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BEHAVIORAL FINANCE IN INVESTING

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By Sid Muralidhar and Arun Muralidhar, PhD

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ABSTRACT

Using case studies of two investment companies, this paper highlights that organizations may have "investment tribes," i.e., groups of individuals who appear to exhibit similar risk tendencies for gambles involving gains or losses, possibly with a wide spread of risk preferences. Tribes and risk-preference diversity can influence and impact decision-making. Quantifying and making transparent the existence of these tribes and individual preferences, using the Risktyle methodology, which extends the original Kahneman and Tversky (1979) approach to identifying risk biases, could improve decision-making, especially in market crises such as that of March 2020. The framework presented can be helpful for investment firms and investment advisors, allowing them to become aware of potential biases. It also can be useful for asset owners that delegate decisions to third parties, because it allows them to understand how the investment firms they delegate to might behave when drawdowns result during market crises.

BACKGROUND

Kahneman and Tversky (1979)—hereafter KT—introduced the notion that individuals might not behave as postulated in expected utility theory (EUT); namely, they were not "rational utility maximizers." It appeared that individuals were biased by how gambles were framed, and individuals were seemingly risk-averse and also loss-averse—that is, they are more significantly affected by losses than gains. Subsequent research in behavioral finance has shown that individuals display other behaviorally affected decisions (BADs), including the endowment effect, recency bias, overconfidence, etc. (Wiggins 2019). However, existing behavioral finance theory used by many financial firms applies broad generalizations to all individuals (based in part on KT and other researchers' findings), assuming, for example, that all individuals suffer from loss aversion, the endowment effect, framing, etc. KT appear to miss the nuance that each individual is unique. For example, not every individual is loss-averse, and it's impossible to perfectly group individuals with these biases based on gender, age, or education, because each individual is unique (Muralidhar 2018). Broad generalizations can apply to these groups, but there is a danger that applying these generalizations risks misunderstanding the individual biases of the members of the group and the entire group dynamic.

March 2020 provided an unexpected shock to investment firms that revealed challenges in investment decision-making processes and potential risk biases. For example, DeCambre (2020) highlights that Ray Dalio, chief investment officer of Bridgewater Associates, acknowledged that the "world's largest hedge fund 'didn't know how to navigate' [the] coronavirus stock-market selloff and should have 'cut all risk' but failed to react." An investment firm is composed of individuals, all clearly with their own individual biases, but how these individual biases coalesce into the group bias is influenced and determined by the investment process the firm adopts.

Understanding individual or group biases has serious implications for investment firms or investment advisors that manage money for clients and even for asset owners such as pension funds or endowments that delegate investment decisions to these companies. Bridgewater Associates adopts a largely systematic approach to decision-making but apparently has the discretion to override the model, which is not uncommon among quantitative strategies.

Understanding risk-preference biases is also important for firms that have a discretionary decision-making process, in which most or all investment decisions are made by human beings rather than models. Although a qualitative decision process may allow for the ability to react to changing market conditions immediately, it also allows decision-makers to battle their own emotions when picking trades to enter and exit (Sharma 2012). Asset owners want to ensure that the firm they have delegated decisions to will not "gamble with other people's money." Therefore, any insight into the behavioral biases of these investment firms could greatly improve the due diligence process of selecting and retaining delegated agents.

Why does risk-preference diversity within an investment team matter? Assume that the investment firm is experiencing losses, as was the case for many firms in March 2020. If all team members are loss-averse as assumed by KT, then they

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could have cut risk and missed the entire rebound in markets. Alternatively, an investment team with a wide dispersion in risk preferences likely would have considered a wider range of investment decisions (i.e., cut risk, increase risk, do nothing), and may have caught the market rebound. Just as investment diversification is touted as a way to improve risk-adjusted performance, so too, one can argue, risk-preference diversification might be a critical facet of any investment organization, because it allows for behavioral biases to be diversified as well.

To demonstrate how group biases can be understood and to glean new insights that can impact overall decision-making, this paper presents two case studies: (1) a systematic investment management firm with five investment professionals, and (2) a discretionary private equity firm that takes minority stakes in asset managers with six investment professionals. These two organizations occupy very different spaces in the investment management community. The first is a systematic (with a qualitative overlay), liquid-asset, short-term manager; the second is a discretionary, illiquid, long-term asset manager. We see risk-preference diversity among investment professionals in these very different investment operations—which could be seen as a positive because it shows diversity of opinion among the decision-makers. We also see clustering in biases (i.e., investment tribes) that may impact how decisions are made for gambles involving gains and losses in both types of firms. Most of the individuals described in these case studies are highly trained and experienced in finance, and they all identify as male, validating an earlier finding that biases cannot be grouped by gender, age, or education, especially in an investment firm.[1] Importantly, this research suggests that even in a small investment firm there can be multiple investment tribes, namely groups of individuals who may behave similarly under certain conditions (e.g., prospective losses or gains), and the members of these tribes can change based on whether the gambles result in gains or losses. Equally important, a desire for diversity in investment organizations based on physical characteristics (e.g., gender and race), actively sought by investors who delegate, may need to be complemented by analyses of risk-preference diversity because it directly impacts decision-making.

Our results reinforce the earlier point about not using a broad-brush KT or BADs lens to apply all biases to all individuals or even subgroups (i.e., males versus females). The recognition and quantification of individual and group risk biases is meant to help investment firms improve their decision-making and to help asset owners better understand how their delegated agents may behave in certain situations, such as when the firm experiences drawdowns or large losses, as in March 2020, or even large gains such as in April 2020.

This paper uses the Risktyle methodology to understand individual risk biases; the model is based on KT and is detailed in appendix A. Muralidhar and Berlik (2017), hereafter MB, provided a methodology to examine individual risk preferences using KT's definition of risky gambles, and Muralidhar (2018) analyzed and compared the risk appetite of teens, adult nonprofessionals, and adult investment professionals. MB examined the risk tolerance on gains and losses and commented on the consistency of individual decision-making. In addition to demonstrating how the KT questionnaire could help individual respondents gauge their own risk tolerances and biases using the Risktyle model, they also made interesting observations and broad generalizations about these groups; namely, in aggregate, the risk-seeking behavior in teens, as it pertains to potential losses, seems to moderate with age and financial sophistication[2]; investment professionals who are adult men are relatively more risk-seeking than investment professionals who are adult women, especially on gains; and that there is wide dispersion in risk tolerance within these groups. To be clear, just because, in aggregate, adult male investment professionals appear to be more risk-seeking than adult female investment professionals does not mean that in selecting between a male and female candidate for, say, an investment position, one can assume that the male candidate is more risk-seeking than the female candidate. In fact, MB demonstrate how an adult female nonprofessional displayed very high risk-seeking behavior given her personal circumstance. Risktyle instead argues that each individual is unique and easily could have individual preferences very different from the group aggregate, and hence each candidate's risk behavior needs to be tested and analyzed. More critically, in addition to wide dispersion in risk tolerance among individuals and groups, MB argue that KT may have repeated a challenge with EUT and overgeneralized the results because not all individuals are loss-averse or "irrational."

Risktyle argues that each individual is unique and easily could have individual preferences very different from the group aggregate, and hence each candidate's risk behavior needs to be tested and analyzed.

Further, this paper applies these techniques to examine the behavioral biases of specific investment organizations to demonstrate how a clearer understanding of BADs can help investment decision-makers better understand the likely functioning of an investment organization.

This paper presents two specific case studies, but this method also has been applied to other groups, including a real estate asset manager with a large registered investment advisor (RIA) network, and a subset of the staff of a $30-billion public pension plan. In short, the method can be applied to any investment operation, whether for retail or institutional investors.

THE RISKTYLE METHOD

KT provided a high-level suggestion of risk to survey preferences in the aggregate but no information to respondents about their own specific preferences. MB quantify the risk appetite of individuals—ranging from risk-averse, to moderately risk-averse, to moderately risk-seeking, to risk-seeking—using the Risktyle model. Risktyle stays true to KT's original survey and uses fourteen of KT's strictly numerical questions, which are included in appendix B. The typical KT question asked individuals to choose between outcome x_A with probability p_A and outcome x_B with probability p_B. In some cases, the expected values are identical; in others, the expected value of gamble A dominates or is dominated by gamble B. Risktyle then assigns a numerical score to every gamble in every question, where the numerical score is a relative risk-adjusted performance measure. Scoring is based on each gamble relative to the other option available within the specific question (see table 1). For example, gamble A, defined as a \$4,000 outcome with an 80-percent probability, gets a score of −1.24 versus gamble B, defined as a \$3,000 outcome with a 100-percent probability, which gets a score of 1.09 (table 1, KT question 3, columns 3 and 4, respectively). The KT majority response for question 3 was "B," and therefore column 5 scores that as a 1.09 for the KT respondent. If the individual picks the riskier gamble (e.g., a \$4,000 outcome with an 80-percent probability or option A for question 3), the individual is assigned the more negative value (−1.24) for that question. Additionally, to ensure basic robustness of the test, one KT question is asked twice; if the individual answers differently despite being posed the same question, the efficacy of the test to measure an individual's results may come into question.

An individual's overall risk appetite is gauged by summing up the individual's score for each of the fourteen questions. Further, risk appetite also can be segmented based on the responses to gambles with gains and gambles with losses. Table 1 shows how this calculation can be conducted for KT responses (column 5). Where an individual's aggregate risk score falls within the range of values (with a minimum −25.37, or very risk-seeking, and a maximum value of 5.97, or very risk-averse) determines the individual's risk behavior.[3] For example, the aggregate KT response would lead to a score of −4.10 (sum of column 5).

For simplicity, for this article, we have split the entire risk appetite range into four equal buckets and labeled them as follows: Risk-averse (RA) for scores of +5.97 to −1.87; moderately risk-averse (MRA) for scores of −1.88 to −9.70; moderately risk-seeking (MRS) for scores of −9.71 to −17.50; and risk-seeking (RS) for scores of −17.51 to −25.37. Using this scale, the KT aggregate is MRA overall, illustrated in figure 1. On gains, the KT aggregate would be risk-averse or RA; on losses the KT aggregate would be moderately risk-seeking or MRS.[4]

CASE STUDY #1

The first case study was conducted in April 2019 of an approximately \$2-billion minority-owned asset management firm with five investment professionals that manages money for institutional clients.

This multi-asset firm trades liquid stocks, bonds, commodities, and currencies and uses futures for execution, with a one- to three-month investment horizon. A systematic model forms

Table 1

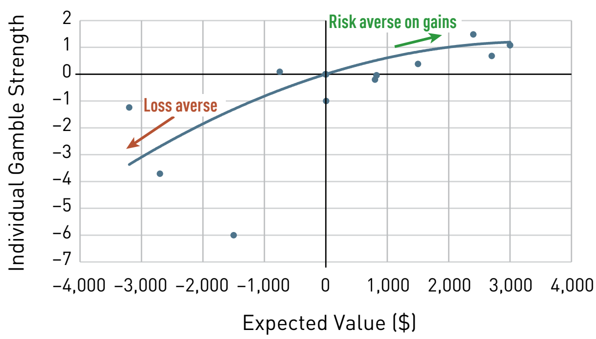
STRENGTH OF RISK APPETITE OF KAHNEMAN AND TVERSKY'S AGGREGATES (ON A SCALE OF −25.37 TO 5.97)

KT Questions (1)	KT Aggregate Answer (2)	Gamble Strength of A (3)	Gamble Strength of B (4)	KT Risk Appetite Score (5)
1	B	-1.01	1.48	1.48
2	A	-0.04	0.03	-0.04
3	B	-1.24	1.09	1.09
4	A	-0.20	0.09	-0.20
7	B	-3.71	0.68	0.68
8	A	-0.01	0.00	-0.01
13	B	-6.00	0.38	0.38
14	A	-1.00	0.00	-1.00
3'	A	-1.24	1.08	-1.24
4'	B	-0.20	0.09	0.09
7'	A	0.68	-3.71	0.68
8'	B	0.00	-0.01	-0.01
13'	A	-6.00	0.38	-6.00
14'	B	-1.00	0.00	0.00
Total				-4.10

Source: Adapted from Muralidhar and Berlik (2017, table 1).

Figure 1

KAHNEMAN AND TVERSKY'S VALUE FUNCTION FORMALIZED



the primary basis for decision-making, but it requires the investment committee (IC) to oversee the positions and potentially adjust positions based on market conditions that cannot be modeled or are unanticipated by the model (e.g., during the coronavirus market disruption). This method of decision-making can be referred to as a "systematic process with a discretionary overlay." The goal of the IC is to ensure that its interactions add value, but ideally excess returns should be negatively correlated to the model's return, thereby enhancing overall risk management. In other words, the IC seeks to add value when the model is underperforming and potentially clip the upside when the model is outperforming, thereby lowering overall volatility and raising the Sharpe ratio (Sharpe 1994) relative to the pure model-based approach.

The IC is made up of five adult male professionals: two co-chief investment officers each with an MBA in finance, one client portfolio manager with a PhD in economics and finance, the head of research with an MA in economics, and a senior research analyst with an MA in finance. This ordering also reflects the age of the five individuals: the two co-chief investment officers are the oldest and the senior research analyst is the youngest. The decision-making hierarchy is flat; namely, each IC member has an equal vote, so decisions are uninfluenced by age, title, or seniority. To preserve anonymity, we use the naming convention of Individual #1–5 for the team members, in no particular order.

For this team, any qualitative decision is based entirely on a majority vote. The model is developed, and periodically reviewed, based on the IC's majority vote. The model also formalizes the qualitative decisions about factors and risk profile (i.e., Sharpe ratio, permissible drawdowns, success ratios). The model is run daily, and execution takes place only after an IC discussion and approval. Although the model may not change positions daily, the IC still meets daily because non-market events (e.g., geopolitical tensions in the Middle East, elections, tariffs, etc.) can impact the performance of outstanding positions. Therefore, the individual and group behavioral preferences influence the choice of model and its implementation. It is reasonable to expect that all other systematic financial firms operate somewhat similarly with varying degrees of qualitative input.

The goal of the IC is to ensure that its interactions add value, but ideally excess returns should be negatively correlated to the model's return, thereby enhancing overall risk management.

ANALYSIS TO QUANTIFY RISK-PREFERENCE DIVERSITY AND DISCOVER INVESTMENT TRIBES

A Risktyle analysis of each of the five individuals, followed by an analysis of the group, is summarized in table 2. For each of the categories—aggregate risk biases, gains, or losses—the team is diverse with moderate risk tolerances for each (table 2, column 6), but of particular interest to clients is moderate risk aversion for losses. Table 2 suggests that these individuals are unlikely to gamble to claw back from a drawdown. Compare this with the KT analysis for the case of gambles with prospective losses, where respondents were likely to choose the riskier options in an attempt to avoid losses, thereby significantly increasing the risk of a large loss. This analysis demonstrates in the simplest terms how this firm in aggregate, and these individual members of the IC, differ from the KT profile. Importantly, all members passed the duplicate question test.

Table 2

RISK BIASES OF EACH MEMBER OF THE IC AND TEAM AGGREGATE FOR FIRM #1

	Individual 1 (1)	Individual 2 (2)	Individual 3 (3)	Individual 4 (4)	Individual 5 (5)	Team (6)
Aggregate Rating	MRA	MRA	MRS	MRA	MRS	MRA
Gains	MRS	MRA	MRS	MRA	MRS	MRS
Losses	MRA	MRA	MRA	MRA	MRS	MRA
Tribe	Gains #1	Gains #2 and Losses	Gains #1 and Losses	Gains #2 and Losses	Gains #1	3 Tribes
Comment	Most risk-seeking on gains; most risk-averse on losses	Most risk-averse overall	Belongs to two tribes	Very similar to Individual #2	Most risk-seeking	No dominant bias

Ratings are denoted as follows: Risk-Averse (RA); Moderately Risk-Averse (MRA); Moderately Risk-Seeking (MRS); Risk-Seeking (RS). Consistency scores are out of 11.

Figure 2

THE THREE INVESTMENT TRIBES—TWO GAINS TRIBES

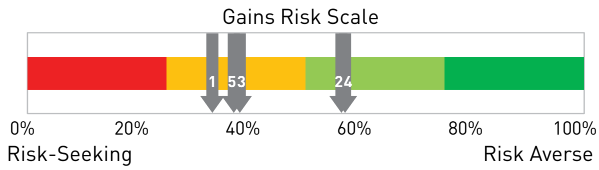


Figure 3

THE THREE INVESTMENT TRIBES—ONE LOSSES TRIBE

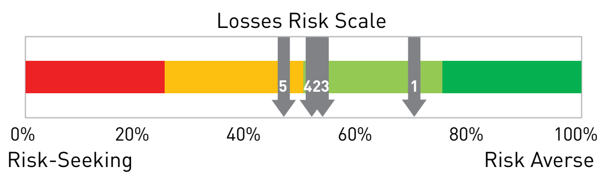


Figure 4

OVERALL AVERAGE BEHAVIOR OF THE INVESTMENT MANAGER

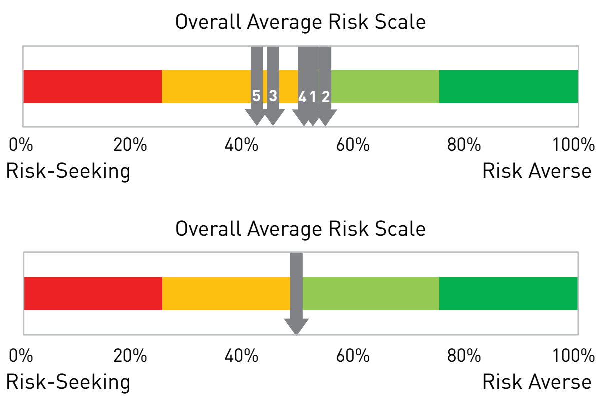
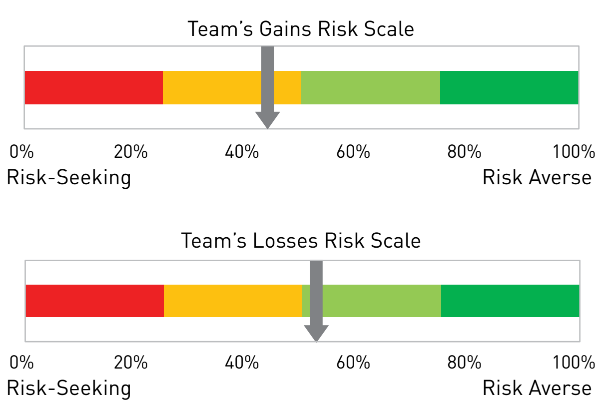


Figure 5

AVERAGE BEHAVIOR ON GAINS AND LOSSES



The most interesting finding in table 2 is the presence of three investment tribes of individuals who behave similarly for gains or losses. Each individual might be unique across all behaviors, but we see clustering of behaviors for specific subcategories that the Risktyle numerical score and the responses to the fourteen questions help identify. An investment tribe is marked by individuals whose Risktyle scores are within 5 percent of each other, as denoted by overlapping arrows in figures 2 and 3. As a result, a member can theoretically be a part of two investment tribes on one scale (i.e., gains or losses) by being the upper extreme of one tribe and the lower extreme of another.

As figure 2 shows, there are two investment tribes on gains—Individuals #1, #3, and #5 have similar preferences, clustering in the moderately risk-seeking quadrant, whereas Individuals #2 and #4 cluster in the moderately risk-averse quadrant.

For losses, depicted in figure 3, there seems to be one major investment tribe—Individuals #2, #3, and #4 all cluster within MRA, and Individuals #2 and #3 behave exactly the same.

Individual #1 seems to be a relatively extreme team member in terms of risk appetite. On gains, Individual #1 is the most risk-seeking and close to being out of the moderately risk-seeking tribe; on losses, Individual #1 is the most risk-averse. This could cause Individual #1 to be an extremely valuable part of the team by bringing a tolerance for risk on gains and intolerance for risk on losses that may not otherwise be considered. Interestingly, and intuitively, this finding is not uncovered when looking at the scale of overall behavior (simply, gains plus losses risk scores), shown in figure 4, because Individual #1's extremeness on either end of the spectrum seems to cancel out, making Individual #1 moderate in aggregate behavior. This example shows the importance of discerning behavior separately on gains and losses.

As shown in figure 5, the average behaviors on gains and losses tend to be moderate in nature, despite having members relatively dispersed on the spectrum. This is another valuable finding—although overall and even individual behavior seems moderate, the IC itself embodies diversity. Interestingly, in March 2020, the IC's qualitative management of the model allowed the firm to record meaningful positive performance. Intuitively, with losses, where there is one tribe, the average seems to settle near where the tribe lies.

CASE STUDY #2

The analysis for the second investment organization, the one with approximately $500 million in assets under management, was conducted in July 2019. This private equity manager provides capital solutions for other asset managers in exchange for minority stakes and has a long-term investment horizon.

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Table 3

RISK BIASES OF EACH MEMBER OF THE IC AND TEAM AGGREGATE FOR FIRM #2

	Individual 1 (1)	Individual 2 (2)	Individual 3 (3)	Individual 4 (4)	Individual 5 (5)	Individual 6 (6)	Team (7)
Aggregate Rating	RA	MRA	MRS	MRS	MRA	MRA	MRA
Gains	MRA	MRA	MRS	MRS	RA	MRS	MRA
Losses	RA	MRA	MRS	RS	MRS	MRA	MRS
Tribe	Gains #1	Gains #1	None	Gains #1	None	None	One Gains Tribe
Comment	Most (and only) risk-averse overall	Moderate in behavior, against team expectations		Most risk-seeking overall	Most risk-averse on gains	Most risk-seeking on gains	Risk-Preference Diversity

Ratings are denoted as follows: Risk-Averse (RA); Moderately Risk-Averse (MRA); Moderately Risk-Seeking (MRS); Risk-Seeking (RS). Consistency scores are out of 11

The IC is made up of six adult male professionals: a chief executive officer with an MBA in finance, an executive chairman with an MA in history and an MS in journalism, a managing partner who was a former PhD candidate, a chief operating officer with a BA in political science, and a vice president with a BBA in finance and economics. Similar to the first firm, titles are correlated with age but the decision-making structure is flat because each individual contributes equally to any final decision.

The team meets and interviews the management teams of all asset managers and completes both top-down (i.e., broader market trends) and bottom-up analyses. The investment decision-making process involves quantitative analysis and screens, but the ultimate investment is discretionary.

This firm is very different from the firm in the first case study. Firms one and two have different time horizons (short-term versus long-term), liquidity and reversibility of decisions (liquid versus illiquid investments), and decision-making processes (systematic versus qualitative).

Figure 6

GAINS, ONE TRIBE, DECENT SPREAD

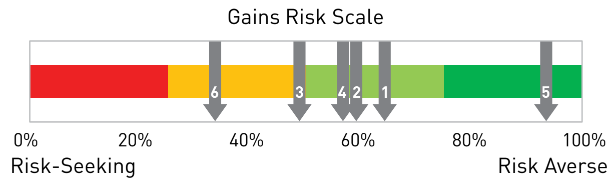
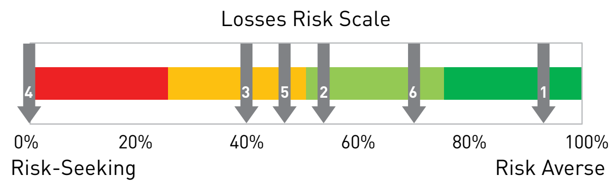


Figure 7

NO DISCERNIBLE TRIBES, WIDE SPREAD IN PREFERENCES



ANALYSIS TO QUANTIFY RISK-PREFERENCE DIVERSITY AND DISCOVER INVESTMENT TRIBES

Using the same naming convention used in case study one, table 3 summarizes a Risktyle analysis of each of the six individuals, followed by an analysis of the group. All members passed the duplicate question test, providing basic confidence in the individual results. Unlike the first firm, there is only one tribe—on gains with three members (Individuals #1, #2, and #4).

The team has a much wider diversity of risk preferences than the first firm, on both gains and (especially) losses. The nature of private equity investments, largely irreversible and experienced over long-term horizons, may lend itself to a wider spread of risk opinions. Conversely, in a systematic process, it is likely that risk preferences gradually coalesce around the model applied to implement investment decisions. Despite this dispersion in risk preferences, the average behavior was also moderate on both gains and losses, because more extreme behaviors on either side of the risk spectrum neutralized each other. The second firm was more risk-averse on gains and risk-seeking on losses than the first, a systematic, short-term, liquid asset firm. Anecdotally, in the midst of the coronavirus crisis, the second firm closed a deal. This could possibly be a testament to the firm's greater tolerance for risk but also probably because the firm's underwriting process is based on strong confidence in its cash-flow projections.

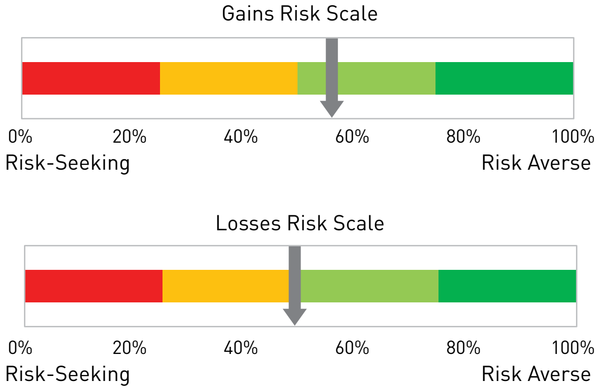
Figure 6 shows that half the team composes the lone investment tribe on gains, with Individuals #1, #2, and #4 clustering in the moderately risk-averse quadrant.

Figure 7 shows there are no investment tribes for losses. Instead, there is a wide spread in preferences, with Individual #4 being strongly risk-seeking, Individual #1 being strongly risk-averse, and the other members dispersed in between. We term this risk-preference diversity.

To put the second firm's risk preference diversity in context, the standard deviation on gains for the second firm was almost

Figure 8

OVERALL BEHAVIOR OF THE ASSET MANAGER ON GAINS AND LOSSES



twice as much (1.72x) as that of the first firm. On losses, the standard deviation was almost four times as much (3.58x).

Despite this greater diversity in risk preferences, the second firm's average behavior on gains and losses seems to be moderate, as shown in figure 8. In other words, despite extreme behaviors within the IC, the team is not biased strongly toward one end of the spectrum or the other. It seems that when there is just one tribe (in this case, for gains), the average settles near the tribe's position.

IMPLICATIONS FOR INVESTMENT FIRMS AND ASSET OWNERS

The analysis above suggests the following:

For the first firm (systematic, liquid, short-term asset manager): If the model is making money and the likelihood of future profits is reasonable, the team as a whole could achieve the negative correlation desired by taking profits, because one tribe is moderately risk-averse (MRA) and the second tribe is only moderately risk-seeking (MRS). However, when losses are being incurred, the team as a whole is more likely to generate the negative correlation by cutting risk to preserve capital and mitigate drawdowns.

For the second firm (discretionary, illiquid, long-term manager): Such a firm would be likely to pursue deals where the probability of cash flows is high, even guaranteed. This insight fits the firm's business model, which takes passive minority equity stakes in companies with a reasonable cash-flow cushion, thereby limiting the downside.

One can see how, in different organizations—with larger numbers of individuals in the IC, and with different weighting of individual decision-makers' inputs—tribes can drive very different outcomes. For example, if Individual #1 in the first firm had primary decision-making authority, the result could be a more dramatic skew in behavioral biases than the equally weighted scheme would suggest. In other words, for hierarchical organizations, the existence of tribes or dispersion of risk preferences may not matter as much as they do in firms with flat decision-making processes.

Identifying and quantifying behavioral biases allows for a better understanding of how individual team members behave and which ones are likely to be allies when the firm is experiencing gains or losses. Although professionals at both firms indicated they had a general sense of the similarities (in the first firm) and dispersion (within the second firm) among individuals before this analysis, the quantification of risk biases formalized the evaluation.

An IC also could use this method and analysis when hiring decision-makers to increase committee diversity, specifically as it pertains to risk preferences. In many requests for proposals, asset owners require information about the diversity of the team, where diversity is defined solely in terms of ethnicity or gender. Committees that lack diversity—ethnic, gender, or behavioral—and fall prey to groupthink are likely to make less-than-optimal decisions (Arnerich et al. 2019). The individual and group behavioral analysis shown in this paper can help identify talent that theoretically would increase the pool of diversity within a committee, thus avoiding the pitfalls of uniformity or polarization that may result in extreme decision-making. Baumgartner (2019) reports that being different creates alpha and edge, or competitive advantage—and thus the ability to quantify the level of being different is valuable. Muralidhar (2018) shows that, although it is possible to add ethnic and gender diversity, these changes may not necessarily translate to investment decision-making diversity if the risk biases of those hired are similar or the same as those already working on the team.

For asset owners, understanding IC biases ensures they are receiving the best advice, management, and information (Baker et al. 2017) and that the firms they hire to manage money on a delegated basis have a risk profile similar to their own. For example, an asset owner that is highly risk-averse may want to hire managers that also are highly risk-averse. Alternatively, because risk-taking may not be in the DNA, or rewarded or appreciated, asset owners may want to hire managers with a greater risk appetite that are better suited to take risk. In this fashion, conducting an analysis of risk appetite and behavioral biases, as part of the due diligence process, can help asset owners identify the investment firms that best match their risk tolerance in general or for specific types of likely outcomes (i.e., gains or losses). As Schelling (2014) notes, due diligence can be a source of alpha, but a behavioral risk assessment as a part of the due diligence process can also be a source of better risk diversification.

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Whyte (2019) highlights how a private equity investment officer at a large public fund notes that many firms do not appear to be conducting personality or behavioral profiling. In the increasingly competitive asset management environment, where trends of consolidation and compressed fees are becoming the norm (Pfeuti 2018), any edge could benefit a manager, or even an asset owner, in the decision-making process, and the screen presented in this paper could provide that edge.

EXTENSIONS AND CAVEATS

Like all aspects of the social sciences, this evaluation is not 100-percent guaranteed because it is based on one-time individual responses to highly customized and contrived KT gambles and not necessarily real-life investment examples. Both case studies were biased because both ICs were made up of only men. Furthermore, there is a difference between responding to these gambles in a survey versus decisions made on real money with meaningful consequences. As a few respondents to these questions noted, KT did not allow for indifference in choices with equal expected values. Moreover, the range of questions was not based on a continuous sample of outcomes thereby resulting in having to fit curves over discrete and potentially disjoined points.[5] However, this test has been applied successfully to more than 700 individuals, including more than 100 from the financial services industry. All the prior shortcomings notwithstanding, as KT note, the goal is to establish some estimate of individual behaviors on the assumption that individuals respond "as if" these were real gambles, and it is probably better than no analysis. Other methodologies can be applied (Choi et al. 2007), but this technique is simple and easy to implement in any organization. Feasibility of implementation is a major roadblock for a lot of high-tech and advanced due diligence processes (Calvello and Schelling 2018), so this method's ease of use is appealing. Moreover, this paper has shown how this approach can reveal risk biases regardless of its simplicity.

In addition, this is just a static analysis at a particular point in time, whereas money management is a multi-year engagement. As a result, intelligent managers of investment firms and asset owners would be well-advised to consider how behaviors change (e.g., in the middle of a crisis versus normal periods), and possibly even how the membership in investment tribes may change based on changes in age or individual circumstances (e.g., sending a child to college, which is expensive and requires a steady income; change in health conditions; change in the profitability of the investment business or competition from peers). This would suggest the ongoing evaluation of risk behaviors and a longitudinal representation of one's preferences to see its evolution. For example, one area of research being considered is to examine the risk biases of these same firms during the coronavirus crisis to see if an unanticipated market shock has altered risk biases.

One question not answered easily from this small sample size is whether the differences in aggregate behavior of the two firms represent the nature of their investments (liquid versus illiquid, short-term versus long-term, systematic versus discretionary, etc.) or whether it is a function of the team composition. This will be explored in future research.

… a potential concern about asset owners implementing such a behavioral screen for fund managers might be that the managers may feel uncomfortable, refuse to take it, or try and 'game' it.

It will be interesting to examine other investment organizations with more extreme decision-making processes and hierarchies (e.g., a very hierarchical qualitative asset management organization) that might offer different insights. The two case studies involved firms with different products and processes, but they both lacked hierarchies and involved flat decision-making. Moreover, it might be interesting to attribute risk-adjusted added value to each individual and tribe and examine *ex post* how the behavioral risk analyses might predict likely outcomes. Muralidhar (2015) has advocated for an enhancement of performance attribution reports to include who made the decisions, and that level of attribution will validate some of these findings.

Finally, a potential concern about asset owners implementing such a behavioral screen for fund managers might be that the managers may feel uncomfortable, refuse to take it, or try and "game" it (Whyte 2019). It may be revealing whether an asset owner can trust the manager that behaves in this manner, because trust is becoming more important in the financial services industry (Thakor and Merton 2018).

At the very least, the screen could be used as a valuable in-house tool, similar to the approach successfully applied to the two asset managers reviewed in this article and the aforementioned initial tests with the real estate firm and pension fund.

CONCLUSION

Investment organizations are complex because decisions are influenced by multiple individuals, whether the firm applies quantitative or qualitative investment approaches, because the first step in a quantitative approach is a qualitative statement of the investment hypothesis that is formalized by models. The complexity holds for managers investing in the liquid and illiquid markets, with short- and long-term horizons, respectively. Increasingly, finance practice is recognizing that individuals are not "rational utility maximizers" and do not all process information the same way; rather they are complex psychological beings who can exhibit complex behaviors. Kahneman and Tversky (1979) introduced this notion, but they did not provide a methodology to examine individual biases.

This paper provides case studies of two very different asset management companies that occupy different corners of the asset management market—one focused on liquid, systematic, short-term decision-making and another focused on illiquid, discretionary, long-term decision-making. In addition to demonstrating that each individual in the investment committee is unique and providing individual diagnostics that age and education need not lead to a particular behavior, this paper highlights organizational diversity by pointing out that there is no one dominant behavior for gambles involving either gains or losses. More importantly, it appears that these organizations had distinct investment tribes; namely, groups of individuals who are similar in the context of gambles involving gains or losses. These tribes can influence and impact decision-making. Risk-preference diversification might be a critical facet of any investment organization, because it allows for behavioral biases to be diversified as well.

These case studies can be helpful for investment firms and also for asset owners that delegate decisions to third parties or registered investment advisors to help them understand how outsourced managers might behave under drawdown conditions.

As a result, quantifying these tribes and making them transparent could improve decision-making by raising awareness about their biases. Depending on the investment process, risk-preference diversity might be preferred to tribes.

These case studies can be helpful for investment firms and also for asset owners that delegate decisions to third parties or registered investment advisors to help them understand how outsourced managers might behave under drawdown conditions. This paper suggests an additional aspect to be included in due diligence: matching the desired risk biases of the asset owner to delegated agents who display similar or opposite characteristics. This exercise is recommended to all investors that are open to using a quantification of risk biases to improve decision-making at all levels of the investment process.

Sid Muralidhar is the founder of Risktyle and the chief executive officer of Commodity Investing by Students (COINS) at Virginia Tech. Contact him at sidmuralidhar.risktyle@gmail.com.

Arun Muralidhar, PhD, is a co-founder of Mcube Investment Technologies, LLC and client chief investment officer of AlphaEngine Global Investment Solutions, LLC. Contact him at asmuralidhar@mcubeit.com.

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APPENDIX A: RISKTYLE MODEL

Risktyle is a model and application that measures risk behavior; it is based on the survey from Kahneman and Tversky's (1979) Nobel Prize-winning research.

As Choi et al. (2007) point out, KT's pairwise choices were created for the specific purpose of violating the axioms it sought to expose, thereby limiting the use of the data collected. However, KT's questions provide the probabilities and outcomes of each option, presented to the respondents, and this paper seeks to show that they are adequate to extract risk appetite. Thus, research on KT's results must go a step further to extract important information from the decisions made by the subjects.

One attractive feature of modern portfolio theory (MPT) is that two investments can be compared by examining their risk-adjusted returns either on an absolute basis (Sharpe 1994 or Modigliani and Modigliani 1997), or by examining them on a relative basis (Sharpe 1994 or Muralidhar 2000). In short, the Sharpe ratio is calculated by dividing the expected return of the investment (either absolute or relative) by the appropriate volatility of the investment, and the investment with the higher ratio typically is preferred to the investment with the lower ratio if one is risk-averse. The calculation of the M-square measure of risk-adjusted performance is a bit more complex and requires normalizing for differences in volatility and makes the comparison in terms of risk-adjusted returns. This analysis is easy to conduct for an investment professional, but the average individual typically does not know the expected return of a stock or bond investment. Moreover, the knowledge of Sharpe ratios or M-square is beyond the understanding of a financially illiterate individual. Therefore, it is hard to use MPT-based examples to establish the risk tolerance of individuals.

On the other hand, the simple gambles posed by KT that are shown in appendix B lend themselves to a much broader audience and can be answered easily by teens, adults, and investment professionals alike. However, the challenge is now on the researcher to convert the responses into a reasonable measure of risk tolerance. We attempt to do so by developing a formal equation to plot the value function that KT hypothesized was representative of individual behavior. The Risktyle model attempts to do so by converting each option in a gamble into a form of a risk-adjusted performance measure so that once it is quantified, it can be compared to other risky gambles (both in terms of sign and magnitude), and potentially aggregated across subgroups.

One goal of Risktyle is to explain why individuals appear to answer questions the way they did in KT's original survey (i.e., different than EUT). The Risktyle model examines individual gambles in each question or prospect, relative to its alternative, and tries to formalize the likely psychological process conducted by the individual in selecting that gamble. This is a tall order, and Risktyle is, at best, a dynamic first step, charting new territory in quantifying risk aversion and risk-seeking investment behavior using KT's hypothetical gambles.

The Risktyle model derives or assigns a numerical value for each gamble (i.e., Option A and Option B) in each prospect. The attractiveness of Option A is influenced by Option B and vice versa, each effectively serving as a reference point to the other. Once the value of every gamble in each prospect is established, one can plot the value function of each individual, based on the gamble chosen for every prospect. Simply put, the model is calibrated strictly to KT's questions, and it is possible it may not work for a different set of questions.

In every KT gamble, there is a unique probability (p e.g., 80 percent) and a unique outcome (x e.g., $4,000), and effectively a complementary probability (1–p e.g., 20 percent) and an alternative outcome (usually zero for both gambles, with a few exceptions). Comparing the (x_A, p_A) of Option A to the (x_B, p_B) of Option B is potentially an apples-to-oranges comparison, because $x_A \neq x_B$ and $p_A \neq p_B$ in all KT's prospects, even if the expected value is the same. Instead, Risktyle starts by comparing gambles in a prospect by defining relative risk based on complementary probabilities (1–p) for the exact same alternative outcome (i.e., the zeros). The (1–p) is easier to compare than p, because they are both anchored to the same outcome.

Prospects in which the probabilities and outcomes are the same do not need to be considered for two reasons: (1) KT's questionnaire did not contain any such problems, and (2) when probabilities are exactly the same (i.e., 50 percent versus 50 percent) or when outcomes are the same (i.e., $4,000 versus $4,000), it is assumed individuals will choose the higher sum of money or probability, or in the case of equal sums they will be indifferent.

In EUT, to be considered rational, an individual should pick gambles with the highest expected value. KT shows that humans do not make choices based on expected value, and Risktyle attempts to explain the behavior. Recall, in Risktyle, the reference point for Gamble A is Gamble B and vice versa. Because KT never chose identical p's and x's in every question, we can do a few simple things in our model's five-step process.

Define the base variables as follows:

	Gamble A	Gamble B
Gain/Loss	x_a	x_b
Probability	p_a	p_b
Expected Value (EV)	$EV_a = x_a \times p_a$	$EV_b = x_b \times p_b$

Step 1: Calculate gamble risk (relative to its reference point). Gamble risk has two terms: (1) the probability (1–p) of obtaining the outcome common to both gambles (zero), (2) added to the difference between the probability of the other gamble and its reference (or $p_A - p_B$). The higher this value, the higher the uncertainty relative to the reference gamble. The second term (or $p_A - p_B$) serves two purposes. Not only does it ensure the overall gamble risk is not zero, if p is 100 percent, but it also turns gamble risk into a relative calculation. This proves useful later in the model to derive the final value of a bet (or "individual gamble strength"). Negative gamble risk is possible because one gamble can be much more certain than another. Once the gamble risk is calculated, each value is adjusted, by taking the minimum of 1 and the gamble risk of each gamble calculated before. This ensures relative risk cannot exceed 1, causing gamble risk to be bound within [–1, 1]. This is useful in problems such as KT #14, in which the probability variance between gambles is enormous (0.1 percent versus 100 percent).

STEP 1: CALCULATE GAMBLE RISK

Gamble Risk of A (GR_a) = $(1 - p_a) + (p_b - p_a) = 1 - 2p_a + p_b$

Gamble Risk of B (GR_b) = $(1 - p_b) + (p_a - p_b) = 1 - 2p_b + p_a$

Adjusted Gamble Risk of A (AGR_a) = $\min(1, GR_a)$

Adjusted Gamble Risk of B (AGR_b) = $\min(1, GR_b)$

Step 2: Calculate relative gamble risk by dividing each respective gamble by the absolute value of its reference point, within each prospect, creating a truly relative value from one gamble to another. The absolute value of the divisor negates the bias caused by a negative adjusted gamble risk. Ignoring the absolute value could flip the order of risk between the two gambles incorrectly. By design of the model, the relative gamble risk of A is always greater than the relative gamble risk of B. This is because Gamble A has a lower probability of a nonzero outcome, thus a greater uncertainty, leading to Gamble A having greater relative gamble risk.

STEP 2: CALCULATE RELATIVE GAMBLE RISK

Relative Gamble Risk of A (RGR_a) = $\dfrac{AGR_a}{|AGR_b|}$

Relative Gamble Risk of B (RGR_b) = $\dfrac{AGR_b}{|AGR_a|}$

Step 3: Calculate relative expected value, defined as the expected value of one gamble divided by the expected value of the reference point within a prospect. Expected value is made relative to manipulate it against relative risk.

STEP 3: CALCULATE RELATIVE EXPECTED VALUE

Relative Expected Value of A (REV_a) = $\dfrac{EV_a}{EV_b}$

Relative Expected Value of B (REV_b) = $\dfrac{EV_b}{EV_a}$

Step 4: Calculate individual gamble strength (IGS), which is similar in principle to risk-adjusted performance calculations in traditional finance. IGS measures the relative risk-adjusted value of each gamble by subtracting the relative gamble risk from the relative expected value and multiplying that value by the relative size of the bet. The more negative (positive) the value of the IGS, the greater (lower) the risk involved for the possible reward in relation to the alternative gamble. Note that IGS is only comparable within a prospect, not across prospects.[6] The IGS score of each gamble is the critical number needed to evaluate risk tolerance and provide valuable insights on behavioral biases of individuals, subgroups, or even entire populations. The IGS scores and expected value of each gamble in all fourteen selected prospects are listed in table B1. A plot of the expected value and IGS score of a respondent's answers is the first step to estimate a value function as shown later.

STEP 4: CALCULATE INDIVIDUAL GAMBLE STRENGTH

Individual Gamble Strength of A (IGS_a) =
$(REV_a - RGR_a) \times \left(\dfrac{x_a}{x_b}\right)$

Individual Gamble Strength of B (IGS_b) =
$(REV_b - RGR_b) \times \left(\dfrac{x_b}{x_a}\right)$

Table A1

CALCULATING THE IGS VALUE AND EXPECTED VALUE OF KAHNEMAN AND TVERSKY'S QUESTIONS

KT Questions	Prospect Strength	Individual Gamble Strength of A	Individual Gamble Strength of B	Expected Value of A	Expected Value of B
KT 1	2.49	-1.01	1.48	$2,409	$2,400
KT 2	0.07	-0.04	0.03	$825	$816
KT 3	2.32	-1.24	1.08	$3,200	$3,000
KT 4	0.29	-0.20	0.09	$800	$750
KT 7	4.39	-3.71	0.68	$2,700	$2,700
KT 8	0.01	-0.01	0.00	$6	$6
KT 13	6.38	-6.00	0.38	$1,500	$1,500
KT 14	1.00	-1.00	0.00	$5	$5
KT 3'	2.32	-1.24	1.08	($3,200)	($3,000)
KT 4'	0.29	-0.20	0.09	($800)	($750)
KT 7'	4.39	0.68	-3.71	($2,700)	($2,700)
KT 8'	0.01	0.00	-0.01	($6)	($6)
KT 13'	6.38	-6.00	0.38	($1,500)	($1,500)
KT 14'	1.00	-1.00	0.00	$(5)	$(5)

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Step 5: Calculate prospect strength. For the purpose of explaining KT's results, Risktyle goes one step further: It calculates the prospect strength (PS) of each prospect (second column in table B1). PS measures the total disparity in IGS_A and IGS_B, calculated by taking the absolute value of IGS_B subtracted by the IGS_A. To explain KT, for gains (losses), when PS is greater (less) than some threshold, investors choose B (choose A). The model reveals this threshold is 2, and it is possible for different questions and populations, this threshold could differ (a point for further research).

STEP 5: CALCULATE PROSPECT STRENGTH

Relative Bet Strength (PS_{ab}) = $|IGS_b - IGS_b|$

APPENDIX B: 14 QUESTIONS SELECTED FROM KAHNEMAN AND TVERSKY (1979)

The Risktyle model uses the following questions from Kahneman and Tversky (1979), questions 1, 2, 3, 4, 7, 8, 13, 14, 3', 4', 7', 8', 13', and 14'.

Table B1

14 QUESTIONS SELECTED FROM KAHNEMAN AND TVERSKY (1979)

	Option A	Option B
KT #1	33% chance of winning $2,500	100% chance of winning $2,400
	66% chance of winning $2,400	
	1% chance of winning $0	
KT #2	33% chance of winning $2,500	34% chance of winning $2,400
	67% chance of winning $0	66% chance of winning $0
KT #3	80% chance of winning $4,000	100% chance of winning $3,000
KT #4	20% chance of winning $4,000	25% chance of winning $3,000
KT #7	45% chance of winning $6,000	90% chance of winning $3,000
KT #13	0.1% chance of winning $6,000	25% chance of winning $4,000
		25% chance of winning $2,000
KT #14	0.1% chance of winning $5,000	25% chance of winning $2,000
KT #3'	80% chance of losing $4,000	100% chance of losing $3,000
KT #4'	20% chance of losing $4,000	25% chance of losing $3,000
KT #7'	90% chance of losing $3,000	45% chance of losing $6,000
KT #8'	0.2% chance of losing $3,000	0.1% chance of losing $6,000
KT #13'	25% chance of losing $6,000	25% chance of losing $4,000
		25% chance of losing $2,000
KT #14'	0.1% chance of losing $5,000	100% chance of losing $5

ENDNOTES

1. This study does not examine risk diversity across gender given the two case studies chosen, but this will be explored in future research.
2. This result is not based on longitudinal data but rather on comparing teens to adults.
3. Except in KT7′ and KT8′, the riskier option is choice A. As a result, calculating the maximum and minimum is not just the sum of the columns 4 and 5, but it requires an adjustment for these two questions.
4. For one to take the diagnostic for themselves, refer to the selected questions in appendix B and score responses in accordance with table A1.
5. The authors thank Chris Schelling and Sanjay Muralidhar for this observation.
6. An IGS(A) =1 in, say, KT #7 is not identical or comparable to an IGS(A) = 1 in KT #8 because it depends also on the IGS (B), expected value, etc., in both questions.

REFERENCES

Arnerich, T., J. Ellis, J. Perkins, and C. Van Dyke. 2019. Investment Committees: More Than the Sum of Their Parts. http://arnerichmassena.com/pdf/pr/Investment_committees_April_2019.pdf.

Baker, H. K., G. Filbeck, and V. Ricciardi. 2017. How Behavioural Biases Affect Finance Professionals. *European Financial Review* (December–January): 25–29. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2899214.

Baumgartner, M. 2019. Minority Rapport: In Praise of Being Different. *NMS Exchange* 3–12 (December). https://www.tiff.org/wp-content/uploads/2019/12/Minority-Rapport-In-Praise-of-Being-Different-by-Mark-Baumgartner.pdf.

Calvello, A., and C. Schelling. 2018. Why Are Allocators in the Manager Selection Stone Age? *Institutional Investor* (June 12). https://www.institutionalinvestor.com/article/b18m1s9b5bwyyl/why-are-allocators-in-the-manager-selection-stone-age.

Choi, S., R. Fisman, D. Gale, and S. Kariv. 2007. Consistency and Heterogeneity of Individual Behavior under Uncertainty. *American Economic Review* 97, no. 5 (December): 1,921–1,938.

DeCambre, M. 2020. Billionaire Ray Dalio Says World's Largest Hedge Fund 'Didn't Know How to Navigate' Coronavirus Stock-Market Selloff and Should Have 'Cut All Risk' but Failed to React. *MarketWatch* (March 15). https://www.marketwatch.com/story/head-of-worlds-largest-hedge-fund-says-his-firm-didnt-know-how-to-navigate-coronavirus-stock-selloff-and-should-have-cut-all-risk-but-failed-to-react-2020-03-15.

Kahneman, D., and A. Tversky. 1979. Prospect Theory: An Analysis of Decision Under Risk. *Econometrica* 47, no. 2 (March): 263–292.

Modigliani, F., and L. Modigliani. 1997. Risk-Adjusted Performance. *Journal of Portfolio Management* 23, no. 2 (winter): 45–54.

Muralidhar, A. 2000. Risk-Adjusted Performance: The Correlation Correction. *Financial Analysts Journal* 56, no. 5 (September/October): 63–71.

——. 2015. Attribution Hears a Who! The Case for Decision-Maker Based Attribution. (December 18). *Journal of Performance Measurement* 20, no. 3 (spring 2016): 6-16

Muralidhar, S. 2018. The Consistency Smile: How Consistency of Investment Decisions Relates to Risk Appetite. *Journal of Personal Finance* 17, no. 2: 23-35

Muralidhar, S., and E. Berlik. 2017. What's Your Risk Appetite? Helping Financial Advisors Better Serve Clients (by Quantifying Kahneman–Tversky's Value Function). *Journal of Personal Finance* 16, no. 2: 20–36.

Pfeuti, E. 2018. Manager Consolidation, Fee Compression to Continue in 2019: Fitch. *IPE Magazine* (December 5). https://www.ipe.com/manager-consolidation-fee-compression-to-continue-in-2019-fitch/10028477.article.

Schelling, C. 2014. Due Diligence as a Source of Alpha. Chapter 15 in R. M. Levich and M. Pojarliev (eds.), *The Role of Currency in Institutional Portfolios* (pp. 355–399). London: Risk Books.

Sharma, R. 2012. Systematic vs. Discretionary CTA's: Understanding Each Investment. aiSource (February 27). https://www.managedfuturesinvesting.com/systematic-vs-discretionary-ctas-understanding-each-investment/.

Sharpe, W. 1994. The Sharpe Ratio. *Journal of Portfolio Management* 21, no. 1 (fall): 49–58.

Thakor, R. T., and R. C. Merton. 2018. Trust in Lending (June 23). MIT Sloan Research Paper No. 5524-18; 9th Miami Behavioral Finance Conference 2018. https://ssrn.com/abstract=3201689.

Whyte, A. 2019. Sports Cars, Psychopaths, and Testosterone: Inside the New Frontier of Fund Manager Research. *Institutional Investor* (July 31). https://www.institutionalinvestor.com/article/b1ghpmmp796w07/Sports-Cars-Psychopaths-and-Testosterone-Inside-the-New-Frontier-of-Fund-Manager-Research.

Wiggins, J. 2019. A Behavioural Finance Toolkit: Six Steps to Better Investment Decision Making (March). https://www.aberdeenstandard.com/docs?editionId=b1f2e37e-1173-4039-b079-c8863068b74a.

5619 DTC Parkway, Suite 500
Greenwood Village, CO 80111
Phone: +1 303-770-3377
www.investmentsandwealth.org