

Introducing GR8

A new approach to factor risk management



APRIL 2026

Table of Contents

Factor models and why we need them	03
Short review of GR8's predecessor	04
The new features of the GR8 risk model	05
General remarks	08
Conclusion and looking ahead	08
APPENDIX A GR8 model vs. empirical risk measures	10
APPENDIX B GR8 model geographic coverage	14

Introduction

The GR8 Global Equity Risk Factor Model is an extension of the long-established Wilshire GR6, maintaining its core principles of stability, transparency, and empirical robustness while introducing several methodological improvements. GR8 is designed to align with the current state of portfolio research and investment workflows, where both passive and active strategies require more granular and interpretable factor signals. The model incorporates updated statistical techniques, refined factor construction, and an expanded factor set to capture a broader and more precise representation of equity risk. In addition, GR8 introduces new definitions for several specific factors, reflecting structural changes in global markets and offering enhanced explanatory power. These developments provide a more detailed decomposition of risk and a more consistent platform for attribution, optimization, and forecasting across diverse investment use cases.

WRITTEN BY

Emilian Belev, CFA, ARPM
Head, Risk Factor Models

Factor models and why we need them

In this section we offer a quick refresher on the importance of risk models to asset management and portfolio construction, some of the classic categories, and where the GR8 model belongs and why this choice was made.

The need for risk factor models arises from the fact that sheer number of available instruments in the investable universe presents a basic problem of estimating portfolio risk in a reliable and intuitive fashion. This task requires a dimensionality reduction which involves distilling common risk drivers across the investable universe, that separates the direction and size of co-movements among investments from their idiosyncratic behavior.

The importance of this practice is threefold:

- accurate risk estimation,
- constructing efficient portfolios,
- and allowing asset managers to keep their implemented strategy to be consistent with their insights, and avoid unintended drifts that can hurt performance.

From an estimation standpoint, there are four major types of risk factor models: **cross-sectional**, **time-series**, **statistical**, and **hybrid** among the previous three types.

With **cross-sectional models** the security characteristics – a combination of financial statement metrics, exhibited market behaviors, and regional and industry characteristics are used as independent variables in econometric estimation to describe the contemporaneous cross-section of security returns. The benefit of these models is that they allow an unparalleled ability to distinguish risk drivers based on a very vast set of security characteristics, even those that are not directly exhibited in the market place, and also to respond in a timely fashion to evolving characteristics – changing growth, leverage, liquidity, etc. – in the mathematics of the estimation of the model.

Those models are particularly suitable for managers who recognize or have adopted strategies that center on distinguishing common behaviors among groups of securities or have stock picking abilities that leverage such analysis.

Time series model on the other hand use observable economic and macro variables – performance of broad indices, interest rates, FX, etc. – as risk drivers and perform econometric estimation to determine the “average” sensitivities of investments to these risk drivers over time.

Even though this type of estimation can be used to distinguish between common behavior among groups of stocks – e.g. high vs. low dividend, emerging vs. developed – they are mainly used by managers employed macro strategies.

Statistical models extract both the risk drivers and the investment exposures to these drivers from the data. While these models allow unparalleled ability to calibrate the extent to which common variance is extracted from the reference investment universe, one of the major drawbacks of this approach is that such models lack interpretability and direct connection to most managers investment strategies. That is why they are most often relegated to “back-up” models used by risk managers.

Both the GR8 model and its predecessor are estimated cross-sectionally due to the apparent advantages of this approach to the broad universe of asset managers.

Short review of GR8’s predecessor

The GR6 model incorporates a set of established “style” factors, including earnings-to-price, book-to-price, the logarithm of market capitalization, volatility, momentum, and beta to the home market, alongside region and sector classifications. These factors are calculated using both monthly and daily data, with factor returns and covariance matrices estimated through two alternative weighting schemes which the client can select at risk estimation time – equal-weighted and exponentially weighted over time.

Factor estimation follows a two-stage cross-sectional regression process. In the first stage, indicator variables for region and industry membership are included together with the other style factors.

The second stage isolates the stock’s beta to its home market, allowing this measure to represent the model’s “country” factor exposure. This separation helps ensure that country effects are captured distinctly from the other structural and style driven characteristics incorporated earlier.

Idiosyncratic risk in the GR6 model is not taken as a simple regression residual. Instead, it is estimated through a Bayesian adjustment that conditions on key security attributes such as country, industry, and size. This approach provides a more stable and informative estimate of security specific risk.

For further technical details, please refer to the full GR6 model documentation available from our client services desk.

The new features of the GR8 risk model

While the new model leverages to the full extent the benefits of its predecessor, it also introduces new aspects to reflect the evolution of the requirements of the investment management industry, and in-house model research. In this section, we make an overview of the new factors and features introduced by the GR8 model.

Growth risk factor, defined by co-movements according to the size of earnings growth exposures of the universe of stocks. The view that a low E/P multiple defines a stock with high growth has gradually been debunked with the advent of large technology firm stocks. While many of them do not necessarily feature observable growth of earnings, or even positive earnings for that matter, they have extraordinarily low E/P ratios. That is due to the promise of outsized future earnings growth. Therefore, CWAN makes the distinction of stock having a low E/P ratio (a pre-existing exposure in the equity model) conditional on earnings growth, which necessitates this new model factor.

Leverage risk factor, defined by co-movements of stock according to the size of their leverage ratio (Assets-to-Equity) exposures. In different environments, asset managers may prefer to invest or disinvest in high leverage firms, perhaps because they expect changes in the interest rate or economic growth environment and, with that, the ability of firms to withstand the burden of higher vs. lower debt. Such capital flows affect supply and demand for such stocks to realize returns commensurate of the investors preference shift.

Quality risk factor, defined by co-movements of stock according to the size of their earnings quality ratio (operating-cash-flow-per share divided by earning-per-share) exposures. In broad analogy to the leverage risk factor, in different environments, asset managers may prefer to invest or disinvest in stocks bringing in more cash flows, or able to generate more cash flows, either because the investors would prefer more funding liquidity themselves, or the managers predicts that the economy and market may shift to tighter external liquidity, therefore, firms with better operating cash flows will withstand the pressure and fair better.

Drawdown risk factor, defined by co-movements of stock according to the size of their drawdown metric. Drawdown is defined as the maximal relative drop of the value of stock within a given period – e.g. a year. Note that drawdown is distinct from an investment loss and is at least equal to it, as it may reflect forgone profit of any accumulated gains after the beginning of the period. Therefore, the concept of a drawdown simultaneously carries both behavioral finance and statistical meaning. The first one relates to an investor perceived loss which may have higher disutility to them rather the actual loss, and the latter relates to a size of a loss that maps in the far tail of the periodic probability distribution of the stock, and with that an objective measure of higher distributional moments. Shifting preferences of investors and managers for such stocks would generate market returns for them accordingly.

Market liquidity risk factor, defined by co-movements of stock according to the size of their average daily volume over the most recent month relative to the total number of shares outstanding. The relative size of the pool of shares that change hand in the market is an indication of how many investors are typically engaged in trading that stock. The implication of smaller relative volumes is that when opinions on either the long or short side prevail over the alternative, the volume pressure may produce what is known as market impact in the form of extra positive or negative return.

Crowding risk factor, defined by co-movements of stocks according to the size of their crowding metric. Crowding is a derived measure of recent net moves in or out of a stock relative to shares outstanding that has also generated and aligned directional moves in the price of the stock over that period. It can be reasonably expected that investors may choose to avoid buying or to sell short stocks that recently have been “overbought”, or buy and margin stocks that have been “oversold”. Or investors may choose to propagate the trend in what can appear as short-term momentum. Such preferences may cause fund flows that generate associated returns in the stock. Instead of tracking trade flow of various investors, data that is generally limited to US investment portfolios, we took a more effective approach to measure crowding exposure. We observe the product of relative volume for a stock in a period and its return over that period. At one end of the spectrum, a strong increase in volume combined with a strong increase in price implies that the long trade has become crowded, whereby demand overwhelms supply in a short period of time. At the other end of the spectrum, a strong increase in volume combined with a strong decrease in price implies the short trade became crowded whereby supply overwhelms demand in a short period of time.

Reversal risk factor, defined by co-movements of stock according to the size of the time series autocorrelation of their weekly returns. Reversals center on the idea that stochastic processes underlying stock returns are not always or most often an “infinitely increasing diffusion” pattern but exhibit some higher conditional probability for up moves after down moves, and vice versa. The often-stated reason for such behavior is that there is a strong mean trend in the value of the stock and the fluctuations on the downside and upside will be respectively propped or curbed by fundamental value anchoring, arbitrage, corporate actions, and other factors. Some stocks may exhibit stronger reversal than others, and investor preferences may shift stock prices accordingly, potentially supporting the short-term counter-cyclical behavior they have encountered.

Profitability risk factor. The intuition of this factor is that investors may prefer firms with which perhaps already have maturity in the marketplace, have cornered a significant part of market share, and have been able to build out to a higher level of profits (earnings) compared to their total assets. Systemic effects that may contribute to common behavior of companies with this characteristic may have to do with dimensions of investor risk aversion to companies that have not proven themselves to be profitable business ventures, independent of growth potential, or how the rest of the market values those profits in present value terms. We have chosen to use ROA instead of ROE exposure metric of profitability to avoid the impact of leverage embedded in the ROE measure.

Payout risk factor. The intuition behind this factor is that investors may prefer firms that reinvest a larger portion of their earnings (lower payout) in their operations, i.e. rely on organic vs. external growth. That may either signal investor concerns of the relative scarcity of the availability of future external growth capital in certain times, or preferences to companies that potentially have a clear agenda and roadmap for future growth. Our choice not to use dividend yield instead of payout was that it points to a mixture of “value” and “reinvestment” stock characteristics. The standard metric for Payout exposure we have adopted is ratio of dividend per share to earnings per share.

Value risk factor. The B/P and E/P factors were combined into a single Value factor to derive a composite picture of a stock’s “value” characteristics and avoid the ambiguity of using two separate metrics.

In addition to the new factors introduced, we have made the following changes were made to the estimation of the model.

Single-Stage Cross Sectional Regression. All of the cross-sectional parameters were included into a single rather than the two-stage regression described previously. This regression restructuring gives the market “beta” factor higher priority in explaining security returns, resulting in more intuitive results in line with manager’s views on the relative size of contributions of various risk drivers. In this respect, it should be noted that many competitive risk models have a sizable single statistical intercept which is camouflaged as a “global market factor”. This leads to the paradoxical situation where such models have both a “market factor” and a “market sensitivity factor” (i.e. a beta market factor). The simple explanation is that such models are missing factors, and they bundle as a statistically unidentified average additional return in the intercept. The GR8 model is devoid of this problem by design. That is because, even though the model regressions do exhibit statistically significant intercepts, they are strictly attributed to regional market behavior among the eight regions of the model and therefore distinct from country level market effects in terms of economic interpretation.

New Scandinavia and Eastern Europe Regions. We have introduced two new regions to the factor definitions – Scandinavia, and Eastern Europe. This provides more precise granularity of assignment for the stocks from the respective countries and captures more precisely region-specific behavior alongside the markets and the economies of these geographies.

General remarks on the design philosophy and application of the model

The well-established APT theory assumes that investors cannot generate higher returns from stocks that are subject to common risk factors without incurring higher risk. In the APT paradigm, both the risk and the expected return premium per factor scale with exposure of the portfolio to that factor. Therefore, a benchmark to a portfolio is exposed to the same risk factors as the portfolio, and when the portfolio betas are appropriately chosen to be identical to those of the benchmark in the long run, the portfolio will have the same risk and expected return as the benchmark over that long

horizon, therefore, leaving no possibility of active return. Note that by providing the risk model, CWANWilshire does not make an assertion to support or oppose the APT assumptions. In fact, many portfolio managers have been known to use these and similar factors to make active bets on stocks or time the market by tilting the factor betas of the portfolios temporarily away from the benchmark. The CWAN GR8 equity model is compatible and equally useful in both the “active” and “passive” manager paradigms by not making a statement on a benchmark-relative factor alphas different than zeros, while focusing on estimating tracking and stand-alone risk from the risk factor covariance matrix. The latter has been made more robust with the addition of these new factors with demonstrable added explanatory power over market movements.

Conclusion and looking ahead

The investment management industry has long relied on risk factor models to navigate the complexity of global equity markets, and the demands placed on those models have only grown. Portfolio strategies have become more sophisticated, market structures have shifted, and the line between passive and active management has blurred. Against that backdrop, the limitations of any static framework become apparent over time. GR8 is our response to those shifts.

The evidence is clear: the GR6 model provided a durable and well-validated foundation, but the evolution of global equity markets—particularly the emergence of high-growth technology firms that defy traditional valuation conventions, the deepening relevance of profitability and payout dynamics, and the need for finer regional granularity—called for a model that could keep pace. GR8 delivers that, while preserving the stability, transparency, and empirical rigor that have defined our approach to risk factor modeling from the start.

The improvements embedded in GR8 are not incremental for their own sake. The introduction of distinct Growth, Profitability, and Payout risk factors reflects structural changes in how companies create and distribute value—changes that earlier frameworks were not designed to capture cleanly. The consolidation of B/P and E/P into a unified Value factor, combined with the shift to a single-stage cross-sectional regression, eliminates a well-known source of model ambiguity and produces results that are more intuitive and more aligned with how portfolio managers think about risk.

The expansion of regional definitions further sharpens the model's ability to attribute return and risk across an increasingly heterogeneous global investment universe. Taken together, these refinements translate into measurably stronger explanatory power—both in-sample and out—as demonstrated by the model's empirical performance across the observed history.

For our clients, the practical implications are meaningful. Whether the investment mandate is benchmark-relative or standalone, active or passive, the GR8 model provides a consistent and interpretable framework for risk decomposition, portfolio construction, and return attribution. It becomes a foundation for better decisions—not by introducing complexity, but by reducing the noise that obscures what is actually driving portfolio behavior.

Looking ahead, we see the continued development of factor modeling capability as central to our broader mission. The GR8 model does not exist in isolation. It is part of a unified, cloud-native platform that integrates risk analytics with portfolio management, performance attribution, compliance, and reporting in a single system. As our clients' portfolios grow more complex—spanning public and private markets, crossing more geographies, and responding to faster-moving market signals—the value of having a robust, continuously maintained risk model embedded directly in that workflow compounds significantly.

Several areas will shape the evolution of our factor modeling work in the years ahead:

- 1** Expanding coverage across asset classes. As alternatives become a core allocation for many institutional investors, the need for factor-based risk frameworks that span private credit, real assets, and other non-traditional exposures will continue to grow. Extending the rigor of GR8's approach beyond public equities is a natural next step.
- 2** Integrating AI-driven model diagnostics. The same generative AI capabilities CWAN is deploying across the investment lifecycle offer meaningful opportunities to enhance how factor models are monitored, validated, and communicated—enabling faster identification of model drift and more accessible interpretation of results for non-specialist users.
- 3** Deepening regional and sector granularity. Global markets continue to diverge in ways that aggregate classifications can obscure. CWAN will continue to evaluate where additional regional or sector distinctions would meaningfully improve the model's explanatory power and practical utility.
- 4** Strengthening the link between risk and decision-making. The ultimate value of a risk model is realized not in the model itself, but in the investment decisions it informs. Our ongoing work will focus on making factor-based risk insights more actionable—more directly connected to portfolio construction, scenario analysis, and real-time monitoring workflows.

The shift toward more sophisticated, interpretable risk factor frameworks is structural in nature—driven by the growing complexity of investment mandates, the increasing scrutiny of risk attribution, and the broader demand for transparency in how institutional capital is managed.

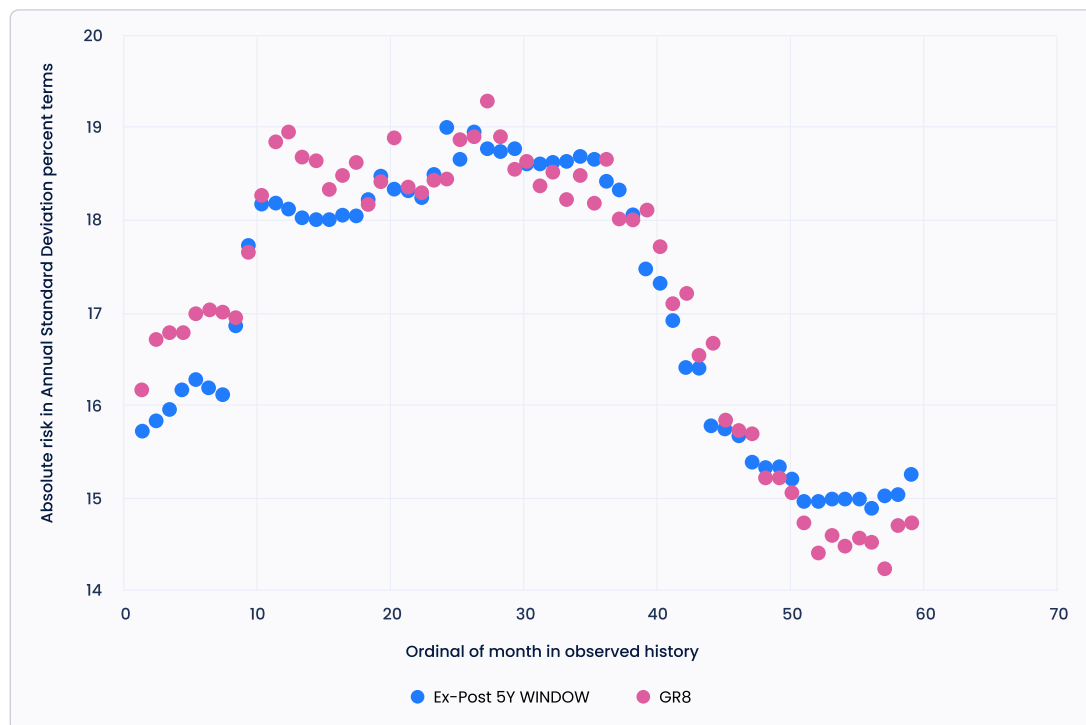
GR8 is CWAN's contribution to meeting that standard today, with a clear-eyed view toward what will be required tomorrow.

GR8 model vs. empirical risk measures

Our tests of the model demonstrate extremely strong in and out of sample performance, which supports robust risk and return factor attribution. The new factors have also notably reduced regression intercepts which shift away regional effects into more granular explanation of risk and return sources.

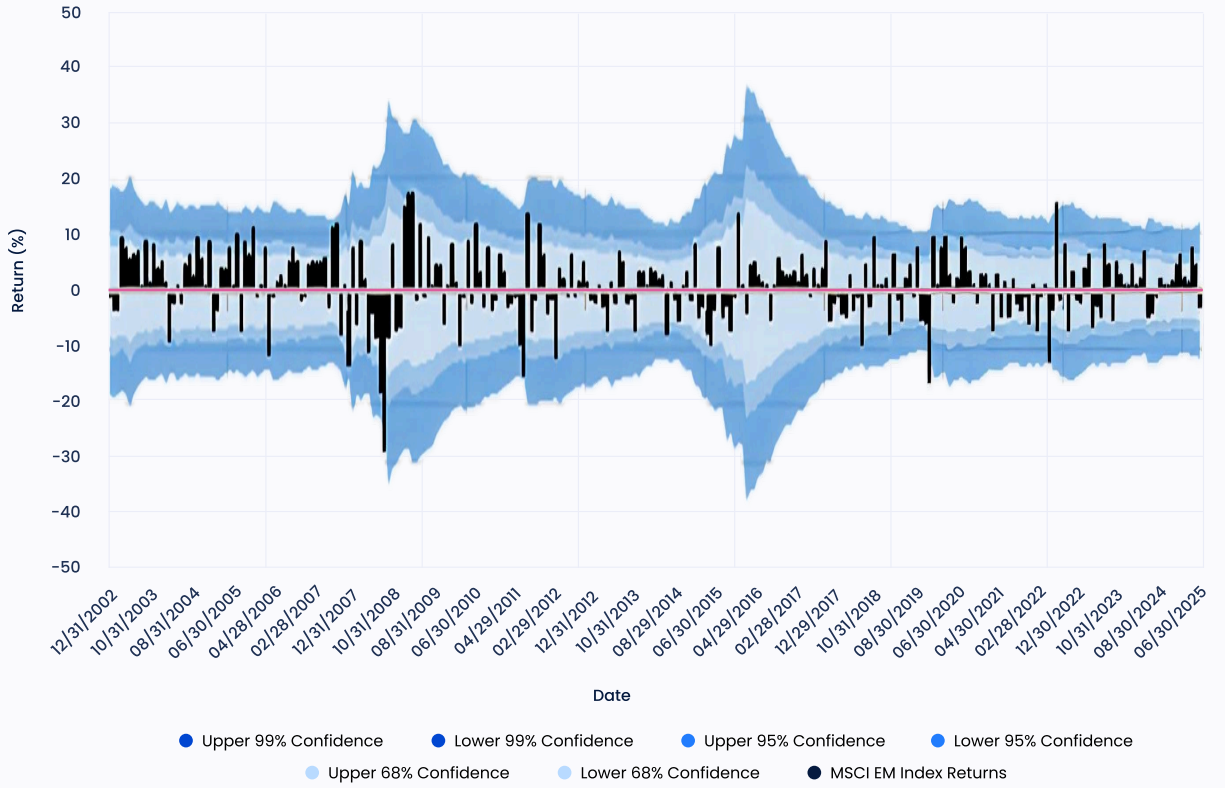
The first graph demonstrates how close the in sample empirical observations are reproduced by the model for the S&P500. That is a measure of how well the asset covariance matrix constructed using the model reproduces the empirical asset return covariance matrix. Such a comparison is important to establish a baseline that there is no statistically significant difference due to the dimensionality reduction (factorization of stock returns) at the core of the risk factor model estimation.

Model risk vs. realized volatility

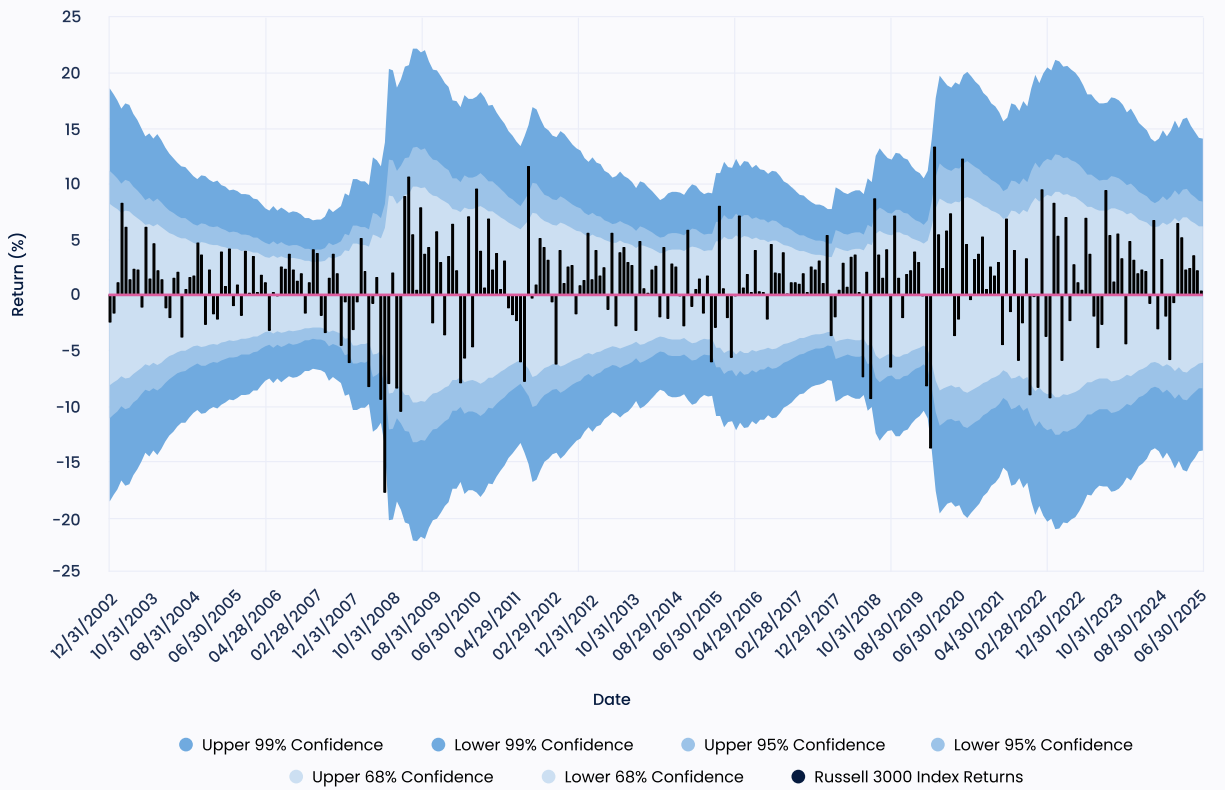


The following tests demonstrate the out-of-sample model performance with respect to several well-known index composites that capture different geographical or capitalization constituencies globally. The test approach follows the traditional framework familiar from banking model risk regulatory guidelines. Out of sample return realization are plotted against a critical confidence level (e.g. lower 99%) and any exceedances measured in proportion to the probability of occurrence suggested by the confidence level. For each pairwise exceedance comparison, the confidence level is calculated from the risk factor model data immediately preceding the corresponding return realization with which it is compared. This avoids look-ahead bias. In simple terms, observing that realizations are almost exclusively within the upper and lower 99% confidence levels indicates that the model that predicts reliably portfolio risk.

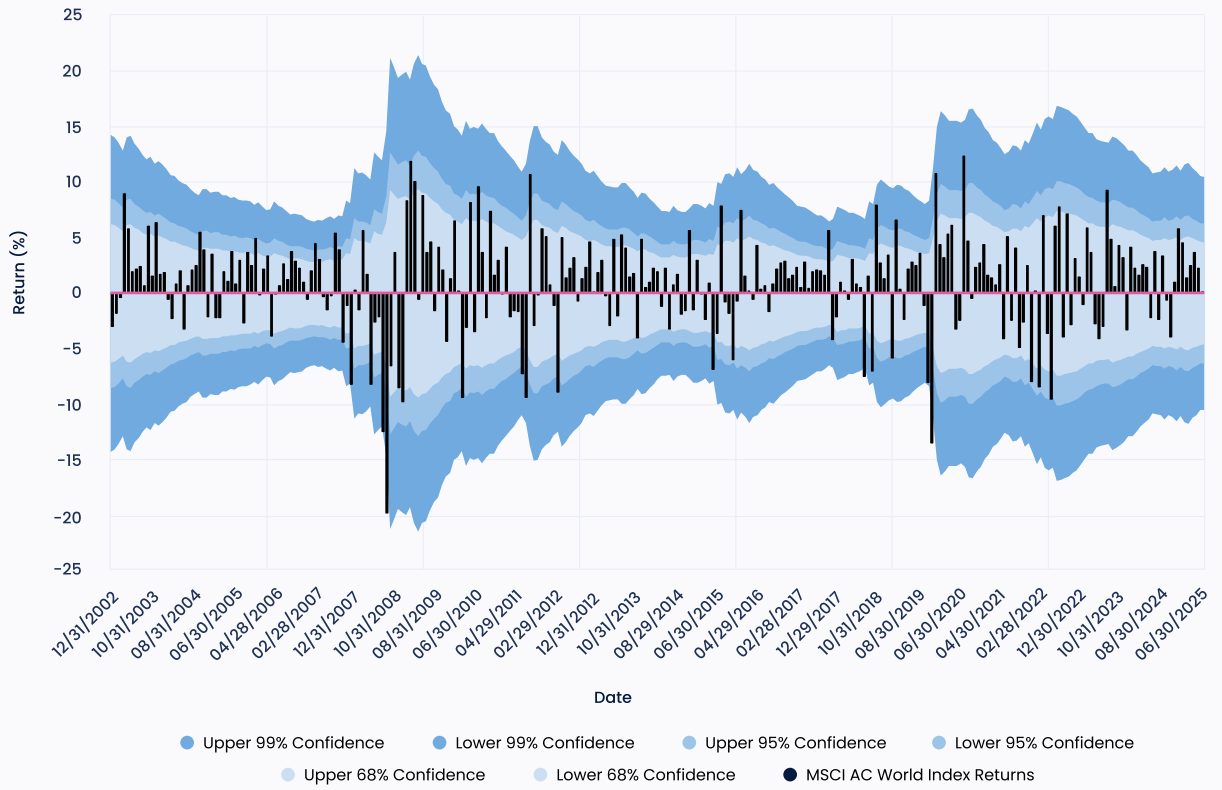
Out-of-sample MSCI EM monthly index returns vs. GR8 exponentially weighted model implied probability thresholds for T-Distribution (5 DoF)



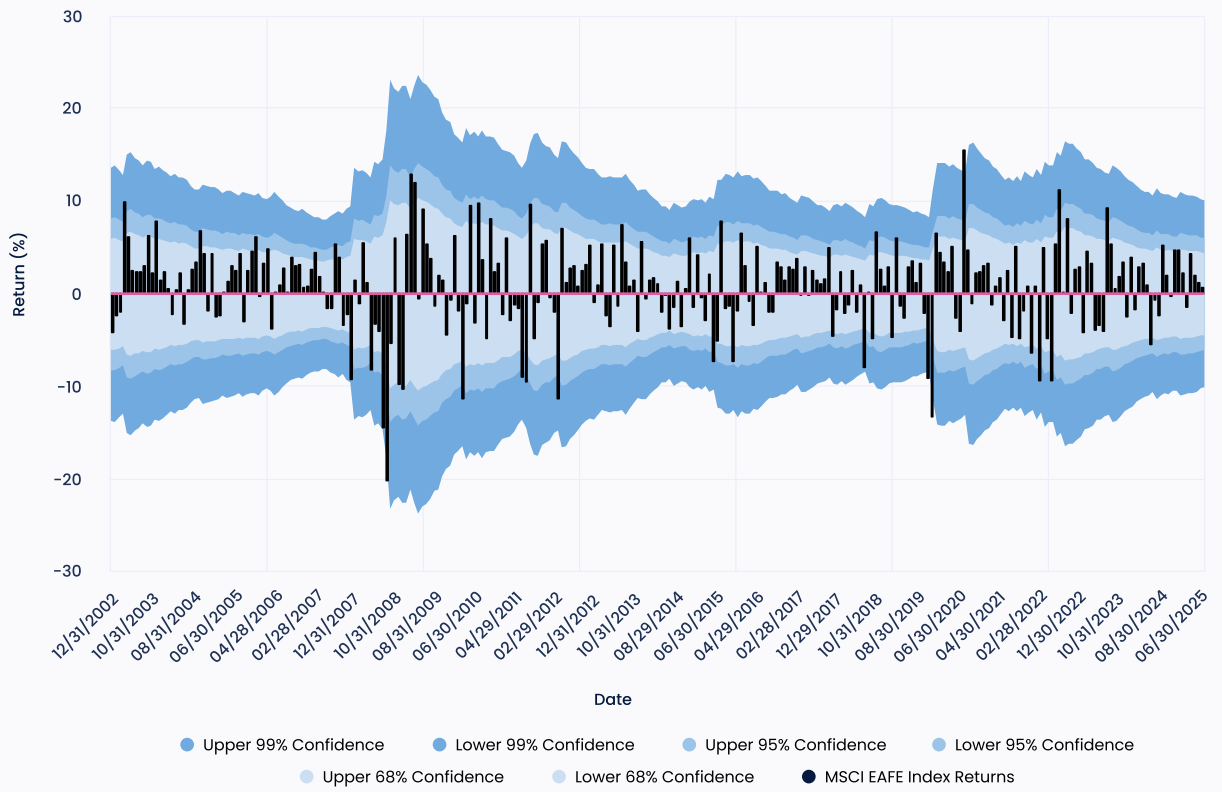
Out-of-sample Russell 3000 monthly index returns vs. GR8 exponentially weighted model implied probability thresholds for T-Distribution (5 DoF)



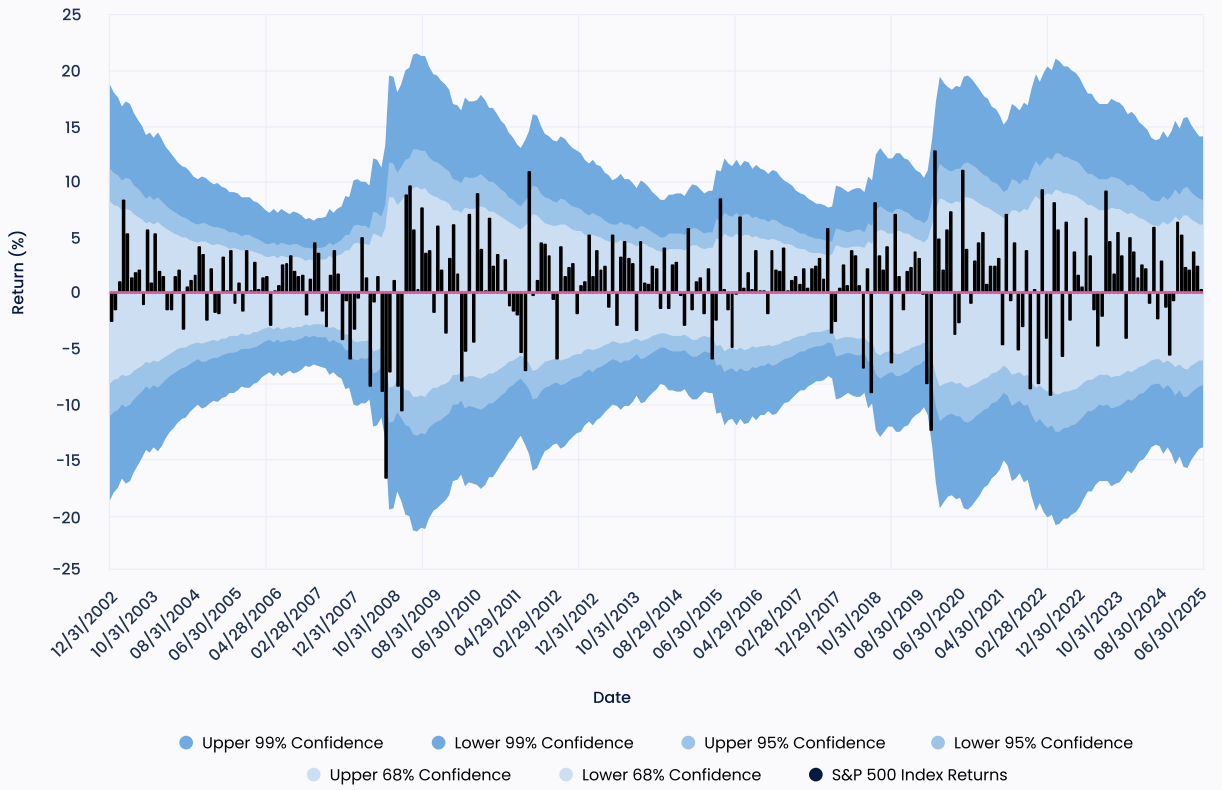
Out-of-sample MSCI AC World monthly index returns vs. GR8 exponentially weighted model implied probability thresholds for T-Distribution (5 DoF)



Out-of-sample MSCI EAFE monthly index returns vs. GR8 exponentially weighted model implied probability thresholds for T-Distribution (5 DoF)



Out-of-sample S&P monthly index returns vs. GR8 exponentially weighted model implied probability thresholds for T-Distribution (5 DoF)



Geographic Breakdown of the Estimation Universe of the Model

GR8 model geographic coverage

SUBTOTALS	COUNT
Developed	
Europe	
Austria	49
Belgium	54
Denmark	52
France	128
Germany	114
Greece	47
Ireland	12
Israel	178
Italy	88
Luxembourg	1
Netherlands	49
Portugal	39
Spain	86
Switzerland	75
United Kingdom	297
EURO Subtotal:	1,269

North America	
Canada	261
United States	2,915
NAMR Subtotal:	3,176
Pacific	
Australia	293
Hong Kong	133
Japan	1,120
New Zealand	54
Singapore	112
PAC Subtotal:	1,712
Scandanavia	
Finland	52
Norway	80
Sweden	161
SCAN Subtotal:	293
DEV Subtotal:	6,450
Emerging	
Asia	
Bangladesh	326
China	5,141
India	4,451
Indonesia	652
Malaysia	1,009
Pakistan	455
Philippines	256
South Korea	2,576
Sri Lanka	284

Taiwan	2,138
Thailand	1,147
Vietnam	612
Asia Subtotal:	19,047

Eastern Europe	
Bulgaria	162
Czech Republic	25
Estonia	27
Hungary	55
Latvia	9
Lithuania	24
Poland	617
Romania	28
Russia	10
Ukraine	2
EEUR Subtotal:	959

Latin America	
Argentina	73
Bermuda	6
Brazil	270
Chile	162
Colombia	55
Ecuador	13
Jamaica	73
Mexico	107
Peru	112
Trinidad & Tobago	25
Venezuela	36
LATN Subtotal:	932

Medit. / Africa / ME	
Bahrain	32
Botswana	19
Croatia	35
Cyprus	34
Egypt	199
Ghana	23
Iceland	23
Ivory Coast	22
Jordan	141
Kazakhstan	18
Kenya	52
Kuwait	126
Lebanon	4
Malawi	13
Malta	12
Mauritius	53
Morocco	69
Namibia	7
Nigeria	121
Oman	99
Qatar	50
Saudi Arabia	353
Senegal	1
Serbia	22
Slovakia	6
Slovenia	25
South Africa	189
Tanzania	17
Tunisia	67
Turkey	570

Uganda	8
United Arab Emirates	129
Zambia	22
MEDI Subtotal:	2,561
EMER Subtotal:	23,499
Equity Total:	29,949



Clearwater Analytics (NYSE: CWAN) is transforming investment management with the industry's most comprehensive cloud-native platform for institutional investors across global public and private markets. White legacy systems create risk, inefficiency, and data fragmentation, Clearwater's single-instance, multi-tenant architecture delivers real-time data and AI-driven insights throughout the investment lifecycle. The platform eliminates information silos by integrating portfolio management, trading, investment accounting, reconciliation, regulatory reporting, performance, compliance, and risk analytics in one unified system. Learn more at www.cwan.com.

© 2026 Clearwater Analytics. All rights reserved. This material is for information purposes only. Clearwater makes no warranties, express or implied, in this summary. All technologies described herein are registered trademarks of their respective owners in the United States and/or other countries.