Scientific Climate **Indices**
An EDHEC Venture

The Importance of Being Earnest About Risk Modelling in Climate Indices

Risk Management Series
Episode 3

SciX Insights — November 2026



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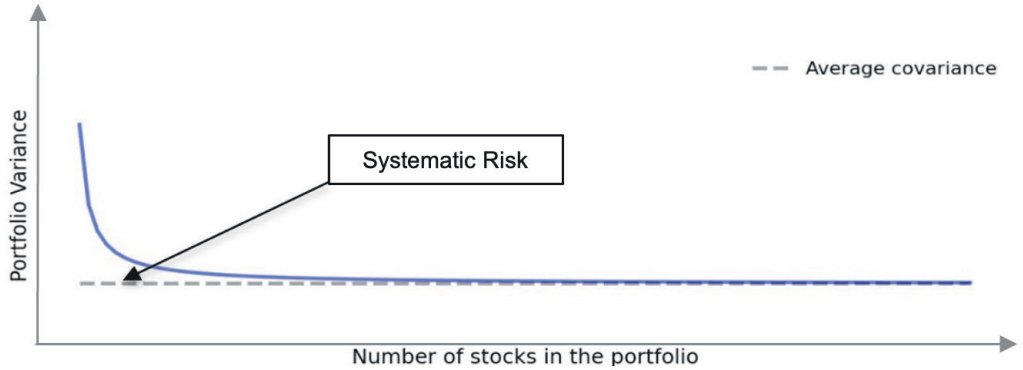
In this third episode of our Risk Management Series, we focus on the concrete benefits of the SciX equity risk model for portfolio construction and risk management purposes when designing climate indices. We compare four approaches to building covariance matrices and test them to minimize the ex-ante tracking error of a climate-aware strategy.

Key takeaways:
- **Accurately estimating and predicting risk** is the foundation of robust portfolio construction and financially disciplined climate indices
- Simple statistical techniques break down when applied to **large-scale diversified institutional portfolios**, calling for advanced risk modelling.
- The **SciX risk model** combines the interpretability of fundamental factors with the numerical stability of statistical ones, within a single framework for all geographies.
- Out of sample, it delivers the most **accurate ex-ante risk forecasts**, including during periods of market turmoil such as the Great Financial Crisis and Covid.
- It does so with the **lowest turnover** among covariance-based approaches, thus keeping transaction costs under control.

Why use a risk model to design financially disciplined climate indices?

The short answer is that a risk model is required to effectively and dynamically manage the financial risk profile of diversified institutional equity portfolios. So any fiduciary investor subject to a risk budget will benefit from a risk model. The slightly longer answer goes back to the fundamentals of portfolio construction. Portfolio theory was developed to help investors access more efficient investment opportunities in the face of uncertainty. Efficiency is largely obtained thanks to the benefits of diversification, a risk mitigation technique often seen as the only free lunch in finance. However, as useful as diversification may be, it alone is not sufficient to construct a portfolio because some sources of common risk cannot be fully diversified away, as evidenced in Exhibit 1 for a hypothetical equity portfolio.

Exhibit 1: Variance of an equally weighted portfolio as a function of the number of stocks



Source: SciX. The variance of the hypothetical equally weighted portfolio is analytically computed assuming each stock has the same volatility, and each pair of stocks has the same correlation of returns.

The level of the plateau reached in Exhibit 1 is, by design, the portion of equity risk that could not be entirely eliminated through diversification, also called systematic risk (as opposed to the idiosyncratic risk that is fully diversified away). It happens to be equal to the average covariance of returns, across every stock pair in the portfolio. Understanding the source and structure of covariance (i.e., volatilities and correlations) between stocks is therefore a prerequisite to identifying, quantifying and managing the (systematic) risks of diversified equity portfolios.

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Equity risk modelling at its core is therefore an attempt to accurately estimate the covariance matrix of stock returns: the latter is then used in portfolio construction to measure the ex-ante risk of stocks and optimize portfolios that will respect investors' risk budget. The covariance matrix could simply be estimated using high school algebra and a sample of historical stock returns. However, it has been well documented in academic literature that a large-scale sample covariance matrix is prone to estimation error due to the curse of dimensionality. As an illustration, for a portfolio of 500 stocks, the number of parameters that need to be estimated is 125,250, corresponding to the estimation of 500 volatilities and 124,750 correlations! Moreover, the sample covariance matrix is ill-conditioned, meaning that its inversion (required when solving for the optimal portfolio) is numerically unstable and its use in an optimizer will lead to the so-called "error maximization" problem, namely that the optimizer will overweight those risk estimates that are the most inaccurate. Consequently, the sample covariance matrix is a poor basis for building robust risk-aware equity portfolios.

What are the common risk modelling approaches?

Two main methods have been developed to overcome the shortcomings of the sample covariance matrix: shrinkage techniques and factor risk models. Shrinkage is a statistical technique designed to improve the properties of the sample covariance matrix[1] by reducing the influence of estimation errors. This is achieved by optimally combining the sample covariance matrix with a target matrix that is less subject to estimation risk. For instance, the target matrix can be the identity matrix, which assumes that all stocks have the same volatilities and correlations.

Factor models seek to explain the cross-section of asset returns by distinguishing the portion of returns that are driven by systematic sources of risk to which stocks are collectively exposed, and the portion of returns that are specific to the stock itself. Consequently, the curse of dimensionality is significantly reduced as we only need to estimate stock exposures to the systematic risk factors to estimate the covariance matrix[2]. There are three common types of factor models: i) statistical models, where both factors and factor exposures, i.e., betas, are assumed unobservable and need to be estimated, ii) fundamental time series models, which are popular with academics and where factors are assumed observable, such as the Fama-French factors, but not betas, and iii) fundamental cross-sectional models, used by popular risk engines in the industry and where betas are assumed observable but not factors.

Statistical models only require stock returns to infer both exposures and factors. These models use techniques inspired by Principal Component Analysis (PCA) to extract systematic factors which explain most of the variability of stock returns, and their associated betas. This simple implementation is the main benefit but also the main problem of statistical models: there is no intuitive definition of the factors, the number of factors to use is subjective and data-dependent[3], and, most importantly, these statistical factors do not have any economic or financial interpretation (unlike the fundamental factors). Fundamental time series-based models rely on observable portfolios of stocks with specific characteristics such as the popular Fama-French factors. For instance, the returns of the Small-minus-Big (SMB) factor from Fama and French correspond to the returns of a portfolio that is long in stocks with small capitalization and short in stocks of large companies (Fama and French, 1992)[4]. These factors are economically and financially interpretable and exposures to fundamental factors can be estimated via standard statistical techniques. However, there is no clear consensus on the number of fundamental factors that we should use and how we should define them, a challenge often referred to as the "factor zoo" in the literature. Finally, cross-sectional fundamental models assume that the

1 - See Ledoit and Wolf (2004)
2 - Using our previous example, the number of parameters would be reduced from 125,250 to only 1001, which corresponds to the estimation of 500 stock-level volatilities, 500 market betas (or exposures to the market factor) and the market volatility.
3 - Statistical techniques are used to limit the number of statistical factors.
4 - Exposures or betas to the Fama-French factors can be estimated using standard regression techniques.

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exposures are observable, whereas the return series of the factors are not. Hence, factor returns must be inferred from the stock exposures and the stock returns[5]. Exposures (betas) are often based on accounting information, such as price-to-earnings ratio, book-to-price ratio, or sector and regional information. Although more complex, this approach allows for the smooth integration of many more factors (achieved through the systematic disentanglement of informational overlaps), which is particularly helpful for the purpose of analyzing risk and returns across a large number of dimensions. Because of their flexibility and depth, cross-sectional models are widely used by practitioners.

Why do factor risk models work in practice?

Why should one expect factor risk models to work and accurately forecast portfolio risk out of sample over horizons of a few months?

Their effectiveness rests on well-established empirical facts. First, stocks' exposures to systematic risk factors tend to be reasonably stable over short horizons, because a company's underlying economic and financial characteristics do not change overnight. At the portfolio level, this stability becomes more pronounced because stock-specific fluctuations tend to cancel out; it also becomes more relevant because diversified portfolios are mostly driven by systematic risks. Second, while factor returns are notoriously difficult to predict, factor volatilities exhibit well-documented persistence and clustering effects: periods of elevated volatility tend to be followed by similarly volatile periods, thus making risk more predictable than returns. Limitations exist (regime shifts, market sell-offs or unwinding of crowded positions may create unexpected changes in portfolio risk) but overall factor models provide a robust framework for producing short-term conditional risk forecasts that tend to be accurate on average.

How is the SciX risk model designed?

The SciX risk model relies on the Instrumented Principal Component Analysis (IPCA) pioneered by Fan and Liao (2016) and Kelly and Pruitt (2019). It was developed to have the intuitive appeal of a fundamental time series approach, the flexibility of a cross-sectional approach, and the parsimony of a statistical approach.

The key ingredients of the model are the stock-level betas that we obtain via a set of fundamental style and sector-based factors. We use six academically grounded style factors: size, value, momentum, profitability, investment and volatility. These style factors are defined using a univariate definition in line with the work of Fama and French. We complement these style factors with ten sector-based factors and the market factor. Betas are then estimated using historical stock returns and the style, market and sector factor returns within each geography. This is in stark contrast to traditional cross-sectional fundamental models which use accounting information such as price-to-book that may be difficult to compare across companies because of accounting norms, sector or regional specificities. Moreover, accounting information is by nature backward-looking and available only at low frequencies. Conversely, betas can be estimated at a daily frequency and can capture the latest market expectations. The homogeneous and timely nature of our betas is particularly useful because they directly feed into our covariance matrices used to optimize equity portfolios subject to risk budgets.

Once we have stock-level betas, the IPCA model feeds them into the cross-sectional engine which in turn disentangles the informational overlaps between fundamental style betas and sector betas. However, the cross-sectional disentangling does not address the risk of overspecification, i.e., the fact that there are possibly too many betas. That is why our IPCA model also includes a feature designed

5 - See Burmeister et al. (1994) or Jacobs and Levy (2021)

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to avoid overspecification (in many ways similar to what PCA-based statistical models do) and reduce the dimensionality of the model behind the scenes.[6] This ensures there is no "double counting" and makes the model results more robust. The main output of the model is an exhaustive decomposition of the systematic risk of the portfolio across all factors, each associated with an intuitive and meaningful risk dimension.

To recap, the SciX risk model has the following features:

i. **Consistent estimation of stock exposures** – The model uses exposures that correspond to the stocks' betas to a set of style, sector and market factors. Hence, the model only requires stock returns (rather than harmonized accounting data), which enables the consistent estimation of betas across a wide spectrum of risk factors, sectors and regions.

ii. **Interpretability** – The model uses academically grounded style factors such as the Fama-French factors, as well as market and sector-based factors. The fact that these factors are economically and financially meaningful (and not simple statistical artifacts) facilitates a clear financial interpretation of the sources of risk.

iii. **Parsimony** – The model does not use all stock-level financial characteristics available. Indeed, some information might be redundant as there are overlaps between style and sector factors. Only the most important information is used, avoiding potential double counting of exposures. This ensures that only information that matters is used.

iv. **One model for all geographies** – The consistent estimation of characteristics across a wide range of risk factors enables the construction of risk models for portfolios exposed to many different styles and geographies. The ability to examine the risk of a global portfolio with a single model sharply reduces the possibility of unintended risk exposures resulting from the aggregation of individual strategies.

The direct benefits of these features are that the SciX risk model can effectively support advanced institutional-grade portfolio construction and risk management. The model accommodates a large number of meaningful risk factors while also maintaining a high level of numerical stability: this ensures the resulting covariance matrix will help accurately predict risk out of sample while avoiding overfitting and will therefore be a reliable input for portfolio optimization.

Comparing different risk models in climate-aware strategies

To illustrate the benefits of the SciX risk model, we compare the out-of-sample performance of four different covariance matrices (each effectively representing a risk model) in a tracking error minimization problem applied to a given climate-aware equity strategy:

i. Identity matrix ("Active Share")
ii. Sample covariance matrix using Ledoit & Wolf shrinkage to the identity matrix ("Ledoit & Wolf")
iii. Principal Component Analysis ("PCA")
iv. SciX's IPCA-based risk model ("SciX")

Note that using the identity matrix as a replacement for the covariance matrix implies that all stocks have the same risk estimates. Even though it might seem a bold assumption at first sight, this corresponds exactly to the objective of *active share minimization*[7], which is very popular in the industry. Hence, we include this approach in our comparative review, as it is often argued that active share minimization is more robust and more transparent than tracking error minimization.

6 - The IPCA model uses stock-level betas and stock returns to construct orthogonal implicit factor returns that explain most of the variability of the cross-section of stock returns. This leads to well-conditioned covariance matrices that can in turn be used to build robust risk-aware portfolios. The implicit factors are statistical in nature and different from fundamental style and sector-based factors but the IPCA model maps them to those fundamental factors to retain interpretability, while keeping the benefits of the statistical approaches.

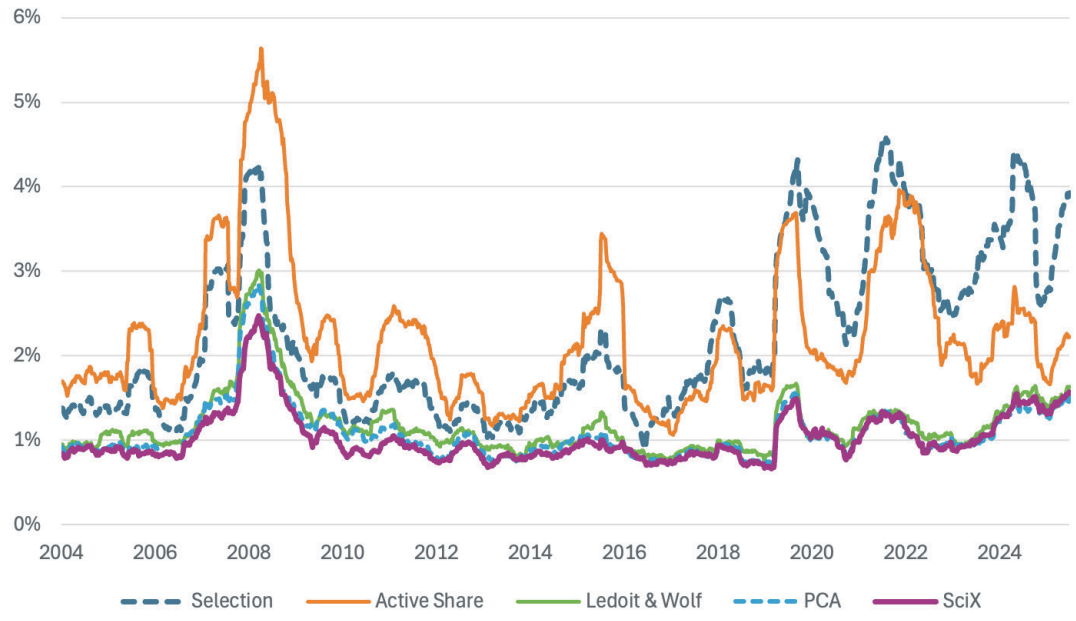
7 - Indeed if all the stocks are assumed to have the same risk characteristics, then controlling tracking error boils down to controlling, for every stock, the "absolute dollar deviation" versus a benchmark allocation.

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The climate-aware strategy we consider follows a best-in-class approach. Each quarter, the top 50% of stocks by climate score are selected within each sector. We then use an optimizer to minimize the ex-ante tracking error of the portfolio invested in the selected stocks relative to the benchmark. To ensure comparability between the different covariance matrices, we add a constraint on the climate score, which must be no worse than the climate score achieved by a naïve "Selection" portfolio comprised of the selected stocks weighted proportionally to their free-float market capitalization.

The out-of-sample performance of a risk model is assessed using different metrics. We first look at the realized tracking error of each climate strategy (see Exhibit 2). We include in the analysis the naïve Selection portfolio, where stocks are weighted proportionally to their free-float market capitalization; this reflects the natural tracking error of the selected stocks. We clearly see that the use of a covariance matrix is the only way to significantly reduce the tracking error of the Selection portfolio. The SciX risk model has the lowest tracking error among the four risk models (including the model equivalent to active share minimization), consistently across time and across crises such as the Great Financial Crisis or the Covid crisis. Put another way, for a given level of climate ambition, the SciX risk model helps construct the most financially efficient portfolio. We will illustrate this even further in the following paragraphs. It is also very clear that the minimum active share approach does not do a great job at reducing the tracking error compared to the naïve Selection portfolio. This is particularly true around and during the Great Financial Crisis of 2008–2009. This does not come as a surprise and can be explained by the fact that the approach implicitly assumes equal volatilities and correlations across all stocks, which can lead to overweighting stocks with high active risks and high correlation to other assets, while these stocks are underweighted when an estimated covariance model is used. Interestingly, the approach happened to perform slightly better over the last 10 years of the sample, as it did reduce the tracking error compared to the Selection portfolio. This might explain why this approach has been favored by some investors, as it is not common practice to run very long-term backtests to assess the robustness of portfolio designs.

Exhibit 2: Realized 6-month rolling tracking error

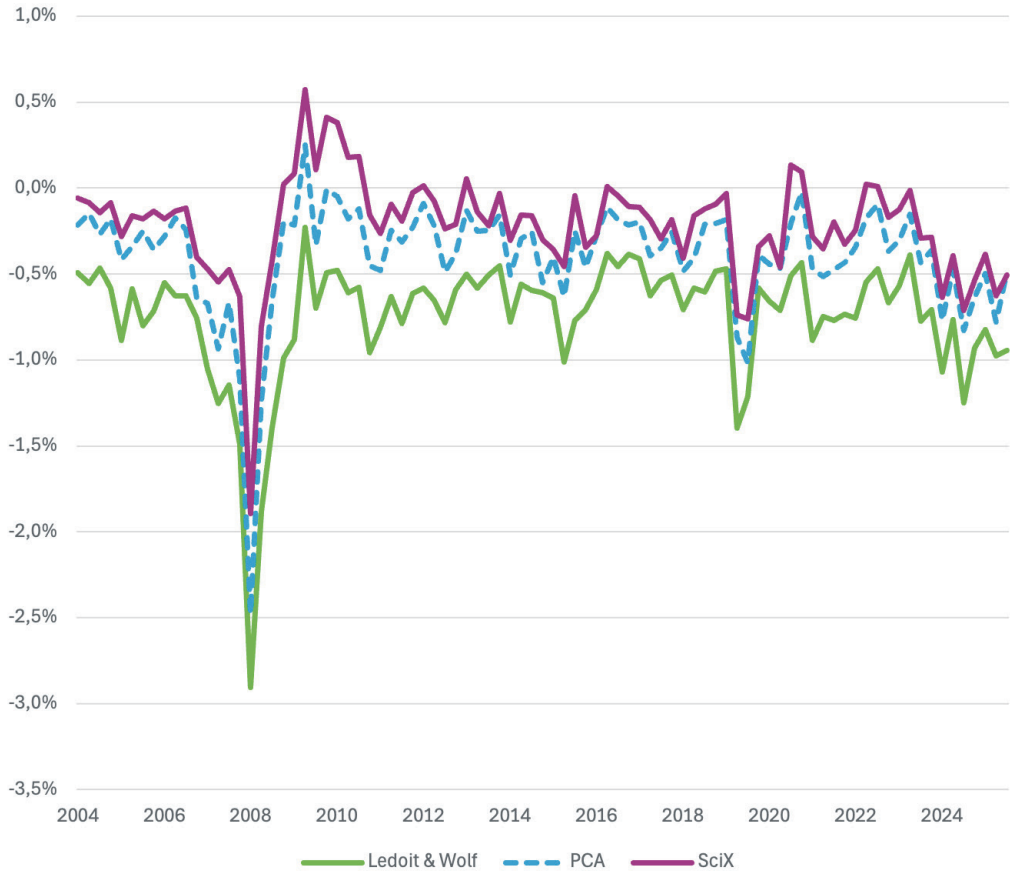


Source: SciX. The tracking error is annualized. It is measured using USD daily total returns with 6-month windows rolling in weekly steps. The SciX Developed index is used as the benchmark.

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The second analysis looks at the difference between the ex-ante measure of risk and its ex-post realization, for the three more advanced risk models (Ledoit & Wolf, PCA, SciX)[8]. Each quarter, we measure the ex-ante tracking error implied by each covariance matrix and we evaluate the next quarter's realized tracking error (see Exhibit 3). The difference between the two is what we call the forecasting error. The smaller the error, the more precise the ex-ante measure of risk is. We observe that the SciX covariance matrix has the best performance as its forecast error is closest to zero, which corresponds to a perfect forecast. The model outperforms both the PCA and the Ledoit & Wolf covariance matrices, both on average but also during the crisis periods, as highlighted before. This is particularly true during the Great Financial Crisis or the Covid crisis, where the forecast error is reduced by more than 25% compared to the two other covariance matrices. Having a risk model that delivers not only on average but also when it matters the most is key to ensuring disciplined risk management of equity portfolios.

Exhibit 3: Quarterly forecast error of the different covariance matrices



Source: SciX. The forecast error is measured each quarter. It is the difference between the annualized ex-ante tracking error measured at the current rebalancing date and the annualized tracking error realized between the current rebalancing date and the next rebalancing date. The rebalancing dates follow the SciX calendar review schedule and correspond to the third Friday of March, June, September and December. Note that returns used to measure the covariance matrices and the ex-ante tracking error at each rebalancing date are frozen three weeks before the rebalancing date.

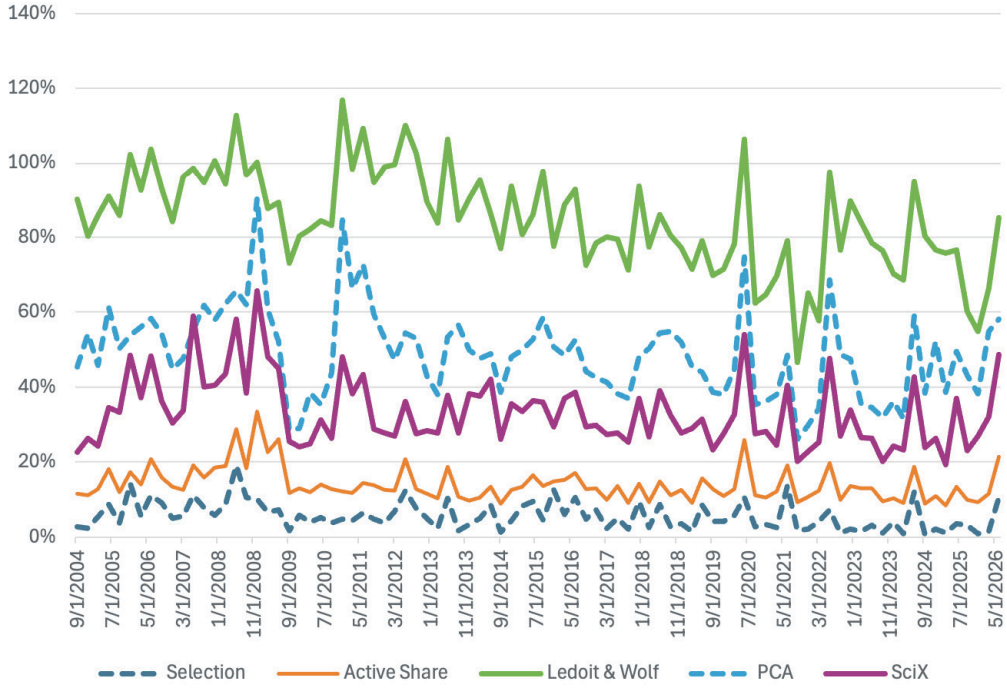
We conclude our analysis by looking at the turnover implied by the different risk models. It might seem surprising to look at this question, but turnover is a dimension often overlooked when studying the performance of covariance matrices, while it is of primary importance for investors. Indeed, there is no point using a risk model, even if its forecasts are incredibly accurate compared to other models, if it implies huge turnover and transaction costs. In Exhibit 4, we report the turnover of the same five climate strategies as in Exhibit 2: the naïve Selection portfolio and the four optimized portfolios (Active Share, Ledoit & Wolf, PCA, SciX). We see that the Selection and the Active Share strategies have the

8 - We do not include the minimum active share as it does not estimate ex-ante risks per se.

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lowest 1-way annualized turnover with 6% and 14%, respectively. Among the three risk models, the SciX model delivers the lowest turnover, with an average 1-way turnover of 33%, compared to 49% for PCA and 85% for Ledoit & Wolf. The use of a risk model to minimize a risk parameter such as tracking error will necessarily have a cost in terms of turnover; this is something investors expect. However, this cost can be mitigated when using a carefully designed risk model. The previously listed features of the SciX model, i.e., relying on financially meaningful and interpretable factors, estimating exposures consistently across factors, sectors and geographies, and maximizing parsimony to avoid overfitting, are precisely what lead to the stability displayed in Exhibit 4, with turnover controlled explicitly via a constraint in the optimization.

Exhibit 4: 1-way annualized turnover



Source: SciX. Turnover is computed using quarterly data from June 2004 to June 2026.

Better risk forecasts, lower turnover: the SciX edge for financially disciplined climate indices

A risk model is only as good as the portfolios it helps to build. The evidence is clear: the sample covariance matrix is too noisy to rely on, and minimizing active share offers little protection when markets turn. The SciX risk model closes this gap. By combining the interpretability of fundamental factors with the robustness of statistical ones, it delivers the most accurate ex-ante risk forecasts, including during the Great Financial Crisis and Covid, when accuracy matters most. It does so with the lowest turnover among the risk models tested, keeping implementation costs under control. Better risk forecasts, fewer surprises, controlled turnover: this is the recipe for building ambitious climate-aware portfolios that stay within their risk budget.

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About Scientific Climate Indices (SciX)

Scientific Climate Indices, or SciX, is an EDHEC Venture and European provider of climate equity indices for institutional investors, asset managers and investment-product providers. SciX translates climate science, climate-risk data and quantitative risk management into investable equity indices. Its approach combines scientifically grounded methodologies with transparent and financially disciplined customization.

SciX has launched two initial index ranges reflecting areas where investor demand is particularly pressing:

- The SciX Physical Climate Resilience Index Series is designed to integrate physical climate risk into core equity allocations. Existing physical-risk climate analytics often rely on highly granular bottom-up approaches that can be difficult to scale for index design across broad investment universes. SciX addresses this challenge through an original top-down framework designed for index construction, which can be enriched with company-level data as well as customized to client-specific requirements. In its Core version, the series targets an average 15% reduction in long-term physical climate risk for around one percentage point of tracking error relative to the benchmark.
- The SciX Climate Mitigation Index Series addresses the need for more pragmatic and financially disciplined approaches to climate mitigation, in response to investors' desire to focus on real-world decarbonization and their disappointment with respect to the first generation of low-carbon indices. The methodology recognizes the limitations and noise in emissions data and trajectories, the structural differences in carbon footprint between economic sectors and the undesirable consequences of broad exclusions. It also recognizes the importance of testing company-level emissions trends against independent external real-world assessments rather than relying mechanically on self-reported information.

For both ranges, SciX has introduced a new series of core indices based on the robust implementation of defined climate objectives designed to remain very close to traditional benchmarks. These core indices can be used as climate-aware building blocks or replacements for traditional capitalization-weighted benchmarks, or as the starting point for further customization.

Where investors require different climate objectives, exclusions or financial constraints, SciX applies a disciplined customization framework, relying on live analytics, backtesting and simulation to assess the financial and climate consequences of design choices before implementation, including benchmark deviation, sector exposures, risk concentrations and portfolio constraints.

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