Q1 2025

A New Paradigm in Active Equity

Navigating Concentrated Markets and Harnessing New Technologies

Executive Summary

Equity market concentration and technological innovation are two hot topics for active equity investors today. This paper explores both. First, we address the challenges of investing in concentrated markets, and discuss how this environment is impacting different approaches to active management. Second, we explore the role of new technologies, such as large language models and machine learning, and alternative data sources.

We argue that a systematic approach is uniquely positioned to capitalize on these shifts.

Charles Fattouche
Managing Director, Global Stock Selection Research

Thomas Maloney
Managing Director, Portfolio Solutions Group

Alfie Brixton
Executive Director, Portfolio Solutions Group

Contents

We thank Chris Doheny, Harry Houldsworth, Daniel Villalon, and Daniel Whitehouse for their helpful comments.

Introduction

Concerns about equity market concentration tend to fall into two main categories: the apparent concentration of risk in market cap-weighted indices dominated by U.S. mega-cap stocks (we might call this the beta challenge), and the apparently diminishing effectiveness of active management (the alpha challenge). We address these challenges in the first two sections, arguing that concentrated markets don't necessarily equate to riskier markets, and that while market concentration does pose a challenge for active managers, this is greater for discretionary stock pickers than for systematic managers. We explore what makes a systematic investment approach more resilient to market concentration.

The second significant change in the active management landscape is the "rise of the machines." For us, this phrase is far less ominous than in the 2003 cult classic. Whether it's called artificial intelligence, machine learning, or deep learning, as our Head of Machine Learning Bryan Kelly might say, “it's just statistics!” In this paper, we'll discuss how machine learning tools have enabled sophisticated quant managers to enhance stock selection models. This discussion will highlight how some quant managers have advanced far beyond "smart beta" investment approaches into the realm of innovative learning.

Does Higher Market Concentration Mean Higher Risk?

Market concentration can be measured in various ways, but the attention-grabbing evidence often cited is the weight of the top 10 stocks in a cap-weighted index. **Exhibit 1** illustrates this measure for three common regional indices. The increase in the weight of the top 10 stocks in the S&P 500 index from around 18% ten years ago to over 35% today certainly raises eyebrows.

Additional concerns about concentration arise when examining country and sector concentration levels. The weight of U.S. stocks in the MSCI World Index has increased from 56% ten years ago to over 70% as of year-end 2024, and the weight of the IT sector in the S&P 500 Index has risen from 19% to 30%.[1]

It's important to note that current levels of concentration are not unprecedented, though they haven’t been seen for a long time. The weight of the top 10 stocks in the U.S. market was close to 40% in the early 1960s.

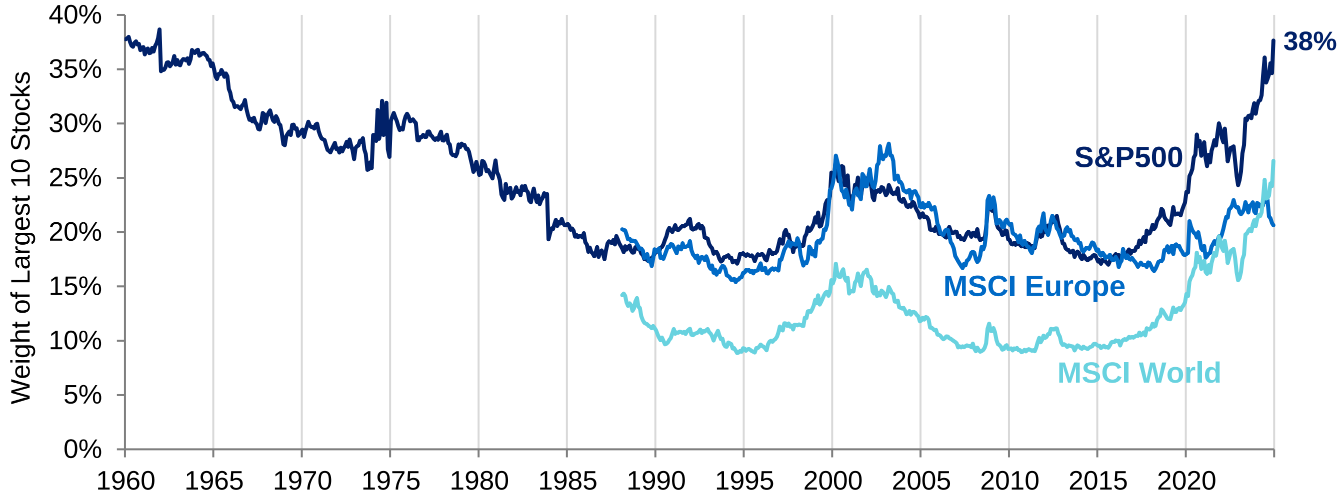
Investors are understandably wary of rising concentration, which many assume is associated with higher market risk. However, if we want to assess concentration as a driver of market risk, we can, and should, measure this directly. **Exhibit 2** shows the rolling volatility of a capitalization-weighted U.S. equity index *relative* to an equal-weighted index. If higher concentration had led to increased equity market risk, we would expect to see a rise in relative risk from 2015 through 2024, but this is not the case. There was an increase in market volatility alongside concentration during the tech bubble of the late 1990s, but this hasn’t materialized in the 2020s so far.

[1] Source: MSCI, S&P.

Rising weights for the largest companies don't necessarily equate to more concentrated risks, if those large companies are themselves very diverse.[2] So, while markets appear more concentrated than in recent history, this does not seem to have caused increased risk – at least, not yet. There remains the possibility that the largest companies might become exposed to a common risk factor, perhaps related to regulatory scrutiny or market sentiment, and this could raise market risk. Investors should continue to monitor this. In the next section we turn to the alpha challenge and address the potential implications of market concentration for active management.

Exhibit 1: Market Concentration Is Elevated

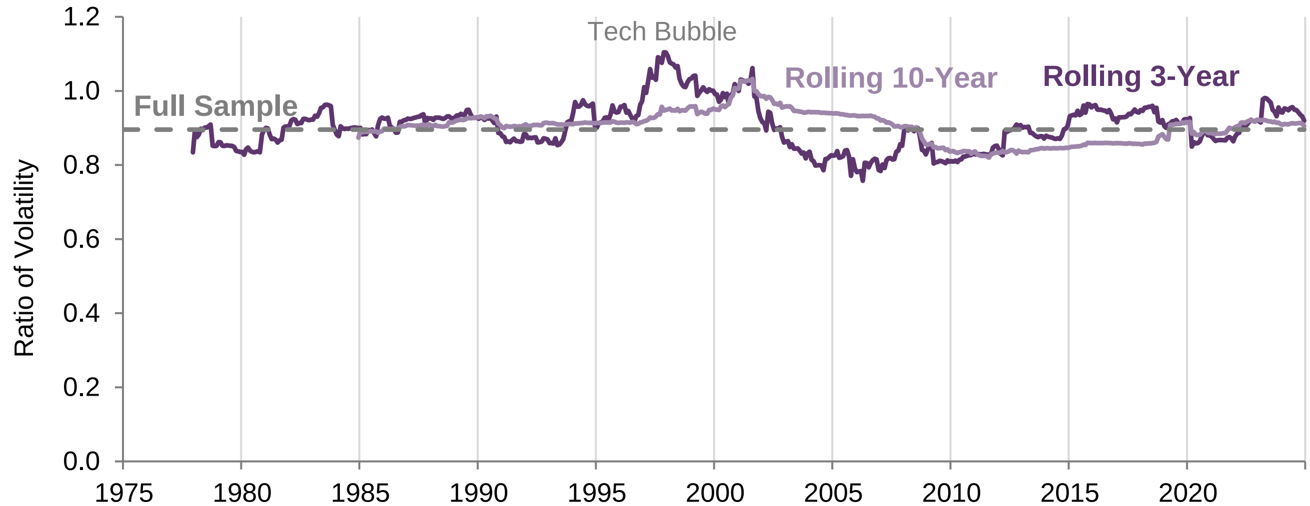
Weight of the 10 Largest Companies, Jan 1, 1960 – Dec 31, 2024



Source: AQR, Bloomberg. Chart shows the sum of the market-cap weights of the largest 10 stocks in each index at each point in time.

Exhibit 2: Concentration Doesn't Seem to Have Increased Market Risk (So Far)

Relative Volatility of Cap- and Equal-Weighted U.S. Equities, Jan 1, 1975 – Dec 31, 2024



Source: AQR, MSCI. Chart shows ratio of volatilities of MSCI U.S. Cap-Weighted and Equal-Weighted indices, based on monthly data. A ratio trending upwards would suggest that the cap-weighted index is becoming relatively riskier. Daily data shows a similar pattern.

---

[2] Lamont (2024) provides the example of AT&T which, in 1984, was forced to split into seven independent companies. This action reduced the measured concentration of the index overnight, but market risk was probably little changed.

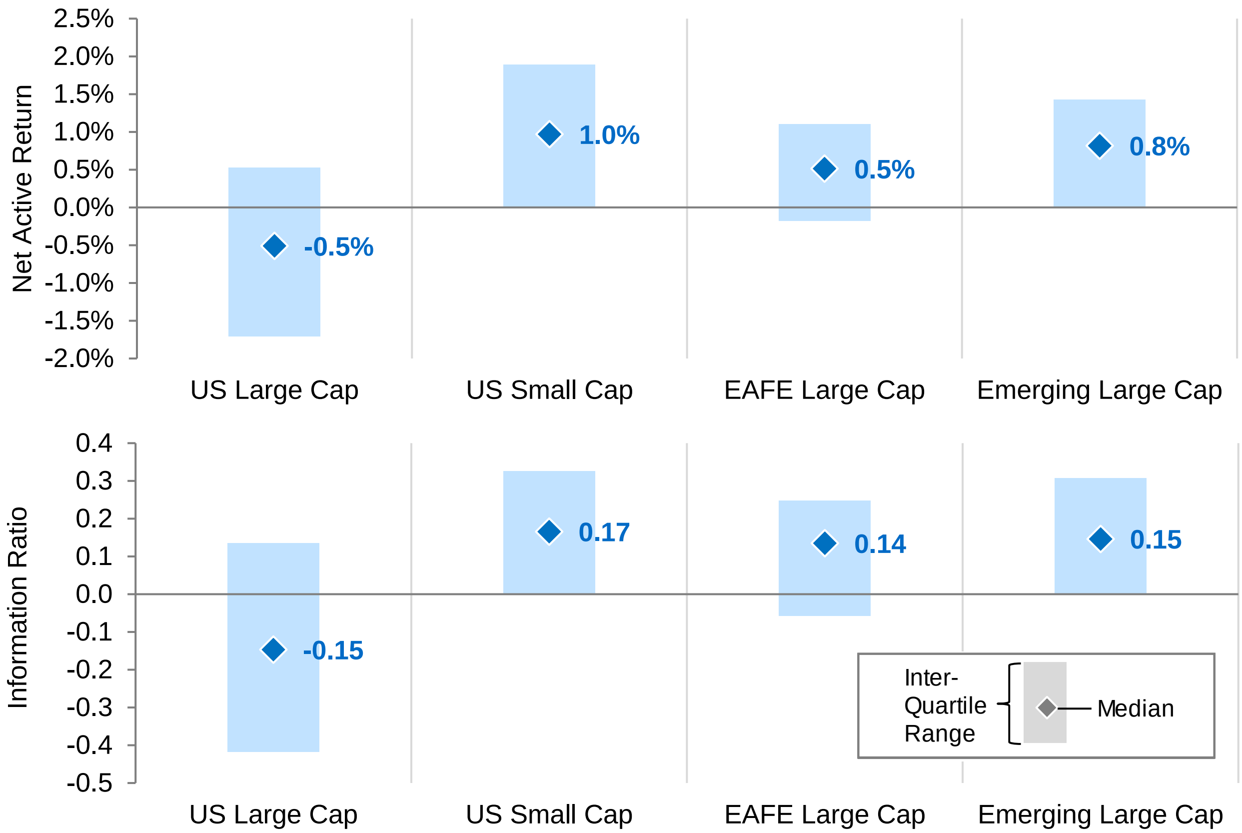
Finding Alpha in Concentrated Markets

The past decade has undoubtedly been tough for active equity managers in aggregate, especially in the more concentrated U.S. large cap universe. As shown in **Exhibit 3**, only top-quartile managers have outperformed the benchmark after fees. There may be several reasons why the U.S. large cap universe has been more challenging for active managers. Greater competition and market efficiency may lead to slimmer opportunities than are available in small caps or emerging markets, and the best-performing benchmark is often hardest to beat.

Market concentration has probably also played a role. A long-only manager can only go underweight a stock by as much as the stock's weight in the index. Increased concentration makes it harder to express negative views (without shorting) because most stocks have very small weights in the index.[3]

Exhibit 3: A Tough Decade for Active Management in U.S. Large Cap

Net Active Return and Information Ratio, Trailing 10 Years ending Dec 31, 2024



Source: AQR, eVestment. Regional equity universes shown are categories within the eVestment database which are described in the Disclosures. We start with all managers in each category and remove all managers who do not have at least 10-years of returns. Manager active returns are calculated by eVestment relative to manager preferred benchmarks and are reported either gross or net of fees. For managers who report returns gross of fees, we convert the returns to net using the median fee of the universe. Information ratio is calculated as the average net active return per unit of tracking error relative to the manager's preferred benchmark. Time period is the trailing 10-year period ending December 31, 2024. Past performance does not predict future returns.

[3] Portfolios that allow some shorting such as "relaxed constraint" (also popularly known as "130/30") strategies can provide more "elbow room" to express negative views but some investors are constrained in their ability to short even indirectly via outsourced management. To learn more about relaxed constraint strategies see Ang, Michalka, and Ross (2017).

Also, when a stock market is dominated by a few large conglomerates, this means reduced competition and fewer opportunities to express stock selection views. For instance, if I have a positive view on one sub-business within Amazon and a negative view on another, I cannot express this view on the underlying businesses while they are part of a conglomerate.[4]

Thirdly, when a period of strong performance is driven by the largest companies, any active manager with a more equal weighting is likely to lag behind.

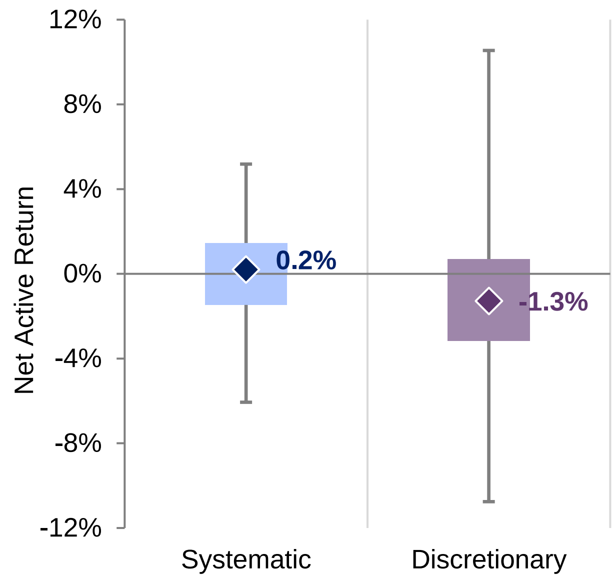
Are all active managers affected equally by these challenges of market concentration? Let us consider two broad categories:

1. **Systematic** managers with diversified portfolios designed to seek exposure to characteristics rather than individual companies, and
2. **Discretionary** stock pickers with more concentrated portfolios of high-conviction holdings.

Exhibit 4 shows the distribution of recent performance for systematic and discretionary U.S. large cap managers. While return dispersion tends to be slightly wider for discretionary managers on average, this has been particularly extreme in recent years. Over this period the average discretionary U.S. large cap manager underperformed their benchmark, whilst the average systematic manager modestly outperformed.

Exhibit 4: More Dispersion Among Discretionary Managers in Recent Years

Distribution of U.S. Large Cap Manager Active Returns, Jan 1, 2022 – Dec 31, 2024



Source: AQR, eVestment. Whiskers show maximum and minimum values, box shows the inter-quartile range, and marker is the median value. Manager returns are for U.S. Large Cap Equity managers in the eVestment database. See Disclosures for a description of the universe. Discretionary and Systematic refer to managers who have reported their primary investment approach as fundamental and quantitative in eVestment respectively. We remove managers who do not have returns over the full period shown. Manager active returns are calculated by eVestment relative to manager preferred benchmarks and are reported either gross or net of fees. For managers who report returns gross of fees, we convert the returns to net using the median fee of the universe. Time period is January 1, 2022 to December 31, 2024. Past performance does not predict future returns.

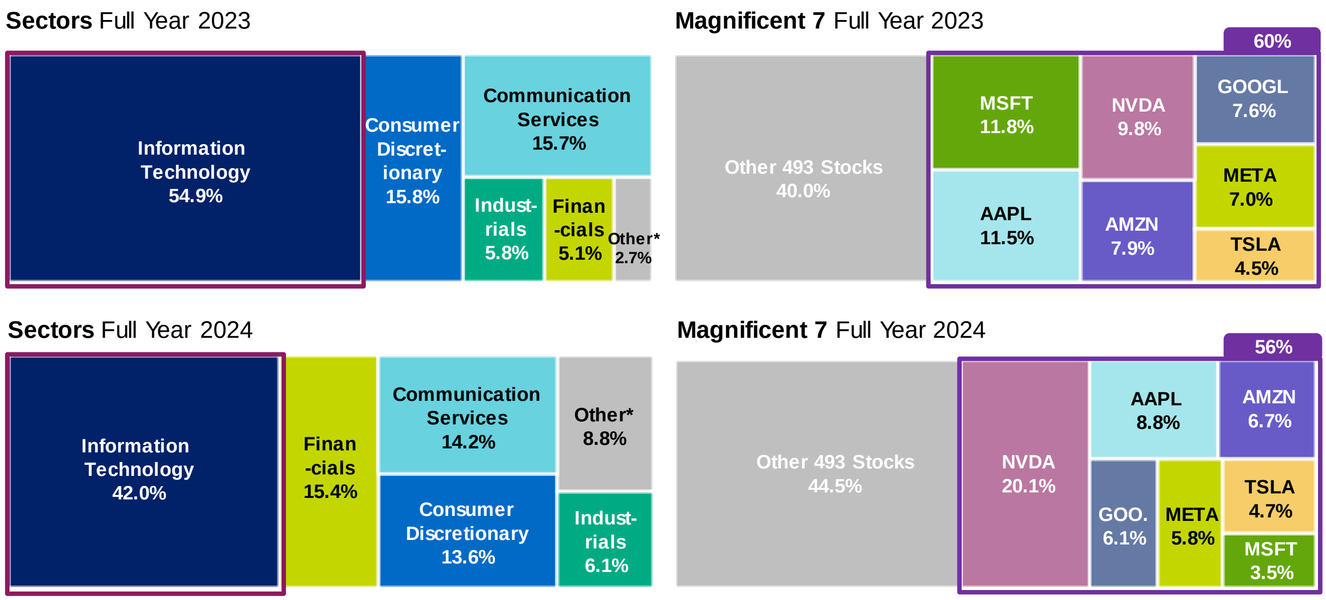
What is driving this return dispersion? We hypothesize that the recent dominance of U.S. mega-cap stocks may have increased performance dispersion for discretionary managers more than it has for systematic managers. Let's explore this further.

[4] Of course, if my universe is a fixed number of stocks like the S&P 500, I still have that number of stocks to choose between. But it will be harder to express positive and negative views efficiently if many of the stocks have tiny index weights.

Exhibit 5 illustrates the tale of the tape for U.S. equity market performance in 2023 (upper panel) and 2024 (lower panel). In 2023, the IT sector was responsible for over half of the index gains. Viewed from a single stock perspective, the so-called Magnificent Seven earned an even bigger share. In 2024, we saw a similar pattern of narrow-based performance, with Nvidia alone delivering one fifth of the market return. Investment success in these years was a story of "haves" and "have-nots," with the "haves" being those who owned enough of the Mag-7.

Exhibit 5: Recent U.S. Market Performance Was Narrow-Based

Sector and Mag-7 Percent Contributions to S&P 500 Total Return, 2023 & 2024



*Includes real estate, materials, health care, consumer staples, energy, and utilities.
Source: AQR, Bloomberg, S&P Global. "Magnificent 7" refers to the companies Alphabet (GOOGL), Amazon (AMZN), Apple (AAPL), Meta (META), Microsoft (MSFT), Nvidia (NVDA), and Tesla (TSLA). Sector returns are for companies in the S&P 500 categorized by the relevant GICS® sector classification. We approximate the return contribution to the S&P 500 cumulative return by market cap-weighting the cumulative return of each sector or stock and dividing by the total S&P 500 return in the relevant year. Not representative of a portfolio AQR currently manages. Chart is for illustrative purposes only and not a recommendation to purchase any securities mentioned herein. Past performance does not predict future returns. The elements of this methodology do not indicate the possibility of profits or losses within a portfolio or for the securities selected. The securities were selected merely as an example.

The theory underlying our hypothesis hinges on the way discretionary and systematic managers take risks. Discretionary managers hold concentrated portfolios with far fewer securities than typical systematic managers. Some likely had no exposure at all to some of the Mag-7 companies, while others held large positions in them. This concentrated approach exposes them to binary have/have-not outcomes when a few stocks are driving market performance. Systematic managers are not exposed to this risk in the same way because they generally spread their active risk across many small bets, and often explicitly control any sector and industry risks. A typical systematic manager would hold all of the Mag-7 stocks, with some of them slightly overweight and some slightly underweight, and similarly would be only slightly over- or underweight any given sector or industry.

This can be seen in practice in **Exhibit 6, Panel A**, which shows the distribution of active exposure to a Mag-7 factor for systematic and discretionary managers. Discretionary managers exhibit a wide distribution of active exposure to the Mag-7, meaning that the performance of the

Mag-7 will be a significant driver of their active returns, whilst the distribution is tighter for systematic managers.

Panel B shows the median annualized alpha for the same regression, which is equivalent to the average active return *unexplained* by Mag-7 exposure. We see that, on average, discretionary managers delivered negative alpha after controlling for the Mag-7, suggesting that active views beyond the Mag-7 detracted from performance. In contrast, systematic managers exhibited positive alpha.[5] We will elaborate further on why quantitative approaches differ in the next section.

Exhibit 6, Panel A: Discretionary Managers More Exposed to Mag-7 Performance

Distribution of Mag-7 Exposure,
Jan 1, 2022 – Dec 31, 2024

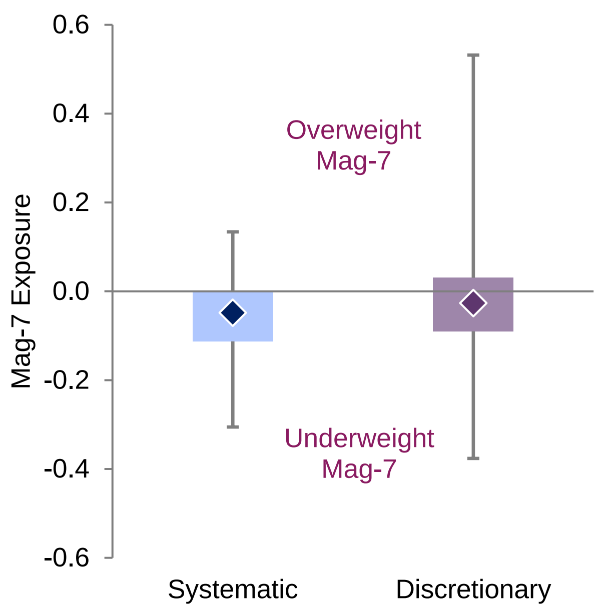
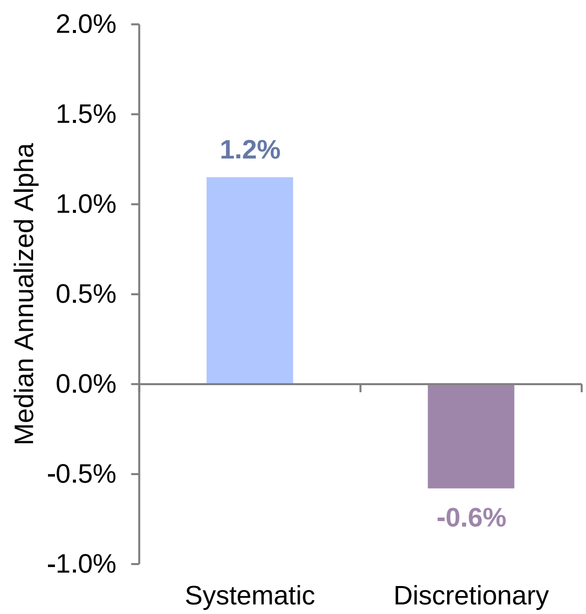


Exhibit 6, Panel B: Systematic Managers Harvested More Alpha Outside the Mag-7

Median Alpha Controlling for Mag-7 Exposure,
Jan 1, 2022 – Dec 31, 2024



Source: AQR, eVestment. Manager returns are for U.S. Large Cap Equity managers in the eVestment database. See Disclosures for a description of the universe. Discretionary and Systematic refer to managers who have reported their primary investment approach as fundamental and quantitative in eVestment respectively. We remove managers who do not have returns over the full period shown. "Mag-7 exposure" is calculated based on a returns based regression of manager active returns on returns on the S&P 500 and a market neutral "Mag-7 Factor". "Alpha controlling for Mag-7 exposure" is annualized alpha from the same regression. Time period is January 1, 2022 to December 31, 2024. Past performance does not predict future returns.

---

[5] 59% of discretionary managers had a negative alpha from this regression, whilst 71% of systematic managers earned positive alpha.

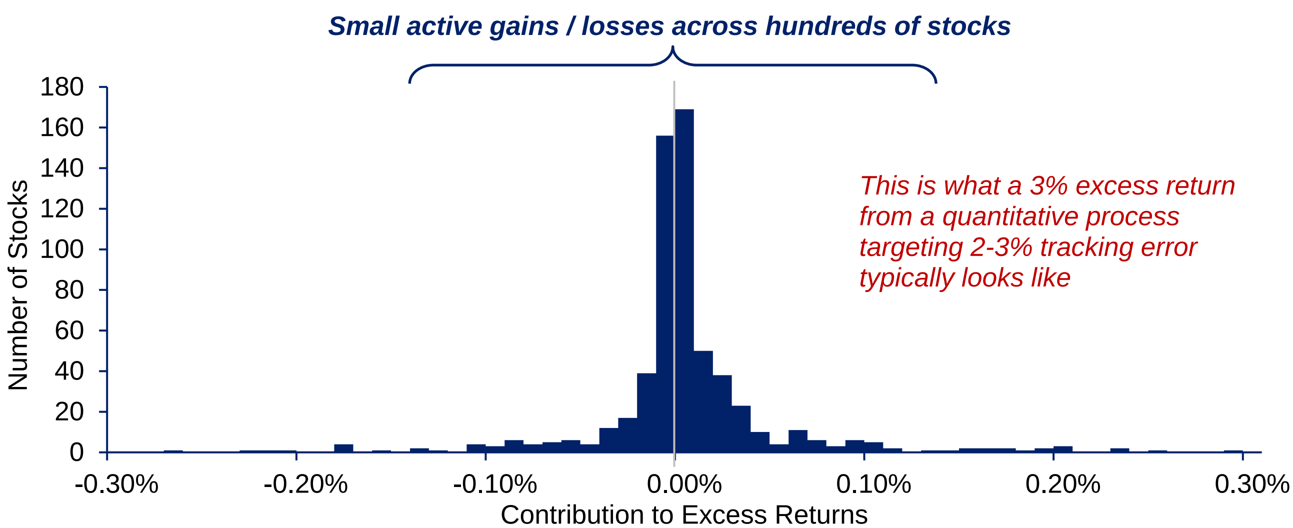
Why Quant Is Different

Two fundamental principles underpin quantitative active management: (1) diversify across intended bets and (2) eliminate unwanted exposures.[6] Quants hold a large number of securities spread across industries, sectors, countries and market cap segments, while taking only modest active bets on any given stock. The intention is to deliver exposure to characteristics associated with higher returns, rather than stock-specific risk. This approach has the potential to improve risk-adjusted returns and their consistency over time.

While diversification might seem like an obvious proposal, it has significant implications. In a well-diversified portfolio, outperformance (or underperformance) typically results from small gains (or losses) across many stocks, rather than large gains (or losses) in a few. **Exhibit 7** illustrates the typical distribution of returns for a quantitative process over a given one-year period. The average contributions from individual winners and losers are typically small in absolute terms. It is the main body of the distribution that drives excess returns, rather than the extremes. With sufficient diversification, attractive performance can be achieved even if the success rate on individual securities is only slightly above 50%. In other words, a small advantage spread across many unique bets provides a quant manager with conviction, rather than relying on a concentrated "all eggs in one basket" strategy.

Exhibit 7: A Typical Quantitative Process Harvests Many Small Gains

Illustrative Distribution of Active Returns over a 1-Year Period



Source: AQR. For illustrative purposes only and not representative of an actual portfolio AQR currently manages. Please see the Disclosures section for important disclosures.

The second important principle is to eliminate unwanted exposures, which means avoiding unintentional industry bets and primarily taking within-industry relative positions. This approach offers multiple benefits. Firstly, stocks within the same industry are more clearly comparable by

---

[6] A prime example of unwanted exposure is the industry bet that accompanies an under- or overweight bet on any stock. A thoughtful quant process separates within-industry and cross-industry views, and sizes them according to breadth and conviction. In contrast, many discretionary managers take substantial industry bets as a by-product of their stock-level views.

many different metrics, leading to higher conviction in our relative views. Additionally, during periods of market concentration, managers with an industry-neutral approach can deliver an excess return profile that is less influenced by whether they were net overweight or underweight specific industries or market segments, such as Information Technology. By maintaining industry neutrality, managers can deliver more consistent returns over time and may better withstand market fluctuations.

Sophisticated quant managers may take this an important step further, not just considering the familiar sector and industry classifications, but also defining other peer groups of related companies, such as those with economic linkages. This enhancement captures relationships between companies that may not be well represented by standard industry classifications, such as companies sharing the same customers or suppliers. Additionally, it provides extra breadth to a stock selection strategy by adding another dimension for comparing stocks – and we know from the fundamental law of active management[7] that information ratio is proportional to the square root of breadth.

While diversification and industry-neutrality have long been staples of quantitative active equity management, recent years have seen a significant evolution in quant managers' approaches. In the next section, we highlight the importance of leveraging new technologies to stay ahead in an increasingly competitive market.

The Evolution of Quant Active Management: Beyond Smart Beta

Quantitative active management is rooted in factor investing, which focuses on identifying characteristics like value or momentum to explain stock returns. While some of the original investment philosophy still applies today, particularly the desire to uncover signals with economic grounding and a clear rationale for persistence of returns, quant investing has evolved significantly. It has moved well beyond traditional factor-based or smart beta-type approaches, leveraging advancements in technology and data science.

In recent years, some quant managers have embraced more sophisticated models, including those driven by alternative data sources, machine learning, and natural language processing. These advancements, coupled with improved computational capabilities, enable deeper insights into market inefficiencies and investor behavior, allowing strategies to adapt dynamically to changing market conditions. This renaissance in quantitative investing reflects a shift towards more nuanced, multi-factor approaches that combine robust theoretical underpinnings with cutting-edge technological applications, with the intention of delivering sustained outperformance in increasingly complex markets.

Alpha Signal Innovation

One of the key areas to have benefitted from these advancements is alpha signal innovation. A prime example is Momentum investing, which aims to capitalize on the tendency of investors underreacting to new information. Traditionally, Momentum has been implemented by favoring stocks with strong recent performance relative to

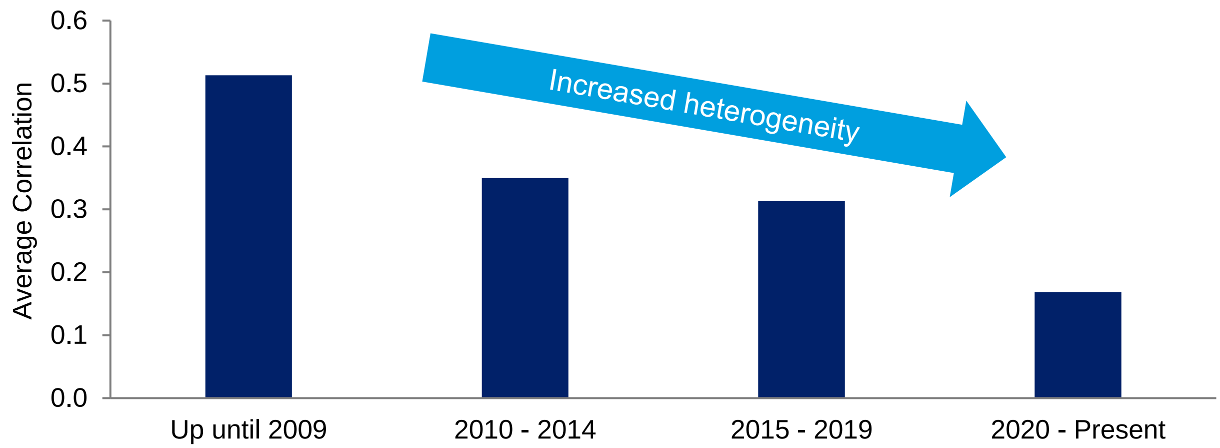
[7] See Grinold (1989).

peers and taking opposite positions in stocks with poor relative performance. Over the past decade, methods for exploiting Momentum have significantly evolved. These methods have expanded from price-based momentum metrics to fundamental metrics (such as earnings momentum and changes in analysts' forecasts), indirect momentum metrics that capture spillover effects between economically linked companies, natural-language processing (NLP) that analyzes patterns in unstructured data, and factor momentum, among others. As the definitions of Momentum have multiplied, the heterogeneity across momentum-related signals has increased (**Exhibit 8**).

The average pairwise correlation of Momentum-related signals has fallen so much that it may no longer make sense to group them all under the same "Momentum" label. We will elaborate on this issue later when discussing the evolution of signal weighting approaches.

Exhibit 8: New Signals Are Lowly Correlated to Classic Quant Factors

Average Pairwise Correlation Across Momentum-related Signals, Jan 1, 1998 – September 30, 2024



Source: AQR. The chart shows the average pairwise correlation across a range of signals that are deemed related to momentum, and across different time periods. Universe is a U.S. large cap stock universe similar to the Russell 1000 Index. For illustrative purposes only and not representative of an actual portfolio AQR currently manages. Please see Disclosures section for important disclosures.

Technological advancements have opened new doors for those quant managers willing and able to harness them, steadily expanding into types of information that it was previously thought we "can't put a number on". A prime example is the interpretation of text, where the field of NLP has seen significant progress with the development of large language models. These models have enabled the extraction of valuable insights from vast amounts of textual data, providing a more nuanced understanding of market dynamics and further advancing the field of alpha signal innovation. Innovations in NLP have typically evolved along three key dimensions: data, methods (such as text representation, inference types, or supervision labels), and infrastructure (including efficient data storage and GPU cloud computing). Another example is "alternative data". Quant managers have increasingly turned to alternative data sources, such as transaction data, which is now used broadly across the industry to construct alpha signals and gain actionable insights beyond what traditional data provides.

As data has evolved, so too have the tools and methods used to analyze it. Machine learning techniques have increasingly been integrated into quantitative active management, offering innovative approaches for analyzing both traditional and alternative data to uncover previously unknown complex relationships. For quants who have embraced these innovations, stock selection models have evolved significantly from just a few years ago.

However, financial markets present unique challenges for machine learning due to their low signal-to-noise ratios, constantly evolving nature, and limited data availability[8]. Unlike fields with high predictability, such as image recognition, financial markets have a low signal-to-noise ratio and are dynamic, making it difficult for machine learning models to maintain accuracy over time. As new signals are discovered and exploited, they quickly become absorbed into market pricing, reducing their effectiveness. Additionally, financial research often deals with small data sets.[9] These challenges require machine learning tools that can adapt to new information and changing market conditions, highlighting the need for specialized approaches in the finance industry.

Machine learning should be integrated as part of the normal R&D process, rather than being siloed or “tacked-on.” This can help to ensure that quantitative methods place an emphasis on economic priors. Given the unique challenges of financial data described above, it is crucial to develop methods tailored to this domain, as opposed to the heavily parameterized models used in other non-finance machine learning domains. Sophisticated managers have been incorporating machine learning concepts into their processes for some time, and we believe its importance will grow as these capabilities continue to develop.

Signal Weighting Innovation

Another significant area of improvement is signal weighting. Traditionally, signals were grouped within themes or factor groups. However, the increased heterogeneity within these groups and the rising number of signals have naturally loosened the rationale for such an approach. One effective solution has been to adopt a bottom-up signal weighting approach, which avoids making arbitrary decisions required in a top-down approach, such as how signals should be grouped and how those groups should be weighted.

Consider two different approaches or philosophies for determining how to allocate risk across a set of different signals. The "fundamentalist" approach uses anchor weights based on judgment and economic intuition, while the "statistician" approach relies solely on data to estimate a signal's efficacy and determine its weight. These approaches should be reconciled using methods such as Bayesian learning models. Bayesian learning is a method of statistical inference that continuously refines predictions as more out-of-sample data is gathered, making a model more accurate over time. For example, imagine we have a coin and want to determine if it's fair (i.e., has a 50% chance of landing heads). Initially, without data, we might assume it's fair (the fundamentalist approach). As we flip the coin and observe the outcomes, we update our belief based on the results. If we flip the coin 10 times and get 7 heads, we might start to think the coin is biased towards heads. Bayesian learning allows us to quantify this updated belief, and as we continue to flip the coin, we rely less on our initial assumption and more on observed data, gradually aligning more with the statistician approach.

---

[8] For further details, see “Can Machines “Learn” Finance” by Israel, Kelly and Moskowitz (2020).

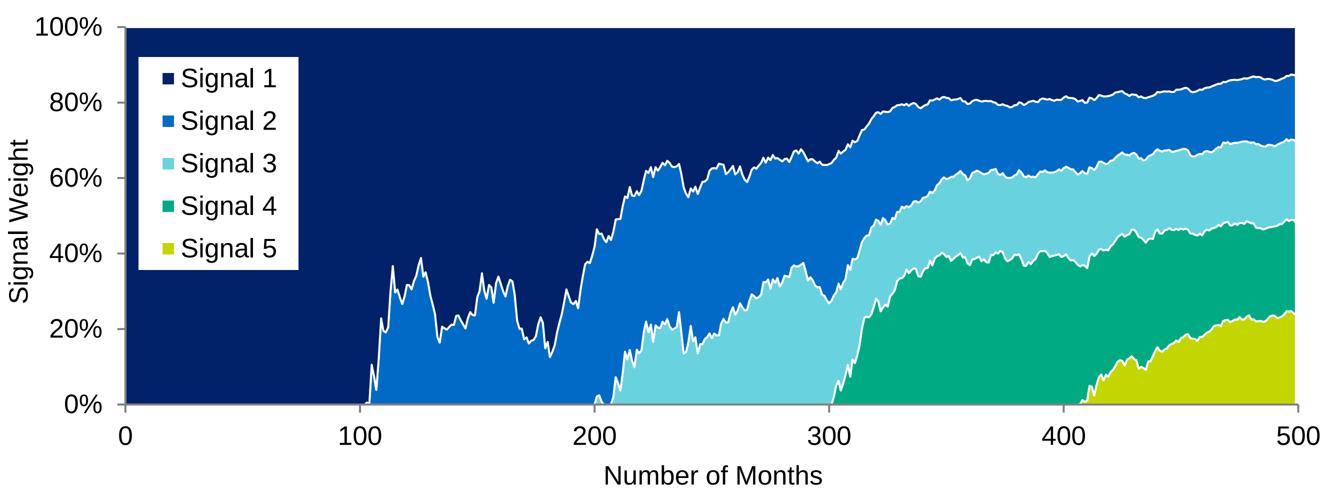
[9] “Small” in comparison to other machine learning fields, like image recognition or self-driving vehicles, where infinite data can be generated. Statistical analysis of finance is a time series discipline, so the explanatory variable is limited to the time period available and will only increase with the passage of time.

Exhibit 9 Panel A illustrates one such framework that finds a middle ground between economic priors and data-driven methods to determine optimal weights across different signals. **Panel B** shows a simplified example of how weights could be distributed across a set of signals as new signals are periodically introduced to the model. In this example, based on simulated data, newer signals are assumed to be more richly compensated: each signal is introduced with a low weight but can earn a higher weight once there is sufficient data to validate stronger performance. The model remains well-diversified across available signals. While this example contains only five signals, a similar process can be applied to hundreds of predictors. This adaptive approach can allow a manager to keep their models relevant over time and could enhance the overall robustness and adaptability of their investment strategies.

Exhibit 9: New Signals Require New Approaches to Signal Weighting

Figure A: Bayesian Framework for Leveraging Theory and Data to Make Decisions at Scale

Figure B: Example of Dynamic Signal Weights as New Signals Are Introduced Using Bayesian Framework



Source: AQR. For illustrative purposes only. Chart assumes one new signal is introduced every 100 months, with newer signals having higher expected returns. Based on simulated data and not representative of any portfolio that AQR currently manages.

Tactical Considerations

We have often emphasized the challenges of incorporating tactical views to add value beyond strategic diversification.[10] Tactical timing is inherently more difficult than it appears, and tactical tilts tend to forgo some powerful diversification benefits. As methods for strategic signal weighting have evolved, so have methods for tactical weighting, such as using sophisticated machine learning models. These tactical overlays enable quant managers to dynamically adjust signal weights based on the environment. By incorporating tactical overlays, managers can respond to shorter-term market movements and fine-tune their strategies to capitalize on emerging opportunities. This flexibility is crucial in today's fast-paced and ever-changing markets, allowing the more sophisticated quant managers to maintain a competitive edge.

Our recent Alternative Thinking papers, titled "Can Machines Time Markets? The Virtue of Complexity in Return Prediction" (May 2024) and "Can Machines Build Better Stock Portfolios?" (November 2024), offer frameworks that demonstrate how machine learning can be used to incorporate tactical views for timing market exposure and selecting equity factor weights in stock portfolios.

Concluding Thoughts

Equity market concentration and technological innovation are top-of-mind concerns for active equity investors. Concentration in U.S. mega-cap technology companies is elevated by historical standards, but we argue that this does not necessarily point to higher market risk. The past decade has been a difficult period for active management, which may partly be due to challenges posed by the rise in concentration. A systematic investment approach can offer refuge from concentration concerns because this diversified and industry-neutral investment approach tends to be less exposed to the relative performance outcomes of the few largest companies.

Technological advancements have introduced new tools to the investment management industry and quantitative investment managers have been uniquely positioned to harness this innovation. This rapid evolution has led to significant improvements in methods, techniques, and data compared to just five years ago. Innovations across data sources, machine learning, natural language processing, and infrastructure have enabled more sophisticated analysis and deeper insights. These advancements may lead to more effective investment strategies, which are expected to drive robust returns over time.

[10] See for example AQR Alternative Thinking Q4 2014.

References

O. Lamont, 2024, “Higher Stock Market Concentration Does Not Mean Higher Risk,” white paper.

I. Ang, A. Michalka, and A. Ross, 2017, “Understanding Relaxed Constraint Equity Strategies,” white paper.

R. Grinold, 1989, “The Fundamental Law of Active Management,” *Journal of Portfolio Management*.

R. Israel, B. Kelly, and T. Moskowitz, 2020, “Can Machines “Learn” Finance,” *Journal of Investment Management*.

AQR *Alternative Thinking* 2014 Q4, “Challenges of Incorporating Tactical Views,” white paper.

AQR *Alternative Thinking* 2024 Q2, “Can Machines Time Markets? The Virtue of Complexity in Return Prediction,” white paper.

AQR *Alternative Thinking* 2024 Q4, “"Can Machines Build Better Stock Portfolios?” white paper.

Disclosures

Broad-based securities indices are unmanaged and are not subject to fees and expenses typically associated with managed accounts or investment funds. Investments cannot be made directly in an index.

The S&P 500 Index is the Standard & Poor's composite index of 500 stocks, a widely recognized, unmanaged index of common stock prices.

The MSCI World Index captures large and mid cap representation across Developed Markets countries. The index covers approximately 85% of the free float-adjusted market capitalization in each country.

The MSCI Europe Index captures large and mid cap representation across 15 Developed Markets (DM) countries in Europe. With 414 constituents, the index covers approximately 85% of the free float-adjusted market capitalization across the European Developed Markets equity universe.

The MSCI USA Index is designed to measure the performance of the large and mid cap segments of the US market. With 602 constituents, the index covers approximately 84% of the free float-adjusted market capitalization in the US.

The MSCI USA Equal Weighted Index represents an alternative weighting scheme to its market cap weighted parent index, the MSCI USA Index. The index includes the same constituents as its parent (large and mid cap securities from US markets).

eVestment manager universe descriptions: US Large Cap Equity consists of US Equity products that primarily invest in large capitalization stocks regardless of the style (growth, value, or core) focus. Universe ID: 1130. Date Added: 10/2/2009. US Small Cap Equity consists of US Equity products that primarily invest in small capitalization stocks regardless of the style (growth, value, or core) focus. Universe ID: 1139. Date Added: 10/2/2009. EAFE Large Cap Equity consists of EAFE Equity products that primarily invest in large capitalization stocks regardless of the style (growth, value, or core) focus. Universe ID: 1151. Date Added: 10/2/2009. Global Emerging Mkts Large Cap Equity consists of Global Emerging Markets Equity products that primarily invest in large capitalization stocks regardless of the style (growth, value, or core) focus. Universe ID: 214060. Date Added: 10/31/2011.

Canadian recipients of fund information: These materials are provided by AQR Capital Management (Canada), LLC, Canadian placement agent for the AQR funds.

Please note for materials distributed through AQR Capital Management (Asia): This presentation may not be copied, reproduced, republished, posted, transmitted, disclosed, distributed, or disseminated, in whole or in part, in any way without the prior written consent of AQR Capital Management (Asia) Limited (together with its affiliates, "AQR") or as required by applicable law.

This presentation and the information contained herein are for educational and informational purposes only and do not constitute and should not be construed as an offering of advisory services or as an invitation, inducement, or offer to sell or solicitation of an offer to buy any securities, related financial instruments, or financial products in any jurisdiction.

Investments described herein will involve significant risk factors, which will be set out in the offering documents for such investments and are not described in this presentation. The information in this presentation is general only, and you should refer to the final private information memorandum for complete information. To the extent there is any conflict between this presentation and the private information memorandum, the private information memorandum shall prevail.

The contents of this presentation have not been reviewed by any regulatory authority in Hong Kong. You are advised to exercise caution, and if you are in any doubt about any of the contents of this presentation, you should obtain independent professional advice.

The information set forth herein has been prepared and issued by AQR Capital Management (Europe), LLP, a UK limited liability partnership with its registered office at Charles House 5-11 Regent Street, London, SW1Y 4LR, which is authorized by the UK Financial Conduct Authority ("FCA").

AQR in the European Economic Area is AQR Capital Management (Germany) GmbH, a German limited liability company (Gesellschaft mit beschränkter Haftung; "GmbH"), with registered offices at Maximilianstrasse 13, 80539 Munich, authorized and regulated

by the German Federal Financial Supervisory Authority (Bundesanstalt für Finanzdienstleistungsaufsicht, "BaFin"), with offices at Marie-Curie-Str. 24-28, 60439, Frankfurt am Main und Graurheindorfer Str. 108, 53117 Bonn, to provide the services of

investment advice (Anlageberatung) and investment broking (Anlagevermittlung) pursuant to the German Securities Institutions Act (Wertpapierinstitutsgesetz; "WpIG"). The Complaint Handling Procedure for clients and prospective clients of AQR in the European Economic Area can be found here: https://ucits.aqr.com/Legal-and-Regulatory.

Request ID: 393300 (update of 392484)

www.aqr.com

AQR Capital Management, LLC One Greenwich Plaza, Greenwich, CT 06830 **P** +1.203.742.3600 **F** +1.203.742.3100