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Our Systematic Investing Strategies (SIS) Alpha Thesis:
Deploying Data Science Tools in Multi-Asset Investing

SIS Alpha Thesis: In Brief

In this paper, we discuss the core tenets of our investment philosophy and the three components of our flexible platform for designing portfolios through a quantitative, systematic and highly active approach to capturing positive performance, or alpha.

MAY 2022

We also highlight some of the tools and problem-solving approaches that we have drawn from other disciplines—artificial intelligence, engineering, astrophysics, healthcare, logistics and other applied sciences—and offer our perspective on why we believe these tools are suited to the investing universe.

- Applying Data Science Tools to Investing
- **PART 1**: Our Alpha R&D Process
- **PART 2:** How We Model Performance Cycles
- **PART 3:** Optimizing Across Our Library of Strategies
- Applying the SIS Framework to Investment Goals
- A Modern Approach to Systematic Investing

Applying Data Science Tools to Investing

We are living through a transformational era of data creation. According to estimates from Statista, 64.2 zettabytes of data were created globally in 2020—that's 64,200,000,000,000,000,000,000 bytes. The annual total is expected to nearly triple by 2025.[i]

For investors, the information age offers a prime opportunity to uncover new insights and make better decisions. Consider weather forecasting; the accuracy of weather forecasts has skyrocketed as data scientists are able to compute the hundreds of thousands of mathematical variables that figure into models of the atmosphere. In 2015, six-day forecasts were as accurate as three-day forecasts were in 1975. By 2025, two-week forecasts are expected to be able to predict major weather events, according to *The New Yorker.*[ii]

Investors should not be on the sidelines or merely interested observers during this remarkable age of digital transformation. Yet, finance has significantly lagged other fields in embracing new technologies and advanced data-modeling techniques—tools that investors could be using to identify alpha opportunities and act on trends in the market.

Machine learning, signal processing, natural language processing, complex network analysis, systems design and advanced optimization techniques are tools used in fields as wide-ranging as astrophysics, medicine and retail logistics. Investors can apply these same methods to complex financial and economic data sets, both traditional and alternative, to reveal actionable insights.

Ultimately, we believe that this process can generate alpha by helping investors determine what combination of investments, and in what proportion or mix, may be best suited to achieve each investment goal.

When adapted to the nuances of financial data, these tools seek to enable investors to interpret millions of data sets in real time—far more than a human brain can manage—while minimizing biases and drift. We believe this allows investors to monitor the trends and cross-interactions across the market at a far greater scope and speed than what is possible manually, with the ultimate goal of generating positive performance, or alpha.

We do not believe systematic and human-led investing are mutually exclusive when it comes to pursuing alpha. Rather than creating a “black box” of code to interpret the investment universe, we believe investors should use these multidisciplinary tools to amplify and apply the skills and viewpoints that are vital to active investing.

Our Approach: Alpha Generation Powered by Data Science

Loomis Sayles created the Systematic Investing Strategies (SIS) platform to bridge the gap between what is currently being achieved in other scientific fields and what remains unexplored and untapped in investing. We cast a wide net to accomplish this. We hired theorists, scientists and engineers from leading universities and companies at the cutting edge of innovation across a variety of disciplines. We deliberately aimed to create a team with diversity of thought that could look at investing problems with fresh perspectives.

We use data science tools across the three core components of our multi-asset alpha platform:

- **Creating and refining a library of alpha sources:** We maintain a research and development (R&D) process to continually build and refine a library of strategies, including our proprietary construction of classic factors and risk premia; we also explore new factors and other alpha strategies.
- **Modeling the performance regime of each alpha strategy:** We treat the investable universe, including our strategy library and economic and financial data, as a complex astrophysical system; we use our custom-built machine-learning algorithm to model the performance cycles of each trade in our library.
- **Dynamically allocating portfolios:** We use advanced optimization processes to construct opportunistic allocations that combine our modeled performance expectations with measures of uncertainty. This approach seeks to look at the entire opportunity set systematically.

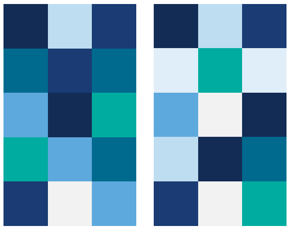
Together, we believe these parts give us an array of tools that we can use to address nearly any specific investing goals. Just as a conductor knows which collection—and in what balance—of brass, string, woodwind and percussion instruments are needed to achieve the desired sound for a symphony, we believe that systematic investing requires knowing how to engage and coordinate the right mix of tools for generating alpha.

With this approach – which is both systematic and active – we seek to unlock the full potential of this super-data era in how we design solutions. We believe it gives us the potential to align opportunistic investments with specific goals in a way that is both innovative and efficient. We use this multi-asset, multi-alpha framework to design targeted solutions for a range of needs: goal-based mandates such as income generation, inflation hedging or absolute return; asset-class portfolios to fit in traditional allocations; or highly customized strategies to bridge specific gaps or incorporate an investor's values.

3 Components of Our Systematic Investing Platform

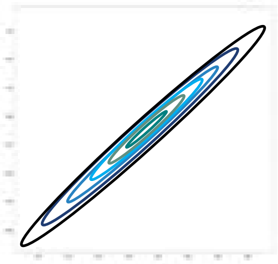
Whether we are designing an absolute-return strategy, a factor portfolio or an asset class mandate, we selectively draw from the three core components of our framework:

1. **Alpha R&D:** Through ongoing research and development, we continually expand and refine our library of dozens of alpha strategies, including factors, alternative risk premia and other alpha opportunities.



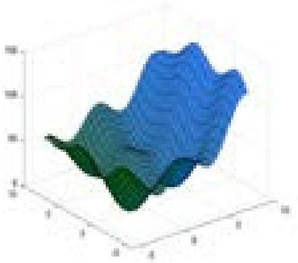
Design & develop sophisticated yet simple risk premia strategies

2. **Modeling Performance Cycles:** Using proprietary machine-learning models, we create a forward-looking forecast of the performance cycle or "orbit" of every trade. Essentially, we treat the investable universe, including our strategy library and economic and financial data, as a complex astrophysical system.



Regime detection using advanced machine-learning algorithms

3. **Allocating Across Our Library:** We apply an optimization process that unites performance forecasts with measures of uncertainty. This approach seeks to produce allocations that minimize turnover, consider transaction costs and navigate tail risk.



Robust Optimization-based asset allocation decisions seek to provide a stable medium with low turnover

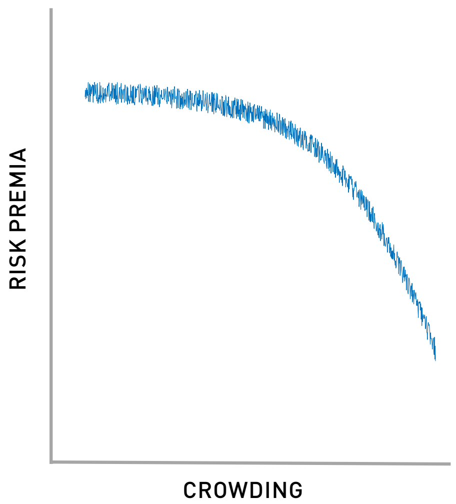
Source: Loomis Sayles.

Performance Decay Is a Feature, Not a Bug

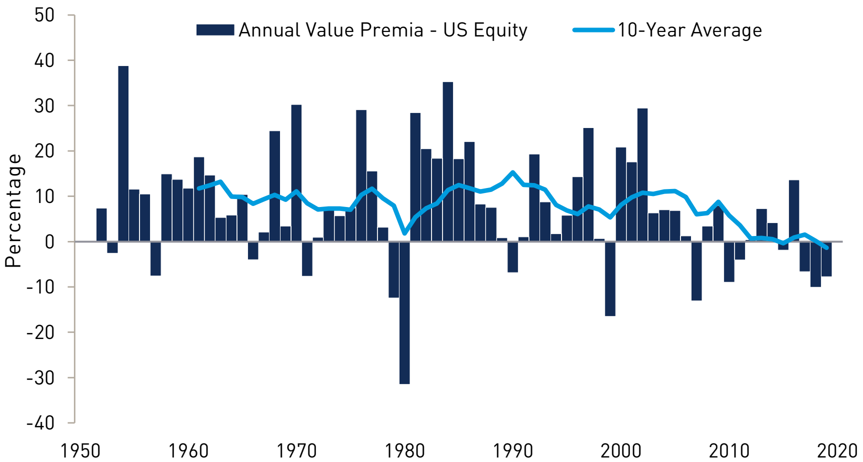
Our system of investing is rooted in our observation that the investment returns of any strategy are cyclical and subject to decay. Factor returns, risk premia and other alpha strategies are time-varying.[iii] Each cycles through phases or regimes, punctuated by crises that return the strategy to an attractive valuation after a period of lagging performance. In other words, performance decay is a feature of our investment approach, not a bug.

In our opinion, this performance decay means that investors need to continually evaluate the cyclical status of all alpha strategies—active and inactive—and use innovative methods to develop new ones. In our view, it can also mean dynamic allocation is essential. If we can identify which alpha strategies are in an opportunistic stage and which are in decay, we believe that we can allocate accordingly.[iv]

PREMIUM DECAY IN THEORY



PREMIUM DECAY IN ACTION



Source: Loomis Sayles and Bloomberg. Annual US Equity Value Premia between 1951 and 2020 with a 10-year rolling average.

Alpha R&D: Continuous Innovation Is Essential

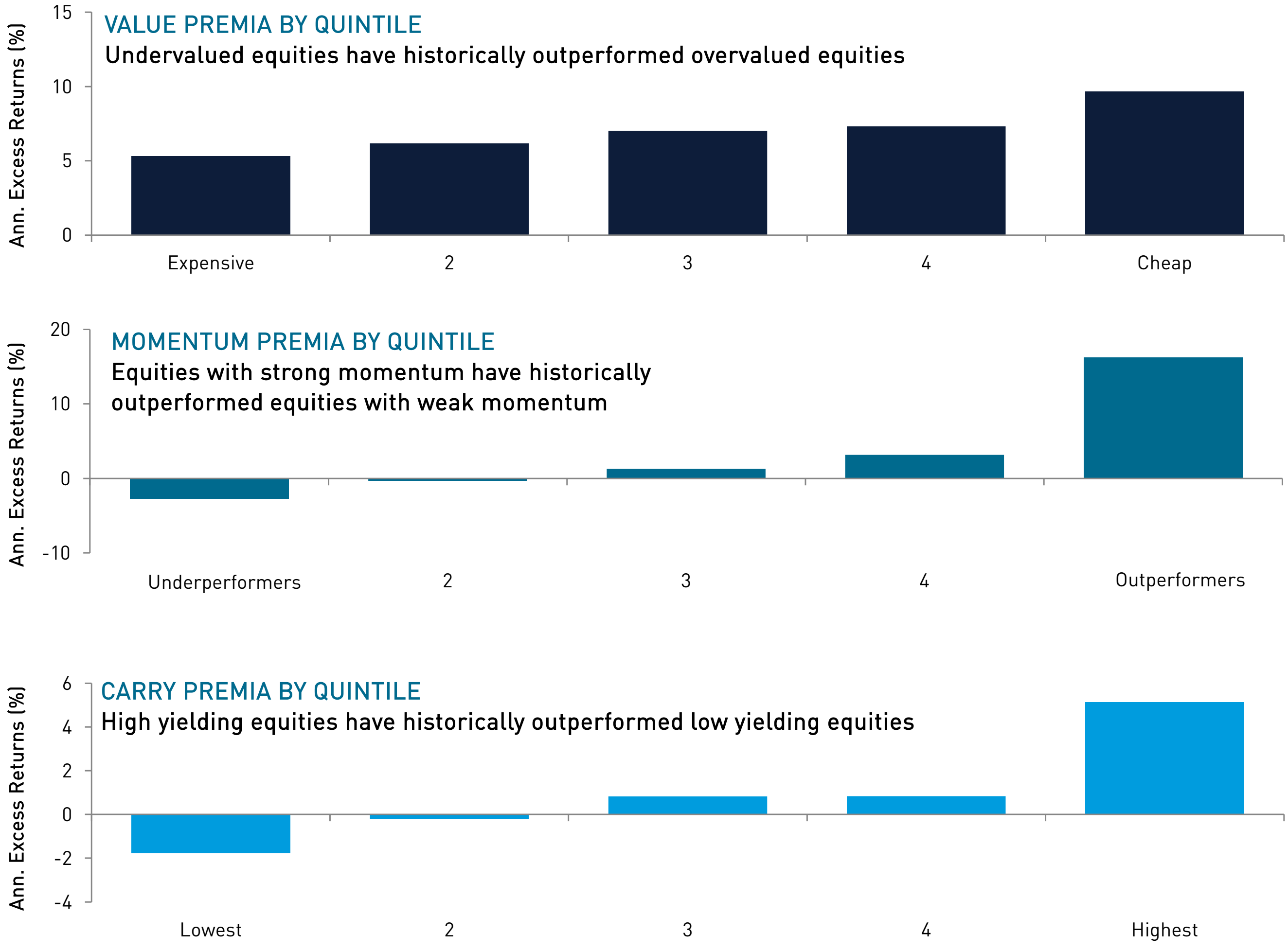
Factors have been part of investors' understanding of asset performance for nearly 60 years, originating with the establishment of market beta in William Sharpe's 1964 Capital Asset Pricing Model. We think of the classic factor set for equity as including beta, size, value, momentum, profitability, investment and low volatility, while the classic fixed income factor set includes credit, carry and curve factors. With the proliferation of factor research through many market cycles, the academic world has largely come to agree on the quality of evidence for classic factors—that they are robust and generate persistent performance.[1]

[1] *Important Source: https://www.chicagofed.org › wp2020-01-pdfPDF*

Factor Returns Are Robust and Persistent…

Examining the value, momentum and carry premia illustrates the robustness of factor returns. When we sort a batch of stocks according to their factor rank (such as price/book ratio for the value factor), divide the sorted list into quintiles, and calculate the average returns of each quintile, we can see that return levels cascade across quintiles.

HISTORICAL RETURN DIFFERENTIAL BY QUINTILES



Source: Loomis Sayles and Kenneth French Data Library, data from 1960 to June 2018.
Past performance is no guarantee of future results.

Large cap stock universe data is sorted based on a value, momentum or carry metric and bucketed into five quintiles with 100 stocks each with yearly rebalancing.

Each bar represents the annual average return for a particular quintile. Stocks are then equally weighted to obtain returns by quintile on a monthly basis.

Taking long positions in best quintile (e.g. cheap value) and taking short positions in the worst quintile (e.g. expensive value) creates the possibility to capture positive performance.

Data shows persisstence in favtor returns and how factor exposures have performed.

But "robust and persistent" does not mean "constant." All sources of performance, including factors, risk premia and other alpha strategies, are subject to cyclical or permanent decay. Performance decay is caused by several drivers, which can co-occur:

- **Crowding.** As investors pile into the same trade, they bid prices up and capture the complete alpha opportunity in a short time. An M&A arbitrage trade is an example of a crowding decay pattern.

- **Extinction of an underlying, fundamental trend.** In a case where a fundamental change is driving outperformance, such as a company sweeping up additional market share with a new product launch, the surge may last for a finite period before reaching a new equilibrium.

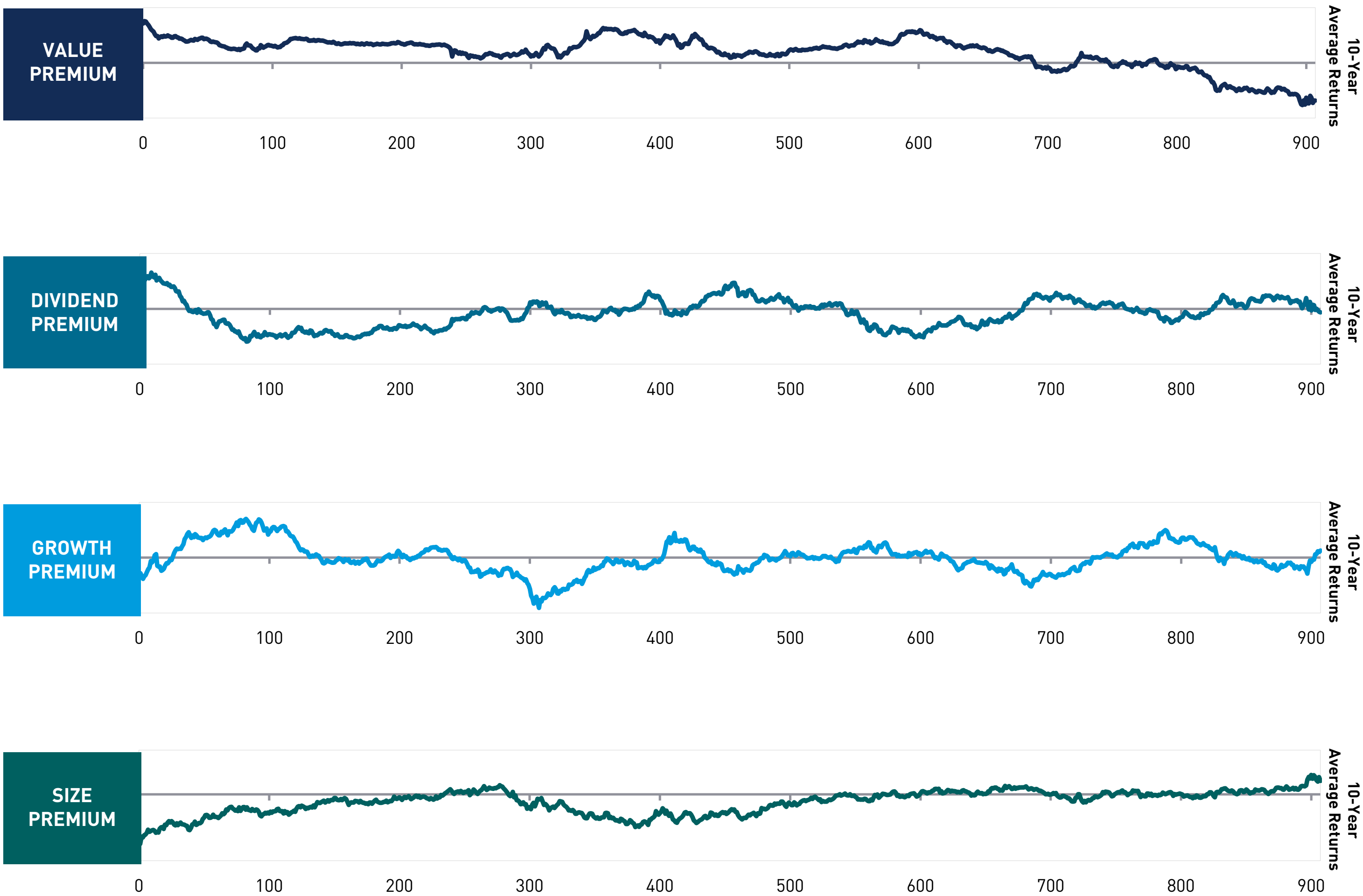
- **Macroeconomic developments prompting a change in the market environment.** A change in the broader macro environment, such as an uptick in oil prices or falling interest rates, can prompt a market shift that favors certain factors. For example, the value factor offered a persistent premium over growth stocks for decades but then underperformed after the Global Financial Crisis through most of 2020; value began outperforming in late 2020 amid expectations of rising interest rates. Some researchers believe the prevailing low-interest-rate environment favors growth stocks because it raises the present value of distant, growing cash flows.[v]

The performance decay of factors, risk premia and alpha strategies is the core reason that we maintain a deep library of alpha strategies. We do not discard strategies; instead we monitor our library of active and inactive strategies, monitoring their decay status while learning better information about their behaviors in every new period. Every trade goes through periodic crises in its performance cycle, which can bring valuation for that trade back to an attractive level.

…But Not Constant

Factors, risk premia and alpha opportunities exhibit time-varying performance. We believe it is important not to discard strategies that have faltered in recent history, but instead wait for them to become attractive again.

FACTOR RETURNS OVER TIME (10-YEAR AVERAGE RETURN, TIME IN WEEKS)



Source: Bloomberg US Equity Style Premias – As of 30 June 2020. Time in weeks.

Returns shown are gross of management fees and trading costs. This does not represent an actual investment account.

Investments carry the possibility for loss as well as profit.

Past performance is no guarantee of future results.

Alpha from Construction and Implementation of the "Classics"

One way that we use the data science tools of other non-financial disciplines is in our proprietary approach to constructing and implementing factors and other well-known alpha strategies.

Among factor-investing practitioners, there are two schools of construction. The "purist" approach constructs factors exactly as defined in the seminal research papers. For instance, purists use the original academic definition of value (price-to-book) or the original signal for momentum (a 12-month lookback period to identify "winner" and "loser" stocks).[vi,vii] For purists, the factor-construction process has already been completed.

A second school of thought, however, takes an approach rooted in continuous improvement and innovation. These practitioners—a group that we are firmly a part of—assume that the optimal implementation of even classic factors requires ongoing research and refinement. This is a core tenet behind our alpha research and development. We believe that there can be multiple valid ways to construct a single factor and that each version could have distinctive performance patterns and characteristics. (As we discuss later, we also use this process in our research and development of new factors.)

As we develop our library of factors, risk premia and alpha strategies, we apply the tools of other disciplines to discover nuances and new observations that shape how we refine classic factors and drive our proprietary construction of the strategies in our library. For example, we believe mathematical applications of signal processing used in the medical field are well suited to a new construction approach for the momentum factor.[viii]

APPLYING EKG SIGNAL PROCESSING: FILTERING OUT NOISE TO FIND THE TRUE TRENDS

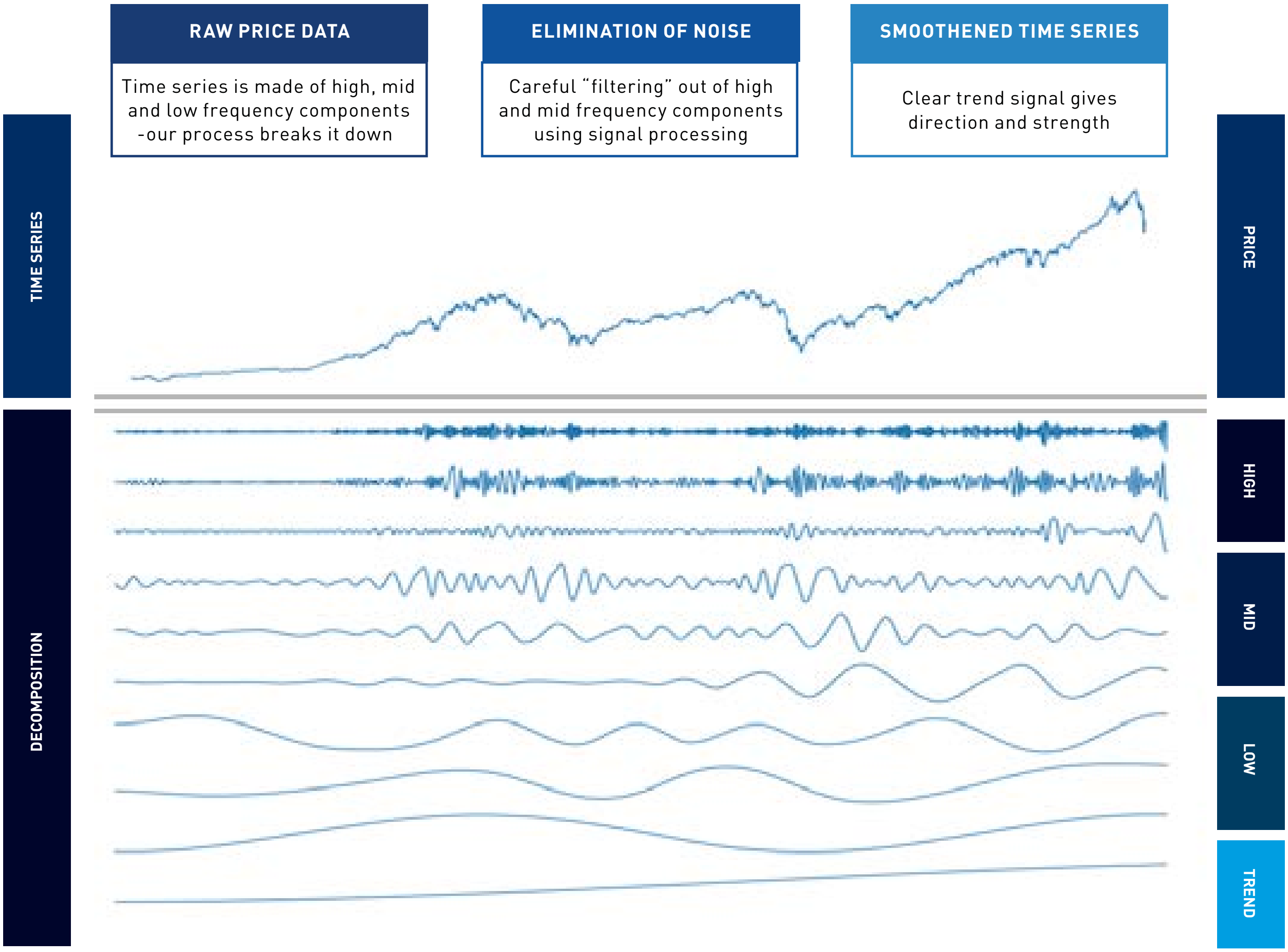
When you get an electrocardiogram (EKG) at a doctor's office, you see an image of the peaks and valleys of a heartbeat. It looks like a simple measure of straightforward data. Flat, up, down, flat. In reality, the true electrical signals coming from your heart are much noisier than what is shown on the screen. This is a classic example of how too much data and noise could cause the practitioner to miss the important trend. The EKG solves for this by using a signal-processing algorithm to filter out the unimportant noise so that it can correctly map the true heartbeat—and provide actionable signals to the cardiologist.

EKG HEARTBEAT SIGNAL

Interpreting Stock Market Prices With Varying Versions of Signal Processing

Financial data is also very noisy. We seek to use the same signal processing tools at work in an EKG to decide what variations are noise and what variations are truly reflecting a trend in financial data.

The first chart below shows the simple time series of price information, and the second chart decomposes that data into varying frequencies, from high to low. This range of frequencies shows the importance of knowing how to use the right level of signal processing to uncover the meaningful trends. We believe under-processing can create too-frequent signals that drive transaction costs up, while over-processing or over-smoothing can lead to missed alpha opportunities.



Source: Loomis Sayles.

Investments carry the possibility for loss as well as profit. Commodity, interest and derivative trading involves substantial risk of loss. *This is not intended to represent any actual portfolio. Views and opinions expressed reflect the current opinions of the investment team, and views are subject to change at any time without notice. Other industry analysts and investment personnel may have different views and opinions.*

Multidisciplinary Tools for Development of New Alpha Strategies

In addition to creating our own construction of the classic factors and risk premia, our team applies multidisciplinary tools to the search for new factors, alpha opportunities and better signals about where markets are headed next.

We believe that the ongoing evolution of financial markets, economic systems and technology suggest that there are many factors that have yet to be identified. We also believe that factors that do not exist today will continue to emerge. To identify these opportunities, research methodologies must continue to evolve as well. That is why we rely on data science tools, such as natural language processing (NLP), to guide our search for these emerging factors.

Natural Language Processing: Scouring the World's News for Alpha Signals

Natural language processing (NLP), which is the product of computer science, engineering and linguistics, is one tool we use to monitor enormous quantities of language—from global news reports, Federal Reserve meeting transcripts, blog entries or any other source of language—for developments regarding specific companies, sectors or broader macroeconomic metrics. NLP can seek out nuanced signals that indicate turning points or escalating trends.[ix,x]

For instance, our NLP model discovered the global uptick in the news of a novel topic, "coronavirus," in mid-January of 2020. Our Classifier, the functionality of the NLP model that labels a topic as positive or negative for market action, correctly predicted a downward market reaction with nearly one month of lead time. As an artificial intelligence (AI) tool, NLP gets smarter over time.

NLP is a tool that can help us identify non-momentum signals—that is, signals of trends in underlying sentiment, rather than trends in security prices—by conducting mass analysis of real-time global news. But we are also applying NLP and other AI tools in an ongoing search for new robust, persistent factors and for more finite alpha opportunities. ESG (environmental, social and governance) investing is a fertile topic for research using this approach, as it unites a mix of fundamental developments with complex information about company operations, decisions and values to help understand performance trends.

Modeling Regimes: Applying Machine Learning

The second element in our investing framework is our approach to modeling regimes. At the heart of our investment philosophy is our belief idea that the performance of every beta and every alpha strategy follows a decay cycle. Every factor, trade or strategy has a regime—and each regime flows through periods of expansion, pre-crisis, crisis and recovery.

On a given day, we believe that one strategy will be in pre-crisis while another could be in recovery while another is in crisis, and so on. We can imagine these decay cycles like individual “orbits,” akin to the orbital path of a planet. We model these orbits using machine-learning (ML) models, as we will describe here.

Specifically, we have built machine-learning models that forecast beta and alpha. The output of these algorithms is a forward-looking probability of crisis in each of the modeled betas and alphas. We will walk through examples of modeling both beta and alpha strategies in our framework.

BETA FORECASTING: IDENTIFYING REGIMES (AND OTHER PATTERNS) THROUGH NETWORK ANALYSIS

One way to think about performance patterns is to look at the prices of assets and all related economic and company-specific data as a complex network. Network analysis is a framework that is applied across many disciplines, including computer and telecommunication networks, as well as cognitive and semantic networks. The framework is even applied in sociology, where researchers use it as a tool to explore kinship structure, corporate power dynamics, international trade exploitation and all kinds of other complex interactions.[xi] We seek to apply the network analysis framework to forecast the market beta regime.[xii]

All the beta trades in our library are constantly monitored in a machine-learning model we designed to conduct complex network analysis.[xiii] Pathway tracking and forecasting is our way of thinking about each trade’s performance decay cycle. One mainstream example of this is to consider how equity market risk, or the beta factor, performs.

Many investors are familiar with a cycle where beta has the highest gains in periods of early economic expansion or points when company profits are accelerating, and losses in periods where profits are poised to contract. This cycle starts anew when early indicators of economic growth reappear.

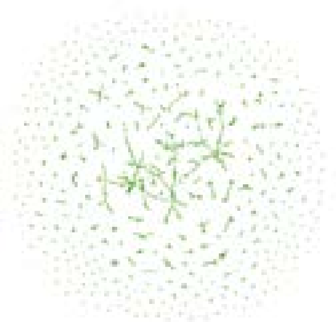
Now consider how a complex network model would address the performance cycle of beta. In the complete network of financial assets and related economic data, the model sees a certain degree of performance dispersion across individual stocks in periods of expansion but recognizes performance clustering ahead of a crisis. Investors commonly say that in a downturn, “correlation goes to 1”—meaning that when a beta crisis hits, the correlation of returns between any two stocks approaches 100%.

In fact, performance clustering begins to happen before the full crisis—it is an early warning sign. In our model, we track this phenomenon in the network using a measure we call the Crisis Sensitivity Ratio (CSR). It helps us forecast the near-term returns for beta, and it also helps us to forecast the near-term performance of other trades that react to the same drivers.

CRISIS SENSITIVITY RATIO: DETECTING WARNING SIGNS OF MARKET TURBULENCE

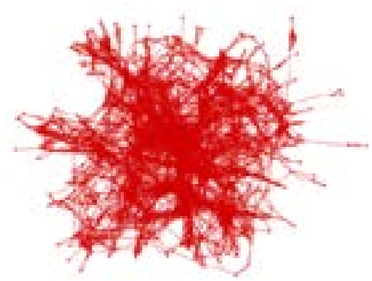
We can apply network analysis to a universe of stocks to see what patterns emerge.[xiv] In normal periods of positive beta returns, the network exhibits a lower degree of performance correlation across stocks. But just before a beta crisis, stock returns begin to cluster. Seeing this pattern, our network model alerts us when the probability of a beta crisis is climbing, an indicator that we refer to as the Crisis Sensitivity Ratio. We believe the ability to detect these crisis signals is a powerful component of our model because financial markets behave so differently in beta crisis and non-crisis periods.[xv]

STOCK NETWORK DURING LOW CSR



Clustering of stocks in crisis vs normal periods

STOCK NETWORK DURING HIGH CSR



Source: Loomis Sayles. Investments carry the possibility for loss as well as profit.
Commodity, interest and derivative trading involves substantial risk of loss.
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ALPHA FORECASTING: PREDICTING THE ORBIT OF AN ALPHA STRATEGY

Just as planets follow distinct orbits, each alpha strategy travels through its own cycle of growth, pre-crisis, crisis and recovery. Our machine-learning model is essentially sensing where each factor or other strategy is in its orbit and what the current length and shape of the orbit look like. With this pathway mapped, the model seeks to forecast what returns for that alpha/risk premia will be in the coming periods.

CUSTOMIZED MACHINE LEARNING: BUILDING ALGORITHMS THAT UNDERSTAND NON-STATIONARY DATA

"History doesn't repeat itself, but it often rhymes."

This quote, which is often attributed to Mark Twain, captures an important reality of financial data—one that should guide any quantitative approach to asset management.

There are many off-the-shelf machine learning (ML) tools that are available for financial practitioners. The problem with these is that they are designed for stationary data—data that follows consistent patterns or cycles linked to a stationary anchor. Algorithms built to process stationary data work well in closed-loop systems, such as a vacuum robot that learns to sweep the floors of a house where the footprint is the same every time.

But financial markets are about as non-stationary as they come. The trendline of returns reverts toward a mean, but the mean is always changing. Likewise, no two market cycles are exactly alike. We believe there are, however, certain relationships across assets and data that are quite stable—or, as the quote suggests, it is possible to determine rhyming patterns if you are looking for the right signals.

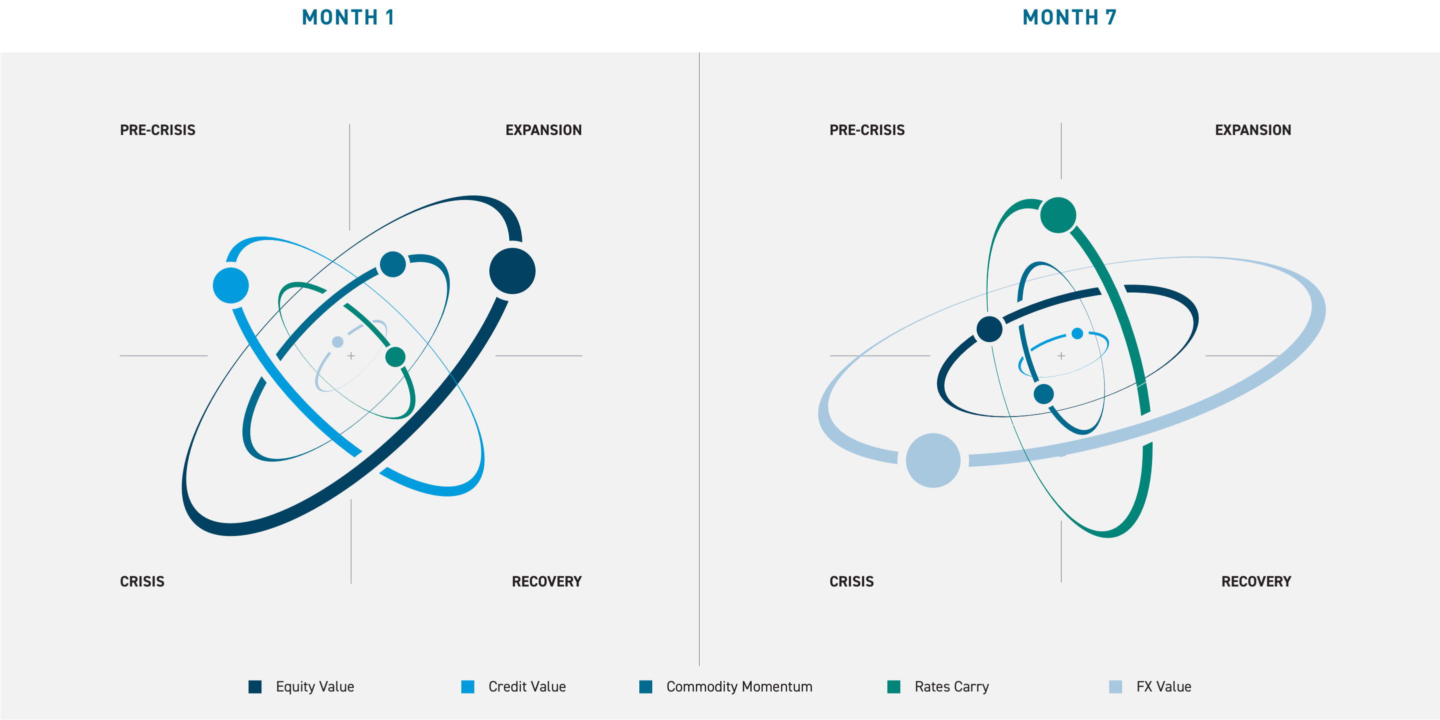
That is why we build customized ML tools that fit the non-stationary nature of financial data. Drawing on our experience in other disciplines, we design our own ML tools to better understand financial markets.

Like any analogy, however, the comparison of planetary orbits and performance cycles has limits. Whereas the earth always takes 365 ¼ days to orbit the sun, always following the same path, financial cycles are not nearly so fixed and forecastable. (See above, Customized Machine Learning: Building Algorithms That Understand Non-Stationary Data.) No two financial cycles are exactly the same, so it is important to think of an alpha strategy's orbit as something that changes in length and shape constantly.

This is how we model all the long-short strategies, risk premia and other alpha trades in our library—each has its own dynamic orbit. Our ML tool evaluates each alpha strategy and updates the trade's orbital length and shape in real-time. In this way, the model seeks to forecast where each trade will be in the following period along with a probability measure for that forecast.

Modeling Factor Orbits

Every alpha strategy has its own performance decay cycle, which we can think of as an orbital path. On a given day, one alpha strategy will be in the expansion phase of its orbit, while another will be in pre-crisis. Our model seeks to identify where each trade is in its own orbit and forecasts where its performance is expected to be in coming periods. We believe this forward-looking view is helpful in making allocation decisions in a portfolio consisting of several alpha strategies. The examples below illustrate how dramatically an alpha strategy's positioning on its orbit, as well as the shape of that orbit, can shift over six months.



Source: Loomis Sayles.
Graphics are illustrative for presentation purposes only, as a sampling of research and analysis. Some, or all, of the information on these charts may be dated, and, therefore, should not be the basis to purchase or sell any securities. The information is not intended to represent any actual portfolio.

Dynamic Allocation: Optimization That Incorporates Uncertainty

All the painstaking work we put into identifying alpha strategies and mapping their orbits would be for naught if we did not have an equally vigorous process to dynamically allocate capital according to cyclical opportunities. The third component of our investment framework is our allocation process. Again, we draw on data science tools used across non-financial disciplines to seek to apply fresh thinking to the optimization process.

ALLOCATING ACROSS CYCLES AND ORBITS

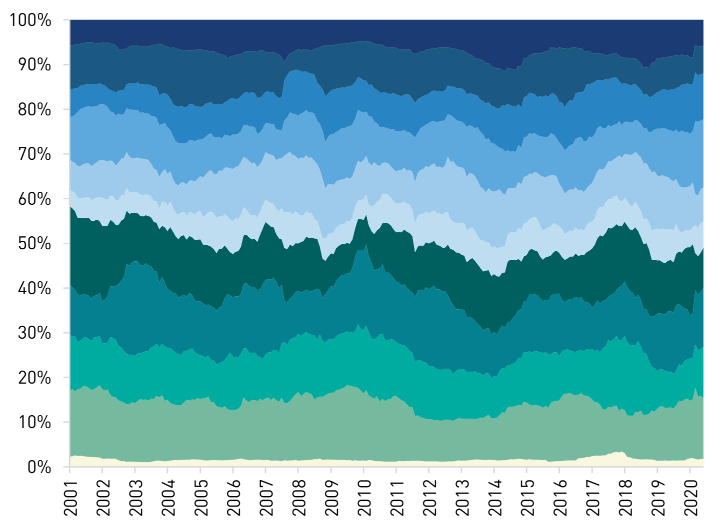
Active allocation is the natural outgrowth of our core investment belief that factors and other sources of performance follow time-varying cycles punctuated by crises. If we can identify good times and bad times to invest in every alpha strategy across our library, we need an allocation framework to navigate those cycles and optimize our portfolio from one period to the next.

Our allocation methodology draws from the insights generated by our mapping of the current and forecasted orbital path of each strategy (as discussed in the previous section) along with an uncertainty set that reflects the confidence of each forecast. Based on these inputs, our allocation methodology then seeks to optimize a portfolio mix designed to capitalize on emerging opportunities while limiting transaction costs.

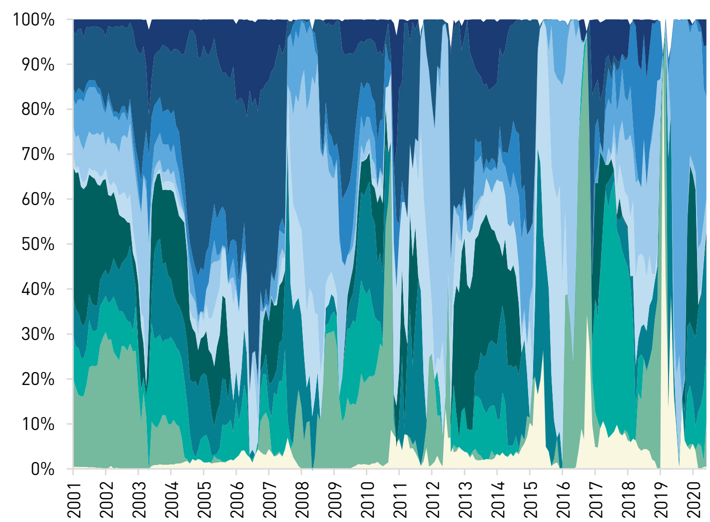
COMPARING A STATIC 'RISK PARITY' ALLOCATION (LEFT) TO OUR DYNAMIC MODEL (RIGHT)

Many factor strategies use a risk-parity model where allocations are set at the beginning of a period and left to fluctuate based on market value, rather than through active trading. In contrast, our dynamic model can move tactically through allocations in a process that incorporates an uncertainty measure on each forecast while considering transaction costs.

STATIC ALLOCATION MODEL



DYNAMIC ACTIVE ALLOCATION MODEL



S&P 500 Index ■ US Dividend Premia ■ US Earnings Premia ■ US Growth Premia ■ US Leverage Premia ■ US Momentum Premia ■ US Profit Premia ■ US Size Premia ■ US Trade Premia ■ US Value Premia ■ US Volatility Premia

Source: Loomis Sayles and Bloomberg.
Indices are unmanaged and do not incur fees. It is not possible to invest directly in an index.
Please see disclosure statement at the end of this document for related definitions.

Moving Beyond MVO

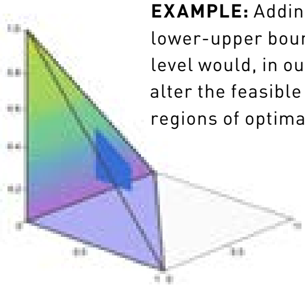
For many investors, mean-variance optimization (MVO) continues to be the primary allocation tool, though we believe its limits are considerable. First, MVO tends to produce extreme outcomes in the form of unacceptable concentrations for a single asset class or trade. To avoid these extreme outcomes, MVO users must set upper and lower limits on allocations at the outset—and once these limits are imposed, the outcome becomes suboptimal. Second, MVO is a clumsy tool for incorporating transaction costs for portfolio changes, so its users must intervene again.

Third, MVO relies on three inputs that we believe may not be the best representation of the forecastable market environment: 1) expected returns, 2) a measure of the standard deviation of returns (typically the historical value) and 3) a correlation matrix across all asset classes or alpha strategies in the optimizing universe (also typically the historical values). We believe that a historical correlation matrix is a blunt tool for a task that requires precision. A historical correlation matrix lumps all market environments together to capture an average relationship among asset classes or trades. In reality, we think that the correlations across assets behave very differently in crisis and non-crisis environments. Tail risk becomes a muted input in such a model, a fact that we believe investors are now trying to address by adding specific tail-risk strategies to their portfolios.

Last, we believe MVO fails to incorporate a confidence measure across its inputs—i.e., a probability that reflects the degree of uncertainty. All forecastable values in an investing universe do not carry the same confidence rating, so we think that true optimization requires a model that reflects these varying degrees of uncertainty.

UPGRADING OPTIMIZATION

In real-life investing, traditional mean-variance optimization is never used without artificial constraints to prevent extreme allocation outcomes. However, we believe such constraints diminish the integrity of the optimization tool, producing somewhat arbitrary and suboptimal outcomes. Instead, we apply a framework called Robust Optimization that is common outside of investing.



EXAMPLE: Adding a **20%-80%** lower-upper bound at instrument level would, in our view, significantly alter the feasible areas and close off regions of optimality.

CHALLENGES WITH TRADITIONAL MVO	ROBUST OPTIMIZATION APPROACH	POTENTIAL ADVANTAGES
Mean Variance Optimization (MVO) in its original form cannot be used by practitioners without use of stringent constraints. This can lead to unintended consequences in our view.	Under this framework, inputs are assumed to belong to a so called "uncertainty set" or "distribution" of choice.	- No need for artificial leverage or turnover constraints. - Optimal portfolio that is not sensitive to inputs.

Source: Loomis Sayles.
Graphic is illustrative for presentation purposes only, as a sampling of research and analysis. Some, or all, of the information on the chart may be dated, and, therefore, should not be the basis to purchase or sell any securities.The information is not intended to represent any actual portfolio.

The Robust Optimization Approach

Given the limitations of MVO, we are constantly drawing from non-financial disciplines to develop and refine more effective optimization processes. One such technique is Robust Optimization. Under this framework, inputs are assumed to belong to a so-called "uncertainty set" or "distribution of choice." The framework marries the expected outcome (the performance in a future period) with a measure of confidence, incorporating uncertainty into the process.[xvi]

This method is used in massive real-time logistics operations and supply-chain decisions. It can also be applied to other networks, populations or other forecasting problems involving optimization across varied outputs.[xvii]

ROBUST OPTIMIZATION: WHAT INVESTORS CAN LEARN FROM WAREHOUSE LOGISTICS

There are many ways to optimize a group, population or system. RO is a technique that specifically incorporates the uncertainty of data into its process. With roots in applied sciences going back decades, the principles of RO came together in the 1990s.[2] The methodology is now used in several fields, including warehouse logistics.

Consider an online market selling billions of items to millions of customers; the business will need to forecast demand across an enormously wide inventory so that it can keep an optimal mix of stock in warehouses. The demand for some items can be forecast with high certainty, while others will face very low certainty. The consequences of these allocation decisions are high because of the substantial costs involved in maintaining inventory and the potential business losses from poor forecasting.

We believe that RO may be an excellent tool for solving such problems, as well as for forecasting demand deeper into a supply chain. The RO framework is also used extensively across engineering for problems such as optimizing the temperature control of component surfaces in electronics manufacturing.[3]

[2] *http://www.princeton.edu/~aaa/Public/Teaching/ORF52 3/ORF523_Lec16.pdf*

[3] *http://www.princeton.edu/~aaa/Public/Teaching/ORF52 3/ORF523_Lec16.pdf Part V, Selected Applications, PDF pages 443 onward.*

Applying the SIS Framework to Investment Goals

The three-part SIS framework was first conceived as a method for investing in absolute return strategies, factors or alternative risk premia. As the team has grown and the platform has expanded, we now apply it more broadly to a complete range of investment goals.

- **Goal-based mandates.** We can rely on the insights of our system to assemble portfolios targeted to achieve a host of specific objectives in a portfolio, including protecting against equity tail risk, hedging against surging inflation, generating income or maximizing absolute return. We rely on the same inputs—our library of strategies and our real-time model of performance cycles—and use allocation tools such as Robust Optimization to optimize the portfolio mix toward the specific investment goal.

- **Optimized asset allocation.** We also use this framework to assemble traditional asset class allocations. Asset class exposures can be fundamentally broken down into their component risk premia. We can therefore seek to use our strategy library to reassemble the component risk premia in the most opportunistic mix, given the current status of each component in its unique performance cycle.

- **Customized solutions that address portfolio gaps.** We believe the SIS approach and the wide range of data science tools at our disposal are also suited to customized investment solutions. For instance, ESG preferences can be implemented with the aid of the NLP (natural language processing) tools we already use to track broader market signals and company-specific trends. Furthermore, we can use this framework to blend goals; for example, designing an emerging markets debt portfolio with ESG preferences or constructing an inflation-protection portfolio that avoids U.S. holdings. We believe we have all the ingredients to optimize custom strategies that fit the specific gaps or needs of each investor.

A PRIMARY OBJECTIVE: DIVERSIFYING RETURN

For many investors, the need to generate diversified return streams that complement the factor exposures driving traditional asset classes is the key challenge of portfolio construction. The SIS framework is designed to address this challenge. Because it has the flexibility to draw on all three components of our platform in response to evolving market conditions, we believe the platform is particularly well-suited to create solutions that prioritize income or absolute return.

Deploying the Best Tools for the Modern Era

Data science is advancing rapidly. As technological progress creates data in ever-increasing quantities, the tools to parse, analyze and interpret data are becoming more sophisticated and yet easier to use. Outside the realm of finance, these techniques are mainstream. Applications in fields such as engineering, physics, healthcare, retail logistics and even sociology provide valuable lessons for how investors can better process financial data and make optimized decisions in real time.

Investing has always been dependent on data analysis, but we believe that it has lagged other fields in embracing the power of data science tools. As new forms of data become available every year, investors face a prime opportunity to explore the power of data science tools to identify patterns and relationships. These tools amplify the real-time processing power that investors have at their disposal. When we apply data science tools thoughtfully, we believe we can arm ourselves with a broader and more useful set of inputs for making investment decisions.

None of these tools eliminate or diminish the importance of human judgement and investing acumen. In our systematic and highly active SIS platform, the insights of our team members drive the models and direct the way that we interpret signals and implement portfolio decisions. Drawing on training and experience across a range of non-financial disciplines, our team seeks to deploy the best data science tools of the modern era in our quest to navigate the performance cycles across the investable universe to construct solutions for investors.

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Disclosure

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The technological tools and processes referred to herein do not guarantee against any loss of principal, nor do they guarantee that any objectives described herein will be achieved

Performance data shown represents past performance and is no guarantee of, and not necessarily indicative of, future results.

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Premia Definitions

Carry and Curve: The Alternative Risk Premia Carry and Curve approach assumes numerous models and types of trades that could be included in the group and was created out of the universe of outright carry, spread and curve trades that span the equities, rates, currencies, credit, and commodities asset classes. Spread trades include currency carry and credit carry. Curve trades include rates and commodity curves. Outright carry includes equity dividend and FX carry strategies.

Value: The Alternative Risk Premia Value approach assumes numerous models and types of trades that could be included in the Value group and was created out of the universe of trades that span the equities, rates, currencies, credit, and commodities asset classes. Trades are implemented via single name equity and bonds, futures or forwards, and are long-short for equities, currencies and commodities (e.g., long positions with instruments that have an attractive profile, short positions in those with unattractive profiles), rates and credit. Our proprietary process seeks to measure relative values among instruments within each assets with a technical and macro indicators that drive positioning.

Momentum: The Alternative Risk Premia Momentum approach includes trades that are grouped by asset class and trade the following markets: equity, rates, credit, currencies and commodities. The model assumes the current trend within each market will last and seeks to measure the scale of momentum using multiple technical indicators. Appropriate methods are employed in order to mitigate drawdowns caused by sudden market reversion. Trades are implemented via via single name equity and bonds, futures or forwards, and are long-short for equities, rates, currencies, commodities (e.g., long positions with instruments that have an upward trend, short positions in those with a downward trend), and credit .

Volatility: The Alternative Risk Premia Volatility approach seeks to benefit from volatility in equity, commodity and currency markets. The approach employs methods designed to mitigate drawdowns caused by sudden market reversion and to reduce unnecessary turnover caused by temporary market turbulence. Trades are implemented via futures and forwards, and are long-short with equal weights.