Invesco

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Marty Flanagan
President and CEO
of Invesco Ltd.

In this edition of Risk & Reward we provide you broad insight into Invesco's research capabilities. From multi-period portfolio selection to ESG return optimization, new applications for attribution analysis to AI-assisted coverage of earnings calls – our problem-solving approach is as comprehensive as it is innovative. And there's one element that ties it all together: effective quantitative investment management.

Our lead article addresses common portfolio construction issues that a conventional one-period approach cannot solve. Learn how we make use of computing power to effectively manage duration, account for illiquidities, and maximize wealth over multi-period investment horizons. And you won't want to miss our interview with Nobel Laureate Harry Markowitz, co-author of the study and pioneer of modern portfolio theory.

We've also included two articles about ESG, the first of which looks at commercial real estate, the considerable greenhouse gas emissions associated with the asset class and the rebounding impacts of global warming on real estate asset performance. The second article examines how a well-known technique from passive management – optimized sampling – can be used to integrate ESG into a portfolio while matching the tracking error to the original, non-ESG allocation.

And we explore the topic of attribution analysis for fixed income. Much more than just a reporting tool, attribution analysis can help investment professionals comprehend the many complexities involved in translating theoretical investment concepts into real-world trading strategies – to ensure that factor portfolios behave as intended.

Finally, we break down the true relationship between the tone on display in earnings calls and expected stock performance. A data mining approach helps separate the signal from the noise.

We hope you enjoy this latest edition of Risk & Reward!

Best regards,

Mark L. Flanagan

Marty Flanagan
President and CEO of Invesco Ltd.

Multi-period portfolio selection: a practical simulation-based framework[1]

By Kenneth Blay, Anish Ghosh, Harry Markowitz, Nicholas Savoulides and Qi Zheng

Since the advent of portfolio theory in 1952, investment researchers have made notable advances in optimal portfolio selection. However, research on multi-period portfolio selection has been limited in its practical application by 'the curse of dimensionality' – the exponential increase in computational requirements with each additional state variable. Real-world multi-period problems include numerous state variables that make the computation of solutions impractical if not infeasible. And, while relevant computational, theoretical and numerical methods have improved significantly, many important aspects of multi-period investing still remain unaddressed.

> Duration management should be a key consideration for long horizon optimizations in the presence of inflows and outflows.

We develop a simulation-based portfolio selection (SBPS) approach that addresses three requirements for practical multi-period portfolio selection solutions:

1. **Effective duration management**
2. **Incorporation of real-world asset dynamics**
3. **Consideration of investment frictions and illiquidity**

We start with an analytical model that provides intuition and offers some guiding principles on how allocations and duration should evolve across a multi-period investment horizon. We then unveil our SBPS approach and demonstrate how it provides solutions for common investor objectives that are intuitive and flexible, and which satisfy our requirements for practical multi-period solutions.

Single-period versus multi-period portfolio selection

A key distinction between single-period and multi-period portfolio selection is the consideration of intermediate actions within an investment horizon that extends over many periods. In the single-period setting, an investor decides how to invest at the beginning of the period and then waits until the end of the period to assess the outcome. In practice, however, investing is rarely so straightforward. Pension fund managers, retirement investors and other long-term investors fund their portfolios over time and often pursue many objectives across a multi-stage investment horizon, necessitating a variety of intermediate steps.

Multi-period portfolio selection must therefore consider these intermediate events while seeking to determine efficient, time-varying portfolio allocations across the investment horizon.

Requirements for multi-period portfolio selection

In practice, three requirements must be fulfilled for practical multi-period portfolio selection solutions:

1. Solutions must evolve allocations and duration over time to align with expected cash flows

The long investment horizons and expected cash inflows and outflows of multi-period investing must be reflected in the evolution of allocations and duration profiles across the investment horizon.

For example, consider the risk-free asset, which in a single-period context is usually cash or US Treasury bills, due to their low volatility. Over long investment horizons, these assets are not 'risk free' as they expose investors to meaningful uncertainty.

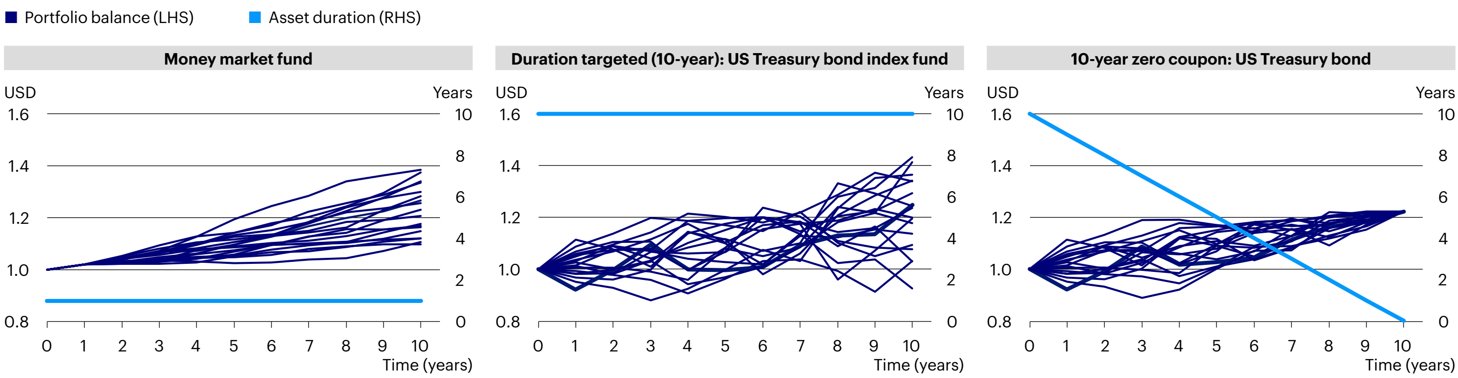
Figure 1 illustrates this, presenting 20 simulated paths for each of three duration approaches. Of the three options, a 10-year zero-coupon US Treasury bond has the lowest risk if held until maturity, despite exhibiting material volatility across the investment horizon.

This demonstrates how essential effective duration management is to multi-period solutions. In cases like this, hold-to-maturity investments can be the most efficient assets to employ. In more complex cases, time-varying combinations of short and long-duration bond funds may be used to achieve the desired outcome.

2. Solutions must consider real-world asset dynamics

Asset pricing dynamics may exhibit unique characteristics over long horizons, which can materially impact the performance of theoretical solutions when implemented in the real world. For example, equity valuations exhibit mean-reverting tendencies that result in negative autocorrelation over longer horizons. Additionally, fixed income returns may be skewed in a low rate environment where rates have limitations as to how low they can go. For these and other reasons, a log-normal model of asset price dynamics may produce unrealistic – if not utterly implausible – results.

Figure 1
Twenty simulated paths of USD 1 invested in three different ways



Source: Invesco.

3. Solutions must consider investment frictions and illiquidity

Real-world portfolios implemented across multiple periods may be updated for a variety of reasons. These updates can include cash inflows, cash outflows, the purchase, sale or replacement of investments, and portfolio rebalancing. All such intermediate portfolio management activities can have transaction cost and/or tax implications.

Over the short term, these real-world elements may only result in negligible differences in expected outcomes. Over the long term, however, significant differences between actual and expected outcomes can arise from not adequately accounting for their impact.

Analytical framework

To provide intuition for the multi-period portfolio selection problem in the presence of cash flows, we address two central ideas analytically:

1) Optimal asset allocation through time
2) Optimal duration management through time

To this end, we develop an analytical solution to the mean-variance problem in the multi-period context with intermediate cash flows. Our findings are best understood in a two-asset world in which, at any given time, the investor has access to an equity asset and a government bond with arbitrary duration.

1. Optimal asset allocation through time

Making some simplifying assumptions, we derive an analytical solution for optimal asset allocation.[2] The analytical solution is best understood in a standard accumulation-decumulation problem depicted in figure 2(a); it shows inflows and outflows, and how the portfolio balance increases and decreases over time.

The optimal analytical solution suggests that, the dollar risk should stay constant through time. In a two-asset context, it implies that the portfolio dollar allocated to the high risk asset (equity) stays roughly constant through time. This is depicted in figure 2(b) for three different solutions, depending on the investor's risk preference. This constant dollar equity allocation gives rise to a U-shaped glidepath in the accumulation-decumulation problem.

2. Optimal duration management through time

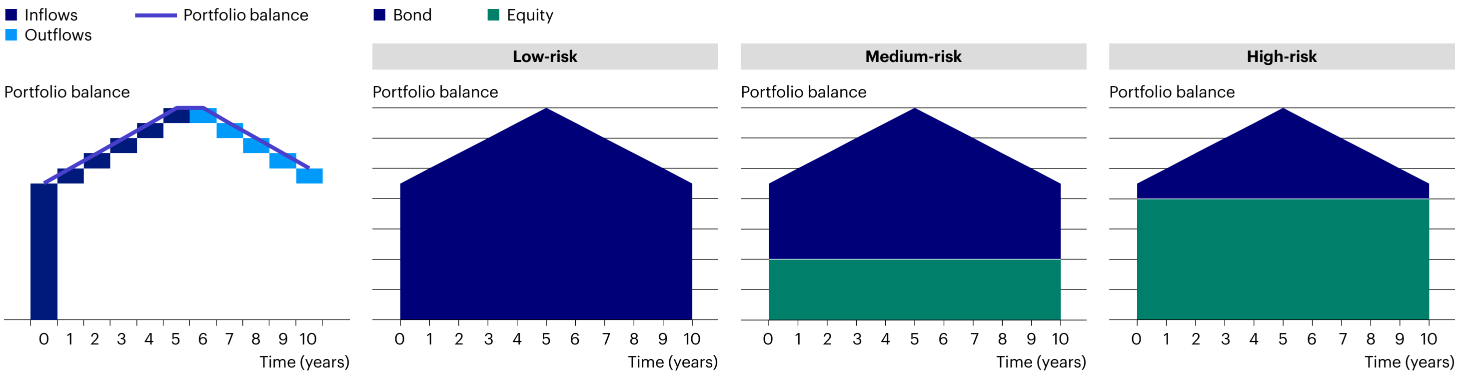
Similarly, we obtained an analytical solution for optimal duration. It is driven by four components, as shown in figure 3: expected cash flows, bonds-equity correlation, expected yield curve changes, and yield curve slope.

Analytically driven guiding principles

To better understand the first order impact of cash flows and various other parameters on allocation and duration decisions, we introduce an example: a standard accumulation-decumulation problem on a shorter timescale. We assume an investor with a 10-year investment horizon starting

Figure 2
Stylized accumulation-decumulation problem

a) Cash flows and portfolio balance **b) Allocation of portfolio balance for low, medium and high risk solutions**



Source: Invesco.

Figure 3
Components driving optimal duration and their directional impact

Duration = **Magnitude and timing of cash flows** (Inflows (+), Outflows (–)) + **Correlation with equity** (Positive (–), Negative (+)) + **Yield curve drift** (Increasing yields (–), Decreasing yields (+)) + **Yield curve slope** (Positive (+), Negative (–))

Source: Invesco.

with USD 1,000 of initial capital, yearly inflows (contributions) of USD 500 for the first five years and outflows (withdrawals) of USD 500 for the last five years. The investor seeks to maximize mean terminal wealth, subject to a given level of risk as measured by its variance.

Figure 4 presents the optimal equity-bond allocation and optimal duration profile over time. Specifically, we consider the sensitivity of the solution to different levels of yield curve slope and bond-equity correlation.

For this example, we will assume the equity asset has an average 6% annual return and annualized volatility of 15%. We also assume that the instantaneous yield for the bond asset starts at 2% with no drift and exhibits an annualized volatility of 1%.

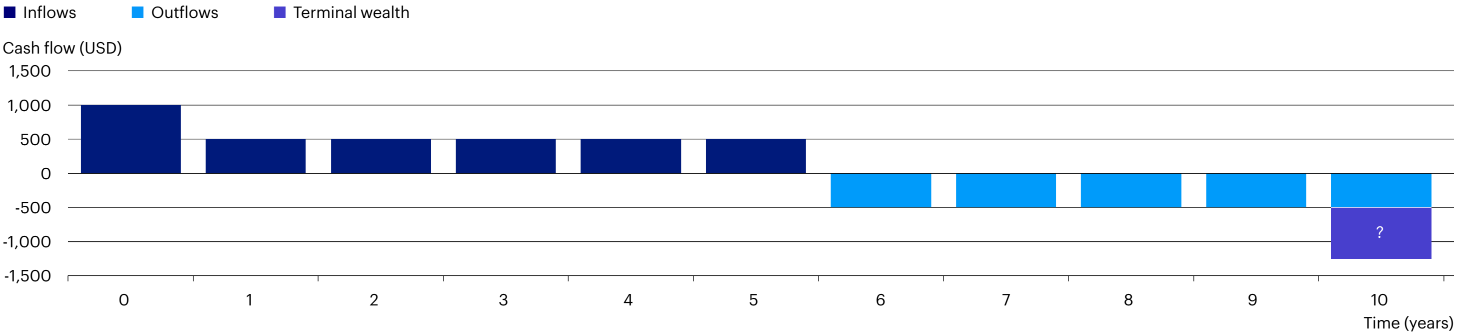
Based on the analysis and the example presented, we make the following key observations:

1. Allocations should shift to safer (riskier) allocations as inflows (outflows) occur

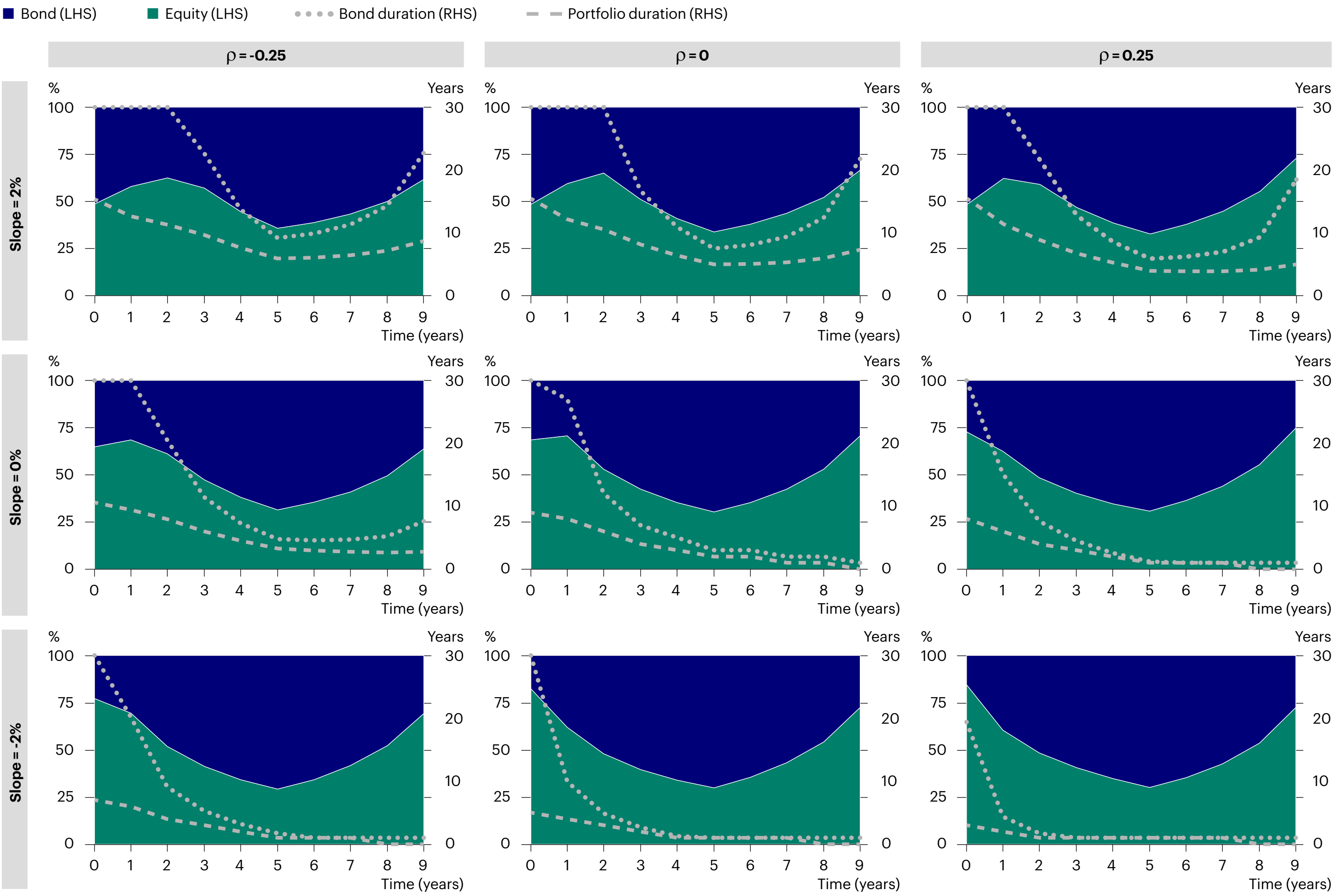
As we have shown, the lowest-risk solution has 100% allocation to bonds and exhibits zero risk. For higher-risk solutions, the analytical solution suggests an approximately constant dollar allocation to equity through time. To maintain such a constant dollar allocation, the investor will allocate

Figure 4
Maximizing mean terminal wealth in the analytical model

Inflows, outflows, and terminal wealth



Asset allocation and duration for nine combinations of asset class correlation (ρ) and yield curve slope



Source: Invesco.

conservatively when the portfolio balance is high and aggressively when it is low. This results in a U-shaped allocation to risk assets across the investment horizon. As the probability of running out of money increases because of extended or higher withdrawals, allocations shift back to safer assets.

2. Asset duration should match the investment horizon when there are no cash flows

In the case with no yield curve slope and no correlation between bond and equity assets, the duration of the bond mirrors the remaining investment horizon. This follows from the cash flow contribution of the duration equation.

In this simple example, the desired duration profile could be implemented with a buy-and-hold strategy using a duration-matched zero-coupon US Treasury bond. Notice the contrast with liability-driven investing (LDI), which focuses on managing funding ratio volatility, seeking to match the portfolio's overall duration to the investment horizon and leading to longer duration targets than are suggested here. While the LDI approach makes sense for a plan fiduciary, it may be overly restrictive and suboptimal for an investor seeking to maximize terminal wealth.

3. Duration should be extended (shortened) with expected inflows (outflows)

When inflows and outflows are introduced, we see a very dramatic change to the duration profile. By extending (or shortening) duration, the investor can effectively lock in buying (selling) bonds with future inflows (outflows) at today's rate.

The implications are profound, particularly in situations with prolonged inflows, where optimal solutions could require dramatic duration extensions. While this might seem counterintuitive, in the absence of directional views on interest rates, this will lead to more efficient long-term results.

4. Duration should be adjusted based on the slope of the yield curve, expected correlation of bond and equity assets and expected yield curve changes

If the yield curve is positively sloped, duration should be extended. This allows investors to earn higher returns by investing in higher-yielding parts of the yield curve. And it provides the opportunity to potentially earn additional roll-down returns. If yields are positively correlated with equity returns (that is, if bond returns are negatively correlated with equity returns), duration should be extended, in line with standard diversification seeking to exploit negative correlations. If yields are expected to increase, duration should be shortened so that assets can be reinvested at increasingly higher rates.

Although it is difficult to develop expectations about future yields, the general shape of the yield curve and the correlation of its movements with equity asset returns may offer guidance on adjusting portfolio durations.

Simulation-based portfolio selection (SBPS)

Traditional approaches to solving multi-period problems employ dynamic programing. SPBS builds on much of the traditional thinking to date on long-horizon multi-period investing but diverges in that it does not employ this technique. Instead, we propose a much more flexible framework that decomposes the multi-period problem into three distinct parts:

1. The objective function (the investment objective)
2. Simulation
3. Optimization

This provides substantial flexibility in addressing the central challenges of implementing and managing portfolios across a multi-period investment horizon. The approach allows us to consider any objective function and incorporate real-world asset dynamics and investment frictions through advanced simulation methods. At the core of SBPS is the optimization algorithm that incorporates simulated investment outcomes (based on the objective function selected and the simulation engine used) and optimizes all the asset weight vectors through time all at once. This stands in contrast to dynamic programming approaches where consideration of many real-world aspects of multi-period portfolio management would likely require a non-trivial reformulation of the solution to be used.

Examples and key insights

We present unconstrained SBPS solutions for the investor problem introduced in the analytical section. Instead of optimizing the mean versus variance objective, here we are interested in the median versus median -5% value at risk objective. The investment opportunity set includes US equity, international developed equity, emerging market equity, and 1-year to 30-year maturity STRIPS indexes (separate trading of interest and principal securities). Figure 5 shows cash flows, the efficient frontier, and the optimal allocations and durations for three selected solutions on the frontier: low, medium, and high risk.

The SBPS-based optimization results, coupled with our analytical intuition from the previous section, leads us to the following observations:

1. SBPS generates allocations and duration profiles aligned with analytical expectations

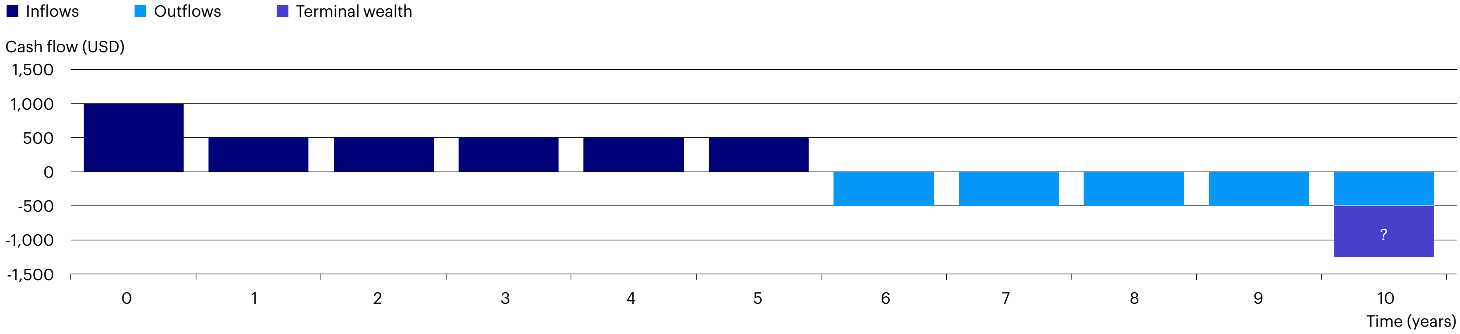
All the key principles derived from our analytical examples still hold true. Specifically, allocations shift to safer (riskier) assets as inflows (outflows) occur and duration is extended (shortened) in the presence of future inflows (outflows).

2. SBPS allows for long-term real-world asset dynamics
We can model assets more flexibly and realistically than with the more simplistic analytical model. For example, SBPS prices fixed income instruments based on simulated interest rate curves. This results in more consistent pricing while better reflecting current market realities. For example, in a low rate environment, when bond returns are materially skewed, the simulator is better aligned with market realities. Additionally, correlations between rates and equities in SBPS are assumed to be slightly negative, as opposed to their slightly positive correlation over the past decade. Details such as these can meaningfully affect our solutions.

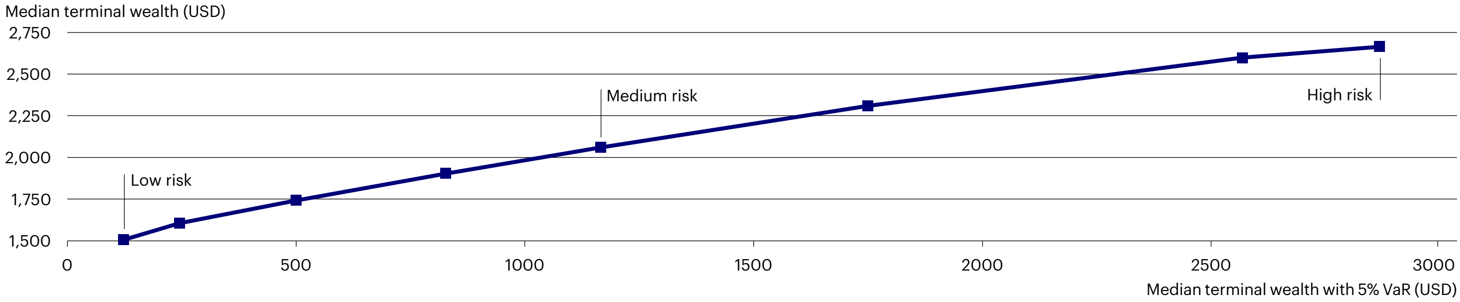
3. SBPS allows for the consideration of investment frictions and illiquidity
Simulation also lets us consider real-world investment challenges, including assumed transaction costs (we assume 50 bps per transaction). This not only incorporates the impact of transaction costs on expected outcomes but also encourages the optimization process to produce solutions with lower turnover.

Figure 5
Maximizing median terminal wealth with SBPS

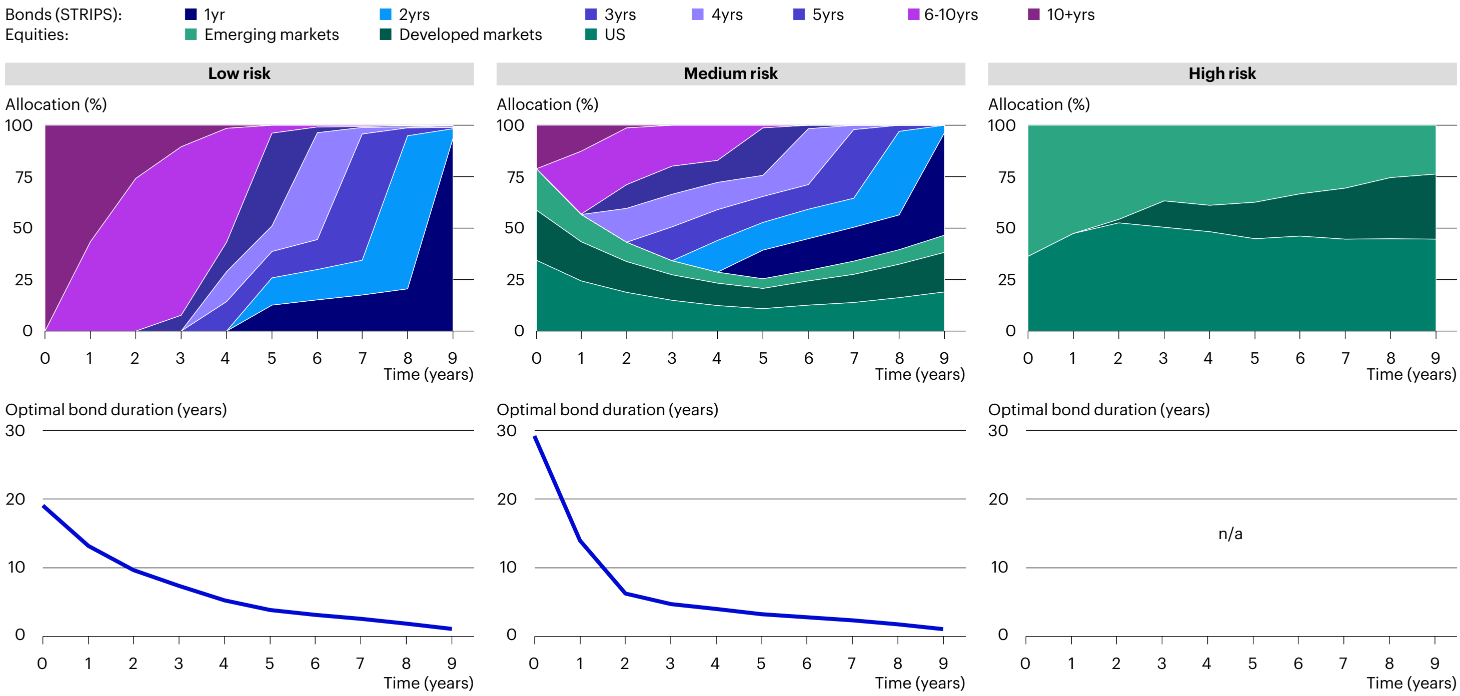
Inflows, outflows and terminal wealth



Efficient frontier



Optimal allocations and durations



Source: Invesco.

> The goal of income maximization is to identify the solution that leads to the highest probability of success for a given level of income.

SBPS for the income investor

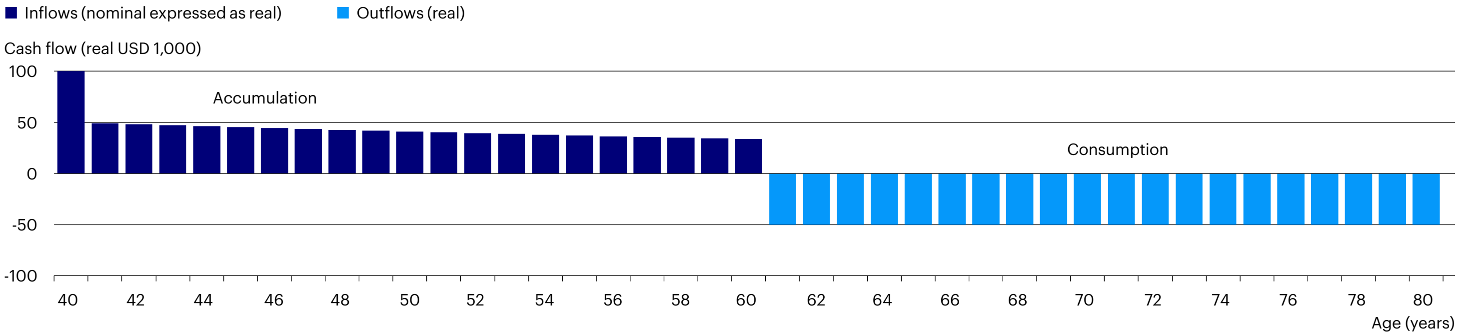
To demonstrate the flexibility of our SBPS approach, we now consider the retirement income problem. We consider a 40-year-old investor who plans to retire at age 60, at which time he expects to withdraw a fixed annual income for 20 years. We assume:

- An initial investment of USD 100,000
- Annual inflows of USD 50,000 (nominal) for 20 years towards retirement
- Annual outflows (real) beginning in year 20 and continuing to year 40

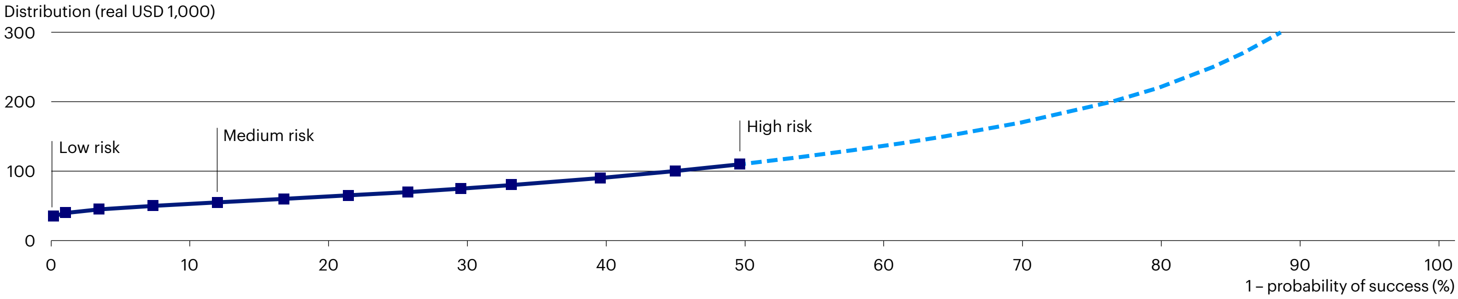
As before, the investment opportunity set includes US equities, non-US developed market equities, emerging market equities and 1-year to 30-year maturity STRIPS indexes. In addition, 1 to 30-year TIPS indexes (Treasury inflation protected securities) are also available. Note that we can work with both nominal cash flows (contributions) and real cash flows (income withdrawals). In real dollar terms, nominal contributions have less value as we go out into the future. The ability to convert nominal dollars into real dollars and vice versa allows us to work in one single unit.

Figure 6
SBPS for the income investor

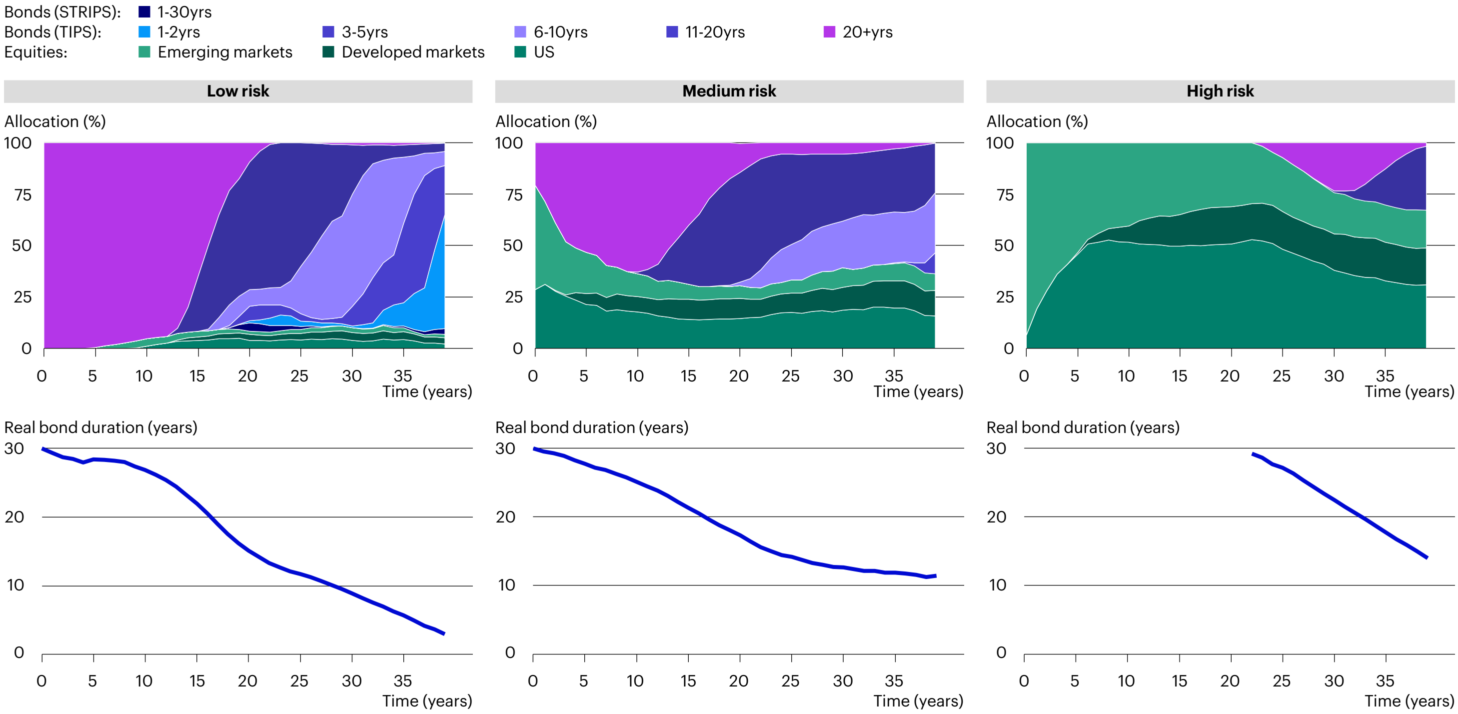
Inflows and outflows



Efficient frontier



Optimal allocations and durations



Source: Invesco.

SBPS provides substantial flexibility in addressing the major challenges of implementing and managing portfolios across multi-period horizons.

The goal of income maximization is to identify the solution that leads to the highest probability of success for a given level of income. Figure 6 shows the cash flows in real dollar terms, the income investor's efficient frontier, and the optimal allocations and real durations for three selected solutions on the frontier: low, medium, and high risk.

From our results, we can see the following:

1. Low-risk solutions seek duration early on and diversify with growth assets in later years

In the low-risk allocation, the solution focuses on duration assets with extended durations early in the investment horizon. At this stage, it is most important to eliminate the interest rate risk associated with future purchases (and dispositions) of bonds that may be required from (for) upcoming inflows (outflows). As the portfolio progresses through the investment horizon and expected outflows increasingly outweigh expected inflows, allocations gradually shift to shorter duration bonds and introduce equity exposures for diversification.

2. High-risk solutions focus early on growth assets, with duration added in later years

In the high-risk solution, instead of maintaining a 100% allocation to equity assets through time, the solution moves to safer assets as outflows begin. Intuitively, during inflows, the solution seeks maximum return and, consequently, maximum risk. Once outflows begin, they are assumed to be constant. There is also no utility to any remaining portfolio balance following outflows. The result is that, for a given outflow amount, the successful paths will have no remaining upside and will be exposed only to the risk of becoming insolvent. To mitigate this effect, once the outflows begin, the portfolio gradually moves to some duration assets.

Conclusion: SBPS is more intuitive, flexible, and adaptable

We first presented the results of an analytical framework we developed that provides a theoretical foundation for multi-period portfolio selection and lends intuition for how portfolio allocations and duration should evolve over time. We then present SBPS and demonstrate how it addresses the three key requirements we laid out for multi-period portfolio selection solutions: (1) It produces solutions that align portfolio durations with expected cash flows, (2) it incorporates real-world asset dynamics, and (3) it considers investment frictions and illiquidities. It also allows for the inclusion of individual hold-to-maturity and defined-maturity investments.

SBPS provides substantial flexibility in addressing the major challenges of implementing and managing portfolios across multi-period horizons. Decomposing the multi-period problem into three distinct parts (the objective function, simulation, and optimization) also facilitates further research into multi-period portfolio selection, as innovations in any of these three areas can easily be incorporated into our framework.

Finally, SBPS readily accommodates new methods of leveraging advances in computing and optimization algorithms to solve multi-period portfolio selection problems using a simulation-based approach.

Notes

1 The full version of this article was published in the fourth quarter 2020 issue of The Journal of Investment Management. Charts and content used with permission from the Journal of Investment Management.

2 For more details and the analytical solutions, please refer to the full version of this article.

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“Simulation has been a focus for me over much of my career.”

Interview with Harry Markowitz

In this edition of Risk & Reward, we are proud to present an exclusive interview with Dr. Harry Markowitz, father of modern portfolio theory, 1990 Nobel Laureate and co-author of our feature article on multi-period portfolio selection.

Risk & Reward
Dr. Markowitz, your 1952 Portfolio Selection paper has been called the big bang of modern finance and presented a single period portfolio selection framework. In your 1959 Portfolio Selection book, you build out the theory on the single-period framework and briefly discuss multi-period portfolio selection. What is the difference between single-period and multi-period portfolio selection?

Harry Markowitz
As the name implies, the single-period framework considers optimal action over a single, finite period. However, the investor can take no intermediate action over that period. Consider the problem of maximizing a series of cash flows. This can’t be accomplished over a single period. Now, the length of the period could be 30 years, one decade, one month – or anything you like. And you might approach the problem by optimizing a sequence of single periods and withdrawing cash flows in between each. But, for a number of reasons, this wouldn’t be the optimal solution. That requires a multi-period approach which optimizes outcomes while considering the entire length of the investment horizon, portfolio inflows and outflows, transaction costs and other frictions – as well as an investor’s intermediate actions.

Risk & Reward
In your 1959 book, you point to dynamic programming to solve multi-period problems. But in your work with the Invesco team, you use a simulation-based approach instead. Why?

Harry Markowitz
Let me first point out that, while most people know me for my portfolio selection work and the Nobel Prize that resulted from it, I was also awarded the John von Neumann Theory Prize in 1989 for my work on simulation, the development of the SIMSCRIPT simulation programming language, portfolio theory and sparse matrix techniques. So, simulation has been a focus for me over much of my career.

The general approach for implementing dynamic programming is to work backwards through time. You begin by determining the best action for each of the possible circumstances in the last period, then the next to last, and so on until you work your way back to the first period. The problem is that the possible circumstances in each period increase exponentially as you consider additional variables. This is what is known as the curse of dimensionality. And this is also the reason we have yet to see full-fledged implementations of dynamic programming solutions to practical multi-period problems. Dynamic programming methods are certainly used to inform portfolio construction. But the number of variables that have to be considered continues to be a key limiting factor. Moreover, customizing dynamic programming solutions is a non-trivial exercise that can require a complete reformulation of the problem being considered.

The simulation approach we've taken provides a way around the dimensionality problem. By decomposing the problem into three distinct parts – the objective function, simulation and optimization – we also gain a great deal of flexibility in the types of problems that can be solved and in the ability to develop solutions that address specific investor needs.

Risk & Reward
How would you characterize Simulation-Based Portfolio Selection, or SBPS for short, the latest iteration of your portfolio selection work with Invesco?

Harry Markowitz
Our SBPS research builds on previous work in both portfolio selection and simulation. Specifically, it expands on an article I wrote together with Kenneth Blay back in 2013.[1] Based on the insight that the impact of taxes is path-dependent, we simulated after-tax investment outcomes over multi-period investment horizons for different asset classes, investment types (active and passive) and account types (taxable, tax-deferred and tax-exempt). We then optimized the net present value (NPV) of those outcomes. That work addressed the taxation question – and it also considered multi-period investment horizons.

The SBPS framework we developed with Invesco significantly evolved that work and, more importantly, generalized it to address a number of other practical realities of multi-period investing – like duration management over long investment horizons, investment frictions and real-world asset dynamics. The Invesco framework also allows for the incorporation of individual bonds in developing solutions.

Risk & Reward
Could you tell us a bit more about the collaboration with Invesco?

Harry Markowitz
The team at Invesco has done a tremendous job. They've successfully developed the analytical intuition for how portfolio allocations should evolve over time given different objectives and in developing the optimization algorithm for computing these types of problems. That isn't easy work. And they not only made it work for our research effort, but they've also made the capability accessible to their clients through the Invesco Vision portfolio risk and research platform. This is a great example of theory turned into practical application.

Risk & Reward
Dr. Markowitz, thank you very much for your time!

Note
1 Blay, K. and H. Markowitz. 2016. "Tax-Cognizant Portfolio Analysis: A Methodology for Maximizing After-Tax Wealth." Journal of Investment Management, Vol 14, no. 1, 26-64.

Managing climate risk - a 21st century approach for commercial real estate investors

By Louis Wright and Zachary Marschik

Not only is real estate a major contributor to CO_2 emissions, as an asset class it is also suffering increasingly from the very natural disasters global warming brings about. With climate risk accelerating around the world, real estate investors need to consider the impact on their strategies. Read on to learn how we approach these growing challenges at Invesco Real Estate (IRE).

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Global economic losses from natural and man-made catastrophes totaled USD 202 bn in 2020.

Populations around the globe face heightening climate risk. In 2021 alone, the world witnessed severe flooding in Western Europe and China, ice storms in Texas and wildfires in California – all of which exacted enormous economic and human costs.

Re-insurance data highlights the increasing cost of such disasters: Global economic losses from natural and man-made catastrophes totaled USD 202 bn in 2020, up from USD 150 bn in 2019.[1] Figure 1 shows global losses broken down in line with the industry standard categorization of climate events into primary perils and secondary perils. Primary perils are natural disasters with known severe loss potential for the insurance industry, such as tropical cyclones or earthquakes, whereas secondary perils are smaller to moderate events or the secondary effects of a primary peril. Examples include river flooding, torrential rainfall, drought, wildfire, thunderstorms and tsunamis. Secondary perils are often not modeled and have historically received little monitoring from the insurance industry. Though the annual costs of both types of climate event are increasing, the share represented by secondary perils is growing.

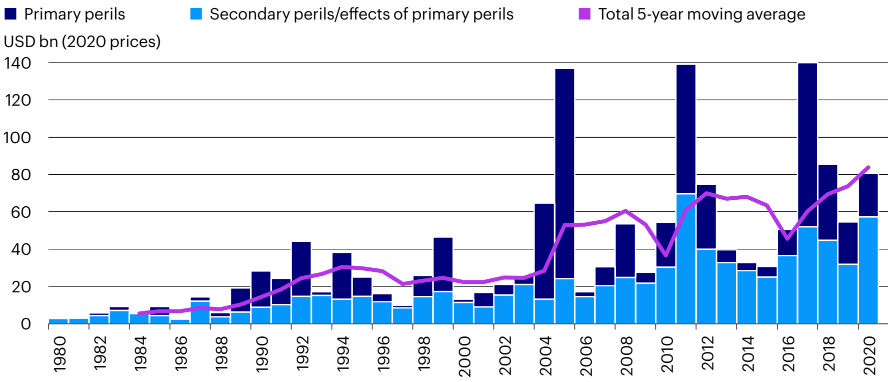
The overwhelming majority of climate scientists and academics agree that global warming is caused by human activity.[2]

As figure 2 shows, global temperature anomalies have risen considerably over the last 100 years, and there is consensus that this is the main reason for the rise in the frequency and severity of natural disasters. Though governments, not-for-profit organizations and the private sector have joined the fight against climate change, even the most drastic of interventions will require many years to reverse the global warming trend, and the cost of extreme weather is expected to continue climbing into the foreseeable future.

Real estate and the climate challenge

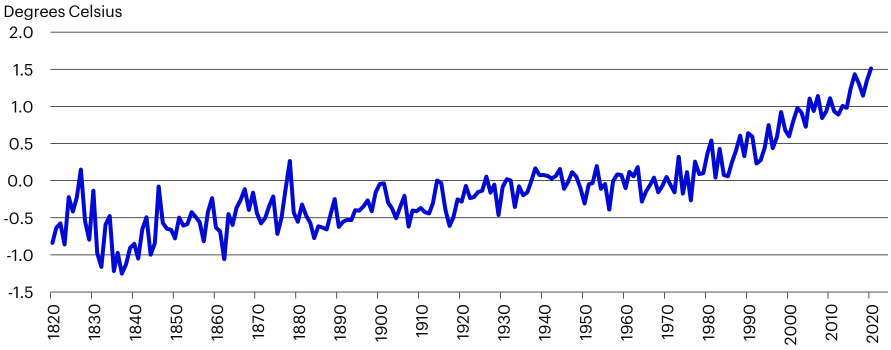
Real estate is a major contributor to global CO_2 emissions. In 2020, the built environment was estimated to be responsible for 75% of annual global greenhouse gas emissions,[3] with buildings alone accounting for about half of this amount.[4] Around 50% of emissions from new buildings are embedded in the construction materials. The other half arises from operation of the building.[5] This sets the real estate industry before the dual challenge of creating spaces that are more efficient in use while reducing the up-front carbon emissions involved in construction and refurbishment. This should be kept in mind as we concentrate on identifying climate risks for existing assets.

Figure 1
Global insured losses from climate events



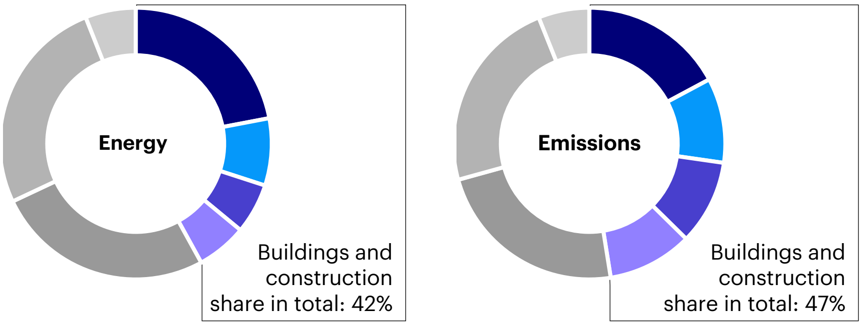
Source: Swiss RE (2021); "In 5 charts: natural catastrophes in a changing climate", https://www.swissre.com/risk-knowledge/mitigating-climate-risk/sigma-in-5-charts.html

Figure 2
Annual global temperature anomalies since 1820



Source: Berkley Earth; temperature anomalies relative to the Jan 1951-Dec 1980 average.

Figure 3
Buildings and construction share of global energy and energy-related CO_2 emissions (2020)



	Energy	Emissions
Residential	22%	17%
Non-residential	8%	10%
Buildings construction industry	6%	10%
Other construction industry	6%	10%
Other industry	26%	23%
Transport	26%	23%
Other	6%	6%

Source: IEA (2021a).

> Determining the the financial impacts of extreme weather on real estate is complex.

Financial impacts of climate risk on real estate

Determining the financial impact of extreme weather on real estate is complex and extends far beyond calculating the potential repair costs of a building. Climate risk can influence real estate pricing via various channels, with effects varying in severity and longevity. A recent United Nations Environment Programme Finance Initiative (UNEPFI) report presents a meta-analysis of research into such impacts as reduced rental income, longer re-leasing times, greater cash flow volatility, higher insurance costs, lower capital growth, higher financing rates and reduced liquidity for commercial properties (table 1). In the most severe cases, a property could become a stranded asset with its capital value reduced to zero.

The UNEPFI report found that the financial consequences of climate risk to real estate depend on multiple conditions. One key finding was that access to information on risks is a contributing factor in valuation and pricing, with evidence that better

Table 1
Potential effects of climate risk on commercial real estate asset performance

Broad impact	Transmission channel	Specific financial consequences
Effects on cash flow	Income	• Reduced rent from fall in demand • Reduced occupancy rate from fall in demand • Longer to re-let space/weaker tenants • Changes to feasible uses impacting on income
	Outgoings	• Increased operating costs (building services) • Increased capital costs (repair/restoration) • Higher insurance premiums to reflect higher risks • Higher property taxes (clean up and mitigation costs)
Effects on capitalization rate	Risk premiums	• Greater cash flow volatility • Reduced liquidity/saleability of asset • Reduced insurability of asset • Greater site and location risks
	Expected growth	• Reduced rental prospects for location • Increased depreciation for non-resilient buildings • Reduced future occupancy rates • Increased operating and capital costs, taxes, etc.
Effects on financing	Cost of finance	• Higher margins stemming from increased risk • Higher DSCRs to cover cash flow volatility
	Availability of finance	• Reduced willingness to lend in location • Lower amounts lent/more security sought • Fewer potential equity partners

Source: Clayton J, van de Wetering J, Sayce S & Devaney S (2021); UNEPFI report "Climate risk and commercial property values: a review and analysis of the literature".

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Moody’s methodology is deeply data driven.

information leads to greater awareness, acceptance and integration of climate impacts on transacted prices.

Measuring climate risk

Climate risk is not a singular metric, but refers to multiple, interacting risks that can compound and cascade, making it very difficult to estimate. Measuring climate risk requires quantifying both the likelihood and consequences of climate change in a particular location. Here, we focus on the physical elements of climate risk rather than ‘transition risks’, i.e., the potential costs from moving towards a less polluting, greener economy. Though still important, transition risks have fundamentally different characteristics to physical climate risks and should therefore be modeled and analyzed separately.

Assessing a specific location’s vulnerability to future climate events has traditionally been the remit of a handful of highly skilled professionals such as actuaries or academics, and it required access to private datasets plugged into specialized software. But growing awareness of and interest in climate risk have broadened demand for these tools. Recent advancements in geospatial modeling techniques coupled with the emergence of open-source data and software has helped proliferate climate risk services available to businesses and organizations.

To understand the exposure of IRE’s global property portfolio to climate change, we needed a tool with consistent and robust scoring across various countries, regions and sectors. Moody’s ESG Solutions (previously Four Twenty Seven) is a leading provider of physical climate and environmental risk analysis with a climate risk application well-suited for a globally diversified asset manager like IRE.

Moody’s methodology is deeply data driven and leverages large public and private databases to generate more than 25 underlying risk indicators, each linked to known business consequences of climate change. Scoring is forward looking and focuses on thresholds near the tail end of the risk distribution because such events are the most likely sources of disruption and damage – especially as extreme events grow in severity and/or frequency. High-level risk indicators in Moody’s service include exposure to floods, heat stress, hurricanes and typhoons, sea level rise, water stress, wildfires, and also earthquakes (which are technically a geological hazard rather than a climate risk but have also been included due to increasing client demand).

Moody’s risk scores are standardized (ranging from 0 to 100) and globally comparable. The assigned risk levels (none, low, medium, high, red flag) aid interpretability. For example, a flood risk score of 70/100 equates to a high risk level and means a location is susceptible to some flooding and inundation during rainfall or riverine flood events.

Subcategory metrics are also available, such as the expected flood return period (i.e., flood frequency in years), rainfall intensity and inundation level from a 1-in-100-year flood.

Democratizing climate risk data

The Moody’s tool can be used to evaluate the climate risk of almost any location across the globe, including IRE’s entire direct real estate holdings, which comprise more than 500 commercial assets across North America, Asia, Oceania and Europe.

Moody’s subscription-based model allows users to generate location-specific climate risk scorecards. These reports are detailed and valuable, but optimizing their use at IRE required building additional tools to better visualize and disseminate the data. The information could not be easily accessed by the wider IRE teams who did not have a Moody’s ESG login. So, in order to leverage the information for better investment and asset management decision making, we needed to democratize our climate risk process – in particular streamlining the delivery of information to teams involved in the appraisal of asset acquisitions (transaction teams) and those managing existing assets and funds (asset and fund managers).

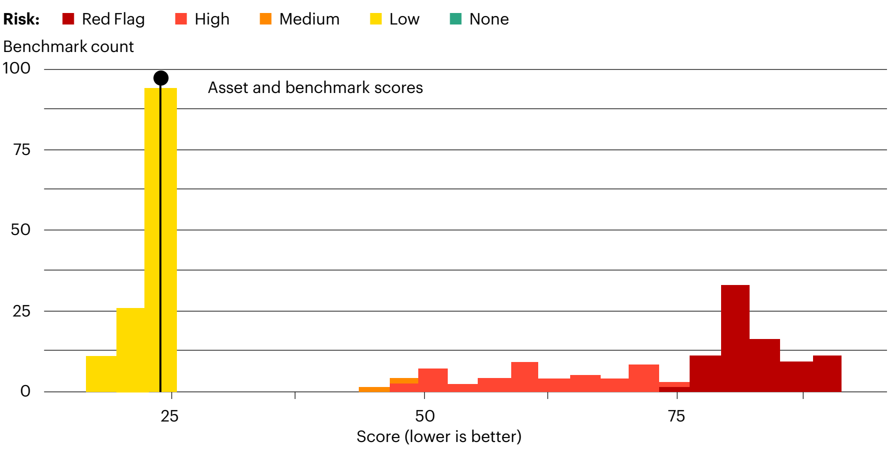
The solution found by IRE’s Strategic Analytics team was a Climate Risk Dashboard, which links directly to Moody’s database and allows users to instantly identify the climate risk exposure of each address they enter. The dashboard displays the risks pertaining to our portfolio assets and summarizes and filters risks by fund, using maps and charts to highlight key information.

Benchmarking asset risk

Investments do not happen in a vacuum. While the clear first step in contextualizing climate risk is to democratize the asset-level data, further understanding can be achieved by considering how one investment compares to another for insight into the relative risk. This can be done by benchmarking, or matching an asset’s climate risk against other locations in the surrounding area. For instance, a well-located property with access to plenty of amenities might see its locational benefits outweigh its climate risk. However, it may still be more ideal to own a relatively less risky asset in the same area to minimize the climate risk while enjoying the benefits of the amenities.

Our benchmarking is achieved by utilizing Moody’s ESG scoring on strategically generated sample points within a boundary of interest (submarket, block group, etc.). With a series of sample points now available, the scores can be summarized at the defined boundary levels, and scores of individual assets of interest can be placed within the distribution. Figure 4 shows a building in Tokyo and how its flood risk compares to the surrounding area. In this location, the low score conveys that the asset is not

Figure 4
A benchmarking example



Source: IRE Strategic Analytics.

> All areas with the largest wildfires had been properly scored as high-risk locations.

very exposed to flood risk. However, as the distribution in figure 4 shows, there are parts of Tokyo with high risk values, meaning that the sample building might be a well-positioned asset, close to amenities but far enough away from the low-lying areas to avoid being too risky.

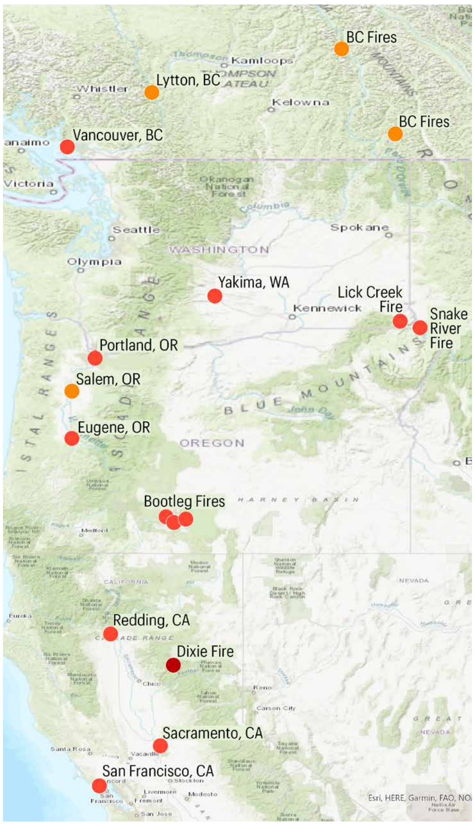
Recent extreme weather events: Two case studies

Finally, we assess the validity and accuracy of Moody's ESG scores with the help of two case studies of recent climate events.

North American wildfires

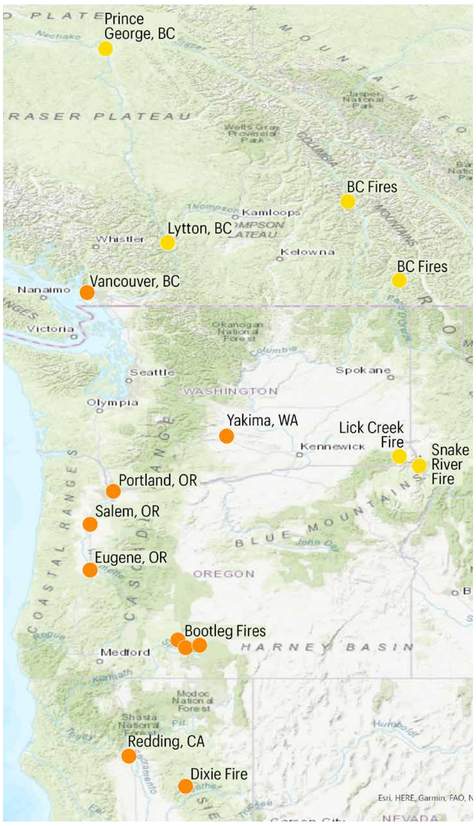
In the summer of 2021, several areas in western North America experienced historic wildfires while much of the region experienced record high temperatures. To test the utility of the Moody's ESG scores using a real-world example, we looked at the Moody's wildfire scores for locations in the Pacific Northwest. The results proved encouragingly accurate: Apart from medium risk scores in British Columbia, all areas with the largest wildfires had been properly scored as high-risk locations (figure 5).

Figure 5
Moody's wildfire scores



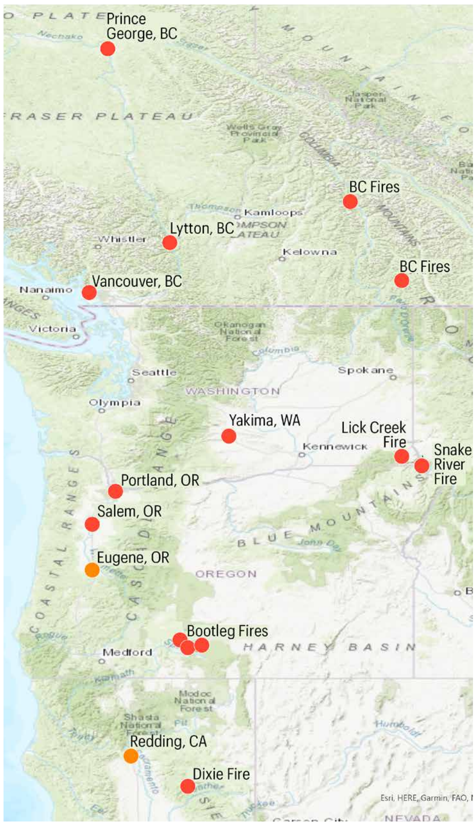
Source: IRE Strategic Analytics.

Figure 6
Moody's heat scores



Source: IRE Strategic Analytics.

Figure 7
Moody's future extreme temperatures sub-scores



Source: IRE Strategic Analytics.

Investors can no longer afford to leave climate risk information out of their decision making.

Additionally, we analyzed Moody's heat scores to see if the record-high temperatures were something that could have been foreseen. While overall heat scores (figure 6) did not seem to be good predictors, the subcategory score for future change in extreme temperatures (figure 7) seemed to provide a warning that extreme heat is only going to get worse. This sub-score provides valuable information for investors, and the high scores for future change are supported by the events of summer 2021.

European floods

In July 2021, a number of Western European countries experienced extreme flooding. Worst affected were Germany, Belgium, Netherlands and Austria. A total of 242 deaths are attributed to the flooding, of which 196 were in Germany. To test the validity of Moody's ESG scores, we sampled flood risk scores across five towns devastated by the floods (Schönau am Königssee, Hagen, Schuld and Bad Neuenahr in Germany, and Hallein in Austria). Unsurprisingly, each town had a large river running through its center. Almost all the sample points near a river and/or at relatively low elevation had a high or red flag risk level in Moody's scoring system. Equally, sample locations with medium-to-low flood risk were sufficiently distanced from a river and/or had much higher land elevations.

Conclusion

Many real estate investors still ignore extreme weather events as they are unpredictable and difficult to quantify. Nonetheless, climate-related events are expected to become more common and more severe, calling into question this style of approach: Investors can no longer afford to leave climate risk information out of their decision making. IRE's Climate Risk Dashboard is designed to deliver timely and reliable information to identify and mitigate, or completely avoid, potential climate risk exposure. This will ultimately help us better preserve and grow capital and deliver stronger and more secure returns for our clients.

Notes

1 Swiss RE (2021) Natural catastrophes in 2020: secondary perils in the spotlight, but don't forget primary-peril risks. Sigma 1/2021.
2 For instance, Carbon Brief (2021) Mapped: How climate change affects extreme weather around the world. https://www.carbonbrief.org/mapped-how-climate-change-affects-extreme-weather-around-the-world; NASA (2021) Scientific Consensus: Earth's Climate Is Warming. https://climate.nasa.gov/scientific-consensus/
3 Architecture 2030 (2021) The 2030 Challenge. https://architecture2030.org/2030_challenges/2030-challenge/
4 39% of CO2 emissions according to Architecture 2030; 37% of CO2 emissions and 36% of global energy consumption according to the UN Environment Programme.
5 World Green Building Council (2021) Beyond the Business Case report 2021. https://www.worldgbc.org/business-case

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Optimized sampling: ESG integration the smart way

By Georg Elsaesser, Dr. Martin Kolrep and Michael Rosentritt

In a benchmark-relative context, optimized sampling helps preserve the intended portfolio characteristics after ESG integration, reduces tracking error and limits transaction costs. This systematic approach can be applied just as well to equities as it can to fixed income portfolios.

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Investors operating in a strategic asset allocation (SAA) framework often prefer to stick to their traditional capitalization-weighted (non-ESG) indices.

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Optimized sampling permits just as much active risk (tracking error) as needed for implementation of a desired ESG profile.

Originally, sampling of equity or fixed income benchmarks – instead of full physical replication – was intended to reduce transaction costs and implement portfolios more efficiently while taking account of limited liquidity or availability of certain benchmark securities (especially in fixed income). These benefits are as relevant now as they have ever been. However, with the growing focus on ESG, new challenges have emerged – some of which can also be tackled using optimized sampling.

Many new ESG benchmarks offer only limited history and visibility, especially for bespoke requirements, so that investors operating in a strategic asset allocation (SAA) framework often prefer to stick to their traditional capitalization-weighted (non-ESG) indices. Hence, an essential requirement for ESG integration into passive portfolios with traditional benchmarks is the realization of the lowest possible tracking error, i.e., deviations from the key benchmark characteristics.

Integrating ESG requirements into a portfolio is not simply done by excluding certain lines and reweighting the remaining holdings back to 100%. Instead, optimized sampling is a method by which a portfolio is aligned as best as possible to a given benchmark, reweighting all holdings to achieve a minimal tracking error and matching the resulting portfolio to the benchmark as closely as possible, for example in terms of factor exposures.

In addition, a sampling strategy could even integrate controls on carbon emissions of the underlying, striving for a certain level of reduction compared to the benchmark. It could also target a certain level of what each holding is contributing to the global temperature rise (temperature alignment), something that is not achievable with a simple reweighting method.

The fundamental issue, however, is to avoid unintended portfolio tilts resulting from ESG considerations. For example, compared to traditional fixed income portfolios, an ESG overlay would typically gravitate the portfolio towards better ratings, lower credit beta and lower spreads, eventually reducing the return potential. To avoid these lower returns, it is common to add lower quality or even high yield exposures to compensate for the lower spread impact of ESG. A factor-based sampling approach, however, can help re-establish the intended portfolio characteristics without increasing credit risk. In the same manner, equity portfolio factor exposures can be aligned with the initial benchmark during the optimization process.

Technically, the portfolio construction is a tracking error minimization of a portfolio relative to its benchmark subject to constraints. These constraints can include specific ESG targets such as carbon reduction or temperature alignment. They can reflect exclusions and will take account of transaction costs, and they may also include overall portfolio characteristics such as beta, volatility, yield or duration. The subsequent optimization will seek to realize the lowest active risk subject to these constraints.

While the idea of optimized sampling helps investors remain as close to their traditional benchmarks as technically possible, this does not necessarily have to remain the last step. Since a certain degree of tracking error must simply be accepted when implementing ESG, this can also be the first step to active portfolio construction using return-seeking elements such as a multi-factor overlay, both in equity or fixed-income portfolios.

Customizing ESG implementation in passive and active portfolios

Optimized sampling permits just as much active risk (tracking error) as needed for implementation of a desired ESG profile. Investors need not commit to a stable set of ESG criteria: The optimization engine can flexibly implement the modification of ESG requirements over time as investor preferences and regulations evolve.

Investors are also able to maintain their existing portfolio allocations – the optimization approach can be applied to existing portfolios and will implement desired ESG characteristics with the smallest possible deviations from the original portfolio composition. As a quantitative investment team, we use a variety of data vendors for different ESG data, making use of our extensive experience in processing large data volumes and translating the output into systematic investment portfolios.

Our process in detail, as illustrated by a step-by-step equity example:

Step 1: Definition of the investment universe taking account of existing portfolios

Our starting point is a traditional (non-ESG) equity universe, with certain minimum requirements for average daily trading volumes and transaction cost limits.

Step 2: Definition of ESG requirements

Various ESG requirements are possible, examples include:

- ESG Exposure Control, i.e., ensuring the portfolio does not score worse than the benchmark on certain ESG categories
- Adverse ESG Momentum, i.e., excluding stocks with sharp downgrades in ESG ratings
- Exclusions of controversial industries (such as tobacco, controversial weapons and nuclear power), countries and themes
- Desired carbon reduction targets (Scope 1, 2 or 3 emissions)
- Carbon transition risk penalties
- Temperature alignment goals
- Additional individual preferences

Our optimization successfully limits carbon exposure to the desired 30% reduction target without distorting the portfolio's overall return and risk profile.

Step 3: Adding risk-management constraints
By adding risk-management constraints, we ensure the desired portfolio characteristics in terms of beta, maximum active sector, industry and country weights. In addition, there are certain requirements for standard parameters like size, growth and liquidity. Our proprietary risk model also includes additional bespoke factors, such as: Value, Momentum and Quality.

Step 4: Constructing the optimal portfolio
We minimize the tracking error to the reference portfolio or benchmark, subject to ESG and other constraints.

Step 5: Optionally adding return-seeking elements
Examples include an explicit multi-factor overlay in a tracking error and risk-controlled setup to achieve an additional active return.

Step 6: Efficient execution
Our global trading desk with access to alternative trading venues and liquidity pools executes proprietary algorithms to keep information leakage and market impact low.

Implementation examples

Carbon reduction for an active UK equity portfolio
We constructed a UK equity portfolio with a beta of 1 and the aim to implement a 30% carbon reduction target (Scope 1+2 emissions) versus its benchmark. Our optimization successfully limits carbon exposure to the desired 30% reduction target without distorting the portfolio's overall return and risk profile. Implementing the target required a tracking error of only 0.5% versus the FTSE All Share ex Investment Trusts benchmark, while the active share against the benchmark was just 6.4% (as of November 30, 2021).

A global portfolio with flexible ESG considerations
We also constructed a global portfolio aiming to track the MSCI World ex EMU benchmark as closely as possible, with flexible ESG considerations that can be adjusted on demand. Currently, companies involved in controversial and nuclear weapons, civilian firearms, tobacco, thermal coal and oil sands are excluded, while a best-in-class overlay and the Invesco Quantitative Strategies (IQS) team's ESG exposure control are applied. The IQS optimization engine is capable of implementing these characteristics with a tracking error of just 0.31% (as of November 30, 2021).

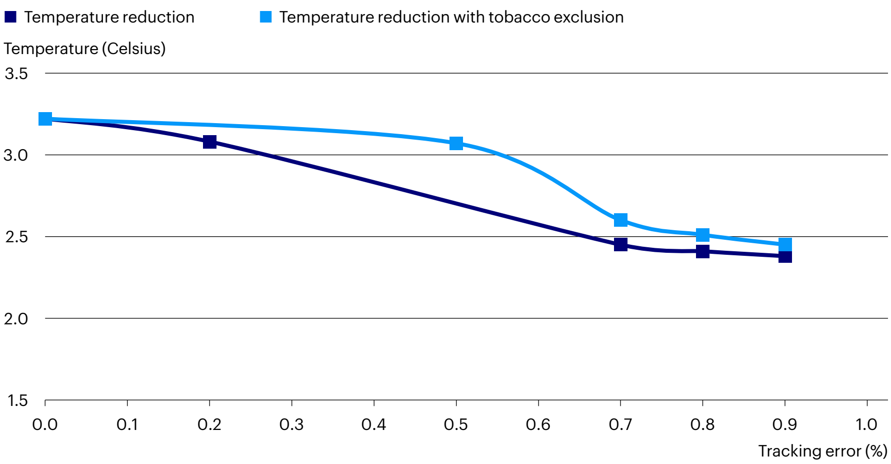
Regional portfolios with carbon reduction
We implemented regional portfolios tracking the MSCI Europe, MSCI North America and MSCI Pacific with a 50% carbon reduction target against the respective index (Scope 3 emissions). We restricted companies with thermal coal mining activity and electricity or heat/ steam production from coal and excluded companies involved in antipersonnel mines, cluster munitions, chemical weapons and tobacco, as well as excluding certain tax-haven countries. Overall tracking error was 0.48%, 0.41% and 0.29%, respectively, for the European, North American and Pacific indices (as of November 30, 2021).

Temperature alignment and tobacco exclusion in the UK
Finally, we integrated a temperature alignment path and tobacco exclusion into a UK portfolio. With the IQS optimization approach, we can demonstrate to the investor precisely how much tracking error is required to implement the desired ESG characteristics. In this particular case, the IQS team analyzed the level of active risk needed to minimize the 'temperature' of an existing portfolio (figure 1) with the option of implementing a tobacco exclusion at the same time.

Advantages abound

As can be seen from these examples, optimized sampling strategies offer a variety of advantages in addition to the

Figure 1
Temperature alignment and active risk



Source: Invesco, for illustrative purposes only.

well-known benefits such as more efficient implementation and reduction of transaction costs:

- **Flexibility:** Active ESG may entail different aspects, with positive tilts, significant carbon reduction and temperature alignment required in addition to exclusions. A sophisticated portfolio optimization approach can take account of different aspects and result in a portfolio as close as possible to the original benchmark in terms of tracking error while executing with a focus on transaction costs.

- **Risk budgeting:** Precise information about tracking error levels required for a given set of ESG constraints provides an essential basis for decisions on budgeting active ESG risks and potentially re-thinking ESG requirements with a view to the associated active risk.

- **Moving targets:** ESG requirements are evolving and paths to Paris-aligned investment profiles will inevitably require adjustment over the course of time. Optimized sampling offers investors a flexible tool to adapt ESG constraints as requirements change over time without discarding traditional benchmarks (which will also change over the course of time).

- **History:** Traditional (non-ESG) benchmarks offer the possibility for detailed historical analysis, while newer ESG benchmarks tend to have limited real-life history. Even if similar sets of constraints are applied to new benchmark construction, the resulting indices may still exhibit massive deviations from one another – and from the traditional benchmarks.

- **Active ownership:** Proxy voting and engagement are increasingly important and, while difficult to execute when tracking ESG benchmarks, committed active ownership can be exercised in passive separate accounts by way of an optimized sampling approach run by an active manager. Investors can thus execute active ownership by moving towards a sampling approach that involves an active manager.

- **Customization:** Additional active return-seeking elements, such as a multi-factor overlay, offer investors a path to return/risk profiles above and beyond passive. A particular benefit arises from the distinct and transparent view on the ESG portion of the portfolio and the active return element as well as the interplay between these two parts of portfolio construction.

- **Biases:** A smart way to mitigate quality biases and, hence, lower spread biases in fixed income ESG portfolios, for example, is to enrich systematic portfolio construction with an explicit factor view. While non-factor-managed ESG integration tends to shift portfolio allocations toward the better ratings segment of the market, a factor lens helps to identify attractive ESG bonds within individual factors, such as Value, which can result in higher spread levels. In combination with systematic portfolio construction, the desired portfolio characteristics can be maintained without increasing credit risk and while managing tracking error to remain low.[1]

Conclusion

An optimized sampling approach can be attractive for all investors who wish to implement active ESG in their portfolios, passive or active, with the lowest possible tracking error and without altering their existing target asset allocation while at the same time maintaining the flexibility needed to adjust the portfolios' ESG characteristics as required over time. Active ESG implementation in a strictly risk-controlled framework gives investors the possibility to dynamically react to changes in their ESG preferences and changes in the regulatory environment, or to incorporate carbon reduction and temperature alignment paths and much more – all within their existing target asset allocation. In addition, ESG concerns can be expressed directly and actively via proxy voting and engagement. For fixed income portfolios, mitigation of ESG-induced biases to maintain desired portfolio characteristics even after ESG integration is another important benefit.

Note

1 For details, see: Jay Raol, Nancy Razzouk, Benton Chambers, Marcus Axthelm and Erhard Radatz (2021), The Influence of ESG on Fixed Income Portfolio Manager Behavior, Invesco White Paper.

About the authors

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An innovative approach to performance attribution in fixed income factor portfolios

By Jay Raol, Ph.D., Benton Chambers, Amritpal Sidhu and Bin Yang

For portfolio managers and clients alike, attribution analysis delivers important information. But traditional approaches have their drawbacks, particularly when applied to factor portfolios. We show how traditional attribution analysis can be adapted for different fixed income factor strategies, including one-factor, multi-factor and factor target portfolio strategies – three examples that correspond to the three stages of our factor investment process for fixed income.

> Attribution is as an ex-post assessment tool to ensure that a fund's return is driven by the intended drivers.

> A robust attribution system should be flexible, precise and easy to communicate.

Successful fixed income factor investing requires translating theoretical investment concepts into real-world trading strategies. And the process can be quite complex. Beyond looking at factor exposures and risk, portfolio managers must consider corporate actions, re-investment of cash flows and index rebalancing. And given that the Bloomberg Barclays Investment Grade Index contains more than 4,000 securities, funds seeking to minimize tracking error must hold a representative subset. For these and other reasons, robust performance attribution is a must for portfolio managers – as well as something clients increasingly demand.

Attribution is as an ex-post assessment tool to ensure that a fund's return is driven by the intended drivers rather than unintended bets. If the attribution approach is flexible and built around a faithful implementation of how the funds are constructed and traded, it has great potential to identify shortcomings and improve future portfolio management decisions. Furthermore, accurate and easy-to-interpret attribution is a powerful communication tool. For example, if we say a fund is heavily invested in the value factor, that should be reflected in the attribution results.

Attribution analysis broadly falls into two categories: explicit methods that clearly assign a security to a given sector (such as AA-rated debt), or implicit methods using cross-sectional regressions or other time series approaches to compute the contribution of a given security to returns.[1]

An example of an explicit method is the classic active weight-based attribution model, also called the Brinson model,[2] under which both portfolio and benchmark return are described as the sum of the products of sector weights and sector returns. The difference between portfolio and benchmark return, i.e., the total value added, can then be broken down into the sector allocation effect (excess return due to different sector weights), the bond selection effect (excess return of different weights within the sectors) and the interaction effect (or residual), which results from the interplay between active sector allocation and active bond selection within the sectors.

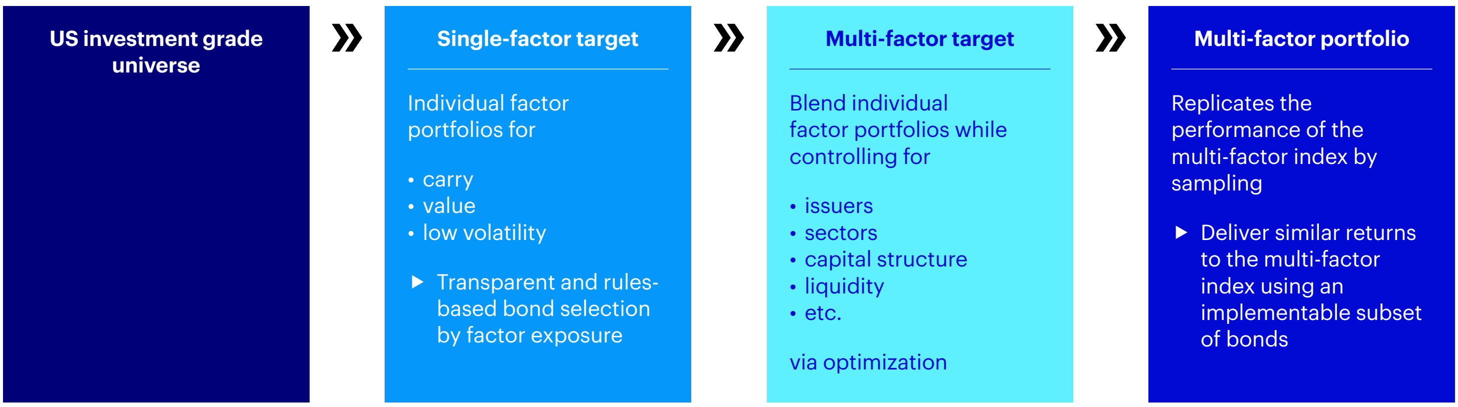
Such a statistical approach can be applied to any portfolio. But in the standard version, changes in reporting or portfolio construction parameters can lead to drastically different results, and statistical approaches all too often produce large residuals.[3]

In our view, and following Brinson (1986), a robust attribution system should be flexible, precise and easy to communicate. Flexible means that multiple portfolio construction choices, such as allocation or, in this case, factor bets, can be easily investigated. Precise means that results have no residual, unlike many statistically driven approaches to factor investing. Finally, easy to communicate implies that results can be explained to clients as well as used internally to drive future fund improvements.

Figure 1 shows the investment process of the Invesco Fixed Income Factor team. We start with a universe of eligible bonds, in this case US investment grade bonds. Next, three factors are defined (carry, value, low volatility). All bonds in the universe are ranked based on factor attractiveness, with the most attractive becoming part of the three factor target portfolios. In the third step, the three target portfolios are combined, with optimization controlling for well-known fixed income risk factors. Finally, the portfolio is implemented using a sampling method.

In three examples, we will show how attribution can be used to monitor all steps of the investment process. First, we show how attribution of a single factor can provide key insights into minimizing unrewarded bets in that factor. Next, we discuss how the attribution of a multi-factor target portfolio can ensure that factor exposures are the key drivers.

Figure 1
The Invesco Fixed Income factor investment approach



Source: Invesco. For illustrative purposes only.

Finally, we analyze the attribution of a portfolio sampled to a multi-factor target portfolio to demonstrate how attribution can monitor unintended biases. Since implicit approaches are difficult to communicate, we adopt an explicit attribution approach.

Example 1:
Minimizing unrewarded bets in a single factor though attribution

We look at a single-factor value target portfolio with the market-value weighted US investment grade bond universe as its benchmark. Our analysis is based on monthly data over a 20-year period from 2002 to 2021.

The Invesco Fixed Income Factor team implements value in a way such that it does not take large allocation bets across metrics such as sector or rating against the index.[4] We found that value still delivers statistically significant alpha when such metrics are controlled. Otherwise, a value portfolio would often take large unnecessary bets. Since they are not needed for outperformance, we classify them as unintended.

Figure 2 shows a box plot for a simulated value factor target portfolio without controls. The value signal is formed by buying the top 20% in value rank in every month, market-value weighted. As a result, the average active weight for some maturity buckets is above 15 or below 15 percentage points. Obviously, the value factor tends to take large asset allocation bets on metrics such as time to maturity. But that is undesirable and not needed for outperformance.

Therefore, we have developed a value factor index which is controlled for maturity (figure 3). Large sector asset allocation bets are almost eliminated in this version so that the active weights of the maturity buckets are now between -2.5 and +2.5 percentage points.

The final value portfolio, which is controlled for sector, maturity and rating, generates most of its outperformance through security selection. Table 1 shows its attribution across the dimensions of sector, maturity and rating. Controlling active weights has led to low asset allocation impacts. The main driver of outperformance was security selection. A -481 basis point impact of rating

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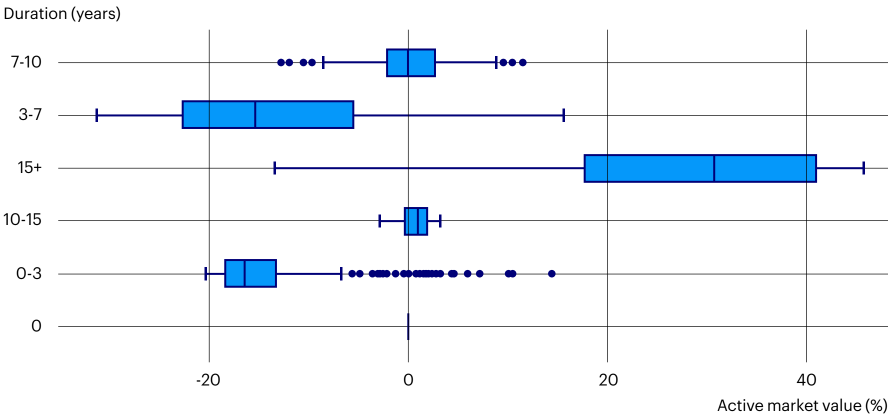
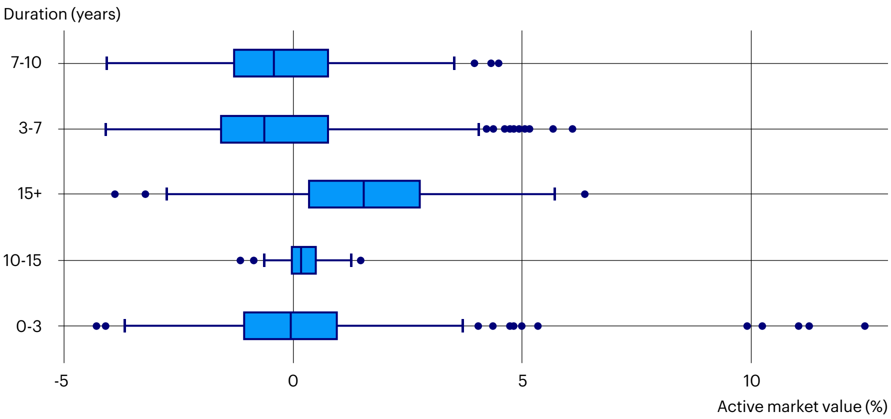
Clean construction and portfolio implementation can result in clean attribution and good results.

Figure 2
Active maturity bucket weights of an uncontrolled value portfolio



Against the Bloomberg Barclays US Investment Grade Index, based on monthly data from January 2002 to December 2021.
Source: Invesco.

Figure 3
Active maturity bucket weights of a value portfolio controlled for maturity



Against the Bloomberg Barclays US Investment Grade Index, based on monthly data from January 2002 to December 2021.
Source: Invesco.

Table 1
Attribution for a value factor portfolio controlled for sector, maturity and rating

Factor	Breakdown	Security selection	Asset allocation
Value	Maturity	3,457	38
Value	Sector	3,502	-7
Value	Rating	3,976	-481

Against the Bloomberg Barclays US Investment Grade Index, based on monthly data from January 2002 to December 2021. Source: Invesco.

allocation may seem large but, over the 20-year period, this represents only a few basis points each month.

These results highlight how clean construction and portfolio implementation can result in clean attribution and good results. The new value signal with controls of various dimensions has almost no asset allocation impact over the 20-year period. With an explicit method such as Brinson attribution, we can easily analyze the construction of research indexes and portfolios. Avoiding asset allocation bets and ensuring that most of the factor returns come from security selection makes for easier integration into multi-factor indexes and portfolios.

Example 2:
Ensuring that factor exposures are the key drivers of a multi-factor target portfolio

Implementing a Brinson-style attribution for a multi-factor portfolio requires scoring every bond in the universe and allocating it to one or more factor sleeves based on its factor ranks (defined as the factor scores relative to the investment universe or index). For example, a bond with a value rank above 70% may be bucketed in the value sleeve.

The bucketing operation itself is straightforward for securities that load heavily on only one factor. But it is more complicated when a security exceeds the threshold for multiple factors. In such a case, weighting is divided up pro rata based on the target factor allocations. For example, if the target factor allocation for an asset class was 50% value, 20% carry and 30% low volatility, and a bond clears both the value and carry thresholds, 5/7 of its market value weight would be assigned to the value sleeve and 2/7 to the carry sleeve. Table 2 gives examples of several securities.[5]

The pro-rata allocation is the only somewhat subjective decision in the process. However, it is in exact alignment with how the internal factor portfolios are constructed – the multi-factor targets are simple pro-rata allocations to single-factor portfolios. Also, the same allocation scheme is used to analyze portfolios both pre and post trade. Whenever a security is evaluated in the trade process, its factor loadings and their contributions to the factor sleeve weights are considered as part of the buy and sell decisions, and portfolios are traded to hit the target allocations. Because of the heavy integration and monitoring of the asset allocation targets in the investment process, we regard the ex-post pro-rata weight assignment as appropriate and unbiased.[6]

In a second step, the individual single-factor target portfolios (such as the value portfolio in example 1) are blended in a pro rata fashion into a multi-factor target portfolio. Optimization is used to control for tracking error by owning bonds that help to keep issuer concentration as well as sector, capital structure exposures, etc. fairly close to the benchmark.

The performance of the multi-factor target portfolio can be cleanly attributed to the various factor sleeves, as in the example in table 3. Over the past 20 years, the index achieved a return of over 200 percentage points. Therefore, as expected, value and carry would have performed well as they usually do in up markets. Low volatility, on the other hand, may have been the largest

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The performance of the multi-factor target portfolio can be cleanly attributed to the various factor sleeves.

Table 2
Distribution of a bond’s weight in the factor allocation framework

Bond	Weight (bp)	Carry (%)	Value (%)	Low Vol (%)	Target allocation			Allocation denominator	Weight			
					Carry	Value	Low Vol		Carry	Value	Low Vol	Beta
A	100	83	90	20	0.1	0.4	0.5	0.5	20	80	0	0
B	150	34	75	89	0.1	0.4	0.5	0.9	0	67	83	0
C	200	35	65	43	0.1	0.4	0.5	0.0	0	0	0	200
D	100	87	65	35	0.1	0.4	0.5	0.1	100	0	0	0

In this example, the threshold for a bond to be included in a factor sleeve is 70%. Bond A loads above 70% for both value and carry. Since the target allocations are 10% to carry and 40% to value, the denominator used in the allocation ratio is 0.1+0.4 = 0.5. The carry allocation for bond A is then computed as the target allocation divided by the sum of all target allocations the bond loads on, or (0.1/0.5)*100bp = 20bp in the carry sleeve. Value is then computed as (0.4/0.5)*100bp = 80 bp. Bonds that load on one factor (e.g., bond D) are 100% allocated to that factor, while bonds that don’t load on any factor (such as C) are counted 100% in the beta sleeve.
Source: Invesco. For illustrative purposes only.

Table 3
Factor-based return attribution of a US investment grade blended factor target portfolio

Factor sleeve	Market value (average)	Portfolio excess return	Portfolio excess return contribution	Index excess return	Active excess return contribution
Full portfolio	100%	7,040	7,040	2,208	4,833
Low volatility	45%	2,599	1,167	2,208	174
Value	36%	12,574	4,567	2,208	3,772
Carry	9%	13,261	1,083	2,208	885
Tracking error control	10%	2,229	223	2,208	2

Cumulative data (basis points) against the Bloomberg Barclays US Investment Grade Index, based on monthly data from January 2002 to December 2021.
Source: Invesco.

Table 4
Deconstructing the attribution impact from the low volatility sleeve into security selection and asset allocation across 10 different breakdowns

Sleeve	Breakdown	Security selection	Asset allocation	Total attribution impact
Low volatility	Rating	477	-299	178
Low volatility	OAS bucket	309	-132	178
Low volatility	Carry bucket	308	-131	178
Low volatility	Size bucket	271	-93	178
Low volatility	Sector	219	-41	178
Low volatility	Age bucket	218	-40	178
Low volatility	Value bucket	104.4	73	178
Low volatility	OAD bucket	81	97	178
Low volatility	Maturity bucket	-58.6	236	178
Low volatility	DTS bucket	-372	550	178

Cumulative data (basis points) against the Bloomberg Barclays US Investment Grade Index, based on monthly data from January 2002 to December 2021.
Source: Invesco.

allocation, but would have contributed comparatively little to the overall performance, again as expected.

These results highlight how the attribution can be used to validate research. When markets are rising, factors like carry and value should perform well and, in our example, they account for 1083 bp and 4567 bp return contribution, i.e., for almost all of the return of the blended factor target portfolio.

We can further break down the performance of each sleeve and quickly isolate any unintended asset allocation choices in any of the individual single-factor indexes by running the Brinson analysis across numerous breakdowns – traditional ones based on sector and maturity, as well as others based on metrics such as bond age, spread duration or any other metric our research may deem relevant.

Table 4 summarizes different attribution breakdowns of the low volatility factor. Broadly, these results are not surprising since it was an up market, and the large asset allocation impacts of metrics like duration or maturity are intrinsic to the construction of the factor. The table shows that, as long as most securities in each universe have the metric or label, we can cleanly apply Brinson attribution, deconstructing the returns into security and asset allocation impacts. This helps us better understand and monitor fund performance.

Example 3: Avoiding unintended biases in a portfolio sampled to a multi-factor target portfolio

Finally, we track portfolio factor performance against the target factor portfolio.[7] Ideally, the sampled portfolio would replicate the target perfectly. But, given that buying the entire target portfolio and perfectly matching its holdings is not viable, Brinson attribution can be used to analyze how the portfolio performs against its factor, sector, rating or maturity targets. This helps ensure that no major unintended bets are taken, which often materialize as large asset allocation impacts.

In table 5, a simulated US investment grade portfolio is run against the factor target portfolio serving as the ‘index’. The asset allocation impacts are driven by over or underweights of the factor sleeves relative to the target, and security selection impacts are driven by the performance differences between the factor sleeves in the simulated portfolio and the corresponding sleeves in the target

Table 5
Attribution for a simulated US investment grade fund against a factor target portfolio

Factor sleeve	Portfolio market value	Index market value	Portfolio excess return	Target excess return	Portfolio excess return contribution	Active excess return contribution	Security selection	Asset allocation
Portfolio total	100%	100%	124	118	124	6	2	4
Value	40%	36%	156	146	62	10	4	6
Low volatility	39%	45%	85	92	33	-8	-3	-5
Carry	12%	9%	176	167	21	6	1	5
Non-factor	9%	10%	84	92	8	-2	-1	-1

Cumulative data (basis points) against the target portfolio, based on monthly data from January 2002 to December 2021.
Source: Invesco.

Table 6
Asset allocation and security selection impacts of the value sleeve across various dimensions

Sleeve	Breakdown	Security selection	Asset allocation	Total impact
Value	Sector	-6	4	-2
Value	Maturity	5	-7	-2
Value	Rating	7	-9	-2
Value	Age	3	-5	-2
Value	Country (of issuer)	-5	3	-2

Not all relevant columns or sub groupings are shown. Cumulative data (basis points) against the target portfolio, based on monthly data from January 2002 to December 2021.
Source: Invesco.

portfolio. In our example, the portfolio is overweight value and underweight low volatility. Monitoring factor exposure and return impacts in detail facilitates rebalancing and helps track the factor targets.

The portfolio outperformed the factor target portfolio by 6 bp, two-thirds of which were generated by security selection and one-third by asset allocation. Value generated a positive security selection effect of 4 bp. The positive security selection of value, however, was negated by the underperformance of low volatility, which generated 85 bp against the target portfolio's 92 bp.

The most useful metric to monitor is asset allocation: A large asset allocation impact of a sector means that the portfolio is taking large over or underweights relative to the target. In table 6, we compare the value factor sleeves.

On average, the asset allocation impact is 3 bp, so that 12 bp of the 15 bp total impact can be attributed to security selection. This is as intended, as our implementation is not designed to take large asset allocation bets.

Conclusion

We have presented an attribution framework that is flexible and easy to apply to fixed income factor portfolios constructed through portfolio blending. The method explicitly allocates security weights into different factor sleeves, and it can allocate a bond's weight to multiple sleeves should the security load high on more than one factor. Our approach can be applied to any portfolio that has only security-level factor scores. It allows for numerous dimensions of portfolio construction to be explored and, unlike many other statistically driven approaches, does not produce residuals. In factor portfolio construction, this approach provides a reliable way to ensure the efficacy of certain risk controls.

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In factor portfolio construction, this approach provides a reliable way to ensure the efficacy of certain risk controls.

Notes
1 See Clarke, de Silva and Thorley (2020).
2 See Brinson et al. (1986).
3 Residuals in statistically driven approaches have been a major issue for several decades, e.g., Clarke et al. (2002).
4 See Raol and Pope (2018).
5 Details of the mathematics required for linking the factor sleeves can be found in Frongello (2005).
6 Once the portfolio is described in a sleeved format, Brinson-style attribution is relatively straightforward. Brinson analysis to investigate portfolio returns across novel or new dimensions becomes routine, e.g., being overweight or underweight high ESG names in the case of ESG bets. We could simply merge ESG scores into the holding data and run the Brinson analysis along this metric. For text labels, the labels themselves serve as buckets; for numeric columns, the data is portioned into a set number of buckets, e.g., 5 or 10.
7 The approach is similar to analyzing factor returns against the index, but there is a slight difference: When analyzing results against an index, each factor sleeve is run as a stand-alone portfolio and then weighted so that asset allocation and security selection impacts are relative to the entire index. When attribution is run against an internal factor target, the entire portfolio is regarded as an entity, resulting in like-for-like factor sleeves in portfolio and target. The resulting security selection and asset allocation impacts are thus relative to each other, and not to the entire investment universe. Total contributions will, of course, be the same.

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Earnings conference call tone and stock returns: evidence across the globe

By Tarun Gupta, Ph.D., and Yifei Shea, Ph.D.

We show how the tone on display during earnings calls can help predict stock returns. Our result is based on evidence from five investment regions: United States, Canada, Europe (ex-United Kingdom), United Kingdom and Australia.

Coverage of earnings call transcripts has improved considerably over time and, as we will show, long and short factor portfolios based on the textual tone signal demonstrate favorable risk/return profiles. Supported by several studies of robustness, our findings suggest that the manager tone signal, despite being correlated with momentum, is an implementable source of value-add in a global equity portfolio.

Corporate managers possess superior information about a company (e.g., Healy and Palepu, 2001), and earnings conference calls are widely followed by investors. The Q&A segment, when managers address probing questions from analysts who closely follow the company, can be especially revealing given its unscripted nature. Moreover, research (e.g., Price et al., 2012) shows that information extracted from the Q&A segment of the call (as opposed to the prepared statement) is less likely to be already contained in the press release.

Most academic research on earnings call tone focuses on the US market, deriving the tone signal from both analysts' questions and managers' answers (e.g., Price et al., 2012 and Druz et al., 2020). Indeed, previous evidence of whether investors react more to analyst tone or manager tone is mixed: Using data from a 16-quarter sample period for US stocks, Brockman et al. (2015) find that analyst tone leads to stronger investor reaction; however, Brockman et al. (2017) note precisely the opposite when they investigate earnings conference call transcripts of companies with securities trading in the Stock Exchange of Hong Kong.

Our earnings call tone signal aims to capture sentiment expressed by corporate managers that is potentially predictive of a company's future stock performance. In a robustness study, we also examine the sentiment expressed by analysts and managers combined. Different from most academic literature focusing on tone derived from earnings calls in one region (mainly the United States), and sometimes over a short time span, we investigate the predictive power of the manager tone signal on stock returns in five regions across the globe over a decade.

In this article, we first look at the coverage and characteristics of English-language conference call transcripts across all regions of interest. Next, we outline our rationale and steps for constructing a manager tone signal which is implementable in a multi-factor portfolio management framework. Then, we discuss the signal's stand-alone performance as well as its relationship with common equity factors. Finally, we conduct several robustness tests, including alternative methods of signal construction.

Characteristics of earnings call transcripts

As a first step, we investigate the historical coverage of English-language earnings call transcripts for companies in five regions: United States (US), Canada (CA), Europe excluding United Kingdom (EXU), United Kingdom (UK) and Australia (AU) – sourced from FactSet Research Systems, Inc. We find that US has the best coverage, while coverage in other regions has improved over time. Additionally, we note that the coverage is generally better for larger than for smaller companies; for instance, on average only 55.7% of companies with securities included in the UK All Cap universe have earnings call transcripts available over the decade from January 1, 2010 to December 31, 2019, whereas transcript coverage is 74.5% for the companies with securities included in the UK Large Cap universe.[1]

To balance the market breadth and transcripts coverage, we chose to investigate manager tone in the following investable universes:

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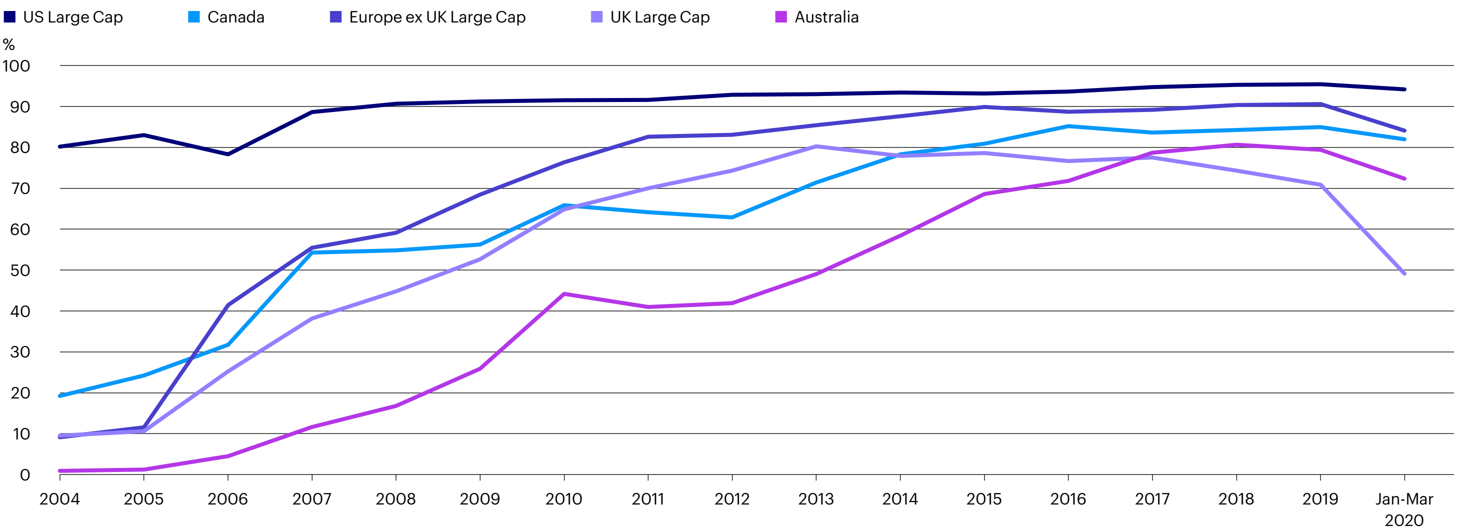
Our earnings call tone signal aims to capture sentiment expressed by corporate managers that is potentially predictive of a company's future stock performance.

Figure 1
Coverage of earnings call transcripts through time by region



Source: FactSet, Invesco calculations.

US Large Cap, CA All Cap, EXU Large Cap, UK Large Cap and AU All Cap.[2] Figure 1 shows the percentage of companies with English transcripts available by year, from January 1, 2004 to March 31, 2020. Note that the coverage-decline in 2020 is artificial since our sample only includes transcripts until end of Q1 2020. Based on figure 1, it seems reasonable to investigate a tone signal extracted from earnings call transcripts starting from the end of 2009, which provides us with over a decade of consistent history across all five sample universes. In practice, coverage based on market cap is also important, which works in our favor given our observation that larger companies tend to have better transcripts coverage.

Interestingly, figure 1 also shows that companies with securities in the EXU Large Cap universe have higher coverage of English-language transcripts than all other universes investigated, except for US Large Cap. This is likely because those are typically large global companies with good analyst coverage. We further examined transcripts coverage of these companies by country and through time: e.g., during 2019, 94% of French companies and 86% of German companies have earnings call transcripts available in English, though the actual number of English earnings call transcripts is higher for German companies than for French due to the more frequent earnings releases in Germany. In addition to frequency, we inspected the timing of earnings transcripts, which corresponds with reporting cycles, as expected. For instance, most earnings call transcripts for Australian companies become available in February and August each year.

To proceed, we parsed the transcripts available in XML format to identify call participants and their associated sentences in the Q&A segment. We used a strict multi-step filtering process to ensure that the identified text indeed came from a specific participant, given that it is possible for one person to be mapped into multiple identifiers (detailed steps for identifying managers and their answers can be found in Fraikin and Gerard, 2018). To gain a more comprehensive overview of all call participants and to facilitate robustness testing, we also identified each analyst and associated question(s). We report statistics to capture characteristics of conference calls for each of the five stock universes in our sample; table 1 illustrates such sample statistics for the UK Large Cap universe, annually from January 1, 2004 to March 31, 2020, as well as summary statistics across the same period. We can see that, on average, 2 to 3 managers are on each call. The most active manager speaks 110 sentences and the least active manager speaks 37 sentences. On average, 162 sentences are extracted from all managers speaking in each call. By comparison, 6 to 7 analysts participate in a conference call on average, with the most active analyst speaking 17 sentences

Table 1
Characteristics of call participants during Q&A, UK Large Cap

	Number of conference calls	Managers per call	Sentences per call: most active manager	Sentences per call: least active manager	Sentences per call: all managers	Sentences analyzed: Managers	Analysts per call	Sentences per call: most active analyst	Sentences per call: least active analyst	Sentences per call: all analysts	Sentences analyzed: analysts
2004	1.80	1.96	94	47	132	238					
2005	1.89	1.94	105	48	142	269	10.00	18	5	110	110
2006	1.65	2.15	93	41	135	223	4.00	9	4	27	27
2007	1.93	2.12	97	42	138	266	5.50	14	4	51	67
2008	2.23	2.09	104	46	147	329	6.20	16	4	58	64
2009	2.42	2.36	110	42	161	390	6.60	16	6	61	69
2010	2.23	2.80	113	34	173	384	7.30	17	5	69	154
2011	2.28	2.76	114	35	173	393	7.43	17	5	71	159
2012	2.27	2.73	118	33	175	398	7.37	17	5	73	168
2013	2.22	2.74	124	36	182	405	7.41	18	5	76	169
2014	2.23	2.60	120	36	176	392	7.21	18	5	75	166
2015	2.23	2.59	115	35	171	381	6.66	17	5	70	156
2016	2.16	2.52	112	37	167	361	6.78	17	5	70	152
2017	2.18	2.47	101	34	149	324	6.39	17	5	66	145
2018	2.15	2.43	100	37	149	321	6.21	17	5	64	138
2019	2.02	2.48	102	35	150	303	6.22	16	5	64	130
2020*	1.02	2.57	106	32	158	161	5.72	17	5	61	62
Total	2.17**	2.52	110	37	162	351**	6.81	17	5	69	149**

*as of Q1 2020; ** only includes data from January 1, 2004 to December 31, 2019.
Source: Invesco. Before August 2009 few analysts were tagged in the transcripts.

and the least active analyst 5 sentences. The questions from all analysts total an average of 69 sentences per call. Since there are around 2 conference calls per UK company per year, this gives us a total of 351 sentences from managers' answers and 149 sentences from analysts' questions on average each year from 2004 to 2019. We also observed that, across regions, analysts were tagged only very occasionally before August 2009.

Capturing manager tone from earnings call transcripts

In order to capture manager tone from the Q&A section of the transcripts, we use a modified version of the Loughran and McDonald (LM) financial dictionary,[3] coupled with simple rules. Figure 2 shows two word clouds for positive and negative sentiment words from the LM dictionary based on manager answers extracted from sample 2019 earnings call transcripts in the UK Large Cap universe. Modifications were made to better reflect the context of our study: e.g., we do not consider the word 'good' positive if it appears in phrases such as 'good morning' or 'good afternoon', and the words 'question' and 'questions' most likely do not have negative meaning. We also implement rules to address negation words detected in the sentences.

Our first tone signal is the sentiment expressed by all managers during Q&A. Each sentence is counted as positive, negative or neutral when checked against our sentiment dictionary and rules. The total score is calculated as the difference between the number of positive and negative sentences, scaled by the total number of sentences spoken by the managers. To construct the sentiment signal, we aggregate information conveyed from earnings calls of a given firm over previous 12 months, instead of focusing on the most recent earnings call. We also assume a conservative five-day lag between earnings call and transcript availability date. This setup not only results in implementable trading signals with moderate turnover, but also allows more sensible cross-sectional comparison of manager sentiment for firms with different call timings and/or call frequencies.

A sentiment signal constructed as such, however, is known to suffer from several drawbacks. To begin, Demers and Vega (2008) argue that it is the unanticipated component of sentiment that drives abnormal returns. Accordingly, we also introduce a second tone signal – change in sentiment – which is a natural and simple proxy for sentiment surprise. Taking into account the change in sentiment also greatly mitigates the issue that cross-sectional comparisons of sentiment levels may be affected by the choice of words in an industry,[4] as highlighted in previous literature such as Feldman et al. (2010) and Loughran and McDonald (2016). Last but not least, the sentiment signal may lose efficacy over time if more managers are trained to speak optimistically (see, for instance, Cao et al., 2020). This concern is alleviated to some extent by looking at change in sentiment, since any inflation in sentiment change driven by adjustments of linguistic style should only be transitory.

Consistent with our rationale for the sentiment signal, we construct year-over-year (y-o-y) change in sentiment, calculated as the difference between aggregate sentiment over the past year and aggregate sentiment over the year prior. In addition to reducing signal turnover, our change in sentiment signal is robust to potential seasonality associated with earnings call sentiment, as compared to alternative approaches such as taking the difference in manager sentiment between two consecutive calls.

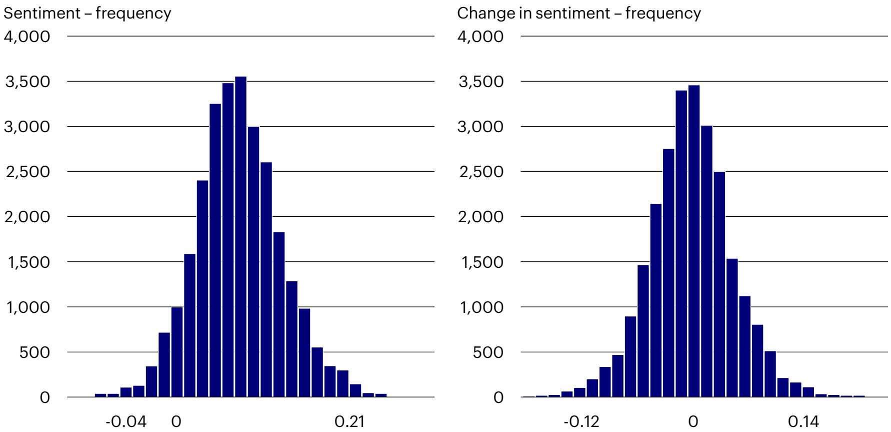
Based on our examination of transcript coverage (see previous section), we compute monthly sentiment and change in sentiment scores for all five regions from December 31, 2009 to March 31, 2020.[5] Figure 3 shows the histograms of calculated sentiment and y-o-y change in sentiment scores for all stocks in the UK Large Cap universe from December 31, 2009 to March 31, 2020. As expected, the average

Our first tone signal is the sentiment expressed by all managers during Q&A.
We also introduce a second tone signal – change in sentiment – which is a natural and simple proxy for sentiment surprise.

Figure 2
Word clouds of positive and negative sentiment words

For illustrative purposes only. Based on frequency of word hits in manager answers extracted from UK Large Cap earnings call transcripts in 2019. The word 'good' is excluded from the positive sentiment word cloud due to its special treatment (e.g., 'good' in 'good morning' does not have positive meaning).
Source: Invesco, Loughran McDonald dictionary.

Figure 3
Histogram of sentiment and change in sentiment
UK Large Cap universe, December 31, 2009 to March 31, 2020



The sentiment signal has a 1st percentile of -0.04, a median of 0.07 and a 99th percentile of 0.21; the change in sentiment signal has a 1st percentile of -0.12, a median of 0 and a 99th percentile of 0.14.
Source: Invesco.

> A long/short factor portfolio based on tone generated statistically significant returns in liquid large cap universes of US, Europe (ex-UK) and UK.

manager sentiment is positive (0.07), while the average change in sentiment is 0.

We recognize that our y-o-y change in sentiment signal, like the sentiment signal itself, is not a perfect metric on its own. For instance, it is not an exact measurement of 'true' sentiment surprise. Indeed, we attempt to address some of these concerns in the 'robustness study' section of this article. Rather than replacing sentiment with sentiment change, we believe both signals are reasonable proxies of manager tone, and each adds value on top of the other. Therefore, we studied the performance efficacy of both the sentiment and change in sentiment signals before building a parsimonious manager tone signal as a simple 50/50 combination of the two. In the next section, we investigate the performance of our manager tone signal as well as its relationship with traditional equity factors.

Evaluating the manager tone signal

To construct the manager tone signal each month for every stock, we first convert sentiment and change in sentiment scores into percentiles within the respective universe and then take the average. Next, we transform the manager tone signal into dollar-neutral portfolio weights (100% long and 100% short). The portfolios are also constructed to ensure no active bets on market or sector within each region,[6] resembling how our factor portfolios are managed in practice.

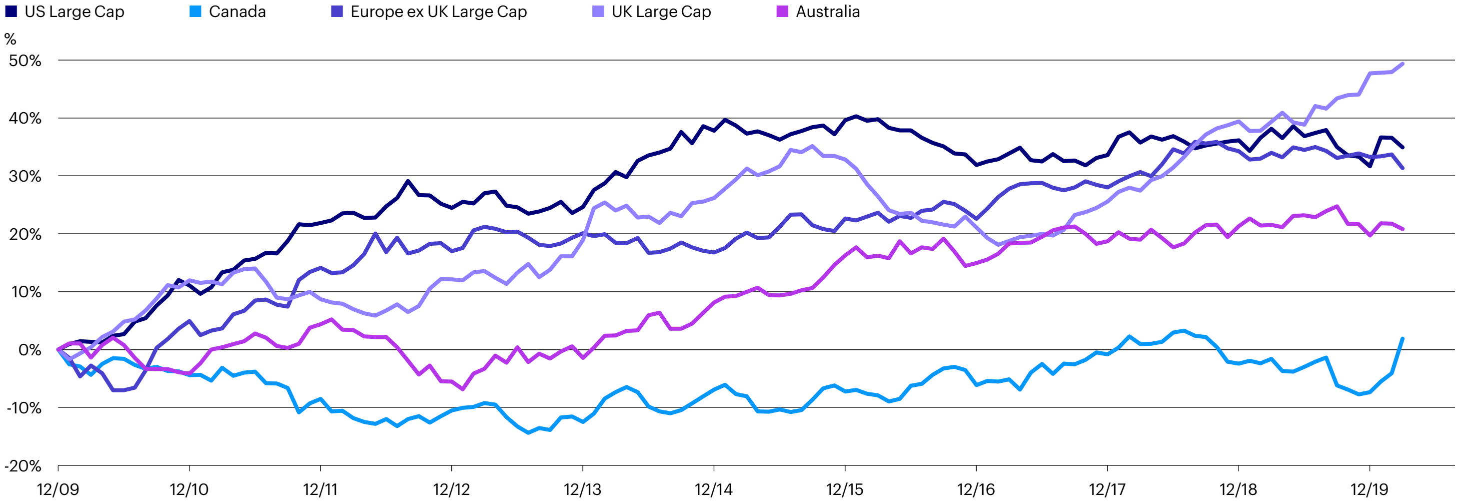
Table 2 presents the performance of such portfolios in all five sample universes based on the textual tone signal, rebalanced monthly from December 31, 2009 to March 31, 2020. Information Ratio (IR), defined as the ratio of annualized return and annualized standard deviation of a portfolio, measures the risk and reward trade-off of the associated strategy. In all our sample universes, portfolios based on the manager tone signal demonstrate positive IRs; IR in UK Large Cap (close to 1) is the highest during this period and the lowest IR (close to 0) is in CA. In addition, t-statistics[7] and corresponding p-values of the strategy returns indicate that the average monthly portfolio returns are significantly different from 0 in US Large Cap, EXU Large Cap and UK Large Cap, at a 0.05 level of significance. In unreported results, we also find that, while the efficacy of manager tone signal comes mainly from the short side in the US Large Cap universe, it was the long side of the signal that drives performance in EXU Large Cap and UK Large Cap.

Table 2
Performance and coverage of manager tone signal

Stock universe	Performance					Coverage	
	Annualized return	Annualized standard deviation	Information Ratio	t-statistic	p-value	By number of stocks	By market cap
US Large Cap	1.5%	2.1%	0.73	2.34	0.02	90.6%	90.5%
Canada	0.3%	5.3%	0.06	0.18	0.86	70.8%	81.5%
Europe ex UK Large Cap	2.3%	3.4%	0.68	2.19	0.03	78.2%	85.7%
UK Large Cap	3.9%	3.9%	0.99	3.20	0.00	64.4%	87.7%
Australia	2.5%	5.7%	0.43	1.39	0.17	48.7%	78.3%

Manager tone signal is defined as 50/50 combination of sentiment and change in sentiment. The signal is transformed into a market and sector-neutral portfolio within each universe; in the US Large Cap universe, the portfolio is additionally industry-neutral. The portfolios are rebalanced monthly from December 31, 2009 to March 31, 2020. **Past performance is not a guide to future returns.**
Source: Invesco.

Figure 4
Cumulative returns of Long/Short factor portfolios based on manager tone signal



Manager tone signal is defined as 50/50 combination of sentiment and change in sentiment. The signal is transformed into a market and sector-neutral portfolio within each universe; in the US Large Cap universe, the portfolio is additionally industry-neutral. The portfolios are rebalanced monthly from December 31, 2009 to March 31, 2020. Monthly strategy returns are rescaled ex-post so that all portfolios have annual risk of 5% from December 31, 2009 to April 30, 2020 (last portfolio formation on March 31, 2020). **Past performance is not a guide to future returns.**
Source: Inveco.

Table 2 also shows manager tone signal coverage as measured by either number of stocks or market capitalization, averaged from December 31, 2009 to March 31, 2020. As expected, transcript coverage based on market cap is generally higher than coverage based on the number of stocks.

Next, we look at the performance of the manager tone signal over time, presented in figure 4. Since our long/short portfolios based on the textual tone signal manifest different ex-post risk levels in each region (see Annualized standard deviation in table 2), we rescale the monthly returns such that all strategies have the same ex-post volatility of 5% per annum. Therefore, in figure 4, the strategies showing higher cumulative returns are also those with higher IRs.

Given the relatively low transcript coverage in the initial years of our sample period, especially for the AU universe (figure 1), performance during these years should also be taken with a grain of salt (except for US Large Cap, where there was already decent coverage). Figure 4 suggests that, excluding the first few years in our testing period, the performance of the manager tone signal is reasonably consistent across all regions, except for CA.[8] In more recent years, signal performance in UK Large Cap is particularly strong, in contrast with the lackluster performance in US Large Cap since 2015.

In practice, we are interested not only in the performance of the tone signal as a stand-alone factor, but also its value-added above traditional equity factors. Table 3 shows Pearson correlations between monthly returns from factor portfolios based on the manager tone signal and those from common factor portfolios, such as quality, momentum and value (QMV)[9] over the period from December 31, 2009 to April 30, 2020. Note that we separate the momentum factor into price momentum and earnings momentum[10] to potentially gain additional insights.

As expected, manager tone across regions exhibits moderately high correlations with both price and earnings momentum, while

Table 3
Return correlations between manager tone and quality, momentum and value (QMV) factor portfolios

	Price momentum	Earnings momentum	Quality	Value
US Large Cap	0.25	0.22	0.07	-0.12
Canada	0.23	0.20	0.00	-0.23
Europe ex UK Large Cap	0.34	0.34	0.10	-0.13
UK Large Cap	0.14	0.15	-0.04	0.00
Australia	0.16	0.21	0.22	0.15

Pearson correlations between monthly returns from portfolios based on manager tone signal and QMV factor portfolios for the period from December 31, 2009 to April 30, 2020 in each stock universe (last portfolio formation on March 31, 2020). Momentum signals are separated into price momentum and earnings momentum to form separate factor portfolios.
Source: Invesco.

> Manager tone exhibits moderately high correlations with both price and earnings momentum, while the correlations with quality and value are low to negative.

the correlations with quality and value are low to negative. Interestingly, the only exception is Australia, where manager tone has a moderately high correlation with quality as well as a positive correlation with value. Additionally, it is the only universe in which manager tone appears to have a slightly higher return correlation with earnings momentum than with price momentum.

In general, our analysis shows it is reasonable to consider manager tone a momentum type of factor, which is consistent with our rationale for the signal. In unreported results, we show that the textual tone signal provides added value above and beyond traditional momentum factors for a multi-factor portfolio, driven by both its stand-alone performance and diversification benefits.

Finally, strategies based on manager tone also demonstrate lower portfolio turnover than traditional momentum factor portfolios, and only moderately higher turnover compared to value and quality factor portfolios. This is as expected since our construction of the manager tone signal was intended to generate implementable trading strategies.

Robustness studies

We performed a number of robustness tests for the manager tone signal. First and foremost, we used the same construction of tone signal across all five sample universes, and observed relatively consistent results – which is implicitly a robustness test on its own. We also used an alternative proprietary sentiment dictionary and associated rules and found similar results across regions.

Next, we conducted two robustness studies on signal construction. In finance literature, most dictionary-based sentiment approaches use words as units (e.g., Loughran and McDonald, 2011; Price et al., 2012; Druz et al., 2020). We adopted a different approach by using sentences as units for computing the sentiment score, which we think is reasonable; it is also consistent with linguistics literature (e.g., Ordenes et al., 2017). To make sure our results are not specific to this choice, we constructed two word-count-based tone signals[11] and observed similar yet overall slightly weaker performance compared to our original construction.

Another signal construction-related robustness test was inspired by academic studies which find that some managers are more optimistic than others (Davis et al., 2015) and, more generally, that managers have different tone styles.[12] A natural question is thus whether it makes sense to calculate change in sentiment for each manager and then aggregate into a signal at company level. The rationale for such a signal construction method, however, appears flawed given that each manager's tone is influenced by the specific questions they address during a call. Additionally, for calculating a sensible sentiment score, a sufficiently large number of total sentences is required in the denominator. Therefore, sentiment information from managers who do not speak many sentences in a call may be lost in such manager-specific sentiment calculation. In the end, we decided to test sentiment and change in sentiment signals defined by aggregating individual manager information[13] only as a robustness study instead of a competing signal construction methodology. As expected, such signals demonstrated slightly poorer coverage compared to our original company-based signals. We also observed similar yet slightly worse performance across regions when we define sentiment and sentiment change by aggregating individual manager information.

> The tone signal is robust to the sentiment dictionary and several alternative signal definitions.

Finally, we examined the predictability of cross-section stock returns based on overall tone from analysts and managers during Q&A, as opposed to manager tone alone. This study is also motivated by the fact that manager tone can be related to questions asked by analysts and their tone. Additionally, analysts who ask questions during earnings calls tend to follow the company closely, and their sentiment is potentially a leading indicator for subsequent forecast revisions and stock performance. Indeed, we find generally similar performance of sentiment and change in sentiment signals derived from only managers or all participants during the Q&A. We also note that, on average, sentiment expressed by managers alone is more positive compared to that expressed by managers and analysts combined – an observation which is unsurprising and robust across all five regions investigated.

Summary and concluding remarks

We mined textual data, more specifically earnings call transcripts, to extract a tone signal which captures manager sentiment that is unlikely already priced into the stock. Our construction of the tone signal yields generally consistent performance across five sample universes over the recent decade. A long/short factor portfolio based on tone generated statistically significant returns in liquid large cap universes of US, Europe (ex-UK) and UK. The manager tone signal is diversifying and adds value atop traditional QMV factors. Furthermore, it comes with a moderately low turnover rate, which leads to implementable trading strategies. We have also shown that the tone signal is robust to the sentiment dictionary and several alternative signal definitions.

A number of off-the-shelf rule-based or machine learning algorithms are available for generating sentiment scores. Some of these are not specific to the financial context. Others, such as FinBert,[14] are trained on financial textual data and sometimes directly based on earnings call transcripts. While we think a machine learning approach may augment the tone signal, a simple dictionary and rule-based sentiment approach offers great transparency and is not fitted to any data – thus truly out-of-sample.

Notes

1 UK All Cap universe is constructed based on FTSE All Shares ex InvTrust and further expanded to capture 99% of free float market cap, and UK Large Cap universe is constructed based on FTSE 100 ex InvTrust and further expanded to capture 98% of free float market cap in UK.
2 The investable universes are constructed to include the largest and most liquid stocks. For the period of January 31, 2004 through March 31, 2020, the monthly average number of stocks is 1,278 in the US Large Cap universe, 317 in CA All Cap, 520 in EXU Large Cap, 315 in UK Large Cap and 305 in AU All Cap.
3 Available online at: https://sraf.nd.edu/textual-analysis/resources/
4 For instance, words such as 'waste', 'casualty', 'catastrophe' do not have negative meaning for certain industries.
5 This means we utilize earnings call information from December 2008 for calculation of the sentiment signal. Similarly, for the y-o-y change in sentiment signal, earnings call information from as early as December 2007 may be incorporated.
6 In the US Large Cap universe, we also ensure the portfolio has no active bets at industry level. We use our own industry/sector definitions, which closely follow GICS classifications, as well as Axioma predicted betas for enforcing ex-ante market neutrality.
7 Defined as average monthly returns divided by its standard error. Therefore, t-statistic is mathematically equivalent to the product of IR and sqrt(N/12), where N is the number of months in our sample, which is 124.
8 The relatively flat performance of the manager tone signal in CA is driven by the 'change in sentiment' component, which yields slightly negative and statistically insignificant monthly returns during the testing period. In one of the robustness studies, we also construct 'change in sentiment' by aggregating individual manager sentiment change, and find that such constructed sentiment change signal has a positive IR of 0.2 for CA stocks, but the mean return is still not significantly different from 0.
9 Quality (Q) consists of factors such as external financing and return on equity. Momentum (M) is a combination of various price momentum and earnings momentum factors. Value (V) includes free-cash-flow yield and gross profit yield, etc.
10 Price momentum includes factors such as specific and risk-adjusted momentum; earnings momentum includes earnings revision, sales revision and earnings surprise, etc.
11 Both versions use the difference in number of positive and negative sentiment words in the numerator; in one version, total number of sentiment words is the denominator, and in the other version, total number of words spoken is the denominator.
12 For instance, Dzieliński et al., (2017) find that managers display distinct styles during earnings calls, e.g., the 'vague talkers' (as opposed to 'straight talkers') often use words indicating uncertainty such as 'probably' and 'maybe'.
13 We use average number of sentences spoken as weights for aggregation of individual manager sentiment and change in sentiment.
14 For instance, see Araci (2019) and Huang et al. (2020).

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