FINANCE 772/442
Student – Managed Investments
Spring 2016 Report
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I. Investment Policy Statement

A. PURPOSE
The objective of the course is to provide students the opportunity to expand their knowledge of finance and investments through hands-on experience in investment research, valuation analytics, portfolio management, and financial consulting. The advanced curriculum will expose students to the decision-making process used in design of professionally managed investment portfolios, especially with respect to the analysis and selection of investments needed to achieve particular investment objectives. The program will combine classroom pedagogy and out-of-class research, which will provide students with practical experience in an area that is of considerable interest to both students and their prospective employers.

B. STUDENT PARTICIPATION
Students will help establish investment objectives, including targeted asset allocations and appropriate benchmarks to evaluate performance. They will make decisions concerning the composition of the portfolio based on evaluations of such factors as economic expectations, industry growth, and fund-specific characteristics, including return/risk relationships, the potential for growth, and portfolio strategy and structure. Based on their analyses, students will communicate, implement, and monitor the investment strategies that they develop. Students will receive no monetary compensation for participation in the class.

C. SELECTION OF STUDENTS
Students will apply for admission to the course by submitting a resume and potentially sitting for an interview, and the faculty member coordinating the class will select the qualifying participants. Students will be recruited primarily from the Moore School of Business graduate programs. The class will consist of between 10 and 15 students. Selection will be based on the student’s academic background, career goals, prior finance experiences, and overall motivation.

D. OPERATION OF THE FUND
The Supervising Faculty Member has the authority to approve or reject the asset classes, to determine the general allocation of funds within these classes, to accept the specific securities traded, and to execute trades. The students have the authority to manage the Fund and to approve trades within established allocation guidelines. Initially, the operating guidelines, which can be amended, will be as follows:
1. Fund proceeds are provided by the Business Partnership Foundation of the Moore School of Business. The Fund is designated as a Global Equity Fund for purposes of meeting investment objectives.

2. The principal investment medium will be equities, including, and limited to, common stock, preferred stock, Real Estate Investment Trusts (REITs), mutual funds, master limited partnerships, exchange-traded funds (ETFs), and American Depository Receipts (ADRs).
   a) Securities shall be limited to those traded on highly liquid exchanges such as the NASDAQ and NYSE.

3. The Fund may invest in debt instruments of U.S. entities, either corporate or government.
   a) Such debt shall not be rated lower than the minimum level to be considered investment grade (i.e., Baa or BBB);
   b) Unless, lower-rated or non-rated debt is deemed acceptable by a majority of students and the Supervising Instructor;
   c) Provided appropriate supporting credit analysis has been done and appropriate required documentation provided for consideration.

4. The Fund may not invest in derivatives unless:
   a) The Supervising Faculty Member deems them to be consistent with the investment objectives of the fund, and;
   b) The Supervising Faculty Member and a Majority of Students deem the potential investment to be financially sound in light of the associated risk and the risk of the portfolio as a whole.

E. Selection of Securities
In general, the Fund will be considered a “total return” portfolio. As a result, decisions to include investments in the Fund will be based on total return, without regard to whether the source of the return is principal at sale or maturity, dividends and interest, reinvestment income, or any combination. Because market conditions will differ at different time periods, various analyses and valuation models will be used to help make selection decisions. The following general principles will apply to the selection process:
1. **GROWTH INVESTING:**
Investments will be made in securities that provide reasonable expected returns relative to associated risks, which include securities of firms that are leaders in their industries. Such firms are expected to be profitable, generate sufficient cash flows, and have investment opportunities that result in positive growth.

2. **VALUE INVESTING:**
There may be occasions when investments seem to be undervalued, or out of equilibrium in terms of a “normal” price, relative to existing conditions. Such investments will be selected based on fundamental valuation techniques, including financial statement analysis and industry and economic factors.

3. **ASSET ALLOCATION:**
The portfolio will include assets such that the allocation of funds is across a variety of investment classes. The determination of such investments will be based on risk/return characteristics and how the investments are related to each other (i.e., correlation). The use of style or class-specific mutual funds and exchange-traded funds is acceptable toward meeting targeted allocation weightings.

4. **MARKET SECTOR ALLOCATIONS:**
When implementing a risk-reduction strategy, single sectors of the market will not be limited but will be based on the output of the model. Any market sector allocation weightings are left to the discretion of the Supervising Faculty member and should be considered prior to implementing a portfolio strategy.

5. **REBALANCING:**
There is no restriction on the frequency of rebalancing, though during the spring 2016 semester we aimed to rebalance every 3-4 weeks. Decisions should be based on the goal of maximizing total return within acceptable risk guidelines. Thus, excessive transaction costs should be avoided and decisions should be sensitive to high turnover of the portfolio’s assets. The faculty advisor must approve any policy exception.
F. **STUDENT ASSIGNMENTS**
The Supervising Faculty Member has the authority to organize the portfolio management the way he/she deems productive. The structure and day-to-day deliverables of the course are to be determined by the Supervising Faculty Member. Grading and assignments are left to the discretion of the Supervising Faculty Member. At the end of each year, the team will prepare a presentation for the Business Partnership Foundation and a more detailed annual report of the portfolio’s activities. In addition, the portfolio’s activities will be audited annually. The structure of the end-of-year report will be similar to an annual shareholder report constructed by a publicly traded corporation.

G. **SUPERVISING FACULTY MEMBER**
The Finance Department Chair in consultation with the Dean of the Moore School will select the Supervising Faculty Member. The faculty member’s responsibilities will include: ensuring that the course provides the desired learning experience for students, supervising the program such that the focus is on activities required to operate a professionally managed portfolio, and maintaining appropriate records of investment transactions.

H. **CUSTODIAN & BROKERAGE**
All transactions will be executed through an account in the name of the Fund, which will be held with a custodian firm. Students in the course will neither take custody nor have direct access to the funds invested in the portfolio. Only the Finance Department Chair and Supervising Faculty Member have the authority to execute trades. In the event that this (these) individual(s) is (are) not able to execute trades, one of the Associate Deans of the Moore School of Business is authorized to execute trades.

I. **FEES & COSTS**
No fees will be paid from the Fund to the students, either in cash or in kind. Saving the management fees that would be charged by professional managers will result, incrementally, in a benefit to the Fund and a higher overall return. From time to time, incidental expenses might be incurred that will be considered expenses of the Fund. Those expenses, which will be charged to the Fund, will not be charged to the Fund without the express approval of the Supervising Faculty Member.

J. **REGULATORY COMPLIANCE**
Participants are not considered to be investment advisors or investment counsel, either privately or publicly, as defined by the Investment Advisors Act of 1970 (as amended) or as defined by the state of South Carolina. Individual participants, acting in their capacity as managers and analysts associated with the Fund, are specifically prohibited from using such
descriptions, because to do so might violate state and federal regulations. Participants cannot actively seek additional accounts or individuals’ funds to manage. As such, participants of the Fund are relying on a reasonable interpretation of the de minimus exemption to regulation and are not pursuing registration as Investment Advisors.

K. **AMENDMENTS**

Any change to the investment policy statement requires 3/5 (three-fifths) majority approval by students. However, the Managing Faculty Member has veto power and ultimate decision-making authority.
II. Class Overview

A. HISTORY

The Student Managed Investment Fund has been active for over 15 years but the course was not offered (the fund was not managed) for several years before Dr. Shingo Goto took the role of the Supervising Faculty Member of the Fund in 2011. The course (FINA 772) was limited only to graduate students in the Spring semester. Under Dr. Goto’s instruction and guidance, students conducted research to develop a unique investment model and a systematic/disciplined investment process in Spring 2011 and Spring 2012 semesters. The Fund’s first model and process came into live early 2013. This report covers how the Fund has performed with its unique investment model and process since 2013. With the successful implementation of the systematic investment process, Dr. Goto has recently opened the course to undergraduate students (FINA 472) in 2015. In the Spring 2016 semester, students in FINA772 and FINA 472 courses formed a joint team to manage the fund.

B. A SPECIAL THANK YOU

The students of FINA 772/442 would like to give a special thanks to Professor Goto for his incredible effort supporting the Student-Managed Investments class. It is an honor to learn from an expert in the field, who is also passionate about investing. The class is lucky to have had the opportunity to learn from Professor Goto and we wish him the best in his future endeavors.

C. STRUCTURE

The students of FINA 472 (undergraduate) and Finance 772 (graduate) jointly manage the Fund each semester and are organized into three teams: Management, Asset Allocation and Stock Selection. The goal is to provide a similar structure to that of an investment management firm, as opposed to an investment club.

*Image: FINA 772/442 Team Structure
In addition to managing the FINA 772* Portfolio on behalf of the University of South Carolina Business Partnership Foundation, students engage with investment professionals outside of the classroom through monthly Columbia Investment Forum meetings and guest speaker events.

*Note: FINA 772 will be utilized for the remainder of the report for simplicity*

D. TEAM MEMBERS
During the Spring 2016 semester, 12 graduate and 14 undergraduate students managed the Fund under the guidance of Professor Goto.

1. **Supervising Faculty Member**: Dr. Shingo Goto
2. **Management Team**:
   a. Ross Hogan, Graduate Student (Team Leader)
   b. Rick Southard, Graduate Student
   c. Camron Gilstrap, Undergraduate Student
   d. Richard “Alex” Smolen, Undergraduate Student
   e. Lindsay Williamson, Undergraduate Student (Joint appointment with Asset Allocation Team)
3. **Stock Selection Team**:
   a. Rion Cartin, Graduate Student (Team Leader)
   b. Taimour Khan, Graduate Student (Joint appointment with Management Team)
   c. Trey Cherry, Undergraduate Student
   d. Grant Griffin, Undergraduate Student
   e. Chris Hall, Undergraduate Student
   f. Mitchell Learmont, Undergraduate Student
   g. David Stephens, Undergraduate Student
   h. Huihe Zhong, Undergraduate Student
4. **Asset Allocation Team**:
   a. James Carlisle, Graduate Student (Team Leader)
   b. Michael Kirschke, Graduate Student (Team Leader)
   c. Shiwen Shen, Ph.D. Student--Statistics (Portfolio Analytics)
   d. Dhruv Ahluwalra, Graduate Student
   e. Kyle Jansen, Graduate Student (Data Analytics)
   f. Spoorthi Purumala, Graduate Student
   g. Brandon A. Anderson, Undergraduate Student
   h. Bernard Hughes, Undergraduate Student
   i. Gilberto Mandalka, Undergraduate Student
   j. Ryohei Roy Oishi, Undergraduate Student
   k. Chun Kau Wong, Undergraduate Student (Joint appointment with Management Team)
5. **Keeping Up with Academic Finance Research:**
   a. Gerardo Pinto, Ph.D. Student—Finance (Empirical Regularities and Methodology)
   b. Robert Viglione, Ph.D. Student—Finance (Empirical Regularities and Methodology)

E. **TIMELINE**

1. **Week 1:** Student introductions. Students familiarize with SigFig (Portfolio Performance tracking) and Portfolio 123 (Stock Selection tool). Students review existing portfolio holdings and begin to gather data to test effectiveness of current strategies.

2. **Week 2:** Students are placed on teams and identify tasks and research topics for which to engage in over the semester. First Columbia Investment Forum meeting.

3. **Weeks 3-5:** Discussion and evaluation of the core ETF portfolio and stock selection strategies. First rebalancing of portfolio. Teams present their work/research goals for the semester. Guest speaker: Jeffrey Stock from Tenet Wealth Management.

4. **Weeks 6-8:** Ph.D. in Finance students present. Second Columbia Investment Forum meeting. Management Team, Stock Selection Team and Asset Allocation Team interim reports, presenting preliminary findings. Guest speaker: Marc Murray from Wallick Investments.

5. **Week 9:** Spring Break and second rebalancing of portfolio.

6. **Weeks 10-12:** Visit from College of Charleston student-managed investment team. Each group presented their investment process and shared ideas. Third Columbia Investment Forum meeting. Further Ph.D. presentations. Third rebalancing of portfolio.

7. **Week 13:** College of Charleston hosts Strategic Investment Symposium. Students finalize research findings and summarize Q1 2016 performance.

8. **Week 14:** Students make final presentation to members of the USC Business Partnership Foundation and Moore School Finance Faculty.

9. **Week 15:** Students make final presentation to the Columbia Investment Forum. Select-student research presented to members of Nomura Asset Management.

10. **Weeks 16-17:** Final written portfolio report compiled and submitted to Business Partnership Foundation and Finance Chair.
III. Portfolio Performance

A. BACKGROUND & INVESTMENT PHILOSOPHY

Active portfolio management is a difficult endeavor. According to popular measures from *S&P Dow Jones Indices*, in 2015 over 70% of U.S. Equity Mutual Funds were outperformed by their respective benchmark indices. Over a five-year time horizon, performance is even worse - almost 90% of Equity Mutual Funds were outperformed by their benchmarks. The Student-Managed Investments Team researches, tests and implements leading investment strategies from both academics and industry practice with the goal of improving the odds of outperforming the market. The Team also understands that performance can be improved not only through return generation but also through risk reduction. Thus, a key to the FINA 772 Portfolio is the use of asset allocation strategies to minimize portfolio volatility.

We believe financial markets are *largely* efficient and we respect the difficulty in attempting to outperform the market. We do not believe we have better information than other market participants have and therefore do not engage in ad hoc “stock picking” nor attempt to “time the market.” However, we do not necessarily believe that passive index funds are mean-variance efficient. Thus, our implementation of leading strategies can potentially improve odds of generating superior portfolio returns and/or definitely reduce portfolio volatility relative passive index funds. In our endeavor to accomplish this, we follow a scientifically motivated process and rely on data and evidence.

Aside from managing the portfolio, certain students have performed further research on a particular area of the Portfolio or on market indices. In the Appendix (Section VII.) there are 6 student research reports summarizing results from various studies which were completed in the Spring 2016 semester.

B. PORTFOLIO COMPOSITION

The FINA 772 Class manages a global equity portfolio comprised of both Equities and ETFs, all of which are carefully selected and monitored. Our ETF Portfolio as of 4/1/2016 was comprised of 7 total ETFs (4 Sector ETFs and 3 Country ETFs). The ETF portfolio is where we implement Asset Allocation strategies in order to minimize the volatility of portfolio returns.

The stock portfolio is comprised of 50 individual stocks and is the section of the portfolio where we seek to generate excess returns beyond comparable benchmark equity indices. We currently employ 2 stock selection strategies and 35 Equities come from our *High Quality + Low Beta strategy* and 15 Equities come from our *Value + Improved Quality Strategy*.

Using a sports metaphor, it can be stated that the Stock Portfolio represents “playing offense” and the ETF Portfolio represents “playing defense.” About 1% of the Portfolio’s assets are held in cash.
C. BENCHMARKS

FINA772 Portfolio performance is measured against 3 equity indices:

1. **SPY**: S&P 500
2. **IWV**: Russell 3000
3. **ACWI**: MSCI All Country World Index

D. PERFORMANCE

1. **Cumulative Returns**

$1 invested in the FINA 772 Portfolio at the beginning of 2013 would have grown to $1.60 at 3/31/16, more than it would have by investing in any of the 3 benchmark indices.
2. Yearly Returns
The FINA772 Portfolio has outperformed the benchmark indices during the last 3-year time periods outlined in the chart below. The 2013 period (4/2013 – 3/2014) was one of very strong returns for the S&P 500 (21.77%), yet the FINA 772 portfolio returned 23.43% during this time. During the most recent 2015 period (4/2015 – 3/2016) the broader market was largely flat (S&P 500 1.68% return) and the FINA 772 Portfolio still generated a superior return (1.92%). In fact, the FINA 772 Portfolio has outperformed the S&P 500 8 of the last 13 quarters (through 3/31/16).

3. Risk vs. Return
The Portfolio’s annualized return from Jan 2013 – March 2016 was 15.2%, which is greater than the annualized return of each of the benchmark indices (evidenced by the higher position on the y-axis in the chart below).
Additionally, it is essential to measure the standard deviation (volatility) of portfolio returns in order to determine the level of risk taken to achieve returns. A popular measure is the **Sharpe Ratio** (*Excess Return/standard deviation*).

Below is a chart showing *annualized* excess (over the risk free rate) Returns on the y-axis and *annualized* Standard Deviation of Returns on the x-axis, with the corresponding Sharpe Ratio plotted. Investors prefer portfolios to be as far to the upper-left (North West) corner of this chart as possible (highest Sharpe Ratio).

FINA 772 not only has a greater average annual return (15.2%) but also exhibits a lower annualized standard deviation (10.1%) relative to the benchmarks, which all have annualized standard deviations of >11%. Thus, the FINA 772 Portfolio has the highest Sharpe ratio (1.5).

*Chart: FINA 772/442 Sharpe Ratio vs. Benchmarks*

4. **Alpha and Beta**
   Another method to analyze returns is to regress excess (over the risk free rate) return data of the FINA 772 Portfolio against the benchmark indices. The regression results provide popular data points such as **Alpha** and **Beta**. The **alpha** measure is the intercept of the regression result of FINA 772 returns vs. benchmark index returns and tells an investor if a portfolio is in fact beating the benchmark (positive alpha). FINA 772 shows a positive alpha against the S&P
500 and the Russell 3000 during the period from Jan 2013 – Mar 2016. The annualized alpha in the chart below signifies that the FINA 772 Portfolio has outperformed the S&P 500 benchmark by 3.86% per year and the Russell 3000 by 4.47% per year.

**Beta** is a measure of relative volatility of FINA 772 returns when compared to the volatility of the benchmark index returns. The FINA 772 Portfolio exhibits a Beta of about 0.8 relative to the S&P 500 and the Russell 3000, which means that the volatility of FINA 772 returns are less than those of the market indices (Market indices have a Beta of 1). This makes sense given our stock selection strategies, which attempt to select lower-risk, high quality companies with conservative capital structures.

*Chart: FINA 772/442 Sharpe Ratio vs. Benchmarks*

<table>
<thead>
<tr>
<th></th>
<th>FINA 772 vs. SPY (S&amp;P500 ETF)</th>
<th>FINA 772 vs. IWW (Russell 3k ETF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BETA</td>
<td>0.81</td>
<td>0.80</td>
</tr>
<tr>
<td>ALPHA (annualized)</td>
<td>3.86%</td>
<td>4.47%</td>
</tr>
<tr>
<td>Residual St.Dev. (annualized)</td>
<td>4.42%</td>
<td>4.44%</td>
</tr>
<tr>
<td>Info Ratio (IR) (annualized)</td>
<td>0.87</td>
<td>1.01</td>
</tr>
</tbody>
</table>

**IV. Stock Selection**

As previously mentioned, the Stock Portfolio is the area of the portfolio where FINA 772 seeks to “play offense” by generating superior returns relative to benchmark indices. However, FINA 772 students still bear in mind risk factors in managing this part of the portfolio.

**A. IDEA SOURCING & RESEARCH**

Students follow a disciplined, evidenced-based approach to selecting equities through custom screening built and tested using a tool provided by Portfolio 123. FINA 772 relies on research from academics such as Eugene Fama (University of Chicago), Kenneth French (Dartmouth), John Cochrane (University of Chicago) and Joseph Piotroski (Stanford University). Students also source ideas from investment management firms such as AQR, Bridgewater Associates, and Dimensional Fund Advisors.
B. FACTOR INVESTING

FINA 772 seeks to identify certain factors of firms, which help explain and produce excess stock returns. “Factor Investing” involves investing in these return generating attributes such as Firm Size or Firm Value (a measure of the relative expense or price of a stock). Many large pension funds such as CalPERS have allocated more of their portfolios to managers who engage in factor investing. Pension funds outside of the U.S. such as GPIF (Japan) and the Government Pension Fund of Norway (largest in Europe) are also believers in factor-based investing strategies.

The original factor that attempted to explain stock returns was the Market Beta, resulting from Eugene Fama’s CAPM equation. Much research has been done since, but it turns out that the Market Beta does not do a great job of predicting stock returns. This led to the Fama-French 3 Factor Model which introduced additional Value and Size factors to help explain stock returns. Their results showed that over a very long history small-cap equities outperformed large cap equities and relatively inexpensive stocks (high book value relative to market value) outperformed more expensive stocks (low book value relative to market value). More recent research has expanded upon the Fama-French 3 Factor Model, introducing even more factors such as Momentum (focus is on stocks with strong recent performance), Quality (focus is on firm characteristics such as profitability & use of leverage), and Investment (focus is on pace of firm asset growth).

It is worth mentioning the use of the terms “Style Investing” and “Smart Beta” strategies as one is likely to come across them in publications or in the media. The additional factors mentioned above can be considered “smart betas” and taking advantage of small caps vs. large caps (size) or value vs. growth (value) can be considered a particular “style.”

C. STOCK SELECTION PORTFOLIO

FINA 772 students monitor, measure and test all of these factors with a goal of developing a model, one which is feasible and selects superior return-generating equities without taking on unnecessary risk.

During the Spring 2016 semester the class relied largely on a model which focuses on the Quality factor. The FINA 772 class calls this the High Quality + Low Beta strategy as it is based on firm quality elements, but also incorporates other screening criteria. There are 35 Equities in our portfolio selected by the High Quality + Low Beta model.

Towards the end of the semester, we implemented a second strategy based on the Value factor, but again added additional screening criteria outside of what is commonly utilized with a value strategy. This second strategy implemented in March 2016 is called Value + Improved Quality. 15 equities at the close of the semester were selected from this model.
1) Value + Improved Quality Strategy (15 Stocks)

The Fund’s Value + Improved Quality strategy stems from academic research conducted by Stanford University professor Joseph Piotroski. He provides evidence that suggests the market does not fully incorporate historical financial information into prices in a timely manner. He developed a set of nine accounting-based stock selection criteria called F-scores that are used to identify sound investments. Using this theory as a foundation, FINA 772 implemented Piotroski’s insights within our own capabilities to identify relatively inexpensive stocks with improving measures of quality.

For example, Piotroski used the traditional value measure of a firm’s book value to market value. FINA 772 has added additional value metrics such as Cash Flow to Price and Forward Earnings to Price. In terms of Improved Quality, FINA 772 screens for companies with improving measures for Return on Assets (ROA) and Cash Flow from Operations. Additionally, the model screens for improving liquidity and gross margins and does not favor companies who issue many new shares (dilution).

For each measure students do not just rely on the traditional way to calculate the financial ratio. Oftentimes students create their own measure to pinpoint significantly strong company performance. For example, accounting profit can be “muddied” accruals so students would not simply rely on Net Income in computing these ratios. Another subtlety is that the model looks at these measures comparing firms within their respective industries, which helps select top performers. This also eliminates potential noise and faulty comparisons of firms across industries where fundamentals differ based on the industry and not necessarily company performance.

As mentioned previously, we “turned this strategy on” in March of 2016. A version of this value strategy had previously been “turned off” early in 2016 as testing showed poor performance and evidence of near-term struggles for value strategies was permeating in the market. However, prospects for the strategy improved and the additional Improved Quality screening allowed us to feel comfortable in utilizing the strategy to select a small number of stocks (15).

2) High Quality + Low Beta (35 Stocks)

This strategy stems from the success of Warren Buffet’s investment portfolio while at Berkshire Hathaway, but the idea source for the model comes from an academic paper called “Buffet’s Alpha.” Researchers and practitioners (Andrea Frazzini, Clifford S. Asness, and Lasse H. Pedersen) affiliated with AQR performed the study, seeking to identify the key factors employed by Buffet’s stock portfolio, which could help explain his superior investment performance.
The Factors identified from the report were called “Quality minus Junk” (QMJ) and “Betting against Beta” (BAB). The Quality minus Junk factor is essentially a quality factor which focuses on the selection of firms based on quality of earnings, strong profitability and limited leverage. The “Betting against Beta” factor is one that touches on the CAPM Market Beta factor previously discussed. Whereas the CAPM equation says that firms with a high market beta should generate larger expected returns, this study pointed out that the firms exhibiting lower Market Betas were actually generating the higher returns. Thus, FINA 772 has combined elements of both factors revealed from the study into the High Quality + Low Beta strategy.

An example firm selected by this strategy is Boston Beer Company (SAM) which has no debt in its capital structure and has shown strong growth while maintaining profitability. A similar story can be told for Michael Kors (KORS). KORS also has essentially no debt and maintains a current ratio (>3) well-above its retail competitors. The company generates healthy returns and valuations are not extreme for the quality and performance obtained.

B. STOCK SELECTION RESEARCH

The Stock Selection Team not only conducts research to improve upon existing strategies, but the team also attempts to develop new stock selection models.

a) O’Neil Strategy

The Stock Selection Team sought to find answers as to why value strategies were underperforming in late 2015 – early 2016 and this led the group to a strategy called “The O’Neil” strategy (derived from the well-known investor William O’Neil). Historically the strategy produced high returns but this came with high volatility. The strategy is focused on the financial sector and utilizes earnings momentum, company growth, industry growth, relative market strength, and earnings stability.

This was intriguing, as the FINA 772 Portfolio did not have any exposure to financials. The intent of the research was to determine if adding exposure to financials using the O’Neil model would enhance overall portfolio performance.

Ultimately, the strategy worked well in terms of identifying stocks within the financial sector; however, the volatility of these stocks were above our threshold for inclusion in the Portfolio. As such, members of the Stock Selection team dug in to determine if it was possible to adjust the model to decrease volatility, while not sacrificing returns. This was done by manipulating the constraints placed on specific elements of selection criteria. After adjusting elements such as historical earnings per share the Stock Selection Team was able to produce back-testing results with lower volatility.
Specifically, the adjusted model realized a reduction in maximum drawdown and beta. The adjusted model did in fact lower returns, but not to a level lower than FINA 772 benchmarks. In summation, it was a beneficial exercise in sourcing an idea and adjusting the resulting model to fit the needs and expectations of the FINA 772 Portfolio.

b) Ranking Strategy
Students during Spring 2016 saw the opportunity to improve the primary High Quality + Low Beta model. The inherited model used screening criteria to select or eliminate stocks based off specific criteria. The objective of the research was to use similar criteria to design a model that ranked stocks as opposed to eliminating and selecting stocks. First, the Team identified criteria in the current model that eliminated stocks and excluded those criteria from the model. Next, the Team focused on the criteria that analyzed company performance and utilized these criteria for our model:

1. Negative Accruals (TTM) / Assets (most recent Quarter)
2. Free Cash Flow (TTM) / Assets (most recent Quarter)
3. Operating Cash Flows (TTM) / Assets (most recent Quarter)
4. ROE (TTM)
5. Sustainable Growth Rate = Internal Growth Rate
6. Beta with respect to S&P500 returns (3-year, daily)

Once the ranking criteria was selected, the Team identified the optimal weighting structure for the model. We employed several weighting strategies to identify which strategy yielded highest returns. The results proved to be less than significant for any weight adjustment applied. Therefore, we utilized an equal weighting strategy for each criteria.

In conclusion, the model performed well. The top 10% of the stocks ranked by this model beat the S&P500’s annualized return by 5% over the past 10 years. The lowest 10% of the ranked stocks had very low returns and as we got to the higher percentages of our ranked stocks, the returns increased. Future students can utilize the research conducted surrounding this ranking strategy to identify stocks that would benefit the portfolio.

V. Asset Allocation
The Asset Allocation team is responsible for the implementation of a risk-based portfolio strategy aimed at reducing Portfolio volatility as a counterbalance to the returns-seeking strategy of the Stock Selection Team. Whereas the Stock Selection Team invests in individual stocks, the Asset Allocation
team invests in ETFs corresponding to various countries and industry sectors. The universe of ETFs available to the team consists of 27 ETFs, pulled from a much larger list in order to remove duplicative investments and increase the diversification of the portfolio.

The current Asset Allocation strategy utilizes two risk-minimization techniques: the Global Minimum Variance Portfolio (GMVP) and the Maximum Diversification Strategy with a larger significance on GMVP. The key to calculating any risk minimization strategy is to obtain the Covariance Matrix of returns, which measure the inter-relationships of returns amongst the various ETFs. FINA 772 calculates the covariance matrix with daily returns and places a higher weight on more recent return data relative to older return data.

According to financial theory, a given universe of investable assets yields an efficient frontier: the set of portfolio constructions that yields the highest return for unit of risk. On this efficient frontier (the solid curved line in the illustration below), there are two portfolios of note: the **tangency portfolio** and the **GMVP**. The tangency portfolio is the portfolio that, when combined with a risk-free investment, yields the highest return for unit of risk. The GMVP is the portfolio that simply yields the lowest level of risk (lowest volatility), regardless of returns.

![Efficient Frontier and Visualization of GMVP](chart.png)

While it is a natural tendency to seek higher returns by constructing a portfolio of ETFs that have performed well in the recent past (the tangency portfolio), in practice it is extremely difficult to predict future returns. If we examine the excess returns of our ETFs for the year 2015, for example, it is possible to find the portfolio of ETFs that would have been perfectly mean-variance efficient — the
tangency portfolio. However, taking these backward-looking (ex-post) optimal portfolios and attempting to implement them ex-ante (future) frequently results in poor performance and high volatility.

If markets are efficient, then it is naïve to believe FINA 772 has information that larger professional traders do not also possess. However, that does not necessary imply that all investors should surrender to whatever returns a passive indexing strategy will provide. Rather, FINA 772 can utilize portfolio optimization to improve overall performance by controlling for volatility and reducing the standard deviation of portfolio returns.

In fact, neither the GMVP nor the Maximum Diversification portfolio require any return forecasting at all. The GMVP is the only portfolio on the efficient frontier that requires no return forecasting, while the Maximum Diversification portfolio seeks to equalize the contributed risk of each individual ETF.

In a 1975 paper, professors Robert Haugen and James Heins documented a negative relationship between risk and return in both the U.S. stock market and bond market, over the period from 1926 – 1971. This provided evidence contrary to the CAPM, which suggested that stocks with high levels of systematic risk should compensate their owners by providing superior returns. Haugen and Heins’ findings have been substantiated by numerous other papers, including Jagannathan & Ma, 2003; Blitz and van Vliet, 2007; Ang, Hodrick, Xing and Zhang, 2006; among others. Because high levels of risk seem to be correlated with low returns, FINA 772 has chosen to follow this academic research and construct portfolios that seek to reduce volatility.

A. ETF ALLOCATION

Students in previous classes have tracked our positions in various ETFs which proved to be a good starting point for the Asset Allocation team. The total volume of shares held has stayed between 6,000 and 11,000 over the past 4 years, with the current total position being the lowest.

The Malaysia ETF has been in the portfolio the longest. The Guggenheim Consumer Staple ETF was included in the portfolio in March 2014 and has been a significant piece in all subsequent months. The top two holdings are actually both Consumer Staple ETFs and therefore illustrates why the ETF portfolio “plays a good defense.” However, we will discuss why the low risk of these (and the Utilities ETF) are important to overall risk contribution of the portfolio in the final section.
VI. Portfolio Analytics

A. Marginal Risk Contribution

In order for a portfolio to be optimal, each asset’s expected return (in excess of the risk free rate) must be proportional to the asset’s marginal impact to the portfolio volatility (called Marginal Risk Contribution, or MRC). Put differently, one can use an assets’ MRC to infer the “implicit” expected excess return.

In the table below (and in the chart above) one can see the large positions in Consumer Staples and Utilities. This does not mean we are “betting on” these sectors. Their MRCs are the lowest, meaning that holding a large portion makes sense given our expectations of low returns for these sectors.

The table shows FINA 772 Stock Selection Strategies: High Quality + Low Beta and Value + Improved Quality. They have higher MRCs than our ETF holdings and this is consistent with our strategy because we are “betting on” these factors.

FINA 772 students pay attention to other markets such as Europe and other sectors such as Biotech, but we would not want to invest in these ETFs unless we have a strong conviction that they have higher expected returns than our Stock Selection strategies. We do not have any evidence to support this at the conclusion of the semester.
### Table: Marginal Risk Contribution (MRC) of each Asset in FINA 772 Portfolio

<table>
<thead>
<tr>
<th>Sorted by MRC</th>
<th>MRC</th>
<th>$Weight</th>
<th>Risk Budget</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utilities</td>
<td>VPU</td>
<td>0.605</td>
<td>7.3%</td>
</tr>
<tr>
<td>Cons. Staples</td>
<td>VDC</td>
<td>0.688</td>
<td>15.8%</td>
</tr>
<tr>
<td>Cons. Staples (Eq.Wgt)</td>
<td>RHS</td>
<td>0.705</td>
<td>22.4%</td>
</tr>
<tr>
<td>Telecomm</td>
<td>VOX</td>
<td>0.763</td>
<td>0.0%</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>EWH</td>
<td>0.769</td>
<td>0.0%</td>
</tr>
<tr>
<td>Malaysia</td>
<td>EWM</td>
<td>0.786</td>
<td>1.4%</td>
</tr>
<tr>
<td>Switzerland</td>
<td>EWL</td>
<td>0.792</td>
<td>2.5%</td>
</tr>
<tr>
<td>Singapore</td>
<td>EWS</td>
<td>0.825</td>
<td>0.9%</td>
</tr>
<tr>
<td>Healthcare</td>
<td>VHT</td>
<td>0.865</td>
<td>0.0%</td>
</tr>
<tr>
<td>REITs</td>
<td>VNQ</td>
<td>0.868</td>
<td>1.1%</td>
</tr>
<tr>
<td>Taiwan</td>
<td>EWT</td>
<td>0.896</td>
<td>0.0%</td>
</tr>
<tr>
<td>High Quality Low Beta</td>
<td>BAB</td>
<td>0.939</td>
<td>36.9%</td>
</tr>
<tr>
<td>Cons. Disc.</td>
<td>VCR</td>
<td>0.941</td>
<td>0.0%</td>
</tr>
<tr>
<td>Japan</td>
<td>DXJ</td>
<td>0.946</td>
<td>0.0%</td>
</tr>
<tr>
<td>Thailand</td>
<td>THD</td>
<td>0.961</td>
<td>0.0%</td>
</tr>
<tr>
<td>Info. Technology</td>
<td>VGT</td>
<td>0.962</td>
<td>0.0%</td>
</tr>
<tr>
<td>UK</td>
<td>EWU</td>
<td>0.985</td>
<td>0.0%</td>
</tr>
<tr>
<td>Pacific</td>
<td>EPP</td>
<td>0.988</td>
<td>0.0%</td>
</tr>
<tr>
<td>Korea</td>
<td>EWW</td>
<td>0.994</td>
<td>0.0%</td>
</tr>
<tr>
<td>Mid-cap</td>
<td>VO</td>
<td>0.995</td>
<td>0.0%</td>
</tr>
<tr>
<td>Mexico</td>
<td>EWW</td>
<td>1.004</td>
<td>0.0%</td>
</tr>
<tr>
<td>Industrials</td>
<td>VIS</td>
<td>1.010</td>
<td>0.0%</td>
</tr>
<tr>
<td>Value + Improved Quality</td>
<td>PIOT</td>
<td>1.028</td>
<td>10.6%</td>
</tr>
<tr>
<td>Materials</td>
<td>VAW</td>
<td>1.036</td>
<td>0.0%</td>
</tr>
<tr>
<td>Financials</td>
<td>VFH</td>
<td>1.050</td>
<td>0.0%</td>
</tr>
<tr>
<td>Energy</td>
<td>VDE</td>
<td>1.051</td>
<td>0.0%</td>
</tr>
<tr>
<td>China</td>
<td>GXC</td>
<td>1.068</td>
<td>0.0%</td>
</tr>
<tr>
<td>Small-Cap</td>
<td>VB</td>
<td>1.073</td>
<td>0.0%</td>
</tr>
<tr>
<td>Latin America</td>
<td>ILF</td>
<td>1.098</td>
<td>0.0%</td>
</tr>
<tr>
<td>Biotech</td>
<td>IBB</td>
<td>1.099</td>
<td>0.0%</td>
</tr>
<tr>
<td>Europe</td>
<td>VGK</td>
<td>1.107</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

### B. EXPOSURE TO FACTORS

The table below illustrates the FINA 772 Portfolio exposure to many Factors discussed in this report. We pull data from the Fama/French website to obtain returns on hypothetical portfolios built for each respective factor. Next, we run a regression of FINA 772 returns against each of these portfolios. The results help explain where the FINA 772 Portfolio returns are coming from.

In looking at the Fama-French 3 Factor Model (2nd Column), it is interesting to note that neither the size factor nor the value factor explain our portfolio performance (negative beta coefficient). FINA 772 Portfolio performance must be explained by other Factors.
When we look at the effects of the 5 Factor model (3rd Column), we can see that we have significant exposure to the Investment factor. This means we have exposure to firms who invest conservatively relative to their peers (typically measured by asset growth). This makes sense given our Stock Selection criteria, which selects companies that do not spend aggressively on capital investments. Even after controlling for 5 Factors, FINA 772 shows an annualized alpha of 4.5%.

Lastly, we look at the final column which includes the 5 Factors + Momentum. Interestingly, our portfolio has a significant positive exposure to the Momentum factor and we are not explicitly implementing a Momentum strategy. However, our models are looking for strong performers and particularly improved performance so we are inherently gaining exposure to the Momentum factor. Even after controlling for all 5 Factors + Momentum, the FINA 772 Portfolio shows a 2.6% alpha (per year).

*Table: Performance Attribution Analysis*

<table>
<thead>
<tr>
<th>FINA 472/772 Portfolio (Jan. 2013 - Feb. 2016; 38 months)</th>
<th>Benchmark Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CAPM</td>
</tr>
<tr>
<td>Annualized</td>
<td></td>
</tr>
<tr>
<td>Alpha (%)</td>
<td>4.686</td>
</tr>
<tr>
<td>Residual Volatility (%)</td>
<td>4.660</td>
</tr>
<tr>
<td>Information Ratio</td>
<td>1.006</td>
</tr>
<tr>
<td>Factor Betas/Loadings</td>
<td></td>
</tr>
<tr>
<td>Mkrt-Rf</td>
<td>0.790</td>
</tr>
<tr>
<td>SMB (Size)</td>
<td>0.109</td>
</tr>
<tr>
<td>HML (Value)</td>
<td>0.010</td>
</tr>
<tr>
<td>RMW (Profitability)</td>
<td>0.096</td>
</tr>
<tr>
<td>CMA (Investments)</td>
<td>0.694</td>
</tr>
<tr>
<td>MOM (Momentum)</td>
<td>0.238</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.791</td>
</tr>
</tbody>
</table>

Factor returns are from Professor Kenneth French’s website.
Factor returns are available only through February 2016.
Bold letters indicate significance at 5% level.
FINANCE 772/442
Student – Managed Investments
Appendix: Research Reports
A. AN INVESTIGATION OF FACTORS AS A PREDICTOR OF INDUSTRY RETURNS

James Carlisle, Gilberto Mandalka and Spoorthi Purumala

Asset Allocation / ETF Sectors Team

Professor Shingo Goto – FINA 472/772

Abstract

We present research based on the Fama Macbeth methodology intended to which from a specified set of common financial metrics are most indicative of future returns of sector indices. We find that several of the factors that we investigated showed relatively persistent relationship to returns for the next month that warranted further research. We narrowed these factors to two specific factor from which we developed the CMP 50/150 Sector Index.

Introduction

The student-managed portion of the University of South Carolina Business Partnership Foundation Fund is currently divided approximately equally into two distinct portfolios: a stock selection portfolio and an asset allocation portfolio. The current strategy of the asset allocation portfolio is largely risk-based, using a combination of global minimum variance portfolio strategy and maximum diversification portfolio strategy to identify the specific country and industry ETFs as well as their weights within the portfolio.

It was our goal with this research to identify which, if any, common fundamental metrics could be used to predict future returns of sector indices, with the goal of eventually incorporating the findings into a returns-based strategy to enhance the current asset allocation strategy.

Data Collection

The data in this study is collected from Bloomberg and includes bottom-up aggregated variables for the MSCI sectors indexes for both US and MSCI world (developed markets) universes. 10 sectors listed below are considered through 22 MSCI Indexes.
The sector level aggregated data set is categorized meaningfully for research purposes into variables reflecting information about:

1. Balance Sheet
2. Valuation
3. Financials
4. Cash Flow Statement
5. Market Variables

In all, our data included 80 different variables within these categories. However, the scope of our research was limited to 15 for various reasons including our judgment that certain factors were redundant or duplicative. We also limited our research to those variables for which data was available for every sector for the entirety of the time period of our data (1996 – 2016).

The data is organized monthly across the years 1996-2016 for all the sectors to observe the trend across time for all the factors.

**Methodology**

To assess the strength of a factor in predicting future returns, we employed a version of the methodology developed by Fama and Macbeth to arrive at factor premia for each of the factors we investigated. The methodology involves:

1. Developing Information Coefficients (ICs) for each factor, for each period
2. Measuring the persistence of the ICs for each factor over time.
Developing ICs

Slope IC: We utilized two different Information Coefficients in our analysis. First, we used linear regression to measure the relationship between the factor and the next month’s returns. For each month \((t)\), we regressed (using the Excel function SLOPE) the factor value \((\text{Factor})\) for all the assets \((i)\) against next month’s returns for all the assets.

\[
IC_{i,t} = \beta_{i,t}
\]

\[
\text{Return}_{i,t+1} = \alpha_{i,t} + \beta_{i,t}(\text{Factor}_{i,t}) + \varepsilon
\]

Spearman Correlation IC: The second IC we calculated was based on the Spearman rank correlation methodology. For each time period, each asset was ranked by both its Factor value and next month return. The Spearman IC was calculated as the correlation (Excel function: CORREL) between the Factor ranks and the return ranks. The Spearman correlation is useful because it adjusts for the impact of outliers. It also normalizes the factor values and returns and bounds the IC between -1 and 1, allowing us to directly compare the ICs across factors.

For each of our ICs, a positive value indicates a positive relationship between the value of the Factor and the next month’s returns. A negative IC indicates the opposite relationship and implies that a lower value for that specific Factor should be favored. In either case, the more extreme value of the IC (i.e. the higher absolute value for the IC), the stronger the implied relationship between the factor and future returns.

Note: All factors were ranked as higher is better. So while one may intuitively expect that a higher moving average-adjusted P/B factor would be less favorable (in other words, a particular sector index’s P/B ratio is relatively higher than its 12 month average), the ranking in our data regards the higher factor value as better. This was done primarily for the ease of implementation of our methodology across factors without having to adjust the ranking system each time.

Modifying the Factors: Moving Average Adjustments

In our initial exploration of the data, we realized that certain industries may have intrinsically higher or lower factor values than other industries and that this could muddle our findings. For instance, in considering the Profit Margin factor, it may be the case that the Information Technology sector index has a consistently higher profit margin than the other sector indices simply due to the nature of the IT industry. So while the IT index may show a weakening profitability for a certain period and a corresponding poor return for the following month, this would not be reflected in the IC for that period because the IT index would still have the highest profit margin (in spite of the deterioration).

To account for this, we made an adjustment for the factors used in our analysis. Instead of using the factor value of a sector index for a given period, we have adjusted the factor to be a ratio relative to the average of that factor for the previous twelve months. So for a given factor for industry index \(i\) for period \(t\), the new moving average-adjusted factor used in our analysis is given by the following:

\[
\frac{\text{Factor}_{i,t}}{\text{Average}(\text{Factor}_{i,t-13} - \text{Factor}_{i,t-1})}
\]
While this adjustment changes the interpretation of the factor, it is our opinion that this modification adds valuable nuance to the analysis. See Appendix 2 for an example of the impact of the adjustment on the P/B factor.

**Measuring Persistence Over Time**

Having arrived at Slope and Spearman Information Coefficients for each time period in our data set, we are left with a time series for each IC. To evaluate the persistence of the IC over time, we calculated the mean and standard deviation of the IC over the full time period of our data (approximately 20 years). For each IC, a T statistic was calculated as an indication of the statistical strength of the IC mean (i.e. is the IC mean statistically different from 0). The T-Stat for Factor $i$ was defined as follows where $\mu$ is the mean for the ICs over time, $\sigma$ is the standard deviation of the ICs and $n$ is the number of periods (228).

$$T_i = \frac{\mu_i}{\sigma_i \sqrt{n}}$$

For our purposes, we determined that any factor yielding T statistics over 1.5 for both ICs would pass our screen and warrant further investigation.

A line chart plotting the cumulative sum of the ICs over time was also used as a visual representation of the persistence of the IC over time. A plot that shows a steadily increasing (or decreasing) line indicates that the factor is consistently indicative of higher (or lower) returns over time. A plot that shows a high degree of volatility (numerous peaks and valleys) indicates that the relationship between the factor and returns is not consistent over time and therefore limited in its applicability to an investing strategy.

The charts below show examples of what we categorized as “Strong” and “Weak” visual indicators of the ICs.
Quintiles/ Top-Minus-Bottom Analysis

For those factors that passed our initial screen (T-Stat over 1.5 and a strong visualization pattern), a quintiles analysis was conducted as an initial step towards elucidating the practicality of the factor as an investment criteria.

For the quintiles analysis, we first ranked the sector indices for each period by their factor value. The sectors were then categorized into quintiles (4-4-6-4-4). The returns for the next month were then calculated for each quintile and plotted on a bar chart.

The chart was evaluated for monotonicity (the consistency with which returns increase with each successive quintile).

For the top-minus-bottom analysis, the returns of the 1st quintile (lowest factor value) were subtracted from the 5th quintile (highest factor values). The resulting series of returns were then averaged and compared to the standard deviation in a T-Stat to evaluate the persistence/consistency of the performance of the 5th quintile over the 1st over time. As with the IC analysis, a higher T-Stat indicates that the excess returns of the 5th over the 1st quintile are statistically different from 0, indicating a practical investment application (buy those in the 5th quintile, short those in the 1st).

Results

IC and Visualization Analysis Results

The results of the Information Coefficient and IC visualization analysis are provided in the table below.
Overall, the results of our analysis indicated that the overall correlation between individual factors and the returns in the following month were fairly weak. The clearest interpretation of this is in the Spearman Correlation analysis. A strong relationship would be evidenced by a Spearman Correlation mean close to 1. However, in our research, the strongest Spearman correlation mean among our factors was the moving average-adjusted P/B factor with a mean Spearman correlation of just 0.049.

Despite the initial indications that there is a lack of a strong relationship between our factors and returns, several factors did pass our screen. Each of these showed a T-stat (in either the regression IC or the Spearman correlation IC) of close to 2 and showed a “Strong” visualization.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>T-Stat</th>
<th>Visual (Weak/Strong)</th>
<th>Spearman Correlation Mean</th>
<th>Standard Deviation</th>
<th>T-Stat</th>
<th>Visual (Weak/Strong)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price/Book</td>
<td>2.400</td>
<td>11.764</td>
<td>3.081</td>
<td>Strong</td>
<td>0.049</td>
<td>0.340</td>
<td>2.179</td>
<td>Strong</td>
</tr>
<tr>
<td>Payout Ratio</td>
<td>-1.023</td>
<td>5.857</td>
<td>2.636</td>
<td>Strong</td>
<td>-0.041</td>
<td>0.288</td>
<td>2.150</td>
<td>Strong</td>
</tr>
<tr>
<td>TTM EPS</td>
<td>1.068</td>
<td>7.690</td>
<td>2.097</td>
<td>Strong</td>
<td>0.033</td>
<td>0.306</td>
<td>1.628</td>
<td>Strong</td>
</tr>
<tr>
<td>Profit Margin</td>
<td>0.513</td>
<td>5.014</td>
<td>1.546</td>
<td>Strong</td>
<td>0.038</td>
<td>0.285</td>
<td>2.035</td>
<td>Strong</td>
</tr>
<tr>
<td>TTM Operating Margin</td>
<td>0.873</td>
<td>12.671</td>
<td>1.040</td>
<td>Strong</td>
<td>0.042</td>
<td>0.322</td>
<td>1.970</td>
<td>Strong</td>
</tr>
<tr>
<td>TTM Sales per share</td>
<td>3.297</td>
<td>25.904</td>
<td>1.922</td>
<td>Weak</td>
<td>0.037</td>
<td>0.304</td>
<td>1.838</td>
<td>Weak</td>
</tr>
<tr>
<td>Book Value</td>
<td>3.531</td>
<td>33.108</td>
<td>1.610</td>
<td>Weak</td>
<td>0.035</td>
<td>0.329</td>
<td>1.620</td>
<td>Weak</td>
</tr>
<tr>
<td>Total Assets</td>
<td>2.478</td>
<td>29.061</td>
<td>1.288</td>
<td>Weak</td>
<td>0.035</td>
<td>0.297</td>
<td>1.779</td>
<td>Weak</td>
</tr>
<tr>
<td>Debt/Equity Ratio</td>
<td>-1.414</td>
<td>21.136</td>
<td>1.010</td>
<td>Weak</td>
<td>0.000</td>
<td>0.279</td>
<td>0.000</td>
<td>Weak</td>
</tr>
<tr>
<td>P/E Ratio</td>
<td>-0.522</td>
<td>8.783</td>
<td>0.898</td>
<td>Weak</td>
<td>-0.011</td>
<td>0.294</td>
<td>0.565</td>
<td>Weak</td>
</tr>
<tr>
<td>Total Debt</td>
<td>0.828</td>
<td>18.081</td>
<td>0.691</td>
<td>Weak</td>
<td>0.032</td>
<td>0.261</td>
<td>1.851</td>
<td>Weak</td>
</tr>
<tr>
<td>Dividend/Share</td>
<td>-0.798</td>
<td>20.964</td>
<td>0.575</td>
<td>Weak</td>
<td>-0.003</td>
<td>0.295</td>
<td>0.154</td>
<td>Weak</td>
</tr>
<tr>
<td>No. of Employees</td>
<td>-0.417</td>
<td>21.564</td>
<td>0.292</td>
<td>Weak</td>
<td>0.011</td>
<td>0.243</td>
<td>0.706</td>
<td>Weak</td>
</tr>
<tr>
<td>Sales/Employee</td>
<td>0.105</td>
<td>11.780</td>
<td>0.135</td>
<td>Weak</td>
<td>-0.004</td>
<td>0.260</td>
<td>0.232</td>
<td>Weak</td>
</tr>
<tr>
<td>Cash/Share</td>
<td>0.006</td>
<td>10.893</td>
<td>0.009</td>
<td>Weak</td>
<td>0.008</td>
<td>0.266</td>
<td>0.454</td>
<td>Weak</td>
</tr>
</tbody>
</table>

While each of these factors passed our screen, what we notice is that several of them (EPS, Profit Margin, and Operating Margin) are common in that they are each reflective of improving profitability. Payout ratio’s negative relationship to returns also is likely reflective of improving profitability (as dividends tend to be “sticky”, improved profitability results in lower payout ratio, generating the negative IC).
That our moving average-adjusted P/B factor passed our screen was initially perceived as counterintuitive to the Fama-French value factor. However, we believe this is a byproduct of the moving average adjustment which essentially transformed P/B from a value metric into a momentum factor.

**Quintiles/Top-Minus-Bottom Analysis Results**

For the factors that passed our initial screen, the results of the quintiles and top-minus-bottom analysis are provided in the charts below.
The bar chart visualizations of the quintile analysis indicate that there is a fairly strong difference in the mean returns for the 1st and 5th quintiles. However, there is a consistent lack of monotonicity when it comes to the 5th quintile (1st for the Payout Ratio factor: given that a lower moving average adjusted payout ratio factor is correlated with higher returns, the quintile coding for this variable was reversed). In fact, each of the charts shows a very clear monotonic pattern until it comes to what we would have expected to be the highest performing quintile. The precise reason for this anomaly was not clear, but could possibly be a mean-reversion effect. Nevertheless, the implications of this anomaly are detrimental to the prospects of implementing these results into an investment strategy.

Looking at the Top-Minus-Bottom analysis results, we see that moving average-adjusted Payout Ratio and P/B factors have the strongest Sharpe Ratios (one month) and T-Stats, consistent with the IC analysis. Given that the remaining three have T-Stats below 1.5 and are (from a theory perspective) likely explained by improving profitability which is already captured in the Payout ratio factor, our results indicate that the moving average P/B and Payout Ratio factors are the most likely candidates for practical implementation.

<table>
<thead>
<tr>
<th>Sectors - Top-Minus-Bottom Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor</td>
</tr>
<tr>
<td>Payout Ratio</td>
</tr>
<tr>
<td>Price/Book</td>
</tr>
<tr>
<td>TTM EPS</td>
</tr>
<tr>
<td>TTM Operating Margin</td>
</tr>
<tr>
<td>Profit Margin</td>
</tr>
</tbody>
</table>
Having identified moving average-adjusted P/B ratio and moving average-adjusted Payout ratio as the strongest factors in terms of predicting future returns in the next month, we went about constructing an index.

**Index Construction**

The steps we followed for the creation of the index are described below:

1. After arranging the data to have the two factors and next month returns for each time period, the first step was to create a score for each sector to determine its weight in the index. Each factor was given a multiplier, which was developed based on a transformation of the top-minus-bottom T-stat.
2. We then ranked each sector by its factor value for both factors (1 being most favorable based on the results of our previous analysis).
3. The ranking for each sector was then multiplied by the corresponding multiplier and then summed for each sector to arrive at a score for each sector for a given period. For our index, a lower score is more favorable.
4. The sectors were then segmented into two halves: the 11 with the lowest scores and the 11 with the highest. Weights for each sector within the index were calculated as follows:
   a. For each of the 11 sectors in the lower half, the score was raised to the -1 and then divided by the sum all the inverted scores for those 11 sectors. This arrived at a weighting for each sector within the top (more favorable half) with the weights summing to 1.
   b. For the sectors in the bottom half, each sector score was divided by the sum of the 11 scores in the bottom half to arrive at a weighting for each of the least favorable sectors (least favorable having the highest weight within this segment).
   c. For each sector in the top half, their weights were multiplied by 1.5 while each sector in the bottom (less favorable) half had their weight multiplied by -0.5.

For each period, the weights for each sector were calculated and then multiplied by the returns in the following month to arrive at the performance of the index. The results are shown below:
The results of the CMP Index indicate a strong enhancement in returns over the S&P 500 index while taking on only slightly higher volatility.

**Conclusion/Next Steps**

The research we conducted has given some further validity to the momentum and profitability factors (as evidenced by the moving average-adjusted P/B ratio factor and the moving average-payout ratio factor, respectively) identified by Fama and French. In our analysis, we only looked at these factors within the context of predicting future returns in the next month among sector indices. We would recommend further research continue to examine these results. Most notably, further research should examine whether implementing a “lag” in the returns negatively impacts the results of the IC analysis.
and the CMP Index performance. Also, our research utilized industry sector indices. Further research should be conducted based on investable assets such as ETFs rather than indices.

**Exhibits/Appendices**

Appendix 1: Impact of the moving average adjustment on the Spearman IC cumulative sum chart for the P/B factor.

The chart to the right shows the cumulative sum of the Spearman correlation IC over time for the P/B ratio factor (unadjusted). The chart shows there is an overall positive relationship between P/B ratio and returns in the following month (possibly indicative of a momentum effect) that is interrupted by a period where the relationship is negative (indicated by the “valley” in the chart).

The moving average-adjusted P/B factor performs much better as indicated by the much more consistent positive slope of the line in the chart.

The implication is that sectors with P/B ratios relatively higher than their previous 12 month average P/B see higher returns in the next month.
B. Time-series adjusted value model and weighted implementation of a new momentum strategy final report

James Carlisle, Gilberto Mandalka and Spoorthi Purumala

Asset Allocation / ETF Sectors Team

Professor Shingo Goto – FINA 472/772

The following research is based on our initial findings over what type of factors – such as Asset Growth, Momentum, Value, etc. – are useful for sector allocations. Our preliminary thoughts were directed towards examining each one of those factors and calculating two simple Information Coefficient (IC) measures: the Pearson and Spearman correlations. By obtaining these two IC measures under a time-series frame and relating them to the forward return of each period of time, we were able to analyze the magnitude of the impact of each factor and in what periods it actually worked (giving us a glimpse of how industry timing and specific factors are related).

Once we investigated those numbers, our group started to work on a new challenge: the cumulative sum of both our IC over time did not show any promising results, as we were not able to observe any consistent upward sloping (which would suggest a positive correlation between the factor and future returns). We decided therefore to readjust our factors by subtracting a 12-month moving average, and by applying a cross-sectional Fama-MacBeth analysis approach, we were able to isolate a couple of interesting results, such as a couple of variables with consistent impact over future returns in our time-series adjusted value model and the findings of this specific investigation: a weighted implementation of a new momentum strategy.

Methodology

In the initial part of this research, the objective was to obtain the Pearson and Spearman correlations, two very common IC measures. While the Pearson’s correlation is the usual IC measure and consists of the simple correlation coefficient between returns in the following month and current factor, another effective measure of IC is the Spearman correlation, which is the rank correlation between the ranked return in the following month and the ranked factor in each period of time. This IC measure is less sensitive to outliers, thus we decided it would be informative to report both to avoid any discrepancy in our interpretations. The following table illustrates average and standard deviation for the measures of different factors, while the plot charts for the cumulative sum of both IC measures over time for the Price/Book factor can be find under the appendix.
Once we examined those results, we decided to redesign our factors in order to follow our analysis. The second step of our investigation was to apply a logarithmic transformation over our raw variables (such as Price-to-book) and subtract the moving average of each industry, a fairly simple mathematical transformation that would isolate any possible outliers of specific industries (leaving us with a more monotonic and smoother variable), thus providing us a better approach to follow up with our time-series cross-sectional Fama-MacBeth analysis.

\[
\frac{P}{B} \to \ln \left( \frac{P}{B} \right) \to \ln \left( \frac{P}{B} \right)_t - \sum_{i=0}^{12} \ln \left( \frac{P}{B} \right)_i \to \ln P - \ln B + \sum_{i=0}^{12} \ln P - \sum_{i=0}^{12} \ln B \leftrightarrow p + \sum_{i=0}^{12} p - b - \sum_{i=0}^{12} b
\]

(1)

By obtaining this new variable, our final step was to implement the Fama-MacBeth based analysis. Since we separated our data inputs in 22 different sectors and over a 241 period-time (month by month, from Jan-1996 to Jan-2016), we decided to estimate the impact of the factors in each period of time by running a cross-sectional regression at each period of time, thus giving us 241 betas (slopes), which we would later combine in order to observe the cumulative effect of it. Mathematically, we considered a simple regression of \( R_{t+1} \) on \( F_t \) for each period of time:

\[
R_{t+1} = \alpha + \beta F_t + \varepsilon_{t+1}
\]

(2)

Where \( \varepsilon_{t+1} \) is the residual term.

Obtaining thus 241 betas, which in simple words represent if the factor is positively or negatively related, the final task was to analyze whether there is a constant correlation between future returns and our redesigned factors.
Results

By only focusing on the Price-to-book factor, this part of our research turned out to have bigger findings on momentum strategies. After realizing the Fama-MacBeth regressions and obtaining betas for each period of time, the first cumulative chart of those presented a meaningful positive correlation between future returns and our Price-to-Book factor, as illustrated by the following table:

<table>
<thead>
<tr>
<th>Returns</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Sharpe Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly Returns</td>
<td>17.797</td>
<td>16.837</td>
<td>3.662</td>
</tr>
<tr>
<td>F1Mo Returns</td>
<td>3.349</td>
<td>19.483</td>
<td>0.596</td>
</tr>
<tr>
<td>F3Mo Returns</td>
<td>7.464</td>
<td>29.629</td>
<td>0.873</td>
</tr>
<tr>
<td>F6Mo Returns</td>
<td>10.877</td>
<td>42.405</td>
<td>0.889</td>
</tr>
<tr>
<td>F9Mo Returns</td>
<td>14.822</td>
<td>53.029</td>
<td>0.968</td>
</tr>
<tr>
<td>F12Mo Returns</td>
<td>16.270</td>
<td>60.838</td>
<td>0.926</td>
</tr>
</tbody>
</table>

Nonetheless, we realized that this factor was not quite powerful in explaining time-series and accounting-based value, basically due to the fact that the time-frame of our moving average – which was only 12 months – was actually too short to retain any significant value change of the accounting components of our factors (in this case the book value). At this point, we started to suspect that the positive slope of the price-to-book factor might be majorly a momentum effect and thus our focus changed to identifying at what degree each of the components were responsible for the positive correlation. The mechanics used for this interpretation were to create two other simple momentum strategies to use as benchmarks against our own new 12 months weight-implemented strategy:

\[
\ln P_t - \sum_{i=0}^{12} \ln P_i \quad \text{and} \quad \ln P_t - \ln P_{t-12}
\]

(3)

Now, by obtaining the slopes for those two new variables, we would be able to compare the performance of each one of them and draw conclusion over whether our new weight-implemented strategy is actually more efficient than the simple momentum strategy (analyzing the gap between the strategies) and whether or not the value-based component of our factor has actually a meaningful impact over the positive correlation with future returns (in other words, our goal was to identify any major differences between \( \ln P_t - \sum_{i=0}^{12} \ln P_i \) and \( \ln P_t - \ln B + \sum_{i=0}^{12} \ln P_i - \sum_{i=0}^{12} \ln B \)).
Analyzing the tabulated results of each strategy’s slopes, as well as the cumulative sum of each one of them (appendix), or final conclusion suggest that even if there is no meaningful impact of the book value over the positive correlation between our factor and the future returns (that is, our betas are mainly driven by the price effect, which means that $\ln B \approx 0$ and therefore $\sum_{i=0}^{12} \ln B \approx 0$), there is actually a very significant difference between a simple momentum strategy and the weight-implemented ones, meaning that by using this type of strategy the portfolio could actually improve its value over the time.

Future research upon this effect might solidify our hypothesis that a weight-implemented strategy can actually be beneficial when analyzing momentum effect. Another interesting approach might be to work with this data-set under a ranking-based criteria (somewhere similar to the Spearman’s correlation method): by ranking each industry’s future return and price-to-book ratio for each period of time, and then separating in quintiles, some interesting results may become visible. Initial findings under this method can be found under the appendix.

References


Appendix

FIGURE 1 – Methodology

FIGURE 2 – Methodology
FIGURE 5 – Results / Conclusion

Quintile Returns: \( \ln P/B \) – MA \( \ln P/B \)

Quintile Returns: \( \ln P(t) \) – \( \ln P(t-12) \)
C. Is there any room for improvement in MSCI Diversified Multiple Factor Index?

Ryohei Oishi
Asset Allocation
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The Smart-beta strategy and factor investing have been more and more focused by institutional investors recently. MSCI Inc. creates so-called diversified multiple factor index which goes through risk optimization process and have exposure to several common factors. Is it possible to achieve higher efficiency than diversified multiple factor index by employing different allocation strategy of factors? Dybvig-Ross analysis and GRS test, which are traditionally employed to test benchmark asset pricing model, are implemented to test the mean-variance efficiency of diversified multiple factor index and concludes it is unlikely to achieve higher efficiency among six MSCI factor indexes.

Smart-beta strategy and factor investment have been paid attention both from the academic and practical viewpoint. Many institutional investors, including CalPERS and GPIF, are implementing smart-beta strategy into their portfolios.

One of the reasons why smart-beta strategy is becoming so popular would be the invention of the rule-based index, or factor index. The purpose of factor indexes is to maximize the exposure to a specific common factor while maintaining risk profile similar to the underlying parent index, i.e. market cap weighted index in a given universe. Many index providers, e.g. MSCI Inc., FTSE group, are offering factor indexes, and institutional investors can easily combine smart-beta strategy into their portfolios by purchasing some ETFs tracking those indexes. MSCI also provides another index called diversified multiple factor index. This index is somewhat avaricious index. This aims to represent high exposure to several common factors while maintaining market risk exposure similar to the underlying parent index. (MSCI 2015)

Active portfolio managers, especially those who apply smart-beta strategy, might think if it is possible to achieve higher efficiency than passive managers who tracks diversified multiple factor index provided by MSCI, which is investigated in this paper.

Figure 1 shows the performance of the S&P500, some other MSCI factor indexes, as well as the diversified multiple factor index in the U.S. universe. Although S&P500 has been performing pretty well in recent years, the diversified multiple factor index still has been outperforming S&P 500.

One way to answer the question of the possibility to beat the diversified multiple factor index is to employ many allocation strategies and see if it achieves higher efficiency, which is quite inductive. This
approach can be a practical way as many active managers are trying to do so in real business. However, some change of viewpoints is made in this paper. The approach of conducting the mean-variance efficiency test of diversified multiple factor index is employed, rather than applying a ton of allocation strategies.

In this paper, analysis conducted by Dybvig and Ross (1985), hereafter DR analysis, and statistical test invented by Gibbons, Ross and Shanken (1989) known as GRS test is applied. Although they are traditionally used to test the benchmark asset pricing model, they are applied to test the mean-variance efficiency in this analysis.

The analysis showed that the hypothesis that diversified multiple factor index is mean-variance efficient is not rejected. This suggests it is quite unlikely to achieve higher efficiency than the diversified multiple factor index by executing any portfolio allocation strategy among six factors.

The structure of this paper is as follows. In the next chapter, simple introduction to factor investing, smart-beta strategy, as well as MSCI factor index is given. In the second chapter, one similar analysis given by Grinold (1992) will be reviewed. In the third chapter, the methodology used in this paper in order to test the mean-variance efficiency is discussed. The fourth chapter describes the dataset used in this analysis and the fifth chapter will give you the summary of the result. The sixth chapter concludes the discussion. Appendix contains the detailed explanation for each factor index and the mean-variance efficiency in the world universe, which is quite similar to that in the U.S. universe.

I. Introduction of the factor investing and MSCI indexes

A. Factor investment

In a traditional capital asset pricing model invented by Sharpe (1964), there supposed to be no alpha, and all the excess returns for the risky assets were thought to be explained by market excess return, i.e. market factor. In an empirical viewpoint, however, significant alpha in a CAPM model has been observed. Fama and French (1992) suggested multiple factor model, which takes into consideration some other factors, i.e. value and size factors. And now, more and more common factors have been discovered in both academic and practical research. Fama and French (2015) suggested two other factors, which are profitability and investment.

B. MSCI factor index

MSCI Inc., (hereafter MSCI) one of the biggest index providers, is creating so-called factor indexes. They assume there are six main factors that can explain the excess return of risky assets in the market. The six factors are, size, value, low volatility, quality, high dividend yield, as well as momentum. Firstly, they create a normal index called parent index. This is similar to S&P 500 in the case of U.S.A universe while this covers about 85% of American large-cap and mid-cap and put weights depending on their market capital size. A parent index can be thought as a general benchmark. Inside of the parent index universe, they create six factor indexes where they maximize the exposure to one of the factors above. There are various investment universes, such as AWCI, world, and U.S.¹, and MSCI creates those factor indexes.

¹ AWCI universe includes both developing countries and developed countries, while world universe only includes developed economy
indexes for some of the investment universes. In addition to this, they create a diversified multiple factor index, in which they try to maximize the exposure to the value, size, low volatility, and quality factor while maintaining a total risk profile similar to that of the underlying parent index at the time of rebalancing (MSCI 2015). For the more detailed explanation for the factor indexes, please see the appendix.

II. Review of former research

Grinold analyzed five country benchmark indexes to judge if they are mean-variance efficient or not. DR analysis and GRS test are also employed in his research. His analysis includes the United States, the United Kingdom, Australia, Japan, as well as Germany. The benchmark indexes are the S&P500, the FTA, the ALLORDS, the TOPIX, as well as the DAX. He concluded that the former four indexes are not mean-variance efficient.

III. Data and descriptive statistics

In this analysis, the investment universe is U.S universe. The dataset contains 180 monthly excess return data from January 2001 to December 2015.

Table 1 shows the summary statistics of an excess return for each factor index, the parent index, as well as the diversified multiple factor index. The diversified multiple factor index and minimum volatility factor index have the highest sharp ratio 0.14. Parent index has the lowest sharp ratio, which makes sense to some extent as it is just a market cap weighted index.

Table 2 shows the correlation matrix for the every index used in this analysis. High dividend yield index and momentum index have the least correlation 0.74 while the correlation between equal weighted index and value weighted index is the highest 0.98.

IV. Methodology

A. DR analysis

In this paper, DR analysis and GRS test, which are traditionally used for the efficiency of the benchmark index, are employed to test the mean-variance efficiency of the diversified multiple factor index and parent index for comparison.

For the DR analysis, the regression model is as follows. The independent variable is the excess return of factor index in time $t$, and the dependent variable is the excess return of the index that you would like to test the efficiency, which is, in our case, the parent index or the diversified multiple factor index. You will observe each alpha and each beta for each factor indexes.

$$ r_{i,t} - r_{f,t} = \alpha_i + \beta_i (r_{D,t} - r_{f,t}) + \epsilon_t $$

Where $r_{i,t}$ denotes the factor index return in time $t$ for index $i = \{\text{equally weighted index, value weighted index, quality index, minimum volatility index, high dividend yield index, momentum index}\}$, and
\( r_t \) denotes risk free rate in time \( t \), \( r_{D,t} \) is the return of index \( D = \{ \text{parent index, diversified multiple factor index} \} \).

\( \varepsilon_t \) is an error term.

DR analysis suggests that if the equation (1) has significantly positive alpha for \( i \)th factor, putting more weight on factor \( i \) would have improved the portfolio efficiency and vice versa. Therefore, the null hypothesis in this analysis that the parent index or the diversified multiple factor index is mean-variance efficient can be written as follows.

\[
H_0: \alpha_i = 0 \text{ for each } i
\]

B. GRS test

In the DR analysis, the significance of each alpha in each regression equation has been tested. GRS test can make it possible to put stronger statement or constraint on the efficiency. The new null hypothesis in this test is that all the alphas are jointly equal to zero.

\[
H_0: \alpha_i = 0 \ \forall i
\]

V. Result

Table 3 shows the result of DR analysis for the parent index. As for the parent index in the US universe, every factor has positive alpha, and equally weighted index, minimum volatility index, as well as quality index have significantly positive alpha. This suggests that if putting more weight on the above three factor with significant alpha might have improved the efficiency of the parent index. This result is not surprising as parent index does not go through any optimization process and it is just a market cap size weighted index. This result is consistent with the result of Grinold (2002).

Table 4 shows the result for diversified multiple factor index. Even though there are both negative and positive alphas here, every alpha is not significant even at 10 percent significant level. This result might suggest that diversified multiple factor index is mean-variance efficient among the six factor indexes.

Table 5 shows the GRS test result. The null hypothesis that all the alphas in the DR analysis are jointly zero is analyzed in GRS test. The p-value of the parent index and the diversified multiple factor index is 1.14 and 28.01, respectively. This suggests that the null hypothesis is rejected for the parent index while cannot be rejected for the diversified multiple factor index. The result for the parent index is also consistent with Grinold (2002). As for the diversified multiple factor index, the stronger constraint for the mean-variance efficiency cannot be rejected. This would be a strong evidence that diversified multiple factor index in the U.S. universe can be mean-variance allocation of the six factors.
VI. Conclusion

In this paper, the mean-variance efficiency of the MSCI parent index and the diversified multiple factor index in the U.S. universe have been analyzed.

One new contribution of this paper is the application of Dybvig and Ross analysis (1895) and GRS test (Gibbons et al 1989), which are traditionally used for the benchmark asset pricing model, for the test of the mean-variance efficiency of the factor based index.

While the mean-variance efficiency hypothesis for the parent index is rejected, that for the diversified multiple factor index is not rejected. This result suggests that it is quite unlikely to achieve a higher efficiency by using different allocation strategy of those factors. This might be a bad news for active portfolio managers who allocate factors used in MSCI factor indexes. However, this result also motivates both practitioner and academic researchers to discover new factors in the market so that they can enjoy higher efficiency than the diversified multiple factor index.

[Figure 1]

**Figure 1.** MSCI indices and S&P500
### Table 1. Summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Equal Weighted</th>
<th>Minimum Volatility</th>
<th>Value Weighted</th>
<th>High Dividend Yield</th>
</tr>
</thead>
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<tr>
<td>Mean</td>
<td>0.60</td>
<td>0.49</td>
<td>0.45</td>
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<td>0.91</td>
<td>0.98</td>
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<td>Standard Deviation</td>
<td>5.13</td>
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<td>4.65</td>
<td>3.83</td>
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<td>Sharp Ratio</td>
<td>0.12</td>
<td>0.14</td>
<td>0.14</td>
<td>0.13</td>
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<tr>
<td>Minimum</td>
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<td>13.72</td>
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<td>180.00</td>
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### Table 2. Correlation Matrix

<table>
<thead>
<tr>
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<th>Equal Weighted</th>
<th>Minimum Volatility</th>
<th>Value Weighted</th>
<th>High Dividend Yield</th>
<th>Momentum</th>
<th>Quality</th>
<th>Diversified Multi-Factor</th>
<th>Parent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equal Weighted</td>
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<td></td>
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<td></td>
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<td>Minimum Volatility</td>
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<tr>
<td>Value Weighted</td>
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<td>0.92</td>
<td>1.00</td>
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</tr>
<tr>
<td>High Dividend Yield</td>
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<td>0.94</td>
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<td>1.00</td>
<td></td>
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<tr>
<td>Momentum</td>
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<td>Quality</td>
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<td>Diversified Multi-Factor</td>
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<td>Parent</td>
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<td>0.87</td>
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### Table 3. Dybvig-Ross analysis for parent index

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<th>(5)</th>
<th>(6)</th>
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<tbody>
<tr>
<td><strong>parent</strong></td>
<td>1.14***</td>
<td>0.71***</td>
<td>1.05***</td>
<td>0.78***</td>
<td>0.88***</td>
<td>0.87***</td>
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<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.015)</td>
<td>(0.031)</td>
<td>(0.016)</td>
<td>(0.038)</td>
</tr>
<tr>
<td><strong>alpha (annual)</strong></td>
<td>1.98*</td>
<td>2.52**</td>
<td>0.56</td>
<td>2.48</td>
<td>1.45*</td>
<td>2.64</td>
</tr>
<tr>
<td></td>
<td>(1.14)</td>
<td>(1.13)</td>
<td>(1.16)</td>
<td>(1.61)</td>
<td>(0.86)</td>
<td>(1.98)</td>
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<td>180</td>
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</tr>
</tbody>
</table>

*Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Table 4. Dybvig-Ross analysis for diversified multiple factor index

<table>
<thead>
<tr>
<th></th>
<th>(1) eq_weight</th>
<th>(2) min_vol</th>
<th>(3) value</th>
<th>(4) hdy</th>
<th>(5) quality</th>
<th>(6) momentum</th>
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</thead>
<tbody>
<tr>
<td>multi_factor</td>
<td>1.12***</td>
<td>0.69***</td>
<td>1.00***</td>
<td>0.73***</td>
<td>0.83***</td>
<td>0.92***</td>
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<tr>
<td></td>
<td>(0.026)</td>
<td>(0.025)</td>
<td>(0.028)</td>
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<td>(0.031)</td>
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<tr>
<td>alpha (annual)</td>
<td>-1.24</td>
<td>0.56</td>
<td>-2.15</td>
<td>0.57</td>
<td>-0.77</td>
<td>-0.27</td>
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<tr>
<td></td>
<td>(1.38)</td>
<td>(1.3)</td>
<td>(1.46)</td>
<td>(1.93)</td>
<td>(1.42)</td>
<td>(1.64)</td>
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<tr>
<td>N</td>
<td>180</td>
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<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
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</tbody>
</table>

Standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 5. GRS test results

<table>
<thead>
<tr>
<th>GRS test</th>
<th>Parent Index</th>
<th>Diversified Multiple Factor Index</th>
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<tbody>
<tr>
<td>GRS test Statistics</td>
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<td>1.27</td>
</tr>
<tr>
<td>P-value(%)</td>
<td>1.14</td>
<td>28.01</td>
</tr>
<tr>
<td>Null Hypothesis</td>
<td>Rejected</td>
<td>Cannot be rejected</td>
</tr>
</tbody>
</table>
Appendix

A. MSCI factor indexes

In this appendix, all the factor indexes used in this analysis are explained.

Equally weighted index: Small firm effect implies that the smaller companies from the perspective of market cap sizes tend to outperform the larger companies. By putting the equal weight on each constituent of the index (the weight of each constituent is $1/N$ where $N$ is the number of constituents of the index), this index captures the small firm effect.

Minimum volatility index: Through optimization process, this index tries to realize the global minimum variance portfolio with the constituents of underlying parent index. This index historically demonstrates lower beta, lower volatility, as well as lower cap bias than the parent index, and successfully have a bias towards stocks with low idiosyncratic risk.

Value weighted index: In other words, value tilted index. This index applies value investment strategy. The weight of each constituent is determined depending on some accounting data such as sales, book value, earnings, as well as cash earnings.

High dividend yield index: This index focuses on dividend yield by selecting companies with a sustainable and persistent dividend, high dividend yield, 5-year non-negative DPS growth rates, and so forth. This index excludes companies with extremely high dividend payout ratio. This suggests that this index takes the future dividend sustainability into consideration.

Quality index: This index reflects a quality growth strategy where companies with durable business model and sustainable competitive advantages are selected. These characteristics are measured by high ROE, stable earnings, as well as strong balance sheets with low financial leverage.

Momentum Index: Momentum strategy suggests that previous winner is likely to win again. This index chooses companies with high price performance in the recent history, up to 12 months.

Diversified multiple factor index: This index maximizes the exposure to the following four common factors- value, momentum, size, as well as quality- while maintaining market risk exposure similar to the underlying parent index. There is some evidence showing that single factor underperforms market cap weighted benchmark for several years. This index, however, diversifies the exposure to a range of factors.

B. Efficiency test in the World Universe

Basically, all the results are similar to that of the U.S. universe.

As table 1 shows, some significant alphas are observed in parent index, while there is only one significant alpha for the diversified multiple factor index. As for the GRS test, the mean-variance hypothesis is rejected for the parent index, but not for the diversified multiple factor index. Yet, note that the result for the diversified multiple factor index is quite marginal, which might reflect
the negatively significant value factor in DR analysis. Value factor has not been performing well in the recent period, so this might be the reflection of the bad performance of the value strategy.

[Table 1]

**World Parent Index**

<table>
<thead>
<tr>
<th></th>
<th>(1) eq_weight</th>
<th>(2) min_vol</th>
<th>(3) value</th>
<th>(4) hly</th>
<th>(5) quality</th>
<th>(6) momentum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>parent</strong></td>
<td>1.03***</td>
<td>0.63***</td>
<td>1.03***</td>
<td>0.92***</td>
<td>0.86***</td>
<td>0.88***</td>
</tr>
<tr>
<td></td>
<td>(0.0214)</td>
<td>(0.0221)</td>
<td>(0.0153)</td>
<td>(0.0258)</td>
<td>(0.0166)</td>
<td>(0.0372)</td>
</tr>
<tr>
<td><strong>alpha (annual)</strong></td>
<td>2.81**</td>
<td>2.71**</td>
<td>0.82</td>
<td>1.46</td>
<td>1.63*</td>
<td>2.86</td>
</tr>
<tr>
<td></td>
<td>(1.16)</td>
<td>(1.20)</td>
<td>(0.83)</td>
<td>(1.39)</td>
<td>(0.9)</td>
<td>(2.02)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>204</td>
<td>204</td>
<td>204</td>
<td>204</td>
<td>204</td>
<td>204</td>
</tr>
</tbody>
</table>

*Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 1. Dybvig-Ross analysis for parent index in world universe**

[Table 2]

**World Diversified Multiple Factor Index**

<table>
<thead>
<tr>
<th></th>
<th>(1) eq_weight</th>
<th>(2) min_vol</th>
<th>(3) value</th>
<th>(4) hly</th>
<th>(5) quality</th>
<th>(6) momentum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>multi_factor</strong></td>
<td>1.00***</td>
<td>0.61***</td>
<td>0.98***</td>
<td>0.87***</td>
<td>0.81***</td>
<td>0.91***</td>
</tr>
<tr>
<td></td>
<td>(0.0246)</td>
<td>(0.0232)</td>
<td>(0.0257)</td>
<td>(0.0314)</td>
<td>(0.0234)</td>
<td>(0.0308)</td>
</tr>
<tr>
<td><strong>alpha (annual)</strong></td>
<td>-1.70</td>
<td>-0.05</td>
<td>-3.47**</td>
<td>-2.36</td>
<td>-1.94</td>
<td>-1.48</td>
</tr>
<tr>
<td></td>
<td>(1.36)</td>
<td>(1.28)</td>
<td>(1.43)</td>
<td>(1.73)</td>
<td>(1.30)</td>
<td>(1.70)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>204</td>
<td>204</td>
<td>204</td>
<td>204</td>
<td>204</td>
<td>204</td>
</tr>
</tbody>
</table>

*Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 2. Dybvig-Ross analysis for the diversified multiple factor index in world universe**
### GRS test result for the world universe

<table>
<thead>
<tr>
<th></th>
<th>World (Parent)</th>
<th>World (Diversified multiple factor index)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GRS test statistics</td>
<td>3.63</td>
<td>2.07</td>
</tr>
<tr>
<td>P-value(%)</td>
<td>0.2</td>
<td>5.83</td>
</tr>
<tr>
<td>Null Hypothesis(95% significance level)</td>
<td>Rejected</td>
<td>Cannot be rejected</td>
</tr>
</tbody>
</table>

Table 1. GRS test result for the world universe

C. Efficiency test for FTSE indexes

References


JENNIFER Bender, REMY Briand, DIMITRIS Melas and RAMAN Subramanian (2013) “Foundations of Factor Investing”


Dataset from Bloomberg

Dataset from Kenneth R. French website
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
Momentum Analysis

1. Question/Motivation

Coming into FINA472 I did not have any practical knowledge of investing, thus making the opportunity to learn Momentum very intriguing. At first momentum sounded fairly simple, just taking the ETFs that showed a positive trend while divesting in holdings that showed a negative trend. My general question was to calculate a momentum strategy for our ETF holdings and see if it would result in positive returns while rebalancing on a monthly basis. The ETFs used in this analysis were the past 31 ETFs that were held by this class over the past 5 years.

2. Methodology and Data

The methodology for this strategy was based on a simple momentum analysis, using the Long on Top 10 and Short on Bottom 10 approach. The initial step was to input all of the ETFs into the stock downloader which would report the Total USD Returns for the given period on a monthly basis. From these returns, the next step was to calculate the percentage change from one year to the next, for each ETF individually. These returns varied, showing both positive and negative results throughout. These percentages were then ranked out of the total sample size, on a simple numerical basis from 1 to 31 (1 being the highest ranking, 31 being the lowest). To implement the Top 10 and Bottom 10 strategy, the rankings were given a value of “1” if the return was part of the 10 highest returns from the given period. The 10 lowest percentage change values were given a value of “-1” while the median 11 were given a value of “0”.

The Total USD Returns and ranking system (based off of percentage change of Total USD Returns) were the two most important factors in calculating the Momentum Strategy. For each period starting in May of 2011, the momentum was calculated. This was done by the given month’s Total USD Returns and multiplying them by the ranking system with the prior month’s data being skipped. For example, the May 2011 Total USD Returns were multiplied by the March 2011 ranking system. This momentum was calculated independently on a month to month basis; however, the cumulative chart gives a better representation of our portfolio returns over the given 5-year period. The biggest monthly loss for the portfolio is -6.3% in April of 2015. The biggest gain was in May of 2012 with an increase of 6.01%.
3. **Results**

The above chart shows the 59 periods in which this data was calculated. The beginning value of 1 represented the initial holding, with a return of 38% over the given period. The average monthly return over this 59-period analysis was .55% with a standard deviation of .028. This low standard deviation implies that this strategy is relatively safe, and can provide a good “defense” to riskier strategies. The Z-Score was calculated by taking the average monthly return and dividing it by the standard deviation of the given period. The result was a Z-Score of .191, which indicates that the individual months typically represented a higher return than the mean, indicating a fairly average return.
E. Effects of a Leveraged Bond ETF on the Student Managed Investment Portfolio

Michael Kirschke, Dhruv Ahluwalia

Asset Allocation

Professor Shingo Goto – FINA 472/772

Introduction

In this research, we attempted to determine if adding a leveraged bond ETF to our ETF portfolio could have benefits in either reducing overall portfolio volatility or increasing average returns. Because of the negative correlations of treasury bond funds with the majority of our ETFs, we believed that adding a leveraged bond fund to our portfolio would at least lower the portfolio volatility and possible push the efficient frontier out to the northwest of the mean-variance chart. Our analysis provides observed results, but not a formal hypothesis test.

Methodology

Our first step was to collect historical prices from the Student Managed Investment Fund ETF universe, defined as 32 international and industry sector ETFs, plus an additional ETF to track the long term U.S. Government bond market. We chose to collect closing prices from April 1, 2008 to March 1, 2016. Ideally, we would have preferred to analyze data going back to 2003 or earlier, but many of the ETFs in our portfolio did not exist prior to 2008. A more comprehensive study will need to choose representative proxies for these ETFs, or will have to analyze a completely different portfolio of international and sector-specific mutual funds with long histories.

After collecting return data from each ETF, we calculated daily returns and adjusted for the historical risk-free rate to create a table of excess returns. The bond ETF that we used was TLT – iShares 20+ Year Treasury Bond ETF. This fund has a weighted average maturity of 26.54 years, and an average duration of 17.63 years, making it very sensitive to interest rate movements. In order to replicate the characteristics of a leveraged bond ETF, we used the following formula: \( R(f) + 3(TLT \text{ returns} - R(f)) \). It would have been simpler to analyze returns from an existing leveraged bond fund, but the only similar ETF, TMF, does not have a long history. After adjusting the TLT returns, we ran a correlation test against the returns of TMF and found an \( R^2 \) of 0.997.

After creating a table of excess returns from 4/2/2008 – 3/1/2016, we analyzed the entire dataset to determine if there was any justification to our theory. We calculated the average daily returns and volatility for each ETF, and created two separate covariance matrices: a 32x32 control matrix which excluded TLT, and a 33x33 matrix which included TLT. We then used the vector of average daily returns multiplied by the corresponding covariance matrix to create the optimal ex-post tangency portfolio and minimum variance portfolio (MVP). By shorting the tangency portfolio and going long the MVP in different ratios, and then vice-versa, we were able to create the ex-post efficient frontiers displayed in the chart below.
Based on historical returns, it appeared that adding a leveraged bond ETF could have beneficial diversification effects for our portfolio. We continued our research by applying past return data to future, out-of-sample (OOS) data. In order to do this, we analyzed four years of prior return data and applied it forward to one year of out-of-sample (OOS) data. For the year 2012, we used the data from 2008 – 2011, calculated average daily returns, built two separate covariance matrices, and calculated optimal MVP portfolio weights and Maximum Diversification (MaxDiv) portfolio weights. These portfolio weights were then applied forward to the 2012 data:
In 2012, using a leveraged bond fund similar to TLT would have resulted in our GMVP portfolio achieving equal returns (11.57%), with a reduction in volatility of 183 basis points. The MaxDiv portfolio, if it included TLTx3, would have returned 2.75% less than a portfolio without TLTx3, while lowering volatility by 146 basis points. We then repeated the analysis for the years 2013-2015. Those charts are included below without the efficient frontiers drawn.
In 2013, the portfolios which included the leveraged bond ETF performed significantly worse than their counterparts in terms of total returns, while the leveraged MaxDiv portfolio saw a reduction in volatility at the expense of over 1500 basis points in total returns.
In 2014, the portfolios including the leveraged bond ETF performed better both in terms of total returns and volatility.

In 2015 the results were mixed. Better returns and lower volatility for the MaxDiv portfolio, with slightly lower returns and lower volatility for the GMVP portfolio.
After applying all of our optimal portfolios to OOS data, we charted the growth of $100 invested in each of the four possible funds at the beginning of 2012 through the end of 2015:

Conclusion

Without more scientific testing methods and sample data with significantly longer historical returns, we are unable to make any specific recommendations. Additionally, with more frequent rebalancing, the portfolios may have performed differently. The leveraged bond ETF performed so poorly in 2013 that a monthly rebalancing strategy may have lead us to reduce its weighting, or we may have made the decision as a class to remove the fund due to extensive losses. As our results show, the portfolios which include the leveraged bond ETF do not generate returns as high as their counterparts. However, including the leveraged bond ETF seems to reduce volatility in most years.

For future research, we would recommend that this strategy be studied using historical returns going back to 1999 or earlier. Capturing the collapse of the tech bubble in 2001-2003 as well as the global financial crisis from 2007-2009 would certainly be instructive, and could produce very beneficial results. Because the leveraged bond ETF is so sensitive to interest rate adjustments, any downward movement in interest rates would result in significantly higher returns for the bond ETF, thus mitigating some of the negative returns experienced in the equity markets during recessions and market corrections. Additionally, we would recommend rebalancing on a monthly or quarterly basis, as well as using covariance matrices that cover different lengths of time, or place more weight on recent returns than those further in the past.
F. Searching for New Factors for the Country Allocation Strategy

Chunkau Wong, Ryohei Oishi

Asset Allocation

Professor Shingo Goto – FINA 472

This paper aims to investigate the factors that can be applied in country allocation strategies across 23 developed countries\(^2\) in the MSCI World Index. Some useful factors are discovered, including Cash Flow/Enterprise Value, Cash Holding/Asset and Long-term GDP Growth Forecast as the three best factors. There are also some potential factors such as momentum and unemployment rate even though they were not robust in the world universe excluding the U.S. As unemployment rate gives a counter intuitive result, detailed case study is included.

I. Introduction

MSCI Inc. is one of the biggest index provider across world, and it is providing so called diversified multiple factor index for various investment universe. In the analysis of the efficiency of the diversified multiple factor index, the hypothesis that diversified multiple factor index is mean variance efficient was not statistically rejected. This suggests that it is unlikely to achieve higher efficiency by employing different allocation strategy of MSCI factor indexes. This result motivates the researchers to discover new factors that can provide more efficient facto investment and smart beta strategy.

MSCI World Index consists of 1,600 constituents across 23 countries. It covers 85% of the entire market capitalization of each country. As such a comprehensive index, it is exposed to a lot of factors that may have dilution effect on its final performance. This paper aims to extract factors which have the strongest explanatory power for performance in country allocation. In empirical terms, we would examine factors that could give out high return through an assimilation of index mixing.

\(^2\) Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK and the US
II. Methodology

Our purpose here is to build various “factor” portfolios and compared their monthly return to the parent index. The first step is to calculate the cross-sectional weighted Z-score for each country at one time. Second, the Z-score is computed into a final score through sigmoid function.

\[ S(t) = \frac{1}{1 + e^{-t}} \]

In this investigation we employ a shape value of 4 to increase the level of selection. However, it should be noted that this application is arbitrary.

\[ S(t) = \frac{1}{1 + e^{-4t}} \]

The set of final score is multiplied by the market capitalization of each country and to come up with the portfolio weight after normalization.

Return of the portfolio is calculated by multiplying the historical return of each country index by the new weight. The portfolio would rebalance each month.

III. Data

1. This analysis employs the total gross return data of all the 23 countries indexes in MSCI and the benchmark MSCI World Index for investigation.
2. All market-capitalization value is denominated in USD.
3. We obtain macro-economic data mainly from national statistical bureaus and aggregate bottom-up data from MSCI (NYSE: MSCI) respectively.
4. The period of investigation starts from June 2003 and ends in September 2015.
5. All portfolio rebalances on a monthly basis.
### IV. Result

A. Robust Factors

<table>
<thead>
<tr>
<th>Indicator</th>
<th>MSCI World</th>
<th>Cash Flow</th>
<th>Cash Holding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Excess Return (percent/p.a)</td>
<td>7.9</td>
<td>9.55</td>
<td>9.37</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.52</td>
<td>0.61</td>
<td>0.61</td>
</tr>
<tr>
<td>IR (percent p.a)</td>
<td>0</td>
<td>0.86</td>
<td>0.71</td>
</tr>
<tr>
<td>Alpha wrt MSCI World</td>
<td>0</td>
<td>1.42</td>
<td>1.49</td>
</tr>
<tr>
<td>Beta wrt MSCI World</td>
<td>1</td>
<td>1.03</td>
<td>1</td>
</tr>
<tr>
<td>Turnover</td>
<td>0</td>
<td>48.50%</td>
<td>72.70%</td>
</tr>
</tbody>
</table>

Cash Flow/Enterprise Value: We hypothesize that high cash flow is indicative of high stock return. In this investigation, the portfolio formed by using “cash flow” as a factor has a satisfactory result, having the strongest average excess return, sharpe ratio and information ratio. When it is regressed against MSCI World, it achieved a positive alpha of 1.42. The data suggests that a high cash flow returns a high stock return in country allocation strategy.
Cash Holding/Asset: The portfolio formed by using “cash holding” as a factor also results in good performance, having better average excess return, sharpe ratio, positive information ratio and alpha. Contrast to the thought that high cash holding would lead to waste of capital/ overspending from the management, the result suggests that high cash holding is actually good for stock return.

Long-term GDP Growth Forecast: The portfolio formed by using “GDP growth forecast” employs GDP growth forecast data from IMF\(^3\). The factor is composed by taking a negative number of the revision of 5-Year forecast. This portfolio also has similar good result as cash flow and cash holding. One possible explanation is long-term GDP growth forecast represents the expected return. A negative revision means investors are willing to accept lower return, improving overall stock return.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>MSCI World exUS</th>
<th>Cash Flow exUS</th>
<th>Cash Holding exUS</th>
<th>GDP Forecast exUS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Excess Return(percent/p.a)</td>
<td>7.84</td>
<td>8.97</td>
<td>8.43</td>
<td>10.04</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.45</td>
<td>0.51</td>
<td>0.46</td>
<td>0.57</td>
</tr>
<tr>
<td>IR(percent p.a)</td>
<td>0</td>
<td>0.52</td>
<td>0.23</td>
<td>0.61</td>
</tr>
<tr>
<td>Alpha wrt MSCI World</td>
<td>0</td>
<td>1</td>
<td>0.15</td>
<td>2.23</td>
</tr>
<tr>
<td>Beta wrt MSCI World</td>
<td>1</td>
<td>1.02</td>
<td>1.06</td>
<td>1</td>
</tr>
<tr>
<td>Turnover</td>
<td>/</td>
<td>81.90%</td>
<td>70.70%</td>
<td>88.00%</td>
</tr>
</tbody>
</table>

As a robustness check, these three factors are used to compute portfolios that exclude the U.S. market, for the sake that the U.S. account for 60% of the portfolio in MSCI World. The result suggests that while cash flow and long-term GDP forecast remains consistent with the previous finding, the supremacy of cash holding seems to disappear.

Back-test return of a portfolio combing the three factors, compared against MSCI World Index from 2003 to 2015 Figure(1)

B. Some Less Robust Factors

<table>
<thead>
<tr>
<th>Indicator</th>
<th>MSCI World</th>
<th>Exchange Rate</th>
<th>Momentum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turnover (percent p.a)</td>
<td>0%</td>
<td>143.80%</td>
<td>123.20%</td>
</tr>
<tr>
<td>Transaction Cost</td>
<td>0</td>
<td>0bp TC</td>
<td>50bp TC</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0bp TC</td>
<td>50bp TC</td>
</tr>
<tr>
<td>Average Excess Return (percent p.a)</td>
<td>7.9</td>
<td>9.42</td>
<td>8.019</td>
</tr>
<tr>
<td>Sharpe Ratio (percent p.a)</td>
<td>0.52</td>
<td>0.58</td>
<td>0.49</td>
</tr>
<tr>
<td>Indicators</td>
<td>MSCI World</td>
<td>Unemployment</td>
<td>MSCI World</td>
</tr>
<tr>
<td>------------</td>
<td>------------</td>
<td>--------------</td>
<td>------------</td>
</tr>
<tr>
<td>Average Excess Return</td>
<td>7.9</td>
<td>9.15</td>
<td>7.43</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.52</td>
<td>0.57</td>
<td>0.43</td>
</tr>
<tr>
<td>IR(percent)</td>
<td>0</td>
<td>0.61</td>
<td>0</td>
</tr>
<tr>
<td>Alpha wrt MSCI World</td>
<td>0.96</td>
<td>0</td>
<td>-0.13</td>
</tr>
<tr>
<td>Turnover</td>
<td>/</td>
<td>22.30%</td>
<td>/</td>
</tr>
</tbody>
</table>

Unemployment rate factor refers to the negative number of unemployment rate. The factor is very strong in the world universe. However, the advantage disappears after excluding the U.S. market.
V. Case Study for unemployment rate factor

One possible explanation why unemployment rate can work as a factor can be given from the perspectives of behavioral economics. Generally, as investors have a risk averse characteristics, they would require a higher rate of return, i.e. higher discount rate, in a bad economic condition, and vice versa. This leads to the stock price goes down, and investors should buy at this point in time. However, in order to implement this strategy where one put more weight on a bad economy country and less on a good economic country, it is indispensable to observe business cycle in real time, which is nearly impossible. Hereby, using unemployment rate to track the business cycle is suggested.

The structure of this report is as follows. In the second chapter, detailed explanation of the relationship among risk aversion, stock price, as well as business cycle is given. This chapter also shows a distinct difference of interpretation of business cycle between investment viewpoint and normal economists’ viewpoint. In the third chapter, the idea of tracking business cycle by using unemployment rate would be introduced. Methodology for the empirical analysis is also given here. In the fourth chapter, empirical evidence which supports the effectiveness of tracking business cycle by using unemployment rate will be given. In the final paragraph, the discussion is concluded with a suggestion for future research.

VI. Risk aversion and investment strategy

Normally investors have a risk averse characteristics to some extent. They would require a higher rate of return, i.e. discount rate, in a bad economic condition since they are worried investing money into risky assets and anxious to be compensated for bearing the risk. As many stock pricing model shows, a stock price and discount rate have a negative relationship. This means that in a bad economic condition the stock price would be low while it is high in a good economic condition where investors have a lower discount rate.

The principle of investment is that sell low and buy high. From the discussion above, it seems to be a good strategy to put more weight on a country whose economic condition is bad and put less on a bad economy country.
Note that distinctly different information from the business cycle is used here. As figure 1 shows, generally economists focus on the upward trend and downward trend as economic contraction and economic expansion respectively. However, in choosing investment target and determining the weight in each country, it is more informative to focus on the different side of the business cycle, as shown in figure 2. Looking at if the economy is in good condition or bad condition, not focusing on if it is expanding or contracting, one can access the information of investors risk aversion, and can decide the weight on the each country in the universe.

It is necessary, however, to observe real-time business cycle across countries in your investable universe in order to implement this strategy, which is nearly impossible. Therefore, some economic indicators which is standardized, observable, and available across countries are necessary. And one possible candidate for this role is unemployment rate, and this is why the unemployment rate can work as a factor in smart beta strategy. In the next section, the method how to analyze the empirical relationship between unemployment rate and the business cycle is given.

VII. Unemployment rate as a tracking tool of business cycle

In this section, the methodology to derive the empirical evidence that unemployment rate can track the business cycle is given. In order to assess the relationship, historical data of unemployment rate and the business cycle is needed. While it is easy to obtain numerical, and statistical data of unemployment rate, it is quite difficult to observe historical data of business cycle as it is invisible. However, it is suggested by Stock and Watson (1999) that

“Although the business cycle technically is defined by co-movements across many sectors and series, fluctuations in aggregate output are at the core of the business cycle so the cyclical component of real GDP is a useful proxy for the overall business cycle and is thus a useful benchmark for comparisons across series.”

Therefore, real GDP in the U.S. is used as a proxy of the business cycle. Table3 shows a natural log of real GDP in the U.S. from the first quarter in 1948 to the first quarter in 2016. As you can explicitly observe from the graph, real GDP has an upward trend, which means that real GDP is non-stationary data. In order to separate the trend and periodic cycle, and extract fluctuations from real GDP data, i.e. detrend the data, some economic filter is needed. Even though there are various filters invented, here the filter
invented by King and Baxter (1999) is used. This filter is also used in Stock and Watson (1999). This filter requires researchers to set two parameters; minimum and maximum period of the business cycle and lag period. The lag period has a tradeoff between the efficiency of approximation and sample size. The more lag added in the filter, the more precise the approximation would be while the less sample period you have. In this paper, the minimum business cycle is supposed to be six-quarter and maximum thirty-two quarter. The lag period is set as 12. All the parameters here are suggested by King and Baxter (1999) or Burns and Mitchell (1946) for U.S. business cycle. The empirical result is shown in the next chapter.

VIII. Empirical Evidence

Figure 4 shows the filtered natural log of real GDP and frequency response function.

Figure 5 shows the historical relationship between U.S. business cycle, i.e. King and Baxter filtered natural log of real GDP. Graphically, unemployment rate seems to be have been moving counter-cyclically. Chart one shows the cross-autocorrelation shown as

\[ \text{cor}(x_t, y_{t-k}) \]

where \( t = \text{from Q1 in 1951 to Q1 2013 and } k = -4, -3, ..., 3, 4 \)

\( x_t \) denotes unemployment rate at time \( t \) and \( y \) is filtered real GDP

Panel A reports the autocorrelation using full sample period, and panel B reports the correlation using data from first quarter in 1980 to the end, and panel C uses data from quarter C to end. As chart one shows, the lagged correlation coefficient between unemployment peaks around time \( t \) and \( k=t \), which means that unemployment rate and business cycle move in an opposite direction simultaneously.
IX. Conclusion

This paper has examined the explanatory power of some ready-to-use factors on stock return in country allocation. In MSCI World Index, where all constituents are in developed countries, cash flow, cash holding and GDP growth forecast seem to suggest very good explanatory power on the historical performance of the index. Through this exercise, exchange rate, momentum and unemployment are factors that also demonstrate strong explanatory power, but they may need to go through some adjustments to pass the robustness check.

X: Appendix

[Figure 1]

Figure 1. General Economist’s Business Cycle
Figure 2. More Informative Business Cycle

Figure 3. Natural Log of Real GDP in the U.S.
Figure 4. Baxter and King filtered natural log of real GDP.

Table 1

Panel A cross autocorrelation (full data, lowest three in yellow, sample = 248 in k=0)

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<th>t-2</th>
<th>t-1</th>
<th>t</th>
<th>t+1</th>
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Panel B cross autocorrelation (full data, lowest three in yellow, sample = 248 in k=0)

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Panel C cross autocorrelation (full data, lowest three in yellow, sample = 248 in k=0)

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References


