Cornell University

ORIE 5370 Project 2

Value Oriented Macro Factor Hedging Model

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Abstract

Macroeconomic factors can be used to predict future stock return. However lagging factors can pose timing issue of the re-balancing of portfolio, as the market will move before these factors being updated. In this project, we extended our first project by exploring a different set of leading macro-economic factors and developed a timely warning system to protect the portfolio from a sudden market crash. We also replaced variance constraints with expected shortfall constraints and compare that to the result of our first project. We found that our new model had better performance than the old one in terms of both return and volatility. Most importantly, we improved our previous strategy in terms of beta measurement and stock pool adjustment, and the updated strategy did successfully outperformed the old one.

Based on this project findings, we conclude that our warning system design is effective; limiting factors to those of high explanatory power help improve the performance of portfolio; a more concentrated value portfolio has better results.

Contents

1 Introduction

Our first project analyzed portfolio's exposure to various macro-economic factors and our strategy was to hedge the portfolio's exposure to these factors so that the negative macro-economic influence on the portfolio is limited. However, the results showed that our strategy did not outperform either equally-weighted value-stock portfolio or S&P 500. In this project, we build upon the first project and tries to improve the performance of our portfolio by using different macro-economic variables, and adding different constraints.

We made three major improvements from last project, including: changing lagging indicators to leading indicators(Section 3); replacing variance limit with expected shortfall limit(Section 4); implementing a warning system that predicts for financial downturn(Section 5); exploring and comparing different methods to select macro factors and compute sensitivity matrix(Section 7).

2 Unchanged part compared to Project 1

Since this project is an updated version of project 1, here we list some unchanged part compared to the last project.

1. **Stock Pool:** In Figure 1 (extracted from project 1) below, we can see the performance of the benchmark portfolio beat the S&P 500 from 2000 to 2017. This indicates that we have chosen a fairly good stock pool and we will continue using them in this project.

2. **Benchmark Portfolio:** The benchmark portfolio weight allocation still remains the same, that is, each risky asset takes the equal weight, $\frac{1}{27}$ in the portfolio. Hence, the benchmark variance and benchmark exposure vector also remain the same.

3. **Linear Regression and Sensitivity Matrix:** In this project, we have refreshed our macro-economic factors, details described in Section 3. The way we build the sensitivity matrix is still the same: run linear regression of the 26 stocks against the 9 new macro-economic factors to derive a 9×26 sensitive matrix.

4. **Constraints:** We noticed that in the last project, although we have a relatively low volatility, the portfolio return is not promising and the maximum draw-down is still very large (Figure 1). Hence, here we remove the constraints on the portfolio variance and keep the rest of the constraints. We then added some other constraints to better reduce the maximum draw-down and optimized the portfolio return, see Section 4 and Section 5. Here, we just list the unchanged constraints:

   - Total transaction cost will be minimized.
   - The final weight of each stock in our portfolio will not deviate from the one in the benchmark portfolio by 5%.
   - Limiting certain macroeconomic exposure.

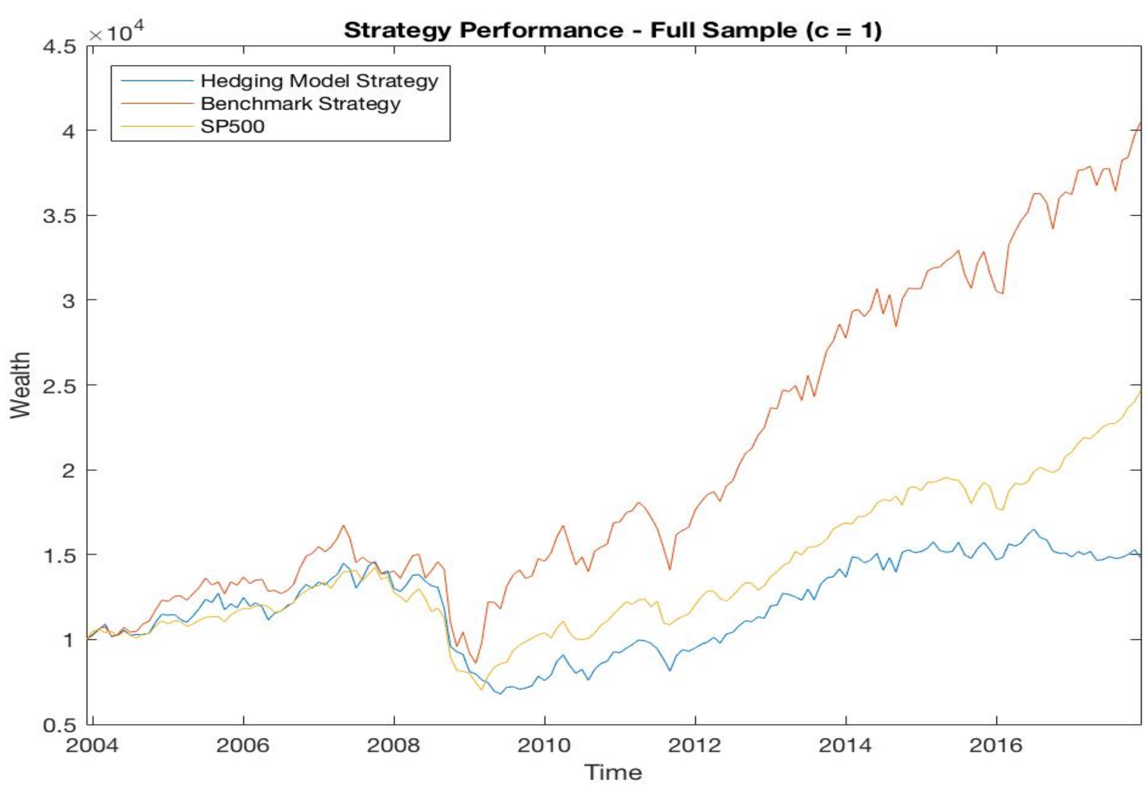

Figure 1: Strategy Performance in the Previous Project

3 New Macroeconomic Factors

3.1 Macroeconomic Factor Source

We recognized that majority of the chosen macroeconomic factors in the last project are lagging factors. Using such lagging factors to hedge the financial crisis is not a wise choice. Hence, in this project, we decided to use more leading economic indicators, for example, the consumer sentiments. Figure 2 [1]shows the consumer sentiment plot from 2000 to 2017 and Figure 3 [2]shows the SP500 Index plot from 2000 to 2017. It is rather clear that consumer sentiment start to plummet around 2007-Jan, which is 10 months prior to the dropping date 2007-Oct for the stock market. Hence we decide to take leading indicators like consumer sentiment to help us decide when and how to hedge our portfolio.

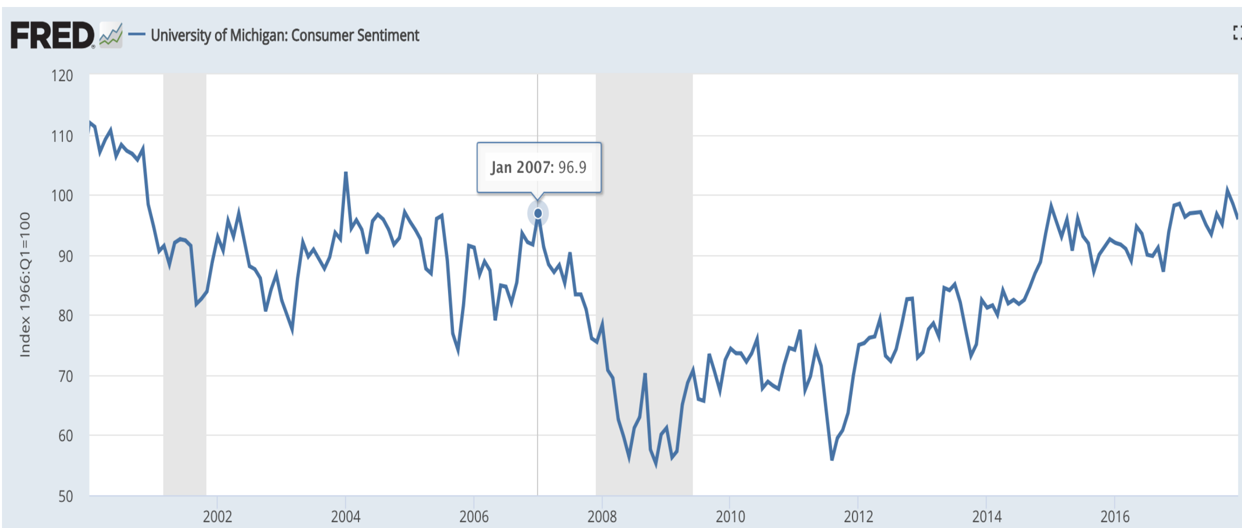

Figure 2: Consumer Sentiment plot from 2000 to 2017

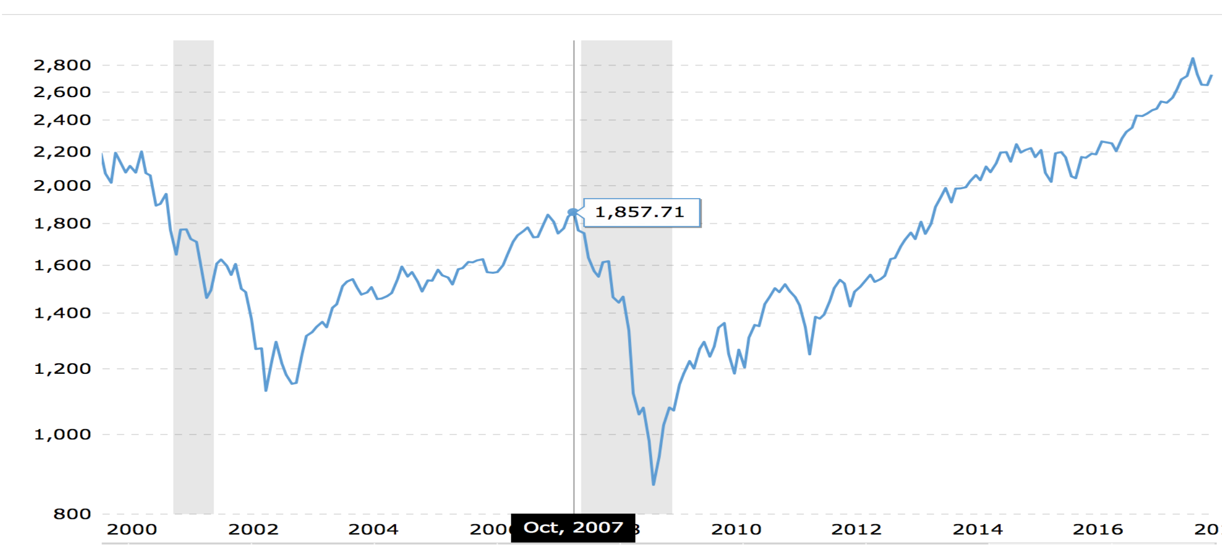

Figure 3: S&P500 Index plot from 2000 to 2017

Here are the 9 Leading Macro-Economic Factors from online source:[3]

1. **Average weekly hours (manufacturing)** — Adjustments to the working hours of existing employees are usually made in advance of new hires or layoffs. Because of this, the average weekly hours can be used as a leading indicator of the general economy strength.

2. **Average weekly jobless claims for unemployment insurance** — Positive value of jobless claim suggests an increase in unemployment. Because of the weekly reporting

[1]From https://fred.stlouisfed.org/series/UMCSENT/
[2]From http://www.macrotrends.net/2324/sp-500-historical-chart-data
[3]From https://www.conference-board.org/data/bcicountry.cfm?cid=1

frequency. The initial jobless-claims data is more sensitive to business conditions than other measures of unemployment.

3. **Manufacturers' new orders for consumer goods/materials** — This component is considered a leading indicator because the increases in new orders for consumer goods and materials usually mean positive changes in actual production, which can be predictive to the change in the real economy output (GDP).

4. **Manufacturers' new orders for non-defense capital goods** — As stated above, new orders lead the business cycle because increases in orders usually mean positive changes in actual production and perhaps rising demand. This measure is the producer's counterpart of new orders for consumer goods/materials component.

5. **Building permits for new private housing units.** - the building permits suggests housing developers' confidence in the real estate market, which is closely related to the banking industry; thus it

6. **The Standard & Poor's 500 stock index** — The S&P 500 is considered a leading indicator because changes in stock prices reflect investor's expectations for the future of the economy and interest rates. The index can be of a measure of investors' sentiment.

7. **Money Supply (M2)** — The money supply measures both saving and checking account. Here, M2 is adjusted for inflation by means of the deflator published by the federal government in the GDP report. Bank lending, a factor contributing to account deposits, usually declines when inflation increases faster than the money supply, which can make economic expansion more difficult. Thus, an increase in demand deposits will indicate expectations that inflation will rise, resulting in a decrease in bank lending and an increase in savings.

8. **Interest rate spread (10-year Treasury vs. Federal Funds target)** — The interest rate spread is often referred to as the yield curve and implies the expected direction of short-, medium- and long-term interest rates. Changes in the yield curve have been the most accurate predictors of downturns in the economic cycle. This is particularly true when the curve becomes inverted, that is, when the longer-term returns are expected to be less than the short rates.

9. **Index of consumer expectations** — This component leads the business cycle because consumer expectations can indicate future consumer spending or tightening. The data for this component comes from the University of Michigan's Survey Research Center, and is released once a month.

3.2 Factor Explanatory Power

Given the above 9 leading economic indicators, we are expecting that they can be used to explained the stock returns effectively. However, stock returns may have different patterns, so not all factors have high explanatory values for each stock. In this section, we are going to run regressions on each stock using all 9 leading factors on the period from January, 2000 to December, 2003 before the backtesting year 2004. Then we would figure out common factors that have high explanatory values for all stocks, and specific significant factors for each single stock. In Section 7, we will also compare models using all 9 factors with the ones using factors only of high explanatory values to our stocks.

To see the explanatory power for each factor on every stock, for each stock we compute the p-values of every factor coefficient (sensitivity). If the p-value of a factor is relatively low, then we can conclude that it has relatively high explanatory power for that stock.

To figure out the average explanatory power for each factor on all stocks, we use the average p-value of the factor's coefficients as the average explanatory value. The following table shows the average p-values for all 9 factors, and stocks for which the factor has high explanatory power (p-value < 0.1).

Table 1: Explanatory Power for Macro Factors

Factors	Average p-values	Stocks (p-value < 0.1)
working hours	0.32	BMY, NEE, PXD, DLX, INGR
sp500	0.41	LPX, DHI, FINL, RWT, CAL, ORCL
capital order	0.41	TAP, NEE, PXD, DVN, INGR
consumer sentiment	0.47	CLI, UVV, EIX
consumer order	0.49	RWT, HELE, UVV
spread	0.50	FBC, RWT, UVV
jobless claim	0.54	T
M2	0.56	
permit	0.59	CLI, NEE

We can see that the average p-values are not small, which means that not all macro factors have high explanatory values for stock returns. Actually, most macroeconomic factors have low explanatory power. However, there still exist some factors with sufficient explanatory power for stock returns, so we still want to see whether our hedging model can extract some information from these macroeconomic factors. In Section 7, we will modify the sensitivity matrix (**B**) to construct a reduced hedging model according to the explanatory power of factors on each stock, and compare it with the original ones.

3.3 Smaller Stock Pool

From table 1, we realize 7 out of 26 stocks (MTH, STC, RNR, CLI, MD, CLGX, FCN, CMTL) in our portfolio cannot be statistically explained by any single macro-economic factors. Hence, to better apply the macro-economic factors hedging model, (explained by the last constraint in project 1), we are considering only use the remaining 19 stocks (still in 11 sectors) to build our portfolio, please refer to Table 2.

Table 2: Risky Assets in Smaller Stock Pool

Sector	Stock ID	Stock Name
Basic Materials	LPX	Louisiana-Pacific Corporation
Consumer Cyclical	DHI	D.R. Horton, Inc.
	FINL	The Finish Line, Inc.
Financial Services	FBC	Flagstar Bancorp, Inc.
Real Estate	RWT	Redwood Trust, Inc.
Consumer Defensive	HELE	Helen of Troy Limited
	TAP	Molson Coors Brewing Company
	UVV	Universal Corporation
Healthcare	MD	MEDNAX, Inc.
	BMY	Bristol-Myers Squibb Company
Utilities	EIX	Edison International
	NEE	NextEra Energy, Inc.
Communication Services	T	AT&T Inc.
Energy	PXD	Pioneer Natural Resources Company
	DVN	Devon Energy Corporation
Industrials	CLGX	CoreLogic, Inc.
	FCN	FTI Consulting, Inc.
Technology	INGR	Ingredion Incorporated
	ORCL	Oracle Corporation

Note: considering the smaller number of risky assets in the portfolio will also pose implication to the return and volatility, the smaller portfolio (contained only 19 stocks) will only be applied in Section 7, Strategy Performance. In Section 4,5 and 6, we still proceed our project on the portfolio that contain all the stocks.

4 Expected Shortfall

4.1 Reason

As mentioned in the Section 2, in this hedging model, it is not enough to limit the exposure of specific macro-economic factors in the financial downturn. In the severe financial crisis, majority of the macro-economic factors don't work because the sudden and short spanning nature of the crisis makes the monthly or quarterly macro-economic data not timely enough and our re-balancing timing become lagged. Hence we will resort to a coherent risk measure to limit the total loss in this period. In our project, we applied expected shortfall constraints to replace variance constraints in our former project.

The expected shortfall measures the average of all loss in the worst α percent case. It takes into account the worst case scenario and is expected to be a better measure of Value at Risk measure, which only gives the α percent worst loss threshold. We define the expected shortfall as follows:

$$ES_\alpha(x) = -\frac{1}{\alpha}\int_0^\alpha VaR_\gamma(X)d\gamma$$

In the optimization problem, to make the CVX in MATLAB work with the expected shortfall, we will re-define the expected shortfall (at level α) as

$$ES_\alpha(x) = \frac{1}{1-\alpha} min_l\{(1-\alpha)l + \Sigma_{\omega\in\Omega}\, p(\omega)\max\{loss(x,\omega) - l, 0\}\}$$

and

$$ES_\alpha(x) = l + \frac{1}{1-\alpha}\Sigma_{\omega\in\Omega}\, p(\omega)\max\{loss(x,\omega) - l, 0\}$$

is a convex function in variable $l, x_1, x_2, \cdot, x_n$, if for each $\omega \in \Omega$, the loss function is convex.

4.2 Implementation

In this project, we choose the loss function $loss(x,\omega) = -R(\omega)^T x$, where x is the vector of the weight of each stock in our portfolio. The benchmark expected shortfall ES^{B}_α can be calculated by minimizing the above function on the equally-weighted portfolio. We can choose different αs to get different ES^{B}_α and in this project, we chose α fixed, to be 0.99, 0.95 and 0.85.

Hence, we can have a new constraint: the portfolio expected shortfall is smaller than some scale k of the benchmark portfolio expected shortfall.

$$ES_\alpha \leq k \cdot ES^{\mathrm{B}}_\alpha$$

The scale vector k represents the allowable risk, so we run some back-tests to figure out how changes of the allowable risk will affect the performance of the strategy. Table 4 list out how the choice of vector k for the three $ES_\alpha(x)$.

4.3 A Pilot Run

In the back-tests, we just changed the macro factors into the above 9 leading indicators, and replaced the expected shortfall constraints compared to the strategy of our project 1. The following tables and figure are our results.

Table 3: Comparisons of old and new (new macro factors and ES constraints) models

$Models$	return	volatility	sharpe ratio	maximum drawdown
New Model ($k = (1, 1.25, 1.5)^T$)	3.29%	16.33%	0.27	59.38%
Old Model	2.85%	14.64%	0.19	53.55%
Benchmark(equally-weighted)	10.46%	17.41%	0.65	48.73%

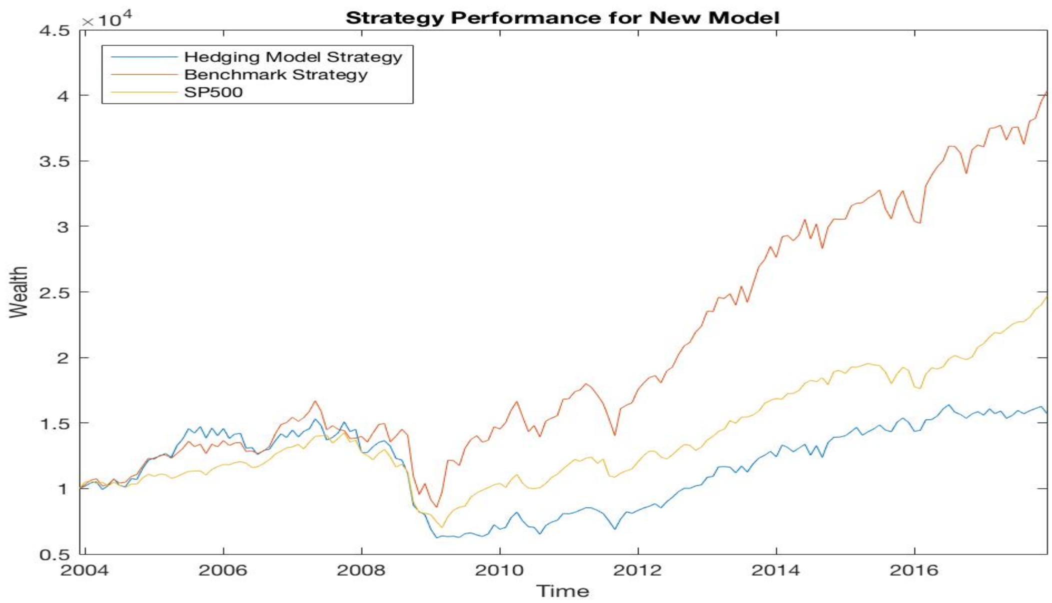

Figure 4: Strategy Performance of the New Model

Comparing new and old models, we can see that the new model has better Sharpe ratio than the old one though the improvement is not large. Also, the new one still under-performs the equally-weighted strategy and S&P 500.

Table 4: Different combinations of scale vector k in Expected Shortfall Model

Experiment	k	return	volatility	sharpe ratio	maximum draw-down
1	$k = (1, 1.25, 1.5)^T$	3.29%	16.33%	0.27	59.38%
2	$k = (2, 2.5, 3)^T$	3.41%	16.49%	0.27	59.38%
3	$k = (0.5, 0.625, 0.75)^T$	2.59%	14.76%	0.22	58.00%
4	$k = (1.5, 1, 1.25)^T$	3.31%	16.41%	0.27	59.38%
5	$k = (1.25, 1.5, 1)^T$	3.83%	16.10%	0.30	59.37%
6	$k = (5, 6.25, 7.5)^T$	3.41%	16.49%	0.27	59.38%
7	$k = (0.2, 0.25, 0.3)^T$	-2.27%	13.84%	-0.10	54.60%

From the results of different combinations of scale vector k in the new model, we can see that in general, the differences of the performance for different k are not large. Larger k (experiment 1,2,6), i.e., larger allowable risk will lead to higher volatility and higher returns, but with larger maximum draw-down. Smaller k (experiment 1,3,7) gives slightly better results on the maximum draw-down but lower return. Also, the permutation of k (experiment 1,4,5) to different confidence level α not likely affected our portfolio performance.

All the results show that our new model did not give a large improvement to the strategy, especially during the 2008 financial crisis. Thus other methods are needed to further minimize the downturn risk.

Note: In our project later on, we will stick to $k = (1, 1.25, 1.5)$

5 Warning System

5.1 Reason

Because of the low frequency of the macro-economic data and severe nature of financial crisis, the beta we measured during non-crisis time will be completely thrown off and the strategy failed to improve the portfolio's sharpe ratio. Therefore, to better protect the portfolio from large-scale financial crisis and improve return performance, we developed a warning system that alarms for potential crisis times. When the warning systems is triggered, the portfolio's allocation to risky asset is greatly reduced and instead, we overweight the risk-free asset to maximized our return and limit exposure to risk.

5.2 Application

5.2.1 Threshold Choice

From the Figure 5, we can see the consumer sentiment index have a strong leading effect to the stock market, especially in 2008 Financial Crisis. Hence, we decide to apply consumer sentiment index as the alarming indicator of the warning system: if there are consecutive decreasing changes above our threshold in the consumer sentiment, the warning system will alarm, and the portfolio will enter the crisis state where the weight of risky assets is reduced; after alarm is triggered if there are consecutive increasing in the consumer sentiment above the threshold, the warning system will be shut down, and the portfolio will revert to the normal state.

Here, we define the threshold such that the portfolio will enter the crisis or normal system based on historical trend. Since the training data is from 2000-2003, we analyze the decreasing rate and increasing rate of consumer sentiment before and after crisis in 2000 and define the threshold based on those rates.

Figure 5: Normalized Consumer Sentiment and SP500 from 2000-2017

Figure 6: Normalized Consumer Sentiment and SP500 from 2000-2003

- **Warning System Open Threshold**

  From Figure 6 (zoom in to 2000-2003 of Figure 5),we can see there is a sharp decreasing from 2000-Nov to 2001-Apr in consumer sentiment before S&P 500 started to trend down, which evolved into the 2000 Dot Com Bubble Crisis. From Table 5 below, we calculated the average decreasing rate of the consumer sentiment Index during the pre-crisis time, which is -3.8%. Hence, we define the warning system open threshold to be $-\mathbf{4}\%$ and are going to apply this threshold in the test data which is from 2004 to 2017.

Table 5: Decreasing rate of Consumer Sentiment in Year 2000 Dot Bubble

2000Nov-Dec	2000Dec-2001Jan	2001Jan-Feb	2001Feb-Mar	2001Mar-Apr
-8.55%	-3.76%	-4.3%	0.99%	-3.39%

- **Warning System Close Threshold**

  From the plot we can see there is a quick increasing from 2001-Sep to 2002-Jan in Consumer Sentiment. Hence from the Table 6 below, we calculate the average increasing rate of the Consumer Sentiment Index, which is 3.27%. Hence we define the warning system close threshold is **3**% and are going to apply this threshold in the test data which is from 2004 to 2017.

Table 6: Year 2000 Dot Bubble Recovery

2001Sep-Oct	2001Oct-Nov	2001Nov-Dec	2001Dec-2002Jan
1.1%	1.45%	5.84%	4.72%

5.2.2 Crisis and Normal State

- **Crisis State**

  In our project, we set the portfolio as entering the warning system when there are **3 consecutive** consumer sentiment Index rate decrease **smaller** than the **warning system open threshold**. When the consumer sentiment Index rate decrease below our warning system open threshold at the first time, this might be caused by consumers' conjectures and herd behaviour. When the consumer sentiment Index rate decrease below our Warning system Threshold at the second time, the overall market may be bearish and consumers are pessimistic to the stock market and risk averse sentiment might increase. When the consumer sentiment Index rate decrease below our warning system threshold at the third time, the likelihood of a financial crisis is very high and our portfolio will enter the Financial Crisis State.

- **Normal State**

  In our project, we set the portfolio to normal state when there are **2 consecutive** consumer sentiment index rate changes **greater** than the **Warning System Close Threshold**. During the financial crisis and when the consumer sentiment Index rate increase above our threshold at the first time, this maybe a false appearance of the economic recovery, for example, the Consumer Index rate fall harshly again at 2001-Aug after an increasing in 2001-Apr. Hence, we need a second consecutive increasing in the Consumer Sentiment Index rate above the Close Threshold to confirm the real recovery and our portfolio will enter the Normal State.

5.2.3 Portfolio Adjustment

- **Crisis State**

  In the Crisis State, we reduce our portfolio's exposure to risky asset and overweight risk-free asset in our portfolio. Hence, in our portfolio, we assign the **weights of risk-free to be greater or equal to 80**% and the rest **20**% of the portfolio will be risky assets (stocks) under the **macro-economic exposure hedging system**, which is the last constraint in Project 1.

- **Normal State**

  In the Normal State, we still apply the **macro-economic exposure hedging system** all the way, however, we will not short-sell the stocks, i.e. **the weights of all stocks are greater than 0**. This is because we assume the Normal State are under bullish market, especially in the economy recovery. If short-selling is allowed, then we are bearing the unnecessary risk of backfired by the re-bounce of stock market recovery. At the same time, the macro-economic hedging system will still secure our portfolio from the unfavorable macro-economic factors.

6 Overall Optimization System

6.1 Variables

Table 7: notation for mathematical expression of the linear programming

μ_0	the risk-free rate
μ	the vector of expected returns for risky assets
σ	a user chosen upper bound on portfolio risk
xx_0	the proportion of wealth currently in the bank
xx	the proportions currently invested in risky assets
trans_cost	the transaction cost per wealth unit bought or sold
k	the scale vector on benchmark ES_α for various confidence levels
α	a vector of confidence level that ES_α could lose in worst $1-\alpha\%$ scenarios
crisis_flag	the Boolean variable that determine financial crisis happening

6.2 Optimization

We are going to use Markowitz Model to calculate the weights of risk free and risky asset in our portfolio. The objective is still to maximize the portfolio return. We have several modified constraints:

- The loss function is defined as the negative of the portfolio returns per day.
- The portfolio Expected Shortfall cannot exceed the scale of the benchmark portfolio Expected Shortfall at all the 3 risk levels, $99\%, 95\%, 90\%$
- The total weight of the portfolio plus the transaction cost is 1.
- Total transaction cost will be minimized.
- The final weight of each stock in our portfolio will not deviate from the one in the benchmark portfolio by 5%.
- We want to optimize our portfolio and reduce risk by limiting certain macroeconomic exposure.
- If there is no crisis warning, we incorporate short sales limit, all stock are with positive weights.

Mathematical Expression:

$$\begin{aligned}
\underset{x0,x}{\text{maximize}} \quad & \mu_0 x_0 + \mu^T x \\
\text{subject to} \quad & ES_\alpha \leq k \cdot ES_\alpha^{\mathrm{B}} \\
& x_0 + e^T x + \text{total_trans_cost} = 1 \\
& x = xx + y \\
& \text{trans_cost} \times \sum_{i=1}^{n} |y_i| \leq \text{total_trans_cost} \\
& x_0 \geq 0 \\
& |x_i - \frac{1}{n+1}| \leq 0.05, \ i = 1 \rightarrow n \\
& |B \times x| \leq cz \\
& \text{If crisis_flag} = 0, \text{then}\, x \geq 0
\end{aligned}$$

7 Strategy Performance

7.1 Strategy with Warning System

After incorporating the warning system into our new model, we have constructed our final optimization strategy. We conducted back-tests of the complete model **from January 2004 to December 2017**. The following tables and figures are the summary of the strategy performance.

Table 8: Strategy Summary Statistics - Full Sample

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
New model without warning	3.29%	16.33%	0.27	59.38%
New Model with warning	8.14%	13.92%	0.61	34.99%
Benchmark	10.46%	17.41%	0.65	48.73%

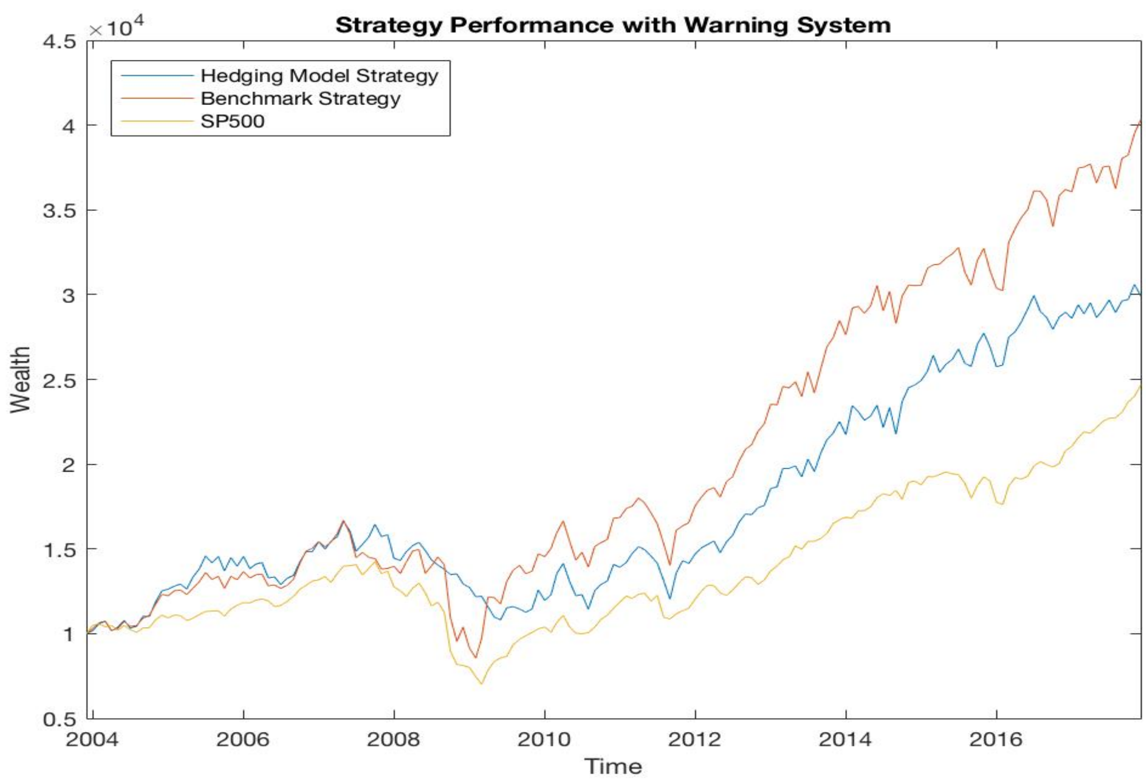

Figure 7: Strategy Performance of the New Model with Waring System

From table 8 and figure 7, warning system gives substantial improvement in all aspects. Compared to the benchmark portfolio, the new model has a lower annual return and a slightly lower Sharpe ratio, but a far better maximum draw-down and volatility.

More importantly, from Figure 7, we can tell there is a very deep decrease for benchmark portfolio and SP500 at Financial Crisis, however, the decrease for our portfolio is rather slow and flat. This is a very important characteristic of our portfolio: even in the huge economic crisis, its performance will not be severely and immediately affected, this can give the portfolio manager time to adjust the portfolio and further reduce the potential loss. Thus, it turns out that our warning system can efficiently, at least effectively avoid large downturn risk during 2008 or even in future financial crisis.

Note: In the rest of this section, we will keep using warning system.

7.2 Strategies with Different Sensitivity Matrices

All the above strategies are constructed using all 9 leading factors. However, as we mentioned in Section 3.2, some factors may have little explanatory power on some stocks. Thus, we try to modify the strategy by limiting factors to be the ones with high explanatory values.

7.2.1 Static Factor Selection

As we mentioned in Section 3.2, we ran regressions from January 2000 to December 2003 on stock returns using all 9 leading factors, and calculated the average explanatory power for each factors. In this section, we tried to reduce the number of factors to 5, that is, we only used the first five factors with the highest average explanatory values in our macro hedging model. These factors are **average weekly hours, S&P 500, new orders for capital goods, consumer sentiment and new orders for consumer goods**. Hence, we derive a 5×26 sensitivity matrix and use this matrix to conduct the macro-economic hedging in the second last constraint in Section 6.

Table 9: Strategy Summary Statistics - Static Factor Selection

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Static 5 Factors	8.50%	13.90%	0.64	33.31%
All 9 Factors	8.14%	13.92%	0.61	34.99%
Benchmark	10.46%	17.41%	0.65	48.73%

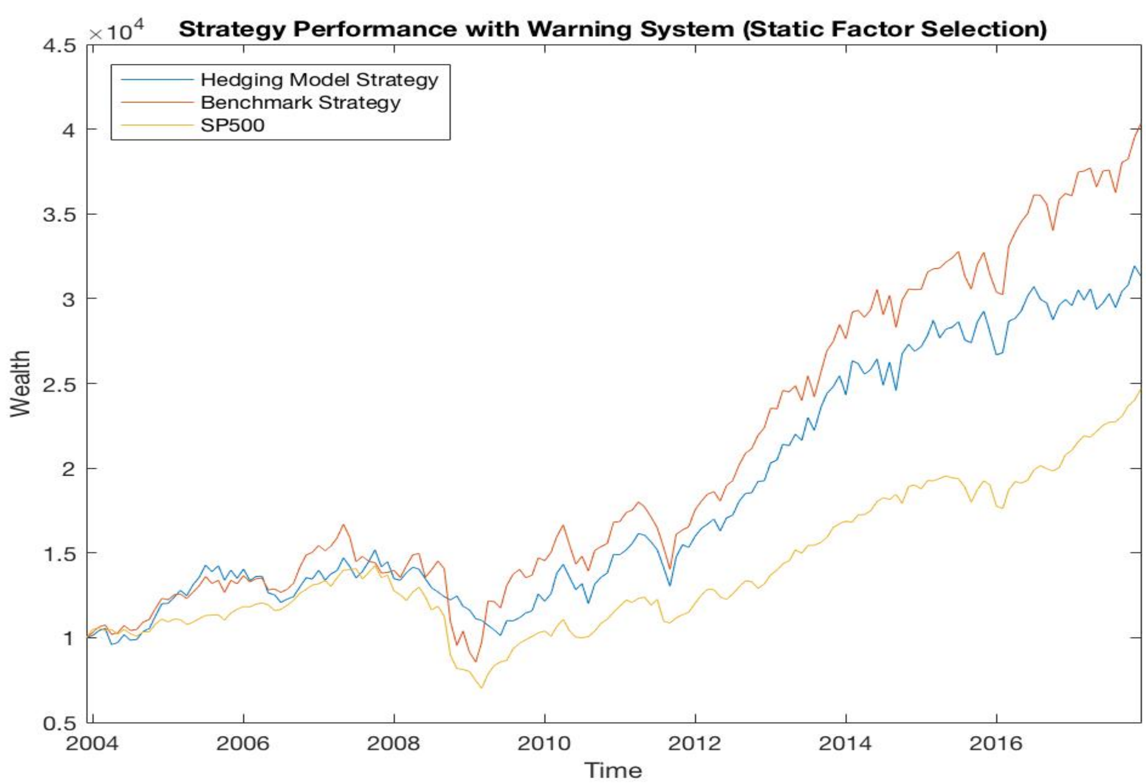

Figure 8: Strategy Performance of the New Model with Static Factor Selection

From table 9 and figure 8, we can see that models using 5 factors with the highest explanatory power have better performance than models with all 9 factors. It has higher annual return, lower volatility, higher Sharpe ratio and lower maximum draw-down. The reason for this improvement may be that removing factors with low explanatory power may avoid calculating incorrect sensitivity matrix, which may lead to over-hedge or under-hedge.

7.2.2 Dynamic Factor Selection (5 factors limit)

Here is the second way to build the 9×26 sensitivity matrix. For every time we ran the regression from 2004-Jan to 2017-Dec, we can find the 9×1 vector of estimates β_j, i.e.

each entry in β_j represents the estimate of factor i on the stock j. At the same time, the regression can also give us the p-values of each estimates. In this model, we sort the p-values from smallest to largest for each β_j. Among the 9 entries of β_j, we assign the 4 entries corresponding to the largest 4 p-values to 0. Hence, for each β_j, in the end, we have 5 entries with estimates and 4 entries to be 0. And the modified sensitivity matrix have more 0s compared to the previous sensitivity matrix. For every month before rebalancing, we rebuild our sensitivity matrix with 5-factor limit dynamically. The reason why we choose this method is to see the performance of the hedging strategy by excluding the factors that have negligible effect in the macro hedging constraints.

Table 10: Strategy Summary Statistics - Dynamic Factor Selection (5 Factors limit)

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Dynamic (5 factors limit)	8.07%	13.77%	0.61	32.51%
All 9 Factors	8.14%	13.92%	0.61	34.99%
Benchmark	10.46%	17.41%	0.65	48.73%

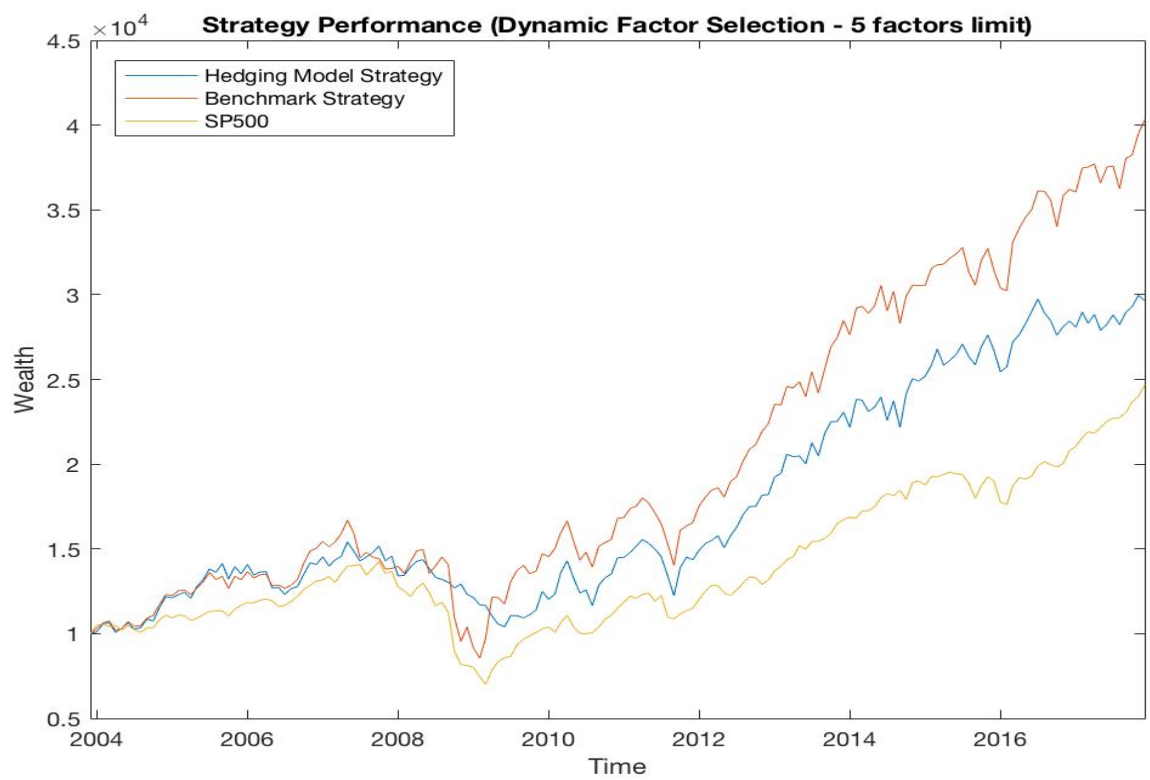

Figure 9: Strategy Performance (Dynamic Factor Selection - 5 factors limit)

From table 10 and figure 9, we can see when we dynamically used the top five factors with highest explanatory values in our hedging model every month, the strategy would not be significantly different from using all 9 factors every month. It did not give an improvement to our strategy.

7.2.3 Dynamic Factor Selection (p-value limits)

The third model is built upon the second model and the third one is even more harsh. In the second model, for each β_j, we assign the 4 entries corresponding to the largest 4 p-values to 0. In the third model, we instead assign the entries corresponding to the p-values greater than 0.1 to 0. To be clearer, if the p-value of the estimates is greater than 0.1, we will set this estimate to be 0. Hence, it is more probably that β_j has more 0s and the resultant sensitivity matrix have more 0s compared to the sensitivity matrix in second model.

Table 11: Strategy Summary Statistics - Dynamic Factor Selection (p-value limit)

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Dynamic (p-value limit)	5.76%	14.12%	0.45	35.31%
All 9 Factors	8.14%	13.92%	0.61	34.99%
Benchmark	10.46%	17.41%	0.65	48.73%

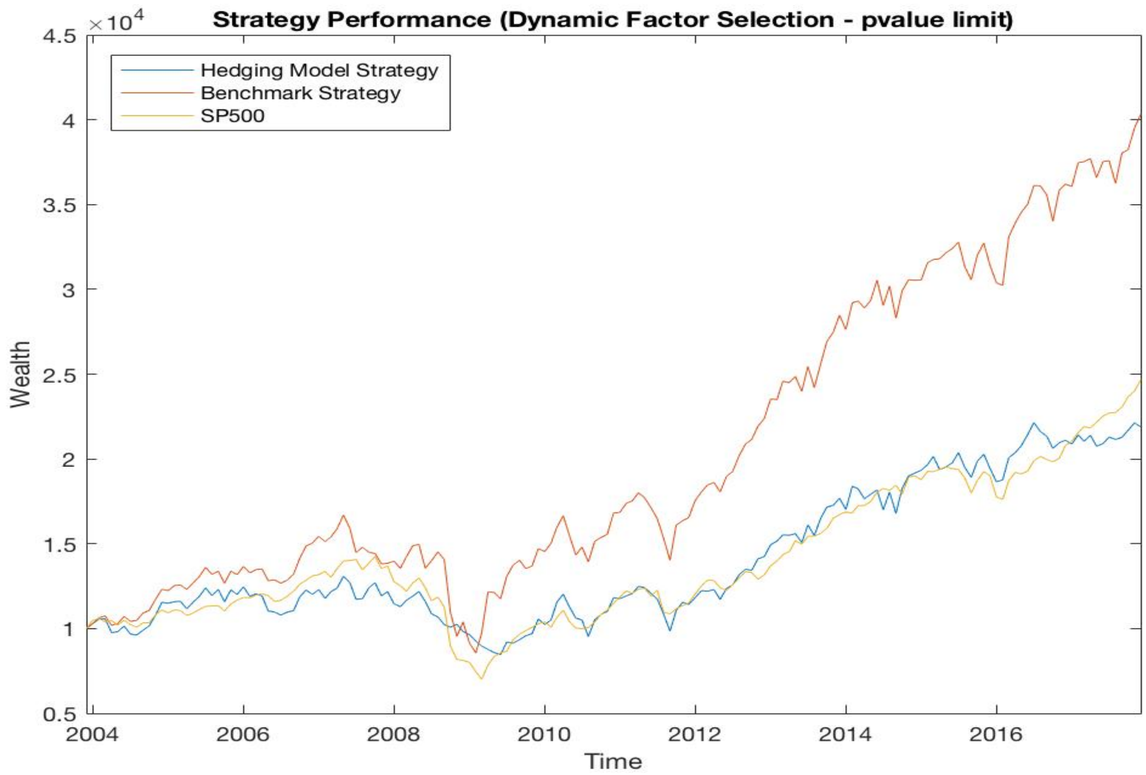

Figure 10: Strategy Performance (Dynamic Factor Selection - pvalue limit)

From table 11 and figure 10, we can see this dynamic model based on the p-value limit selection give very bad results compared to the previous two models: lower return and sharpe ratio, higher volatility and maximum draw-down. This result is not surprising since this model is very harsh and the sensitivity matrix is a very sparse matrix which lefts our portfolio severely under-hedged.

So far, from table 12 we know **the best way to build the sensitivity matrix: static factor selection.**

Table 12: Strategy Summary Statistics - Models with Different Sensitivity Matrix

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Static 5 Factors	8.50%	13.90%	0.64	33.31%
Dynamic (5 factors limit)	8.07%	13.77%	0.61	32.51%
Dynamic (pvalue)	5.76%	14.12%	0.45	35.31%
All 9 Factors	8.14%	13.92%	0.61	34.99%
Benchmark	10.46%	17.41%	0.65	48.73%

7.3 Strategies with Smaller Stock Pool

In Section 3 table 2, we constructed a smaller stock pool (more concentrated) based on the p-value which only contains 19 stocks. Here we want to see after adding the expected shortfall and warning system, whether this portfolio can give us a better performance.

Table 13: Strategy Summary Statistics - Smaller portfolio

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Smaller portfolio 9 Factors	9.00%	12.77%	0.72	22.24%
Full portfolio 9 Factors	8.14%	13.92%	0.61	34.99%
Benchmark	10.46%	17.41%	0.65	48.73%

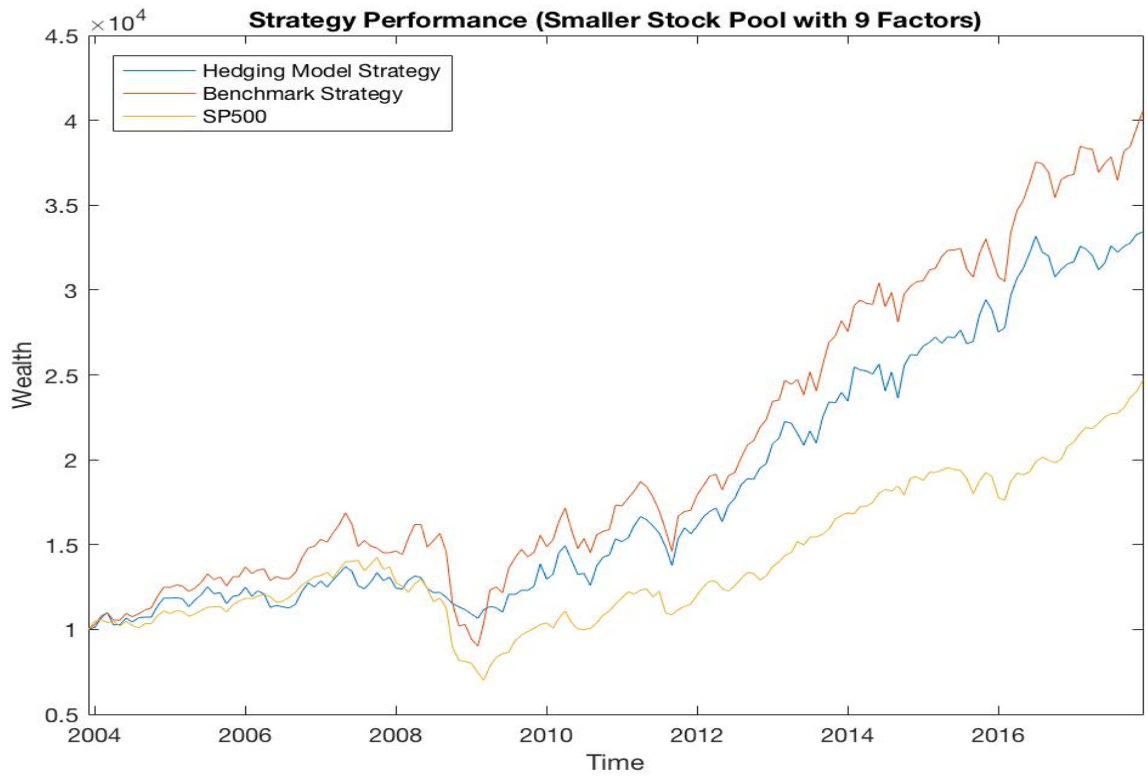

Figure 11: Strategy Performance (Smaller Stock Pools with 9 Factors)

Indeed, from table 13 and figure 11, we can see the smaller portfolio gives an higher return and Sharpe ratio, smaller volatility and maximum draw-down. The possible reason is that the smaller portfolio performance is more relevant to our macro-economic factor and the deleted stocks coincidentally perform less well than the rest.

7.4 Best Model

From Section 7.2 table 12, we have selected the best way, static factor selection, to build the sensitivity matrix. From Section 7.3, we understand the smaller stock pool can give us even better performance. Here, we want to apply this matrix to the smaller portfolio to see under the smaller portfolio whether the new sensitivity matrix can give us a better performance.

Table 14: Strategy Summary Statistics - Static Factor Selection with smaller portfolio

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Smaller portfolio 5 Factors	9.08%	13.01%	0.71	19.19%
Full portfolio 9 Factors	8.14%	13.92%	0.61	34.99%
Benchmark	10.46%	17.41%	0.65	48.73%

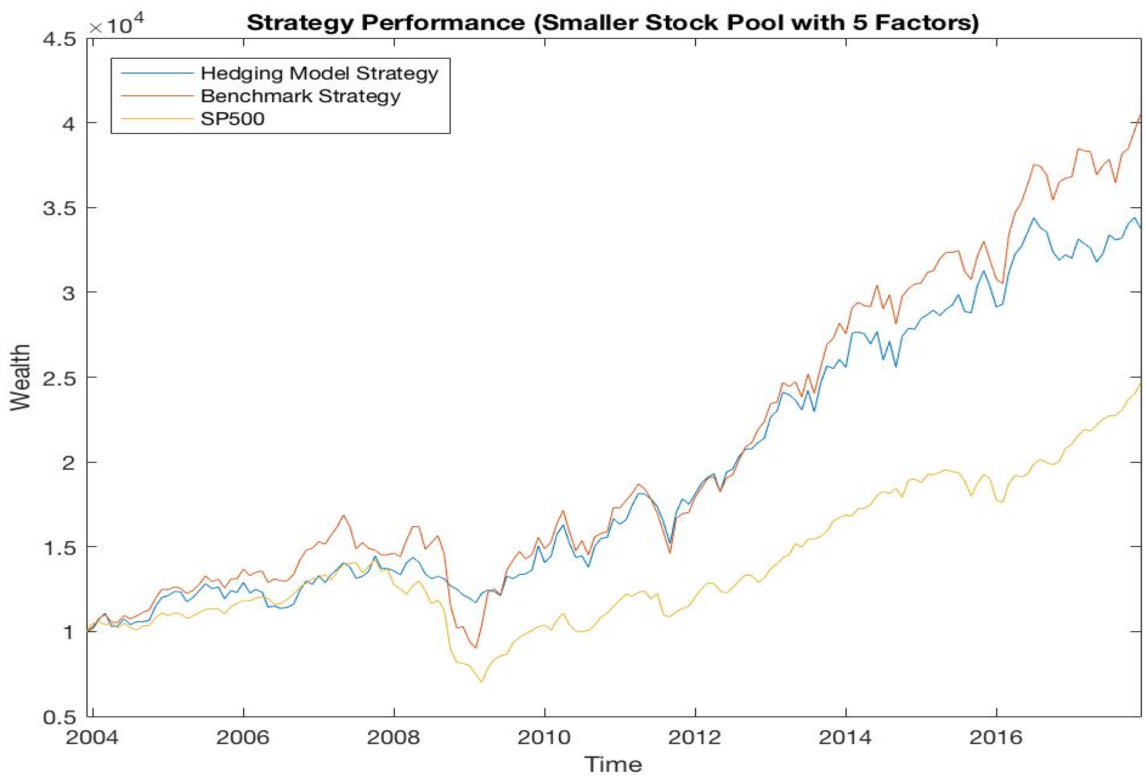

Figure 12: Strategy Performance (Smaller Stock Pools with 5 Factors)

From table 14 and figure 12, we can see under the smaller stock-pool (19 stocks) with static 5 factors (average weekly hours, S&P 500, new orders for capital goods, consumer sentiment and new orders for consumer goods) strategy, our portfolio give the best results. Though with a slightly higher volatility, our final strategy gives a higher annual return and significantly smaller maximum draw-down than the benchmark portfolio. It is clear in Figure 12, our portfolio was only slightly affected by the 2008 Financial Crisis and have a higher return than the benchmark portfolio. We can finally conclude this hedging strategy is **successful**.

8 Conclusion

The second project is an updated version of the first project. We changed the lagging macro-economic indicators from project 1 to leading indicators and switched the optimization constraints from minimizing variance to expected shortfall. The result of leading indicators portfolio didn't show much improvement; our macro-hedging strategy still under-performs the benchmark portfolio — the equally-weighted value portfolio, in terms of both return and volatility. The performance of our macro-hedging strategy was improved significantly compared to the old model when the warning system is implemented though, especially during 2008 financial crisis where the maximum draw-down is improved greatly. However, the overall portfolio's Sharpe ratio is still less than that of benchmark portfolio.

We then designed two methods to improve our portfolio performance. One is to only hedge the macro-economic factors that have significant explanatory power, which is based on the p-values. In addition, we explored the change in portfolio performance if we dynamically select macro-economic factors to hedge. Both the static version and dynamic version of selective macro-factor hedging model performs almost the same as the basic macro-factor hedging model in terms of Sharpe ratio. While they have smaller maximum draw-down than the benchmark, both models still under-perform the benchmark value portfolio in terms of Sharpe ratio. The other method is to reduce stock pool to only include stocks that have significant betas to macro-economic factors. The strategy with smaller stock pool actually increased the Sharpe ratio and decreased the maximum draw-down sharply.

Lastly, we combined the small stock pool with the static factor selection method and get a portfolio that performs the best and beat the benchmark value portfolio in both Sharpe ratio and maximum draw-down. Thus, we concluded that a moderately concentrated value portfolios with significant macro-economic factors to hedge performs the best.