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Copy Trading

Jose Apesteguia, Jörg Oechssler, and Simon Weidenholzer

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Jose Apesteguia, Jörg Oechssler, and Simon Weidenholzer†

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Abstract

Copy trading allows traders in social networks to receive information on the success of other agents in financial markets and to directly copy their trades. Internet platforms like eToro, ZuluTrade, and Tradeo have attracted millions of users in recent years. The present paper studies the implications of copy trading for the risk taking of investors. Implementing an experimental financial asset market, we show that providing information on the success of others leads to a significant increase in risk taking of subjects. This increase in risk taking is even larger when subjects are provided with the option to directly copy others. We conclude that copy trading reduces ex-ante welfare, and leads to excessive risk taking.

JEL codes: C91, D81, G12, G20, G41.
Keywords: Copy trading; Financial markets; Social networks; Imitation; Experiment.

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† `Apesteguia`: ICREA, Universitat Pompeu Fabra and Barcelona GSE, 08005 Barcelona, Spain, email: jose.apesteguia@upf.edu. `Oechssler`: Department of Economics, University of Heidelberg, Bergheimer Str. 58, 69115 Heidelberg, Germany, email: oechssler@uni-hd.de. `Weidenholzer`: Department of Economics, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, United Kingdom, email: sweide@essex.ac.uk.

1 Introduction

The last years have witnessed the proliferation of a variety of copy trading platforms. These are online brokerage platforms where users, embedded in a social network, receive information about the financial positions of others and, most importantly, can decide to automatically copy the financial decisions of other users. That is, copy trading platforms offer the possibility of allocating a monetary endowment to reproduce the financial strategies of the user one wants to copy. There are currently more than a dozen such platforms, with millions of users spread all over the world.[1] This is a new trading mechanism with potentially significant welfare consequences, both for the individual investors involved in such platforms and for societies in general. In this paper we conduct, for the first time, a series of controlled laboratory experiments to study several aspects of copy trading.

Copy trading platforms may influence behavior in various ways. It seems reasonable to think, though, that their very nature, their main institutional characteristics, are conducive of imitative behavior, both indirectly and directly. Indirectly, through providing information on portfolios and success of others that users may try to emulate by themselves, and directly by allowing agents to directly copy others by the click of a button. Copy trading platforms, thus, provide an institutionalized framework for imitation to take place. As already observed by Offerman and Schotter (2009) in a different context, when payoffs are noisy, imitation may lead subjects to adopt risky choices. In the setting of a financial market, where asset prices are naturally volatile, imitation – for example in the form of copy trading – may have particularly stark implications. To see this, note that agents with high earnings may have just been lucky. Under copy trading other agents are inclined to imitate those lucky agents. To make matters worse, high returns might be associated with high risk taking of the copied agents. Thus, successful agents might not only have been lucky, but may have also taken more risk. Copiers may, hence, be more likely to adopt risky investment strategies. Thus, copy trading may well result in excessive risk taking and individually and socially suboptimal outcomes.

In this paper we examine copy trading and its implications for risk taking in a series of laboratory experiments. The experimental laboratory allows us to control for a number of key variables that would be very difficult, if not impossible, to do so in the field. For example, in our studies we will measure risk preferences outside the financial markets,

[1] See Section 3 for a more detailed description of copy trading and for a survey of various copy trading platforms.

which will permit us to determine optimal behavior in the choice of assets at the individual level. Moreover, the experimental approach allows us to directly test the influence of the main characteristics of copy trading platforms, namely, the provision of information on the financial decision and success of others, and the possibility of copying others. That is, it enables us to compare outcomes under copy trading to the counterfactual of not being able to copy trade, and test whether this induces more risk taking behavior. Moreover, we will have full control of the menu of financial assets, the portfolio of the investors, information on the characteristics of the assets, and of the market results.

Our experiment consisted of three parts. In the first part we elicited subjects' risk preferences. The second part is composed of two blocks of investment decisions. In these decisions subjects had to choose one of multiple assets whose prices evolved according to a Brownian motion (approximated by a Binomial tree model in discrete time; Cox, Ross, and Rubinstein, 1979). The assets were characterized by different state dependent rates of return. Further, some assets featured tail risk, which we modeled as the probability of a crash to a relatively low price. Subjects were made aware of all attributes of the available assets. After choosing their assets, subjects for a number of periods had to decide whether to sell the asset at the current price or keep it.

In the second block subjects were confronted with the same investment problem. Depending on the treatment, there were additional components. In the BASELINE treatment, the second block consisted of the exact repetition of the investment situation subjects confronted in the first block. In our main treatment, COPY, agents received a list containing the decisions and realized profits in the first block of all the agents in BASELINE, ordered from highest to lowest realized payoffs. Then, subjects could either make their own investment choice, or could choose to copy the unknown investment decisions in the second block of a subject of their choice from the list. In the latter case, copiers then simply received the payoffs the copied subjects had earned in the second block. In addition, we ran an INFO treatment in which subjects received the same information on the first block decisions and outcomes of the BASELINE participants than in COPY, but in this case did not have the option of copying any investment strategy.

We are interested in the determinants of copying behavior. The comparison between BASELINE and INFO allows to ascertain the behavioral effect of the mere provision of information on others. The comparison between INFO and COPY shows the influence of the main characteristic of copy trading platforms: the possibility of copying the financial decision of others by the click of a button. The comparison of BASELINE and COPY

allows for the evaluation of the joint effect of the provision of information on others, and the possibility of copying them.

Before any investment decision were made, subjects were provided with a tool that allowed them to simulate price path realizations for each of the assets. The purpose of this simulator was to familiarize subjects in a user friendly way with the possible outcomes of the various assets and to mitigate the role of the additional information subjects received from peers in the COPY and INFO treatments. Analogous tools are being offered in practice by financial institutions to private investors, at the time of buying financial products such as mortgages, or pension plans.

In the third, and last, part of the experiments, we collected some potentially important information like gender, age, and education. We also implemented a questionnaire asking for subjects' experience in the stock market, their self assessment of their risk attitude, and how they perceive their tendency to follow others. Additionally, we assessed subjects' ability to calculate a simple expected value.

Thus, our experimental design uses a financial setting, that allows us to directly study, for the first time, the influence of the key characteristics of copy trading platforms on financial decision-making, while controlling for important background information, such as risk preferences.

The main results are the following. We observe that when giving participants the possibility of copying others a sizable fraction does so, and that the distribution of asset choices shifts markedly towards riskier ones. Concretely, 35% of participants in COPY chose to copy someone in the list and, of these, the vast majority copied somebody who had chosen the riskiest possible asset in Block 1. Moreover, those who did not choose to copy anybody also shifted their asset choices towards riskier assets, when compared to the choices in the Block 2 of BASELINE. The latter observation is reinforced by the shift towards riskier assets in the second block choices of participants in INFO. The mere presentation of the ordered list of BASELINE investors prompts other investors to take significantly more risks. We therefore observe that the type of information provided and the possibility of copying others present in copy trading platforms, is ex-ante welfare reducing, as investors choose suboptimal assets, when judged either from the perspective of the risk aversion revealed in the asset choices of Block 1, or from the lottery choices in Part 1.

We further address the question of who decides to become a copier. Here we find that risk aversion plays a determinant role. The more risk averse subjects are, the more likely they are to copy others. Ironically, it is thus those with a revealed low tolerance for risk

taking who are enticed through copy trading to take on more risk.

The remaining of the paper is organized as follows. Section 2 briefly reviews the most relevant literature. In Section 3 we explain in some detail how the copy trading platforms work. Section 4 details the experimental design and establishes the theoretical framework. Section 5 reports the experimental results. Section 6 discusses our results and concludes. The Appendix contains the proof to the main theoretical result of Section 4 and the experimental instructions.

2 Related Literature

Our paper relates to several strands of literature. First, imitation as a behavioral heuristic has attracted the attention of the economics literature. It has been shown that imitation can represent an attractive decision procedure in certain circumstances (Alós-Ferrer and Schlag, 2009), but it can lead to sub-optimal outcomes in other settings, such as Cournot games (Vega-Redondo, 1999; Apesteguia, Huck, and Oechssler, 2007). Imitation has also been shown to play an important role in traditional investment decision making (see e.g. Scharfstein and Stein, 1990; De Long, Shleifer, Summers, and Waldmann, 1990; or Bikhchandani, Hirshleifer, and Welch, 1992).

The closest papers to us are Offerman and Schotter (2009) and Baghestanian, Gortner, and van der Weele (2016). While these contributions experimentally study the implications of providing information on peers on risk taking in economic decision making, we are the first to explicitly study copy trading in an experimental setting. In contrast to our financial setting, Offerman and Schotter (2009) use a production choice and a takeover game to study the role of peer information in environments where payoffs are influenced by a random component. While imitation is not optimal in their setting, they nonetheless find that it plays an important role in explaining subjects' behavior and may lead to more risky behavior. Further, in our setting the potential scope of imitation is further limited by the asset simulator. Baghestanian et al. (2016) experimentally study double auctions of Arrow-Debreu securities with and without peer information. In their setting, observing other traders yields less risky portfolios. This might be caused by the provision of information of states of the world that are not realized, thus making less risky portfolios more salient. In addition to explicitly allowing subjects to copy others at the click of a button, we deviate from these contributions by studying a financial task designed to closely resemble the setting of copy trading platforms.

There are also a number of recent papers that study copy trading platforms empirically. Using data from the copy trading platform *eToro*, Pan, Altshuler, and Pentland (2012) find that followed traders are, often but not always, the most successful. In addition, they show that users of the trading platform tend to increase the trading strategy volatility and market overreaction. Further, Liu et al. (2014) show that copied trades have a larger probability of positive returns than standard trades, but the return on investment of successful copy trades is smaller than the return of standard successful trades. Further, in case of negative returns, losses are typically higher for copied trades. Also using data from *eToro*, Pelster and Hoffmann (2018) show that investors who are being copied by other investors are more likely to suffer from a disposition effect.

Publicly available performance rankings are one aspect of copy trading but they might by themselves have an effect on investors. For example, Kirchler, Lindner, and Weitzel (2017) find that rankings increase the risk taking of underperforming financial market professionals. Of course, rankings in the mutual fund industry make chasing past performance a very common phenomenon (see e.g. Sirri and Tufano, 1998 who find that only the very top performing funds experience inflows). However, in contrast to our study, the welfare effects of chasing past performance are less clear. If performance is not consistent, chasing past performance does not help but need not hurt investors (apart from high fees).

The binomial tree model we use to implement a stylized financial market has been used elsewhere in the economic and finance literature to study a variety of questions. For instance, Oprea et al. (2009) and Sandri et al. (2010) study circumstances under which individuals optimally (de)-invest in assets, the prices of which evolve according to binomial tree models. Further, Ensthaler et al. (2017) demonstrate in a binomial tree model framework that subjects face difficulties predicting the median and skewness of asset price distributions resulting from multiplicative growth processes. Note that the use of the asset simulator in our experiment should mitigate these concerns.

3 Copy Trading Platforms

The rise of network platforms such as Uber, Twitter, or TripAdvisor has profoundly shaped social interactions and fundamentally changed entire industries such as transport, news media, or tourism. Using similar ideas, specialized social networking platforms that cater to financial investors have been created, thus giving rise to social trading. While still in its infancy, social trading might have similar transformative impact on the finance industry.

Social trading platforms typically also double as online brokerage firms, providing their members the possibility to trade financial assets via a web-interface or a mobile app. In addition to these traditional trading features, social trading platforms provide individual investors with means to communicate with each other (through e.g. a chat function or public posts) and enable them to access information on current and past investments. Many of these platforms supplement the exchange of information by allowing traders to directly copy the investment choices of other traders.

Copying another investor entails dedicating a share of one's budget to follow the trades of the copied individual (from now on we call such investors "leaders"). After an investor has decided to copy a given leader, all trades of the leader are replicated for the copier simultaneously and in real time.[2] All trades are proportional to one's budget, i.e. if leaders invest 1% of their portfolio, copiers do so as well. The copier may at any time decide to un-copy the leader at which time the relationship ends and all copied positions are closed at the current market price. Unlike more traditional investment vehicles, such as mutual funds, there are no regulations in place limiting the conduct of leaders.

Platforms usually also provide ways to rank traders according to certain performance criteria such as return in the previous month or year or percentage of profitable trades. Additional filters allow to narrow down the rankings by criteria such as time active, country of origin, or markets in which the trader is active. Some platforms additionally assign risk scores to investors, taking into account indicators such as leverage, volatility of the instruments an investor chooses, and portfolio diversification.

Most platforms reward investors for being copied. For instance, *ZuluTrade* offers its "signal providers" in foreign exchange trading a commission of 0.5pip on trading volume executed through a copier. Similarly, *eToro* under its "popular investor" program offers fixed payments and up to 2% of annual assets under management. In addition, popular investors may receive up to 100% spread rebate on their own trades.[3] These and similar schemes provide incentives for traders to allow others to observe and copy their trades, rather than trading privately.

At the time of writing there are at least a dozen active copy trading platforms. One of the larger of these, *eToro*, has 4.5 million subscribers and according to its CEO has had an

[2] When deciding whether to copy another investor the copier may also choose whether this should include currently open positions. Some platforms additionally allow investors to place stop orders on the performance of the copied individual.

[3] See https://www.etoro.com/en/popular-investor/ and https://www.zulutrade.co.uk/trader-program

annual trading volume in excess of 300bn dollars in 2016.[4] Table 1 provides an overview and some information on ranked traders active on four large copy platforms.[5] Evidently, there are few investors, relative to the number of investors appearing in the rankings, who are copied by others. Specifically, the proportion of those copied ranges from 1.13% to 8.71%. Figure 1 plots the distribution of copiers across the four platforms under consideration. This reveals two further stylized facts about copy trading: Firstly, the vast majority of copied traders are only copied by a few other traders. The fraction of those copied by only one other trader (among those copied) ranges from 20.7% (ZuluTrade) to 59.5% (eToro). Secondly, a few traders account for the majority of copied trades. The top 5% of copied traders accounts for 61.1% (ZuluTrade) to 92.8% (eToro) of copier relationships.

Table 1: Copy trading platforms

Platform	Age in years	Ranked users	Number of leaders	Share of leaders
eToro	14	193,701	2,417	1.25%
ZuluTrade	10	36,416	460	1.26%
Tradeo	13	4,686	53	1.13%
Meta Trader 4	13	3,376	294	8.71%

4 Experimental Design and Theoretical Predictions

Our experiments consisted of three parts; Part 1 involves a standard risk elicitation exercise, Part 2 contains the main financial asset decision problem, and Part 3 implements a questionnaire. We conducted three treatments, that differed only in the second block of the second part. We now explain the details of the experiment.

In Part 1 we elicit risk preferences in a modified Eckel and Grossman (2002) decision task. Individuals had to choose one out of the four lotteries in Table 2, where in each lottery there was a high and a low outcome, both of which occured with probability 1/2. Table 2 also reports the range of coefficients of relative risk aversion, r, that makes choosing

[4] See https://www.etoro.com/en/about/ and 09:16 in an interview with *eToro* CEO Yoni Assia https://www.youtube.com/watch?v=P2yRjHAAPeU&vl=en

[5] Data was obtained in May 2018 using a Python script to automatically collect publicly available information on investors in copy trading platforms.

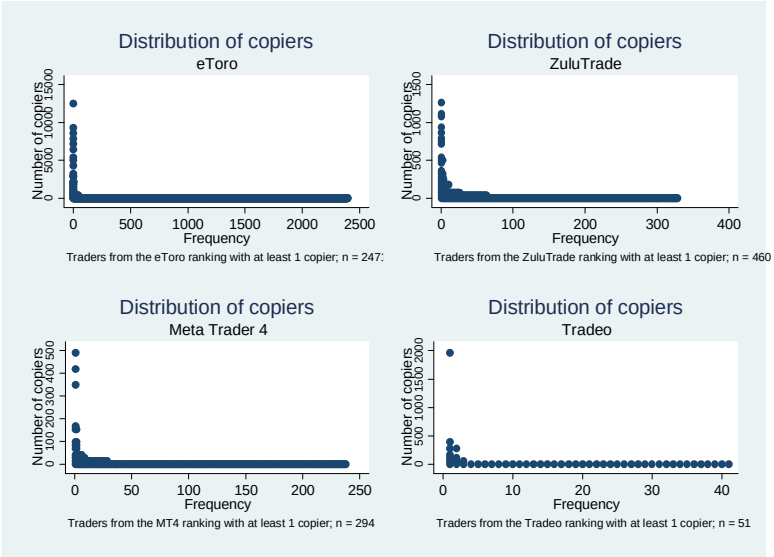

Figure 1: Copiers across platforms. Each dot represents one leader and his/her number of copiers. Shown are only leaders with at least one copier.

the respective lottery optimal under the assumption of expected utility with CRRA.[6] Note that Lottery 4 should only be chosen by risk loving individuals since $r < 0$.

Table 2: Parameters of the Lotteries

Lottery	High outcome	Low outcome	Risk coefficient
1	8€	7.20€	$r > 5$
2	15€	6.40€	$0.34 < r < 5$
3	18.60€	4.00€	$-0.17 < r < 0.34$
4	20.80€	0.80€	$r < -0.17$

Note: The high and low outcomes (in euro) were chosen with probability 1/2 each.

Part 2, the main part of the experiment was divided into two blocks. In Block 1, which was common to all three treatments, subjects were presented with four different financial assets. Every individual had to select one asset out of the four, and once an asset has been chosen, had to decide in each period whether to hold the asset or sell it at the current

[6] That is, the Bernoulli utility function used is $u(x) = x^{1-r}/(1-r)$ for $r \neq 1$ and $u(x) = \log x$ otherwise, where the parameter r represents the (relative) risk aversion coefficient.

price. After an asset was sold, this block was finished for the subject, no further trading could take place.

Asset prices followed a geometric Brownian motion, approximated by a Binomial tree model. The price of asset S at time t, denoted by $S(t)$, moved upwards with probability $(1-p)(1-q)$ to $S(t)(1+u)$ with $u > 0$ and moved downwards with probability $p(1-q)$ to $S(t)(1+d)$ with $d < 0$. With probability q two of the assets crashed to a crash value of 50 and remained there. The four assets had in common that all started with an initial value of 100, involved a maximum of 40 periods, and probability of an uptick (conditional on not crashing) was $p = .5$. The remaining parameters defining the assets are described in Table 3.

Table 3: Parameters of the Assets

Asset	u	d	q	crash value
A	0	0	0	–
B	0.05	−0.04	0	–
C	0.055	−0.03	0.01	50
D	0.1	−0.03	0.04	50

Intuitively, the assets are ordered in terms of the risk they involve, with asset A representing a safe option with a fixed monetary payoff of 100, asset B involving low risk, asset C representing the case of a moderately risky asset, and finally asset D being a highly risky asset. If we again assume CRRA expected utility, we can obtain a precise theoretical prediction on asset choices and selling period conditional on risk attitudes.

Proposition 1 *An investor with CRRA expected utility optimally behaves as follows:*

- *For $r > 5$, the investor buys asset A.*
- *For $0.34 < r \leq 5$, the investor buys asset B and holds it for all periods.*
- *For $-0.17 < r \leq 0.34$, the investor buys asset C and does not sell it for a price below 546.*
- *For $r \leq -0.17$, the investor buys asset D and holds it for all periods.*

The proof of Proposition 1 can be found in the appendix. Importantly, the parameters of the assets and those of the lotteries were chosen so that there is a one to one matching

between the lottery choice in Part 1 of the experiment and the asset choice in Part 2, under the assumption of CRRA expected utility. Hence, we can, in principle, predict asset choices based on the lottery choices.

In order to facilitate the choices of the subjects, we provided subjects with an asset simulator at the begining of Part 2. In the asset simulator, subjects could simulate assets B, C, and D. Each simulation of an asset would graph one possible 40-period realization. The realizations were independent across clicks and individuals. Individuals could simulate any of the assets as many times as they wanted. We recorded the simulation activity for each individual. After participants indicated that they had run enough simulations, they entered the decision stage.

There were three treatments that differed only with respect to Block 2 of Part 2. In treatment BASELINE participants repeated the same asset choice conditions as in Block 1. That is, they had to choose again one of the four assets described above and then decide when to sell.

In treatments INFO and COPY, before deciding which asset to choose in Block 2, participants received information on the Block 1 choices of assets and associated payoffs of all 80 subjects that participated in treatment BASELINE. Subjects were told that these data were generated by subjects in an earlier experiment and that "(t)hey were in the same situation as you, i.e. it was the first time they played this game." The list was ordered from highest to lowest realized payoffs, and presented in blocks of 5 entries. Table 4 reports a sample of the information provided, where the last column was only present in treatment COPY. After inspecting the ranking list, participants had to choose one of the assets, and then period after period had to decide whether to sell the asset at that given moment of time, or hold it one more period.

In treatment COPY, participants received exactly the same information as those in treatment INFO. However, now, in order to reproduce the main feature of copy trading platforms, participants could copy another subject (leader) by pressing the "Copy" botton in Table 4. In this case, the copier would obtain exactly the same payoff the leader had obtained in Block 2 produced by whatever the leader's choice was in Block 2. That is, copying implied that one eventually chooses the same asset, sells in the same period, and obtains the same payoffs as the leaders in their second blocks, but all this information is unknown at the time of copying.

Finally, Part 3 contained a questionnaire where in addition to standard information (gender, age, field of studies, etc.), we gathered further background information on self-

Table 4: Ranking list provided to subjects in INFO and COPY

Rank	Id	Asset	Sold in period	Profits	Option
1	12	D	32	354	Copy
2	23	D	25	281	Copy
3	4	C	40	274	Copy
4	16	D	29	271	Copy
5	18	D	19	254	Copy
				More info	

Note: This is an example for the ranking list subjects in INFO and COPY saw at the beginning of Block 2. The "Copy" botton was present only for COPY. The list was displayed in groups of 5. If subjects wanted to see the next 5 on the list, they had to press the "More info" botton.

assessed risk attitudes and tendency to follow others. Further, subjects were asked to calculate a simple expected value. The full instructions, including the questions used in this final part of the experiment can be found in the appendix.

The experiments were run at the University of Heidelberg in 2017. In total, 176 subjects, of which 55.1% were female and 32.5% were economics students, were recruited via hroot (Bock et al. 2014) from a student subject pool in Heidelberg. In 4 sessions 80 subjects participated in BASELINE, 48 subjects in 4 sessions in INFO, and 48 subjects in 3 sessions in COPY. Participants were paid at the end of the experiment according to one of their decisions from Part 1 (risk elicitation lotteries) or Part 2 (either block 1 or 2 of the asset decision problem). The payoff relevant task was randomly selected by a subject rolling a dice. The payoffs from the lottery were already in euro. The payoffs from the asset decision problem were paid out using an exchange rate of $1T = 0.20$ euro. Average earnings were 11.66 euro and an experimental session took approximately 45 minutes. The experiments were programmed using z-Tree of Fischbacher (2007).

5 Results

We begin by analyzing the lottery choices of the Eckel and Grossman (2002) risk elicitation task. Figure 2 shows the distribution of lottery choices for all 176 subjects, where lotteries are ordered from "1" the least risky lottery to "4" the most risky lottery, as in Table 2. The modal choice is lottery 2, with more than 60% of subjects taking it, indicating a rather low appetite for risk. The next popular choice is lottery 3, chosen by approximately 30%

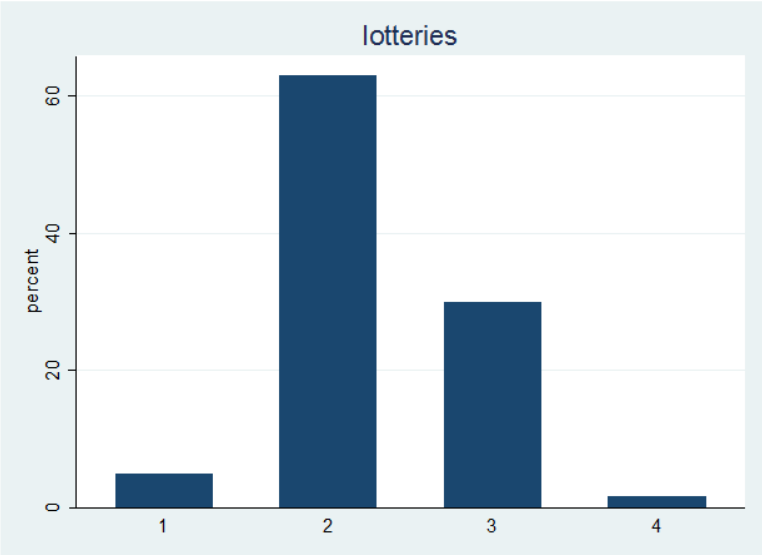

Figure 2: Distribution of lottery choices, all treatments pooled.

of participants, suggesting a significant fraction of subjects willing to take moderate risks. Only a minor portion of participants are either extremely risk averse (5.1%) and even fewer (1.7%) are risk loving and chose lottery 4. These results seem to be in line with other risk aversion elicitation exercises in the literature.[7] Recall from Table 2 and Proposition 1 that the lotteries were designed to predict asset choices under the assumption that subjects have CRRA utility functions. Accordingly, only 3 out of 176 subjects (= 1.7%) are predicted to choose the most risky asset D.

Result 1 *The lottery choices in Eckel and Grossman risk elicitation task reveal that participants are quite risk averse. In particular, only 3 out of 176 subjects are predicted to choose the most risky asset D.*

We now turn to Part 2 of the experiment, the asset choices in our financial market. Figure 3 shows the distribution of asset choices in Block 1 of all 176 subjects. There is a noticeable shift to more risky asset choices as compared to the lottery choices. In fact, 21.6% of subject decided to choose the most risky asset D and 41% of subjects chose an

[7] For example, in Apesteguia and Ballester (2018) the mean population CRRA risk aversion level estimated using structural methods is .752, which falls within the range of levels implied by lottery 2.

asset that was more risky than their chosen lottery. The distribution of asset choices is significantly different from the distribution of lottery choices according to a Wilcoxon test ($p < 0.001$).[8] However, asset and lottery choices are significantly positively correlated ($\rho = 0.23, p < 0.001$) and, although only 45% of subjects chose exactly the asset predicted by their lottery choice, 86% of subjects chose an asset at most one asset lower or higher than their predicted asset.

It seems, therefore, that the financial asset markets makes the population of subjects behave in a riskier manner than the standard lottery choice problem. There may be different reasons behind this observation. For example, it may be the case that the financial market is cognitively more demanding, provoking subjects to behave more erratically. However, our experimental design offered in a user friendly way the possibility of simulating as many realizations of the assets as one wished. This reduced the complexity of the financial decision problem and should have mitigated the impact of cognitive abilities. Furthermore, the fact that the choice distribution shifted in one particular direction, namely towards more risk taking, suggests that complexity is not the only driving force behind this result. It may well be that the mere framing of a decision problem in terms of financial products changes the mind of the participants into a more risk tolerant state. We believe that this is an interesting observation in itself, that deserves to be carefully addressed in future works.[9]

Result 2 *The distribution of asset choices in Block 1 of Part 2 reveals lower levels of risk aversion than the lottery choices of Part 1.*

Of primary interest is of course how the demand for assets changes in Block 2. One of the reasons why we included two blocks even for treatment BASELINE was to allow for the possibility that subjects would change their asset demand simply because they had already experience from the first block. To avoid this confound we now compare asset choice in Block 2 for each treatment. Figure 4 shows the distributions of assets choices in Block 2 separately for the three treatments, where, for the moment, we exclude the copiers in COPY. It is indeed the case that asset choices in BASELINE become more risky in Block

[8] All p-values reported in this paper refer to two-sided tests.

[9] There is research in psychology showing risk aversion to be domain-specific (see, e.g., Weber et al., 2002). Likewise, using actual financial decisions, Einav et al. (2012) find that risk preferences may differ e.g. across insurance and saving decisions. However, they identify a general risk component operating across domains.

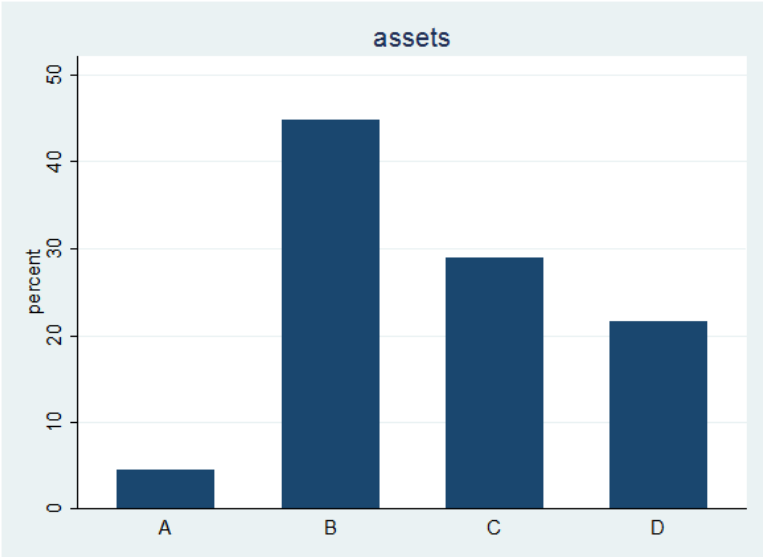

Figure 3: Distribution of asset choices in Block 1, all treatments pooled.

2 with respect to Block 1 (Wilcoxon-test, $p = 0.021$). About 32.5% of subjects choose asset D, as compared to 15% in Block 1.

The percentages of D-choices in treatments COPY and INFO are even higher, 51.6% and 47.9%, respectively. In both treatments, the distribution of asset choices is significantly different in Block 2 from Block 1 ($p = 0.045$ and $p < 0.001$, respectively).

Result 3 *Block 2 asset choices are significantly more risky than Block 1 choices in all three treatments.*

We now compare Block 2 asset choices across the different treatments (see Figure 4 again). Recall that subjects in INFO and COPY saw a list as in Table 4, which contained the Block 1 asset choices and earnings of the 80 subjects from the BASELINE treatment. Subjects always saw the top 5 subjects but had to click a button to see the respective next 5 lower ranked subjects and we recorded the look-up pattern of subjects. While only 4% of subjects in INFO stopped after looking at the top-5 screen, 29% of subjects did so in COPY. Thus, those subjects never saw the possible bad outcomes for asset D. About 40% of subjects in COPY and more than 54% of subjects in INFO looked at the 5 lowest ranked subjects.

Figure 4: Distributions of asset choices in Block 2 by treatment, where in COPY the choices of copiers are not included.

The distribution of assets choices in INFO is significantly different from that in BASELINE (MWU-test, $p = 0.014$). Also, even when excluding the copiers as in Figure 4, the difference in the distribution of assets choices between BASELINE and the non-copiers in COPY is marginally significantly different (MWU-test, $p = 0.078$).[10] Hence, the mere provision of information on previous success of others who were in exactly the same situation increases risk tolerance levels of participants.

Result 4 *Just observing others (as in INFO and COPY, excluding copiers) makes subjects on average more risk taking in terms of their asset choice than in BASELINE.*

Table 5 shows selling periods and selling prices for the different treatments in Block 2. For the pooled data selling periods are similar across treatments but selling prices are significantly higher in COPY and INFO than in BASELINE (MWU-tests, $p = 0.002$ and $p = 0.004$, respectively). It is further revealing to consider selling periods and selling prices for each of the three assets. While these do not vary much for assets B and C, there is

[10] There is no significant difference between COPY and INFO ($p = .89$).

a noticeable difference between BASELINE and the other two treatments for the most risky asset D. In COPY and INFO, subjects hold asset D significantly longer (MWU-tests, $p = 0.002$ and $p = 0.007$, respectively) and wait until it reaches higher prices ($p = 0.018$ and $p = 0.022$).

Result 5 *Observing others (as in INFO and COPY, excluding copiers) induces subjects to sell at higher prices. This effect is mainly driven by those choosing the most risky asset.*

Table 5: Selling periods and prices for different treatments in Block 2

	Asset	BASELINE	COPY	INFO
mean selling period				
	pooled	24.1	24.7	22.8
	B	28.7	25.0	27.8
	C	25.8	33.0	25.5
	D	10.8	21.5	20.6
mean selling price				
	pooled	129.6	173.1	162.8
	B	113.6	117.1	131.1
	C	139.7	137.5	137.5
	D	146.2	207.5	200.8

Thus providing subjects with information on the investment strategies and success of others leads to more risk taking. How copiers strengthen this trend will be addressed next. In total, 17 (35%) subjects in COPY decided to copy someone. All but two of the copiers (88%) chose to imitate a trader from the first page of the list (i.e. from the top five earners). In fact, 12 of the 17 (71%) chose the top earner. And all but two subjects (88%) chose a trader who had chosen asset D, the riskiest asset.

Result 6 *More than a third of subjects in COPY copied the financial decision of some other investor on the list. The vast majority of copiers copied the investor with the highest realized earnings in Block 1. Practically all users copied somebody that chose the riskiest possible asset, D.*

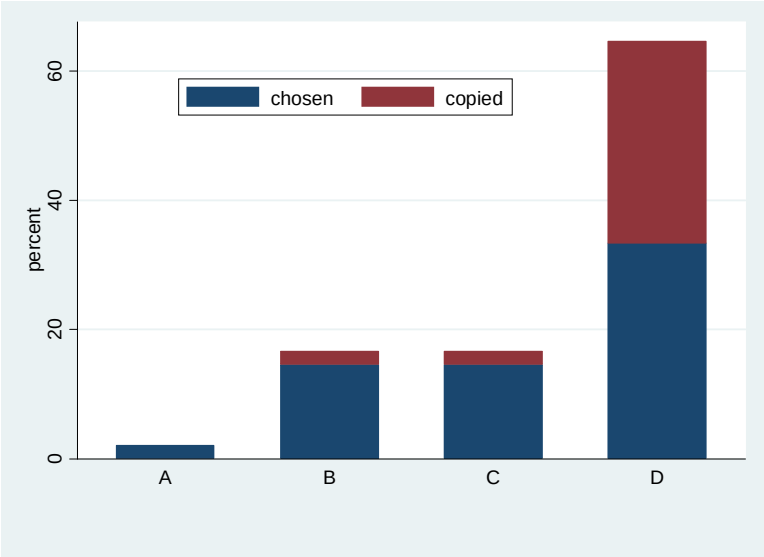

Figure 5: Distributions of asset choices in Block 2 in COPY, including intended choices by copiers.

Figure 5 shows the distribution of assets choices in Block 2 of treatment COPY including the *intended* choices of copiers. When a copier decides to imitate the choice of a leader who chose asset X in Block 1, we assume that the intended choice of the copier in Block 2 was asset X, and leaves the decision when to sell the asset to the leader. We observe that in COPY 65% of subjects either chose asset D themselves or decided to copy someone who had chosen asset D in Block 1. This needs to be contrasted with the 32% of subjects who chose asset D in Block 2 of the BASELINE treatment. We can also relate the asset choice to the lottery choice of subjects. According to the risk aversion expressed by their lottery choice, only 1 subject out of 48 should have chosen asset D in COPY. However, 31 subjects out of 48 (65%) ended up choosing asset D or copied someone who chose asset D.

Result 7 *When considering the intended choices of copiers in treatment COPY, almost 2/3 of subjects choose the most risky asset D.*

What determined whether a subject became a copier? Surprisingly, the only consistent factor that seemed to matter is the risk aversion of subjects as elicited in the lottery choice in Part 1. Table 6 shows logit regressions to explain the probability of becoming a copier.

In all three regressions, the more risk averse subjects (i.e. the lower the lottery number) are, the more likely they copy others, albeit the effect is only weakly significant in the latter two specifications. The marginal effects implied by these regressions are sizeable. For instance, specification (1) implies that subjects with one lottery class lower exhibited a 33% higher probability to copy.[11]

Neither the chosen asset in Block 1 nor the realized earnings from Block 1 have a significant effect. In regression 2 we add variables gathered from the questionnaire. None of them has a significant effect. Finally, in regression 3 we add the "crash experience" of subjects, i.e. whether they experienced a crash in Block 1 or what percentage of their simulations with asset C and D, respectively, crashed. Again, none of them had a significant effect. There is a weakly significant effect of the field of studies (for other fields than economics or science) and an effect of the look-up pattern of subjects: If subjects only look at the top-5 ranking, they are more likely to copy.

Result 8 *The main driving force for investors to copy the financial decisions of a previous investor is their risk aversion level. The lower the tolerance to risk, as elicited in the lottery problem, the higher is the probability of copying.*

We can check the predictions of Proposition 1 with respect to the holding periods for the respective assets. Proposition 1 predicts that subjects with CRRA utility would hold a chosen asset until the last period except for asset C, where the subject would sell not below 546, a price that was never reached in the experiment. Thus, effectively, the prediction is that all subjects would hold their asset until the end of a block. Yet, 66% of subjects sold asset B prematurely, 90% sold asset C prematurely, and not even 1% of subjects held asset D until the end of a block. Furthermore, only about 7% of assets were sold below the starting value of 100. Overall this shows a fairly strong disposition effect (Shefrin and Statman, 1985), as assets are almost never sold at a loss but quickly sold once a small profit is made.[12]

[11] The marginal effects in specifications (2) and (3) are 28% and 26%, respectively.

[12] Magnani (2015) finds a disposition effect in experimental asset markets that are similar to the ones in our experiment. The disposition effect also plays a crucial role on social trading platforms and increases as traders become exposed to the network (Heimer, 2016), are for the first time copied (Pelster and Hofmann, 2018) or price information is made more salient (Frydman and Wang, 2017). Note, however that our design abstracted from all of these additionaly important factors.

Table 6: Probability of becoming a copier: logit regressions

	(1)	(2)	(3)
lottery	-1.64^{**}	-1.51^{*}	-1.68^{*}
	(0.77)	(0.83)	(0.96)
asset in Block 1	0.18	0.22	0.43
	(0.41)	(0.48)	(0.76)
earnings in Block 1	0.01	0.01	−0.00
	(0.01)	(0.01)	(0.01)
imitindex		0.12	0.13
		(0.29)	(0.38)
female		0.43	0.06
		(0.81)	(0.94)
expected value correct		−0.15	−0.37
		(0.83)	(0.96)
field of study: sciences		−1.13	−0.89
		(1.06)	(1.31)
field of study: others		−1.34	-2.19^{*}
		(0.94)	(1.18)
asset crash in Block 1			−1.67
			(2.25)
% of simulations crashed asset D			0.36
			(1.58)
% of simulations crashed asset C			−2.22
			(1.66)
viewed only top 5			1.81^{*}
			(0.93)
constant	1.63	2.09	4.38^{**}
	(1.57)	(2.20)	(3.58)
N	48	47	47

Note: "imitindex" is an index created by taking the differences in responses to questionnaire questions 4 and 5 and to 6 and 7, respectively, and averaging them. Female is a gender dummy. "Expected value correct" is 1 if the subject could calculate the expected value of a simple lottery. Standard errors in parentheses. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Result 9 *There is a noticeable disposition effect as subjects hold losers and sell winners prematurely.*

It is tempting to speculate on the welfare consequences of such choices. As we shall discuss next, this is not at all a straightforward exercise. One option would be to look at ex post realized payoffs for the different subjects. However, it should be fairly obvious that ex post payoffs are unsuitable for welfare statements. The fact that someone was lucky and received a high ex post payoff, does not rectify a suboptimal ex ante decision.[13] Welfare can only be evaluated once we know subjects' true risk preferences, and decisions have to be evaluated in an ex ante sense. In a revealed preference sense we have three decisions (the lottery choice and the asset choices in Blocks 1 and 2) which may reveal subjects' risk preferences. Which of these choices is the best welfare benchmark is difficult to judge. But in any case, the asset choices in Block 2 of COPY and INFO are more distorted and the number of inconsistencies of choices increases in the direction of more risk aversion, independently of whether they are judged from the perspective of the lottery choice or the Block 1 asset choice. Arguably, some of these decisions must have been suboptimal unless preferences changed during the short time span involved in the experiment towards more risk aversion, something that seems very unlikely.

However, our main point remains the fact that choices in INFO and COPY are more distorted than in BASELINE and this implies that copy trading makes ex-ante welfare reducing choices of investors more likely.

6 Discussion

In this paper we have experimentally shown that providing investors with information on previous investment decisions and the success of other traders may lead to an increase in risk taking. This effect is further exacerbated when agents are allowed to directly copy other traders. Imitation through either of these channels leads to a reduction of investor's ex-ante welfare, as established through the elicitation of risk preferences and as manifested in counterfactual investment decisions where imitation is not possible. Our results, thus, suggest that social trading (with or without the option to directly copy others) may be

[13] To prove this point, subjects in our COPY treatment actually received the highest average payoffs. This was mostly due to the fact that the first ranked subject, whom 12 of the 17 copiers followed, unexpectedly chose the moderate asset B in Block 2 and received a relatively high payoff with it.

detrimental to consumer welfare and as such may require increased interest and scrutiny from academics and policy makers alike.

We believe that the implications of copy trading on risk taking may be even stronger on real world copy trading platforms: While we have recruited our participants from a student subject pool, investors on copy trading platforms likely join these platforms with the explicit intent to engage in copy trading. Further, the design of our experiment made the role of luck very salient. In the real world, however, investors' beliefs on the skills and information of leaders might be more optimistic. In addition, whereas our experimental setup allowed subjects to easily asses how risky previous investments of other investors were, such an assessment is much more difficult in the real world. From a social perspective, imitation encourages traders to follow similar investment strategies and could, thus, lead to financial risk through resulting herding and contribute to the formation of financial bubbles. We believe our results are a serious call of attention to copy trading platforms that are proliferating nowadays, and hope the results will trigger more research in the near future.

We believe that the optimal regulatory approach towards social trading should encompass a variety of dimensions and that further research is required to guide it. One possibly fruitful area for consideration lies in studying the factors that potentially mitigate excessive risk taking in social trading. This may include analyzing the role of framing of information provision or classifying traders according to their risk taking, as already done by some copy trading platforms. These risk classifications are typically performed by evaluating previous investments decisions with respect to leverage, portfolio diversification, volatility of the chosen assets, etc. This seems to be a step in the right direction and helps to identify reckless and disproportionately exposed traders. However, it only tames the risk-proliferating nature of copy trading: While past behavior gives some indication of risk attitudes of an individual trader, it may not be a good predictor of future behavior. Further, there are hundreds of thousands of traders active on copy trading platforms. So even when controlling for risk, chances are that -within a certain risk category- the most risk taking investors will still dominate the rankings. A possibly more fruitful avenue could be to advice copiers to copy multiple (diversely invested) traders, thus increasing diversification and reducing exposure to risk. We believe that a better understanding of the implications of the institutional properties of copy trading platforms may ultimately lead to improved outcomes for individual traders and society at large. We hope that this paper is but a first step in this direction.

7 Appendix

7.1 Proof of Proposition 1

Comparison of A vs. B: Let us analyze first optimal behavior in asset B. Consider the last period where a choice between holding the asset or selling it must be made, i.e. $t = 40$. The level of risk aversion r^* that makes the investor indifferent between selling asset B at $t = 40$, or holding it, is the one solving the following equality:

$$u(S(t)) \quad = \quad (1-p)u(S(t)(1+u)) + pu(S(t)(1+d)),$$

that given the CRRA functional form is equivalent to solve:

$$1 \quad = \quad (1-p)(1+u)^{1-r^*} + p(1+d)^{1-r^*}. \tag{1}$$

Note that the equality is independent of the actual value of wealth. Hence, the investor sells if and only if $r \geq r^*$.

Consider now period $t = 39$. We have shown in the previous paragraph that if $r \geq r^*$ the investor sells at $t = 40$, and hence the decision to hold or sell asset B at $t = 39$ is described by equation (1), and consequently by r^*. If $r < r^*$, the level of risk aversion $\widetilde{r}$ that makes the investor indifferent between selling asset B at $t = 39$, or holding it until the end, is the one solving the following equality:

$$u(S(t)) \quad = \quad (1-p)^2 u(S(t)(1+u)^2) + p^2 u(S(t)(1+d)^2) + 2(1-p)pu(S(t)(1+u)(1+d)),$$

that using the CRRA functional form reduces to:

$$1 \quad = \quad [(1-p)(1+u)^{1-\widetilde{r}} + p(1+d)^{1-\widetilde{r}}]^2. \tag{2}$$

Clearly, r^* solves (1) if and only if it solves (2), and hence $r^* = \widetilde{r}$. Therefore, if $r \geq r^*$ the investor sells at $t = 39$ and if $r < r^*$ the investor holds B until the end.

Continuing backwards in the analysis of the decision tree, it is immediate that the above argument extends. Namely, at any period t, if $r \geq r^*$ the investor sells, and if $r < r^*$ compares the value of the asset at t, $S(t)$, with the continuation value of holding it until the end, leading to the following comparison:

$$1 = [(1-p)(1+u)^{1-r} + p(1+d)^{1-r}]^{40-t+1}. \tag{3}$$

The critical risk aversion value of (3) is r^*, and hence we conclude that the DM sells at $t = 1$ whenever $r \geq r^*$ and holds it until the end of the process otherwise. For our set of

parameters, $r^* = 5$. Note that since the sure wealth of asset A coincides with the starting value of asset B, this also represents the risk aversion value where the DM is indifferent between holding asset A or asset B for all periods.

Comparison of B vs. C: With the probability of a crash, the decision is more complex. The decision to hold an asset for one more period depends on current wealth since the relative size of the crash $S(t) - 50$ is increasing in $S(t)$. Consider asset C at the final period 40. Given a level of relative risk aversion r, there exists at most a critical price $\bar{S}_{40}$ such that for all $S(t) > \bar{S}_{40}$ the DM would sell the asset. It is defined by

$$u(\bar{S}_{40}) = (1-q)\left(pu(\bar{S}_{40}(1+d) + (1-p)u(\bar{S}_{40}(1+u)\right) + qu(50). \tag{4}$$

In period 39, the DM faces a similar problem but has more options. He can sell the asset at the current price or he can decide whether to sell the asset in period 40 conditional on whether the price went up or down in period 39. This option value makes holding the asset in period 39 slightly more attractive and leads to $\bar{S}_{39} > \bar{S}_{40}$. By the same logic, $\bar{S}_t > \bar{S}_{40}$ for all $t < 40$. Thus, $\bar{S}_{40}$ is a lower bound for the selling price. Those time-dependent reservation values make for a very complex analysis. However, as it turns out, they are irrelevant for the parameters we consider, as we now argue.

Consider first the utility value of holding asset C until the end. We can calculate the expected utility resulting from this as

$$\sum_{i=0}^{40} \binom{40}{i} p^i (1-p)^{40-i} \left[u\left(S(0)(1+d)^i(1+u)^{40-i}\right)(1-q)^{40} + \left(1-(1-q)^{40}\right)u(50)\right]. \tag{5}$$

Using (5) we find numerically that a DM with $r = 0.34$ would prefer asset C and with $r = 0.35$ would prefer asset B. At $r = 0.34$ we can calculate $\bar{S}_{40} = 546$ using (4) proving the claim that a DM with $r = 0.34$ would not sell below 546. Since $\bar{S}_t$ is decreasing in r, all DM with lower r, would have even higher critical prices, proving the claim.

Since the process reaches 546 only very rarely, the role of the critical prices can be ignored: For example, using $\bar{S}_{40}$ in all periods increases the expected utility only by 1.4×10^{-8} %.

Comparison of C vs. D: For $r < 0.5$ and asset D, the critical $\bar{S}_t$ are never binding (there are no rational solutions to (4)). Thus, we can again use (5) to calculate numerically the r where a DM would switch from asset C to D. We find that for $r < -0.17$ a DM would prefer asset D. □

7.2 Experimental Instructions

Introduction

Welcome to the AWI Lab. The experiment will take about one hour, and at the end of the experiment, you will be paid in cash. The payment you receive for the experiment depends on your own decisions and on chance.

You can make all your choices at your computer. Please do not talk to other participants. If you have any questions, please raise your hand, and someone will come over. Now please read the instructions carefully. You may use paper and pencil and take notes any time.

Timing

Today's experiment is composed of three parts. Part 1 is a questionnaire on lottery choices. Part 2 consists of 2 rounds in which you will have to choose among various financial assets. Part 3 contains another questionnaire.

Payment

At the end of the experiment one of your decisions from Part 1 or 2 will be randomly selected for payment. This is done by you rolling a die. If the die shows "1" or "2", your payment depends on Part 1. If the die shows "3" or "4", the payment depends on the outcome of Part 2, round 1. Finally, if the die shows "5" or "6", the payment depends on the outcome of Part 2, round 2.

You will receive your payment in cash at the end of the experiment. Each participant will only learn his/her own payment.

Part 1

In Part 1 you have to choose one lottery among 4 lotteries. All lotteries have two possible Euro-amounts that depend on a coin flip (which will be carried out if this Part is chosen for payment). The lotteries only differ in the possible Euro-amounts associated to the heads and tails outcomes.

Lottery	Heads	Tails
1	8	7.20
2	15	6.40
3	18.60	4.00
4	20.80	0.80

For example, if you choose lottery 2 and in the end the coin you throw shows tails, then you receive 6.40 Euros if Part 1 is selected for payment.

Part 2

In Part 2 there are two rounds, which are independent of each other. At the beginning of each round you have to select one of four possible financial assets: A, B, C, or D.

The prices of the assets follow different random processes over 40 periods. All assets start with a price of 100 Taler (T).

- The price of asset A is constant at 100 T for all 40 periods.
- The price of asset B in each period moves up by 5% with probability $\frac{1}{2}$ and moves down by 4% with probability $\frac{1}{2}$.
- For asset C in each period there is a 1% chance that there is a market crash and the price of asset C moves to 50T and stays there until the end. If there is no crash, the price of asset C in each period moves up by 5.5% with probability $\frac{1}{2}$ and moves down by 3% with probability $\frac{1}{2}$.
- For asset D in each period there is a 4% chance that there is a market crash and the price of asset D moves to 50T and stays there until the end. If there is no crash, the price of asset D in each period moves up by 10% with probability $\frac{1}{2}$ and moves down by 3% with probability $\frac{1}{2}$.

Price movements in one period are independent of price movements in earlier periods.

After each period you see graphically the price path of the asset you have chosen. Then you have to decide whether you want to hold the asset until the next period or whether you want to sell it at the current price.

Before deciding which asset to choose, you have the option of simulating realizations of the different assets. Note that there are very many different realizations of the stochastic process. The computer will randomly simulate some of these. To start the simulation, you can press the button "Simulations" below the asset you want to simulate. You can press as many times as you wish, and for all the assets you want.

Your payoff is determined by the price at which you sell your asset (or, if you keep it until period 40, by the final price). At the end, each Taler is worth 0.20 Euro. In round 2 of Part 2 you have to choose again among the same 4 assets. Before you do this, you can see the results of a group of subjects who participated in an earlier experiment. They were in the same situation as you, i.e. it was the first time they played this game.[14]

[14] These last two sentences were present only in the instructions of INFO and COPY.

You have now the option to "copy" one of the subjects on the list. When you copy a subject, the computer chooses for you the same asset and holding decisions as the chosen subject in his or her second round (recall that the results in the list are from the subjects? first round). In other words, you will get exactly the same payoff as the chosen subject in his/her second round. Alternatively, you can decide on an asset by yourself and decide on how long to hold it.[15]

Once all subjects are finished with this part, we move on to Part 3, which is a computerized questionnaire.

Part 3

This is the last part of the experiment. It consists in answering a few questions.

1. Your field of study:
   - economics
   - natural sciences
   - math
   - other
2. Your gender: male 0 female
3. If you win 100 euro with probability 1/2 and 20 euro with probability 1/2, what is the expected value of this gamble?
4. "When I buy a new smartphone (or laptop), I usually just pick from the one's that were recommended to me by friends." I agree with this statement, on a scale from 0 to 5, at ...
5. "When I buy a new smartphone (or laptop), I usually read all test reports and then decide for the best one even if none of my friends has such a phone." I agree with this statement, on a scale from 0 to 5, at ...
6. How do you see yourself: Are you generally a person who is going his own way?
7. How do you see yourself: Are you generally a person who follows the lead of others?

[15] This paragraph was only in the instructions for treatment COPY.

References

[1] Alós-Ferrer, C and K. Schlag (2009), "Imitation and Learning," in The Handbook of Rational and Social Choice, ed. by P. Anand, P. Pattanaik, and C. Puppe. Oxford University Press.

[2] Apesteguia, J. and M.A. Ballester (2018), "Monotone Stochastic Choice Models: The Case of Risk and Time Preferences," *Journal of Political Economy*, 126(1):74–106.

[3] Apesteguia, J., S. Huck and J. Oechssler (2007), "Imitation Theory and Experimental Evidence," *Journal of Economic Theory*, 136:217–235.

[4] Baghestanian, S., P.J. Gortner and J.J. van der Weele (2016), "Peer Effects and Risk Sharing in Experimental Asset Markets," mimeo, University of Amsterdam.

[5] Bikhchandani, S., D. Hirshleifer and I. Welch (1992), "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 100(5):992–1026.

[6] Bock, O., I. Baetge, and A. Nicklisch (2014), "hroot: Hamburg registration and organization online tool," *European Economic Review*, 71:117–120.

[7] Cox, J.C., Ross, S.A., and Rubinstein M (1979), "Option pricing: A simplified approach," *Journal of Financial Economics,* 7(3):229–263.

[8] De Long, J.B., A. Shleifer, L.H. Summers, and R.J. Waldmann (1990), "Noise Trader Risk in Financial Markets," *Journal of Political Economy*, 98(4):703–738.

[9] Eckel, C. and P. Grossman (2002), "Sex Differences and Statistical Stereotyping in Attitudes Toward Financial Risk," *Evolution and Human Behavior,* 23(4):281-295.

[10] Einav, L, A. Finkelstein, I. Pascu, and M.R Cullen (2012), "How General Are Risk Preferences? Choices under Uncertainty in Different Domain," *American Economic Review* 102(6):2606-2638.

[11] Ensthaler, L., O. Nottmeyer, G. Weizsäcker and C. Zankiewicz (2017), "Hidden Skewness: On the Difficulty of Multiplicative Compounding Under Random Shocks," *Management Science*, 64(4):1693 - 1706.

[12] Fischbacher, U. (2007), "z-Tree: Zurich Toolbox for ready-made economic experiments," *Experimental Economics* 10(2):171-178.

[13] Frydman, C. and Wang, B. (2017), "The Impact of Salience on Investor Behavior: Evidence from a Natural Experiment," mimeo.

[14] Heimer, R. (2016), "Peer Pressure: Social Interaction and the Disposition Effect", *Review of Financial Studies,* 29:3177-3209.

[15] Kirchler, M., F. Lindner, and U. Weitzel (2017) "Rankings and Risk-Taking in the Finance Industry", *Journal of Finance*, forthcoming.

[16] Liu Y.Y., J.C. Nacher, T. Ochiai, M. Martino and Y. Altshuler (2014), "Prospect Theory for Online Financial Trading," PLoS ONE 9(10).

[17] Magnani, J. (2015), "Testing for the disposition effect on optimal stopping decisions," *American Economic Review*, 105(5): 371-375.

[18] Offerman, T., and A. Schotter (2009), "Imitation and Luck: An Experimental Study on Social Sampling, *Games and Economic Behavior*, 65(2):461–502.

[19] Oprea, R., D. Friedman and S. T. Anderson (2009), "Learning to Wait: A Laboratory Investigation," *Review of Economic Studies*, 76(3):1103–1124.

[20] Pan W., Y. Altshuler and A. Pentland (2012), "Decoding Social Influence and the Wisdom of the Crowd in Financial Trading Network," Proceedings of the 2012 ASE/IEEE International Conference on Social Computing.

[21] Pelster, M. and A. Hoffmann (2018), "About the Fear of Reputational Loss: Social Trading and the Disposition Effect", mimeo, University of Paderborn.

[22] Sandri, S., Schade, C., Musshoff, O., and Odening, M. (2010), "Holding on for too long? An experimental study on inertia in entrepreneurs' and non-entrepreneurs' disinvestment choices." *Journal of Economic Behavior and Organization*, 76(1):30-44.

[23] Scharfstein, D.S. and J.C. Stein (1990), "Herd Behavior and Investment," *American Economic Review,* 80(3):465–79.

[24] Shefrin, H. and Statman, M. (1985), "The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence." *Journal of Finance*, 40:777–790.

[25] Sirri, E. R., and P. Tufano (1998), "Costly search and mutual fund flows", *Journal of Finance*, 53(5):1589–1622.

[26] Vega-Redondo, F. (1997), "The Evolution of Walrasian Behavior," *Econometrica*, 65:375–384.

[27] Weber, E.U., A.-R. Blais, and N.E. Betz (2002),"A Domain-specific Risk-attitude Scale: Measuring Risk Perceptions and Risk Behaviors," *Journal of Behavioral Decision Making*, 15:263–290.