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Behavioral Finance: Insights from experiments I: Theory and financial markets

Darren Duxbury[a]

[a] *Newcastle University Business School,*
Newcastle University, Newcastle-upon-Tyne, NE1 4SE, UK

Abstract

Purpose
The aim, here and in a companion paper (Duxbury, 2015), is to review the insights provided by experimental studies examining financial decisions and market behaviour.

Design/methodology/approach
Focus is directed on those studies examining explicitly, or with direct implications for, the most robustly identified phenomena or stylized facts observed in behavioral finance. The themes for this first paper are theory and financial markets.

Findings
Experiments complement the findings from empirical studies in behavioral finance by avoiding some of the limitations or assumptions implicit in such studies.

Originality/value
We synthesize the valuable contribution made by experimental studies in extending our knowledge of the functioning of financial markets and the financial behavior of individuals.

Keywords: *Experimental finance, Experimental economics, Portfolio theory, Equity premium, Herd behavior*

1. Introduction

Behavioral finance draws on a long standing tradition of experimentation in economics and psychology to motivate its behavioral models and empirical analyses. Over the course of a two-paper review, see Duxbury (2015) for the companion paper, we document the valuable contribution made by experimental studies in extending our knowledge of the functioning of financial markets and the financial behavior of individuals. The vast and growing number of such experiments, necessitates selectivity. We focus on those studies examining explicitly, or with direct implications for, the most robustly identified phenomena or stylized facts observed in behavioral finance. Notwithstanding the need to be selective, we cast the net outside of the standard notion of "experimental finance" to look beyond experimental asset markets examining institutional rules. A number of excellent reviews, both longstanding (e.g. Duxbury, 1995; Sunder, 1995) and more recent (e.g. 2013 special issue of the *Journal of Economics Surveys*), of the experimental asset market literature exist and so we direct the interested reader to these references.

In this paper, we begin by reviewing experiments designed to test specific aspects of finance theory, including the capital asset pricing model (CAPM), separation theorem and mean-variance portfolio theory (e.g. diversification, correlational neglect, home bias). We then turn attention to experiments that shed light on behavior observed in financial markets that is difficult to understand in the context of finance theory, including the equity premium puzzle, herd behavior and financial contagion, along with other stylized facts associated with return distributions, including fat tails and volatility.[i] We return in the second paper to review the contribution of experimental studies to our understanding of heuristics and biases at the heart of behavioral models (e.g. under- and over-reaction, overconfidence) and investor behavior (e.g. prior gains/losses), along with the influence of moods and emotions.

The basic tools of the experimental method (e.g. Friedman and Sunder, 1994; Hey, 1991), namely the ability to observe directly, control, and manipulate variables of theoretical importance, are well suited to a study of behavioral finance. Many of the key variables of interest in behavioral models are unobservable to researchers examining data from naturally occurring financial markets, hence such empirical studies adopt proxies to capture or measure the effect of many variables of theoretical importance. For example, in the context of portfolio decisions, Baltussen and Post (2011) note that challenges arise when analyzing real-life investment portfolios. An evaluation of the merit of an investor's portfolio decisions, requires knowledge of their risk preferences, which assets they considered and their expectations about them. Such data is largely unobservable, and so difficult to measure or control, in studies of real-life data, but can be controlled and manipulated directly in experimental studies. The ability to control allows experimenters to test the impact of variables of interest on investor behavior and the functioning of financial markets free from the confounding effects of other variables. Again in the context of portfolio decisions, Brown and Kagel (2009) note that their experimental design allows them to investigate behavior while controlling for the confounding effects of tax incentives, agency problems, transaction costs etc.. Perhaps the most potent weapon at the hands of the experimenter is the ability to manipulate the levels of treatment factors thus allowing causal tests of the relationship between variables of theoretical interest, and so moving beyond the correlational analysis possible in studies based on proxies of unobserved behavior. As will be seen in the companion paper, Duxbury (2015), this has been particularly enlightening in studies of the effect of overconfidence on financial behavior.

2. Finance theory and portfolio decisions

Finance theory, built on CAPM and mean-variance portfolio theory, presumes that investors optimize their portfolio return-risk trade-off by diversifying over various assets. Testing the CAPM empirically is problematic, however, and investors tend to hold under-diversified portfolios (e.g. Goetzmann and Kumar, 2008, for the US; Duxbury et al., 2013, for China). As such, testing finance theory implications has been an area of fruitful experimental research.[ii]

Kroll et al. (1988a,b) investigate the predictions of the CAPM, separation theorem and mean-variance model in the context of portfolio selection. In Kroll et al. (1988b) participants invest in one or more of three risky assets with known return distributions of different risk-return characteristics, while in Kroll et al. (1988a) participants select a portfolio combining a risky with a riskless asset. Participants in both experiments fail to construct efficient portfolios and frequently request historical return information–-irrelevant given their knowledge of the return distributions–-which the authors suggest may be indicative of individuals searching for patterns in returns over time. To address this possibility, they examine the number of switches from one risky asset to the other. Participants switched assets regularly, with the majority exhibiting a negative recency effect (holding assets performing poorly in the belief they will improve). The evidence in Kroll et al. (1988a,b) casts serious doubt on the validity of both the separation theorem and the CAPM.

Anderson and Settle (1996) suggest that the tasks in Kroll et al. (1988a,b) may have been too complex and so devise simpler tasks. In recognition that individuals have little appreciation of exponential growth, they devise tasks where participants receive 1-year (first) and 10-year (second) risk-return information and then allocate a percentage to invest in a risk-free and risky asset for a period of 10 years. In line with the expectation that the 10-year risk-return information would help participants understand the effect of compounding, a significantly higher percentage was allocated to the risky asset based on the 10-year data than the 1-year data. In other experiments, Anderson and Settle (1996) further simplify the tasks in Kroll et al. (1988a,b). The riskiness of the risky asset is manipulated across two treatment levels, high and low, such that an allocation to the risky asset of x% in the high-risk condition would create a portfolio with the same distributional characteristics as an allocation of 1.5x% in the low-risk condition. In addition, participants were presented with distributional information over the planning horizon, so that they did not have to project the growth of investments. The mean percentage allocated to the low-risk investment was significantly less than 1.5 times that allocated to the high-risk investment, but not significantly different from 1.0 times hence distributional differences seemed to have no effect on choice. It seems that, even when confronted with simplified tasks, participants are unable to form efficient portfolios.

Experimental evidence (e.g. Kroll et al., 1988a,b) suggests that participants do not respond to correlations between alternatives when making portfolio decisions. To examine this issue further, Neugebauer (2008) conducts experiments in which participants select from two risky assets, A and B, that are perfectly negatively correlated and a riskless asset C that yields an inferior payoff to that possible under the riskless combination of A and B. This aspect of the design allows dominated choices to be clearly identified. Despite participants in the experiment having prior knowledge of mean-variance theory, very few identify the negative correlation between the two risky assets and the majority select a dominated portfolio, hence correlation neglect is observed even under conditions of perfect negative correlation. To examine the effect of transparency of dominance, Neugebauer (2008) also conducts an experiment requiring repeated decisions in two tasks. In the first task the majority of decisions involve a dominated choice, but by the second task no participants choose a dominated asset, suggesting that errors cause efficiency losses. On examination of the revealed preferences and stated rationales, Neugebauer (2008) notes that participants seem to first allocate an amount to the riskless asset and then allocate the remainder of their endowment to the most risky, gain-only asset, thus supporting earlier experimental findings whereby participants are averse to losses not variance (Duxbury & Summers, 2004).

In light of the above evidence that individuals find it difficult to construct mean-variance efficient portfolios, interest has turned to a consideration of the diversification heuristics that might be employed. For example, in the context of defined contribution pension plans, Benartzi and Thaler (2001) examine a set of hypothetical questionnaires in which participants are asked to allocate their retirement contributions between pairs of funds. They find that plan participants adopt a naïve 1/n diversification strategy, investing an equal fraction in all funds offered in the plan. When the number of funds increases, Huberman and Jiang (2006) report evidence of a conditional 1/n diversification heuristic, whereby participants apply the 1/n rule to a subset of the funds offered. To better understand the portfolio construction decision and the use of such diversification heuristics, Baltussen and Post (2011) examine experimentally whether decision makers frame their investment decisions narrowly, excluding alternatives that are unattractive when viewed in isolation, but which have diversification benefits from a portfolio perspective. To avoid assumptions about, or the need to measure, risk preferences, Baltussen and Post (2011) analyze the optimality of the chosen portfolios using the criterion of first-order stochastic dominance (FSD). In a series of tasks, participants divide their money between five assets with a small number of equally likely states with known outcomes. One of the assets is unattractive in isolation, but very attractive from a portfolio perspective due to its negative correlation with other assets. A second asset is attractive in isolation, but very unattractive for portfolio diversification purposes to the extent that inclusion of this asset violates FSD portfolio efficiency. Participants were familiar with mean-variance portfolio theory.

Baltussen and Post (2011) find that most participants narrowly focus on the individual outcome distributions of the assets and ignore wider portfolio diversification benefits. Assets that are unattractive in isolation are avoided, despite their diversification benefits if negatively correlated with other assets. Having discarded such assets, many participants follow a conditional 1/n rule, constructing an equal-weighted portfolio of the remaining assets, possibly, Baltussen and Post (2011) claim, because they look very similar. Given the experimental design, such allocations are irrational; violating FSD.

In a series of experiments, Hedesström et al. (2006) examine covariation neglect in investors' portfolio decisions. They find that participants are unable to evaluate how covariation affects portfolio risk, either via intuitive or systematic (cognitive) routes, and so attempt to diversify following the 1/n heuristic, even in situations where this increases portfolio risk due to the covariance of returns of the individual assets (i.e. over-diversification). Informing participants about how covariation affects portfolio risk fails to reduce naïve diversification, but making participants calculate returns for diversified portfolios does, hence Hedesström et al. (2006) conclude that investors need to be better informed about the rationale underlying portfolio diversification in order to counteract the use of naïve strategies. Their findings are supported in a later study, Hedesström et al. (2009), in which they reduce the abstraction level of the experimental task to safeguard ecological validity.

In light of the pervasive evidence, both naturalistic and experimental, that investors make poor portfolio decisions, failing to diversify and constructing inefficient portfolios even in relatively simple settings, it would be informative to understand the psychological factors that may contribute to this behavior. Illusion of control, defined as "an expectancy of a personal success probability inappropriately higher than the objective probability would warrant" (Langer, 1975, p.313), has been proposed and examined in two studies.[iii]

Fellner (2009) examines experimentally the extent to which illusion of control may distort portfolio decisions. After a risk preference elicitation task, participants allocated money across three assets A, B and C. Risky assets A and B each had two possible returns, both with equal probability (0.5) of occurrence. Asset C was risk-less with a sure return. Each period, a profit target was imposed that participants had to achieve before they earned money. For either of the risky assets held in isolation, the target would be achieved each period with probability 0.5, while diversifying across the two assets increased the probability to 0.75. Thus there were clear benefits to diversification. The asset returns each period were determined independently by the experimenter or the participant. In treatment IOC-A (IOC-B) participants determined the outcome of asset A (B), while in treatment IOC-choice participants could choose to control A or B. Across the three IOC-treatments, investment in A (B) was higher and in B (A) lower when participants seemingly exercised control over return on A (B). The effect was even more pronounced in the IOC-choice treatment, where participants were free to choose A or B to control. Fellner (2009) concludes that illusion of control, even in games of chance where the outcome is determined by the throw of a die, appears to distort the portfolio decision and may help to explain why many retirement saving plans are under-diversified and biased toward own-company stock (Benartzi, 2001).

Charness and Gneezy (2010) also investigate the effect of illusion of control, along with ambiguity aversion and myopic loss aversion, on risky investment choice. They employ a relatively straightforward decision task, in which participants decide how much to invest in a risky asset and how much to keep. In all treatments, the roll of a die determines the value of the risky asset. The investor picks three "success numbers"; if any of these comes up, the return is 2.5x the amount invested. Illusion of control was manipulated across different treatment conditions via who roles the die: the investor; the experimenter; the investor decides who and at no cost if self-selects; the investor decides who and pays a cost if self-selects. Charness and Gneezy (2010) report that the majority of people choose control when available to them cost-free, but this disappears when a small cost is introduced. Furthermore, contrary to the results in Fellner (2009), they find that despite a preference for control, this does not impact investment behavior. Examining only those treatments where people could choose who rolls the die, there is little difference in investment percentage between investors who chose to roll and those who chose to have the experimenter roll. Design differences between Fellner (2009) and Charness and Gneezy (2010), including the profit target in the former or the absence of a risk-less asset in the latter, make it difficult to reconcile differences in the impact of illusion of control on portfolio decisions and diversification, hence further experimental analysis is warranted.

An empirically observed phenomenon related to under-diversification is "home bias" (e.g. French and Poterba, 1991; Huberman, 2001). Kilka and Weber (2000) provide early experimental evidence to suggest that home bias may be due to investors being overly optimistic about domestic firm prospects compared to foreign firms. However, while they elicit participants' beliefs about the future prospects of the firms, their experiment does not require them to make investment decisions. In a further experiment, Ackert et al. (2005) investigate the role of familiarity bias in explaining home bias, after controlling for information asymmetry as a possible non-behavioral explanation (by holding the information set constant). Their experiment allows them to separate the impact of firm identity and geographic location on participants' portfolio allocation decisions. Giving participants information about a firm's home base (geographic location), but not its name (firm identity), does not affect portfolio choice. Hence, absent real information asymmetries, investors do not appear to favour buying stock in a company because it is located close to home. However, revealing a firm's identity, in addition to its home base, does impact on portfolio decisions. At the end of the experiment, Ackert et al. (2005) elicit participants' perceived familiarity with the firms they are exposed to, finding a higher degree of familiarity with domestic than foreign firms. Furthermore, they report a strong relationship between participants' perceived familiarity and their portfolio decisions, suggesting that perceived familiarity with domestic firms may be a key determinant of portfolio decisions. A lack of control over investors' disparate information renders an investigation such as that undertaken by Ackert et al. (2005) highly problematic in naturally occurring markets.

Continuing the quest to better understand what might cause under-diversification, Benzion et al. (2010) examine the extent to which it may be driven by adaptive behavior and return chasing. To this end they conduct a simplified multi-period investment experiment, with three risky assets: A and B represent stocks with identical expected return and negative correlation, while M represents a diversified fund, the return of which is the mean of the returns from A and B. Participants, who are required to invest all their money in one of the three assets, are divided into two feedback conditions—-full-feedback in which they observe the outcome for all assets and limited-feedback in which they observe the outcome of the selected asset only—-to allow for an examination of return chasing behavior.

If investors choose on the basis of past returns, then the diversified fund is likely to be chosen less frequently in the full-feedback condition as it is less likely to be the highest yielding alternative. In the limited-feedback condition, the diversified fund is expected to be more attractive over time, particularly in the presence of a positive premium (as is the case in one experiment). In line with this explanation, inefficient portfolios (i.e. lower return or higher risk) are observed with full-feedback, while better diversification is observed under limited-feedback. The authors interpret this as evidence that under-diversification might be the result of attempts to respond to feedback (i.e. return chasing).

In the above experiments, participants make individual portfolio decisions. In contrast, Bogan et al. (2013) investigate portfolio choice in a team decision making environment. Teams of four participants, comprising four, three, two, one or zero males (i.e. five composition-types), make buy/sell decisions choosing between high-risk and low-risk stocks, with the expected return on the stocks equal in some treatment conditions, but different in others. In the equal expected return condition, the high-risk stock poses increased risk without a higher expected return to compensate. Bogan et al. (2013) examine whether the team's gender composition-type impacts on risk aversion and loss aversion, and so influences the tendency to select the high-risk stock. The presence of a male on the team increases the probability of selecting the high-risk stock and decreases the probability of selecting the stock that requires the realization of a larger loss. However, Bogan et al. (2013) find that the risk seeking behavior of a team is not an increasing monotonic function of the number of males. They conclude that non-monotonicity of risk seeking (and loss aversion) with respect to the proportion of males in a team provides strong evidence that team decisions differ from individual decisions. Bogan et al. (2013) note that, due to the low proportion of female fund managers in practice, an examination of the role of gender composition on team portfolio choice based on empirical field data would be problematic from a statistical perspective.

Deriving from the CAPM and the mean-variance model, the mutual fund separation theorem suggests that all investors should hold the same ratio of bonds to shares in their portfolio, with variations in their risk attitudes reflected by the percentage of risk-free asset they hold. However, Canner et al. (1997) suggest an asset allocation puzzle whereby financial advice, which recommends varying the proportions of shares and bonds held to reflect risk attitudes, is at odds with theory. Duxbury et al. (2005) examine this puzzle via an experimental survey, in which participants allocate money across shares, bonds and risk-free assets. They then repeat the allocations for individuals less/more willing to take risk than themselves; thus, identifying how participants thought investment patterns should vary with risk attitudes. Participants thought that the ratio of bonds to shares should vary with risk attitude, with a higher percentage of shares held by individuals willing to take higher risks. Despite holding such beliefs, however, cross-sectional analysis of respondents' actual investment behaviors revealed the proportion of shares and bonds held did not vary with risk attitude. It seems, therefore, that tests of finance theory should be based on observed behavior rather than attitudes or intentions and indeed this is the route taken by many experimental studies in which participants make choices with economic consequences (e.g. financially incentivised decisions).

3. Equity risk premium

One of the classic puzzles in finance is the equity premium puzzle (Mehra and Prescott, 1985), whereby difference in returns on stocks and bonds has historically been too large to be reconciled with plausible levels of investors' risk aversion within a standard paradigm of expected utility maximization. While a number of explanations have been proposed, perhaps the most compelling is myopic loss aversion (MLA) proposed by Benartzi and Thaler (1995). MLA is premised on two well-established ideas from psychology; loss aversion, a key component of prospect theory (Kahneman and Tversky, 1979), coupled with mental accounting (Thaler, 1999), which influences the extent to which outcomes are aggregated or segregated over time. Noting that stock returns are more volatile than bond returns and as such are more likely to produce negative outcomes over short horizons, Benartzi and Thaler (1995) show via simulation that the combination of loss aversion and a short evaluation period makes investors unwilling to bear the risks associated with holding stocks unless they will be compensated by a sufficiently high equity risk premium.

Myopic loss aversion has been the subject of many experimental studies, too many to review here. Instead, we focus on early studies that establish MLA in the laboratory and more recent studies that challenge earlier findings. Gneezy and Potters (1997) provide the first experimental test of the MLA explanation of the equity premium puzzle. In a non-market setting, participants allocate money between a risky and a risk-less asset. The treatment factor of interest is the frequency of feedback. In the high-frequency condition participants play twelve rounds one-by-one and observe individual (i.e. segregated) outcomes, while in the low-frequency condition participants play rounds in blocks of three and observe aggregate outcomes. Gneezy and Potters (1997) report higher stakes under the low-frequency than the high-frequency condition, which they conclude supports the MLA explanation of the equity premium puzzle. Less information feedback causes participants to evaluate risky investments in a more aggregated way and as such they are less likely to be deterred from investing by the occurrence of losses. Through less frequent feedback, Gneezy and Potters (1997) manipulate the degree of myopic mental accounting or narrow bracketing.

A number of concurrent experimental studies, employing approaches similar to Gneezy and Potters (1997), attempt to untangle the effects of feedback frequency and investment horizon (i.e. frequency of investment decision) on MLA. Fellner and Sutter (2009) conduct a 2x2 experiment, manipulating investment horizon (one or three periods) and feedback frequency (every period or every three periods). They find that both treatment factors influence investment levels and hence MLA. Langer and Weber (2008), also observe an increased likelihood of investment in the risky asset, and hence reduced MLA, in the presence of longer investment horizons, while Bellemare et al. (2005) find that low evaluation frequency alone reduces myopia, regardless of investment horizon.

Klos (2013) refers to the approach in the above experiments as the "feedback frequency approach", while using the phrase "distribution approach" to refer to studies that examine MLA by manipulating the presentation format of the return distributions to examine the impact of narrow or broad framing via the use of segregated or aggregated returns. Benartzi and Thaler (1999), an example of this latter category, find that respondents invest significantly more in risky assets when annualized 30-year (aggregated) returns are observed, consistent with MLA. In the feedback frequency approach, Moher and Koehler (2010) fail to replicate MLA when modifying the Gneezy and Potter (1997) design such that participants play similar gambles rather than the same gambles repeatedly, while in the distribution approach, Beshears et al. (2011) report no effect of aggregating return information on the presence of MLA, despite using essentially the same graphical presentation format as Benartzi and Thaler (1999).

Klos (2013) identifies a potential problem with the distribution approach in that it confounds two effects: a framing effect consistent with myopic loss aversion and an effect caused by misestimation of the aggregate returns. Similar to the reasoning of Anderson and Settle (1996) based on difficulties estimating exponential growth, Klos (2013) extends the design of Benartzi and Thaler (1999) by asking participants to estimate the amount of money to which one euro invested today would grow in 30 years if invested in a risky fund and a less risky fund. Participants that observe only one-year returns are prone to misestimate and choose a less risky asset allocation than those that observe thirty-year returns, suggesting that misestimation might play a role in low levels of risky investment independent of MLA. Klos (2013) concludes MLA is less prevalent when attention is drawn towards the final outcome distribution and decision makers are financially literate, and so less prone to return misestimation.

Hardin and Looney (2012) identify three primary mechanisms influencing decision problem framing (i.e. the mental accounting or narrow bracketing component of MLA)--information horizon, evaluation frequency, and decision frequency. Information horizon refers to the length of time over which probabilities and payoffs are presented, with short horizons displaying the distributional properties as a single play (segregated), while long horizons display the combined distributional properties over multiple plays (aggregated). Broader, more aggregated, decision frames invoked by long information horizons have been found to lessen the effects of loss aversion, increasing the attractiveness of riskier assets and stimulating risk taking (Benartzi & Thaler, 1999; Looney & Hardin, 2009; Venkatraman et al., 2006). Evaluation frequency is the rate at which individuals are able to review or observe the outcomes that derive from their decisions. The higher the evaluation frequency, for example observing the outcome after every trial, the greater the induced myopia, while a lower evaluation frequency promotes broad framing, allowing aggregation across multiple trials, and so stimulates risk taking as the possibility of witnessing an overall loss decreases (Bellemare et al., 2005; Gneezy & Potters,1997; Gneezy et al., 2003; Haigh and List, 2005; Langer and Weber, 2005). Decision frequency measures the rate at which investors are able to make changes to their investment decisions. More frequent decisions allow action and promote narrow bracketing, whereby individuals frame the investment as isolated events, thus inducing myopia and reducing the attractiveness of risky assets (Langer & Weber, 2005; Looney & Hardin, 2009).

The approach in many previous studies has been to examine MLA when individuals simultaneously perform evaluations and decisions frequently (Gneezy and Potters, 1997; Gneezy et al., 2003; Haigh and List, 2005; Langer and Weber, 2005; Thaler et al., 1997). Unfortunately, the independent and interactive effects of the two variables cannot be separated in such studies. Some notable exceptions attempt to empirically disentangle evaluation frequency and decision frequency effects. Looney and Hardin (2009) hold evaluation frequency constant at a high level while varying decision frequency and find that risk taking increases when decision frequency is low, even in the presence of frequent evaluation of performance. Langer and Weber (2008) employ a fully-crossed design between evaluation frequency and decision frequency and find evidence of an interaction effect. While myopia is observed when individuals both evaluate portfolios and make decisions frequently, it disappears when evaluation frequency and decision frequency are reduced; either alone appear sufficient to encourage broad framing. However, Bellemare et al. (2005) show that evaluation frequency is the primary driver of myopia. Irrespective of decision frequency, broad decision frames and associated higher risk taking emerge only under infrequent evaluation levels.

While the main effects of each of the three mechanisms have been examined in the literature contradictory findings exist. Hardin and Looney (2012) are critical of prior studies that investigate variables in isolation and embark on a single study that examines holistically the independent and joint effects of all three mechanisms simultaneously. They employ a 2 (information horizon; segregated 1-year versus aggregated 3-year, short v high) x 2 (evaluation frequency; every 1-year versus every 3-year, high v low frequency) x 2 (decision frequency; decision every year versus decision every three years, high v low frequency) x 10 (risk; covariate) mixed experimental design (the first three are between-subjects and risk is within-subjects). Participants choose the percentage to allocate to a risky asset each round, which acts as the dependent variable, risk. Significant main effects were found for all three mechanisms; long-term information horizons, reduced frequency of evaluations, or reduced frequency of evaluations all broaden decision frames and reduce MLA. In addition, a significant interaction between evaluation frequency and decision frequency was observed, which Hardin and Looney (2012) interpret as evidence that low evaluation frequency provides such complete protection against MLA that low decision frequency fails to reduce the effect further. Information horizon does not interact with the other two mechanisms.

In a second experiment, Hardin and Looney (2012) examine the effects of feedback format, varying the manner in which retrospective returns are displayed; segregated or aggregated. Their approach allows them to examine whether evaluation frequency or feedback format drives narrow framing and hence MLA. A 2 (information horizon; short v high) x 2 (decision frequency; high v low) x 2 (feedback format; 3 lots of segregated 1-year returns v 1 lot of aggregated 3-year returns) x 10 (risk; covariate) mixed experimental design is employed. Note that aggregated feedback format cannot be operationalised under high-evaluation frequency, hence only low-evaluation frequency (once every 3 years) is examined. Contrary to expectations, feedback format did not significantly influence MLA, with similar proportions invested in the risky asset across the segregated and aggregated formats. Information horizon again impacted risk taking, while decision frequency did not. The results suggest long-term information horizons reduce myopia, regardless of feedback format or decision frequency. Following the results in Hardin and Looney's (2012) first experiment, the insignificant effect of decision frequency here is to be expected given only low evaluation frequency is present, which completely attenuates MLA leaving no room for low decision frequency to reduce the effect further. Hardin and Looney (2012) conclude that evaluation frequency, not feedback format, drives broad framing, with low evaluation frequency the primary force against myopia.

Other factors that may impact on the presence of MLA have been examined experimentally also. The power of market forces to alleviate the effect of MLA, for example, has been examined, but with no clear effect. In Gneezy et al. (2003) markets fail to overcome MLA, while in Mayhew and Vitalis (2014) there is some evidence of such an effect when experienced participants trade in a market. It is not clear, however, whether this is due to market forces or participants learning individually to overcome MLA. Other studies investigate differences in the tendency to be prone to MLA across different participant pools, but again the evidence is mixed. Haigh and List (2005), for example, test for differences in MLA across professional traders and students, with the former found to succumb to MLA more so than the latter. In contrast, Hardin and Looney (2012) compare the behavior of retirement plan participants with that of students, but fail to find substantive differences.

Building on the experimental design of Gneezy and Potters (1997), Sutter (2007) examines whether decision making in teams attenuates the effects of individuals' MLA. In an investment task where amounts were determined either each round or once every three rounds, participants made decisions individually or in teams of three, with the per capita payoffs and marginal incentives held constant across the individual and team treatment conditions. Sutter (2007) finds that teams invest significantly higher amounts than individuals, due in part to more individuals selecting zero investments than teams, but also to smaller positive amounts (i.e. excluding zero choices) invested by individuals than teams. The evidence suggests that team decision making attenuates, but does not eliminate, myopic loss aversion.

The evidence from experimental studies of MLA suggest that policy interventions promoting longer investment horizons or lower evaluation frequency, in particular the latter, may be designed that help alleviate the negative effects of MLA on risk taking and wealth creation. The evidence in Charness and Gneezy (2010) suggests resistance to such interventions may be experienced, however, as the majority of their participants expressed a clear preference for investing and receiving information every period over every three periods, even in the presence of costly choice. In an intriguing study where participants can switch between treatment conditions (investment horizon or feedback frequency) for a small cost, Fellner and Sutter (2009) find that most individuals stick to the status quo that they experience initially. This suggests that decision inertia and suitably constructed defaults may be exploited to alleviate the negative effects of MLA on risk taking. The experimental method lends itself well to investigations of the impact of policy interventions in ways that offer greater control, and at relatively lower cost, than would be possible in naturalistic settings.

We conclude this section by ending on a note of caution. While the aggregate choice patterns in prior studies support MLA, Blavatskky and Pogrebna (2009) re-examine the data from a number of prior studies to see if individual behavior is consistent too. They find, with the exception of Haigh and List (2005), that the majority of individual choice patterns are inconsistent with MLA. This finding has important implications for empirical behavioral finance studies that examine aggregate behavior and attempt to draw inferences about individual behavior.

4. Herding and financial contagion

Spyrou (2013) provides an insightful review of theory and evidence on herding in financial markets. Here we discuss experimental studies of herd behavior, the majority of which are not discussed in Spyrou (2013).

Bikhchandani and Sharma (2001) note it is difficult to control for underlying fundamentals in field studies, resulting in a breaking of the link between theoretical models and the empirical specifications used to test for herding. The experimental approach provides the ability to control parameters in the environment that are key to the theory, thus it is possible to test theoretical predictions directly and without recourse to imprecise proxies. A fundamental problem inherent in field studies is the inability to observe the private information signals of traders. It is problematic to test for herd behavior in such circumstances, because it is difficult to determine whether traders make similar decisions because they disregard their own private information to imitate other traders (i.e. herd behavior) or because they react to the same public information. In an experimental setting, the private information traders possess is known and controlled by the experimenter. It is possible, therefore, to test models of herding directly in the laboratory.

In an early study of herd behavior in markets, Hey and Morone (2004) examine whether the market may act as a disciplining device, removing socially undesirable herd behavior through market forces that promote the efficient aggregation of private information. They find evidence of herds developing; either due to bad information, a wrong herd developing, or associated with bubbles/crashes. They note that herd behavior might arise in a market setting, even in the presence of a well-defined fundamental value, and conclude that the market is misled by agents privately optimizing.

Two closely related studies by Cipriani and Guarino (2005) and Drehmann et al. (2005) examine informational cascades in financial markets. Central to both studies is the model of Avery and Zemsky (1998), who show that informational cascades (whereby agents ignore their own private information and herd) are impossible in the presence of an efficient price mechanism, whereby the market price aggregates efficiently information contained in the history of past trades. Empirical tests based on field data are not direct tests, but instead examine metrics for correlated trading, clustering of prices and investment decisions (see Spyrou, 2013). Cipriani and Guarino (2005) and Drehmann et al. (2005), on the other hand, devise experimental markets that allow direct tests of the model.

Participants in the markets of Cipriani and Guarino (2005) receive private information concerning the fundamental value of the asset and also observe the history of past trades, they then trade the asset, sequentially, one unit at a time. Cipriani and Guarino (2005) observe the way in which participants use private information and respond to the decisions of other traders, to determine the presence of herding. They compare behavior across two treatment conditions, whereby the price is fixed or flexible. In line with the Avery and Zemsky (1998) model, they find participants ignore their private information and herd less frequently under the flexible price than the fixed price mechanism. Also in line with the model, Drehmann et al. (2005) find no evidence of herding or imitative behavior in an experiment composed of a sequential asset market with privately informed traders. Contrary to the model, however, participants do not always follow their private information, instead they exhibit contrarian behavior, trading against the market and their own signal.

Acknowledging that experimental studies are sometimes criticised for using inexperienced, student participants, Drehmann et al. (2005) conduct a control experiment with 267 consultants, against which they compare the behavior of student participants in their experiment. They find no difference in behavior across the two groups, however, they present no results on the extent of herding or contrarian trading in the consultant control group. Alevy et al. (2007) compare the behavior of market professionals with that of students in an experimental setting that allows the underlying rationality of herd behavior to be identified. They also examine behavior in both the gain and loss domain. The experiment is premised on the notion that, given Bayesian updating of beliefs, it is rational to join an informational cascade. Informational cascades can be viewed as a social phenomenon, hence individual behavior may depend on how the rationality of others is viewed. To this end, Alevy et al. (2007) examine a standard informational cascade game, similar to Hey and Morone (2004), to see how market professionals and students respond to uncertainty about the quality of information due to deviations from Bayesian rationality of other participants. They report that professionals rely on their private information more so than students and so fewer informational cascades are observed with the professionals. Also, while the behavior of students is consistent with loss aversion, the market professionals seem to be unaffected by the domain of earnings. Similarly, Cipriani and Guarino (2009) also use financial professionals in their experimental study. In markets with no event uncertainty, they find little evidence of herd behavior consistent with the model, while in markets with event uncertainty the proportion of herd behavior increased but remained below predictions. Overall, evidence from experiments of herd behavior comparing students and professionals suggests little difference in behavior.

Cipriani and Guarino (2009) note that prior experimental studies test for herd behavior in a market environment where, theoretically, herding should not be observed. To address this they compare two treatments: Treatment I–-participants should use their private information and never herd; Treatment II–-herding is optimal because of uncertainty surrounding the presence of informed traders. In line with theoretical predictions, the proportion of herding in Treatment I is low, while the presence of herding is higher in Treatment II, though lower than predicted. Two other anomalies are also observed. First, in Treatment I, contrarian trading, selling/buying when the price is high/low, is seen in some participants, regardless of their private signal. Second, in both treatments, a tendency to abstain from trading is observed, which runs counter to theoretical predictions and implies lower informational efficiency as the market is unable to infer the private signals of participants. In a later study, Cipriani et al. (2012) re-examine the experimental data from Cipriani and Guarino (2005) using a Bayesian approach to statistical inference. They observe very little herding and contrarianism, as theory suggests, though they again find evidence of a significant proportion of "irresolute" traders following their own private information when it agrees with public information, but not trading otherwise.

Theoretical models and experimental studies of herding tend not to allow traders to choose when to trade nor do they allow them to enter into multiple trades. In an innovative experimental design, Park and Sgroi (2012) explore the effect of introducing more realistic features in a market where participants can trade one or two units and where the timing of trades is determined endogenously rather than exogenously imposed sequential trading. Herding-prone traders might delay their actions, thus enhancing herd behavior relative to exogenous timing settings. Alternatively, given the finding that individuals have a tendency to act as contrarians, another possibility is that herding disappears when the artificial friction of exogenous timing is removed.

Park and Sgroi (2012) find that both herding and contrarianism are observed to a greater extent than is found in comparable studies by Drehmann et al. (2005) or Cipriani and Guarino (2005) that do not allow traders to time their decisions. Park and Sgroi (2012) note that endogenous-timing of trades does not change the predictions derived from sequential models of herd behavior, hence their results suggest that findings in earlier experiments where the sequence of trading is determined exogenously are likely still valid. Herding could be taken to imply not only that people take the same action, but that they do so at (almost) the same time, though this is not present in definitions or models of herding. In support of this, Park and Sgroi (2012) observe traders often acting at almost the same time. Evidence that a sizeable fraction of trades is clustered in time is in the spirit of the mass behavior commonly cited in the media as being associated with herding. This tendency for traders to cluster their actions in time is a key contribution of Park and Sgroi (2012) that has potentially important implications for future research, helping to bridge the gap between experimental studies of herd behavior and empirical studies that investigate herd behavior by observing clustering in naturalistic data.

In the literature, and indeed in the discussion above, the terms informational cascade and herd behavior are largely used interchangeably, though the former implies individuals ignore their private signal, while the latter implies they make identical decisions without necessarily ignoring their private signal. Çelen and Kariv (2004) note that informational cascades, defined in terms of beliefs that are largely unobservable, are more difficult to identify than herds, which are defined in terms of observable actions, in field data. They devise an experiment in which participants draw private signals sequentially from a uniform distribution and are informed about the prior actions of other participants. Their task is to predict the sign of the sum of the private signals and to choose one of two actions accordingly. Instead of asking participants for their actions directly, Çelen and Kariv (2004) ask for a cut-off to determine which action is taken, thus participants reveal their beliefs about the state of the world. All this occurs before a participant observes their private signal. Those participants reporting a cut-off at the extremities of the signal range thus exhibit cascade behavior as their action is determined irrespective of their private signal, while participants reporting a cut-off within the imposed range exhibit herd behavior. While Çelen and Kariv (2004) report herds are observed frequently, all such herds, with one exception, are correct, which is at odds with theory and common perception that mass behavior is flawed. Contrary to theory, they also observe frequent informational cascades. While participants overweight initially their private signal relative to the public information revealed by the behavior of others, ultimately they learn to follow Bayesian updating.

We turn attention briefly to the issue of financial contagion, which has been closely linked to herd behavior in theoretical models (e.g. Cipriani and Guarino, 2008). Pericoli and Sbracia (2003) provide a theoretical framework for the study of contagion and a review of empirical studies. They note that there is no consensus on a definition of contagion and find that early studies do not always distinguish between contagion (with its negative connotations associated with financial crisis) and interdependence between markets.

Cipriani et al. (2013) examine the cross-market rebalancing explanation of financial contagion, though with a simpler model and in an experimental environment that participants could more easily understand. Participants trade assets sequentially in three markets, with fundamental values independent across markets. Participants' payoffs depend both on the return to their investment and on the composition of their portfolios, hence portfolio rebalancing motives are present. Contagion effects are created through the exogenous imposition of optimal portfolio weights. In all experimental sessions, observed prices are very close to equilibrium predictions and cross-market contagion effects are observed, suggesting that portfolio rebalancing may play an important role. Cipriani et al. (2013) conduct treatments with different price elasticities, to test a prediction of the model that lower asymmetric information decreases the costs of rebalancing and so strengthens financial contagion. They find, in support of the model, that as the price in the financial centre becomes less elastic, contagion effects in periphery markets are enhanced.

Trevino (2013) compares experimentally two channels of financial contagion; a fundamental channel based on real financial links and a social learning channel where noisy observations about the behavior of agents in foreign markets drives contagion. An experimental environment is designed in which theory makes clear predictions about which channel should be relevant (switched on) in the different treatment conditions examined. This approach makes it possible to distinguish the relative strength of the two channels on participants' decisions and hence determine which channel drives financial contagion. The main treatment variables determine the strength of each of the channels of contagion, manipulating i) the correlation between fundamentals across countries (fundamental channel) and ii) the precision of the signal about the behavior of other agents (social learning channel).

The results reported in Trevino (2013) show systematic biases related to the two channels of contagion. First, base rate neglect is observed, with participants underweighting prior information when the correlation between states is high. Hence, paradoxically, they put less weight on the fundamental channel in precisely the environment where theory predicts it should have a stronger effect. Second, overreaction to the signal about the behavior of other agents is observed, even in environments where the signal is uninformative, with too much weight placed on the social learning channel.

5. Other stylized facts

We examine briefly the evidence in relation to other stylized facts (Pagan, 1996) associated with return distributions, including fat tails and volatility clustering. Morone (2008) examines whether such features can be reproduced in the laboratory, where control can be exercised over the quality and quantity of information, comparing the characteristics of experimental markets with those of real markets. The results suggest excess kurtosis is also routinely observed and volatility is lower when both quality and quantity of information is high.

Kirchler and Huber (2007, 2009) provide further insight into the emergence of fat tails and volatility clustering, making full use of the control afforded over the dispersion and timing of the arrival of new (fundamental) information in experimental markets; factors that it is impossible to control or observe in naturally occurring markets. Across a number of markets, they vary, among other things, the distribution of fundamental information (homogenous or asymmetric). The asymmetric information structure is implemented by lagging access to fundamental information for traders of different information-levels. Kirchler and Huber (2007, 2009) find excess kurtosis in all their markets, but note that the levels are more than twice as high in markets where uninformed traders are present. The evidence suggests that noise traders play a role in promoting fat tails in return distributions, while the presence of fundamentalist traders may inhibit volatility. They note that volatility spikes with the arrival of new information at the start of each period, with excess kurtosis higher in first half of a trading period than second half, suggesting traders digest the information and form more homogeneous expectations over time (within and across periods). In conclusion, experimental evidence suggests the arrival of new information and the activities of uninformed traders are at the heart of stylized facts associated with return distributions.

6. Concluding comments

In this first of two companion review papers, we begin by highlighting the key strengths of the experimental method, namely the ability to observe directly, control, and manipulate variables of theoretical importance, and note that these are well-suited to the study of behavioral finance. Many of the key variables of interest in behavioral models are not observable directly to researchers examining data from naturally occurring markets, thus empirical studies adopt proxies in attempt to capture or measure the effect of such variables. As we have seen in the discussion above, and will see again in the companion paper to follow, experiments allow researchers to measure directly, and afford a greater degree of control over, variables expected to impact on financial behavior. Techniques for the elicitation of beliefs or the control of private information in experimental studies of herd behavior (e.g. Çelen and Kariv, 2004) or of home bias (e.g. Ackert et al., 2005) provide cases in point. Perhaps the most potent weapon at the hands of the experimenter is the ability to manipulate the levels of treatment factors thus allowing causal tests of the relationship between variables of theoretical interest and observed behavior, thus moving beyond the simple correlational analysis possible in studies reliant on proxies to capture unobserved variables. As will be seen in the companion paper, Duxbury (2015), the experimental evidence suggests that the use of various proxies in empirical studies of the effect of overconfidence on financial behaviour may be problematic.

In this paper, we first review the evidence from experiments designed to test specific aspects of finance theory including the CAPM, separation theorem and mean-variance portfolio theory (e.g. diversification, correlational neglect, home bias). We then turn attention to experimental studies intended to help explain behavior observed in financial markets that is difficult to understand in the context of finance theory, including the equity premium puzzle, herd behavior and financial contagion, along with other stylized facts associated with return distributions. In the companion paper, we return to examine the contribution of experimental studies to our understanding of heuristics and biases at the heart of behavioral models (e.g. under- and over-reaction, overconfidence) and observed investor behavior (e.g. the impact of prior outcomes), along with the influence of moods and emotions on financial behavior. We reserve full discussion until the conclusion of the companion paper.

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[i] The experimental evidence on bubbles/crashes is reviewed in Palan (2013), so we omit this topic from our list of stylized fact.

[ii] In line with our selectivity criteria outlined above, we do not review here the work of Peter Bossaerts, Charles Plott and colleagues testing finance theory and the CAPM in an experimental asset market setting. Instead we direct the reader to Noussair and Tucker (2013).

[iii] Investor overconfidence has also been cited as a cause of under-diversification (DeBondt, 1998). We discuss overconfidence in the context of cognitive biases in the companion paper, Duxbury (2015).