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## Bridgewater Pure Alpha: How Much is Explained by Dynamic Beta?

### Using predictive analytics to reproduce the beta exposures of the largest hedge fund

*“In truth, many hedge funds are packaging up beta and selling it at alpha prices. When we strip many hedge funds “strategies” from the beta that underlines them, we find that quite often, they are not wearing any clothes at all.”*

*Risk Magazine, December 1<sup>st</sup>, 2004*

As reported by Risk Magazine at the end of 2004, Bridgewater Associates emphasized the need to identify systematic risks and separate alpha from beta, stating that many hedge funds’ strategies could be replicated with “naïve” portfolios. A few months later, Markov Processes International (“MPI”) released a report (“Seeing through walls – Bringing greater transparency to mutual fund and hedge fund analysis”<sup>1</sup>) in which MPI introduced its proprietary returns-based technology for better due-diligence and to “reverse engineer” hedge fund returns such as the Bridgewater Pure Alpha Fund. In October 2011, Bridgewater released a new report entitled “Hedge fund returns continue to be dominated by beta”. Inspired by Bridgewater’s new findings, we decided to extend our original analysis and dig deeper into the performances of one of the most successful hedge funds. Using MPI’s *Factor Search* procedure, our endeavor is to capture dynamic betas embedded in the Bridgewater flagship fund’s returns and attempt to reproduce its systematic performance behavior using a simple basket of indices or exchange-traded funds.

### Introduction

Founded in 1975 by Raymond Dalio, Bridgewater Associates provides discretionary investment management and consulting services to institutional clients. Initially, their services were provided to corporations in the management of income and balance sheet exposures through investment in global credit and currency markets. Today, with more than

\$125 billion in assets under management<sup>2</sup> and some of the largest corporate and public pension funds, sovereign wealth funds, endowments, family offices and fund of funds as clients, Bridgewater has become the largest alternative investment management firm in the world.

Bridgewater offers its institutional clients several strategies including an active management strategy (Pure Alpha), a constrained active management strategy that invests in a subset of the markets in which Pure Alpha invests (Pure Alpha Major Markets), and an asset allocation strategy (All Weather). The Pure Alpha Strategy was launched in 1991 with two different versions by volatility: Bridgewater Pure Alpha I, at 12% volatility with around \$10 billion in assets under management, and Bridgewater Pure Alpha II, with a target volatility of 18% and close to \$23 billion in AUM<sup>3</sup>. We decided to focus our analysis on Bridgewater Pure Alpha II Fund, Bridgewater’s largest commingled investment vehicle.

We seek to demonstrate how quantitative analysis and beta modeling techniques can be used by institutional investors to better understand fund behavior, anticipate performance and improve due diligence, risk management and portfolio monitoring of hedge funds.

MPI does not claim to know or insinuate what the actual strategy, positions or holdings of this fund were, nor are we commenting on the quality or merits of Bridgewater Associates’ Pure Alpha strategies. This analysis is purely returns-based and does not reflect actual holdings. Deviations between our analysis and the actual holdings and/or management decisions made by the fund are expected and inherent in any quantitative analysis. MPI makes no warranties or guarantees as to the accuracy of this statistical analysis, nor does it take any responsibility for investment decisions made by any parties based on this analysis.

<sup>1</sup> Original research available on [www.markovprocesses.com](http://www.markovprocesses.com)

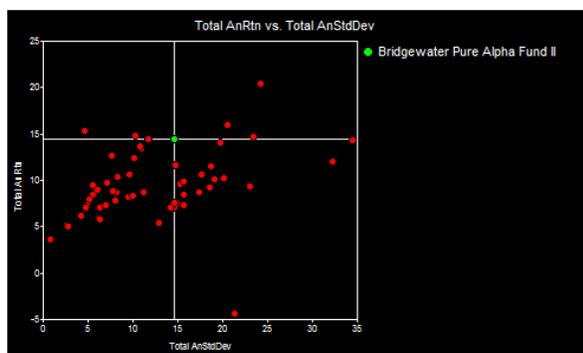
<sup>2</sup> Source: <http://www.bwater.com>

<sup>3</sup> Source: Eurekahedge, November 2011

## Peer Analysis

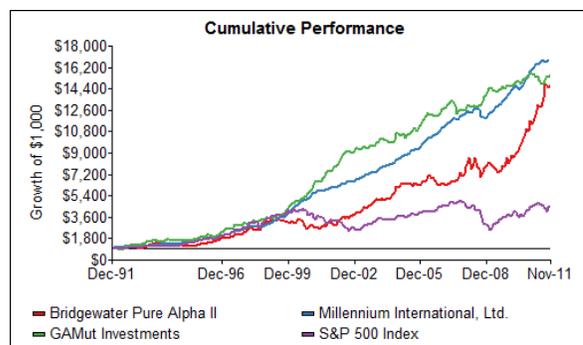
Combining HFR, EurekaHedge and HedgeFund.Net hedge fund databases, we constructed a sub-universe of 59 unique USD-denominated alternative investments that have a track record of close to twenty years (from January 1992) and more than two hundred and fifty million in assets under management as of November 2011. Interestingly, as seen in Figure 1, only two hedge funds (located in the top left quadrant) beat Bridgewater Pure Alpha Fund II (shown in green at the axis intersection), in terms of having higher annualized performance and lower risk over the twenty-year timeframe. Between January 1992 and November 2011, Bridgewater Pure Alpha II's annualized performance was 14.44% with an annualized standard deviation of 14.60%.

Figure 1  
**20-Year Universe Risk/Return Analysis**



Looking closer at the cumulative performance since January 1992 (shown in Figure 2), it is easy to see that Bridgewater Pure Alpha Fund II and the two other funds from our peer analysis – Millennium International and GAMut Investments – have significantly outperformed the S&P 500 Index. Bridgewater Pure Alpha II Fund is represented by the red line and the S&P 500 Index by purple line. But the different performance paths of these funds suggest that the impressive outperformance over the various market cycles of the past twenty years stem from very different alpha and/or beta investment strategies employed by the fund managers.

Figure 2  
**Cumulative Performance**



Over the full time period, Bridgewater has more than tripled the S&P 500 Index performance, but two distinct periods are of specific interest:

- Bridgewater Pure Alpha II has cumulatively outperformed the S&P index only during the second decade, particularly from April 2002.
- The fund has seen a remarkable acceleration in its performance both in absolute and relative terms since the fall of 2008. Consequently we will focus our analysis from October 2008 to end of November 2011, inclusive.

## The Search for Explanatory Variables

The dynamic nature of hedge fund investments, as well as their ability to take significant short positions and leverage, often make traditional regression-based or factor analysis techniques inadequate for such products. In 2004, MPI introduced a proprietary and patented<sup>4</sup> Dynamic Style Analysis (“DSA”) technique based on machine learning technology to model this kind of portfolio. The methodology has since been used effectively in the analysis of many high-profile mutual fund and hedge fund cases<sup>5</sup>.

With its active asset allocation, use of alternative investment practices including leverage, shorting and use of derivatives (as well as its veiled holdings), Bridgewater Pure Alpha Fund II is an excellent candidate for applying MPI’s DSA technology. However, because no information is provided on the fund’s holdings and its unconstrained ability to invest anywhere, anytime and anyhow - selecting the appropriate market factors for a quantitative analysis is a true challenge for any investment professional.

<sup>4</sup> U.S. Patent No. 7,617,142; 8,001,032

<sup>5</sup> For other cases studies and research papers please refer to MPI’s [website](#)

To help analysts and fund buyers identify systematic betas in funds like Bridgewater, MPI is introducing a new proprietary and intelligent factor selection approach entitled Factor Search™. MPI's Factor Search introduces the ability to sift through a large universe of possible factors or risk premia in a short period of time to identify meaningful factor combinations. This search employs a clustering technique to associate indices based on the correlation of their returns and provides feedback on the model improvements during the sequential progression from least to most correlated indices. The guided search, customizable by the investment professional, is set up so that predictive power of the factor set is continually increasing. Predictive power of the exposure analysis is measured by MPI's Predicted R-squared™ which is a proprietary cross-validation statistic used to prevent over-fitting<sup>6</sup>.

## Reproducing Beta Exposures with ETFs

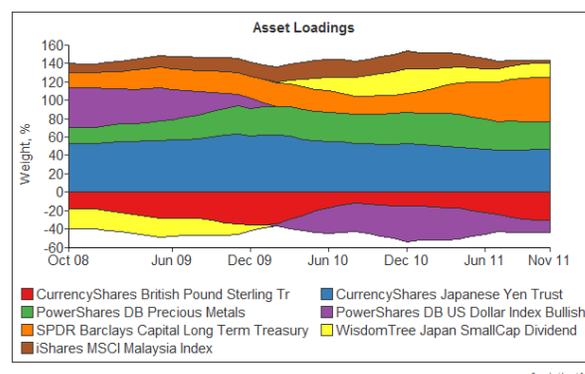
Pure Alpha's investment philosophy is based on Bridgewater's belief that the returns of asset classes are primarily driven by "changing fundamental conditions." The strategy is structured around Bridgewater's proprietary fixed income, equity, currency, and commodity trading strategies. According to their ADV Form Part 2, Bridgewater's Pure Alpha strategy has the flexibility to establish long, short, or spread positions across the markets mentioned above. The strategy utilizes a broad variety of instruments in its implementation, including, but not limited to, exchange traded funds (ETFs), futures contracts, OTC derivatives, cash securities, and spot and forward contracts in the international currency market.

Going a step further than factor analysis with standard market indices, we decided to perform our exposure analysis by searching for an investable portfolio of exchange traded funds (ETFs) that could have potentially simulated the behavior of Bridgewater Associates Pure Alpha Fund II over the past three years – a period of exceptional growth for the fund. The benefits of ETFs (such as intra-day liquidity, flexibility and lower management fees) make them attractive candidates in creating tracking portfolios.

Growth in the ETF industry has ensured that the potential factor set that we selected from the Morningstar Global ETF database is large – over 400

ETFs. The set contains a large number of asset classes, with 84 Morningstar categories represented. The challenge is to identify a stable portfolio which does not fluctuate wildly in exposure with small changes in the fund's returns. For more information on the methodology and detailed steps used in this specific case study please refer to the Appendix. The resulting dynamic exposures from our analysis are shown in Figure 3.

Figure 3  
DSA Exposures



Our analysis presented here suggests that:

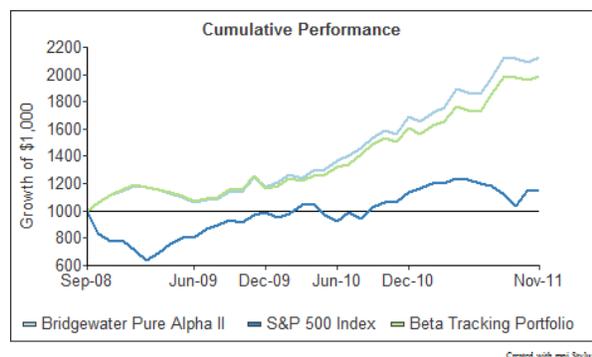
- The exposures indicate a fairly stable portfolio (relatively low turnover of assets) with a limited number of explanatory factors (7 ETFs). The manager makes an active usage of shorting strategies.
- Similar to a Global Tactical Asset Allocation (GTAA) investment strategy, the fund's performance can be explained by a combination of equity, fixed income, and commodity market factors together with currency overlays.
- Currency exposures seem to explain a large proportion of the performance behavior since October 2008. It can be synthesized by a long and sustainable exposure to Japanese Yen, a short exposure to the British Pound and fluctuating exposure to the USD versus a basket of other currencies, particularly the Euro (which currently represents approximately 57% of PowerShares' DB US Dollar Index Bullish). The USD exposure changes from long to short in 2009 but has been reduced significantly since the start of 2011, possibly trending toward a second reversal to regain its long exposure.

<sup>6</sup> For more information about Factor Search please connect to [http://www.markovprocesses.com/download/FactorSearch\\_Factsheet.pdf](http://www.markovprocesses.com/download/FactorSearch_Factsheet.pdf)

- In addition to currencies, the commodity exposure represented here by precious metals and the fixed income exposure represented by long-term treasury bonds appears to have driven a large part of the past performance. It is worth noting that the exposure to long term treasury bonds has significantly increased since the beginning of 2011.
- The equity exposure represented in this specific analysis by a small cap value Japanese ETF, as well as a Malaysian ETF, represents a fairly small percentage of the fund’s exposures potentially implying that the fund is modestly correlated to equity market performance (both developed and emerging markets). The Malaysian ETF can be used as a proxy for emerging markets as Malaysia is the largest country holding within the MSCI Emerging Markets Risk Weighted Index<sup>7</sup>.

Figure 4 shows the cumulative performance of the fund (in light blue) compared to the synthetic returns of the “beta tracking” portfolio (in light green) - which reflects the performance of the asset mix shown in Figure 3. This beta tracking portfolio is essentially a “style” portfolio created from the dynamic market factor exposures identified by the model. Even as “Bridgewater spreads its bets across myriad markets, eventually to more than 100 of them”<sup>8</sup>, the close movement of these two portfolios indicates that an important part of the fund’s performance can be effectively captured by the dynamic investment style depicted in figure 3.

Figure 4  
**Cumulative Performance of the Fund Vs. Its Beta Tracking Portfolio**



<sup>7</sup> Source: MSCI, June 2011, [http://www.msci.com/resources/factsheets/MSCI\\_Emerging\\_Markets\\_Risk\\_Weighted\\_Index.pdf](http://www.msci.com/resources/factsheets/MSCI_Emerging_Markets_Risk_Weighted_Index.pdf)

<sup>8</sup> Source: Bloomberg, “Dalio Returns 25% With Diversified Bets as Markets Convulse”, Richard Teitelbaum - Sept 7, 2011

The difference between the fund’s cumulative return and that of the “beta tracking” portfolio represents the unexplained portion that our model has not been able to estimate. In a high-quality quantitative analysis, this unexplained portion may be attributed to alpha, or the specific bets of the manager. In other cases, the unexplained portion could be attributed to missing factors such as dynamic trading in derivatives instruments, trading at ultra high frequencies or investing in illiquid assets such as real estate, private equity, distressed securities or hard assets like timber - any assets that are not well-reproduced by exchange-traded funds.

The high value of the out-of-sample Predicted R-squared (75%) (high by hedge fund analysis standards) gives credibility to this analysis. However, we would like to stress again that the market factors and systematic betas identified by statistical analysis do not represent the actual holdings of the fund but rather a portfolio of market factors that mimic the return behavior of the fund over the period analyzed.

### Pure Alpha and Pure Beta

In order to gauge its performance, instead of using a standard industry benchmark such as the S&P 500 or the 3-Month T bill, we utilize a custom style benchmark- a portfolio that reflects the historical average exposure weights identified over the entire analysis period and displayed in Table 1.

Table 1  
**Historical Average Exposure, Oct 08-Nov 11**

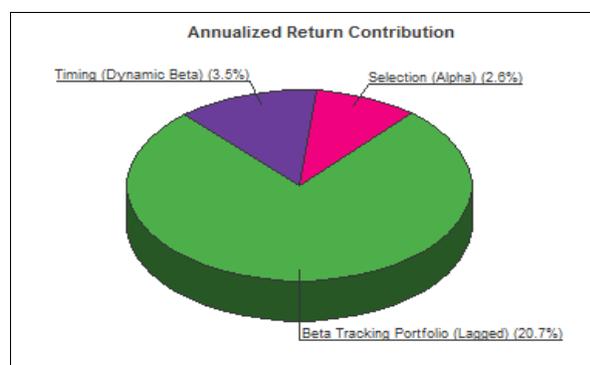
|  |        |
|--|--------|
| CurrencyShares British Pound Sterling Tr | -23.32 |
| CurrencyShares Japanese Yen Trust        | 54.13  |
| PowerShares DB Precious Metals           | 28.76  |
| PowerShares DB US Dollar Index Bullish   | -2.16  |
| SPDR Barclays Capital Long Term Treasury | 26.59  |
| WisdomTree Japan SmallCap Dividend       | 2.20   |
| iShares MSCI Malaysia Index              | 13.80  |

The objective of this exercise is to identify the alpha of the manager compared to a precise dynamic portfolio of market factors. As demonstrated in Figure 5, approximately three quarters of the annualized performance can be attributed to the static “Benchmark” (the historical average beta exposures shown in the table above). Approximately 13% of the performance is explained by timing or “dynamic” beta which is the difference between the performance of the beta tracking portfolio and the static average beta “Benchmark” portfolio. The remaining unexplained portion, 10% of the total

performance (labeled “Selection (Alpha)”), may be attributed to “pure” alpha, or possibly market factors that have not been identified by this analysis or rapid trading. While the greatest portion of the fund’s impressive three year annualized return of 26.8% does appear to be generated by the fundamental choice of asset mix, the returns from both the dynamic allocation of the asset mix and the non-replicable alpha portion are remarkable. It should also be noted that in a portfolio with such a broad mandate, the selection of the basic asset mix (in this case comprising the average beta “benchmark” portfolio) is an important source of value-added in and of itself.

Figure 5

### Annualized Return Contribution



### Investible Dynamic Beta

In an academic paper published in October 2009, Li, Markov and Wermers<sup>9</sup> detailed an approach to monitoring the daily risk of investing in hedge funds. This approach addresses the common problem that confronts investors who wish to monitor their hedge funds on a daily basis—disclosure of returns by hedge funds usually occurs at a monthly frequency, and usually with a time lag. The authors use monthly returns on investable assets or factors to fit monthly fund returns, and then forecast daily returns of the fund for the following month using the publicly observed daily returns of the explanatory factors.

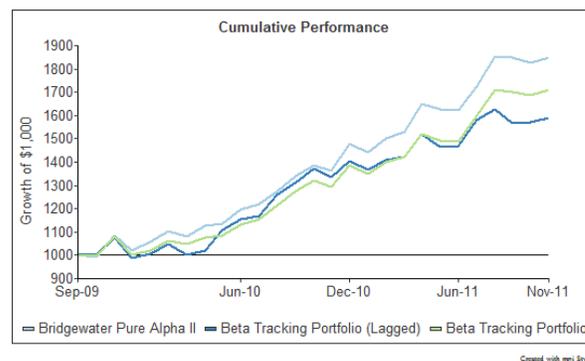
The application of the methodology is primarily in risk management; allowing investors to monitor daily returns which proxy those of their funds in order to immediately mitigate risk rather than waiting until monthly performance numbers are published.

<sup>9</sup> Li, Daniel, Markov, Michael and Wermers, Russ R., Monitoring Daily Hedge Fund Performance When Only Monthly Data is Available (October 1, 2009). Available at SSRN: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1362265](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1362265)

To illustrate this process, we created a portfolio intended to track the dynamic beta exposures of the fund. The most efficient exercise to test the validity, power and precision of any backward-looking statistical analysis is to perform out of sample projections by estimating future values at T+1 based on information at time T. We applied this process to the Bridgewater beta tracking portfolio. The first factor weights were estimated using the first 12 months of data, from Oct, 2008 through Sept, 2009. The tracking portfolio implemented these weights for the month of Oct, 2009. Next, the factor weights were estimated using the 12 months from Oct, 2008 to Oct, 2009. These were implemented for November, and so on<sup>10</sup>. A more precise attempt to replicate the fund’s dynamic beta would likely involve re-evaluating the factors each month. This replication portfolio does not take into account trading costs, nor can a single month’s lag be guaranteed in practice, as it is dependent on a fund’s reporting frequency.

Figure 6

### Cumulative Performance of the Fund Vs. Beta Tracking Portfolio (Lagged)

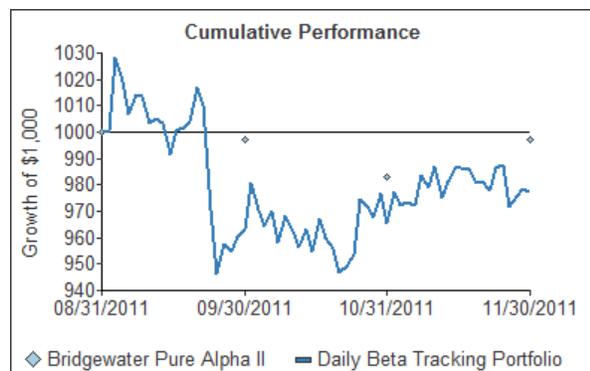


In figure 6 above, it can be seen that the replicating lagged “Beta Tracking” portfolio (dark blue) tracks the Bridgewater Pure Alpha fund (light blue) moderately well (R-Squared of 67%) over the past 26 months. As the tracking portfolio is composed of ETFs, it can be monitored on a daily basis.

A daily monitoring portfolio is shown below in Figure 7 for the three months from Sept 2011 through Nov 2011, inclusive. The cumulative monthly performance of the Pure Alpha fund is shown in light blue diamonds, with the lagged “Beta Tracking” portfolio again shown in dark blue. Note that this allows one to observe a fund’s daily volatility, which is not visible in monthly data.

<sup>10</sup> Please note that this exercise does not truly provide out of sample estimates, as the factors were chosen using the full 38 month time frame. The dynamic weighting process is out of sample.

Figure 7  
**Daily Performance of the Beta Tracking Portfolio**



hedging of market betas embedded in alternative investment mandates.

This case study suggests that a significant part of Bridgewater Alpha Fund II’s performance could be reasonably estimated through dynamic long/short portfolios of ETF products that offer daily liquidity and a simple, low-cost fee structure. However, hedge funds such as Bridgewater Associates are not simple *machina* with lever, pulley and screw as described by Archimedes, but rather complex adaptive systems that will constantly seek to exploit new market opportunities.

## Conclusion

*“Since alternative beta is so complex, it’s no surprise that much of what is now understood to be alternative beta was once thought to be alpha. This hidden beta was disguised as manager alpha simply because earlier models were not sophisticated enough to account for it any other way. The good news for investors is that this is changing. New modeling approaches capture more alternative beta and set the stage for a revolution”.*

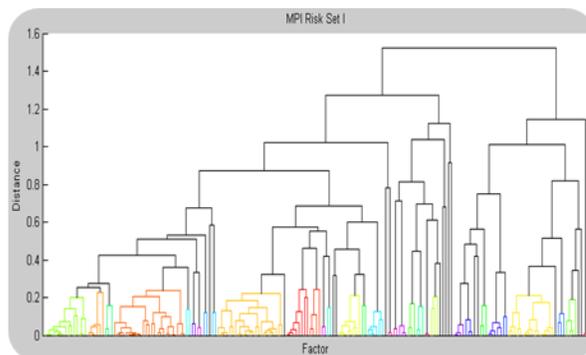
*“Alternative Beta Strategies and Hedge Fund Replication”  
 Wiley Finance, Lars Jaeger and Jeffrey Pease, Nov 2008*

Dr. Lars Jaeger and Jeffrey Pease synthesize well the state of the hedge fund modeling industry. Portable Alpha or Smart Beta, Essential Alpha or Diversified Beta, Traditional Alpha or Alternative Beta, Pure Alpha or Exotic Beta - whatever names are used, the line is blurry between passive and active investment strategies. However, instead of using standard benchmarks, investors can now compare investment funds to dynamic benchmarks in order to better distinguish the alpha, timing and beta skills of their managers.

Estimating time-varying exposures of successful and non-transparent investment managers is not a trivial exercise. It requires precise, credible and fast computing techniques. MPI’s Factor Search™ model, which efficiently reproduces return behaviors in a timely manner, is an example of such predictive analytic techniques. As demonstrated in this analysis, advantages of such methodologies lay in better risk management, portfolio monitoring and possibly

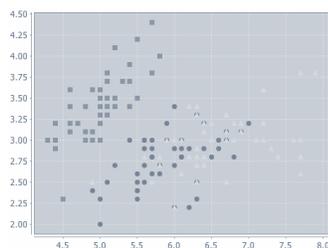
## Appendix: Factor Selection Process

An appropriate set of factors is critical to run a meaningful quantitative exposure analysis. There are a number of obstacles that makes this selection particularly challenging for alternative investments. Many hedge funds have relatively short histories and broad investment mandates. In such cases where the number of data points is small relative to the number of potential factors, over-fitting and the use of incorrect factors is a significant concern. Also, frequent turnover in a portfolio means that simple approaches such as correlation with an investment over time will often produce misleading results. To address these issues, we employ a multi-step adaptive process which analyzes a fund as a dynamic portfolio at each stage and uses Predicted R-Squared, a robust cross-validation measure, to select the factors.



In brief, the process works by structuring a hierarchical cluster tree from a large potential factor set and conducting a separate analysis at each level of the tree. Branches with factors which do not improve the analysis are pruned, and those which do are expanded. The structure is based on correlations between factors, so that highly correlated factors are assigned to the same cluster. The following sequential decision steps have been applied to Bridgewater Pure Alpha II fund analysis:

### Step 1: Factor Candidate Universe



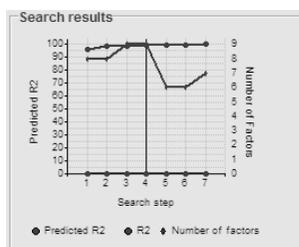
The universe of potential factors to be screened contains as many exposures as possible while limiting superfluous inclusions. In order to obtain an easily investible portfolio to mimic the beta exposures of the fund, we used an ETF database as the data source. Out of the 3,982 active ETFs available in the Morningstar Global Monthly ETF database as of November 2011, we created a sub-universe of 414 ETFs that represents our reasonable determination of potential market factors for such a fund. In particular we only included USD-denominated funds and those with net assets of more than \$50 million, and eliminated those which use leverage or shorting techniques.

### Step 2: Factor Search Procedure

|          |                              |   |
|----------|------------------------------|---|
| <b>1</b> | <b>Structure Universe</b>    | The universe is structured into an agglomerative (bottom up) hierarchical cluster tree, using correlation as the linkage criterion.                 |
| <b>2</b> | <b>Correlation Threshold</b> | A threshold is selected for the minimum correlation within clusters. This in turn determines N distinct clusters at a particular level of the tree. |
| <b>3</b> | <b>Proposed Factor Set</b>   | A set of candidate factors is created, consisting of the centers of each of the N clusters determined in Step 2.                                    |

|          |   |   |
|----------|---|---|
| <b>4</b> | <b>Factor Subset Selection &amp; Validation</b> | A set of candidate factors is created, consisting of the centers of each of the N clusters determined in Step 2. An automated search is run on the set of candidate factors. The subset with the highest Predicted R-Squared, subset A is selected  |
| <b>5</b> | <b>Factor Subset Designation</b>                | Factor subset A is marked as “included” while all others from the initial set of candidates are marked “excluded”. All branches from the excluded set are removed from further consideration. A second set of candidate factors is formed. This consists of factor subset A, plus the centers of the next cluster down the tree for each factor in set A. |
| <b>6</b> | <b>Iteration and Completion</b>                 | Steps 4 and 5 are repeated until no new candidate sets may be formed.   |

### **Step 3: Factor Selection**



The process above produces a number of candidate factor sets. There is one set for each run of the search along the cluster tree, each with an increasing Predicted R2 value. This is primarily in order to understand the progression of the selection process, but a set may be chosen from any stage and it is possible that an intermediate set may be preferable for some reason; perhaps a preference for a smaller number of factors or more generic factors.

The factor set used in this study, the final set with the highest Predicted R2, was chosen after reviewing the search progression, as well as conducting a sensitivity analysis of the factor search process to various model parameters using data to September 2011. The search was run again in December to verify the continuity of the factors and check for reasonable additions or deletions.

The September search included all factors except iShares MSCI Malaysia Index. This last was added as a result of the search for additional factors in December. The exhaustive list of market factors as well as the inclusion path selected by the Factor Search model have been excluded from this paper for the purpose of brevity; however, this information is available upon request.

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### **Correction**

The original paper utilized a peer group, as stated on page 2, that was comprised of funds over one billion in AUM. On January 19<sup>th</sup>, 2012, the paper was updated so that the peer group included funds with over two hundred and fifty million in AUM, resulting in 59 peers.

**About MPI**

Markov Processes International, LLC (MPI) is the leading provider of superior investment research and reporting solutions. MPI's software applications and customized consulting services are employed by the world's finest institutions and financial services organizations to enhance their investment research, reporting, data integration and content distribution. MPI offers the most advanced platform available to analyze hedge funds, mutual funds, portfolios and other investment products, as well as asset allocation and portfolio optimization tools.

MPI's Stylus Pro software is utilized by alternative research groups, hedge fund of funds, family offices, institutional investors, consultants, private banks, asset managers, diversified financial services organizations as well as marketing, product development and IT departments around the world. MPI also offers solutions for private wealth advisors and high net worth professionals. Through its ground-breaking Dynamic Style Analysis model MPI offers hedge fund analysts true due diligence and unparalleled insight. For more information visit [www.markovprocesses.com](http://www.markovprocesses.com) for past MPI research articles.

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