We can learn more from an experiment on behavioural choice between simple and compound lotteries than we can learn from an experiment on asset markets.

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Experimental Economics I

Abstract

In this essay I compare two experimental approaches on financial decision making – namely, experiments on the choice between simple and compound lotteries and experiments on asset markets. Based on behavioural finance literature, I argue that we learn more from the former about individual choice behaviour with assets and more from the latter about how to explain real world financial data.

Keywords: experimental asset market, lottery choice, probability compounding task.

1 Introduction

Both analyses on individual investment behaviour and on asset market outcomes traditionally assume rational agents. Here, agents individually process new information according to Bayes' rule and make decisions in line with the axioms of *Subjective Expected Utility Theory* (Barberis and Thaler, 2003, p.1053). This results in an efficient outcome, i.e. that for example actual asset prices reflect their fundamental values (Fama, 1970, p. 383). However, a large body of literature shows deviations from this traditional paradigm, both in an individual (e.g. use of heuristics, see Kahneman and Tversky, 1983) and in a market dimension (e.g. emergence of bubbles, see Smith et al., 1988). A relatively new economic approach to take these observations into account is *behavioural finance*. Developing psychological models which relax the rationality assumption and relating them to financial markets is the underlying idea (Shiller, 2003, p. 90). Doing so, irrationalities in forming beliefs, in people's preferences, or decision making are frequently observed in laboratory experiments (Barberis and Thaler, 2003, p. 1054).

This essay discusses two approaches in the light of behavioural finance literature. Namely, experiments on the choice between simple and compound lotteries and experiments on asset markets. The reminder of this essay is structured as follows: I explain the approaches and point out which information can be obtained, firstly. Then I compare both and discuss their opportunities to reach a concluding statement towards the proposition in the heading.

2 What can we learn from choices between simple and compound lotteries?

Assume two binary lotteries *X* and *Y* , both having either a success (*SX, SY*) or a non-success (*NX,NY*) outcome. If *pi* > 0 is the probability of success outcome of a lottery *I* then *X* = (*pX, SX*; $p^{-}X$,*NX*) and *Y* = (*pY , SY* ; $p^{-}Y$,*NY*) represent the simple lotteries, where $^{-}$ *pi* is the complementary probability of the success outcome. A compound lottery (*Z*) can be presented by a weighted (*α, β*) combination of simple lotteries. Like *Z* = (*αX* +*βY*), where *α*+*β*= 1. If confronted with a choice between say *X*, *Y* and *Z* rational agents know that the probability of winning the compound lottery cannot be higher than the probability of the less probable success outcome of the simple lotteries (Nilsson, 2008, p. 473). This is known as the monotonicity axiom of probabilities. The winning-probability of the compound lottery can be calculated by reducing *Z* (*pZ* = *pX* · *pY*).

Kahneman and Tversky (1983) document that in verbal compounding tasks (i.e. asking participants to verbally interpret which lottery is more probable – see for example Kahneman and Tversky, 1983, p. 297) subjects neglect these probability laws. This is called the *conjunction fallacy*. Zizzo et al. (2000) explain that this fallacy may lead to a violation of the monotonicity of preferences and Bayes' rule in decisions under risk. In contrast to Kahneman and Tversky (1983), recent experimental investigations of the conjunction fallacy use behavioural compounding tasks (see Fantino and Savastano, 1996; Zizzo, 2001; Zizzo, 2003). Here, participants make a decision among several simple and compound lotteries (Zizzo, 2003, p. 288). In result the conjunction fallacy committal remains robust above 20% (Zizzo, 2003, p. 289).

Fantino and Savastano (1996) find that training in behavioural compounding tasks affect subjects' conjunction fallacy committal. Since this study doesn't differentiate between new and those compounding tasks subjects were already trained on, Zizzo (2001) controls for that. In the practice stage the author faced each participant with 150 decisions between three lotteries. Varying with the treatments 0%, 10% or 20% of those choices were compound lottery tasks. Here, two simple and one compound lottery were offered. Every simple lottery was presented with colour blocks, every compound lottery with stacks of colour blocks associated to the winning probabilities of the lottery components. Feedback after each choice was provided in the practice stage only. In the testing stage every subject made 10 choices from which 7 were new compound lottery tasks. The subjects were not informed that they were dealing with compound lotteries. Zizzo (2001) partly confirms Fantino and Savastano (1996), finding that the conjunction fallacy committal reduces with increasing fraction of compounding tasks in the practice stage. Besides, Zizzo (2001) argues that instead of using

probability laws subjects " [...] average out the probabilities of the two events to assess how good the lottery looks like." (Zizzo, 2001, p.1). Zizzo (2003) adds that decision makers' behaviour is insensitive to different extents of information about the probability compounding.

Sonsino et al. (2002) investigate behavioural choices between simple and complex lotteries. Hereby the authors provide a methodological approach to measure product complexity using compound lotteries. In the experiment they offer choices between simple and compound lotteries of certain complexity levels to subjects. Sonsino et al. (2002) use a dynamic frame to represent the compound lotteries, so that the compound lotteries are complex in two dimensions – time and components. The used complexity measure equals the product of the possible outcomes and the amount of different periods (simple lottery components). It is argued that due to very high levels of complexity agents decide in a context of ambiguity (Sonsino et al., 2002, 937). The authors found that subjects tend to prefer the simple lottery and name this *negative complexity effect*. Among other topics this effect is presented as a reason for inefficient asset portfolio selection (Sonsino et al., 2002, 951).

Sitzia and Zizzo (2011) follow this complexity metric. After providing an initial endowment to every subject, the authors offered either one simple lottery (in period 1 and 2) and one compound lottery (in period 3 and 4) or one simple and one compound lottery (in periods 1 to 4) to each subject. The subjects made buying decisions facing randomly generated prices and in result tended to prefer the more complex product. So, Sitzia and Zizzo (2011) find some evidence for a *complexity exploitation effect* in an individual choice context. However, by introducing the behavioural choice task in a monopolistic market setting this evidence is not robust. Subjects got randomly assigned to be a seller or a buyer. As in the individual choice tasks buyer decided whether to buy a simple/compound lottery (structured as above). Here, the prices were determined by sellers. The results of this posted offer market neither provide evidence for complexity aversion nor for complexity exploitation. Sitzia and Zizzo's analyses (2011) raise some questions about the observable demand price trajectory which are deepened in Sitzia and Zizzo (2012). In a posted offer market task with randomized price dynamics they find that the decision environment influenced the preferences of the participants (*shaping effects*), i.e. that subjects seemed to have no clear preferences over the offered product and thus relied on past price observations.

In sum, those investigations mainly yield to five observations which we keep in mind as key lessons from behavioural compounding tasks: If confronted with a choice between a simple and a compound lottery subjects commit the conjunction fallacy (1). Instead of using probability laws, they use an

averaging heuristic to decide (2). Admittedly, the conjunction fallacy committal can be reduced by training but remains robust above 20% (3). There is mixed evidence whether subjects tend to avoid more complex lotteries (4). It seems that subjects' preferences are influenced by shaping effects (5).

3 What can we learn from experiments on asset markets?

As a distinctive feature, experimental asset markets (EAM) allow for speculative behaviour, i.e. each subject can buy and sell assets (Sunder, 1995, p. 445). The most common approach of 4ithhold4 EAM is the one introduced by Smith et al. (1988). Indeed, there exist alternative approaches[1] which in line with the definition of Noussair and Tucker (2013) can be seen as asset markets. However, because of the huge amount of financial market investigations (Noussair and Tucker, 2013, p. 555) I will concentrate on the Smith et al. framework.

The baseline market as used by Smith et al. (1988) is a single closed book continuous double auction market. All participants are endowed with a certain amount of experimental money and assets. In Smith et al. (1988) these assets could be traded over 15 periods. Every asset holder gets a dividend of each asset in his portfolio which has a positive expected value after every period but a value of zero after the last period. The fundamental value of an asset monotonically declines over the trading periods. All tradings are free from costs and holding money earns no interests. Subjects' eventual experimental money on account is exchanged in real-world currency units. Palan (2013) summarizes the typical volume and price patterns in Smith et al. asset markets, from now on noted as EAM. The author states that the majority of EAM with inexperienced subjects start with an asset price below its fundamental value. Then a bubble is formed (asset price is above the fundamental value) which in the end of the trading phase collapse down to the fundamental (*crash*). Frequently the crash-period and the following periods are characterized by low trading volumes and the fact that subjects tend to sell their assets rather than buying new ones (Porter and Smith, 2008, p. 248).

Recent literature runs investigations by slightly deviating from this approach to compare the emerging price and volume trajectories to the typical patterns. To present what could be learned from these deviations, I concentrate on examples of three fields of literature which are relevant for the proposition at hand: expectation formation (1), individuals in the lab (2) and institutional elements (3).

[1] For instance Walrasian Auction Markets (see Lugovskyy et al., 2010) or Parimutuel Betting Markets (see Plott et al., 2003)

Using their individual information set subjects form expectations about future market developments (Sunder, 1995, p. 445f.). So, a main research interest lies in investigating the effects of informational changes and expectation formation (1). Palan (2013) summarizes that price expectations in EAM are formed by extrapolating past prices. Furthermore, those price forecasts have a smaller range than the occurring experimental market data (Palan, 2013, p.574). Kirchler et al. (2012) argue that subjects' confusion influences mispricing. The authors use a gold mine analogy to frame the market environment differently. That reduced both mispricing and overvaluation of the traded gold. If subjects attended to a comprehension task to clarify the underlying processes in the EAM and if it is public knowledge that every subject attended to this task, bubbles reduce (Cheung et al., 2012, p. 16).

Moreover, the emergence of bubbles in EAM depend on the participants' characteristics (2). Dufwenberg et al. (2005) state that in markets with mixed experienced traders the bubble-crash pattern changes. In detail, subjects which already attended to trading periods were mixed with totally unexperienced traders. As a result training reduces bubbles. Furthermore, in a 2x2 factorial design Hargreaves-Heap and Zizzo (2011) find that excitement at the begin of the period affects bubble emergence. They also point out that buying (excitement) and selling (anxiety) is connected to emotions. King et al. (1993) run an experiment with corporate executives as participants. The authors confirmed robustness of the experiments with student subjects. So, even with experts irrationalities occur.

Experimental laboratories offer the opportunity to manipulate variables of EAM isolated and precisely. These variations change the underlying processes or features of the market – in other words the institutional setting (3). Kirchler et al. (2012) for instance vary both the asset-to-cash-ratio and the fundamental value process in a 2x2 factorial design. The results show a propensity for mispricing in treatments with declining fundamental value process, while overvaluation tends to occur when a declining fundamental value is combined with an increasing asset-to-cash-ratio. As another example, the second dimension of the factorial design in Hargreaves-Heap and Zizzo (2012) allow for a chat to let the traders communicate during the trading periods. They find no evidence for a general influence due to chating opportunities.

4 Discussion

Can we compare both methodologies? Zizzo (2003) gives an intuitive answer: "Probability compounding is a pervasive necessity for any economic agent who needs to make decisions under

risk and who thinks in terms of probabilities." (Zizzo, 2003, p. 304). In line with this, representing an investment opportunity in a risky asset as a simple lottery is mostly oversimplified. The outcome of an asset may depend on various circumstances. So, presenting the asset investment as a compound lottery seems to be more adequate. And indeed we can find some similarities. As Zizzo (2011) and Sonsino et al. (2002) argue if people are confronted with very complex compound lotteries they make decisions in an uncertain environment. As it is in EAM (Bossaerts et al., 2010, pp. 1327.f). Furthermore, in both decisions subjects exhibit irrationalities. In EAM this results in mispricing and overvaluation, in a behavioural compounding task the conjunction fallacy occurs. Likewise we can see that training respectively experience in both cases seem to reduce irrationalities.

Did we learn more from behavioural compounding task than from EAM? EAM are frequently used not without a reason. Its' features balance out real-world financial markets and economic models (Sunder, 1995, p. 491). So, some important findings in field data can be pictured in the laboratory and EAM offer the opportunity to alter variables and institutional features inspired by real-world markets. At the same time double auction markets are considered to be relatively efficient and tend to nipe out irrationalities. Fehr and Falk (1999, pp. 107-108) argue that those markets are one of the most competitive and efficient institutions used in experimental economics. Nevertheless, it is difficult to identify individual preferences since we observe aggregated data only. This data gives information about the market result of decision behaviour and therefore is less clean regarding individuals' preferences. Here, the behavioural compounding task experiments have a clear advantage. We can observe individual decisions with asset-like lotteries showing a preference ordering snapshot (Zizzo, 2003, p. 291). So, if we assume that behavioural compounding experiments give us an insight into what EAM's blind spot is, these experiments have some 6ithhold6. Subjects trading in EAM decide in a relatively artificial task. Lei et al. (2001) state that subjects trade because they attend to an experiment, are asked to trade2[2]and have no other activity to do. Kirchler et al. (2012) show that in EAM some subjects seem to be confused and King et al. (1993) add that even experts are irrational. In contrast, Sitzia and Zizzo (2012) argue that lotteries are new products for all subjects and that subjects don't get tired trading them. Using lotteries instead of assets may frame the individual decision differently and could make the environment more salient. In general, it is difficult to gage how complex the EAM environment seems to participants. With the complexity metric for compound lotteries presented in Sonsino et al. (2002) one could control for various complexity levels of assets. Eventually, for me Sitzia and Zizzo's

[2] *Experimenter Demand Effect* in terms of Zizzo (2010)

investigations (2012) raise an interesting question: Are subjects affected by shaping effects in EAM? Summing up, I argue that we learned more about individual decision behaviour with assets from behavioural compounding tasks than from EAM. These experiments can be seen as a missing part of the EAM puzzle. But about how to explain real-world financial market data EAM has been more powerful.

Could we learn more from experiments on behavioural compounding tasks? So far, observations about behavioural compounding tasks in a market setting are very little. But Sitzia and Zizzo (2011) explain that rich information about subjects' preferences can be obtained. One suggestion could be to design an EAM with probability compounding tasks. Comparing the results and benchmarking them to real-world financial data could give further insights. One could observe how prices behave if simple and compound lotteries are traded in multi-asset markets with varying institutional features. What if the expected (fundamental) value of a complex lottery declines over the trading periods? Alternatively, with support of computational economic methods one could integrate the individual decision observations from behavioural compounding tasks into an agent-based financial market model. In sum, further research to exploit behavioural compounding tasks' full potential is required.

5 Conclusion

In this essay I compared two experimental approaches. Namely, experiments on the choice between simple and compound lotteries and experiments on EAM. I conclude that we learn more from the former about individual choice behaviour with assets and more from the latter about how to explain real-world financial data. Nevertheless, further research on behavioural compounding tasks in market settings could induce me to renew this conclusion.

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