Ensemble Active Management:

The Blueprint for Rescuing Active Management

December 2020

I. INTRODUCTION

There have been innumerable papers written in recent years explaining why passive management is the heir apparent to traditional active management. This is not such a paper. Nor is this a paper urging patience because active management is on the cusp of reclaiming dominance. Without structural change, it cannot. In fact, pivotal data presented in this paper quantifies that evolutionary improvements will be insufficient to alter active management's inferior position versus passive. Status quo has become a permanent trap for active managers.

Fortunately, a structural solution exists, and it is based on **translating proven best practices for predictive analytics from other industries, to that of investments**. This approach, known as **Ensemble Active Management ("EAM")**, has the capacity to generate enough added alpha to allow active management to reclaim dominance in its ongoing battle with passive investing. The improvement is significant enough, and differentiated enough, to arguably be considered a **third category of investing: Passive, Traditional Active, and now Ensemble Active**.

Active managers are inherently in the prediction business. This is not referring to 'market timing', but rather predicting or forecasting – based on research, analytics, experience, and skill – which stocks are most likely to outperform. Other industries have for decades been achieving substantive leaps in predictive accuracy, including weather forecasting, voice and facial recognition, medical diagnostics, car navigation (e.g., Google Maps), credit scoring, and virtually all 'big data' analyses. It is long-overdue for these best practices to be embraced by the investment industry.

EAM is not theory – it has been in live operation for two years, and EAM Portfolios are now commercially available to the public. As will be shown, a critical component of the validation of EAM is live market performance.

EAM is also not a simplistic "AI" alternative to traditional stock picking. EAM does not discard investment professionals in favor of machines. EAM builds upon proven investment concepts and established techniques, and then enhances them through application of modern predictive analytics.

Finally, EAM can operate at massive scale, holds the real potential to persistently outperform passive investing, and is therefore a valid, viable, and achievable blueprint for retooling the existing engines of active management.

II. DEFINING THE PROBLEM

'Success Rate': Key Relative Performance Metric

For this analysis we used rolling one-year relative performance versus a fund's benchmark as our primary metric, and **define a fund's <u>Success Rate</u> as the percent of rolling one-year periods where the fund outperformed its benchmark**.

Success Rates over rolling time periods have several advantages related to large data analyses. They are not dependent on a specific start or end date, and thus are less subject to manipulation. They allow comparison across different market cycles, different asset classes, and funds with both short-term and long-term track records. And they help neutralize the impact of outlier monthly or quarterly returns on overall performance assessments.

To properly evaluate Success Rates, thresholds reflecting varying degrees of success are required:

- A Success Rate of 50% translates to a neutral result (an investor had an equal chance of outperforming or underperforming), and thus **50% is considered the minimum threshold at the fund level**.
- But as an industry, higher-fee active management needs to aspire to achieve better than parity with passive management. Therefore, for this research paper, we assigned **65% as the 'target' Success Rate[1]**.

The Data Set Analyzed[2]

We analyzed performance data for all **1,813 US equity mutual funds** classified by Morningstar as US Equity, non-index (i.e., actively managed), and with a published track record of at least one year. The cumulative assets under management (AUM) for these funds, as of November 2020, totaled **$4.9 trillion**.

We collected daily returns for these funds from January 2005 through November 2020, and then converted the data to rolling one-year returns (for funds with inception dates earlier than 2005, there were a **maximum of 3,755 rolling one-year periods**). Relative performance was obtained by comparing the one-year fund performance versus the corresponding Russell style and capitalization indexes (e.g., Russell 2000 Growth Index was the benchmark for funds classified by Morningstar as Small Growth). This resulted in **5.59 million data points**.

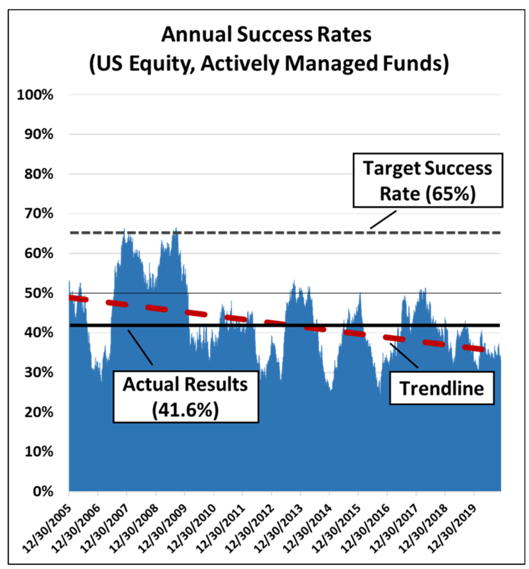
The Results – Part 1: Overall Assessment

*Across all funds and all rolling time periods, the **average Success Rate for the industry was only 41.6%.***

Chart 1 shows, aggregated on an annual basis, the average Success Rates for all funds. As can be seen, **the trend is decidedly negative**. Less than 1% of the annual Success Rates exceeded 65%, and the average relative return reflected a -89.4 basis point underperformance. *(100 basis points = 1%; -89.4 basis points = -0.894%.)*

This data clearly shows that, *as an industry*, 1) active managers failed to achieve their mandate, and 2) the trend is worsening the problem.

Chart 1: Annual Success Rates



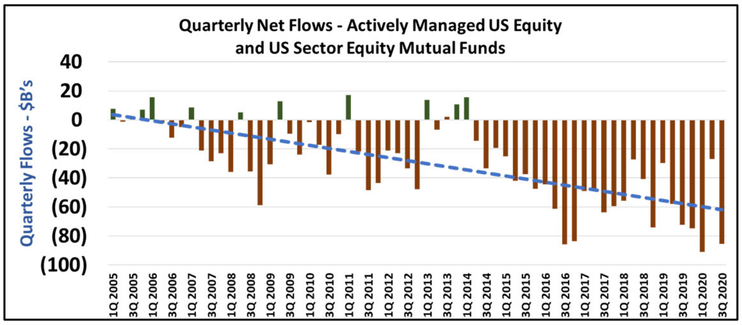
We then evaluated Success Rates at the fund family level, focusing on the largest 50 firms (ranked according to actively managed US equity AUM). These firms have access to the top managers and investment infrastructure, and thus should theoretically have the best capacity to generate persistent outperformance.

Unfortunately, this premise did not prove out, as only **4 of the 50** largest fund families had an average Success Rate for their funds greater than 50%. The best average Success Rate was 56.0%.

Finally, we evaluated Success Rates at the individual fund level, focusing in on each fund's Success Rate over its entire track record. Unfortunately, only **25.9%** of the 1,813 funds had a Success Rate equal to or greater than 50%, and just **4.0%** of these funds had a Success Rate equal to or greater than 65%.

[1]65% was selected by the author, but the conclusions of this paper would have been the same if 60%, 65%, or 70% was chosen.
[2]Source: Morningstar Direct

Chart 2: Net Fund Flows



In light of this data, it should not be particularly surprising that investors are voting with their feet, as can be seen through net fund flows[2].

There have been $1.6 trillion in net outflows from actively managed US equity funds since 2010, with $1.3 trillion in net outflows since 2015. **Adding to the concern, as can be seen in the accompanying chart, the rate of outflows is accelerating**.

The Results – Part 2: Quantifying the 'Alpha Gap'

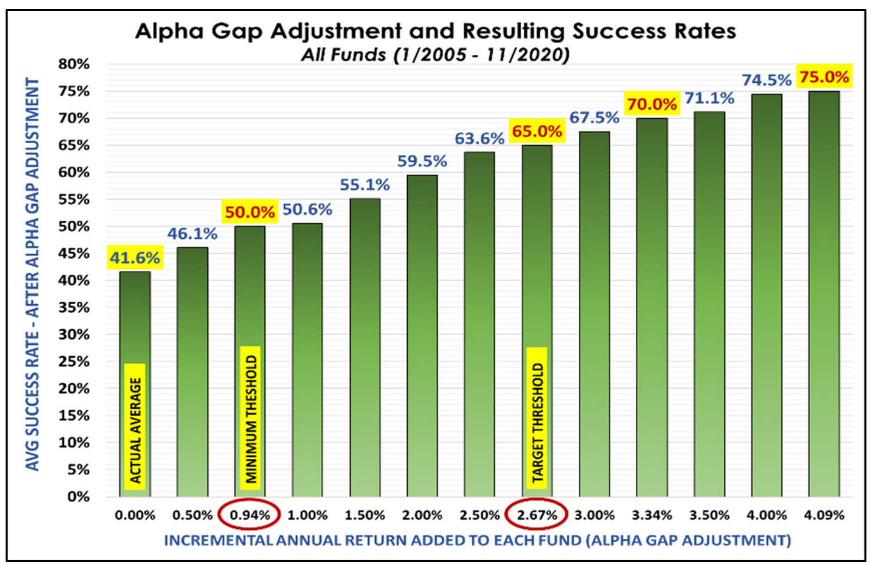
The next phase of our analysis proved to be the most informative regarding the future outlook for active management. Part 1 of the analysis (above) delivered results that mirrored conventional expectations that passive investing has had the upper hand for more than a decade. **Part 2 attempted to quantify if active's underwhelming results are temporary, or structural**.

The concern for the active industry is that the relative underperformance is structural, and that evolutionary improvements in research and portfolio design plus reasonable fee-cutting are insufficient to reverse the current competitive paradigm. Therefore, we quantified how much added alpha would have been required, on a per fund, annual basis, for active funds to either 1) achieve parity versus passive benchmarks (the 50% minimum threshold), or 2) actually succeed (the 65% target threshold). **We refer to this required excess return as the 'Alpha Gap.'**

The Alpha Gap was determined by incrementally adding a fixed amount of return to each fund, for each rolling one-year period, until the active management industry's average Success Rate reached the desired targets (see Chart 3).

- **The average fund had an Alpha Gap of 94 basis points in order to achieve even a 50% Success Rate.**
- **To reach the 65% Success Rate, the Alpha Gap is 267 basis points**.

Chart 3: Alpha Gap Adjustment vs Success Rates



Implications and the Path Forward

The Alpha Gap is at a minimum 94 basis points, and arguably 267 basis points. The lower hurdle appears out of reach, while the higher threshold is all but insurmountable.

The conclusion of Part 2 is therefore that the competitive weakness of active management is, indeed, structural.

Which brings the active management industry to a crossroads: ***Either ignore the data-validated reality that a sustainable relative performance recovery is simply wishful thinking (the so-called 'definition of insanity' approach), or step back, rethink, and re-engage through an improved paradigm.***

The rest of this paper outlines such a new paradigm (EAM), introduces evidence as to why it is <u>supposed</u> to work, provides live performance data demonstrating that it is delivering superior results, and details the blueprint for successfully moving the active investment management industry forward.

III. APPLYING BEST PRACTICES FOR PREDICTIVE ANALYTICS FROM OTHER INDUSTRIES TO THAT OF INVESTMENT MANAGEMENT

One of the more effective tools to solve an old problem is to reframe it.

For decades, the investment industry has approached the challenge of improving performance by **pre-imposing constraints**. Any solution was required to fit within the so-called "three-Ps" model (People, Philosophy, and Process): a single manager/team, delivered as a discrete portfolio, with a singularly defined philosophy and process. However, when significant conceptual boundaries and constraints are imposed *before even attempting to make improvements*, the available options to actually solve the problem are severely constrained.

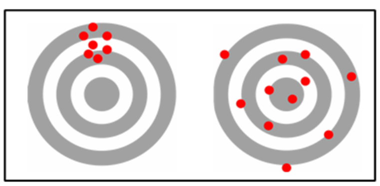
That 'single-expert' paradigm and those pre-imposed constraints are unique to the investment industry. The function of a fund manager in other industries would be described as a **single-expert predictive engine, designed to identify stocks that will outperform the market**. Emphasis on 'predictive engine.'

Building superior predictive engines is an activity for which virtually every industry in the world has become expert, and by reframing the investment function as building the means of making superior security-based predictive forecasts, it opens the door for critical lessons to be shared from other industries to the world of investing.

Ironically, other industries learned a long time ago that **single predictive engines are structurally sub-optimal for solving complex predictive challenges**. *This is not conjecture, but settled science*.

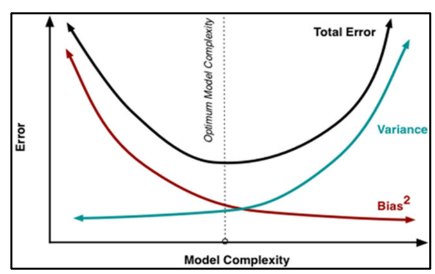
The reason is the Bias-Variance Conflict or Trade-off[3]. Bias occurs when the underlying assumptions in the predictive model are flawed or out of sync, and a 'high bias' predictor will generate results that are consistently off target (left-hand side of Chart 4). Variance refers to its level of accuracy. A 'high variance' algorithm will deliver results that have low accuracy (right-hand side of Chart 4). Unfortunately, at a certain threshold, efforts to reduce errors due to bias can actually dramatically increase errors due to variance, and thus act as a **hard ceiling preventing quality results**.

Chart 4: Bias vs Variance



This trade-off can be seen in Chart 5, where the point of lowest Total Error (black line, equal to the errors from Bias plus Variance) is prevented from reaching an optimal level of reduced error because 1) as the Bias error is reduced to a minimum, Variance error increases exponentially, and 2) as the Variance error is reduced to a minimum, Bias error increases exponentially.

Chart 5: Bias-Variance Tradeoff



The solution to the Bias-Variance Conflict is a four-decades-old mathematical concept known as **Ensemble Methods**. Ensemble Methods are a sub-category of Machine Learning, and are a time-tested, multiple-expert system **explicitly designed to improve the accuracy and stability of single-expert predictive engines.** Ensemble Methods are so fundamental to addressing complex predictive or forecasting challenges that they are viewed as one of the true cornerstones of computational science.

Ensemble Methods works by looking across the series of underlying single-expert forecasts, and **mathematically identifying areas of agreement**. It then uses these areas of agreement to build a 'super predictive engine' with improved predictive outcomes. Ensemble Methods has been described as "*the most influential development in Data Mining and Machine Learning in the past decade. They combine multiple [predictive] models into one [that is] usually more accurate than the best of its components*."[4]

[3]*For more information, see "Ensemble Active Management – The Next Evolution in Investment Management," September 2018.*
[4]*"Ensemble Methods in Data Mining", Giovanni Seni and John Elder*

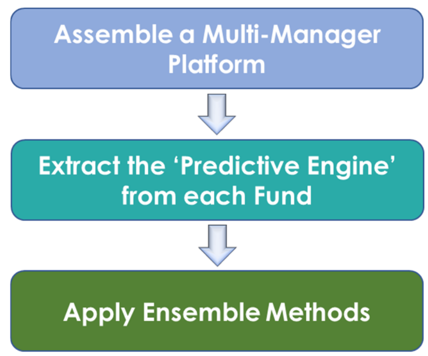
In industries where maximizing predictive accuracy is paramount, it is considered a universal truth that the final predictive solution is built on:

1. **Multiple predictive engines developed or accessed on a parallel basis.**
2. **The predictive engines are integrated through Ensemble Methods as the final step.**

Appendix 1 provides a real-life example of how another industry adopted Ensemble Methods to improve predictive outcomes. It reviews the **Netflix Challenge,** where a $1 million prize was offered to any outside team who could improve Netflix's proprietary *Cinematch* algorithm by 10%. 40,000 entries were submitted, and yet the prize went unclaimed for three years until Ensemble Methods were employed. The final winning solution integrated more than 100 predictive engines through Ensemble Methods. These insights have been available since 2006.

Defining Ensemble Active Management

We have developed a clear and objective 3-step approach for building EAM Portfolios that flows from Ensemble Methods' superior approach to building optimized predictive engines. These steps, taken in combination, provide the springboard for unlocking hundreds of basis points of structural, incremental alpha.



Step 1: Assemble a multi-fund platform. These funds will be the source of the predictive engines used in constructing EAM Portfolios. There are, however, some important considerations for the selection of the underlying funds:

- All of the managers need to target the same investment objective, such as beating a standard index like the S&P 500.
- The majority of the underlying fund managers need to demonstrate a stock selection skill, for at least their highest conviction stock picks, that is better than random selection.
- Ideally, there should be at least 10 underlying funds[5].
- The underlying investment processes need to be independent. This is critical, as it is the diversification at the predictive engine level that allows Ensemble Methods to solve the Bias-Variance Conflict.

Step 2: Extract the 'predictive engine' from each fund. There is a vast difference between a fund's holdings, and the predictive engine that was used to select those stocks. **EAM processes operate through the predictive engines, or the decision frameworks, that each fund manager employs to select stocks and determine daily weightings**.

Since an actual predictive engine is rarely accessible, it can instead be inferred or estimated through the predictive forecasts embedded within a fund's highest overweight and highest underweight positions versus the benchmark, or the manager's highest conviction picks. A dynamic portfolio of each manager's highest conviction security selections can be used to build EAM Portfolios.

Step 3: The extracted, underlying predictive engines are processed through an Ensemble Methods algorithm, which is then used to build an EAM Portfolio. The output of the Ensemble Methods integration is a new and superior predictive engine. This EAM predictive engine is then used to build an EAM Portfolio.

This final step, the application of Ensemble Methods to the underlying predictive engines, creates a new predictive or forecasting engine that is more accurate than the underlying approaches. **The heightened accuracy from the improved EAM predictive engine creates additional alpha.** And as will be shown in Section IV below, the added excess return can be significant. The generation of this added alpha is at the heart of why EAM Portfolios represent the future of active investment management.

[5]*This minimum number was established in a 2018 paper published by Eugene Pinsky, a Professor of Computer Science at Boston University, "Mathematical Foundation for Ensemble Machine Learning and Ensemble Portfolio Analysis."*

Ensemble Active Management versus Multi-Manager Portfolios

It is critical to clarify that an EAM Portfolio is not the same as a multi-manager portfolio.

Multi-manager portfolios ("MMPs") are common, and benefit from added diversification at the process level. This diversification, by definition, is a risk management tool – but it cannot generate incremental alpha. The performance of MMPs is more stabilized than that of single-manager portfolios, with the tails of the distribution curve reduced. However, the MMPs reflect the combined holdings of all of the underlying portfolios, and therefore the return of a multi-manager portfolio is always equal to the weighted-average return of the underlying portfolios.

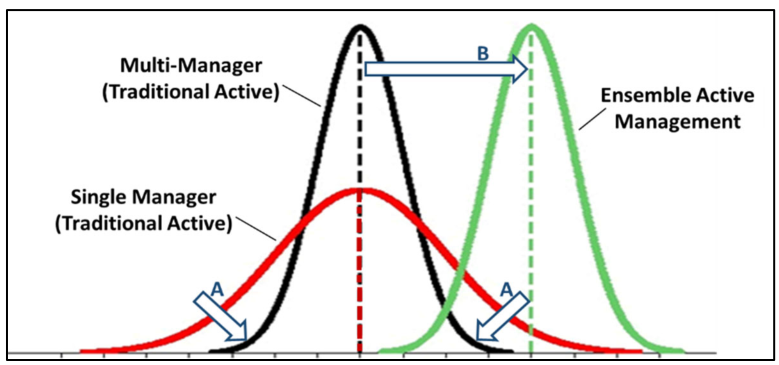
In contrast, EAM Portfolios are built from the **predictive forecasts** that are **extracted** from single manager portfolios (not the underlying portfolios themselves, and not the largest holdings – but **from the decision processes that are used to build those portfolios**). These predictive engines are then integrated through an Ensemble Methods algorithm to create an improved and more accurate predictive engine.

This new 'EAM predictive engine' can be used to generate a superior investment portfolio, based on the enhanced Ensemble Methods-based stock forecasts. The resulting EAM Portfolio will not contain all of the stocks seen in the underlying single-manager portfolios, just the subset of stocks that reflect the highest consensus agreement across the underlying funds' predictive forecasts. The final mathematical output factors in both positive and negative forecasts, and is heavily influenced by demonstrated levels of manager conviction. **EAM Portfolios can thus create additional alpha.**

Please see Appendix 2 for an example of how an EAM Portfolio statistically compares to a multi-manager portfolio.

Chart 6 uses distribution curves to demonstrate how these concepts work:

Chart 6: Impact of EAM on Hypothetical Distribution



- The **Red Curve** reflects a hypothetical distribution of the **aggregate relative performance** outcomes for 10 individual funds, each using traditional active management techniques.
- The **Black Curve** shows the relative performance distribution of the same 10 funds blended into a multi-manager portfolio.
- The **Green Curve** shows the hypothetical relative performance distribution of an EAM Portfolio, built from the same 10 underlying funds.
- Understanding the Chart:
  - The multi-manager design **uses its added risk management to reduce the size of the positive and negative tails versus the single manager portfolios**. This is seen by comparing the **Red Curve** versus the **Black Curve**, where the two "A" arrows show the reduced 'tail risk' of the multi-manager portfolio.
  - As previously mentioned, the **multi-manager portfolio does NOT add alpha**; thus, the median return of both the **Red Curve** and the **Black Curve** remains constant (the vertical dotted black and red lines).
  - **The EAM Green Curve shows the creation of alpha by the EAM methodology**, resulting in a positive shift in the median returns. This can be seen by the "B" arrow moving from the black dotted vertical line (median return of the traditional active portfolio) to the green dotted vertical line (median return of the EAM Portfolio).
  - The **EAM Portfolio also generates a residual risk management benefit**, with reduced tail distributions similar to a multi-manager portfolio. This is due to the use of multiple predictive engines.

IV. PERFORMANCE VALIDATION OF EAM MODEL PORTFOLIOS

EAM Portfolios are not a theoretical concept, as they have been in live production for two years and are currently commercially available to a broad section of financial advisors and investors from multiple firms. The performance of these live EAM Portfolios, together with prior investment research, provide a strong validation of the ability of EAM Portfolios to achieve performance results that had been previously thought unobtainable.

As of the end of November 2020, there were **34 EAM Model Portfolios in live production**, as tracked by Turing Technology[6]. These reflect EAM construction and design specifications from **11 different investment firms**, covering **6 discrete asset classes** (e.g., Mid Cap Blend). **19 of the EAM Portfolios have at least a 12-month history**, with the oldest such Portfolio having a 23-month track record.

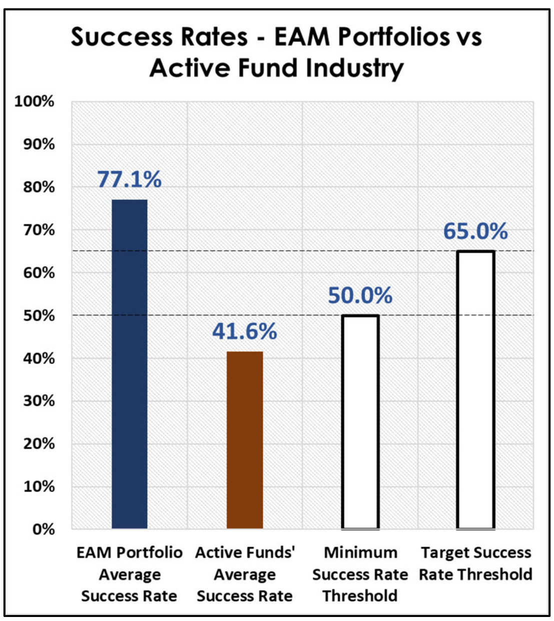
- The firms that built the EAM Portfolios ranged from boutique specialty shops, to multi-billion dollar investment firms, to top ranked international insurance firms; none of which included Turing Technology.

[6]For Turing to reference any EAM Model Portfolio track record, it needs to meet the following standards: Needs to be both based on a client's design and codified through a contract; the track record needs to be able to be validated and verified by an independent third-party.

Performance Metric #1: EAM Success Rates for Live EAM Portfolios

For the 19 EAM Portfolios with at least a 12-month history, there are 2,263 rolling one-year periods. Of those, EAM Portfolios outperformed their respective benchmark 1,786 times, for an **average Success Rate of 78.9%.**

Chart 6: Success Rates



Normally, Model Portfolio performance is measured gross of fee. However, to facilitate comparisons to mutual funds we adjusted the annual return for each of the 2,263 rolling one-year periods by **subtracting 85 basis points** to simulate the impact of fund fees. As a result, there is a slight reduction in the **average Success Rate to 77.1%.**

The comparison of EAM Success Rates versus actively managed US equity funds and the two aspirational Success Rate thresholds referenced earlier are shown in Chart 6. Here, you can see that the EAM Success Rate is nearly double that of traditional actively managed funds, and also exceeded the 65% target Success Rate.

It is worth noting that the EAM Portfolios did not *modestly* outperform over rolling one-year periods. The average annual excess return equaled **885 basis points (after a synthetic fee adjustment)**. **14 of the 19 EAM Portfolios had a perfect Success Rate of 100%.**

To put the EAM Portfolio results into sharp contrast, **the Alpha Gap for the average active fund to reach a 77.1% Success Rate is <u>443 basis points</u>** (please refer back to Chart 3 and corresponding information).

Performance Metric #2: EAM Relative Performance for Live EAM Portfolios

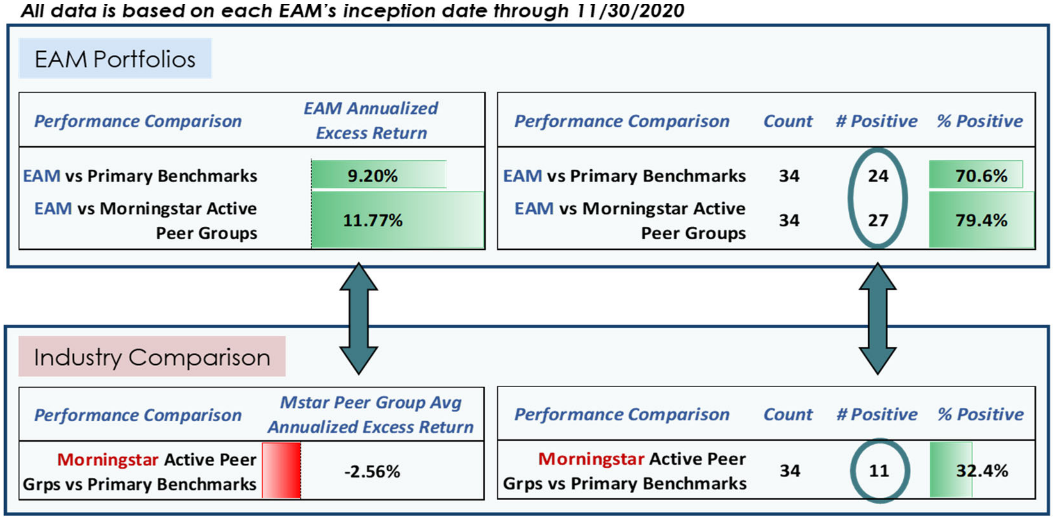
Expanding the sample group back to the full 34 EAM Portfolios (19 with one-plus year's history; 15 with less than one year's history), we compared the relative performance of these EAM Portfolios versus both the corresponding benchmarks and the actively managed fund peer groups (per Morningstar data). All performance is based on the date that each EAM Portfolio went into live production, through the end of November 2020.

As seen in Chart 7:

- **71%** of the EAM Portfolios outperformed their benchmarks.
- EAM Portfolios outperformed **79%** of fund peer groups.
- EAM Portfolios delivered annualized excess return of **920 basis points** versus their benchmarks.

Chart 7: Relative Performance – All EAM Portfolios

All data is based on each EAM's inception date through 11/30/2020



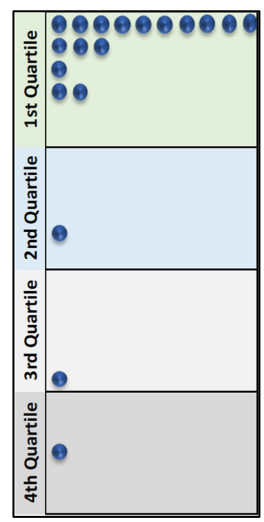
- In contrast, only 11 of the 34 active peer groups (using the same time periods as the EAM Portfolios) outperformed. breakthrough

Performance Metric #3: Implied Peer Group Rankings for Live EAM Portfolios

EAM Portfolios in live production have handily outperformed the corresponding fund peer group averages. The following information addresses the ability of EAM Portfolios to outperform the elite funds within each category.

To test EAM Portfolios against elite funds, we created custom peer groups based on Morningstar Categories (e.g., Large Blend). We then mapped the trailing 12-month returns for the 19 EAM Portfolios with 12-month track records against their fund peer group to determine implied peer group rankings. Again, for comparison purposes, we deducted 85 basis points from each EAM Portfolio's return to simulate the impact of fees.

Chart 8: Implied Peer Group Rankings



The results were more than compelling (see Chart 8 for a visual depiction of rankings):

- **16 of the 19 EAM Portfolios (84.2%) ranked within the top quartile**, with one EAM Portfolio each in the 2nd, 3rd, and 4th quartiles.
- Of the 16 Portfolios in the top quartile:
  - **14 ranked in the top decile** (top three rows of Chart 8).
  - **10 ranked in the top 2 percentile** (top row of Chart 8).

Restated**, 52.6%** of the 19 EAM Portfolios with a 12-month history had an implied peer group ranking in the top 2% of their peer group – after reducing returns by 85 basis points.

To put these results into perspective, none of the 10 largest fund managers (ranked based upon actively managed, US equity fund AUM) had 10 funds in the top 2% of these peer groups. In fact, these top firms did not *collectively* have 10 funds in the top 2% of these peer groups.

Performance Metric #4: Measuring the 'True Nature' of EAM Portfolios

In mathematical circles, it is understood that a single measurement rarely captures the true essence of an item. However, if after using multiple approaches, with different sample sizes, time frames, and metrics the outputs converge on similar results, then you are capturing the true nature of that item.

Fortunately, we are seeing that with EAM Portfolios. Earlier, we presented live performance data demonstrating how EAM Portfolios have delivered very high persistency in outperforming passive benchmarks, and even stronger results versus traditional actively managed mutual funds. And adding to the live performance is a massive test of EAM Portfolios that was published in a September 2018 White Paper **featuring 30,000 randomly constructed EAM Portfolios.** This massive, out-of-sample study evaluated the EAM Portfolios over a period ranging from July 2008 to December 2017, and generated 165 million data points[6].

While the White Paper contains backtested data (shown on the right-hand side of the table below), the **consistency of the results with the live Portfolio metrics actually increases the statistical confidence of all of the results.**

EAM Portfolios With a 12-Month History

Performance Justification:

- **Live returns across multiple asset classes**
  - 19 strategies covering 4 different asset classes
  - 2,263 rolling one-year returns
  - 85 bp annual 'synthetic fee adjustment'

Key Performance Data:

Comparison	Success Rate
vs Benchmarks	77.1%
vs Active Peer Group	85.6%

All 34 EAM Model Portfolios

Performance Justification:

- **Live returns across multiple asset classes**
  - 34 strategies covering 6 different asset classes
  - Strategies designed by 11 different firms
  - 85 bp annual 'synthetic fee adjustment'

Key Performance Data:

Comparison	% Outperforming
vs Benchmarks	70.6%
vs Active Peer Group	79.4%

White Paper (September 2018)

Performance Justification:

- **Massive scale and long time**
  - 30,000 randomly constructed EAM Portfolios
  - 165 million data points
  - 7/2008 – 12/2017
  - 85 bp annual 'synthetic fee adjustment'

Key Performance Data:

Comparison	Success Rate
vs S&P 500	72.3%
vs Active Peer Group	n/a

As is becoming abundantly clear, the 'true nature' of Ensemble Active Management is coming into sharp focus:

- EAM Portfolios have shown to be able to outperform standard passive benchmarks 70% - 75% of the time, and actively managed mutual funds 80% - 85% of the time.
- Using the Alpha Gap metric, **EAM Portfolios generate an additional <u>400+ basis points</u> in excess return**.

[6] *"Ensemble Active Management – The Next Evolution in Investment Management," September 2018. Published by the EAM Research Consortium.*

V. CONCLUSION

This paper used a comprehensive data set to confirm that the actively managed investment industry has failed to meet its mandate of beating passive benchmarks. Additionally, and more importantly, we demonstrated through the Alpha Gap metric that the **hurdle rate to claim victory is effectively beyond its current reach**.

However, the future of active management is not without hope. A **viable blueprint forward exists using Ensemble Active Management**. EAM leverages the proven best practices from the world of computer science to structurally improve the quality and effectiveness of investment decision making. Ensemble Methods are not a randomly applied tool in the broader world; they are **<u>the</u> universal tool to tackling sophisticated predictive challenges.**

The key takeaway is therefore that investment firms need to evolve from a single-manager/single-expert platform to a multi-predictive engine platform, integrated through **Ensemble Methods.** This paper quantifies that, done properly, EAM can annually add more than 400 basis points in desperately needed incremental alpha.

As a final component of the paper, we provided multiple data sets and various performance metrics – most of which came from live EAM Portfolios – that validated the performance potential of EAM, including:

- The 19 EAM Portfolios with at least a 12-month history had an **average Success Rate equal to 77.1% versus benchmarks**, and an average **Success Rate of 85.6% versus the active peer group**.

- 16 of these 19 Portfolios **(84%) achieved an implied peer group ranking in the top quartile** of their corresponding peer groups, and ***more than one-half ranked within the top 2%.***
- The 34 EAM Portfolios in live production have **outperformed their benchmarks 70.6% of the time,** with an average annual excess return of **more than 900 basis points**.
- These 34 EAM Portfolios also **outperformed their peer groups 79.4% of the time**.

Again, to put this data into sharp contrast, the Alpha Gap for the traditional actively managed fund industry to achieve the 77.1% average Success Rate of live EAM Portfolios is **433 basis points**.

Implications for the Industry

Change can be hard. But sometimes, in the face of changing environments and rising competitive threats, change is required. As a sad reminder, the list of iconic firms from established industries that were not able to adapt to shifting landscapes and disruptive competition include Blackberry, Blockbuster Video, Polaroid, and Tower Records.

EAM, with its superior means of generating predictive outcomes, appears to be the inevitable future of active management. We acknowledge that adopting EAM will require change on the part of the existing investment firms, but it is achievable change. The simple key for the industry is that in addition to emphasizing quality strategies, now a premium is also placed on generating a reasonable quantity of active strategies.

An easy first step? Rather than emphasizing teams of investment professionals collaborating to develop a single predictive engine, firms can split the teams into independent silos and then construct the final portfolio through the use of Ensemble Methods. More robust options might include several firms collaborating to gain access to a sufficient number of predictive engines to properly power an EAM solution. Eventually, given the intellectual horsepower embedded in the industry and the immense financial incentives, the **creative solutions are boundless.**

Perhaps the biggest strategic question is whether or not the incumbent investment firms are going to be the ones who embrace EAM first, and thus reap its rewards. Institutional investors can gain access to a wide number of investment strategies today. Rather than treat them as sleeves within a large portfolio, they can take the underlying strategies, extract the predictive engine within each, and use Ensemble Methods to build their own superior EAM Portfolio. The same is true for large broker-dealers and scaled wealth managers. And the potential of technology-based firms to enter and make an impact is real, and even likely.

To paraphrase what Clayton Christensen put forth in his iconic book *The Innovator's Dilemma*, incumbents are not entitled to retain market share as change and innovation sweep through an established industry.

One additional consideration is that early movers can often establish scaled competitive positions that can endure for decades. Vanguard proved that with the advent of index-based investing. SSgA and iShares (now Blackrock) proved that as early movers amidst the emergence of ETFs.

Today, the active investment industry is under assault from index funds and passive ETFs, with a current run-rate of more than a quarter *trillion* in net outflows a year. And, as shown in Section II above, with substantive justification. Will the industry decide to be pro-active, or continue to ignore the facts and embrace status quo?

The successful functioning of active management matters. It matters to the professionals in the investment management industry, and to the hundreds of thousands of professionals in the advice industry that are indirectly supported by successful actively managed portfolios. **And it matters most to the tens of millions of investors in the US alone that are counting on actively managed equity portfolios to provide for their future financial welfare.**

Whether the industry is ready or not, Ensemble Active Management is coming.

For more information on EAM Portfolios, please refer to two previous papers of the author that were published in conjunction with the CFA Institute:

- *"Ensemble Active Management (EAM): Taming Toxic Tails," January 2019, and "The Active Manager Paradox: High Conviction Overweight Positions," October 2019.*
- *"The Active Manager Paradox: High Conviction Overweight Positions," October 2019 showed that the HCOs added, on average, 367 basis points of excess return.*

ABOUT THE AUTHOR

Alexey Panchekha

In a career spanning nearly three decades, Alexey spent ten years in Academia where he focused on nonlinear and dynamic strategies, ten years in the technology industry where he specialized in program design and development, and eight years in Financial Services.

In 2016 he co-founded Turing Technology Associates, Inc. with Vadim Fishman. Prior to Turing, Alexey's professional career includes:

- Specialized in applying mathematical techniques and technology to risk management and alpha generation.
- Involved in the Equity Derivative Trading Technology Platform at Goldman Sachs.
- Led creation of multi-asset multi-geographies Portfolio Risk Management System at Bloomberg.
- Managing Director at Incapital.
- Head of Research at Markov strategy International, a leader in portfolio attribution and analytics.

Alexey is fluent in multiple computer and web programming languages, including Machine Learning, Deep Learning software design and data science.

He earned a Ph.D. from Kharkiv Polytechnic University, with fields of study in Physics and Mathematics. He also earned an MS from Kharkiv Polytechnic University, focused on Physics. Alexey is also a Chartered Financial Analyst (CFA®) charter holder.

*About Turing Technology (**www.turingta.com**):*

Turing Technology is a technology and intellectual property firm founded in 2016 by two world-class applied mathematicians with a long history of innovation and entrepreneurism. The firm's capabilities emerge from the intersection of mathematics, machine learning, and innovation. A principal component of Turing's industry changing technologies includes its Hercules System and Database (a first-of-its-kind database capturing real-time, daily holdings and portfolio weights of actively managed mutual funds; the Database currently reflects information from more than $4.1 trillion in fund assets under management).

Turing is not an investment management or advice firm. It is a technology company that licenses its technology and Intellectual Property to investment management, insurance, brokerage, RIA, and wealth firms to allow them to create and deliver superior investment solutions.

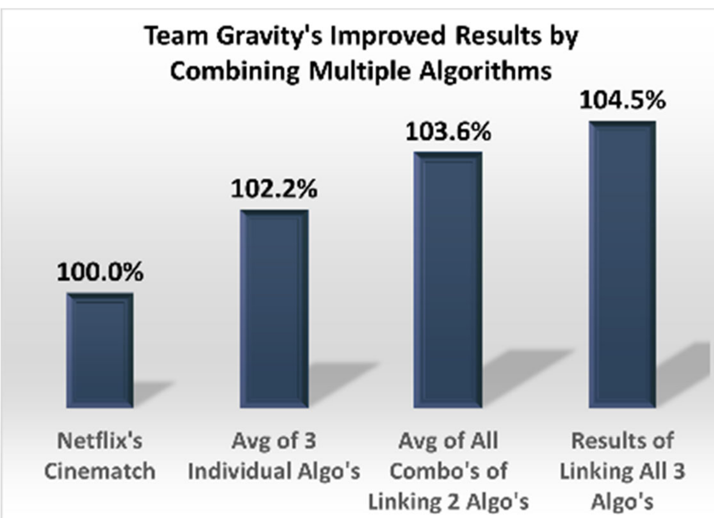
VI. APPENDIX 1 – NETFLIX CHALLENGE CASE STUDY: ENSEMBLE METHODS IN PRACTICE

One of the most interesting examples of the power of Ensemble Methods is the $1 million Netflix Challenge[14, 15], where in 2006 Netflix offered $1,000,000 to the first team that could improve their proprietary *Cinematch* algorithm by 10%. It immediately became a siren's call for every Computer Science grad student, coding-geek, and even some of the biggest research firms in the country (such as AT&T Labs). Eventually, more than 40,000 entrees were submitted, from more than 5,000 teams covering 186 countries.

Initially, all of the entrants took a 'single-expert' approach, with some real signs of progress emerging quickly. The competition was launched October 2, 2006, and by October 15, 2006, three teams had already bested Netflix's Cinematch results by approximately 1%. By the end of 2006, dozens of teams were exceeding Cinematch, many approaching a 5% improvement. But then the proverbial 'glass ceiling' kicked in, and the rate of improvement slowed dramatically.

The first breakthrough came when individual teams began building 'multi-expert' Ensembles from their own predictors. For example, Team Gravity shared the details of their 2007 results obtained by creating Ensembles from three of their internal algorithms (**Figure 5**). They were able to achieve an average of a 2.2% improvement from their three single-expert algorithms, increased their results to an average of a 3.6% improvement by pairing the algorithms, and then achieved a 4.5% improvement over Cinematch when all three predictors were linked together.

Figure 5. Team Gravity's Early Ensembles



But Ensembles of three algorithms did not begin to describe the scale some of the teams were attempting. By the end of 2007, the best result came from team BellKor (from AT&T Labs), which used an *Ensemble of 107 internal algorithms* to achieve an improvement over Cinematch of 8.6%.

It took nearly three years, but eventually the 10% target threshold was reached. On September 18, 2009, Netflix announced the winning team, which was a 'super-Ensemble', created by linking together the efforts of three of the best independent teams: team BellKor, team BigChaos, and team Pragmatic Theory merged to create team **BellKor's Pragmatic Chaos**. Appropriately, the second place team was another super-Ensemble combination named **The Ensemble**.

VII. APPENDIX 2 – STATISTICAL COMPARISON BETWEEN AN EAM PORTFOLIO AND THE CORRESPONDING MULTI-MANAGER PORTFOLIO

In May 2019, a family office launched its second of two EAM Portfolios, this one based on the predictive engines from 10 Large Blend funds, and benchmarked against the S&P 500.

The general profile of the 10 funds is shown in Chart A2_1. As can be seen, there is a wide range of inception dates and fund sizes, and all of the funds would be considered average to above average based on Morningstar Ratings[1].

Chart A2_1: Profile of Mutual Funds

	Morningstar Rating	Inception Date	Fund Size
Fund 1	3	1952	134,772,228,625
Fund 2	4	2010	4,263,567,249
Fund 3	4	1997	18,281,486,268
Fund 4	5	2002	27,692,419,299
Fund 5	5	2006	26,533,490,584
Fund 6	3	1967	136,386,452,668
Fund 7	5	1992	35,838,843,983
Fund 8	4	1977	13,310,788,621
Fund 9	4	1993	93,687,955,151
Fund 10	3	1958	19,995,923,833

To better understand the implications of constructing portfolios using EAM techniques as compared to multi-manager techniques, a multi-manager portfolio was constructed from the **exact same 10 underlying funds.** The daily returns for this portfolio were generated by taking the daily average return of all 10 funds, which could alternatively be described as a portfolio that was rebalanced daily. The EAM Portfolio is based on actual performance data[2].

Chart A2_2 shows the key statistical data for these two portfolios. As can be seen:

- Portfolio Statistics show a critical distinction between the two active portfolios, with the EAM Portfolio comprised of **50 stocks**, and the multi-manager portfolio owning **563 stocks** (as of December 2020).
- The EAM Portfolio generated **superior investment returns, excess return, and alpha**.
- The EAM Portfolio had overall risk metrics that were similar to the multi-manager portfolio, and **lower risk than the S&P 500**.
- Not surprisingly, the EAM Portfolio also had **superior risk-adjusted return results across all metrics**.

Chart A2_2: Key Statistics for EAM Portfolio, Multi-Manager Portfolio, and Benchmark

Key Statistics	EAM.SP500	SP500_Multi-Mgr	S&P 500 Index
Total Return Metrics			
Total Return Since Inception	**44.7%**	40.8%	**40.6%**
Total Return - 2020	**24.2%**	20.8%	**18.4%**
Excess Return vs Benchmark	**2.25**	0.09	**n/a**
Alpha	**2.70**	0.64	**n/a**
Portfolio Statistics			
# of Securities	**50**	563	**500**
Risk Metrics			
Standard Deviation	**20.5**	20.4	**21.0**
Tracking Error	**4.2**	1.75	**n/a**
Beta	**0.96**	0.97	**n/a**
Maximum Drawdown	**-17.3%**	-18.6%	**-19.6%**
Risk-Adjusted Return Metrics			
Sharpe Ratio	**1.24**	1.13	**1.10**
Information Ratio	**0.54**	0.05	**n/a**
Up Capture Ratio	**96.4%**	96.4%	**n/a**
Down Capture Ratio	**83.3%**	92.3%	**n/a**

[1]*Morningstar Ratings range from 1 (lowest) to 5 (highest).*

[2]*This EAM Portfolio's performance was calculated using industry standard methodology for Model Portfolios, resulting in gross of fee returns. If a theoretical 85 basis points was deducted to simulate fees, none of the summary conclusions would change.*