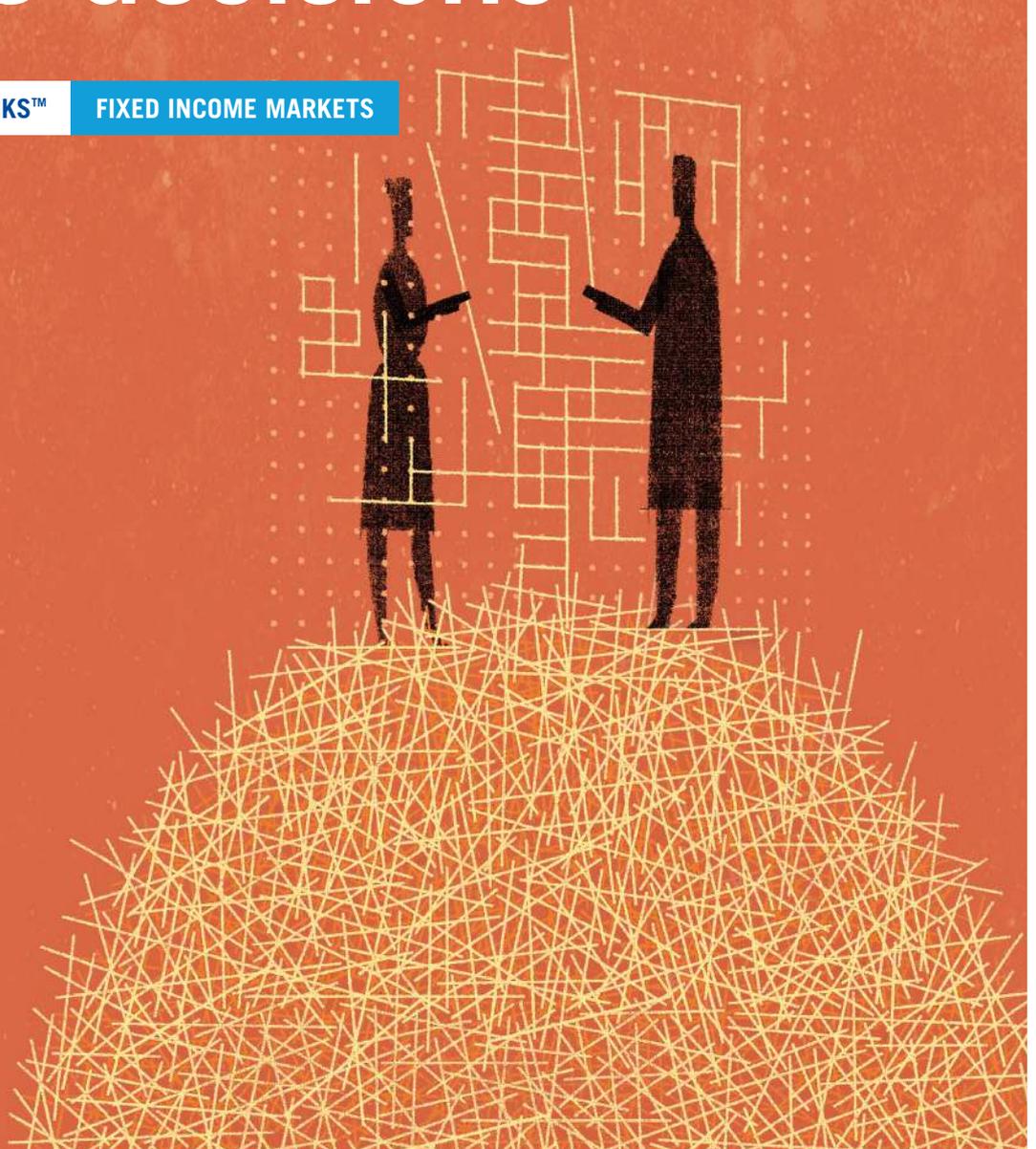


OCTOBER 2019

Quantitative science—actively adding to fixed income decisions

FRANKLIN TEMPLETON THINKS™

FIXED INCOME MARKETS



In this Issue

Fixed income investing has undergone a sea change in the past decade. By tossing out some active management orthodoxies and embracing new technologies and quantitative techniques, we believe some managers are better equipped to capture unique insights and excess returns for their clients.

Several investment shops, however, have cast this transformation as a binary choice—a confrontation between enlightened quantitative approaches and outmoded “traditional” active managers who remain steadfast in the fundamental economic laws of capital markets. We think this quantitative vs. active debate sets up a false dichotomy. In this paper we explain how our active approach to quantitatively derived insights sets apart our “active quant” investment process.

Key takeaways

- We start by explaining the origins of factor investing and the dawn of machine learning techniques that are upsetting the status quo in fixed income portfolio management.
- We discuss top-down macroeconomic research and explain how we use machine learning algorithms to bring objectivity and discipline to the process of forecasting asset prices across a multi-sector fixed income universe.
- We explore the bottom-up process of security selection—comparing factor-driven methods that capture persistent quantifiable drivers of excess returns, with traditional credit security analysis. We explain why deep credit research remains critical to the process of assessing risk premia (i.e., expected returns in excess of the risk-free rate).

Active quant fixed income

Quantitative trends in fixed income

Investing in fixed income markets has undergone a big transformation in recent years. For starters, factor investing—originally popularized by index providers like MSCI and commonly found in equity portfolios—is now spreading into fixed income.¹ Sometimes called “smart beta” or “systematic investing,” these quantitative (“quant”) investment strategies seek to generate active returns by using rules-based factors (like value, momentum and quality) that identify persistent quantifiable drivers of excess returns. These quant-oriented approaches belong to a new investment

category (shown in Exhibit 1) that theoretically sits in between passive index strategies offering market beta and active managers who deliver “alpha” (i.e., excess returns not explained by the overall market’s rate of return, or “beta”).²

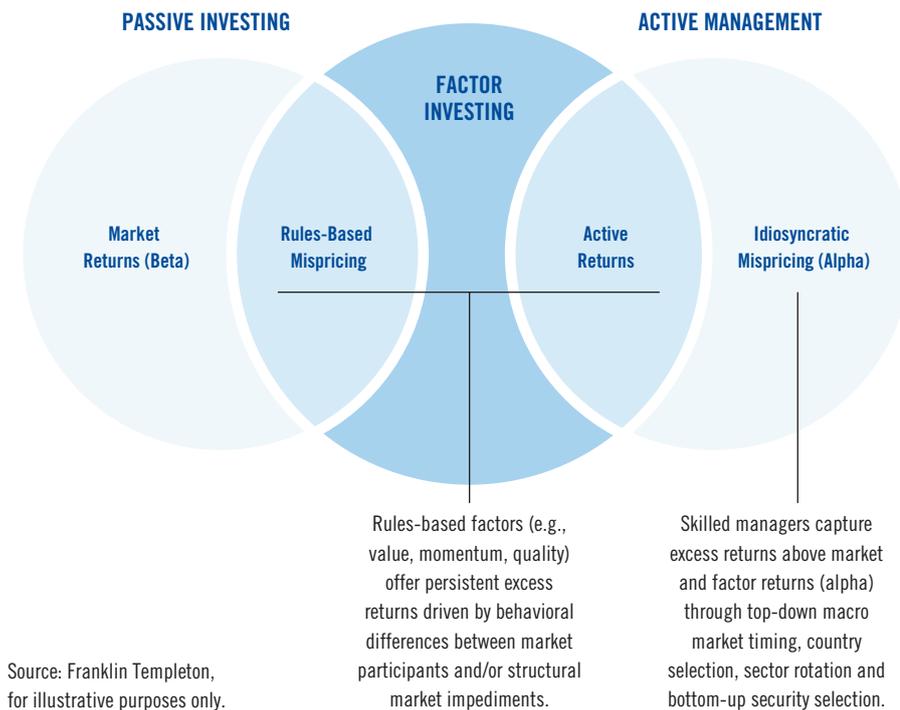
Factor investing methods may still be relatively new. However, the underlying asset pricing mechanisms for equities have been studied for decades in academic literature by the likes of Eugene Fama and Kenneth French, who explained equity market excess returns, and the risk factor pioneer Barr Rosenberg. The real sea change came when index shops and quant-oriented

managers devised transparent methods to measure and capture these factors. Suddenly, quants could outperform the market in ways that only active managers claimed to achieve. To be clear, factor investing doesn’t identify idiosyncratic mispricing (i.e., alpha)—but it began stepping on active manager toes, nonetheless. Why bother with an army of credit analysts who pore through financial statements, if quantitative programs could achieve the same results with a factor lens?

The arrival of bond factor strategies has sparked some robust exchanges between quants and active bond managers. One quarrel that made headlines started when an outspoken quant

QUANTS EXTENDING INTO ACTIVE MANAGER RETURNS

Exhibit 1: Factors sit between beta and alpha



Source: Franklin Templeton, for illustrative purposes only.

alleged in a white paper that most active bond managers offer little in the way of true alpha. Any excess returns, they argued, came mostly from “passive” exposure to corporate credit risks.³ One active bond heavyweight fired back within its own paper, pointing out in careful detail why the accusation was hogwash.⁴ Skillful security selection from seasoned credit analysts still matters, thank you very much.

Factor investing, however, isn’t the only quantitative trend bubbling up in fixed income. Among active managers and hedge funds, whose primary mission is generating alpha, an explosion of big data and machine learning algorithms has ushered in a new investing paradigm that some call the “Fourth Industrial Revolution.”⁵ If machines can drive cars and translate human speech, then algorithms can surely pinpoint market signals and investable opportunities that traditional active managers might miss. In this machine vs. human scenario, some hedge funds now claim in marketing pitches that data science and machine

learning models hold the keys to unlocking real alpha and effectively managing risks.⁶

It’s worth stating upfront that we think this quant vs. active and machine vs. human debate sets up a false dichotomy. Look under the hood of many bond factor strategies or quant-oriented hedge funds, and you’ll find a deep roster of classically trained economists, portfolio managers and traders—all steeped in the fundamental laws of economics. Machine learning algorithms cannot entirely replace human intuition. We believe that sophisticated models, if not properly guided by professionals with specialized financial expertise, can lead to erroneous conclusions. Fundamental credit analysts still uncover valuable insights that factor-based equations gloss over and don’t understand. A purely quantitative approach (we don’t think they exist in all practicality) is no match for navigating highly dynamic capital markets and the economic force of relentless profit maximization.⁷

Factors aren’t foolproof

So, why do some factor-based managers shun “active investing approaches” in their marketing pitches? It’s unclear, especially given recent evidence that factors alone aren’t foolproof solutions. Case in point: factor-based equity strategies are suffering from “terrible” performance in 2019—a blunt confession from a quant pioneer at Morningstar’s annual mutual fund conference (this manager plans to “stick like grim death” to his beliefs in factor investing).⁸

Why the bad performance? Amid the late-cycle market gyrations of 2019, equity factors like value and momentum that historically moved in opposite directions began moving in unison. Quantitative managers long recognized that systematic factors are sensitive to macroeconomic forces; individually, they can underperform for long stretches of time. Building non-correlated multi-factor strategies theoretically alleviated this problem. These diversified factor strategies appeared to work—until they didn’t. Anxious equity investors were told to remain calm and sit tight; this mercurial environment will be short-lived.

Some managers (ourselves included) think static multi-factor exposures are partly to blame. Factor exposures should fluctuate dynamically in response to shifting macroeconomic forces like the rate of unemployment or the overall credit quality of corporate debt markets. Others pound the table and proclaim this poor showing is proof that skilled security selection trumps factors. We think there’s another suggestion: why not capture unique insights from traditionally active and factor approaches at the same time?

Data scientists use the term “ensemble methods” to describe this process of combining different views from multiple algorithms to improve predictive

accuracy. Combining active fundamental and quantitative perspectives is also called “orthogonal thinking”—a term used in science to describe a process where unique insights are discovered by drawing on seemingly unrelated perspectives. This orthogonal process was a crucial element, for example, in the discovery of the human genetic code when physicists moved into the field of biology.

Machine learning to the rescue?

If factor-based strategies aren’t fool-proof solutions, does machine learning offer a better way to generate alpha? The headlines coming out of tech hubs like Silicon Valley and New York City in the United States and Tel Aviv in Israel tell us data-driven algorithms are accomplishing the unthinkable. Machines now have computer vision, pack groceries in warehouses, drive cars, predict your creditworthiness or even how you’ll vote.

In some areas, machines really do have the upper hand. Who or what else but a machine can identify cats in a stack of 20 million pictures with 95% accuracy in less than five minutes?⁹ In other areas, humans still prevail. Consider a commuter successfully navigating his or her car through rush-hour traffic while holding a work conversation (something computers can’t do) and a crying baby in the back seat. Meanwhile, self-driving cars are still crashing into stationary objects and can become disoriented in the rain.

Now, step out of that car and ask yourself this: how could algorithms navigate incredibly complex and dynamic capital markets that are overflowing with signals and noise? It turns out algorithms are hard-pressed to complete basic tasks inside the noisy environment of finance, where signals are weak and frequently transitory. Scientists

describe these environments as having low signal-to-noise ratios.

But there’s good news. Recently published research shows that algorithms can be highly effective when paired with skilled investment professionals (economists and portfolio managers).¹⁰ By themselves, machines have trouble anticipating the complicated human responses of politicians and central bankers that can drive market regime changes. However, when operating within the framework of an economist’s hypothesis, algorithms can forecast expected returns with much-welcomed precision—far better than traditional statistical methods, where forecasts remain deeply shrouded in approximation and estimation errors.

Actively guiding quantitative insights

We think the future of fixed income investing requires moving beyond the active vs. quant stalemate. The ideal investment process starts with two familiar dimensions—top-down

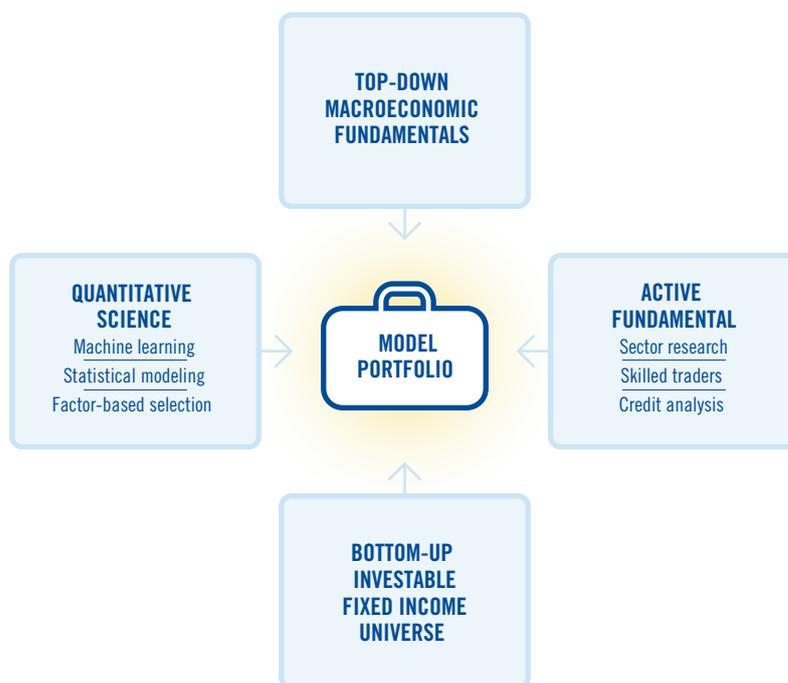
macroeconomic research and bottom-up fundamental security analysis.

The reasons for this division of labor are relatively straightforward: the performance of nearly every fixed income security (outside sovereign bonds) is influenced by unique mixtures of macroeconomic fundamentals—like inflation and stages of the credit cycle—and sources of bottom-up mispricing tied to individual credit issuers. The skills of a trained economist are different from a credit analyst who specializes in the micro economy of an industry. It takes both viewpoints to capture excess returns, as shown in Exhibit 2.

Two additional dimensions—active fundamental and quantitative science—also necessary for alpha generation, also illustrated in Exhibit 2. Factor-based security selection and machine learning techniques bring new skills and fresh insights to fixed income investing. The goal of combining active with quantitative views, however, isn’t to mix them inside a portfolio like a kitchen blender.

COMBINING ACTIVE AND QUANTITATIVE VIEWS

Exhibit 2: Model portfolios incorporate ideas across four dimensions



Source: Franklin Templeton, for illustrative purposes only.

In some instances, quantitative techniques can sharpen fundamental insights with greater precision. Other times, they can challenge assumptions made by fundamental credit analysts and portfolio managers. Through discussion, quantitative views might lead fundamental analysts toward a different conclusion or reconfirm their original hypothesis after a healthy debate and deeper inspection.

It's been our experience that quantitative methods ultimately work best when combined with "traditional" human

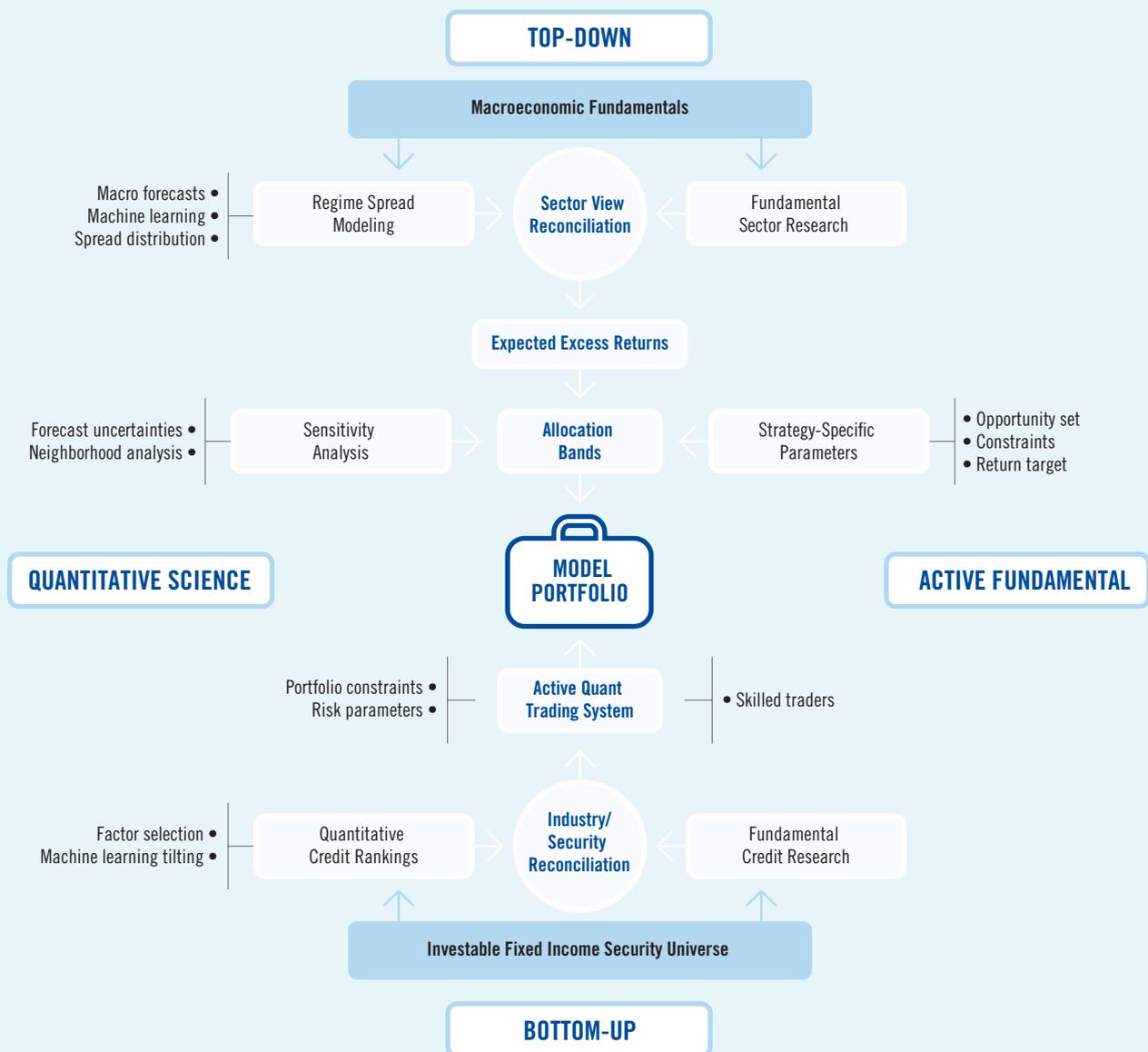
insights derived from the academic disciplines of macroeconomics and fundamental security analysis. Yes, machines offer much-needed precision in predicting asset prices, but we still need deep human expertise to make sense of market complexity. Machines aren't good at assessing turning points in the business cycle or anticipating crowding behaviors from profit-driven traders.

In the next section, we explore top-down macroeconomic research and bottom-up security selection, as shown

in Exhibit 3. In terms of top-down, we discuss the process of transforming macroeconomic research into precise return forecasts with algorithms. These serve as a bridge for communicating macroeconomic views across sector teams who speak different languages. In terms of bottom-up, we compare factor-driven insights with fundamental credit analysis. Although factors offer precision across a breadth of securities, deep credit research is still critical for assessing risk premia.

BRINGING FOUR DIMENSIONS TO THE ALPHA-GENERATING PROCESS

Exhibit 3: Franklin Templeton active quant investment process



Source: Franklin Templeton, for illustrative purposes only.

Active quant top down

Anchored in macroeconomics

Developing a well-informed macroeconomic outlook is critical to identifying what academic finance refers to as “risk premia” (i.e., expected returns in excess of the risk-free rate). This type of research is typically the cornerstone of the investment process for active fixed income managers and quant-oriented hedge funds who are paid to deliver

alpha. Given the complexity and dynamic nature of capital markets, experienced economists are critical to understanding how a myriad of economic variables can shape expected asset prices.

The sets of signals a macroeconomic team uses to generate an outlook are generally quite diverse and driven by an

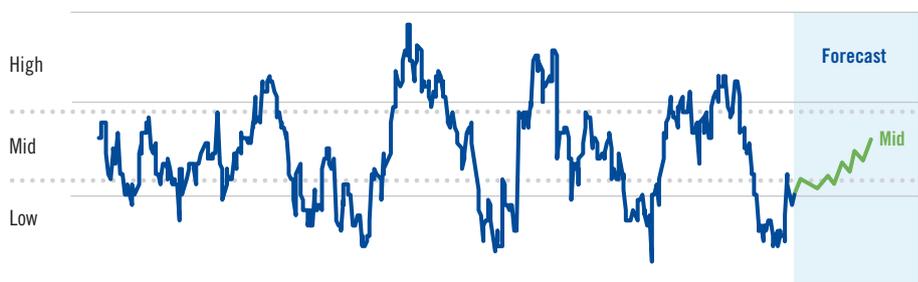
understanding that business cycles are themselves an aggregation of sub-cycles that drive growth (e.g., personal consumption, residential and non-residential loans, industrial production, services, external demand, etc.). These sub-cycles are interdependent and jointly drive monetary and fiscal policy feedback loops, which in turn impact asset prices.

TRANSFORMING A MACRO OUTLOOK INTO SPREAD FORECASTS

Exhibit 4: Example macro variables feed our regression tree algorithms

MACROECONOMIC FORECASTS

Forecasting performance (i.e., spreads) starts with our team’s 12-month macro outlook. We analyze a series of macro variables, including equities, commodities, currencies and inflation, to forecast not just the level of each variable, but also the trend and volatility (where applicable). Instead of assigning numerical values, the team determines whether variables will fall into the low, mid or upper ends of their historical ranges. In this hypothetical example, we think the oil trend will increase to mid-range over the next 12 months.*



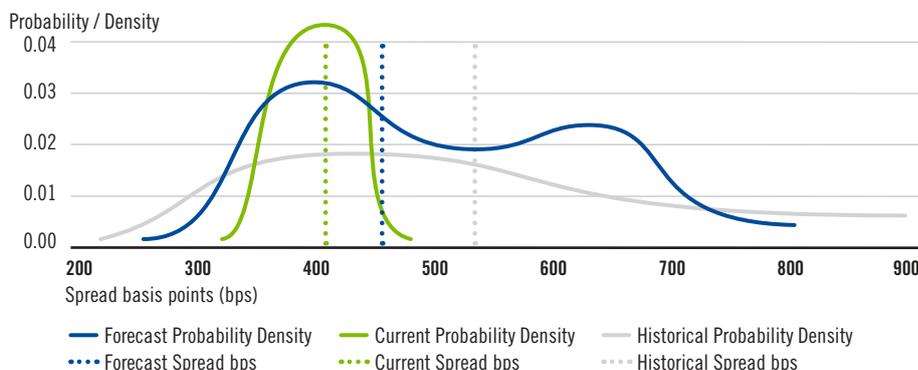
MACHINE LEARNING INPUTS

With outlooks in hand for a range of macro variables, our data science team uses a machine learning decision tree to convert these variables into a macroeconomic regime forecast. Within the context of this expected regime, the algorithm calculates how different sectors will respond by producing spread forecasts* across our fixed income universe (bank loans, high yield, taxable muni bonds, etc.). This algorithm helps teams of people who may speak different languages communicate in a formalized, repeatable manner.

	Oil		US Dollar		Yield Curve	
	Current	Forecast	Current	Forecast	Current	Forecast
Level	Mid	Mid	High	High	Low	Mid
Trend	Low	Mid	High	High	Mid	High
Volatility	Mid	Mid	Low	Low	Low	Mid

BOND SPREAD FORECASTS

Our spread forecasts allow each sector team to visualize how the expected macro regime might impact spreads in their sector. Importantly, the output not only indicates whether spreads might tighten or widen, but also indicates the distribution of spreads as represented by the shape of the curve. In this hypothetical illustration, we see expected spreads are likely to increase (per the dotted blue line) while the spread distribution is quite wide (per solid blue line).* This bi-modal curve suggests a high degree of uncertainty—spreads could remain relatively unchanged or widen dramatically. The data team explains which macro variables have the most impact on spreads.



Source: Franklin Templeton, for illustrative purposes only.

*This hypothetical example is not a prediction or projection of any investment or investment strategy’s performance. It is a hypothetical illustration intended solely to provide insight into how securities are analyzed.

The science of translation

Forecasting sector returns has traditionally been a laborious exercise rife with measurement errors. Analysts typically use statistical techniques like mean reversion (a theory that asset prices eventually revert to long-term averages) or smoothing techniques like moving averages to extrapolate price trends. Some analysts prefer looking backward in time to cherry-pick a previous environment they think best matches the current market regime. All these methods are prone to subjectivity and the likelihood that bond returns may take longer than expected to return to average. Luckily, data scientists have found a better way.

A recently published study on machine learning forecasting and asset prices reflects our own experience modeling expected sector returns (i.e., spreads) using proprietary algorithms. The researchers find that algorithmic models—particularly regression trees that accommodate complex non-linear relationships between multiple variables—“unambiguously improve return prediction” over traditional approaches¹¹ and can also improve portfolio Sharpe ratios.¹² A key strength of algorithmic regression trees is their ability to logically capture complex interactions between multiple variables—relationships that human analysts typically find difficult to map out, even with substantial effort and time.

The Franklin Templeton active quant process starts with a macroeconomic outlook provided by trained economists. In the case of our macroeconomic team, it provides our data science team with a range of economic forecasts across variables such as oil prices, exchange rates, equities, interest rates and inflation-related instruments. The data science team translates these views into standardized macro variables that feed into the regression tree algorithm, as shown in Exhibit 4 on the previous page.

The output from the regime modeling algorithms effectively translates the macroeconomic team’s outlook into sector views that each sector team can understand. The algorithm serves as a bridge, facilitating discussions among the team to compare and debate sector forecasts. The outcome of these in-depth discussions (i.e., reconciliation process) is summarized in writing each quarter, and available to institutional investors.

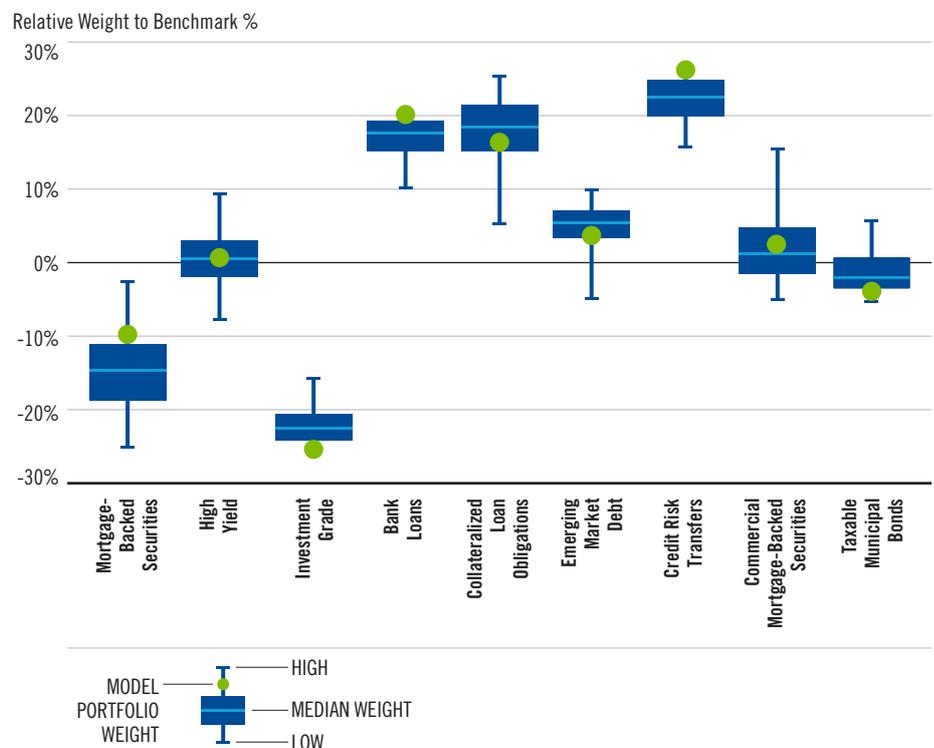
We then translate the reconciled sector views into 12-month expected returns across the global multi-sector fixed income universe. This forms the basis of our proprietary sector allocation process. Determining the optimal mix of weights starts by acknowledging spread uncertainties, which are calculated by using the volatility and correlations of a covariance matrix and our market regime models. The results point to an ideal allocation or “starting

point” along the efficient allocation frontier. Next, by analyzing all the mandated portfolio constraints, the data science team generates a range of allocations that all fall within the “neighborhood” of the ideal starting point—a region that still meets the portfolio’s risk and return parameters.

As illustrated in Exhibit 5, this optimization process gives portfolio managers the flexibility to allocate across allocation bands. In this hypothetical example, the portfolio managers chose to underweight US investment grade credit by the maximum allowed underweight, while overweighting bank loans and credit risk transfers. This process ensures that risk premia in our portfolios are efficiently allocated across the team’s highest conviction views, and done so in a manner that’s consistent, repeatable and designed for accountability.¹³

MANAGERS HAVE THE FLEXIBILITY TO ALLOCATE WITHIN BANDS

Exhibit 5: Portfolio allocation parameters



Source: Franklin Templeton, for illustrative purposes only.

Active quant bottom up

Removing blind spots

When you boil down the benefits of bond factor strategies, the standard marketing pitch usually goes something like this: factor-based bond strategies systematically implement investment ideas (using factors like value or momentum) without taking on risks that won't be compensated (i.e., excessive credit or interest-rate risks). The claim implies that active managers may be doing the opposite—implementing ideas unsystematically (perhaps sloppily), which leads to risk exposures that won't pay off.

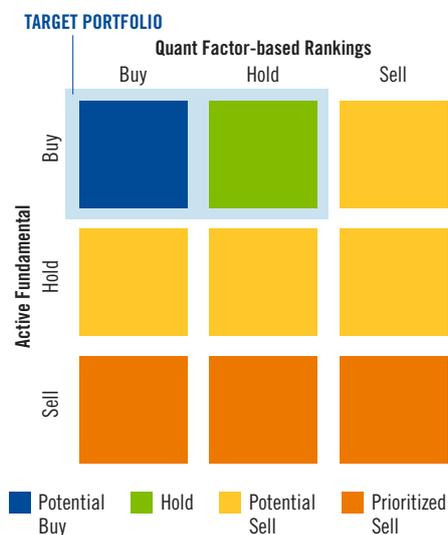
We agree that factor-based strategies offer some advantages, including the ability to methodically (and tirelessly) analyze a wide breadth of securities using precise measures that aren't subject to bias. But factors also have a significant blind spot: they can't see what's causing bond spreads to widen or tighten. On the surface, wide spreads might look attractive to a factor equation, but the equation might be entirely unaware that long-term storm clouds are signaling caution. This blindness can be risky if not supplemented with fundamental research from a seasoned credit analyst—something quants might call “alternative data.”¹⁴

It's the job of the credit analyst to understand how both macroeconomic and microeconomic mechanisms can drive asset prices and explain what's potentially in store for investors. The credit analyst brings a wealth of information to bear on his or her analysis, from the intricacies of a corporate business model and the peculiar genius (or folly) of a management team, to environmental, social and governance issues.

In this simplified illustration (see Exhibit 6) we've captured how Franklin

COMBINING ACTIVE AND QUANT RECOMMENDATIONS

Exhibit 6: Using a Punnett Square to identify our target portfolio



Source: Franklin Templeton, for illustrative purposes only.

Templeton's active quant process brings together quant factor-based security rankings and active fundamental credit recommendations into prioritized, potential buy and sell lists at the security level.

It's important to understand the factor models and credit analysts operate independently from each other, ensuring each team's views remain their own. At the industry level, the “best ideas” from each side are presented in formalized “reconciliation” meetings where credit analysts, portfolio managers and the data team discuss and debate why and how industry views are either synchronized or opposed. Opposing views are entirely welcome—neither quant factors or credit analysts are infallible—and typically lead to deeper analysis and discussion before a resolution is made. We explore this security reconciliation process in the following case study.

Taken together, the active quant process combines potential buy and sell lists with frank discussions and analysis.

The goal is to populate the portfolio with the team's highest conviction (i.e., highly scrutinized) securities within an industry that also satisfy other risk and strategy-specific constraints.

Factor-based security rankings

Factor-based investing initially became popular as a stock selection strategy by identifying broad, persistent drivers of excess return through quantifiable factors that historically earned positive long-run results. Similar to equity factors, the factor styles for corporate bonds with the longest track records include value, momentum and quality factors. As we outline in the **Factor-based security calculations** section on page 10, each of these factors is grounded in commonly observed market dynamics, such as behavioral biases and structural impediments (rules and restrictions) that create opportunities that fundamental factor investors can exploit.

Historically, factor-based bond managers combine multiple factors into a diversified strategy to help mitigate underperformance of any single factor. All bonds are sensitive to macroeconomic changes and therefore can underperform for stretches of time. Because factor styles like value and quality tend to have low correlations, maintaining fixed exposures to both theoretically reduces the length of underperformance regardless of shifting macro environments.

But, what if you could implicitly forecast the near-term credit cycle? Then a machine learning algorithm could dynamically optimize factor weights according to the expected macro environment, with a goal of reducing potential drawdowns and increasing a portfolio's Sharpe ratio.

Case study: A car crash on the horizon

Earlier this year, the team's credit analysts met to discuss their views of the auto industry compared with the factor-based security rankings. The data science team's factor model recommended an overweight to autos, with top-decile rankings assigned to Ford, General Motors and the auto parts supplier Borg Warner. Each offered wide spreads and seemingly attractive yields relative to their credit rating and spread volatility. The auto credit analyst, however, recommended a full underweight to autos. Why such different views?

Three mega-trends (electrification, autonomous mobility and ride-hailing services) have driven an explosion in capital spending across the global auto industry, while a cyclical slowdown in US auto sales (particularly sedans) is moving revenues in the opposite direction. Factor models are entirely blind to the trajectory of secular shifts or the cyclical nature of auto sales.

In the case of Ford, the credit analyst knew the automaker was also facing stiff headwinds from earlier missteps in its car lineup. Back in 2016, Fiat Chrysler Automobiles began winding down production of sedans like the Dodge Dart and Chrysler 200—to focus on Jeep SUVs and big Ram trucks, which US consumers now prefer over sedans. Ford waited until 2018 to announce its plans to discontinue manufacturing and selling most of its sedans in the United States and start reviving its aging line of SUVs. Ford also faced mounting charges from shuttering various manufacturing facilities, and slumping sales in China and South America.

Although the factor models correctly measured the value of Ford's bond returns, the model had no visibility into the seismic secular shifts impacting the industry, or the cyclical nature of revenues that were causing Ford's bonds to behave the way they did. Those causal insights only come from fundamental credit analysis.

One company that the factor models didn't rank as highly was Aptiv, the US auto parts supplier that originally spun out of General Motors in 1999 (then called Delphi Automotive). In recent years, Aptiv has evolved into a formidable tech company specializing in autonomous driving software. Boasting a staff of 15,000 scientists and engineers and a range of patents, Aptiv has fully embraced the three mega-trends upending the auto industry. In particular, Aptiv is demonstrating expertise in vehicle electrical systems, active safety and connectivity products in high demand from customers in Europe and North America. With an eye toward ride-sharing, Aptiv developed its own autonomous driving capabilities, testing cars in Las Vegas, Nevada, through a partnership with Lyft, a US ride-sharing company.

After some discussion, the credit analyst and investment-grade credit portfolio manager decided to underweight autos, overruling the factor industry weight recommendations. They implemented this underweight through companies like Aptiv and Fiat Chrysler Automobiles, which they believed were riding the seismic secular trends better than most. Around six months later, Ford's bonds were downgraded to junk status by Moody's.

Our algorithmic factor tilts

To forecast the credit environment, our data scientists programmed a gradient-boosting algorithm to incorporate a series of macroeconomic variables such as the unemployment rate, the US Federal Reserve's balance sheet, and the credit quality of the investment-grade and high-yield bond markets. Based on these combined variables, the algorithm predicts the future relative performance of our six style factors spanning the value, momentum and quality categories.

In back-testing, the algorithm dynamically adjusted factor exposures during

the global financial crisis—decreasing exposure to Equity Momentum factors and increasing exposure to bonds with lower probabilities of default as measured by Leverage factors and Coverage factors—coverage calculates a company's ability to pay its interest expenses.

As shown in Exhibit 7, the algorithm began in July 2007 with 76% of factor exposures in Value, with a remaining 21% in Equity Momentum and just 3% in Quality issuers. For historical context, four months later, in October 2007, the Dow Jones Industrial Average stock index peaked at over 14,000 points.

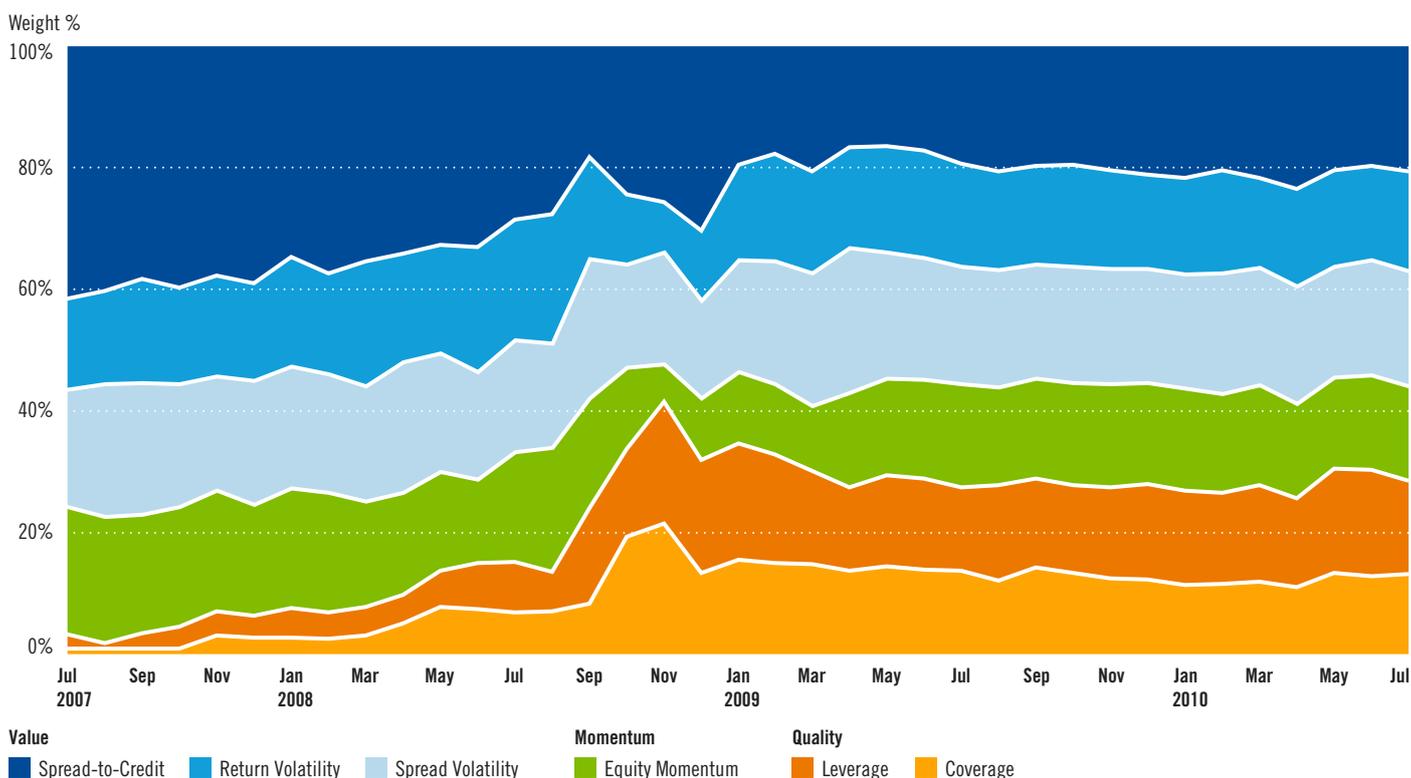
As economic conditions worsened the following year, the algorithm incrementally increased exposure to Quality factors while decreasing exposure to Equity Momentum and Value. Following the dramatic collapse of Lehman Brothers in September 2008, which triggered a global panic, the algorithm increased Quality exposures to 41% by November 2008, with the remaining 52% in Value and just 6% in Equity Momentum.

Instead of a static buy-and-hold approach, our gradient-boosting algorithm shifts factor exposures dynamically to better match overarching macroeconomic environments.

AIMING TO REDUCE DRAWDOWNS

Exhibit 7: Shifting into quality during the global financial crisis

July 2007–July 2010



Factor-based security calculations

How we measure value, momentum and quality bond factors

Value factors

The basic concept driving value factors is that cheap bonds (i.e., spread relative to fundamental risks) have tended to outperform expensive bonds over the long run. There are a multitude of ways to construct a value factor, though most methods start with a bond's current option-adjusted spread ("OAS") and go on to compare this to a range of risk characteristics such as credit ratings and/or return volatility.

Our data science team uses three distinct factor calculations that fall under the Value umbrella. The first is the Spread-to-Credit factor, which focuses on OAS relative to credit risks (i.e., credit ratings) while controlling for industry-specific cyclicity and spread duration. The second two factors measure credit ratings too, but then layer return volatility into their risk assessments while controlling for industry cyclicity and spread duration. The Return Volatility factor uses 12-month excess return volatility to measure risks, while the Spread Volatility factor measures three-month spread change for its volatility measure.

Momentum factor

Corporate bonds from publicly listed issuers with strong recent equity performance tend to perform well since the bonds are senior to equities in the capital structure. Our data scientists use an issuer's three-month equity return to construct the Equity Momentum factor.

Quality factors

Corporate bonds with especially low probabilities of default can outperform higher yielding credit during credit downturns. These securities often don't have the same spreads that some value counterparts offer; instead, their utility comes from their defensive qualities in "risk-off" environments. Instead of measuring a bond's defensive qualities through credit ratings, our data science team uses two distinct measures found in quarterly financial statements. The Leverage factor captures the ratio of a corporate issuer's total net debt to the sum of its net debt and market equity (i.e., enterprise value). The Coverage factor measures a company's profitability (i.e., earnings before interest, taxes and amortization or "EBITA") relative to its 12-month interest expenses.

Four dimensional chess

In today's rapidly evolving investment landscape, the ability to potentially deliver more consistent excess returns has seen profound changes in the quantitative tools and techniques available to institutional fixed income managers. Outspoken quants who championed the arrival of factor-based strategies are challenging the status quo—daring active managers to prove their worth.

Many active heavyweights are more than ready (thrilled in fact) to meet this challenge, with some getting their arms around big data and machine learning techniques to sharpen their edge. By incorporating data science alongside human insights, a simpler two-dimensional process of top-down

and bottom-up analysis has morphed into four-dimensional chess that incorporates fundamental research and quantitative science.

Some managers claim that quants have the upper hand given today's digital technologies. That isn't how things are shaping up in practice, however. Algorithms can't drive themselves in noisy financial environments nor operate successfully without human intuition. Data scientists who lack financial expertise and intuition often don't produce desired investment results.

In the end, the most important skill sets in fixed income remain the ability of trained professionals to explain the

underlying economic mechanisms that drive market regimes and the signals that data science can track and analyze. The future of fixed income has already arrived—it lies in successfully marrying quantitative science with fundamental based active management.

Franklin Templeton Fixed Income Group has engineered a seamless active quant approach—where portfolio managers, analysts, traders and data scientists work as one team to create a synergistic loop between quantitative and fundamental analysis. We believe marrying our data science and fundamental expertise gives us the insights and competitive edge to navigate challenging investment environments and serve our clients better.

Endnotes

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11. There can be no assurance that any model, whether algorithmic, traditional, or otherwise, can predict return.
12. Source: S. Gu, B. Kelly and D. Xiu, "Empirical Asset Pricing via Machine Learning," Chicago Booth Research Paper No. 1818-04. 13 September 2019. The Sharpe ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk.
13. There can be no assurance that adopting this optimization process will have any impact on investment outcomes, or that it will result in profits or that it will minimize losses.
14. Including alternative data in the analysis does not necessarily reduce or eliminate risk.

Franklin Templeton Thinks: Fixed Income Markets highlights the team's ongoing analysis of global economic trends, market cycles and bottom-up sector insights. Each quarterly issue spotlights the team's thinking on different macro forces, and particular sector views that drive our investment process.

Primary contributors to this issue



Patrick Klein, Ph.D.
Portfolio Manager,
Multi-Sector Strategies



Thomas Runkel, CFA
Portfolio Manager



Pururav Thoutireddy, Ph.D.
Quantitative Research Analyst

Editorial review



Sonal Desai, Ph.D.
Chief Investment Officer
Portfolio Manager



David Yuen, CFA, FRM
Director of Quantitative Strategy
Portfolio Manager



John Beck
Director of Fixed Income, London



David Zahn, CFA, FRM
Head of European Fixed Income
Portfolio Manager

The Franklin Templeton Fixed Income Group

Franklin Templeton has been among the first to actively invest in many sectors of the fixed income markets as they have evolved—covering corporate credit, mortgage-based securities, asset-backed securities and municipal bonds since the 1970s, international fixed income since the 1980s and bank loans since the early 2000s. Over 170 investment professionals globally support the

portfolio managers, who oversee more than US\$169 billion in assets under management. Being part of an established investment group at Franklin Templeton gives the portfolio managers access to experts across different areas of the fixed income market, helping them to diversify opportunities and risks across multiple sectors.

Our global reach through Franklin Templeton Investments provides access to additional research, trading, and risk management resources. Portfolio managers have opportunities to exchange insights with other investment groups, and collaborate with an independent risk team that regularly examines risk analytics to help identify and address areas of excessive risk exposure within our portfolios.

WHAT ARE THE RISKS?

All investments involve risks, including possible loss of principal. Bond prices generally move in the opposite direction of interest rates. Thus, as prices of bonds in an investment portfolio adjust to a rise in interest rates, the value of the portfolio may decline. Investments in lower-rated bonds include higher risk of default and loss of principal. Special risks are associated with foreign investing, including currency fluctuations, economic instability and political developments. Investments in emerging markets involve heightened risks related to the same factors, in addition to those associated with these markets' smaller size and lesser liquidity. Investments in fast-growing industries like the technology sector (which historically has been volatile) could result in increased price fluctuation, especially over the short term, due to the rapid pace of product change and development and changes in government regulation of companies emphasizing scientific or technological advancement.

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