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QUANTS' QUANDARY

Crossing the Chasm

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INVESTMENTS & WEALTH INSTITUTE®
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ABSTRACT

Contrary to the mainstream media's portrayal that adoption of quantitative fund investing is widespread, only a small portion of individual and institutional dollars has been allocated to quantitative strategists. The amount of quant-managed fund allocations and the general potential benefits and drawbacks of quantitative investment are described. Results of a survey of more than forty financial advisors and analysts concerning their recommendations on quantitative investment are shared. Everett M. Rogers' *Diffusion of Innovations* (1995) model is applied to explain the slow diffusion of quantitative investment. Additional models of innovation resistance are also discussed in order to understand reluctance and resistance to investment in quantitative strategies. Included is management consultant Geoffrey A. Moore's *Crossing the Chasm* (2013) model to illustrate where quantitative investment currently lies on the "Adopter Categorization" S-curve. Practical recommendations for due diligence are included along with suggestions for promotion of quantitative investing where appropriate for suitable investors.

INTRODUCTION

In a 2017 global hedge fund survey, Preqin, an alternative investment industry researcher and publisher, stated there were approximately 3,600 quantitative investment strategists that managed $1.1 trillion in hedge fund assets.[1] A Morgan Stanley Quant Research note estimates that $2.1 trillion was invested in quantitative hedge funds, quant-managed mutual funds, and smart beta exchange-traded funds (ETFs) as of June 30, 2019.

Morgan Stanley Research tallied $821 billion in quantitative mutual funds, $478 billion in quantitative hedge fund assets, and $857 billion in smart beta ETFs.[2] Recently, Morgan Stanley aligned its smart beta ETF figure with Morningstar's calculation.[3]

In May 2017, a *Wall Street Journal* (*WSJ*) headline blared, "The Quants Run Wall Street Now." This *WSJ* headline was preceded by *Forbes* magazine trumpeting, "The Quants Are Taking Over Wall Street" in August 2016 (Zuckerman and Hope 2017; Vardi 2016).

To put $2.1 trillion in assets under management (AUM) into context, as of this writing (November 25, 2019), the U.S. capital markets are valued at roughly $75.7 trillion. The Investment Company Institute, the mutual fund industry trade and research group, estimated that, in the second quarter of 2019, there were $51.43 trillion in worldwide regulated open-fund assets.[4] McKinsey & Company released an estimate of global AUM in November 2018 and updated this figure in November 2019. McKinsey placed the size of global investment assets at $89.8 trillion as of December 2018.[5] So quantitative investment strategies command 2.25 percent of global investment assets—hardly a quantitative (quant) takeover of Wall Street and global capital markets as alleged by mainstream media conglomerates.

Here is the quants' quandary. Although mainstream media, and even (informed) financial trade press, have declared that quants are taking over Wall Street, the facts show otherwise. These hyper claims are reminiscent of "Gartner's Hype Cycle," which highlights overhyped ideas and technologies then projects when (and if) these trends will reach maturity (Panetta 2018). On the Hype Cycle, there's a trigger—in this case the birth of quant investing—that provides visibility into an innovation. This trigger leads to a "peak of inflated expectations" that is followed by a "trough of disillusionment." Quant pioneers and enthusiasts are still stuck in a decades-long trough where quantitative investing has yet to cross the chasm that separates innovators from the mainstream market of institutional and individual investors.

Compare quantitative investing's adoption to the $5.5-trillion ETF industry.[6] ETFs were born in Canada in 1990. The first exchange-traded product—the Toronto 35 Index Participation units (TIPs)—was listed on the Toronto Stock Exchange in March 1990.[7] In January 1993, the American Stock Exchange and State Street Global launched the Standard & Poor's Depositary Receipts—SPDR (symbol SPY)[8] and ETFs were raised in the United States.

An adolescent industry—smart beta funds—is only a dozen or so years old. (INVESCO launched the FTSE RAFI US 1500 on September 20, 2006.)[9] Yet in December 2017, smart beta fund assets crossed the $1-trillion mark, in only one-fifth of the time it took quantitative funds to reach the $1-trillion AUM milestone (Thompson 2017).[10]

On a related note, FTSE Russell surveyed institutional investors' use of smart beta (factor) funds. For the first time in the survey's history (since 2014), a majority of institutional investors (58 percent) stated that they'd made allocations to smart beta strategies (Whyte 2019). Investors who were re-evaluating allocating to smart beta after previously deciding against it said they were motivated primarily by their increased understanding of the strategy because of new information and education.

Here's the bottom line: Given the size of the U.S. and global capital markets, ETFs' widespread diffusion, and rapid adoption of smart beta funds, why isn't the quantitative investment fund share much bigger than it is? Why are advisors and analysts hesitant to recommend, and investors reluctant to invest in, quant strategies?[11]

THE SURVEY SAYS ...

From October 2017 through May 2019, Little Harbor Advisors, LLC, conducted ad-hoc surveys into the number of financial advisors and analysts who have made client allocations to quantitative investment strategies and funds (funds of all types, hedge funds, mutual funds, separately managed accounts, and ETFs). Maybe we shouldn't have been, but we were genuinely surprised to find that in forty-five Financial Planning Association, CFA Institute, and CAIA Association meetings (total audience approximately 2,100), a small percentage of advisors had made recommendations or client allocations to quantitative funds. Only a mere handful of the Certified Financial Planner®, Chartered Financial Analyst®, and Chartered Alternative Investment Analyst® attendees raised their hands in response to the question, "Have you made an allocation to a quantitative investment fund?"

We're not suggesting our advisor or analyst sampling of quantitative investment use meets a rigorous standard of a scientifically valid survey protocol. But our expectation was that easily 10 percent to 15 percent of these credentialed financial professionals would have conducted due diligence on quant strategies and already have made allocations to client portfolios. Why the resistance or reluctance when it comes to adopting quantitative investment strategies?

QUANT FUND REFRESHER

Before attempting to answer questions on resistance and reluctance to adopt quantitative investment strategies into client portfolios, a quick primer of generic quant funds' potential benefits follows:

THE LAW OF LARGE NUMBERS

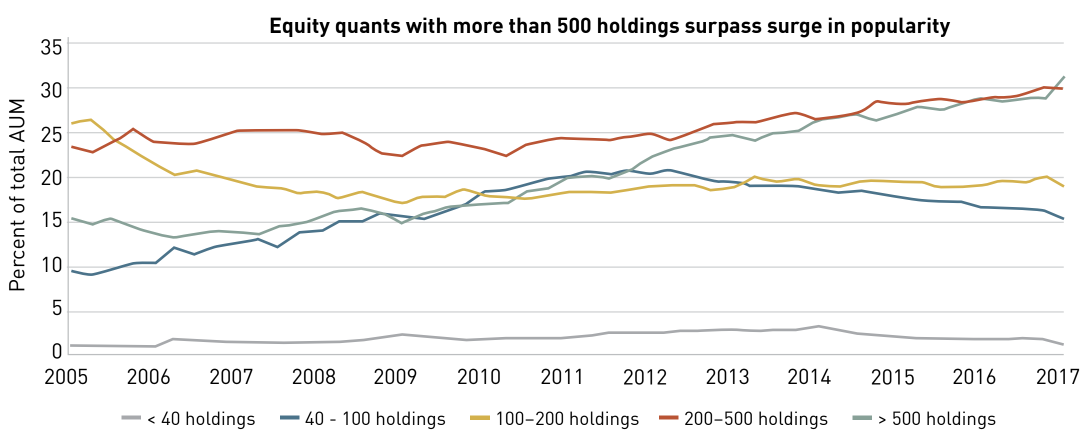
Quantitative investment strategists use automated systems to evaluate a wide swath of securities and potentially benefit from a wider opportunity set. According to Sanford Bernstein Research, a plurality of equity quant managers held at least 500 securities (see figure 1) (Burger 2017). In its most recent Securities and Exchange Commission (SEC) 13F and 13D filings, Renaissance Technologies disclosed that it had 3,415 total holdings including short positions and derivatives.[12] Quantitative Investment Management, a Virginia-based quant hedge fund, disclosed that its program had "over 1,500 active positions at any point in time and expects to make over 1,500 trades per day."[13] In 2009, Tradebot Systems, a Kansas City-based high-frequency trader/quant shop, had its first billion-share trading day.[14] Tradebot Systems states that it trades more than 5,000 companies every month.

In contrast, a recent academic survey of 4,223 distinct mutual fund portfolios found that the median number of holdings in equity funds was seventy-five positions (Brown et al. 2017, 17).

On average, quant strategies have six times more holdings than discretionary or fundamental funds.

Figure 1

WANT INFLOWS? TRY DIVERSIFICATION



Source: eVestment, Sanford Bernstein analysis

Of course, not all quant managers' trades will generate profits. However, due to the high number of portfolio positions, a winning/losing trade ratio of 51/49 may be enough to offer a reasonable likelihood of generating a positive return at the portfolio level.

MORE DIVERSIFIED

It goes without saying that quant funds are more diversified than qualitative or discretionary managers, acknowledging, of course, that in order to achieve genuine diversification, quant strategists need be mindful of the correlations among securities held. A critical component of a quant-model optimizer is its correlation matrix and recognizing that correlations are dynamic. Correlations vary around a long-term central tendency—they're conditional and depend on market states or regime changes (Wade 2009; Waring and Siegel 2016; Preis et al. 2012). Quant fund portfolios tend to be better diversified across individual securities and by sector, country, and currency exposures.[15]

BET-SIZING

Generally speaking, quant strategists are more adept at position-sizing and placing diversified bets than (most) discretionary managers. Full-fledged quantitative strategists use a variety of models, including alpha-seeking, position-sizing, risk-management, and transaction-cost models. The model that predicts the side of the bet (long or short) should be different from the model that determines the size of the bet (Brown 2012; de Prado 2018).

MITIGATE HUMAN ERROR AND COGNITIVE BIAS

Financial analysts, advisors, and portfolio managers—just as all highly evolved humans—are prone to bias. Numerous primitive, unconscious biases and cognitive limitations affect and afflict investor decision-making. Several examples (that won't be explored in-depth in this paper) are confirmation bias, anchoring, loss-aversion, and familiarity bias. Investment algorithms address human weaknesses in speed, attention, fatigue, and biases. Quant models may help minimize human errors (notice we did not say eliminate because of potential bugs and model biases).

A key differentiator of quant strategists is the computational advantage that a disciplined approach has in systematically making predictions on entry and exit points in securities transactions. Quantitative models are superior to discretionary managers when cutting short losses and realizing gains (Agrawal et al. 2018, 53–69). Chincarini (2010) investigated the market timing skill of quantitative versus qualitative strategists. Chincarini found that "quant funds exhibit a positive timing coefficient" and that "... qual funds, on the other hand, have negative and significant timing coefficients."

Over the 39.5-year period examined, Chincarini (2010) documented that quantitative hedge funds achieved higher returns and lower standard deviation than qualitative funds, as well as higher Sharpe and Sortino ratios. Quantitative and qualitative hedge funds performed similarly in up markets, but quantitative funds did significantly better in down markets. During the Global Financial Crisis (GFC, January 2007–June 2009), quantitative hedge funds outperformed their qualitative counterparts by 50 basis points (Chincarini 2010, 9).

EXPOSURE MANAGEMENT

Financial markets invite quantification. Returns, risk factors, and correlations lend themselves to numerical measurement. When it comes to modulating or mitigating exposures, quantitative algorithms work faster than humans and are more consistent.

It's worth noting that, although correlations are time-varying, the systematic global macro quant strategy was genuinely defensive in that its correlation to MSCI ACWI declined during the 2007–2009 GFC.

LOW OR NEGATIVE CORRELATION TO TRADITIONAL ASSET CLASSES

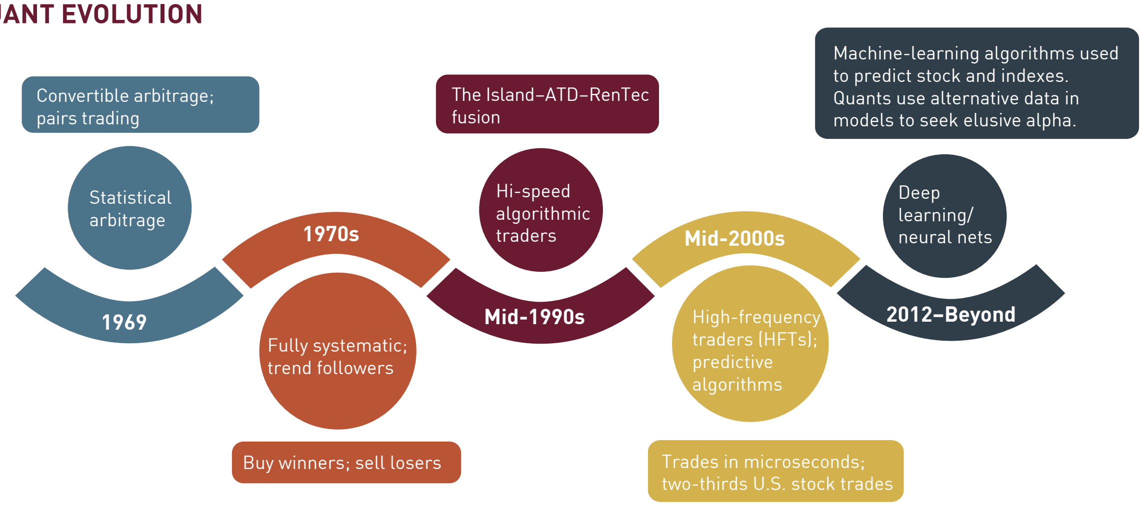
Historical correlations between active returns of quantitative and qualitative investment managers are low, which suggests the potential for investors to benefit by incorporating both approaches in portfolio allocations. Chincarini (2010) also examined the correlations of quantitative and qualitative hedge funds. During January 1970–June 2009, the correlations of these hedge fund types were quite low at 0.27 and 0.25 for quantitative and qualitative, respectively.

Select quant funds, specifically "systematic global macro," have very low correlations to equities and bonds. During January 2001–June 2017, systematic global macro funds' monthly returns had -0.13 correlation to the S&P 500, -0.06 correlation to the MSCI All Country World Index (ACWI), and 0.25 correlation to Barclays Aggregate Bond index.

It's worth noting that, although correlations are time-varying, the systematic global macro quant strategy was genuinely defensive in that its correlation to MSCI ACWI declined during the 2007–2009 GFC (Obregon and Dana 2017, 7, 12). In addition, historical correlations among quants are also low—dispelling the notion that "all quants trade the same signals."[16]

Figure 2

QUANT EVOLUTION



QUANT FUNDS ARE SOLD, NOT BOUGHT

The first quantitative hedge fund was launched by Edward O. Thorp, a PhD math whiz, blackjack card counter, and college professor. In 1969, he co-founded Convertible Hedge Associates, later named Princeton Newport Partners, the first market-neutral hedge fund (Thorp 2017, appendix D). There is a half-century of quantitative investment fund experience (see figure 2).

Ed Thorp has been called "The Godfather of Quants," but quantitative equity investing stands on the shoulders of major theoretical and empirical contributors who laid the groundwork decades or years before Thorp's quant fund launch (Patterson 2010; Maxfield 2017).

- Ben Graham, value investing pioneer, was an early (but non-computer using) quant.[17]
- Alfred Winslow Jones, inventor of the modern-day hedge fund in 1949, was a quant (Loomis 1966).
- Nobel Memorial Prize in Economic Sciences winner Harry Markowitz, PhD, author of "Portfolio Selection" (1952), who has been called "The Father of Quantitative Analysis," is a quant (Narang 2013, 88).
- Another Nobel Memorial Prize in Economic Sciences recipient, William (Bill) Sharpe, who authored "Capital Asset Prices" (Sharpe 1964), is a quant.

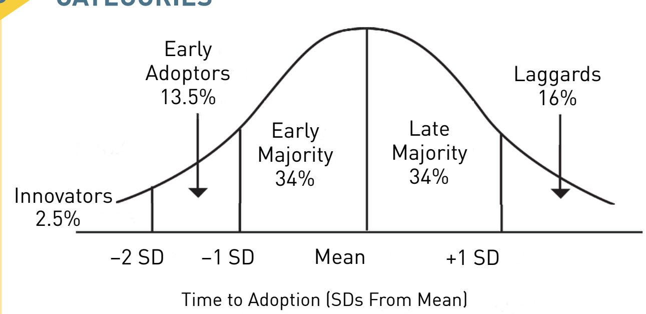
Yet a distinct minority—relatively speaking, a handful—of analysts, advisors, and consultants have recommended quant strategies to their institutional or high-net-worth retail clients. There's enormous room for growth of the quant fund share of investor wallets and portfolios.

For seventy-five years, American anthropologists have exhaustively investigated consumers' likelihood to adopt or reject innovative products and services (Rogers 1995, 40–45). Readers of this article likely are familiar with the late Everett "Ev" M. Rogers' *Diffusion of Innovations* and his "Adoption Categorization on the Basis of Innovativeness" (Rogers 1995, 261–266). This is where Rogers' Bell Curve of five adopter categories from innovators to laggards was first displayed (see figure 3). Rogers classified his five consumer segments using standard deviations in a normal distribution of which his innovators/early adopters and laggards' categories each made up 16 percent. (Note: The "innovator" cohort was only 2.5 percent of the total 16 percent.) Rogers' early majority and late majority categories weighed in at 34 percent each. Below, we'll zero in on the flip side of innovators/early adopters by examining the laggards and non-adopters of quantitative investing.

Different or alternative investment strategies represent change to investors, and resistance or reluctance to change are normal investor responses. Rather than focus on why consumers adopt products or services, we might actually learn more by understanding the underlying reasons for innovation resistance (see figure 4). Social scientists have identified several functional and psychological barriers that result in consumer resistance or reluctance (Laukkanen et al. 2007, 420–421). Functional adoption barriers include usage, perceived value of the innovation,

Figure 3

ROGERS' BELL CURVE OF FIVE ADOPTER CATEGORIES



Source: Rogers (1995, 262)

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and perceived risk of trying a new product or service. The psychological barriers include the habit (tradition) of an existing practice or product usage, the image barrier (for example, it's harder or more complicated for mature consumers to use certain electronic devices), and the information (actually lack of information) barrier (Laukkanen et al. 2007).

Of the major barriers to the diffusion of innovations and adoption among a majority of consumers, three are the most relevant when it comes to quant investing: (1) value, (2) risk, and (3) information. Two of these—value and risk—are functional obstacles. The third barrier—information—is in a class of its own.

Value barrier. The value barrier is based on the purported monetary advantage of the new product. In the case of quant investors, does the substitute offering or new fund offer better performance-to-price compared to alternative investment options or funds? If it doesn't, why bother switching investment strategies? Researchers have found that an important reason most product launches are failures is due to the lack of acceptance by pragmatists who believe the cost of learning about an innovation outweighs the potential benefits it offers.

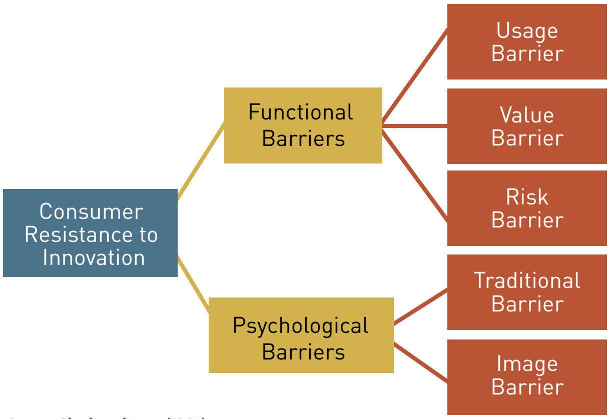
Risk barrier. The risk barrier is the degree of uncertainty that accompanies any new investment choice. It's not the riskiness of the strategy itself (i.e., standard deviation or drawdown risk) but rather the consumer's perception of the characteristics of an untried service or product. A consumer (in our case, institutional or affluent investors) may feel that an investment strategy hasn't been tested fully, may malfunction, or may perform poorly. Because uncertainty is associated with innovations, potential side effects or unintended consequences may be associated with adopting a "new and improved" idea.

Information barrier. Certain technologies (or advanced investment strategies) require a substantial learning effort plus a willingness to acquire, analyze, and process data. A limited amount of relevant information (due diligence) or worse still—misinformation—impedes diffusion of an innovation or adoption of a superior service or product. In our opinion, the information barrier is the greatest obstacle to overcome when it comes to a widespread use of quantitative investment. Financial analysts and advisors fill a critical role as the conduits for accurate, current, and continuing education for their investor clientele.

Some observers question whether standard models of consumer behavior apply equally to institutional investors and their investment consultants. Others believe that institutional investors and consultants share the same consumer resistance and reluctance barriers outlined here. Investment committees and consultants' decision-making processes are hampered and hamstrung by similar functional barriers and identical psychological barriers.

Figure 4

CONSUMER RESISTANCE TO INNOVATIONS



Source: Sheth and Ram (1987)

Some academics have called into question the value of investment consultants altogether. Jenkinson et al. (2016) found "no evidence that these [investment consultants'] recommendations add value …"[18] The authors contend, "Investment consultants have largely avoided the attentions of academics, reflecting the fact that consultants have disclosed too little data to allow rigorous analysis of their activities" (Jenkinson et al. 2016, 2). They used thirteen years of Greenwich Associates' survey data of consultants' recommendations of institutional funds. (Greenwich Associates is a leading global provider of data and analytics to the financial services firms.) Jenkinson et al. (2016, 2) concludes that "… why consultants' recommendations fail to add value, we find a tendency of consultants to recommend large funds, which perform worse."

Innovation resistance typically is triggered either because the innovation proposes change from a satisfactory status quo or because it conflicts with a belief system (habit). Given investor dissatisfaction with many actively managed investment funds' performance (active managers' inability to outperform their benchmarks), you would think that investors would seek alternatives actively.

Although passive investing certainly lowers cost, it leaves investors highly vulnerable to market turbulence and severe drawdowns (e.g., the October 2007–March 2009 S&P 500 peak to trough decline was 56.8 percent[19]). Satisfaction with the status quo doesn't appear to be the cause for investor resistance or indifference to quant fund investing. How do these functional and psychological barriers manifest themselves when it comes to quant fund investing?

DO THE MATH: VALUE BARRIER

The value barrier goes to the heart of whether investors, and the advisors and consultants who work with them, are convinced that quantitative funds are an economically worthwhile and pragmatic substitute for discretionary or fundamental investment management.

When considering investor resistance to quantitative investing—as opposed to consumer resistance and reluctance to product or service adoption—the value barrier may be even higher because of fees. Roughly 60 percent of quant-managed assets reside in hedge fund vehicles. Fees of quant hedge funds have been similar to fees of qualitative hedge funds. The aforementioned "Comparison of Quantitative and Qualitative Hedge Funds" documented that qualitative hedge funds charged management fees that were ten basis points (bps) higher than quantitative hedge funds. The performance fees were roughly the same for both quantitative and qualitative hedge funds (Chincarini 2010).

More recently, Abis (2017) used machine-learning techniques to classify active U.S. equity funds as "quantitative" (using computer-driven models and fixed rules) versus "discretionary" (relying mostly on human judgment). Of the 599 quantitative funds and 1,851 discretionary strategies, Abis found that quantitative funds charge 10-percent lower expense ratios and 9-percent lower management fees. Abis (2017) also found that quantitative funds are younger (13 years versus 14.5 years), smaller ($522 million AUM versus $1.2 billion AUM), and exhibit 10-percent higher turnover than qualitative funds.

Even though fees for all types of funds have been going down, a JP Morgan Chase survey of 227 institutional investors found that only 5 percent of these investors paid a management fee of 2 percent or higher (Flood 2019), and the 2-percent and 20-percent fee structure has almost vanished. Fees matter and may steepen the hurdles required to overcome the value barrier. Lower management fees have been a key driver of the tsunami-like flow of monies into passively managed index funds and ETFs.

STORM THE BARRIERS: RISK BARRIER

Here we consider risk in a different context. For the moment, we don't equate the risk barrier with variance or standard deviation, or the Sharpe or Sortino ratios. In the context of innovation adoption, risk is the perceived risk of trying or buying a new product or service rather than a characteristic of the product itself. It's the fear of the unknown that sparks resistance or reluctance to adoption intention, resulting in the wait-and-see attitude of laggards.

One of the proven ways to overcome the risk barrier when selling new products and services is to use client endorsements or testimonials. When it comes to investing, that avenue is absolutely closed to investment professionals. Section 206(4) of the Investment Advisers Act of 1940 generally prohibits any investment advisor from engaging in any act or practice that the SEC defines as fraudulent, deceptive, or manipulative. In particular, Rule 206(4)-1(a)(1) specifically prohibits "publishing or distributing any advertisement, directly or indirectly, to any testimonial of any kind concerning the investment advisers or any advice, analysis or report or other service rendered by the adviser."[20]

Another obvious way to overcome resistance to adoption is to offer free samples (not an option in our domain) or product trials. A single-digit percentage allocation to a quant fund is one way of acclimating investors to the different traits of quant strategists. Of course, a small slice of quant allocation isn't going to move the portfolio dial. But a small quant allocation isn't made in a vacuum, it's an incremental and additive process. Simple correlation matrixes are available that allow investors to quickly visualize the interaction between various asset managers and investment strategies. Many quantitative funds have low (or negative) correlation to the traditional 60/40 mix. So even a modest allocation to a quant fund can improve the portfolio's risk-return profile.

BIGGEST BARRIER: INFORMATION GAP

One universal truth of adoption intention is the lower the communicability of an innovation, such as quantitative investing, the higher the resistance and reluctance to adopt. The biggest myth about quantitative investment is that it's a black box.

Our view is quite the opposite. Quantitative investment is rules-based, systematic, repeatable, and sustainable (while recognizing that models are subject to alpha decay). Relying on automated trade signals from computer models has the effect of removing human emotion and can mitigate or minimize behavioral biases from the trading process. Discretionary traders can try to justify a gut decision with a story that uses a number of variables to explain why they made the trade (usually with the benefit of 20/20 hindsight), but some of the better-performing quant funds offer remarkable degrees of transparency. That doesn't mean seeing position-level data every single day. It is unrealistic to expect that a quant firm under consideration would share every line of code in its trading models.

Quant fund transparency means managers sharing details about their research processes and the types of asset classes, instruments, and markets in which they trade. What's the typical holding period (days, weeks, or months)? How and who builds their alpha models? What types of models, markets, and trading ideas have worked and, more importantly, what are some examples of ones that have failed? Is the quant firm "eating its own cooking"—that is, how much in personal funds has it invested? Transparency is about the quants shedding light on what they do and how the strategy works to deliver consistent superior risk-adjusted returns on a repeatable basis.

Once quantitative managers explain their process, they arguably can be more transparent than their discretionary peers, because it is the human brain—the brain of a discretionary manager or trader—that is the real black box. One of the most famous discretionary global macro traders is George Soros, the "Billionaire Who Broke the British Pound" (Gara 2016). On Black Wednesday, September 16, 1992, Soros' Quantum Fund made more than £1 billion by pounding (selling short) the pound sterling. Why proffer George Soros, a legendary fundamental discretionary manager, as Exhibit A for human as black box?

Here's how his son, Robert Soros, describes his dad's investment process[21]:

> *My father will sit down and give you theories to explain why he does this or that. But I remember seeing it as a kid and thinking … at least half of this is bull … I mean, you know the reason he changes his position on the market or whatever is because his back starts killing him. It has nothing to do with reason. He literally goes into a spasm, and it's this early warning sign.*

WE'RE ONLY HUMAN …

A quiet revolution is taking place around the world: An ever-increasing number of organizations—private and publicly traded companies and governments at all levels—have embraced algorithms to make what were traditionally human-based decisions. Why? Primarily because algorithms are less biased than their human counterparts (Miller 2018). Humans are born and bound to make mistakes (credit to The Human League).[22]

In exploring the reasons behind algorithmic ascendance, we'll use the same approach used above to discuss the diffusion of innovations. Rather than focus on the adopters, we train our sights on resistance, reluctance, laggards, and non-adopters. Here we'll look at a world without algorithms. Rather than point out the (given) flaws and shortcomings of algorithms, we'll compare their performance with human beings in a handful of domains.

What's an algorithm anyway? It's a sequence of instructions that are carried out to perform a specific task. In investment management, an algorithm is a mathematical recipe that harnesses models, data, computers, and telecommunications to buy or sell securities.

Algorithms have been used for centuries—even millennia. Around the same time that American anthropologists started researching diffusion, social scientists began to compare the performance of humans to algorithms. In 1954, a University of Minnesota psychologist, Paul Meehl, PhD, published "a disturbing little book" documenting twenty research studies that compared the predictions of well-informed human experts to simple algorithms (Meehl 1954).

The score was Algorithms 20, Humans 0. In each of the twenty cases, simple algorithms based on observed data such as past test scores and past treatment modalities beat the human experts. And Meehl's study was done more than sixty years ago. Algorithms since then have advanced significantly. Following Meehl's findings, more than 200 studies have compared statistical prediction rule (SPR) algorithms' performance to human experts. In most cases, SPRs beat subjective judgment. In the handful of cases where they don't, they usually tie (Tetlock and Gardner 2015, 21).

Cognitive scientists Richard Nesbitt and Lee Ross bluntly stated, "Human judges are not merely worse than optimal regression; they are worse than almost any regression equation" (1980, 141). And unlike advanced algorithms powered by machine learning, human cognitive abilities are largely unchanged over recent millennia.

The breadth and depth of domains where algorithms are less biased than humans are instructive and insightful. Here is a sampling of illustrations:

- In 2000, a meta-analysis of 136 studies on the prediction of human health and behavior showed algorithms outperformed human forecasters by 10 percent, on average, and it was far more common for algorithms to generate accurate forecasts than human judges (Dietvorst et al. 2014).
- In 2002, a team of economists studied the impact of fully automated underwriting algorithms in mortgage lending. The "… automated underwriting systems more accurately predict defaults than manual underwriters do … this increased accuracy results in higher borrower approval rates, especially for underserved applicants" (Miller 2018).
- When a job-screening algorithm at a software company decided which applicants got job interviews, the algorithm favored nontraditional candidates much more than human screeners. Compared with human resource folks, the algorithm exhibited significantly less bias against candidates that were underrepresented at the firm (Miller 2018).
- In New York City pre-trial bail hearings, a team of computer scientists and economists found that algorithms have the potential to achieve significantly more-equitable decisions than judges who made bail decisions. Use of the algorithms resulted in fewer jailings, no increase in crime, and less racial disparity (Miller 2018).
- Studies comparing clinical (human) versus actuarial (statistical) predictions show that algorithms frequently outperform experts in predicting the survival of cancer patients, predicting heart attacks, and assessing different kinds of pathologies (Logg 2017).

Much like certain unconscious human cognitive biases, algorithms can be biased, e.g., credit scoring and facial recognition

(Lohr 2018). Algorithms can reflect the biases of programmers and datasets—from data selected, collected, and omitted—to train the model. We're not suggesting that algorithms should be blindly or indiscriminately accepted or followed.

On balance, algorithms have multiple, built-in advantages of increased decision-making capacity, lower costs, minimization of errors (compared to humans), consistency, and when required, anonymity. If anything should concern us, it's why so many important decisions are being made by humans who, prone to unconscious and conscious biases, are overconfident in their own judgments and have poor track records when it comes to decision-making.

When it comes to investing, the $64-trillion question should be, "Is a quantitative approach or algorithmic method superior to a discretionary manager's subjective judgment?" In the vast majority of instances, the answer is to go with the algorithm.

INVESTORS' ALGORITHM AVERSION

As made abundantly clear, research new and old shows that SPRs are more accurate at making forecasts than human forecasters. Yet when forecasters decide whether to prefer a human forecast over an algorithmic one, they often choose the human (Dietvorst et al. 2014). This phenomenon, called algorithm aversion, is costly. If algorithms are better at forecasting than humans, it would be logical for people to go with the algorithms. But often, they don't.

The Wharton School conducted a series of five experiments on algorithm aversion (Dietvorst et al. 2014). Researchers documented that humans made 15–29 percent more errors than did algorithms when given MBA student admission data with the task of predicting how well the students would perform in the MBA program. In a second set of experiments, humans made 90–97 percent more errors than algorithms when predicting the rank of fifty individual states in terms of the number of airline passenger departures from each respective state in 2011. Unsurprisingly, the algorithmic model beat the human forecasters in all five studies.

Here's the rest of the story. Study participants (roughly 741) were given the choice to place bets (and earn bonus dollars) after seeing both humans and algorithms make errors in forecasts. Seeing a model make relatively small mistakes consistently decreased confidence in the model. Participants who saw the model outperform the human in the first stage of the experiment (610 Wharton School students) were among the least likely to tie potential bonuses to the algorithms.

Yet when human forecasters made large errors, it did not cause participants to lose confidence in their fortune-telling skill. This was true even when human forecasters produced nearly twice as many errors as the algorithmic model predictions.

So, while to err is human and can be forgiven and forgotten, many people demand infallibility from algorithms.

Although recent and relevant research shows that people exhibit algorithm aversion, it doesn't explain when or why people pass on algorithms. There are a number of theories why folks prefer human forecasts over computer-derived predictions. Some researchers theorize that algorithm-adverse folks presume that human forecasters will improve through experience. Others feel that it's dehumanizing or unethical to rely on algorithms for important decisions or that people desire perfect forecasts (and for some reason believe that humans are infallible at prediction).

Two Sigma is a leading-edge quantitative investment strategy firm, guided by the scientific method when building its algorithmic models. David Siegel (2015), co-chairman and founder of Two Sigma, summarizes our thoughts on algorithm aversion:

> *The sooner we learn to place our faith in algorithms to perform tasks at which they demonstrably excel, the better off we humans will be. If the fear of the unknown really is driving skeptics' irrational bias against algorithms, then it is the task of the practitioners who do understand their power (and limitations) to make the case in their favor.*

CODE-DEPENDENCY—HUMAN PLUS MACHINE INTELLIGENCE

Simple algorithms commonly outperform unaided expert judgment, but this doesn't mean we should take humans out of the loop. Data features don't appear spontaneously in quantitative models. The most frequently used algorithms in financial services—credit extension and mortgages, financial fraud detection, insurance underwriting—are heavily dependent on domain experts who coach and counsel coders who write the programs. Data scientists and programmers rely on the acquired knowledge of domain experts and end users.

In the hands of talented people, particularly individuals with domain expertise, quantitative finance algorithms can produce positive investment results. Machine-learning algorithms can sniff out patterns—even when there are none (de Prado 2018, 2, 17). There's no shortage of patterns in the history of financial markets, particularly with humans genetically programmed to seek them out. But most have no predictive powers. Quant models can find false positive "discoveries" by overfitting data. Backtesting may indicate an attractive Sharpe ratio, but it might fail miserably on out-of-sample data.

Quant models often uncover spurious correlations. Apple's stock price on January 1 of 2007, 2008, and 2009 had a 0.999995 correlation with visitors to Orlando's SeaWorld (see figure 5). What do tourist visits to SeaWorld in Orlando have to do with Apple's stock price? Nothing.[23] Discovering a correlation but failing to search for an underlying causation occurs rather frequently in quantitative finance. Spurious correlations have been called "the kryptonite of our [quantitative finance] industry" (Wigglesworth 2018). Domain expertise is essential to grasp why a premium exists in the first place.

Today, "next-generation quants" are harnessing advanced machine-learning algorithms running on cloud-based supercomputers for stock selection and market prediction (Guida 2019). These artificial intelligence (AI) quantitative pioneers experiment with alternative investment datasets to seek new sources of uncorrelated "Algorithmic Alphas" (Tulchinsky 2018).

Some of these powerful pattern-seeking algorithms defy human explanation when discovering a previously unknown alpha. The reality is that certain patterns escape human attention because they're too subtle, too numerous, or too fast in the data (Kollo 2019, 4). Some of these purported market inefficiencies will not prove profitable because they're noise, illiquid, or un-investable.

This is where domain expertise is essential to decipher whether an alpha signal is spurious or not. Is the source of return persistent and hopefully sustainable? Are the premia unique, ideally an uncorrelated source of return, and accessible? Are the premia capacity-constrained? If so, what are the limits? Or is it just an alpha mirage that's illusionary, transient, and easily arbitraged away? Generally speaking, there should be an underlying rationale for the source of a premium; otherwise it's fools' gold.

Quant models can decay or become obsolete. Although a model may be static, capital markets certainly are not. Markets are dynamic, complex, and adaptive. Me-too quants hear about factors and risk premia from word-of-mouth and by reading academic journals. They crowd trades and arbitrage away previously under-discovered alpha sources.

Unless the assumptions that underlie their quantitative models remain realistic and relevant in the future, the source of the alpha model's competitive advantage evaporates overnight or gradually fades away. If humans are not there to monitor model performance, to evaluate and make modifications when required, their quant model can run out of steam.

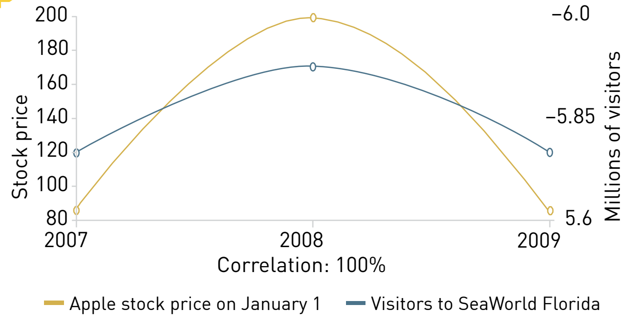
So, we're not ready to throw in the towel and turn investment management over completely to machines. Human and machine intelligence make for an unbeatable combination compared to machine or man alone.

QUANTS' QUANDARY—A REALITY CHECK

Following the Quant Quake of August 2007[24] and the GFC, quant fund AUM declined from its peak percentages of total global investment assets. The asset management industry's 800-pound gorilla, BlackRock, reported that quant AUM

Figure 5

SPURIOUS CORRELATIONS



Sources: Nasdaq and TEA tylervigen.com

dropped 35 percent. And anecdotes from quant practitioners suggested that in strategies such as "long/short global equity," the percentage decline in AUM approached 80 percent (diBartolomeo 2013).

When performance is strong, opaque investment processes are less questioned. In fact, complexity often is viewed in a positive vein as a differentiated trait. However, when market regimes experience seismic events, opaque quant strategies that underperform are mistrusted. When the Quant Quake struck a little more than a decade ago, quant strategists struggled to explain how and why their models failed to perform and many investors subsequently bailed.

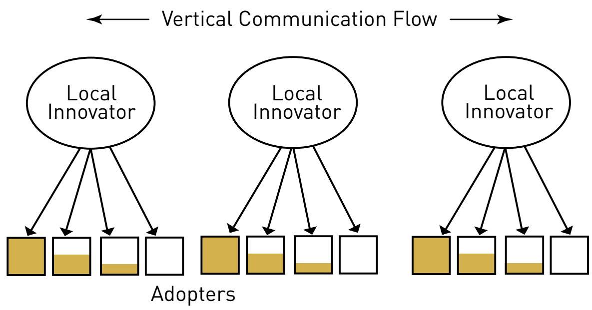
Some industry experts believe "… quants have a public relations problem of their own making" (diBartolomeo 2013, 1). Dan diBartolomeo of Northfield Information Services has said that many quant strategists are enamored with complexity and willingly or unwittingly reinforce the black box stereotype. There's ego gratification in cloaking their investment process from the early adopter or early majority investor types. He believes "… the quant community is unwilling or unable to articulate their investment concepts in common language without falling to the temptation to use misleading statistics to exaggerate the expected benefits" (diBartolomeo 2013, 10) and has stated that how quant managers communicated the effects of the August 2007 Quant Quake to the public via the financial trade press was "abysmal … an exercise in PR spin that spun out of control and discredited the industry" (diBartolomeo 2013, 2–3).

If quant funds are to transform from misunderstood ugly ducklings into gracious swans, what must advisors and analysts do? Taking a page from the *Diffusion of Innovations* playbook, they must take on the role of change agent.

Diffusion itself is a particular form of communication in which the message content that is exchanged is concerned with a (relatively) new idea, product, or service. Many products are not quite overnight success stories. For example, it took about 150 years before the widespread adoption of facsimile (fax)

Figure 6

VERTICAL COMMUNICATION FLOW



machines. The fax was invented in 1843 by Scottish clock maker Alexander Bain (Rogers 1995, 325–326), but it wasn't until the 1980s that fax machines reached critical mass as the price of machines came down. Although fax transmission has been widely displaced by email, tens of millions of fax machines are still in use (Cummins 2018).

To date, the quantitative investment industry has followed a decentralized model as described by Rogers (1995, 364–369) (see figure 6). One of the the first quant fund managers, Edward O. Thorp, is a central character in the diffusion of quantitative investment. Thorp shared his quant concepts (and even the model itself) with a handful of folks.

Among the luminaries in the quant world, Edward Thorp worked with Gerry Bamberger, who generally is credited as a founder of statistical arbitrage while working at Morgan Stanley (Patterson 2010, 41–42). Thorp influenced, coached, counseled, and/or seeded Bill Gross (Bond King), Ken Griffin (Citadel), Blair Hull (Hull Trading), and the principals at TGS Management, a quantitative fund and the fourth largest philanthropic foundation in the United States (Mider 2014).

In the decentralized diffusion model, new ideas spread horizontally via peer networks. A high degree of experimentation and re-invention occurs as innovations are modified to fit the needs of innovators and early adopters. A decentralized diffusion system works best when its users are highly educated and technically competent practitioners. Participants in a decentralized diffusion ecosystem have a sense of control and freedom to make modifications to address specific desires and preferences. As empirical evidence, there are thousands of Thorp quant progeny and variants. But relatively speaking, there are far fewer investors and a lot less AUM in quant strategies versus discretionary-managed funds.

MORE MOORE LAWS

Geoffrey A. Moore, PhD, a management consultant, author, and high-tech sales and marketing executive, built upon and extended Rogers' pioneering work on "Adopter Categorization on the Basis of Innovativeness" (bell curve or S-curve). He explains his technology adoption theory in *Crossing the Chasm: Marketing and Selling High-Tech Products to Mainstream Customers* (Moore 2013). Moore states that many firms' business plans are based on Rogers' "Adoption Lifecycle" where you work the "S-curve" from left to right. You progressively convince each category of user to adopt your innovative product or service. Then you use each "captured" segment as a reference for the next category and on down the line. The traditional model implies or assumes that there's an inevitability of adoption and diffusion. But the real world differs from Rogers' *Diffusion of Innovations* textbook definition.

In 1989, when Geoffrey Moore was writing his first draft of *Crossing the Chasm,* he used a self-driving car as an example of a disruptive technology waiting to be adopted (Moore 2013, 11). Self-driving cars in 1989? Yep, that's right. Carnegie Mellon robotics engineers were driving a retrofitted Army ambulance around campus. It was called ALVINN or Autonomous Land Vehicle in a Neural Network, reached speeds of 70 miles per hour, and traveled 90 miles to Erie, Pennsylvania, driverless (Hawkins 2016).

When Moore revised his book in 1999, he again used a futuristic automobile as the poster child for slow adoption. GM had just mass produced 1,200 EV1 electric cars. The EV1 wasn't available for purchase; it was leased by GM as part of "real world engineering evaluation."[25] Although customer reactions were positive, GM ended up crushing most of the EV1 vehicles (literally) because GM thought electric cars were unprofitable. In his latest update in 2013, Moore did a ditto, with Tesla appearing as poster child.

Glacially slow adoption by hesitant and resistant customers, laggards, and non-adopters has plagued product and service innovations since the dawn of the Industrial Revolution. Even when there are quantifiable advantages and potential benefits from a next-generation service such as quantitative investment management, its diffusion and subsequent adoption by investor segments is not inevitable. Geoffrey Moore set out to understand why.

CHASM SPASMS

Geoffrey Moore's major contribution to the theory of technology product adoption and diffusion is that there are chasms or cracks in the bell curve. A small chasm separates innovators (the 2.5 percenters) from early adopters and an even larger chasm exists between early adopters and the early majority (see figure 7). Each gap represents a chance—a risk—of losing marketing momentum (Moore 2013, 21). If the gap or chasm is not crossed, the new and improved way of doing things won't transit to the next group or consumer cohort. It will be like a muscle contraction or chasm spasm. Marketing strategies that win over one segment won't necessarily work with the next cohort on the S-curve.

In Moore's analysis, visionaries or innovators have very different expectations from more practical early adopters. Moore believed that the disassociation between these groups leads to "… the difficulty any psychographic group will have in accepting a product if it is presented the same way as it was to the group to its immediate left." Innovators aggressively pursue novelty; they want to be the first to try new stuff. However, in order to convince early adopters and subsequent consumer segments, behavioral changes are required. Investors willing to test-drive quant funds must be "quantitatively content" that the proposed benefits of quant investment strategies offset potential drawbacks, downsides, and disadvantages.

Early adopters don't embrace novelty for novelty's sake. They have a wait-and-see attitude. Although early adopters buy into product concepts early on, they're not "technologists" or enthusiasts per se. As shown in figure 7, Moore's first chasm—the smaller chasm—is between the innovators and early adopters. (Author's note: Other depictions of adoption curves show a sixth category—non-adopters.)

Each of these deep and dividing chasms must be crossed in order to facilitate or speed-up adoption of innovations. Moore states that visionaries and enthusiasts (the innovators), who create disruptive or discontinuous technologies (like the Ed Thorps of the quant world), are fundamentally different from early adopters. Applying mathematical and scientific approaches initially to games of chance then to capital markets was a consistent, central, and compulsive curiosity throughout Thorp's life. Yes, Edward O. Thorp is different from you and me.

The key to getting beyond the enthusiasts and winning over early adopters is to show that the new technology or product innovation is a strategic leap forward (Moore 2013, 22). This usually requires a flagship application that showcases the unique value of the innovation and signals early adopters to move forward. In this regard, financial advisors and analysts have their hands tied behind their backs due to the SEC's prohibition on the use of investor testimonials.

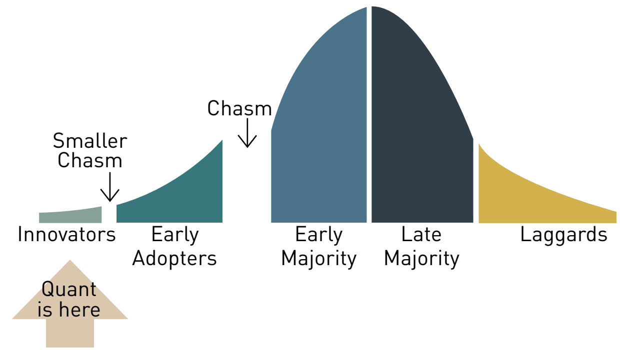
In Moore's telling, the early majority realize that many newfangled inventions end up as passing fads (Moore 2013, 16). They want well-established references before they buy in. Because it's such a large market segment (roughly one-third), persuading the early majority is the key to widespread adoption and market success.

Unfortunately, for quants anyway, we seem to be stuck in the innovator stage where fewer than 2.5 percent of the potential adopters have moved forward with quant allocations.

SUCCESSFUL QUANT CHASM TRANSIT

Crossing the chasm requires moving investment innovations from the comfort of visionaries to countering the skepticism among pragmatists. It means transitioning from the enthusiastic support of quantitative evangelists to an unfamiliar ground of investment-wary generalists.

Figure 7 QUANT FUNDS STALL; TWO CHASMS TO CROSS INTO MAINSTREAM MARKET



The information barrier is the most significant obstacle impeding quantitative investment adoption. Change agents are needed to overcome barriers to the adoption of innovations. By understanding investors' objectives, risk tolerance, and time frames, credentialed advisors and analysts can selectively transmit relevant information that may result in superior investment outcomes.

Change agent success in motivating investors to consider quant strategies as part of a portfolio's composition is related directly to the frequency and clarity of their communications. In studies of innovation diffusion, the one variable most closely related to success is the frequency of contact with the change agent (Rogers 1995, 347). Repetition is the mother of successful innovation adoption.

SOME CLOSING THOUGHTS

This discussion complements theoretical reflections on investor and advisor resistance and reluctance to making allocations to quantitative investment strategies. The intent was to make a novel contribution to literature on quantitative investment by applying the Rogers (1995) model and subsequent research on models of innovation resistance. The goal was to decipher investor reluctance to invest in quantitative strategies and funds, and, in the process, upend widely held and erroneous assumptions by dispelling the myth of widespread quantitative investment management.

The mainstream media may have reported a quantitative groundswell, but the mainstream markets have not yet bought into quant investing. With quant investing at the half-century mark (Ed Thorp's fund launched in 1969), it represents roughly 2.25 percent of the world's global wealth assets.

Investment innovations such as ETFs and alternative investments have been and will continue to be sources of investment progress. Investors resist innovations because they lack information or don't appreciate the potential value of the innovative product. They resist because the innovations seem unduly complex or conflict with prior habits. But investor resistance to quantitative investing can be lowered by credible advisors who communicate clearly the potential advantages and risks.

There are encouraging signs on the future of quant investing. Recent surveys of institutional investors indicate that more than half of investors surveyed (57 percent) plan to significantly or moderately increase their allocations to quantitative strategies over the next three to five years. Pensions and institutional investment consultants indicate an even larger appetite for future allocations to quant investment strategies.[26] All they need is a little push from their advisors and analysts.

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ENDNOTES

1. "2017 Preqin Global Hedge Fund Report" as reported in Man Institute (2017).
2. "Searching for a Winning Strategy (Extended Version)," Morgan Stanley Global Asset Management, October 28, 2019, p. 33.
3. Michael J. Cyprys, executive director, Morgan Stanley Research, email correspondence, November 24, 2019.
4. Investment Company Institute, "Worldwide Regulated Open-End Fund Assets and Flows Second Quarter 2019," Washington, DC, press release, September 25, 2019, https://www.ici.org/research/stats/worldwide/ww_q2_19.
5. Baghai et al. (2018), pp. 2–3; Kevin Cho, McKinsey associate partner, email correspondence, November 13, 2019.
6. See endnote 4, "Table 1: Regional Summary by Type of Fund, 2019: Q2–ETFs."
7. "TSX: Home to Canada's Exchange Traded Funds for 25 Years," Toronto Stock Exchange (March 9, 2015), https://www.tmx.com/newsroom?id=292&year=2015.
8. "History of Innovation," State Street Global Advisors, https://www.ssga.com/global/en/about-us/who-we-are/history-innovation.html.
9. "Smart Beta: A Time-Tested Strategy, Powerful Tool for Both Equity & Fixed Income Investors," INVESCO, https://www.invesco.com/static/us/investors/contentdetail?contentId=6b550854ab96f510VgnVCM100000c2f1bf0aRCRD.
10. There is overlap or double counting among ETF AUM and smart beta-focused funds' AUM.
11. This paper uses the following working definitions to describe quantitative investment strategists versus discretionary or qualitative investment managers:
    - Quantitative refers to whether the required inputs to a manager's allocation and portfolio construction process are predominately objective and quantifiable.
    - Quantitative investment strategists employ trading models and trading signals generated by computer algorithms.
    - Qualitative asset management refers to whether the required inputs are predominately subjective (discretionary) and not quantifiable.
    - Qualitative security selection or asset allocation may be arbitrary whereas quantitative strategies follow a rules-based, disciplined investment process. Both quantitative and discretionary fund investing involve active management.
    - Quants come in all shapes and sizes, but we'll borrow the U.K.-based global alternatives investment specialist firm Man FRM's simple two types of quantitative strategies, which splits the quantitative fund universe into two broad categories, based largely on the source of individual trading ideas:
        - > Micro-based strategies include statistical arbitrage, equity market-neutral, trading ideas, and alpha-capture models that primarily trade equities.
        - > Macro-based strategies include commodity trading advisors, risk parity, and managed futures that trade futures and derivatives across a wide array (hundreds) of commodity, currency, equity index, and fixed income index contracts and markets.
        - > Within each strategy, asset classes traded, holding periods (milliseconds to months), markets, and models used vary widely. Sometimes the boundaries between these two broad categories blur, and larger quant shops and hedge funds often use both types.
12. Accessed from Fintel.io on June 30, 2019, RenTec filing dated May 14, 2019.
13. Quantitative Investment Management, LLC, Part 2A of Form ADV – Brochure (March 31, 2017), p. 4.
14. Tradebot Systems: About Us. Accessed at: tradebotsystems.com/about.asp; and Make the Trade, Dave Cummings, chief executive officer of Tradebot Systems, 2016.
15. "Systematic versus Discretionary," AQR, 'Alternative Thinking, 3Q17, https://www.aqr.com/Insights/Research/Alternative-Thinking/Systematic-vs-Discretionary.
16. See endnote 12.
17. See Moy (2011), which cites Graham (2006) and seven criteria that define the quantitatively tested portfolio; see also Warren Buffet in Columbia Business School video tribute to Graham.
18. See also Clark and Monk (2015).
19. "S&P Bull & Bear Market Tables," Yardeni Research, Inc. (February 13, 2018), p. 4.
20. "Guidance on the Testimonial Rule and Social Media," U.S. SEC Division of Investment Management, No. 2014-04 (March 2014).
21. See Soros (2009) and Dhar (2016).
22. The Human League, a musical group that released the song "Human" in 1986.
23. Spurious Correlations website (http://tylervigen.com/spurious-correlations), Tyler Vigen, PhD, APPL stock price on January 1 versus SeaWorld visitors.
24. MarketWatch, "Goldman, Renaissance, AQR See Losses, But Also Sense Opportunity (August 13, 2007), https://www.marketwatch.com/story/quant-quake-shakes-hedge-fund-giants.
25. "General Motors EV1," accessed on Wikipedia on January 6, 2019.
26. "Periodic Survey of Hedge Fund Investor Sentiment," Credit Suisse Mid-Year Investor Survey (summer 2017, page 6).

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