker      w_bn  weight_pct          MC        BM      beta
35   65875     VZ  0.164313   16.431348  158.494645  0.878566  0.372049
5    17005    CVS  0.105344   10.534393  101.613387  0.760864  0.489535
34   64186     CI  0.090842    9.084205   87.625059  0.605295  0.517421
6    18411     SO  0.079282    7.928181   76.474204  0.567329  0.480279
24   27959    DUK  0.077536    7.753566   74.789892  0.767885  0.439891
21   24109    AEP  0.044280    4.427973   42.711649  0.773552  0.465051
39   89269    CNC  0.041098    4.109848   39.643056  0.660040  0.384810
13   21776    EXC  0.037048    3.704818   35.736188  1.021244  0.503956
19   23931    XEL  0.035417    3.541716   34.162929  0.629198  0.359369
0    11404     ED  0.032558    3.255763   31.404663  0.905502  0.306694

Top-10 concentration: 70.77% of NAV
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Risks & Limitations

There are some easily observed of risks and limitations to my strategy. The first that very easily observed from my tests is that this strategy may not be optimal for those who don't mind risk. The drop in volatility likely wouldn't be worth the drop in returns for someone early in their working career and wanting to get optimal returns. Another risk is the concentration my portfolio assigned to the top 5 assets. If version has a bad year or quarter you will feel it disproportionately. There is also industry risk. Running a specific factor related to utilities would have been very interesting, but I didn't have a column in the data that assigned industry, otherwise we could have used dummy variables to observe our exposure in those sectors. My liquidity constraint (DTV > 10) lends bias toward mega cap defensives. This heavily reduces the amount of investable assets. Lastly another limitation may be our quarterly rebalancing may not be very reactive to quick regime changes. For example, if a new tech/policy comes out that will completely change the utility industry, my portfolio may not react fast enough to avoid massive losses. This means we diversified away from the market but in turn very concentrated in a few noncyclical industries.