A holistic approach to quantitative investing

Abstract

Quantitative approaches to public equity investing continue to introduce new sources of alpha and are now – in select areas – generating research insights in areas formerly reserved for qualitative fundamental analysis. Quant methodologies have been augmented very recently with expanded access to exponentially more powerful computing, as well as the rapid evolution of tools such as machine-learning and natural language processing. These advances have enabled increased analysis of non-traditional data sets that have the potential to provide valuable investment insights and a competitive edge amongst active equity investors.

SECTION I explores the spectrum of quantitative strategies, sheds light on what we term "holistic quant" – a multi-faceted approach utilized by us and a growing number of quants – and touches upon both the advantages and disadvantages of quantitative processes.

SECTION II explores the origins of quantitative investing, the evolution of technologies and investment signals utilized by quants, and the characteristics necessary for factors and new investment signals to have predictive power.

SECTION III explores our perspective – as long-term practitioners of quant – on practices that can improve outcomes amongst quantitative public equity investment approaches. We believe that a more "holistic" approach to quantitative investing can enhance the opportunity for more consistent alpha across a wider array of market environments.

SECTION I

Defining holistic quantitative investing

It is not rare for us to encounter asset owners who eschew all quantitative strategies and lump them into a single bucket, while other former quant advocates abandoned their exposures during "quant winter" – an event that was driven in large part to the space's over-reliance on the value factor. While we concede that single- or even dynamic multi-factor quantitative approaches continue to present the possibility for both unintended exposures and underperformance, we are also resolute in our belief that holistic quantitative investing is not only a readily differentiated approach, but also capable of generating uncorrelated alpha within multi-manager equity structures.

It's worth addressing our definition of holistic quant investing. We define it as any investment process relying heavily on quantitative methods to generate alpha and manage risk while simultaneously incorporating some combination of the following: active positioning, idiosyncratic stock risk, fundamental perspectives, forward- and rearward-looking investment signals, multi-style – including core – positioning, and an awareness of the impact of portfolio implementation. For those that would lump all quant approaches into a single bucket, we differentiate holistic quant from many related approaches in **Figure 1** below, including the concept of "smart beta," the challenges of which we will present in detail in Section III of this paper.

FIGURE 1: SPECTRUM OF QUANTITATIVE INVESTMENT STRATEGIES

SPECTRUM OF QUANTITATIVE STRATEGIES		
Beta		Alpha
Systematic/pre-defined rules/Process driven	Holistic long-only and long/short	Opportunistic/objective decisions/adaptable
Alpha via factor selection	Active long-only and long/short	Alpha via factor selection and stock selection
Low tracking error	Trend following CTAs	Higher tracking error
Accepted academic research/long term	Short enabled style premia	Proprietary factors and investment signals (short and long term)
Rearward focused	Multi-factor active timing	Forward and rearward focused
Rules based rebalancing (monthly/quarterly)	Multi-factor "smart beta" strategies	Daily trading/transaction cost efficacy
Narrow and/or static style exposure	Single-factor "smart beta" strategies	Active style weighting and/or core style
Purely model	Alternative weighted indexes (e.g. equal weighted or fundamental)	Potential for human overlay

Source: Mackenzie Global Quantitative Equity Team.

We omit high frequency trading and statistical arbitrage in our analysis because, quite frankly, it is a markedly different subject, driven by complex algorithms, micro-second decisions, execution-speed and multiple additional variables not typical in fundamental quant strategies.

For clarification on some of our arguments below, we also posit that both quantitative and qualitative approaches can be equally fundamental and bottom-up. As such, we suggest that "qualitative" (as opposed to "fundamental") is the more accurate opposite of "quantitative."

We readily concede that quant investing has not advanced to the stage where it can credibly compete with the depth of many qualitative processes, such as meeting face to face with company management, assessing new product innovation, identifying moats and sustainable franchises, evaluating a restructuring, etc. We do not concede, however, that these limitations give qualitative processes an advantage over quant. Rather our view is that both quantitative and qualitative methods inherently possess their own advantages and disadvantages and hence can be utilized to complement one another in an overall manager structure.

The most prominent advantage for quants is breadth of coverage. The public equity investment universe is massive, with over 3,000 US and 5,000 international developed stocks, and over 10,000 emerging markets and frontier securities. Recognizing that data availability differs by region, quants can fully apply their methodologies to the whole universe, whereas qualitative investors can only fully apply their methodologies to a small subset of their chosen universe.

Our belief that breadth is a distinct advantage for quants is supported by Grinold & Kahn's Fundamental Law of Active Management. Their formula suggest that a manager's alpha is determined by their stock selection skill multiplied by the breadth of investment decisions. Quant has long been viewed as a way to get breadth inexpensively. You don't need the massive teams of analysts on the ground or massive budget for plane tickets to cover a broader universe of opportunities.

Grinold & Kahn's Fundamental Law of Active Management

$$IR = IC \times \sqrt{N}$$

Where:

IR = ratio of portfolio returns above the returns of a benchmark to the volatility of those returns

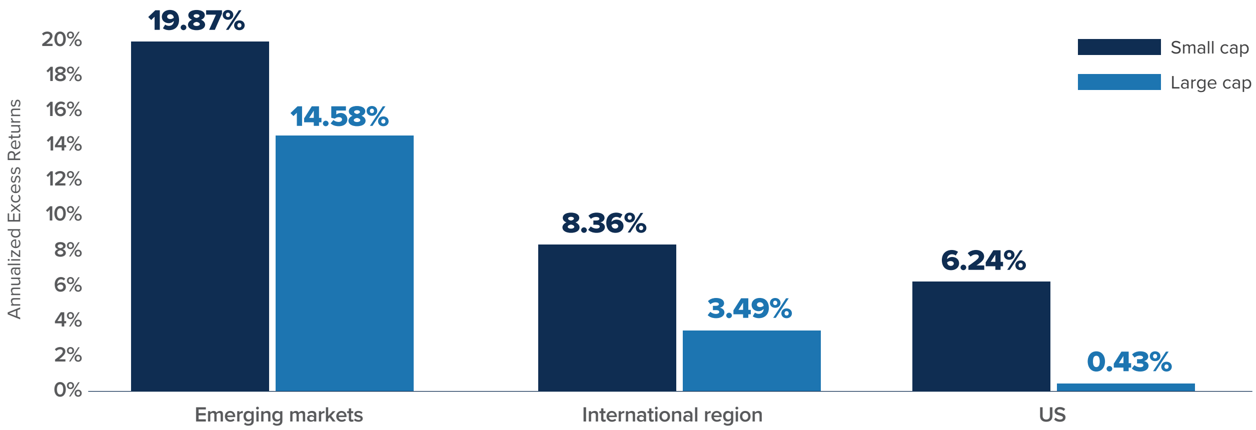
IC = correlation of your return forecasts and outcomes

$\sqrt{N}$ = breadth or the number of independent "bets" taken per unit of time

Source: Richard C. Grinold and Ronald N. Kahn, Active Portfolio Management, November 1999.

We further argue that quants have an advantage in less-efficient market segments such as small cap or emerging markets, where the spread of model returns amongst universe constituents is wider as exhibited in **Figure 2.** Our basic rationale is that a quant's ability to evaluate the entire breadth of a universe also enables them to evaluate a significantly larger range of outcomes.

FIGURE 2: QUANTITATIVE ALPHA EFFICACY SEPTEMBER 2002 - DECEMBER 2023



Bloomberg. Represents inter-quintile return spreads using 50/50 blend of Value and Momentum from September 2002 – December 2023. Source: Mackenzie Global Quantitative Equity boutique proprietary research

Other commonly accepted attributes of quantitative investing would include being:

- More conducive to controlling risk relative to a benchmark.
- More consistent to the extent that their models systematically apply the same methods.
- Less susceptible to human bias and errors in judgement.
- Faster and better at implementation than traditional qualitative analysis.

What is new is the recent paradigm shift in both the access to massive computational power combined with the rapidly advancing capabilities of AI and machine learning to evaluate larger and non-traditional data sets, enabling quantitative managers to identify new and more forward-looking investment signals that have the potential to generate more consistent and differentiated sources of alpha.

SECTION II

Technological advances in quantitative investing

The origins of quantitative investing as we know it today took place in the 1980s with the formation of several quantitative investment firms, many of which are still thriving today. A unique set of conditions were in place to incubate the fledgling industry. Financial data was available in digital format, with data vendors like Bloomberg, IBES and DAIS providing the earliest data sets. Computing power allowed early firms to do quantitative analysis which was previously incredibly tedious to perform.

The foundational concepts for quantitative investing appeared as early as the 1930s, and the technology driving quantitative investing has evolved significantly. Let's consider the example of portfolio optimization. In 1952, Harry Markowitz published the seminal paper *"Portfolio Selection"* in the Journal of Finance, where he laid the theoretical foundation for mean-variance optimization, which continues to be taught in colleges today. Fast forward to 2024, portfolio optimizers have evolved to use sophisticated non-linear optimization algorithms, allowing them to handle complex objective functions and constraints more effectively. The algorithms themselves have also become more efficient, utilizing a technology called parallel processing that enables unprecedented scalability, allowing managers to optimize much larger portfolios with thousands of securities in their universes.

MODERN QUANTITATIVE INVESTING: 100 YEARS IN THE MAKING

1930s – 1980s

- Graham – value factor
- Markowiz – portfolio selection/ optimization
- Ross – arbitrage pricing theory (APT)
- Sharpe – CAPM
- Black / Scholes / Merton
- Bloomberg / IBES / DAIS
- Introduction of quantitative strategies

1990s

- Fama-French three factor model
- Jegadeesh and Titman – momentum investing
- Richard Sloan – quality investing

2000s

- Popularization of "factor" investing
- "Smart beta"
- Extension strategies

2010s

- Natural language processing (LSTM, Transformer Architecture)
- Alternative data sets
- News and sentiment analysis
- Social media data
- Company linkages
- Deep learning (RNN, CNN, ...)

2020s

- Availability of massive computational power
- Large language models
- Generative AI

We are in a new era of technological advancement and would argue that most innovation in public equity portfolio management is taking place on the quantitative side. The convergence of computing power, novel data sets and new techniques is allowing portfolio managers to investigate and capture investment signals that were previously not available to them. Many of the new techniques are broadly categorized under "machine learning" (ML), a field of artificial intelligence that that enables systems to identify patterns and make predictions from data, and also learn and improve from experience without being explicitly programmed. Below are some brief investment-related definitions for some of these technological advancements.

Novel data sets:
Non-traditional sources of data from which investors can generate investment insights. Examples would include credit card usage data showing the sales of a company, satellite pictures of the number of cars parked in the stores of a retail company which could predict a trend in sales, or social media data that could predict investor sentiment.

Natural language processing (NLP):
The analysis of text data using computers to extract information from such sources as 10Ks, 10Qs and earnings transcripts. In the past, reading and inferring from textual information was off limits for quants which is no longer the case.

Large language models (LLM):
AI-powered language models consisting of billions of parameters are now capable of understanding and generating text written in natural language. They can be used for querying information from a large set of data or analysis of textual inputs.

Generative AI:
Models that are capable of generating new, original content rather than simply analyzing existing data or making predictions. Well known examples are OpenAI's ChatGPT and Google's Gemini.

Cloud computing/GPU computing:
Providers such as Amazon, Microsoft and Google allow quantitative investors to rent computers in their data centers which can be accessed remotely over the internet. This offers access to massive computational power combined with the ability to scale up whenever one needs to perform computationally intensive analysis and scale down when no longer needed. It allows quants to perform in hours tasks that used to take days or longer.

These machine learning technologies all contribute towards the production of investment signals, also referred to as alpha signals. Investment signals produce stock-specific alpha scores that quants use as an input into their investment models to predict future price movements. They are utilized as a component of – or an addition to – traditional academically supported investment factors, such as value, quality and growth.

Utilization of quantitative factors and alpha signals

Quantitative factors and investment signals are quantifiable characteristics or metrics used to assess the attractiveness of investing in a security.

One of the earliest known factors is the value factor, introduced by Benjamin Graham in his book *"Security Analysis"* (1934). Graham introduced into the collective consciousness of investors the idea of using a number associated with a company (e.g., price-to-earnings ratio) to make investment decisions.

In 1992, the Fama-French three factor model was introduced by Eugene Fama and Kenneth French, where they combined size, beta and value in a model used to predict stock returns. The following year, Narasimhan Jegadeesh and Sheridan Titman laid the foundations for momentum investing in a paper titled *"Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency"*.

In the years following, academics and practitioners discovered a plethora of factors, populating what we now call the factor zoo, falling into broad classifications of factors such as value, momentum, growth, quality and technical. Without question quants today still rely heavily on academically supported factors as inputs to their models. But they are increasingly utilizing machine learning and novel-data-set driven investment signals in their models. **Figure 3** compares some common established factors with a few examples of the newer investment signals used today.

FIGURE 3: FACTORS VS. INVESTMENT SIGNALS

Established style "factors" with academic support	Newer innovative "investment signals"
Value, Momentum, Quality, Volatilty	Economic linkage, Legislator trading, News sentiment, Earnings call analysis, Employee sentiment

Source: Mackenzie Global Quantitative Equity Team

The very broad range of newer innovative investment signals being discovered by quants is driving an increasing portion of the alpha within quantitative models and further increases the differentiation between quants. They can also define a quant's competitive edge. When researching new factors and investment signals, we believe good candidates for inclusion must have the following attributes:

- They need to make fundamental and intuitive sense. For example, it might be reasonable to base a US investment signal on congressional stock trades. Conversely, it would not be reasonable to use cheese sales in the Netherlands to predict the future returns of the S&P 500 Index, even if it was highly predictive in the past. Such spurious relationships are unlikely to persist in the future.
- They need to have statistical significance in the predictive models they are part of. If they have no predictive power, then they are not good candidates for addition to a model. Many different metrics to measure statistical significance can be used, including T-statistics and R2 values, although a detailed discussion on this is outside the scope of this paper.

- They should have persistent efficacy over time. If a factor only works in brief periods of time, one should have little confidence that it will be effective in the future. Also, if a factor was only predictive in the distant past, but not in the recent past, it could be an indication that the effectiveness of the factor has been arbitraged away by investors, oftentimes referred to as "crowding."
- They should also have widespread efficacy across different geographies and sectors of the economy. While countries and industries differ in meaningful ways, factors that are predictive in stocks across different segments of the global economy are more likely to capture persistent and real patterns.
- Lastly, new factors should be as uncorrelated to existing factors as possible. Adding highly correlated factors is unlikely to improve the overall predictive power of a model significantly, as it already contained information from highly similar factors. Uncorrelated factors inject fresh and more effective perspectives and novel insights into the model.

The last point explains the continuous and never-ending search for novel sources of data and new investment/alpha signals. With such a proliferation of factors and investment signals, quantitative managers must carefully consider the implications of adding them to their investment models. Techniques to do this have also evolved over time. A crude approach is to equally weight the predictions from multiple factors, and then average them. Another simple but more effective approach is to use a linear regression model, which gives more weight to factors that have proven to be more predictive in the past. Today, practitioners use a variety of factor combination techniques, considering non-linear effects as well as interactions between factors. Portfolio optimizers have evolved to use sophisticated non-linear algorithms allowing them to handle complex objective functions and constraints more effectively. The algorithms themselves have also become more efficient, utilizing parallel processing to allow for unprecedented scalability to optimize much larger portfolios with thousands of securities in their universes.

Although perhaps counterintuitive, all of these rapidly evolving tools, data sets, and investment signals require more human oversight, not less. It is critical that quantitative investors apply their experience and expertise to the entire process to help ensure that their data and model outputs make strong fundamental sense and lead to sound investment decisions.

Indeed, as we continue to push the boundaries, one thing is certain: the pursuit of alpha will continue, perpetuating the relentless search for new sources of insight and opportunity.

SECTION III:

A practitioner's insight on improving quantitative outcomes

As long-term practitioners of quantitative investing, we have learned many lessons through a wide variety of market environments that have led us to a differentiated approach we define as "holistic" quant. We have channeled our decades of investment experience into process improvements that we believe enhance our ability to consistently achieve alpha targets for our clients. These enhancements shape the cornerstone aspects of our investment process, and we are excited to share some of them here.

In preview, we run a core investment process without overemphasizing any single investment style. We allow investment signal expected payoffs to vary based on company characteristics – a concept we call contextualization. We emphasize portfolio construction and implementation just as much as investment signal research. Staying nimble gives great advantage to investors, so we place strict AUM capacity limits on our strategies and rebalance all portfolios daily. We also keep our team size efficient to streamline decision making, and we value productivity enhancements to our investment process over headcount. We evaluate our broker trade execution to reduce transaction costs for our clients. We maintain human oversight of our quantitative process to ensure the output makes intuitive sense, and occasionally we make discretionary overrides when we believe opportunities to improve return outcomes presents themselves. We're always seeking ways to improve our alpha model and portfolio construction to mitigate adverse events and maximize alpha.

While each of the concepts discussed is powerful on its own, we believe our advantage comes from our holistic approach of combining everything into a comprehensive investment process that is managed by a cohesive and nimble team.

Core process

Many quantitative strategies rely primarily on a narrower group of commonly accepted factors that are supported by well documented academic research. The challenge for these strategies has been that all factors, when viewed individually, experience both periods of outperformance and underperformance. We believe that a core process that balances a broader array of factors across growth, value and quality dimensions has the potential to generate greater alpha over multi-year cycles. No investment style outperforms across all market environments. This can be clearly seen in **Figure 4** which uses the emerging markets large cap space as an example. It highlights periods (dark green) when a major investment style like value, growth or quality was in favour versus periods (dark red) when the style was out of favour. Each major investment style exhibits strong long-term performance with low return correlation with other styles. As such, we expect our core investment philosophy to deliver better performance over reasonable investment horizons versus managers emphasizing any one of these major factors.

FIGURE 4: STYLE EFFICACY IN EM OVER TIME

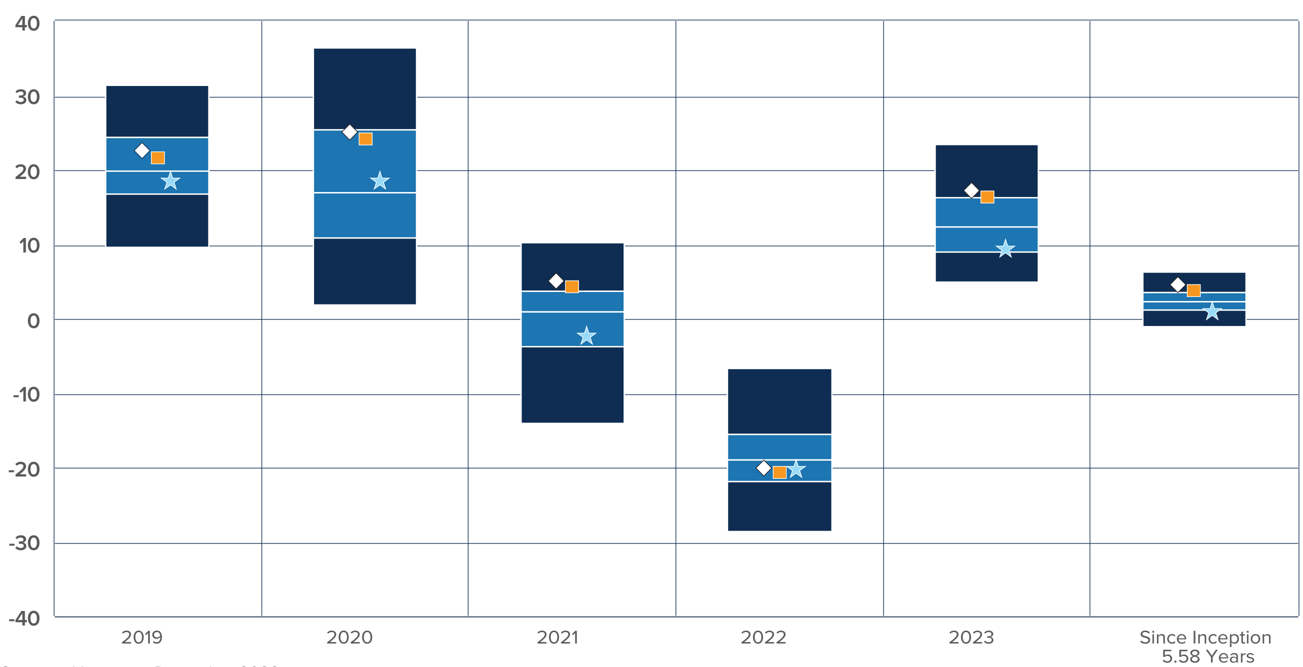
YEAR	VALUE	GROWTH	QUALITY
2000	0.31	0.75	0.64
2001	1.92	0.73	0.44
2002	0.63	0.52	1.20
2003	1.47	0.75	0.50
2004	0.79	0.66	0.62
2005	0.86	1.87	0.08
2006	0.15	0.95	0.30
2007	0.37	1.22	0.14
2008	0.73	-0.67	0.62
2009	1.61	-0.16	0.44
2010	0.49	0.54	0.57
2011	-0.13	0.86	0.86
2012	0.26	0.50	0.12
2013	0.30	1.09	-0.10
2014	0.02	0.65	0.40
2015	0.11	1.15	0.23
2016	1.17	0.00	0.88
2017	0.54	1.45	0.87
2018	0.53	-0.05	0.62
2019	-0.38	0.68	0.15
2020	-0.59	1.68	-0.14
2021	0.39	0.74	-0.11
2022	0.87	0.00	-0.08
2023	0.86	-0.04	0.17
FULL PERIOD	**0.55**	**0.66**	**0.39**
LAST 10 YEARS	**0.35**	**0.63**	**0.30**

Source: Mackenzie Global Quantitative Equity Team

We utilize a core approach with a goal of increasing consistency of investment performance and generating better investment outcomes for our clients. Many quant managers operate with too high of an exposure to traditional value factors such as price-to-sales or price-to-book – what Aswath Damodaran from Stern School of Business termed "lazy value investing". This is often the result of misspecification of expected return models (what we refer to as our "alpha model"). Most investors understand that cheap stocks may be cheap for a reason. As an example, a company expected to grow at 5% will normally trade at lower multiple than one that is expected to grow at 20%. Surprisingly, many quantitative managers struggle to properly account for growth differentials. Good-quality growth forecasts are not readily available, and growth as a factor tends to have weak power historically. We devoted considerable thought and research to make our process core-like by constructing proxies to help predict value-trap situations and tilting our portfolios away from them. Doing so reduces overall value exposure in a quantitative process while retaining a healthy dose of valuation awareness and a tilt towards "real" value opportunities.

As an example, consider the performance of our Emerging Markets Large Cap strategy since its inception in June 2018 through end of 2023 in **Figure 5.** This period has seen major macro-events and associated market volatility, leading to inconsistent performance of common investment styles such as value growth, or quality individually. Yet our Emerging Markets Large Cap strategy outperformed the MSCI EM Index in four out of the five years (only losing by 2 bps in the one year) as well as since inception. Our core-style played a key role in this success.

FIGURE 5: MACKENZIE EM LARGE CAP VS. EVESTMENT GLOBAL EM LARGE CAP UNIVERSE & MSCI EM INDEX



Source: eVestment, December 2023

Universe: eVestment Global Emerging Mkts Large Cap Equity (Percentile)

	2019		2020		2021		2022		2023		5 years		Since inception 5.58 years	
		Rk		Rk		Rk		Rk		Rk		Rk		Rk
Mackenzie Emerging Markets Large Cap Gross	22.57	33	25.07	26	5.05	17	-20.11	59	17.21	19	8.56	9	4.54	12
Mackenzie Emerging Markets Large Cap - Net	21.60	35	24.13	23	4.26	20	-20.71	63	16.33	20	7.74	10	3.75	11
MSCI EM-ND	18.44	64	18.31	44	-2.54	67	-20.09	58	9.83	68	3.69	87	0.90	78

Results displayed in USD. Rk - performance vs. the eVestment Global Emerging Markets Large Cap Equity Universe (percentile).

Contextualization

Contextualization is the process by which we ensure we are ranking stocks on metrics that are most relevant to the underlying characteristics of each. We find that firm characteristics do impact investment signal efficacy. For example, one can reasonably expect valuation measures to be less effective in fast growing businesses or expect price momentum to be more effective in stocks with relatively low liquidity. We systematically test and incorporate such ideas into our alpha model to further increase the predictive power of our forecasts of stock returns. Examples of contextual variables include liquidity, volatility, size and growth.

Portfolio construction and implementation

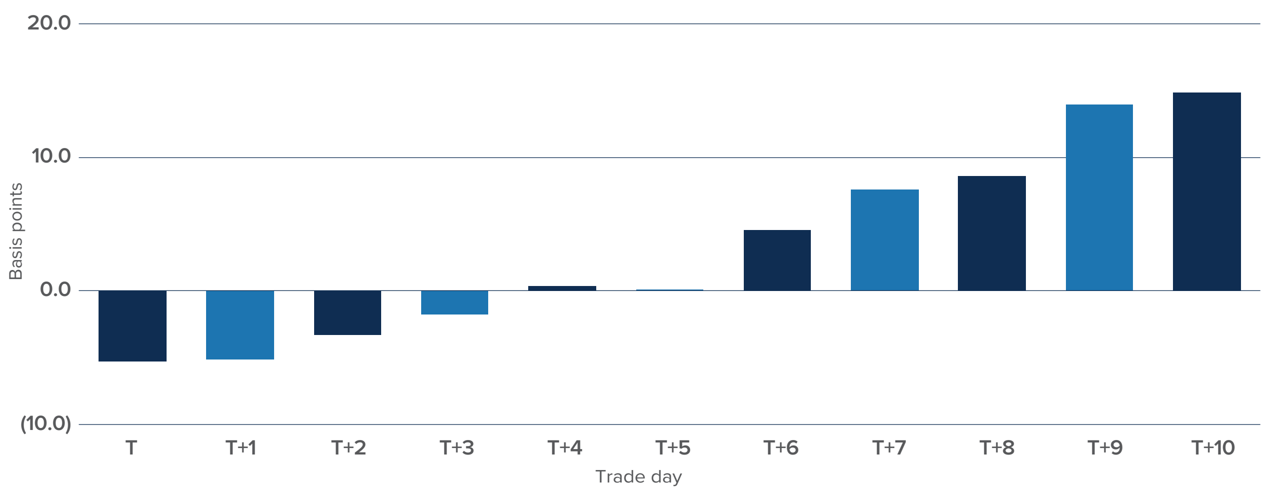
We emphasize portfolio construction and implementation as much as investment signal research. We ensure that everyone on the team deeply understands our alpha model, portfolio construction rules and implementation process. The entire team discusses all aspects of the investment process at our daily morning meetings and regular portfolio positioning reviews. By having one team manage the full investment cycle, from alpha research to portfolio construction to real world implementation, we believe we are well positioned to recommend, evaluate and effectively implement improvements to the investment process.

Continuous portfolio construction research is crucial to our investment success. Decisions on sizing stock positions, constraining known risk factors, managing industry and country exposures, monitoring turnover and targeting levels of active risk all flow from our portfolio construction research. We focus heavily on the days of liquidity that a stock position should have, the transaction cost of each proposed trade and the costs to borrow a security in our short book. We test the sensitivity of portfolio performance to changes in key portfolio construction parameters. We incorporate expected transaction cost models into our process. We utilize custom risk models to monitor the risks attributable to proprietary investment signals that we deploy globally. All of these practices enable us to run realistic historical portfolio simulations using daily rebalancing that are aware of expected transaction costs, predicted risk levels, borrow costs, etc.

Importantly, portfolio construction aligns our portfolios with the alpha model to best capture our investment insights in the live process, which is subject to real world constraints, like transaction costs, limited stock liquidity or controlling risk against a top-heavy benchmark like the S&P 500 Index. For example, it makes no sense to limit annual portfolio turnover to 100% if the alpha model consists entirely of technical signals that have natural turnover rate of 100% per month. Similarly, it makes no sense to have identical position sizing for two regions with vastly different alpha model efficacy, like Emerging Markets versus US Large Cap. As our team manages all aspects of the investment process, we are well positioned to focus on the relevant portfolio construction rules and to properly evaluate their impact on expected portfolio performance.

Implementation is critical to the success of an investment process. At its core, implementation entails taking the alpha model and portfolio construction rules and applying them live. Poor implementation can destroy any advantages afforded by best-in-class alpha and portfolio construction research. We appreciate the importance of air-tight implementation and have invested heavily in the infrastructure to support daily rebalancing of every portfolio, twice daily for global strategies, giving us an advantage over competitors who rebalance weekly or even monthly. Those choosing not to rebalance daily are usually constrained by either sub-par infrastructure or excessive assets under management which necessitates rebalancing groups of portfolios on different days. As **Figure 6** demonstrates, significant excess returns accrue over the first several days following execution of our trades. Rebalancing weekly or monthly would miss out on much of this alpha opportunity.

FIGURE 6: SHORT-TERM PERFORMANCE OF INVESTMENT TRADES



Source: Mackenzie Investments

Performance in bps vs. benchmark for 5/31/2018 - 12/31/2023. Represents all strategies managed by Mackenzie's Global Quantitative Equity team. The information provided is for illustrative purposes only

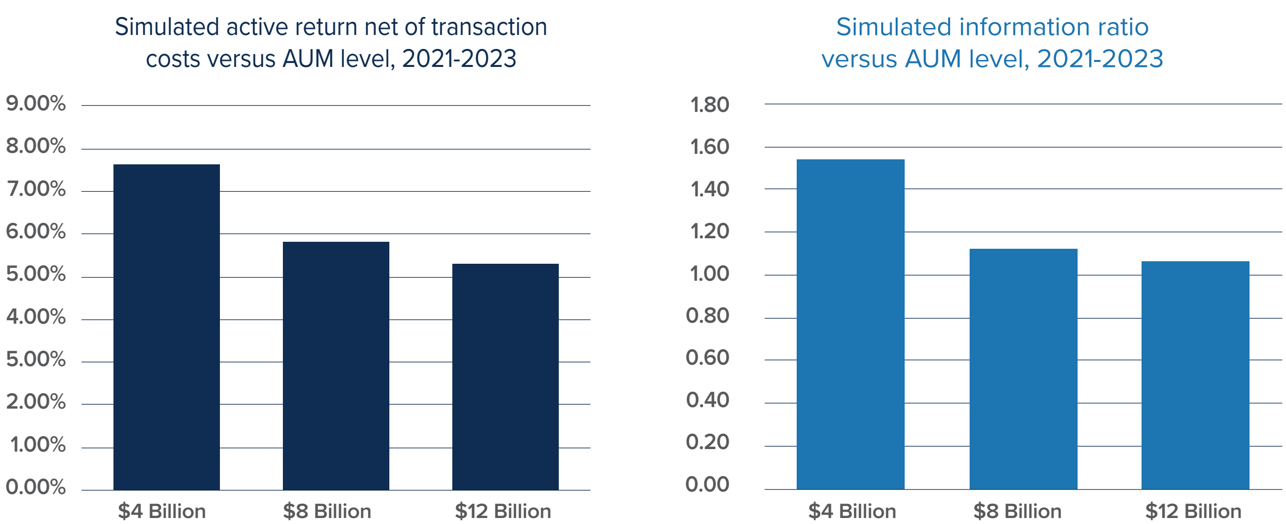
	Trade #	MktVal USD	Price vs close (bps)	Price vs close+1 (bps)	Price vs close+2 (bps)	Price vs close+3 (bps)	Price vs close+4 (bps)	Price vs close+5 (bps)	Price vs close+6 (bps)	Price vs close+7 (bps)	Price vs close+8 (bps)	Price vs close+9 (bps)	Price vs close+10 (bps)
Buy	160,700	$21,121,710,660	(5.7)	(4.9)	(2.5)	(1.6)	0.5	(0.2)	4.0	7.0	8.6	14.2	14.7
Short	13,020	$789,540,441	6.5	(10.6)	(23.1)	(7.3)	(3.7)	6.7	17.9	21.4	8.3	5.5	17.7
Buy+Short	**173,720**	**$21,911,251,100**	**(5.3)**	**(5.1)**	**(3.2)**	**(1.8)**	**0.4**	**0.1**	**4.5**	**7.5**	**8.6**	**13.9**	**14.8**

To further preserve alpha generation potential, we monitor and quantify our trading experiences with brokers. Any issues we identify are discussed with the offending broker and their trade flow is reduced. If execution slippage continues, we stop trading with that broker altogether. For example, based on such post-trade analysis, we stopped routing trades to Credit Suisse well before that firm failed.

Nimble approach

AUM:
For all our strategies, including our less liquid strategies such as small cap and emerging markets, we have committed to strict AUM capacity limits so we can stay nimble in our investments and decision-making process. We believe there is a direct correlation between excessive asset growth and alpha erosion, especially in less liquid markets. Excessive strategy assets in these markets can lead to the inability to establish optimal position weightings and can simultaneously adversely impact stock price. Strategies with excessive AUM can cause a manager to 1) invest in larger and larger percentages of a stock's daily volume, 2) spread trades over more days to avoid impacting stock price, 3) realize worse transaction prices, 4) lower desired position sizes, 5) reallocate capital to less attractive investment opportunities, and 6) down-weight higher turnover signals. As an example, **Figure 7** below shows how our simulations provide an indicative impact of AUM growth on active return and information ratio.

FIGURE 7: GROWTH OF AUM IMPACT ON RETURN AND IR



Simulated active net return and simulated information ratio for global small cap equity strategy for period 12/31/2020 through 12/31/2023. Source: Mackenzie Global Quantitative Equity team. For illustrative purposes only.

In keeping with our objective of delivering consistent alpha, we maintain strict capacity limits to ensure liquidity constraints do not adversely impact our investment process. For small cap equity strategies across all geographies globally, we have committed to a cap of $4 billion USD.

Team:
Although our investment staff will continue to grow commensurate with our asset growth, we not only prize a smaller team size, but also philosophically believe that larger teams can be counterproductive. Keeping our team nimble enables us to focus on the highest value-added projects and increases the efficiency of our decision-making and ability to deploy new alpha signals or modify risk constraints quickly. We believe team cohesion and culture is vital to producing exceptional results. At our daily morning meetings, our entire team discusses all aspects of our investment process and makes all decisions in this setting. This ensures uniform understanding of our process which in turn improves productivity and job satisfaction.

Quantitative strategies amongst investment managers are not homogeneous. Investment signal definitions vary widely. Philosophies on factor efficacy are extensively debated. The sophistication and efficacy of underlying models, portfolio construction and implementation span a broad spectrum. Successful quants ceaselessly research for new signals, better models, more informative data sets and more innovative applications of rapidly evolving technologies.

In summary, our "holistic" approach to quantitative investing incorporates each of the following attributes in an attempt to produce stronger and more consistent outcomes for our clients:

- Core style.
- Contextualization.
- Equal emphasis on factor/signal research, portfolio construction and implementation.
- AUM capacity limits in all strategies.
- Deliberately nimble team structure.
- Acute transaction cost awareness.
- Intuitive human oversight of all research and implementation processes.

Conclusion

Quantitative approaches to public equity investing continue to introduce new sources of alpha and are now – in select areas – generating research insights in areas formerly reserved for qualitative fundamental analysis. Quantitative methodologies have been augmented very recently with expanded access to exponentially more powerful computing as well as the rapid evolution of tools such as machine-learning and natural language processing. These advances have enabled increased analysis of non-traditional data sets that have the potential to provide valuable investment insights and a competitive edge amongst active investors. We believe adopting a more "holistic" approach to quantitative investing can enhance the opportunity for more consistent alpha across a wider array of market environments.

References

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance, 7(1),* 77-91.

Bengio, Y., Ducharme, R., Vincent, P., & Janvin, C. (2003). A Neural Probabilistic Language Model. *The Journal of Machine Learning Research, 3,* 1137–1155.

Graham, Benjamin, and David Dodd. "Security Analysis: Principles and Techniques." *McGraw-Hill*, 1934

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance, 47(2),* 427–465

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance, 48(1),* 65–91

Value Investing 1: The Back Story, Aswath Damodaran, October 23, 2020

MSCI Emerging Markets Index
The MSCI Emerging Markets Index is a free float adjusted, market capitalization weighted index that is designed to measure the large and mid cap equity market performance of emerging markets. It consists of 24 emerging market countries.

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