Cornell University

ORIE 5370 Project 1

Value Oriented Macro Factor Hedging Model

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Abstract

Fundamental and macroeconomic factors provide useful insights in predicting the future returns of stocks. This project leverages fundamental factors to select a pool of value stock candidates and then optimize the stock weight allocation by hedging exposures to different macroeconomic factors through Markowitz portfolio theory. The results shows that value oriented fundamental factors can effectively select stocks that can outperform market. However, the stock allocation by macro hedging through OLS regression cannot give further improvement to our strategy.

Contents

1 Introduction

The classical CAPM model allows people to predict stock return based on the risk-free rate and the stock's market risk exposure. At the same time, it allows people to construct a portfolio to hedge market risk exposure and obtain an absolute return portfolio. However, empirical results suggest that CAPM's single factor model is not enough, since it fails to compensate other risks. Hence our strategy leverages multi-factor macroeconomic models as basis to derive each stock's exposure to different macro-factors and hedge unfavorable factors if they are at historical dangerous level using optimization methods.

There are two phases of our value oriented hedging strategy. The first step is to pick valuable stock from a stock-pool which is based on the value index that we assigned to it. We define risks not just by stock volatility but also think the fundamentals of underlying companies are equivalently important. To truly reduce risk, we should select companies with comparably good historical financial performance and currently valued at fair price. Next, we apply our hedging model according to our analysis on macroeconomic factors' historical influence on our selected stocks and benchmarks. Macroeconomics explain a lot of movement of the general stock market because they are indicators of the overall health of the economy. Our multi-factor model separates each stock's risk exposure to different macro-economic variables and then combined with historical scrutiny of the effects of these variables on the stock market, the goal of our model is to selectively hedge the unfavorable ones, which is expected to generate more stable results compared to unhedged portfolio.

Eventually, we aim to minimize our risk and maximize return by both selecting fundamentally solid companies and constructing a portfolio that hedges negative macro-economic influence.

2 Stock Pool

2.1 Fundamental Factors

Fundamental factors are company specific data or ratio that are directly observable from companies' financial disclosures, or computable using companies' market information. These factors contain many information regarding companies recent and historical performance. In this project, they are used as a filter for selecting companies that are financially healthy. Since fundamental data tends to vary between different industries, we only compare fundamental variables of different companies in the same industry. We choose fundamental variables from four major perspectives: valuation, profitability, growth and solvency.

1. Valuation Factors

   - Price to Earnings Ratio

     The price to earnings ratio is calculated by dividing company's market price per share by the earnings per share. In essence, the price-earnings ratio is the amount of dollars investors need to pay in order to receive 1 dollar of company's earning. It is a price multiple measuring the expensiveness of the stock. However, it also measures the market participants' view of the growth and risk of the underlying stock (Chan et al., 2003; Wu, 2013). Here, we define low P/E to be better and gives the largest score to companies with lowest P/E.

     $$\frac{P}{E} = (1+\frac{1}{r}) + (\frac{\sum_{i=1}^{n} AB_i}{(1+r)^i} - \frac{AB_0}{r}), \text{ Where } AB_i = (ROE_i - r)B_{I-1}$$

   - Price to Book Ratio

     The price to book ratio is calculated by dividing the company's market price by the book value, which is the value of stockholder's equity. The intrinsic P/B value is a measure of company's return of equity (ROE) versus its cost of equity (Re). If the ROE is smaller than Re, then the P/B value are expected to be smaller than 1. A high ROE compared to Re suggests a high P/B ratio. Here, we view a low P/B ratio as good indicator and assign the low companies with low P/B with high scores, because low P/B suggests a low valuation, and the intrinsic P/B might be larger than market P/B.

     $$\frac{P}{B} = B_0 + \sum_{j=1}^{n} \frac{(\mathrm{ROE}_j - r)B_{j-1}}{(1+r)^j} + \frac{(\mathrm{ROE}_n - r)B_{n-1}}{r(1+r)^n}$$

2. Profitability Factors:

   - Return on Equity

     Return on equity is the amount of net income returned as a percentage of shareholder's equity. It measures company's profitability by measuring the amount of profit the company can generate with the money equity shareholder invested. Generally, this ratio varies greatly with different industries and due to economic gravity, the ROEs of companies from the same industry are likely to converge. In our project, we think high ROE is good and we assign largest score to company with highest ROE.

     $$ROE = \frac{\text{Net Income}}{\text{Stakeholder's Equity}}$$

   - EBIT Margin

     EBIT stands for earnings before interest, tax. It is often known as operating margin of companies, which measures the companies' profitability from major operating activities. We think the higher the number the better the company.

3. Growth Factor: EPS Growth

   We use earning per share growth rate as the companies' growth rate. High growth rate from companies' revenue will eventually reflect in high EPS growth rate if the growth rate is generic. Thus, we assign high score to companies with high eps growth rate.

4. Solvency Factor: Interest Coverage Ratio

   Interest coverage is calculated by dividing companies' earnings before interest, tax, depreciation, and amortization to its current portion of interest. It measures the ability of the company to fulfill its short-term liability. The higher the ratio, the healthier the company's financial is.

2.2 Stock Pool Building

2.2.1 Ranking System

We used Quantopian to find the best stocks across all the sectors as the components of risky asset in our portfolio. This selection process is based on a scoring system.

In a Stock Pool with 1267 tradable stocks (with complete financial data available from 2003 to 2017), we will **rank** them according to fundamental factors that are introduced in section 2.1. For example, we can rank these 1267 stocks based on their ROE: The higher the ROE, the higher the rank of the stock is. The stock ranks the first in ROE will get 1267 points and the stock ranks the last in ROE will get 1 point. The reason why we rank the stock based on factors separately instead of adding them up is mainly because different factors have different unit, and we do not want our selected stocks affected by those different scales. We rank all the 1267 stocks similarly based on the other factors. Hence, at the end of the ranking mechanism, we have a total of 1267 scores of these 1267 stocks respectively. Among them we will pick the best stocks with the highest total scores that across all the 11 sectors(defined by quantopian who get the data source from Morningstar).

Table 1: Number of stocks in stock Pool of all Sectors

Sector	Number of Stocks
Basic Materials	78
Consumer Cyclical	223
Financial Services	130
Real Estate	64
Consumer Defensive	81
Healthcare	153
Utilities	64
Communication Services	24
Energy	76
Industrials	162
Technology	212
Total	1267

The number of stocks we choose in each sector is based on the proportion of how many stocks in each section among the 1267 stocks. For example, we want to build a portfolio with 1 risk free asset and 30 risky asset(stocks). Among those 1267 stocks, sector "Basic Materials" has 78 stocks, then we will choose $30 \times \frac{78}{1267} \approx 2$ stocks. In this way, we found in total 30 stocks across 11 sectors. However, 4 out of 30 has missing data from Year 2000 to Year 2003, which cannot be used for regression in our model, hence we only take **26 stocks** in total as our portfolio's risky asset.

2.2.2 Stock Pool

Table 2: Risky Assets in Portfolio

Sector	Stock ID	Stock Name
Basic Materials	LPX	Louisiana-Pacific Corporation
	MTH	Meritage Homes Corporation
Consumer Cyclical	DHI	D.R. Horton, Inc.
	FINL	The Finish Line, Inc.
Financial Services	STC	Stewart Information Services Corporation
	RNR	RenaissanceRe Holdings Ltd.
	FBC	Flagstar Bancorp, Inc.
Real Estate	RWT	Redwood Trust, Inc.
	CLI	Mack-Cali Realty Corporation
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.
	CAL	Capital & Regional Plc
	FCN	FTI Consulting, Inc.
	DLX	Deluxe Corporation
Technology	INGR	Ingredion Incorporated
	CMTL	Comtech Telecommunications Corp.
	ORCL	Oracle Corporation

These stocks are the building blocks in our portfolio. From Bloomberg, we find the daily last price from Jan 2000 to Dec 2017, and for the sake of convenience in rebalancing our portfolio, we use the closing price of each month to construct monthly rebalancing strategies in our model.

In the next chapter, we will talk about how to use Markowitz Theorem to allocate weights to these stocks.

3 Hedging Model Building

3.1 Macro-Economic factor

3.1.1 Rationale

Macroeconomic factors are general factors that exert effects on the entire stock market. It provides insights on how the economy is doing and have been used by many traders as trading parameters. It is frequently updated monthly or quarterly and are measured by government agency or professional organizations. We have picked 8 macroeconomic factors that have historical demonstrates to be influential on the stock return, as indicated below:

1. CPI Growth Rate: The growth of consumer price index is a measure of inflation of the country. It is calculated from the weighted average price of a basket of consumer goods. When this rate is too high, it signifies a "too-hot" economy and will typical result in

2. GDP Growth Rate: Gross domestic production (GDP) measures the sum of the value of goods and service produced within a fiscal year and the growth of GDP is an indicator of the rate of economy development.

3. 10-year Treasury Rate: Also known as the benchmark rate in the bond market. It is the annual yield of the 10-year treasury bond. The 10 year treasury is often viewed as the opportunity cost for stock market and compared to forward E/P of current stock market. A High 10-year treasury bond rate signifies a high opportunity cost and subsequently diminishes the equity market participants.

4. Unemployment Rate: Unemployment rate is the amount of people unavailable to find a job versus the total number of job participants. This number is an indicator of the current economy strength.

5. Dollar Index: Dollar index is an index of value of United States relative to a basket of foreign currency. The index goes up when the U.S dollar gain strength relative to other currencies.

6. VIX It is the ticker symbol for volatility index listed on Chicago Board Option Exchange. It shows market participants' expectation of 30-day volatility. It is often used as the gauge for investors' fear.

7. Federal Fund Rate: This is the rate that bank charges each other to lend the federal reserve overnight. It is set by Federal Open Market Committee where it takes account of the overall economy condition. In general, this is a tool that the Fed's used to achieve its two primary goals, targeted inflation rate and targeted unemployment rate.

8. S&P500: We use S&P500 index to represent the market risk.

3.1.2 Data Selection

We import the Macro-Economic Factor data from Bloomberg, and for the sake of monthly rebalancing, we only compute the monthly data from Jan 2000 to Dec 2017. For the daily data like SP500, VIX index and dollar index,etc, we can compute the monthly average as the value for each month. For the quarterly data like unemployment rate, we can impute the following 2 months' data by the former quarterly data. For the monthly data like CPI, we can remain them unchanged. Then, we calculate the factor returns as the factor value for each month.

Below is a peek of our data look like in Year 2000 and 2001, and the value in the table are factor returns.

year	month	cpi	gdp	federal func	10yr	sp500	UNRATE	dollar index	vix
2000	1	0.00296209	0.071	0.0496369	0.0608859	-0.0021685	0	-0.0016991	0.04706462
2000	2	0.00413467	0.071	0.03367609	-0.0199767	-0.0257519	0.025	0.01258847	0.01695974
2000	3	0.00588235	0.012	0.02211217	-0.0418918	0.03840452	-0.0243902	-0.0001153	-0.0371782
2000	4	-0.0005848	0.012	0.02353747	-0.0423897	0.01327281	-0.05	0.00563303	0.19569938
2000	5	0.00175541	0.012	0.04465032	0.07408671	-0.0293397	0.05263158	0.02201877	-0.0291203
2000	6	0.00584112	0.078	0.0432824	-0.0520994	0.03065222	0	-0.0101148	-0.1832612
2000	7	0.0029036	0.078	-0.0047401	-0.007625	0.00755384	0	0.00248434	-0.0764624
2000	8	0	0.078	-0.0024379	-0.0361287	0.00845604	0.025	0.00688743	-0.0907005
2000	9	0.00521135	0.005	0.0018287	-0.0067306	-0.0117164	-0.0487805	0.01160025	0.08838693
2000	10	0.00172811	0.005	0.00113666	-0.0089123	-0.0530702	0	0.01456936	0.28
2000	11	0.00172513	0.005	0.00021904	-0.005445	-0.0108675	0	0.00814806	0.04693878
2000	12	0.00229621	0.023	-0.0110118	-0.0850751	-0.0320764	0	-0.0082096	0.00559617
2001	1	0.00572738	0.023	-0.0664408	-0.0129143	0.00352956	0.07692308	-0.0011629	-0.0607576
2001	2	0.0022779	0.023	-0.085414	-0.0106929	-0.0223689	0	0.00590909	-0.0604767
2001	3	0.00056818	-0.011	-0.0339467	-0.0423242	-0.0918257	0.02380952	0.01630409	0.21721043
2001	4	0.00170358	-0.011	-0.0953915	0.0523806	0.00336257	0.02325581	0.00770051	-0.0127319
2001	5	0.00510204	-0.011	-0.1209004	0.04651734	0.06768247	-0.0227273	-0.000937	-0.1844711
2001	6	0.00225606	0.021	-0.0662575	-0.0212378	-0.024919	0.04651163	0.0065459	-0.087326
2001	7	-0.0016882	0.021	-0.0431429	-0.0096751	-0.0276604	0.02222222	0.00327396	0.06569642
2001	8	0	0.021	-0.0327949	-0.0476092	-0.0215396	0.06521739	-0.0163625	-0.0203642
2001	9	0.00394589	-0.013	-0.1907277	-0.0467325	-0.1135859	0.02040816	0.00271573	0.603959
2001	10	-0.0028074	-0.013	-0.1546408	-0.0389911	0.03058117	0.06	0.00666881	-0.0668475
2001	11	-0.0005631	-0.013	-0.1574128	0.01734496	0.04931578	0.03773585	0.00424083	-0.186128
2001	12	-0.0005634	0.011	-0.1387571	0.09155817	0.01349641	0.03636364	0.00092521	-0.1093071

Figure 1: Year 2000 & 2001 Macro Data

3.2 Model Building

3.2.1 Linear Regression

Now we have the monthly data of 26 stocks and 8 Macro factors. We run the linear regression to find how does the macro factors affect each of our stock's return, i.e. the sensitivity of our stock return to the macro factors. Here, we use 4-year data, i.e. 48 months to run the regression. For example, let $r_{j,1}$ be the return of the first stock in month j, where $j \in [1:48]$, and let a 48×8 matrix $X_{j,k},\ k \in [1:8]$ store the values of the 8 macro factors in these 48 months. we want to find $\beta_{k,1}$, the **sensitivity of the first stock's return to those eight macro factors**. Mathematically, we can express the above example as $\tilde{\mathbf{r_1}} = \mathbf{X} \times \tilde{\beta_1} + \epsilon_1$

$$\begin{pmatrix} r_{1,1} \\ \vdots \\ r_{48,1} \end{pmatrix} = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,8} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,8} \\ \cdots & & & \\ x_{48,1} & x_{48,2} & \cdots & x_{48,8} \end{pmatrix} \begin{pmatrix} \beta_{1,1} \\ \vdots \\ \beta_{8,1} \end{pmatrix} + \epsilon_1$$

The above expression give us the estimate of the sensitivity of the first stock i.e.$\vec{\beta_1}$ to the macro factors. In the same way, we can find the other βs, $\vec{\beta_2} \cdots \vec{\beta_{26}}$ as well. Then, we combine the estimate of sensitivity vectors β to a 8×26 matrix as our **Sensitivity Matrix** $\mathbf{B_{ki}}$, $i \in [1:26]$, which is one of the most important building block of the hedging strategy, where k denotes the kth macro factor and i denotes the ith stock.

To be more specific, let say from Year 2004 onwards, we will test our portfolio return and rebalance it according to its performance relevant to the macro factors. Here is the method to update the sensitivity matrix: we update our data matrix X in every rebalance day: remove the first row(Jan 2000) and add a new row(Jan 2004). At the same time, we will also update **return vector r**. Hence at Jan 2004, we will have a new Sensitivity Matrix B_{ki}, and so on and so forth. In this way, we create a **dynamic** sensitivity matrix used for portfolio hedging.

3.2.2 Hedging Strategy

We are going to apply the Markowitz Theorem to our Hedging Strategy. We regress each stock in the stock pools against the macroeconomic factors to obtain its exposure to each macroeconomic factor. In addition, we obtain SP 500's exposure to these macroeconomic factors and set it as our benchmark exposure. Then we apply Markowitz method to find the weight of our stock by setting constraint with respect to the benchmark exposure.

To better measure the performance of our strategy, we will set a benchmark portfolio and we will track our performance relative to the benchmark portfolio performance. Here for simplicity, in the benchmark portfolio, we will assign equal weight to every component in the portfolio, i.e. both risk free and each risky asset will take $\frac{1}{27}$ portion of the portfolio. Note that while we rebalance our portfolio, the benchmark portfolio will be rebalanced at the same time, since the benchmark portfolio's return and wealth are keeping changing as well.

The objective is still to maximize the portfolio return. We have several modified constraints:

- The overall risk is still bounded by some scale of the benchmark portfolio risk.
- 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**.

Transaction costs is relevant as our portfolio is being rebalanced rather than built from scratch. High transaction costs are an incentive for changing the portfolio less than if there were no transaction costs. If, for example, trans cost = .015, then for each additional unit of wealth invested (or divested) in a risky asset, there is a charge of 1.5%. Although it would be more realistic to have different transaction costs for different assets, for simplicity, we assume the same transaction cost applies to all assets.

Table 3: notation for mathematical expression of the linear programming

μ_0	the risk-free rate
μ	the vector of expected returns for risky assets
$\mathbf{V}$	the matrix of return covariances 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

We are going to use Markowitz Model to calculate the weights of risk free and risky asset in our portfolio.

$$
\begin{aligned}
\underset{x0,x}{\text{maximize}} \quad & \mu_0 x_0 + \mu^T x \\
\text{subject to} \quad & x^T V x \leq \text{allowable\_risk \_multiple} \times \text{benchmark\_ portfolio\_risk} \\
& x_0 + e^T x + \text{total\_trans\_cost} = 1 \\
& x = xx + y \\
& \text{trans\_cost} \times \sum_{i=1}^{n} |y_i| \leq \text{total\_trans\_cost} \\
& x_0 \geq 0 \\
& |x_i - \frac{1}{n+1}| \leq 0.05, \;\; i = 1 \rightarrow n \\
& |B \times x| \leq cz
\end{aligned}
$$

Explanation:

1. Our objective is to maximize our portfolio return, both from risky and risk free asset.

2. Allowable risk multiple is the level of risk relative to the benchmark portfolio, where risk is measured as standard deviation of portfolio returns. Here we choose this value to equal 1, means exactly the same amount of risk is allowed.

3. The proportion of risk free, risky and total transaction cost will sum to 1.

4. Here we create a new vector of variables y, which represent the changes to the portfolio. For example, the amount in the the first stock, LPX, after rebalancing will be xx(1) + y(1).

5. Instead of taking the strictly equal sign in the fourth constraint, we will put a $\leq$. This is because the left hand side of the transaction cost equation is a convex function and CVX will accept the formulation if the equality is replaced by an inequality $\leq$.

6. We also assume we will not borrow money to leverage our portfolio, so $x_0 \geq 0$.

7. Furthermore, we assume we will not change too much on the weight of each asset in the rebalance process, arbitrarily, we set maximum changing amount per risky asset per rebalance as 0.05.

8. The last constraint is the core of our hedging strategy. Matrix B is the sensitivity matrix mentioned in section 3.2.1, vector x is a vector of weights of all 26 risky assets in our portfolio, and vector z is a vector of **expected exposure** of our portfolio under these 8 macro factors. Hence, in Matrix form, we can express our last constraint as:

$$\begin{pmatrix} \beta_{1,1} & \beta_{1,2} & \cdots & \beta_{1,26} \\ \beta_{2,1} & \beta_{2,2} & \cdots & \beta_{2,26} \\ \cdots & & & \\ \beta_{8,1} & \beta_{8,2} & \cdots & \beta_{8,26} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{26} \end{pmatrix} \leq c \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_8 \end{pmatrix}$$

The product of the **Sensitivity Matrix B** and **Portfolio Weight Vector x** on left hand side of the inequality is the vector of the **total exposure** of our portfolio under **each 8 macro factors**. Since we only want to hedge the exposure of the macro factors to our portfolio, it is not important to care the positive or negative of the exposure, that is why we add an absolute sign. Right hand side of the inequality is the product of a constant c and **Benchmark Exposure Vector z**. Here, c is the allowable proportion of the benchmark exposures to our macro factors. As mentioned earlier, the simplest benchmark portfolio is the one that contains equal weight of both risk free and every component of risky asset. Hence, in the benchmark setting, $x_1, ..., x_{26}$ are equal to $\frac{1}{27}$. Then, for example, $z_1 = \frac{\beta_{1,1} \times x_1 + \beta_{1,2} \times x_2 + \cdots + \beta_{1,26} \times x_{26}}{27}$.

As we have mentioned in section 3.2.1, as time progress, we will **update** our Sensitivity Matrix **B** and we also will update the Benchmark Exposure Vector **z** accordingly, since the component of z is the average of each row in sensitivity matrix. By doing this, we find a <u>dynamic</u> Portfolio Weight Vector **x** that can be used as a reference to our portfolio rebalance. Of course, here, we assume the constituents in our portfolio remain the same and we only update the weights assigned to them.

4 Portfolio Backtest Performance

We backtested our model on the period from January 2004 to December 2017 to check the performance of our model. Furthermore, to analyze how our hedging model performs in different market regimes, we tested our model in different sample periods.

4.1 Full Sample Backtest Results

First, we set $c = 1$, that is, the macro exposure upper constraint is the same as the benchmark exposure. Following is the performance and summary statistics from Jan 2004 to Dec 2017 of our hedging model strategy and benchmark strategy. It turns out that our hedging portfolio's performance does not match our expectation, and even worse than the benchmark portfolio.

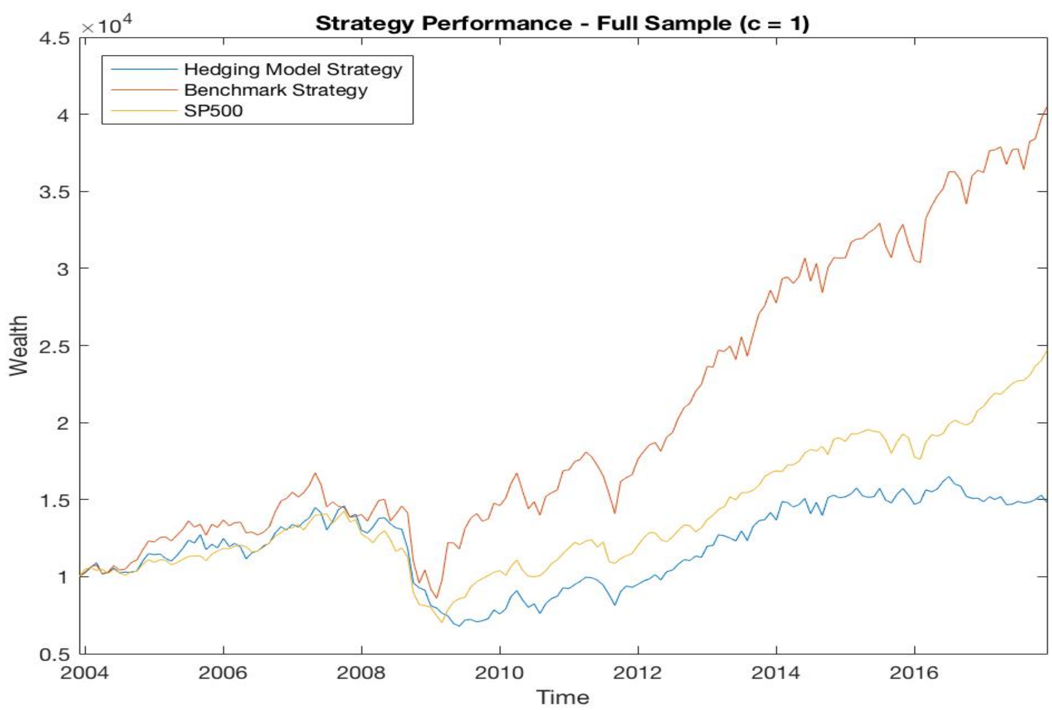

Figure 2: Strategy Performance - Full Sample

Table 4: Strategy Summary Statistics - Full Sample

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Hedging Model	2.85%	14.64%	0.19	53.55%
Benchmark	10.51%	17.41%	0.60	48.68%

From the plot, We can see that our hedging strategy performs quite closely to the benchmark strategy (equal-weighted strategy) from Year 2004 until 2008. During the period of financial crisis in 2008, It seems the hedging cannot help us hedge the downturn risk, and it may even escalate the losses. After 2009, comparing to the upward shape of the benchmark strategy, its performance is rather at a constant level.

Overall, the benchmark strategy performs relatively strong throughout the whole period. More than 10% annual return with 0.6 Sharpe ratio shows that the fundamental factors we chose have excellent ability to select stocks that would outperform the market, as it can beat the SP500 index dramatically. Even in the 2008 Financial Crisis, the maximum drawdown, which is the difference between the peak and trough from that period, is less significant to our hedging portfolio.

In order to see whether our macroeconomic risk hedging is actually reducing risk in our portfolio, we try to change the allowable proportion of exposure c, and see how our hedging strategy performs under different exposure limits. The following table is the result.

Table 5: Comparing models with different exposure limits

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Hedging Model(c=0.1)	-1.19%	7.55%	-0.28	41.52%
Hedging Model(c=0.5)	3.27%	10.87%	0.24	46.19%
Hedging Model(c=1)	2.85%	14.64%	0.19	53.55%
Hedging Model(c=1.5)	0.39%	15.90%	0.03	64.39%
Hedging Model(c=2)	1.13%	15.70%	0.08	62.96%
Hedging Model(c=2.5)	1.11%	15.58%	0.08	62.44%
Hedging Model(c=3)	1.14%	15.49%	0.08	62.45%
Benchmark	14.30%	11.18%	0.97	7.18%

The table shows that when c is set to either small or large value, the hedging would have even poorer performances. That means strict and loose constraints on the macroeconomic exposures would lead to over-hedge or under-hedge, both of which would worsen strategy performance.

4.2 Sub-sample Backtest Results

Considering the financial crisis in 2007 and 2008, in which stocks' returns may change their exposure to macro factors dramatically so that our regression results of the macro factor exposure may become unreliable, and actually, during that period, there is almost no good model can explain the financial trend. Thus, we focus on comparing the following two backtest period:

1. Sample before Crisis: January 2004 - June 2007

2. Sample after Crisis: January 2009 - December 2017

4.2.1 Sample Before Crisis

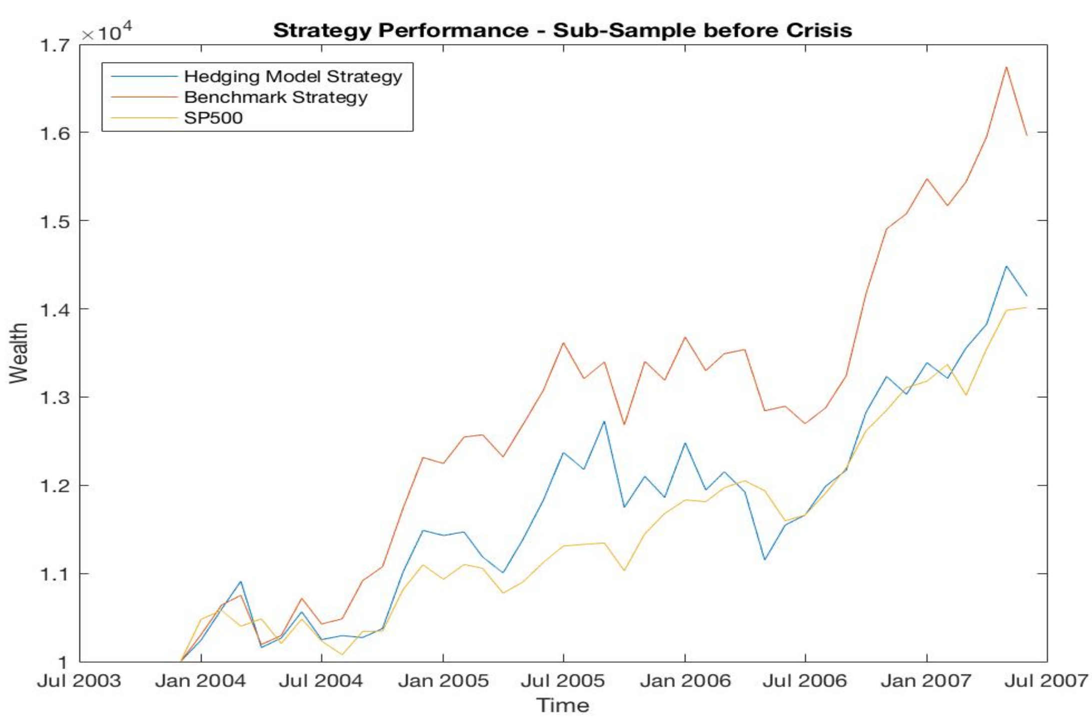

Figure 3: Strategy Performance - Sample before Crisis

Table 6: Strategy Summary Statistics - Sample before Crisis

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Hedging Model	10.41%	11.83%	0.63	12.39%
Benchmark	14.30%	11.18%	0.97	7.18%

It seems our hedging portfolio performs neck by neck with the benchmark portfolio, with the similar return and the sharpe ratio. This indicates, indeed, our strategy is theoretically reasonable and practically feasible, at least in 10 years ago.

4.2.2 Sample After Crisis

Following is the performance and summary statistics of our hedging model strategy and benchmark strategy after Crisis.

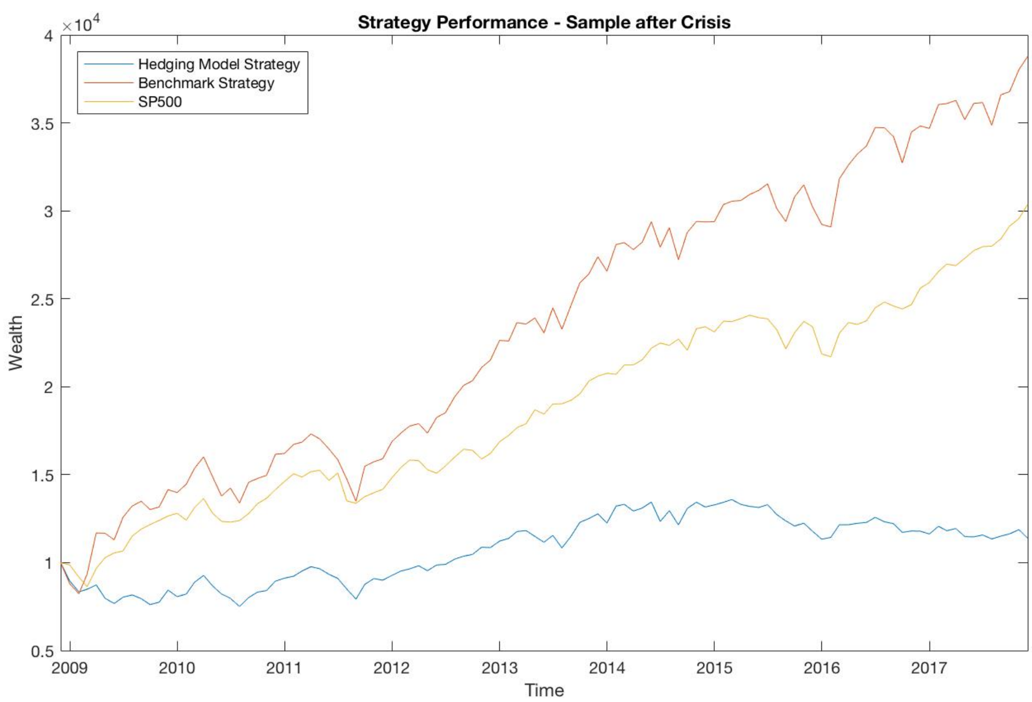

Figure 4: Strategy Performance - Sample after Crisis

Table 7: Strategy Summary Statistics - Sample after Crisis

	Annual Return	Volatility	Sharpe Ratio	Maximum Drawdown
Hedging Model	1.46%	13.91%	0.16	24.96%
Benchmark	16.25%	17.25%	0.95	22.13%

When we consider the period after 2009, we can see that our hedging strategy has an extremely low return, compared to the benchmark portfolio, although our portfolio has a slightly low volatility. One reason to explain this is the economy recovery after the Crisis. All the macro factors indicating a bullish market, hence, if we hedge most of exposures to these macro factors, our hedging strategy may not catch the bullish trend of the market.

5 Further Discussion

Hedging Threshold Setting

Instead of setting the exposure constraints of every macro factor to be the exposures of the equal-weighted portfolio, we might blend our market perspective and prediction into our exposure constraint setting. We will build a threshold model. Instead of finding beta for each of the macroeconomic factor, which might cause multicollinearity issues and boost the error rate, we categorize the risk into fundamental economy risk, credit risk, interest rate risk, and liquidity risk. We choose our current macroeconomic factors that are leading factors as parameters for the likelihood for these risks. The threshold model gives us the likelihood of occurrence of these four risks. If the likelihood of that risk is reached certain level, we simply set the overall exposure to this factor factor as 0. However, this requires we model the threshold model correctly as the entire effectiveness of the strategy relies on it. In addition, it is rather subjective to choose the hedging likelihood level, so apart from our knowledge and perspective to the market, we would rather perform this strategy on a range of likelihood and check the performance to select a best level.

More Accurate Estimates of Sensitivities

One possible reason for the poor performance of our hedging strategy is that it is difficult to predict the stock return sensitivities to different macroeconomic factors. These sensitivities may change unpredictably. Hence, the regression estimate of sensitivities using historical data may not be useful to predict the future sensitivities, and our hedging model may overestimate or underestimate the exposures to the macroeconomic factors. Therefore, in the future work, we might consider using more complex and accurate model to estimate these sensitivities to macro factors.

6 Conclusion

Value stocks outperform extremely well in the long run. In fact, according to Bloomberg's historical major factor return, value factor has on average 148 percent of return while all other types of factors have below 10 percent of return over 20 years' investment span. Our project corroborates this result. Our value portfolio has exhibited 400 percent return from 2004 to 2017, with maximum drawdown of 7.18 percent and a Sharpe ratio of 0.97. This value (benchmark) portfolio has almost outperformed SP 500 and our hedging portfolio entire times, before, during and after the 2008 financial crisis.

Our hedging portfolio didn't perform as expected. During 2008-2009 (Figure 2), our portfolio outperformed the SP 500, but this will not likely be attributable to our hedging strategy, but rather it's because the value stock effect as the hedging strategy underperformed the unhedged value benchmark portfolio. The theory is that by hedging macroeconomic risks, our return during economic recovery will be smaller than unhedged portfolio because of the exclusion of risks and so is the corresponding risk compensation, but during financial crisis, the portfolio should outperform the benchmark by a huge extent. We have failed to achieve this goal and very likely is because of multicollinearity effect and the lagging indicator effect that resulted erroneous beta estimates and wrong hedging allocation. We included SP500 to estimate the market risk. However, all of our other factors, including unemployment, dollar index, treasury rate, etc., can also be considered as market risk; therefore, creating a significant likelihood of multi-collinearity. In addition, unemployment, GDP growth rate are all lagging factors, which can also explain the unsuccessful hedging results. In the future, we proposed a threshold setting model (in Further Discussion section) and introduced the four mutually exclusive categories of major macro-economic risk that won't have severe multi-collinearity effect as revision to our current model. Eventually, we hope the hedging portfolio outperform the benchmark portfolio during 2008 financial crisis and maintain comparable growth to benchmark portfolio when our hedged model doesn't detect significant macro-economic risks, in which our hedged portfolio become unhedged and maintain a beta exposure the same as the value benchmark portfolio.

The divergence between our hedging portfolio and the value portfolio (and SP500) after 2016 confirmed that the hedging portfolio need a switch which makes it able to choose when to hedge and when not, because otherwise it might over hedge frequently. To explain the divergence, the current hedging model does hedge federal fund rate, and this rate started to increase at Dec 2015. That increasing trend triggered our hedging model to hedge the interest rate in a wrong way. The interest rate raise should not propose a significant threat to stock market as the bond yield is low. That means we need to consider multiple macroeconomic factors at the same time rather than look them individually. Therefore, we believe a threshold model will be useful in helping us to achieve the initial objective.