Which heuristics can aid financial-decision-making?

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Abstract

We evaluate the contribution of Nobel Prize-winner Daniel Kahneman, often in association with his late co-author Amos Tversky, to the development of our understanding of financial decision-making and the evolution of behavioural finance as a school of thought within Finance. While a general evaluation of the work of Kahneman would be a massive task, we constrain ourselves to a more narrow discussion of his vision of financial-decision making compared to a possible alternative advanced by Gerd Gigerenzer along with numerous co-authors. Both Kahneman and Gigerenzer agree on the centrality of heuristics in decision making. However, for Kahneman heuristics often appear as a fall back when the standard von-Neumann-Morgenstern axioms of rational decision-making do not describe investors' choices. In contrast, for Gigerenzer heuristics are simply a more effective way of evaluating choices in the rich and changing decision making environment investors must face. Gigerenzer challenges Kahneman to move beyond substantiating the presence of heuristics towards a more tangible, testable, description of their use and disposal within the ever changing decision-making environment financial agents inhabit. Here we see the emphasis placed by Gigerenzer on how context and cognition interact to form new schemata for fast and frugal reasoning as offering a productive vein of new research. We illustrate how the interaction between cognition and context already characterises much empirical research and it appears the fast and frugal reasoning perspective of Gigerenzer can provide a framework to enhance our understanding of how financial decisions are made.

Keywords
Heuristics, behavioural finance, decision making, cognition.

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1. The debate

The publication of Daniel Kahneman's Thinking fast and slow (henceforth TF&S) gives occasion to evaluate the Nobel Prize-winner's contribution, often in association with his late co-author Amos Tversky, to the development of our understanding of financial decision-making and the evolution of behavioural finance as a school of thought within Finance.

While such an evaluation is a massive task, we constrain ourselves here a more narrow discussion of Kahneman's vision of financial-decision making compared to a possible alternative advanced by Gerd Gigerenzer along with numerous co-authors.

Much of the teaching of Finance and financial advice is predicated on the idea that models, incorporating stylised rational behaviour, outperform received wisdom or professional rules of thumb. One of the essential texts of behavioural finance research Gilovich *et al* (2002) is entitled "Heuristics and biases" with the implication being conveyed that if you are smart you will avoid invoking heuristics. But is this true?

Could it be that the race goes to the conventional and naturally incurious rather than the calculative and all seeing "rational"/ Laplacean demon agent (Mcgrayne, 2011)? We believe the answer is yes, or at least it can be yes in a wide variety of evironments/contexts we frequently encounter. This is because Kahneman and Tversky (henceforth K&T), and adherents to expected utility theory in general, may not have the monopoly on what is "rational".

Gigerenzer's definition of rationality is very much an ecological one not a procedural one. He advances tools for the making the best decision in a rapidly changing uncertain environment rather than some optimal decision-making tool for implementation in a risky environment when all the states and the probability of their outcome are known. A central element in the debate is the relative scope of application in financial decision-making of risky, as opposed to truly uncertain, choice. Gigerenzer focuses on the latter, K&T the former.

In a lengthy program of research, yielding many papers in prestigious Journals, Gerd Gigerenzer, of the Max Planck Institute in Berlin, has developed the notion that the reason most of us regularly use heuristics, is simply because they work, i.e. produce better decisions (Gigerenzer and Goldstein, 1996, Gigerenzer and Brighton, 2009, Gigerenzer and Gaissmaier, 2011, Todd and Gigerenzer, 2003). This makes Gigerenzer call for a “heuristics revolution” in our understanding of human decision--making (Gigerenzer, 2014).

Gigerenzer's research shows that in decision-making often less is more and we really need to ``keep it simple stupid'', or at least make it simple to avoid acting stupidly. But Gigerenzer's critique has rarely appeared in major Finance Journals or, more remarkably, even influenced discussion at all[2]. A recent working paper by the Bank of England's Financial Stability Board (Aikman *et al*, 2014) suggests, however, that the appeal amongst economic policy makers of this view may be rising (see also Neth *et al*, 2014).

1.1 Gigerenzer's critique.

Gigerenzer and Todd (1999) cast doubt on the development of ``dual process'' characterisation of cognition. An example of such a characterisation is TF&S's System 1 and 2 schemata, which sees the mind as flipping between superior and inferior modes of thought. Hence for Gigerenzer and Todd

> “The unquestioned assumption behind these [dual process] theories is that more laborious, computationally expensive and non heuristic the strategy the better the judgements to which it gives rise. The more--is--better ideology ignores the ecological rationality of cognitive strategies.” (and Gigerenzer and Todd, 1999, p 20)

[2] According to Google Scholar accessed in June 2015 the work of Kahneman is cited almost 20 times more than that of Gigerenzer in Finance Journals but only about 5 times more often across all fields.

here a heuristic is just a means “to find or discover” (Gigerenzer and Todd, 1998, p 25) and is not clear that the most tortuous mode of discovery is the best.

Indeed Gigerenzer (see Gigerenzer and Goldstein, 1996) has questioned whether some of even the most basic axioms of ``rational'' choice, like transitivity and compensation across choice characteristics, have much predictive value.

> “there seems little empirical evidence for the view of the mind as a Laplacean Demon equipped with the computational powers to perform multiple regressions. But this need not be taken as bad news. The beauty of the nonlinear satisfying algorithms is that they can match the [Laplaceon] Demon's performance with less searching, less knowledge and less computational might.” (Gigerenzer and Goldstein, 1996, p 26)

So this paper outlines a path to pass beyond the mere chronicling of how heuristics and biases are manifest in financial markets, a task brilliantly performed by K&T and those influenced by them, towards the question of when and where heuristics are most strongly made manifest and when is their influence abated.

Gigerenzer's research programme aims to correct a common, and perhaps convenient for some, misunderstanding of Herbert Simon's bounded rationality. This is the view that bounded rationality asserts economic agents are simply incompetent or irrational. Quite conversely bounded rationality envisages decision-makers responding to both their cognitive limitations and the priorities of their environment in a resourceful and adaptive way when the decision-making context itself is constantly changing.

Lockton (2012) shows how Simon's “behavioural scissors”, by capturing the interlocking of cognition and context, can be applied for behavioural modelling in designs aiming to induce behavioural change within the built environment and elsewhere. Applications to financial decision-making of such reasoning will surely emerge soon. We point to some such first fruits of the fast and frugal reasoning approach in the final substantive section of this paper.

Gigerenzer points out that this vision of the mind as a computational machine is very recent and follows on directly from the widespread adoption of random-sampling and the associated use of hypothesis testing for the difference between a control and treated sample (Gigerenzer, 2000(a)). He points out that while in social science statistics are invoked to check the validity of theories in Astronomy the original use of statistics was to screen collected data for unreliable/error--prone observations.

Gigerenzer (1991) "tools to theories" heuristic sees psychological theory as emerging from the investigative tools researchers have to hand. Theories framed by current investigative methods are then employed to understand the nature of the cognitive process. But Gigerenzer (1991) argues that both the calculative power and its motivation to calculate of the human mind has been overplayed by cognitive psychology researchers in the 1950s who were newly baptised in statistical techniques like regression and correlation. Because academics thought in statistical terms it seemed natural to think their subjects also did (Gigerenzer et al 1989).

1.2 The building blocks of heuristics

The central thesis of much of Gigerenzer's research is that the primary determinant of the value of a heuristic in any decision-making context is the environment. Heuristic selection and the environment go together like the two blades of a scissors in Herbert Simon's vivid image (Simon, 1990, p. 7).

Gigerenzer and Brighton (2009, p. 113) identify some common building blocks that might serve as a starting-point. These are

- a *search rule*, say the number of stocks to be included in the portfolio,
- a *stopping rule*, say a yearly portfolio evaluation period,

- *a decision rule*, say a choice of portfolio weights.

TF&S (p 98) define a heuristic as “a very simple procedure that helps find adequate, though often imperfect, answers to difficult questions”. Similarly, but with a more positive view Gigerenzer and Gaissmaier offer the following definition:

> “A heuristic is a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods.” Gigerenzer and Gaissmaier, (2011), p 454.

The emphasis is upon grounded decision-making of practical, frequently encountered, problems rather than stylising choice to its most generalised, abstract, level. An example of this is the adoption of "TIT-FOR-TAT" strategies by players in the Prisoner's dilemma, even though full "rationality" would caution them to defect initially (Axelrod, 1984). Indeed Axelrod (1984) reports that such a simple TIT-FOR-TAT rule won out in a computer programming competition which invited "solutions" to the problem of how best to play the Prisoner's dilemma game.

1.3 Different models or different objectives?

We must be wary of presenting the work of K&T and Gigerzenzer as binary opposites, as in many ways these researchers have somewhat different objectives and not just different research methods to pursue the same objective. To see this let us consider the best known of K&T's work, prospect theory.

Kahneman (1979, 1992, Wakker 2010) evaluates gambles by the impact of choices on changes, *rather than levels*, of wealth and their movement relative to some relevance reference/benchmark level of utility/wealth. In advancing this challenge to the standard utility theory framework the authors' ambition was deliberately modest as TF&S states the case

> “we constructed a theory that modified expected utility theory just enough to explain our collection of observations. That was prospect theory.” TF&S, p. 272.

As such prospect theory can be seen as an evolution from standard expected utility necessitated by the need to accommodate anomalous findings.

As such the K&T agenda can be reduced to simply patching up expected utility theory and allowing the rest of economic analysis to proceed unhindered, save for the need to adopt a revised utility function. TF&S summarises its success as follows:

> “Prospect theory was accepted by many scholars not because it was "true" but because the concepts that it added to utility theory, notably the reference point and loss-aversion, were worth the trouble.” (p. 288)

But this begs the question whether such an incremental adjustment is enough to provide a satisfactory theory of human choice and specifically investment choices? Is it sufficient to embed a few adjustments into a standard utility function and proceed as normal?

Berg and Gigerenzer (2010) argue it is not, interpreting much of behavioural economics as a “repair program” using loose language and the introduction of new parameters into existing neo-classical models as a way of avoiding the thing most needed. These are credible models of financial decisions that both explain current choices and predict future ones. These authors almost find it easy to parody much of the most highly cited and influential work in the field as follows.

> “Behavioural models frequently add new parameters to a neo-classical model, which necessarily increases R-squared. Then this increased R-squared is used as empirical support for behavioural models without subjecting them to out-of-sample prediction tests.” Berg and Gigerenzer, (2010, p 137).

This distinction between descriptive and predictive models is one that has haunted applications of behavioural finance as we shall see in the final section of this paper.

We investigate here a more radical point of departure suggested by Gert Gigerenzer and co-authors as an alternative to the K&T theoretical framework for behavioural finance. As behavioural finance matures it is inevitable different traditions within the perspective will emerge (DeBondt *et al*, 2008).

For Gigerenzer and his co-authors there is no unique rationality to be uncovered anyway, as what is rational is simply context dependent. But perhaps the most striking difference between the Gigerenzer and K&T's viewpoint on financial decision-making is that for Kahneman in TF&S the main choice is between thinking in two different modes, while Gigerenzer prefers to emphasise the intuitive, unthought, nature of so much of our action, including financial trades.

So Gigerenzer draws on the prior work on "unconscious influences" by Hermann von Helmholtz (Gigerenzer, 2007, pp 44). Such influences allow us to thread together a myriad of data regarding context and character to make speedy and largely beneficial decisions. So one way to see the role of unconscious influences is as a sort of extreme fast (System 1) thought process as Gigerenzer puts it

> "Humans would not be called Homo Sapiens if all inferences were like reflexes...... other rules of thumb have all the advantages of perceptual bets -- such as being fast, frugal, and adapted to the environment -- but their use is not fully automatic. Although typically unconscious, they can be subjected to conscious intervention." (Gigerenzer, 2007, p. 45)

Thus the disagreement between the two perspectives on decision-making may be conceived of as turning on the role of conscious deliberation, or more dramatically, the extent to which are actions are preceded by active cognition in any sense.

For the K&T the key distinction is between immediate and deliberative cognition (system 1 and 2 cognition mechanisms) but Gigerenzer's decision-making schemata sees financial decisions as dominated by unconscious influences, whimsy and almost reflex responses conditioned more by culture and social norms than active reasoning.

1.4 The heuristic toolbox for financial decision-making.

In stark contrast to the heuristics and biases research program of K&T Gigerenzer argues that the reason why we make such intensive use of simple rules, heuristic tools, for financial decision-making and much else in life is simply because they work. Probabilistic reasoning, and its associated expected utility calculus, are often discarded in favour of ``fast and frugal reasoning" which focuses on a few cue variables to stylise the choice before us. This happens for two reasons

1. we are boundedly rational and not rational calculating machines, we want to make the right choice but making some choice is even more important.
2. many decisions as considered under conditions of uncertainty not risk. Think of many simple examples. Will Britain leave the European Union? Will Ukraine ultimately join the European Union? While these are clearly sensible questions, which are commonly discussed, we feel often unable to attach probabilities to these events. Certainly any attempt to do so cannot draw on the frequency of previous exits and entries to the Union.

Artinger *et al* (2014) state the central tensions between the heuristics and biases approach and Gigerenzer's fast and frugal reasoning approach as follows

- fast and frugal reasoning focuses upon clearly articulated computational models of heuristics, specifying details of the calculus by which decisions are made, as opposed to the broad labels,
- fast and frugal reasoning invokes a *ecological*, rather than *procedural*, definition of rationality. It always asks is this decision-making process the best one for the environment the decision-maker finds himself in, rather than seeking for a globally applicable "rational" choice architecture.
- less can be more in decision-making, especially in highly uncertain environments where accepting simple biased predictions may be preferable to attempting spuriously accurate estimates.

we trace each of these themes as they emerge in financial decision-making below.

Neth *et al* (2014) point out often in a volatile market the non--stationary nature of financial data means much of the data that does exist is of little use increasing the role of uncertainty, as opposed to risk, in characterising the choice faced.

1.5. When will fast and frugal reasoning work best?

Gigerenzer and Goldstein (2009) state the trade--off between complex forecasting models and simpler heuristics thus

> ”In statistical terms, when faced with out-of-sample or out of population prediction, a forecasting method has to bet on robustness instead of trying to secure and optimal fit to the past, particularly if samples are small, cues are abundant, predictability is moderate or low, and there is a chance of overfitting." (Goldstein and Gigerenzer, 2009, p 761)

In this their views reflect a research tradition little discussed in Finance research arguing for the “robust beauty” of simple models for prediction (Dawes and Corrigan, 1974, Dawes, 1979, Makridas and Hibon, 1979, 2000). While what constitutes an optimal forecast clearly depends on a particular investor's loss-function Lim (2001) it seems clear simple models beat complex ones for a wide-range of purposes.

Each of the Goldstein and Gigerenzer criteria for the desirability of robust decision-making seems to be met in financial markets. Indeed the low predictability of asset prices is a central tenet of the efficient market hypothesis. Another factor favouring the use of simple rules for prediction, as opposed to more complex multivariate models, is measurement error in relationships which are fundamentally monotonic.

Lord (1962) points out that when more than one predictor is measured with error it will often make sense to simply average out the measurement errors made, allowing an underlying multivariate function to be adequately approximated by a simple linear function. Often in financial studies trading costs and taxes will mean true investor expected returns are measured with error implying such arguments for simplicity may have some force.

1.6. Financial decision-making the fast and frugal way.

Based on their insights Gigerenzer and co-authors have developed a set of simple decision-making schemata to enable fast and frugal methods of decision-making.

Prominent amongst these are fast and frugal decision-making trees.

An example of such a tree, perhaps useable by an investor, might take the form of Figure 1.

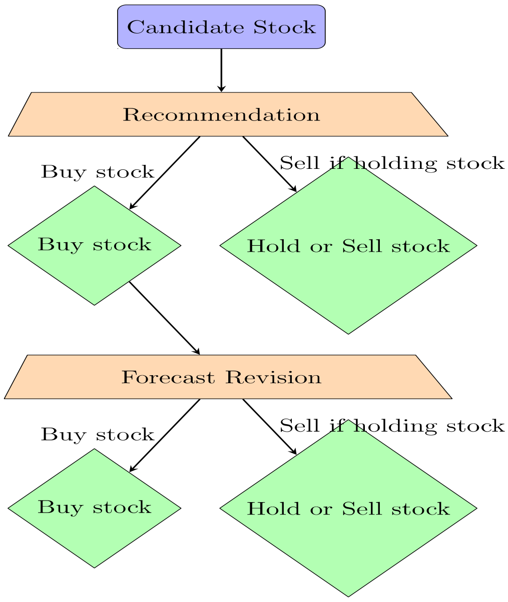

Figure 1: **Fast & frugal tree for using analyst's advice in investment.**

Here the investor simply buys stocks attracting buy recommendations and upward revisions in their forecasted earnings. This investment strategy, of course, ignores the difference between hold and sell recommendations and the difference between stocks with large and small upward revisions. While this ignorance biases our estimates it supplants any need for estimation and hence the damage out-of-sample prediction error does to implied trading profits suggested by the recent presence of in-sample profits. The frugality of this heuristic might be its very strength, with richer alternatives appearing to offer higher, but far less stable, profits.

Neth *et al* (2014) points to three contexts where the parsimony of fast and frugal decision-making of this type might appeal

- highly uncertain choices, where risk based calculations seem forced,
- choices where many options are presented as available, requiring substantial search,
- choices where little information truly relevant to the choice being made is available.

Here a fast and frugal tree method of solution might be preferable to any standard “rational” mode of choice.

1.7 The purpose of heuristics.

The great value to decision-makers of heuristics is in making our choices cleaner, more decisive and less hedged around by fears. As TF&S puts it

> “The most coherent stories are not the most probable, but they are plausible, and the notions of coherence, plausibility and probability are all easily confused by the unwary.” (p 159)

Part of this this desire for coherence derives from a marked preference most of us express for certainty, as opposed to recognising and evaluating, risks (Gigerenzer, 2014). Gigerenzer and Todd (1999) point out such a vision of heuristic choice can be misleading because it misses out on man's adaptive nature. They see the search for abstract logical consistency as detracting from the essence of a heuristic's goal which is to produce, better, more favourable to the heuristic's user, outcomes. For them

> “The focus of heuristics is not to be coherent. Rather their function is to make reasonable, adaptive inferences about the real social and physical world given limited time and knowledge.” (Gigerenzer and Todd, 1999)

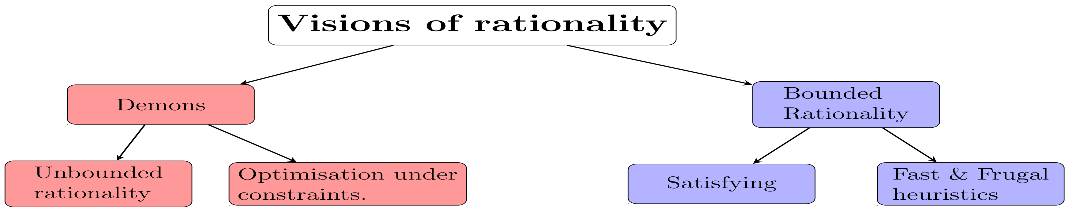

Figure 2: Models of bounded rationality.
Source Figure 3.1, *Bounded Rationality: The adaptive toolbox.*, pp 39, Gigerenzer and Selten, 2001

To resolve this problem of not *whether* investors will act rationally, but *how they will* do so, Gigerenzer develops his adaptive toolbox of decision-making heuristics to this purpose. This toolbox may include calculations of expected utility; but will often demure from doing so in favour of some other mode of fast and frugal reasoning.

Crucially rationality for Gigerenzer is very much ecological and not confined to some given procedural form. This mode of reasoning, while clearly more opportunistic and less consistent in form may still be preferable in its outcomes for investors.

2. K&T versus Gigerenzer: divisions and unities.

The debate between K&T and Gigerenzer thus concerns not so much the presence of biases in investor decision-making but how those biases are best captured to determine when their impact is most intense and, conversely, most ameliorated.

Gigerenzer and his colleagues specifically seek to model the operation and deployment of heuristics in decision-making which extends beyond a mere assertion of their presence. As Gigerenzer states the problem

> "The problem with heuristics is that they explain both too little and too much. Too little because we do not know when these heuristics work and how; too much because post hoc, one of them can be fitted to almost any experimental result." Gigerenzer, 1996, p 592.

So if heuristics are so valuable to investors why have they received such a bad press by Finance academics? Part of the reason seems to be that heuristics, are invoked almost as slogans, or buzz-words of indeterminate (and possibly no) meaning.

2.1 Some examples of heuristics

Examples of decision-making heuristics and their power abound but some simple examples are (see Schwartz, 2010)

1. *representativeness*, or constructing the distribution of expected outcomes according to the data that made most impression on your mind,
2. *availability*, investing in what you know, avoid the unknown/untrusted,
3. *anchoring and adjustment*, using benchmarks, like yesterday's price movement, to judge current returns,
4. *affect or emotion* in financial decisions, for example the effect of variations in the length of day/daily sunlight on the movements of stock markets (Hirshleifer and Shumway, 2003).

2.2 The initial dispute.

While the debate between K&T and Gigerenzer continues it initially surfaced in an exchange of conflicting views in 1996 (see Gigerenzer, 1996, and Kahneman and Tversky, 1996) and the essence of it remains unchanged and unresolved.

To set the scene for later discussion we initially revisit this exchange of views in the *Psychological Review*, the primary research Journal of the American Psychological Association. This began with K&T's article "On the reality of cognitive illusions'' that accused Gigerenzer of greatly misrepresenting their research program in his earlier published work.

K&T object to Gigerenzer's assertion that in their research program they regard the choices their subjects make in an uncertain environment as context free. K&T counter this criticism by pointing to the role of the adoption of decision-making frames in their schemata for decision-making.

So while for both authors context is central to understanding choices made Gigerenzer's adoption of the bounded rationality concept helps him say more about how that context dependence works out in practice. For Gigerenzer the primary issue is not *whether* a particular bias is exhibited at all, but rather the precise *conditions under which it will emerge* and grow.

Overall K&T's initial response to Gigerenzer's critique is one of frustration at what they perceive to be a straw man mischaracterisation of their research agenda, as they put it

> "The position described by Gigerenzer is indeed easy to refute, but it bears little resemblance to ours, it is useful to remember that refutation of a caricature can be no more than a caricature of refutation." Kahneman and Tversky, 1996, p 583.

In their initial reply to Gigerenzer's critique (Kahneman and Tversky, 1996), K&T discuss three issues which have become constant themes of later disputes, these are:

- *base rate neglect* and representation of uncertain outcomes almost regardless of the base probability of an event's occurrence,

- *conjunct errors* of the type which derive from believing the probability a stock will rise in value is less than the probability it will rise by more than 10%,
- *overconfidence*, which K&T claim to chronicle in a variety of contexts but Gigerenzer disputes since this seems to conflate, overconfidence and the ex-ante concept of accuracy, which can only be really known to an investor ex-post.

Specifically Gigerenzer seemed to claim that since probabilistic reasoning has both a frequentist and bayesian/subjective source of justification any invocation of probability in stylising observed choice is either meaningless or opportunistic. This seems a somewhat high-minded philosophical position rather than a practical one in the view of K&T (1996).

Secondly, because many of the "biases" K&T pointed out seemed to be ameliorated, or even removed, when choices were presented in frequency distribution, rather than probabilistic, terms these alleged biases are suspect or more apparent than real in Gigerenzer's view (Meder and Gigerenzer, 2014)

More importantly Gigerenzer's research seems to understand and in the limit predict the sort of contexts in which cognitive illusions of the three types K&T discuss appear and disappear. Hence for Gigerenzer arguments over the strength of evidence for particular biases is largely beside the point. He presents his case in reply to K&T's rejoinder to his critique thus

"In place of plausible heuristics that explain everything and nothing .... we will need models that make surprising (and falsifiable) predictions that reveal mental processes that explain both valid and invalid judgements." (Gigerenzer, 1996), pp. 596.

Gigerenzer, (2014) highlights two particular illusions worthy of our consideration

- confusing risky outcomes for certain ones, for example "you can never go wrong if you buy property",
- confusing risky outcomes with uncertain ones,

The latter type of illusion may be have been a problem for financial professionals and regulators in the recent financial crisis as “once in a lifetime" events cumulated to devastating effect.

2.3 Homo Heuristicus: an alternative objective framework for understanding financial decisions.

For Gigerenzer this limitation of the K&T research agenda reflects at least two sorts of problems (Gigerenzer, 1996)

- the narrow/stylised way in which many alleged norms of behaviour are constructed and invoked to decry deviations from them as “irrational”.
- the invocation of vague heuristics, as opposed to the development of explicit models of how those heuristics might emerge and be used to aid practical decision-making.

The first problem arises when probability judgements and laws are invoked to address often rather unique decisions for which it is unreasonable to expect the subject to construct an even approximate frequency distribution, for example Greece leaving the Euro area (Grexit).

Gigerenzer argues forcefully for the focus of research to shift to a structured model of heuristic development, proliferation, adaption and abandonment according to the decision-making context in which the heuristic will be deployed. That is Gigerenzer's quest is to trace the evolutionary path of heuristic adoption, adaption and abandonment, as opposed to some globally applicable concept of investor rationality.

Gigerenzer thus us states his research objective as follows

> “it is time to overcome the differences between the rational and the psychological and to reunite the two.” Gigerenzer and Goldstein, 1996, p 29.

In order to achieve this objective Gigerenzer and his many co-authors have advanced a set of decision-making rules inspired by Herbert Simon's notion that agents ``satisfice'', rather than maximise, their well-being given the limited time and information resources they have at their disposal (Gigerenzer and Goldstein, 1996).

Such models invoke simple decision-making cues that require minimal computational effort and may even violate the most basic rules of what is typically characterised as “rational” behaviour.

3. Applications to financial decision-making.

In this final substantive section we discuss how the Gigerenzer's insights, and the fast and frugal reasoning approach more generally has already been applied and might be so in the future to understand how financial decisions are made. As will be seen the potential for application is very wide and so the examples we give here should be regarded as simply illustrative, rather than exhaustive, by the reader.

We begin by considering how Gigerenzer's broad message concerning the link between cognition and context repeats itself in many examples of recent Finance scholarship. In a second subsection we discuss heuristic tools embraced by practitioners that are often ridiculed, or simply ignored, by Finance academics.

3.1 Cognition & context in financial decision-making.

While direct application of Gigerenzer's framework is rare (but see Borges *et al*, 1999, Aikman *et al*, 2014, Neth *et al*, 2014) its central intuition can be broadly applied. We begin our consideration of how cognition and context shape each other in financial decisions with the most commonly invoked heuristic in financial markets research, the representativeness heuristic.

3.1.1 Representativeness

Gigerenzer and Brighton (2009) point to ambiguities in application of perhaps the most famous heuristic of all, the representativeness heuristic. This heuristic is sometimes stated to imply that we construct a distribution of expected outcomes according to our distribution of impressions. So, for example, the representative heuristic has been used to explain

- The "hot hand" effect that sometimes a person is "on a roll" and scores from every free-kick, or plants home every shot at basket, forming a streak of good luck (Tversky and Gilovich, 1989), and simultaneously,
- the "gambler's fallacy" or the spoof "law of small numbers", this is the belief that small samples must approximate the population they are drawn from. So after a poor run my "luck must change" (Tversky and Kahneman, 1971, Rabin, 2002)

In a very similar way K&T often attribute base-rate neglect to the operation of the representativeness heuristic. Yet the very opposite tendency, now labelled conservatism, is also seen to derive from the very same representativeness heuristic.

Bulkley and Herrerias (2005) apply the law of small numbers, in the form formalised by Rabin (2002), to understand the stock market's response to profit warnings. These authors report less precise disclosures about the extent of bad news serves to intensify the stock market's negative reaction to a below par earnings announcement. Giving a revised earnings forecast, as opposed to just saying bad news is on the way, mitigates the stock market drop once earnings are finally announced.

So perhaps less information is not more useful in aiding prediction in every context as a quick reading of the fast and frugal literature might suggest. Further it serves to remind us that heuristic--driven choices are often not the best and active (System 2) calculative reasoning has its benefits too. This is especially so when choices are framed to illicit certain heuristics by those presenting the choices (companies, banks, etc)

It appears the invocation of heuristics as little more than slogan/labels results in us attempting to explain almost every sort of behaviour and hence adequately explaining none at all. This has led to behavioural finance research often being seen as a merely a rag bag of jumbled empirical anomalies to which heuristics exhibited in laboratory conditions (usually by students) are applied with little attempt to impose or check for internal consistency (Fama, 1998).

When our understanding of heuristics develops by means of merely anecdotal evidence one should not be surprised at encountering some scepticism amongst critics of behavioural explanations. Stephen Ross (Ross, 2002) states the case neatly in a discussion of the closed-end fund puzzle and the face-off between neoclassical and behavioural explanations of that phenomena.

> "if the only hope is to delve deeply into psychology then I believe that the theorist will find less there than meets the eye." (Ross, 2002, p. 136)

Gigerenzer seeks to advance the discussion about the *presence* of various heuristic tools onto the *nature of their invocation and operation* in practical decision-making, for example in developing trading strategies or implementing prudential bank regulation (Aikman *et al*, 2014). In short he wants to move the heuristics and biases literature on from identification and classification to the development of an overarching theory of heuristic driven choice. Thus he states

> "It is understandable that when heuristics were first proposed as the underlying cognitive processes in the 1970's they were loosely characterised. Yet, 25 years and many experiments later, explanatory notions such as representativeness seem vague, undefined, and unspecified with respect to both the antecedent conditions that elicit (or suppress) them and also to the cognitive processes that underlie them." (Gigerenzer, 1996, p 592)

In this sense we might regard Gigerenzer and his co-authors as completing a research project commenced by K&T, rather than simply critiquing it, although an element of critique and tension between the two approaches must certainly remain.

3.1.2 Reference points, framing and endowments.

For the investor in a standard utility model all that matters is outcomes and their probabilities, with the past, with its joys and sorrows, being irrelevant. But for the prospect theory investor what matters are changes not levels of wealth. So what I had in the past, how "people like me live", matters. Being unable to buy my own house, privately educate my children, or send them to

University may hurt more if they were comforts I enjoyed in my own childhood or are normal amongst my social peers.

So context matters not just the outcomes themselves. In particular losses matter and hurt more than gains of equivalent magnitude please me. So I may stop having weekends in London hotels in the face of price hikes. But price discounts may not necessarily attract me back as a customer because I have become accustomed to being doing without trips to London.

The “endowment effect” teaches us that what I have I hold, for example the tradition of privately educating our children (TFS, p. 290). But unlike Gigerenzer K&T seem to say little about how rationality evolves to allow investors to adopt the best cognitive frame given the trading environment they inhabit.

K&T have specified the context for decision-making with respect to risk into a very simple four-fold typology, suggested by the tenets of prospect theory (TF&S, p 317). This typology stratifies the expected response to prospective outcomes according whether that outcome is a gain or loss and its probability of occurrence. Over gambles with outcomes of fairly high probability, so outcomes are almost known, the standard division between risk-aversion over positive pay-off gambles and risk-seeking in the loss-domain applies.

	Gains	Losses
High probability	Fear of disappointment, *Risk-averse*	Hope to avoid loss, *Risk-seeking*
Low Probability	Hope of large gain *Risk-seeking*	Fear of large loss, *Risk-averse*

Table 1: The four-fold nature of risk-attitudes.

But it appears a risk-averse attitude may extend to losses with a smaller probability of occurrence if this loss is potentially large. Similarly for low probability gains an element of "hope" encourages risk-seeking with respect to those gains. Hence the usual division between risk-seeking over losses and risk-aversion over gains needs to conditioned upon the probability of prospective losses or gains being considered.

Here in the bottom right--hand cell of Table 1 insurance becomes an attractive way of planning for the remote possibility of having to endure a large loss, sudden death or a permanently debilitating injury. Whereas for a loss that was more easily anticipated we might expect to see "gambling for resurrection" of the type commonly observed by traders down on their luck (a pathological example being Nick Leeson of Barings fame in 1995 (Leeson, 1997).

In this typology adoption and disposal of clearly segmented mental frames mimics the simple cues for decision-making Gigerenzer and co-authors adopt in their models. This reminds us that what K&T and Gigerenzer share in their analysis, for example, a sensitivity to variation in mental frames/choice context, is at least a great as what divides them.

3.2 Portfolio theory.

No decent Finance class can be taught without much reference to β sensitivities in the CAPM or some more complicated multi-factor asset pricing model. Much time is spent refining the estimation and testing of such models. But what if simply investing an equal amount in each stock returns turns out to be a more profitable strategy than calculating portfolio weights by means of quadratic optimisation, as suggested by Markowitz, (1952)? It appears this simple heuristic may indeed be very powerful and capable of generating more profitable advice on portfolio selection than standard asset-pricing models in Finance (DiMiguel *et al*, 2009).

The standard rational approach to portfolio composition is that developed by Markowitz (1952, 1956 and 1959). This approach shows how to optimally allocate wealth between risky assets in a static setting assuming investors are only concerned with the mean and variance of a portfolio. This optimisation, while relatively simple in theory, is often difficult to implement in practice. The asset weights produced tend to be unstable over time and perform very poorly out of sample (see, for example, Hodges and Brealey, 1978, Michaud, 1989; Best and Grauer, 1991 and Litterman, 2003). Various methods of selecting portfolios using simple heuristics have been proposed and shown to have some advantages relative to the Markowitzian approach. We discuss two of these below, restricting parameter search and the   rule.

Standard asset pricing models require estimates of risk-factor weights, βs, to determine optimal asset allocations. Such estimates are typically assumed to be drawn from stable distributions. The problem being that such weights are constantly shifting. Hence any model that fits observed market data well may not predict future risk-exposures satisfactorily. Like any good estimate risk-weights must trade--off two important properties

- *bias*, resulting from buying into too much risk at too high a price, or failing to optimally diversify the portfolio.
- *variance*, loading up on a given risk-exposure just as the return to exposure to it is about to fall, yielding an estimation error in predicting returns.

Brighton and Gigerenzer (2015) point out that in a legitimate concern to reduce bias in predicting social and economic outcomes researchers have fallen victim to what they term the "the bias bias'', where

> “To suffer from the bias bias is to develop, deploy, or prefer models that are likely to achieve low bias, while simultaneously paying little attention to models with low variance.” (Brighton and Gigerenzer, 2015, p.1)

Of course great estimates are both precise and stable. But to achieve such precise and stable estimates may require far more data than most asset markets permit.

DeMiguel *et al* (2009) estimate that for the US market if the investor desires to retrieve portfolio weights capable of beating the performance of an equally weighted portfolio he will need

3,000 months (or 250 years) of data to estimate his factor weights over a 25 stock portfolio. This rises to 6,000 months (or 500 years) for a 50 asset portfolio. Knowing this begins to make the heuristic seem attractive. This suggests a simple heuristic might dominate one of the central theoretical tenets of standard Finance as a tool for investment.

Simple heuristics to limit the parameter search can improve the predictive accuracy of models (Jagannathan and Ma, 2003). While practitioners often estimate the optimal portfolio imposing short-sales constraints academic worry that this might induce specification error. Jagannathan and Ma (2003) point out that while the academics concern is true imposing even invalid constraints may help mitigate estimation error by constraining the parameter space considered. The practical value of imposing even invalid constraints depends on the trade-off between the two possible sources of error. In their own empirical work constraining admittedly invalid constraints appeared worthwhile.

The truth, as in many things, may lie somewhere in the middle. Tu and Zhou (2011) report that an average portfolio return produced by combining the forecast returns from the $\frac{1}{N}$ rule with that from the basic Markowitz model, plus various enhancements to that model, exceeds the return offered by either the $\frac{1}{N}$ rule or the basic Markowitz models alone. Once again the context of application determines the best model, or combination thereof, to apply.

3.3 Implications for asset allocation

A related portfolio problem is how to adjust portfolio composition to allow for the risk appetite of investors. In the Markowitz paradigm the mutual fund separation theorem (MFST) applies. That is all investors should hold the same portfolio of risky assets and adjust for their risk preferences by borrowing or investing at the risk free rate. To quote Canner *et al*. (1997)

> "all investors hold risky assets in the same proportions. In particular, every investor holds the same ratio of bonds to stocks. To achieve the desired balance of risk and return,

investors simply vary the fraction of their portfolios made up of the riskless asset?" Canner *et al* (1997), p182.

However, Canner *et al*. (1997) also report a puzzle in that financial advisors use a heuristic in advising their clients that is not consistent with the MFST. Many advisors give guidance consistent with the idea that the more risk averse a client is the higher should be the ratio of bonds to stocks in their portfolio. It has proved a largely fruitless task to try and reconcile such asset allocation advice to standard portfolio theory.

Keasey and Hudson (2007) show that when the reasoning of the advisors is investigated it can be shown that for the worst case scenarios (analogous to Value at Risk) the heuristic financial advisors use frequently outperforms the MFST, given the prevailing non-normal distribution of returns we observe.

3.5 Earnings quality.

A central issue in capital market research in accounting is the quality of announced earnings, this has been measured by earnings persistence, the relative stability of accruals and cash--flows as elements in overall earnings, the information content of accruals, the avoidance of restatements or sanctions by regulatory authorities and other metrics. Initial debate focussed on whether companies with publicly or privately held equity reported higher quality earnings. The relative ranking of earnings quality was unclear because two *opposing*, yet credible, theorisations of the determinants of earnings quality exist (Givoly *et al*, (2010) these are

1. a theory that greater *demand* for high quality earnings ensures public companies report more informative earnings, and so distort accruals less,
2. a theory that public companies have more *opportunity* to mislead investors and for that reason take these opportunities.

Givoly *et al* (2010) study a unique database of companies to resolve this issue. They examine a matched sample of relatively large companies where each company with publicly traded equity is matched to one with publicly traded debt. Of course both these sort of companies face an active demand for high-quality earnings by outside investors. The authors find on a number of commonly employed metrics companies with publicly traded debt, but no traded equity, exhibit higher earnings quality. This finding is striking as it appears to contradict earlier findings by Ball and Shivakumar (2005) that companies traded on stock markets have higher quality earnings in the sense of being more "conservative" by recognising future losses more quickly and thus forewarning equity investors.

This patchwork of contradictory findings depending on the method of sample construction and the measure of ``earnings'' quality used shows that context is all. Earnings quality is many faceted and the most useful definition of that elusive trait will depend on the demands placed on auditors and their opportunities to circumvent those demands.

This contexual nature of earnings quality is important as financial reporting is harmonised by International Reporting Standards (see Soderstrom and Sun (2007) and Barth *et al* (2008)).

Dechow *et al* (2010) after reviewing the various empirical proxies available to capture earnings quality conclude they

> "can reach no single conclusion on what earnings quality is because "quality" is contingent on the decision-context." Dechow *et al*, (2010), p 344.

investors' cognitive perception of quality is formed within a context from which it cannot be separated.

It seems unreasonable to expect the demands made for earnings quality and the opportunities to circumvent providing it to remain constant across the 28 states constituting the European Union[3] which have adopted IFRS standards wholesale. If we accept this, could less earnings quality be more

[3] Even before Albania, Serbia and Macedonia join.

informative for investors, or at least not noticeably less informative, from an investors' perspective in some member states?

3.6 Overreaction, mean-reversion.

Within Finance perhaps the most conclusively documented bias is the failure of investors to recognise regression to the mean, ``trees don't grow to the sky." This inability to recognise that extreme outcomes reflect luck, as well as skill, underpins the overreaction anomaly (Debondt and Thaler, 1985, and 1990). While all of us know Success = Talent + Luck (TF&S, p 177), we nonetheless still prefer to build up our heroes and stigmatise slackers. Indeed it appears much of sports and business commentary is haunted by attempts to rationalise luck. To say Steve Jobs was quite a lucky bunny is just never enough it seems.

Here too both the degree and timing of market overreaction/mean--reversion seems highly context dependent. Lee and Swaminathan, (2000) supply evidence to support the operation of a “Momentum Life Cycle" in which high volume, often glamorous, stocks attract investor attention and thus unsustainable gains/losses while less heavily traded, often value, stocks are set to enter periods of price--correction.

In their representation of the phenomena (see Figure 4 of their paper) momentum is clustered amongst high volume winning stocks and low volume loser stocks. The high volume winner stocks are propelled by a rising tide of “me too” dumb-money investors. Momentum amongst low volume losers is driven by the last of the dumb-money investors quietly closing the door as they depart. All this happening prior to smarter, contrarian, investors re-entering the stock to correct its price to something closer to fundamental value.

In both cases the pattern of momentum/reversion the stock exhibits depends less on its true/intrinsic value and more of the extent of its recent exposure to investor attention and thus trading activity. Once again context is all for overreaction to manifest itself in any particular stock.

This should not be too surprising as it is far from clear we would want to issue predictions that recognise regression to the mean even if we were capable of doing so. Hugely successful serial entrepreneurs often seem to be those who can accept the improbable, if not downright delusional, as a basis for intense commitment (Lewis, 1999).

3.7 Bank failure

In his recent work with the Financial Stability Board (Aikman *et al* 2014) Gigerenzer considers the use of heuristic tools in evaluating a bank's capital adequacy and the related problem of bank failure. Figure 2 illustrates a fast and frugal tree the authors present for assessing the vulnerability of systemically important banks to failure. It assesses a bank's fragility over four key variables which are used to generate four red flags to warn a regulator to intervene and two green flags to suggest no intervention is required.

So any bank with less than 4.1% of equity to cover its debts raises an immediate red flag initiating a possible investigation. Similarly, a bank whose equity covers less than 84% of the market value of its equity raises a second red flag. If the bank's whole funding falls below 177 $bn, or if it has a loan to deposit ratio of above 1.47, then intervention is immediately required. The precise number of red/green flags required for the regulator to act is for experimentation/discussion, but these trigger measures provide an easily followed prudential banking protocol.

As in the earlier example of using earnings forecasts and recommendations in investment, this fast and frugal method of reasoning ignores the numerical variation in these key ratios beyond their trigger points. But accepting this bias might be preferable to attempting to find a model with sufficiently stable coefficients to convert good in-sample explanatory power into good out-of-sample predictions of which banks will fail.

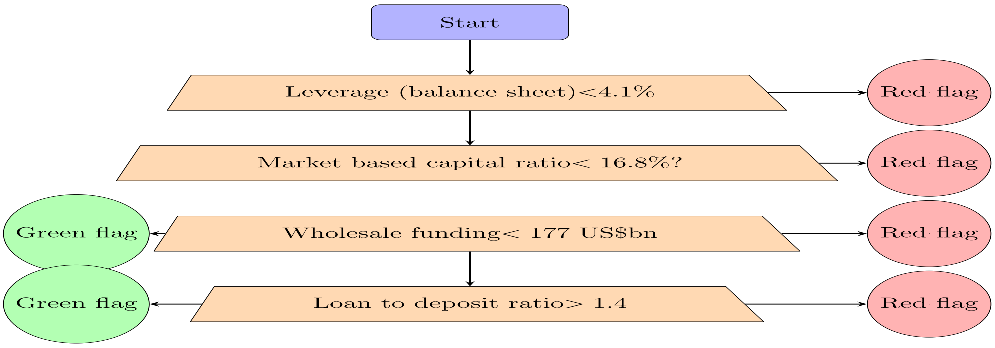

Figure 3: An example of a fast and frugal tree for assessing bank vulnerability. *Note*: Based on Figure 3 on page 19 of Aikman *et al*, 2014.

3.8 Heuristic tools in financial decision-making.

3.8.1 Technical Analysis.

Practitioners have long used technical analysis to predict future price movements on the basis of past price movements, a practice directly at odds with weak-form stock--market efficiency. The associated trading rules can be regarded as heuristics as they are often simple and loosely defined and certainly are not based on any notion of rational optimisation. The historical evolution of technical analysis is traced by Lo and Hasanhodzic (2010). It was used in 18th century Japan where a form of technical analysis known as candlestick charting was used (Park and Irwin, 2007). In the West, Dow Theory which was developed in the late 1800s by Charles Dow, the Editor of the *Wall Street Journal*, and was used in an effort to develop profitable trading strategies (Lo and Hasanhodzic, 2010). Thus technical analysis pre-dates by a wide margin all modern financial economics.

Technical analysis has been and continues to be used very extensively in many financial markets. Smidt (1965) reports that the majority of amateur traders in the US commodity futures markets exclusively use charts to identify trends. Similarly, Billingsley and Chance (1996) find that about 60% of commodity trading advisors make heavy use of computer-guided technical trading systems. More recently, Menkhoff and Taylor (2007) find widespread use of technical analysis in the foreign exchange markets and Menkhoff (2010) finds that the vast majority of fund managers both use technical analysis and prefer using it rather than fundamentals based methods of prediction.

Given the lack of a theoretical basis for the trading rules there has often been a predisposition to dismiss them in the academic literature (see, for example, Malkiel, 1999). The scepticism was reinforced in the early days of financial economics by negative empirical findings regarding the profitability of various technical rules in stock markets (Fama and Blume, 1966,van Horne and Parker, 1967, 1968, Jensen and Benington, 1970). However, there have been many subsequent empirical findings relating to different financial markets showing that technical analysis cannot be dismissed and certainly has predictive power in some markets at certain times (see, Park and Irwin, 2007, for a general survey and Menkhoff and Taylor, 2007 for a discussion relevant to the foreign exchange markets).

The wide use of technical analysis both across all asset classes and over a long time also raises questions about how a practice that is so derided by standard Finance theory can be so persistent. In summary, the particular set of heuristics constituting the “adaptive toolbox” of technical traders should not readily be dismissed as sub-optimal and thus unworthy of reasoned discussion.

3.8.2 Outperformance of Value Stocks.

The case of the outperformance of value stocks is a very interesting one where mainstream theory has converged upon an existing heuristic. The heuristic that value stocks tend to outperform in the stock market has been well-known to practitioners for many decades and is extensively discussed in the seminal book *The Intelligent Investor* by Graham which was first published in 1949 (Graham, 1949).

Graham considered that the value effect was driven by the misconceptions of investors who tend to overvalue glamour stocks and undervalue less exciting value stocks. The notion that value stocks might outperform does not fit into classical MPT from a theoretical point of view, as value could not be expected to be related to risk as measured by standard deviation, and so was sidelined by academics in the early decades of financial economics. Nonetheless the empirical fact that value stocks outperform could not ultimately be ignored. Thus value has been incorporated as one of the factors in the now widely used three-factor model developed as a successor to MPT (see Fama and French, 1993) albeit retaining the notion of rationality by interpreting value as a rational reward for accepting an element of risk not captured by the CAPM.

3.8.3 Seasonal anomalies

Seasonal anomalies or calendar effects have been investigated in a huge academic literature (see Dzhabarov and Ziemba, (2010) for a fairly recent overview of this area) much of which indicates that taking advantage of these patterns may be beneficial in terms of investment timing. These effects generally have not been explained within the standard rational framework but readily lend themselves to being used as simple heuristics. Indeed, in some cases, these heuristics were definitely known and used by practitioners before being reported in the academic literature.

For example, the ``turn of the month'' effect (TOTM), which shows that stock returns are substantially higher around the turn of calendar months, was initially reported by market experts such as Merrill (1966) and only later in academic studies by Ariel (1987) and by Lakonishok and Smidt (1988). The Halloween effect and the very closely related ``sell-in-May-and-go-away'' effect, which indicate that stock returns are lower in the summer months, did not explicitly appear in the academic literature until a paper by Bouman and Jacobsen (2002), although Gultekin and Gultekin (1983) also cover closely related issues. However, as Bouman and Jacobsen (2002) make clear, this rule was well known to market practitioners for many decades before it received academic interest. It had clearly been learned inductively as a trading tool, rather than deduced from any formal theory of financial decision--making.

3.8.4 Investing in what you know.

Familiarity breeds investment (Huberman, 2001) as much research on home-bias puzzle in portfolio allocation attests. A starting point of nearly all such finance research is how unwise investors, particularly individual investors, are to invest in their company's, state's, or nation's stock rather than in an alien, less familiar, one (French and Poterba, 1991, Baxter, 1994). But could it be that in investment a little knowledge is a beautiful thing?

Borges *et al* (1999) claim that it is and invoke what they call the "recognition heuristic" to explain how ignorance can be turned into profit. They construct portfolios based on the ability of German and American experts (Finance class students in Chicago and Munich respectively) and laypeople (people walking the streets in Chicago and Munich) to recognise German and American stocks. The authors simply bought the most recognised stocks and compared their performance to standard benchmark portfolios. They find that recognised stocks outperform unrecognised stocks on most sensible benchmarks, a random draw of stocks, returns earned by large popular mutual funds in the US and Germany, or the S&P 500 and DAX index returns respectively. Furthermore the performance of a portfolio based on the ability of laypeople, strolling in the park, to recognise stocks beats that of a portfolio based on recognition by Finance students, who should at least have some passing interest in investing. Amusingly Gigerenzer's results from this study themselves proved rather context-dependent when Boyd (2001) repeated the study during a subsequent recession and obtained almost completely opposing results.

Note the “recognition heuristic” can only help those with a little knowledge, a professional investor who recognises all the stocks in the S&P 500 or DAX cannot use it. In the same way the utterly clueless, who have not heard of a single stock, cannot rely on the recognition heuristic. For Goldstein and Gigerenzer (2002) the recognition heuristic is a powerful tool in the context of gaps in knowledge. It works best in structured environments where inference from partial knowledge seems worthwhile. Here recognition emerges as a powerful tool of adaptive rationality.

> “the recognition heuristic is a cognitive adaptation. In cases of extremely limited knowledge, it is perhaps the only strategy an organism can follow. However, it is also adaptive in the sense that there are situations... in which the recognition heuristic results in more accurate inferences than a considerable amount of knowledge can achieve.” Goldstein and Gigerenzer, (2002, p 88).

Hence it appears a little knowledge may be a wonderful thing for investors. The fact that experts were at a disadvantage in forming a portfolio for purchase based on their recognition of the stock suggests even quite a lot of ignorance maybe no bad thing in investment. Certainly, experimental evidence reported by Weber *et al* (2005) confirms that familiarity with a stock lowers the perceived risk of holding it in an investor's portfolio. Indeed this underestimate of the risks of the familiar may account for the persistence of observed home bias in investor's portfolios.

It is certainly true that recognition of a stock reflects both its glamour and market capitalisation which are known to be related to investment performance, as demonstrated by their appearance in the ubiquitous Fama and French asset pricing model (1993). But this to some degree makes their outperformance of mutual fund portfolios and national indices more, not less, difficult to understand, because large (presumably well recognised) stocks actually tend to perform poorly, even though glamour (also well recognised) stocks do tend to perform well.

3.8.5 Derivatives valuation.

The standard rational approaches to derivatives valuation are based on the principle of no-arbitrage. The most celebrated model is the Black-Scholes-Merton (BSM) model for option valuation originally developed in papers by Black and Scholes (1973) and Merton (1973). This model is often regarded as the break-through model in financial economics and was certainly a technical tour-de-force, using differential calculus to solve a dynamic hedging problem and yet producing a tractable formula ready for use by those incapable of understanding its derivation.

The BSM formula is ubiquitous in financial markets and so would seem a clear triumph for the rational approach. In reality things are not so clear cut, with some high profile practitioners strongly dissenting from this viewpoint. Huag and Taleb (2011) forcefully argue that, in practice, option traders use heuristics not the BSM formula. They state:

> "Option hedging, pricing and trading are neither philosophy or mathematics, but an extremely rich craft with heuristics with traders learning from traders (or traders copying other traders) and tricks developing under evolutionary pressures, in a bottom-up manner." Haug and Taleb, 2011, 97.

The BSM valuation equation assumes that returns have a Gaussian distribution with a variance that is independent of the strike price of the option and the time to expiry of the option. The assumption of variance independence clearly cannot be supported empirically and if uncorrected leads to very significant option mis-pricing, to the extent that using the pure unadjusted BSM is very likely to lead to financial disaster. Goldstein and Taleb (2007) present evidence that professional traders may not even display a coherent understanding of what volatility measures.

In practice, participants in the options markets use the "volatility smile" a somewhat crude adjustment to the BSM model by which volatility can be adjusted to vary by strike price and time to expiry. The volatility smile is inconsistent with the theory used in the derivation of the BSM model (see Haug and Taleb, 2011, p105) although generally, allowing for this adjustment, practitioners can still be said to be using the BSM model. Given the volatility smile adjustment is very ad hoc it might be more appropriate to say that they are actually using heuristics to value the option and then relate this back to the BSM model.

Millo and MacKenzie (2009) note that the popularity of the BSM model showed no diminution after the 1987 stock market crash when huge surges in stock volatility meant the BSM model implied prices of equity call options well above the stock price of the underlying asset. The reason for its continued appeal was the model offered a common language for traders, clearing houses and regulators to discuss and dispute the impact of shared risks in the markets they jointly inhabited. As such the model was a more of a rhetorical device than the predictive tool it was initially marketed as. It allowed those in the market to communicate fears/hopes concerning an uncertain future they all faced rather than acting as a "risk-management" tool as such.

4. What the dispute implies for finance research.

Few can doubt the importance of K&T in the establishment of behavioural finance as it is currently understood, taught and researched. Both Kahneman and Gigerenzer agree on the centrality of heuristics to decision-making, including financial decisions.

For K&T heuristics often appear as a fall-back once the von-Neumann-Morgenstern axioms of rational decision-making do not describe investors' choices. Heuristics are then a patch-up, or repair job, on the standard financial decision--making model. But for Gigerenzer heuristics are simply a more effective way of evaluating choices in the rich and changing decision--making environment investors must face.

Gigerenzer challenges Kahneman to move beyond substantiating the *presence* of heuristics towards a more tangible, testable, description of their *use* and disposal within the ever changing decision-making environment financial agents inhabit. Here we see the emphasis placed by Gigerenzer on how context and cognition interact to form new schemata for fast and frugal reasoning as offering a productive vein of new research. We have illustrated above how the interaction between cognition and context already characterises much empirical research and it appears the fast and frugal reasoning perspective of Gigerenzer can provide a framework to enhance our understanding of how financial decisions are made.

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