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Copy Trading

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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 a novel 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 leads to excessive risk taking.

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Keywords: copy trading • financial markets • social networks • imitation • experiment

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 investors 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 investors with high earnings may have just been lucky. Under copy trading, other investors are inclined to imitate those lucky investors. To make matters worse, high returns might be associated with high risk taking of the copied investors. Thus, successful investors 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. We, therefore, believe that it is of great importance to study the behavioral implications of copy-trading platforms.

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 control for in the field. For example, in our studies, we will measure risk preferences outside the financial markets, which will permit us to determine optimal asset choices 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 was 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 et al. 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 that subjects confronted in the first block. In our main treatment, COPY, investors received a list containing the decisions and realized profits in the first block of all the investors 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 yet-unknown payoffs that the copied subjects had earned in the second block. Finally, in treatment INFO, subjects saw the same ranking list as in COPY but were not able to copy others. Treatment INFO thus examines the pure effect of providing information on the investment decisions of others. As such, the findings from this treatment do not only apply to copy trading, but extend to the wider domain where investors receive information about peers.[2]

We are interested in the determinants of copying behavior. The comparison between BASELINE and INFO allows us to ascertain the behavioral effect of the mere provision of information about 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 decisions 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 their customers.

In the third, and last, part of the experiment, we collected some potentially important information like gender, age, and education. We also implemented a questionnaire asking how subjects 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 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 toward riskier ones. Concretely, 35% of participants in COPY chose to copy someone in the list, and, of these, 88% 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 toward riskier assets, when compared with the choices in Block 2 of BASELINE. The latter observation is reinforced by the shift toward riskier assets in the second-block choices of participants in INFO. It seems that the mere presentation of the ranking 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 lead investors to 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. We also evaluated the influence of other variables, such as demographics, use of simulator, and realized payoffs in Block 1, finding that none had a significant effect. There is a weak positive effect for fields of study other than economics or science and for those who only inspected the first five investors in the ranking list of BASELINE investors.

The remainder of the paper is organized as follows. Section 2 briefly reviews the most relevant literature. In Section 3, we explain in some detail how copy-trading platforms work. Section 4 details the experimental design and establishes the theoretical framework. In Section 5, we suggest a number of partly competing hypotheses that we later test using our data set. Section 6 reports the experimental results. Section 7 discusses our results and concludes. The appendix contains the proof to the main theoretical result of Section 4, sample price paths of our various assets, 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 (Schlag 1998, Alós-Ferrer and Schlag 2009), but it can lead to suboptimal outcomes in other settings, such as Cournot games (Vega-Redondo 1997; Apesteguia et al. 2007, 2010). Imitation has also been shown to play an important role in traditional investment decision making (see, e.g., De Long et al. 1990, Scharfstein and Stein 1990, Bikhchandani et al. 1992). Relatedly, Goeree and Yariv (2015) and Duffy et al. (2019) show in the context of social learning experiments that a sizeable fraction of subjects has a strong taste to follow others, even when there is no information on performance.

The closest papers to us are Offerman and Schotter (2009), Bursztyn et al. (2014), and Gortner and van der Weele (2019). Although 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 by allowing subjects to copy others at the click of a button. 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. Although 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. Bursztyn et al. (2014) find in a field experiment that financial market professionals are influenced by their peers due to both "social learning" and "social utility." In our setting, objectively, there should be limited scope for social learning, as most of what can be learned by observing others can also be learned by using the tool for simulating assets. One may, however, think that other traders are better in judging when to sell the asset. The social utility channel is clearly important in actual copy-trading platforms, as traders can chat with each other. However, in our experiment, there is no chat, and interaction is anonymous. Moreover, we only offer an anonymized ranking list of investors participating in a different experimental treatment. Our experimental design, therefore, purposely closes the "social channels," in order to isolate the possible behavioral influence of informational ones. Gortner and van der Weele (2019) experimentally study double auctions of Arrow–Debreu securities with and without peer information. In their setting, observing the portfolios of other traders yields traders to buy less risky portfolios. However, this effect is neutralized when traders are ranked by their success. In addition to studying a different trading environment and not considering the possibility to directly copy other traders, there are two further differences to our design: (i) There is no trade-off between expected earnings and risk; and (ii) subjects were constantly updated about the hypothetical payoffs in each state of the world. Both of these features may have pushed subjects toward less risk taking.

There are other related papers studying the effect of providing information on performance rankings on the behavior of investors. For example, Dijk et al. (2014) show that rankings decrease (increase) future risk taking of overperformers (underperformers), and Kirchler et al. (2018) find that rankings increase risk taking of underperforming financial market professionals.[3] Note, however, that in our experiments, participation was anonymous, and the performance rankings involved the results of participants from previous experimental sessions.

There is ample evidence that various forms of social context may affect behavior. Bohnet et al. (2008) and Bolton and Ockenfels (2010) show that risk-taking behavior may not only be affected by the consequences that the available options have for oneself, but also for other subjects. Cooper and Rege (2011) study the effect of information on previous choices by other subjects, but not on their realized outcomes, on decision making under risk and uncertainty. They show that this type of social information leads to less risk taking. In addition, they find evidence in favor of social regret—that is, decisions being influenced by an amelioration of regret considerations if others chose the same option.[4] Note that in our experimental design, the options only had financial consequences for a given investor; social information stemmed from subjects in other treatments and included information on their performance.

There are also a number of recent papers that study copy-trading platforms empirically. Using data from the copy-trading platform *eToro*, Pan et al. (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 the case of negative returns, losses are typically higher for copied trades. Also using data from *eToro*, Pelster and Hofmann (2018) show that investors who are being copied by other investors are more likely to suffer from a disposition effect.[5]

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. Although still in its infancy, social trading might have a similar transformative impact on the finance industry.

Social-trading platforms typically also double as online brokerage firms, providing their members with the possibility to trade financial assets via a web interface or a mobile app. Rather than charging their members subscription fees, social-trading platforms typically earn revenues through the bid–ask spread on transactions. As such, platforms are interested in generating high levels of trading volume. In addition to 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. Typically, 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.[6] For example, *eToro* can guarantee copiers the same prices as those of the leaders by conducting all transactions as contracts-for-differences (see Pelster and Hofmann 2018 for details). Most transactions take place in very liquid markets like foreign exchange markets.[7]

All trades are proportional to one's budget—that is, if leaders invest 1% of their portfolio, copiers do so as well. The copier may at any time decide to uncopy the leader, at which time the relationship ends, and all copied positions are closed at the current market price.

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 users 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 chosen instruments, and portfolio diversification.

Most platforms reward investors for being copied. For instance, *ZuluTrade* offers its "signal providers" in foreign exchange trading a commission of 0.5 pip on trading volume executed through a copier. Similarly, *eToro* under its "popular investor" program offers fixed payments and up to 2% of the amount of equity copying the relevant popular investor. In addition, popular investors may receive up to 100% spread rebate on their own trades.[8] 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. Although they are nowadays relatively small, they involve millions of users spread all over the world, and there are indications that they are rapidly growing in size, employing aggressive marketing strategies. One of the larger of these, *eToro*, has 9 million subscribers and, according to its chief executive officer (CEO), has had an annual trading volume in excess of $300 billion in 2016.[9] Table 1 provides an overview and some information on ranked traders active in May 2018 on four large copy platforms.[10] 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 leaders 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%

Table 1. Copy-Trading Platforms

Platform	Age (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%

of leaders accounts for 61.1% (*ZuluTrade*) to 92.8% (*eToro*) of copier relationships.

4. Experimental Design and Theoretical Predictions

Our experiments consisted of three parts: Part 1 features 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.

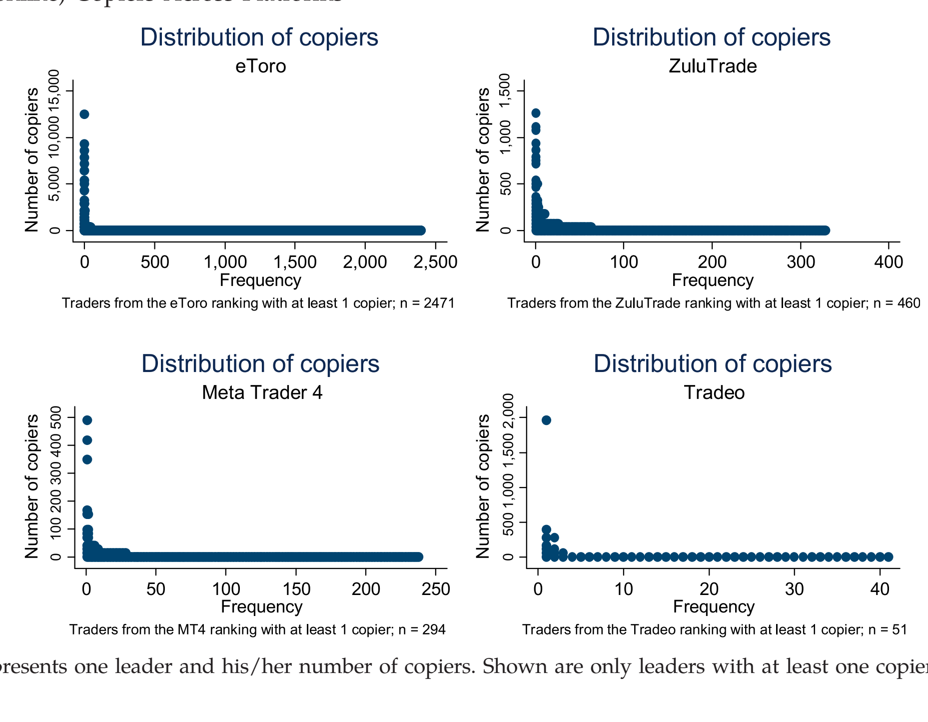
In Part 1, we elicited risk preferences in a modified Eckel and Grossman (2002) decision task. Individuals had to choose one out of the four lotteries in Table 2, where in each lottery, there was a high and a low outcome, both of which occurred with probability 1/2. Table 2 also reports the range of coefficients of relative risk aversion, r, that makes choosing the respective lottery optimal under the assumption of expected utility with constant relative risk aversion (CRRA).[11] Note that Lottery 4 should only be chosen by risk-loving individuals because $r < 0$.

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 had been chosen, had to decide in each period whether to hold the asset or sell it at the current price. If an asset was held until the last period, the individual received the final price as payoff. After an asset was sold, this block was finished for the subject, and no further trading could take place.

The 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 downward with probability $p(1-q)$ to $S(t)(1+d)$ with $d < 0$. With probability q, the asset crashed to a crash value of 50 and remained there. We introduced the crash possibility because it implies a substantial amount of tail risk, which is common in financial assets like options. This should make the riskiness of these assets very transparent and salient.[12]

The four assets had in common that all started with an initial value of 100, involved a maximum of

Figure 1. (Color online) Copiers Across Platforms



Notes. Each dot represents one leader and his/her number of copiers. Shown are only leaders with at least one copier.

Table 2. Parameters of the Lotteries

Lottery	High outcome (€)	Low outcome (€)	Risk coefficient	μ	σ
1	8	7.20	$r > 5$	7.6	0.57
2	15	6.40	$0.34 < r < 5$	10.7	6.08
3	18.60	4.00	$-0.17 < r < 0.34$	11.3	10.32
4	20.80	0.80	$r < -0.17$	10.8	13.63

Notes. The high and low outcomes (in euro) were chosen with probability 1/2 each. μ and σ denote the expected value and standard deviation, respectively.

40 periods, and the probability of an uptick (conditional on not crashing) was $p = 0.5$. The remaining parameters defining the assets are described in Table 3, together with their corresponding expected values and standard deviations, conditional on holding them for all the periods. The realizations of the stochastic processes were independent and identically distributed across periods and participants.

Intuitively, the assets are ordered in terms of the risk they involve, with asset A representing a safe option, giving 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. This would be the ranking of assets for virtually every standard model of decision making under risk. If, in addition, we assume CRRA expected utility, we can obtain a precise theoretical prediction on asset choices and selling period conditional on risk attitudes.

Claim 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 Claim 1 can be found in the appendix; here, we briefly explain its logic. The proof of the claim for assets A and B involves a backward induction argument that exploits the independence of the asset price at time t from the decision to sell or keep the asset one more time period. The proof of the claim involving B and C is more involved because the crash breaks down such an independence. Solving this case, we consider the critical price of the asset at time t for a given level of risk aversion r, $\bar{S}(t, r)$, that makes the investor indifferent between selling the asset or holding it one more period. This price turns out to be decreasing in both t and r. We then use our parameters to obtain that at $r = 0.34$, the investor prefers the expected value of C at $t = 40$ to the corresponding one of B. We then obtain that $\bar{S}(40, .34) = 546$, and hence the comparative statics of $\bar{S}(t, r)$ lead to the result.[13] The comparison of C and D shows that if trader's r is so high that he would pick asset D, then the critical $\bar{S}(t, r)$ is never binding—that is, he would never sell asset D.[14]

Importantly, the parameters of the assets and those of the lotteries were chosen so that there was 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 beginning 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.[15] 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 task as in Block 1. That is, they had to choose again one of the

Table 3. Parameters of the Assets

Asset	Uptick u	Downtick d	Crash probability q	Crash value	μ	σ
A	0	0	0	—	100	0
B	0.05	−0.04	0	—	122.1	35.3
C	0.055	−0.03	0.01	50	126.5	64.9
D	0.1	−0.03	0.04	50	117.6	155.0

Note. The variables μ and σ denote the expected value and standard deviation, respectively, of the assets if held for all 40 periods.

four assets described above and then decide when to sell.

In treatment INFO, before deciding which asset to choose in Block 2, participants received information on the Block 1 choices of assets, selling periods, and associated payoffs of all 80 subjects that participated in treatment BASELINE.[16] Subjects were told that these data were generated by subjects in earlier experimental sessions and that "[t]hey were in the same situation as you—that is, it was the first time they played this game."[17] The list was ordered from highest to lowest realized payoffs and presented in groups of five entries. Table 4 reports a sample of the information provided, where the last two columns were 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 a "Copy" button, as in Table 4. In this case, the copier would obtain exactly the same payoff that 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 copied leader in the second block, but all this information is unknown at the time of copying. To reiterate, all (potential) leaders come from the BASELINE treatment, which was run before the other treatments. Subjects in the COPY treatment could thus only become copiers, not leaders.

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-assessed risk attitudes and tendency to follow others. Further, subjects were asked to calculate a simple expected value. The experiment was run in German. The translations of the 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 four sessions, 80 subjects were randomly assigned to BASELINE, 48 subjects in four sessions to INFO, and 48 subjects in three sessions to 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 die. The payoffs from the lottery were already in euros. The payoffs from the asset decision problem were paid out by using an exchange rate of $1T = 0.20$ euro. Average earnings were 11.66 euros, and an experimental session took approximately 45 minutes. The experiments were programmed by using z-Tree of Fischbacher (2007).

5. Hypotheses

In this section, we suggest a number of partly competing hypotheses, which we then test in our experiment. If subjects are rational and realize that no other subject has any better information than they themselves, they should simply buy in both blocks the asset that corresponds to their lottery choice in Part 1. In particular, the feedback that subjects receive in treatments INFO and COPY about the trading performance of other traders and their chosen assets is not, strictly speaking, any new information because there is complete information on the assets and in addition, each subject has the option to simulate each asset as often as they like.

Hypothesis 1. *Rational subjects buy in both blocks the asset corresponding to their lottery choice. There should be no treatment difference. If, furthermore, subjects' preferences can be described by a CRRA utility function, they will conform to Claim 1.*

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	I don't want to copy choices
4	16	*D*	29	271	Copy	
5	18	*D*	19	254	Copy	
				See the next 5 participants		

Notes. This is an example for the ranking list subjects in INFO and COPY saw at the beginning of Block 2. The "Copy" and "I don't want to copy choices" buttons were 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 "See the next 5 participants" button. If subjects wanted to make their own decisions, they had to press the "I don't want to copy choices" button.

From the experimental literature on imitate-the-best—for example, Huck et al. (1999), Apesteguia et al. (2007), and Offerman and Schotter (2009)—one can deduce that subjects in treatments INFO and COPY may focus their attention on the best-performing subjects when looking at the list of past performances. This is, of course, further enhanced by the chosen order in which the information in Table 4 is presented, as it is typical of copy-trading platforms. As a consequence of this, subjects would receive a distorted view about the *average* performance of the various assets. In particular, given that asset D is likely to dominate the list of top performers, and if subjects use this distorted information to guide their buying decisions in Block 2, we should get:

Hypothesis 2. *Subjects will invest more often in the most risky asset D in Block 2 of treatments INFO and COPY compared with the BASELINE treatment.*

Given the popularity of copy-trading platforms, we expect that some subjects will take the option to copy someone in treatment COPY. With respect to the question why people decide to copy, our experiment is more exploratory. However, given Hypothesis 2, we conjecture about *whom* they will copy if they decide to copy.

Hypothesis 3. *Copiers will copy most often the top performers (and therefore those that invested in the risky asset D).*

6. Results

We begin by analyzing the lottery choices of the Eckel and Grossman (2002) risk-elicitation task. Figure 2 (left) 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 most popular choice is lottery 3, chosen by approximately 30% of participants, suggesting a significant fraction of subjects willing to take moderate risks. Only a minor portion of participants are 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.[18]

Result 1. *The lottery choices in the Eckel and Grossman (2002) risk-elicitation task reveal that participants are quite risk averse. In particular, only 3 out of 176 chose the most risky lottery 4.*

We now turn to Part 2 of the experiment, the asset choices in our financial market. Recall from Table 2 and Claim 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. Figure 2 (right) shows the distribution of asset choices in Block 1 of all 176 subjects, and Table 5 reports the distribution of both lottery and asset choices in Block 1. There is a noticeable shift to more risky asset choices as compared with the lottery choices. This is neatly appreciated in Table 5 in the shift from the diagonal to, primarily, the upper part of the matrix, representing the choice of riskier assets. In fact, 21.6% of subjects decided to choose the most

Figure 2. (Color online) Distribution of Lottery Choices (Left) and Asset Choices in Block 1 (Right), All Treatments Pooled

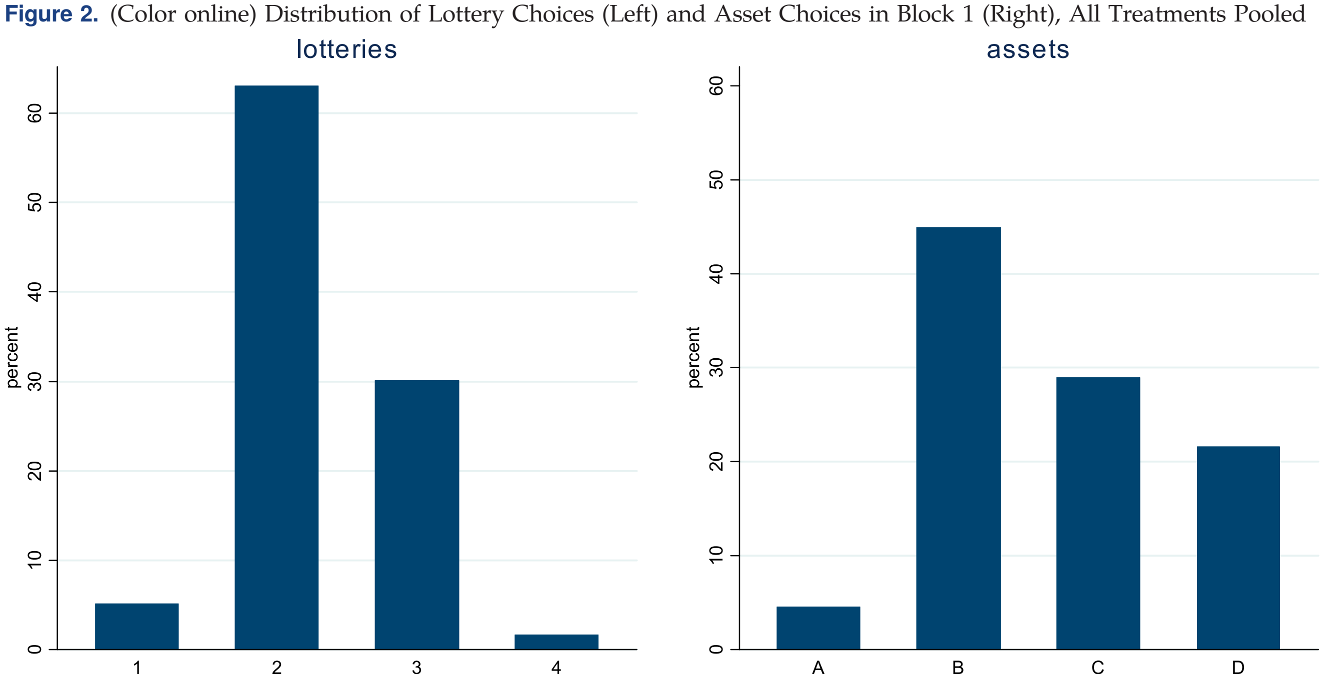


Table 5. Distribution of Lottery and Asset Choices in Block 1

	Asset				
Lotteries	*A*	*B*	*C*	*D*	Total
1	3	4	1	1	9
2	5	55	30	21	111
3	0	18	20	15	53
4	0	2	0	1	3
Total	8	79	51	38	176

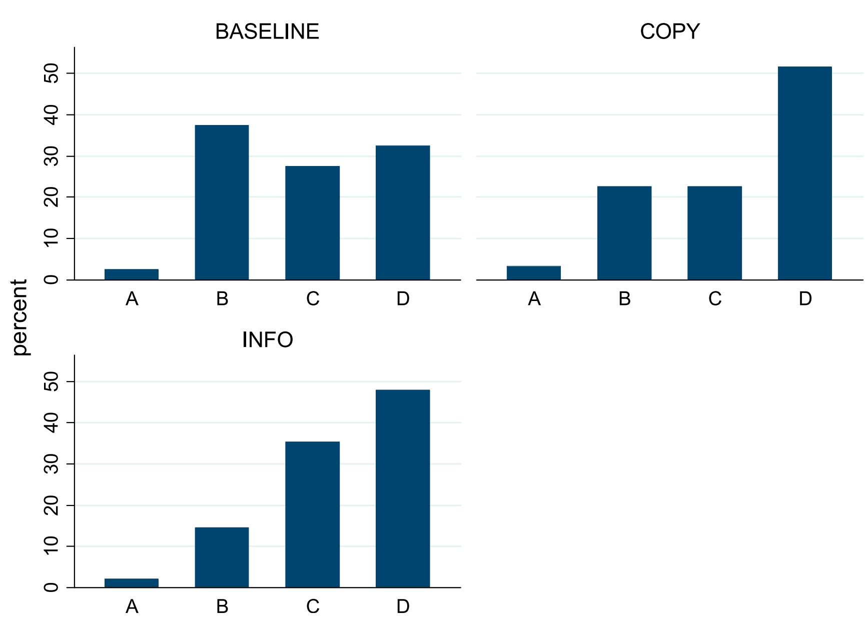
risky asset *D*, and 41% of subjects chose an asset that was more risky than their chosen lottery. The distribution of asset choices is significantly different from the distribution of lottery choices according to a Wilcoxon test ($p < 0.001$) or a *t*-test ($p < 0.001$).[19] However, asset and lottery choices are significantly positively correlated ($\rho = 0.23, p = 0.002$), and, although only 45% of subjects chose exactly the asset predicted by their lottery choice, the entries in the diagonal in Table 5, 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 make 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.[20] This should reduce the complexity of the financial decision problem and should mitigate the impact of cognitive abilities. Furthermore, the fact that the choice distribution shifted in one particular direction—namely, toward 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, which deserves to be carefully addressed in future work.[21]

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, *rejecting Hypothesis* 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 of the experience gained in the first block. To avoid this confound, we now compare asset choice in Block 2 for each treatment. Figure 3 shows the distributions of asset choices in Block 2 separately for the three treatments, where, for the moment, we exclude the copiers in COPY.[22] Figure 3 clearly shows that it is indeed the case that asset choices in BASELINE, INFO, and COPY in Block 2 are significantly different from those in Block 1 (Wilcoxon test, with $p = 0.021$, $p < 0.001$, and $p = 0.045$, respectively, and *t*-test, $p = 0.014$, $p < 0.001$, and $p = 0.077$). The percentages of *D* choices are about 32.5%, 47.9%, and 51.6% in treatments BASELINE, INFO, and COPY, respectively.

Figure 3. (Color online) Distributions of Asset Choices in Block 2 by Treatment, Where in COPY the Choices of Copiers Are Not Included



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

We now compare Block 2 asset choices across the different treatments (see Figure 3). The distribution of assets choices in INFO is significantly different from that in BASELINE [Mann–Whitney U (MWU)-test, $p = 0.014$; t-test, $p = 0.014$]. Also, even when excluding the copiers as in Figure 3, the difference in the distribution of assets choices between BASELINE and the noncopiers in COPY is marginally significantly different (MWU-test, $p = 0.078$).[23] We now consider 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. If we include the intended choices of copiers, we find that the distribution of asset choices is significantly different between BASELINE and COPY at $p < 0.001$, MWU (t-test, $p = 0.001$). It seems, therefore, that 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, confirming Hypothesis* 2.

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. Although 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.

Table 6 shows selling periods and selling prices for the different treatments in Block 2. For the pooled data, selling periods are similar across treatments, but mean selling prices are higher in COPY and INFO than in BASELINE. The distribution of selling prices in BASELINE is significantly different from those in COPY and INFO (MWU tests, $p = 0.002$ and $p = 0.004$, respectively; t-tests, $p < 0.001$). It is further revealing to consider selling periods and selling prices for each of the three assets. Although these do not vary much for assets B and C, there is a noticeable difference between BASELINE and the other two treatments for the most risky asset D. In COPY and INFO, subjects hold asset D longer and wait until it reaches higher prices. The distribution of selling period for asset D in BASELINE is significantly different from those in COPY and INFO (MWU tests, $p = 0.002$ and $p = 0.007$; t-tests, $p = 0.003$ and $p = 0.004$, respectively) and the distribution of selling prices for asset D in BASELINE is significantly different from those in COPY and INFO (MWU test, $p = 0.018$ and $p = 0.022$; t-tests, $p = 0.016$ and $p = 0.014$).

Table 6. Selling Periods and Prices for Different Treatments in Block 2

Asset	BASELINE	INFO	COPY
Mean selling period			
Pooled	24.1	22.8	24.7
B	28.7	21.8	25.0
C	25.8	25.5	33.0
D	10.8	20.6	21.5
Mean selling price			
Pooled	129.6	162.8	173.1
B	113.6	131.1	117.1
C	139.7	137.5	137.5
D	146.2	200.8	207.5

Note. The data for COPY refers to the decisions of the noncopiers.

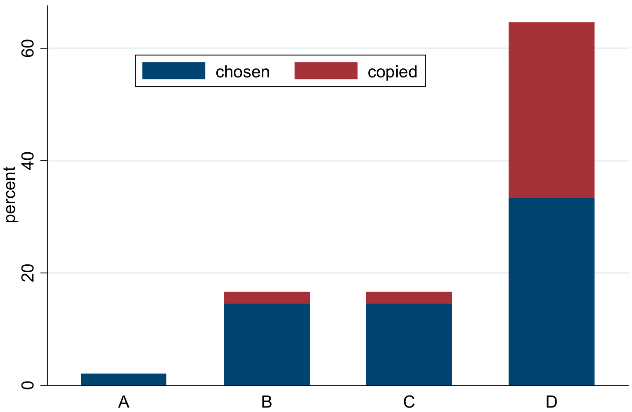
Result 5. *Observing others* (*as in INFO and COPY, excluding copiers*) *induces subjects to sell at higher prices. This effect is mainly driven by those choosing the most risky asset.*

Thus, overall, we find that providing subjects with information on the investment strategies and success of others leads to more risk taking. This is evidence in favor of Hypothesis 2, as opposed to Hypothesis 1. How copiers strengthen this trend will be addressed next. In total, 17 (35%) subjects in COPY decided to copy someone. In line with Hypothesis 3, all but 2 of the copiers (88%) chose to imitate a trader from the first page of the list (i.e., from the top 5 earners). In fact, 12 of the 17 (71%) chose the top earner. And all but 2 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, *confirming Hypothesis* 3.

Figure 4 shows the distribution of assets choices in Block 2 of treatment COPY, including the intended choices of copiers. 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

Figure 4. (Color online) Distributions of Asset Choices in Block 2 in COPY, Including Intended Choices by Copiers



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 two-thirds of subjects choose the most risky asset, D.*

It is tempting to speculate on the welfare consequences of copy trading. 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.[24] Welfare can only be evaluated once we know subjects' true risk preferences, and decisions have to be evaluated in an ex ante sense. From the perspective of revealed preference, we have three decisions (the lottery choice and the asset choices in Blocks 1 and 2) that 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 seeking, 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 toward more risk seeking, something that seems very unlikely. We believe, therefore, that our results suggest that choices in INFO and COPY are more distorted than in BASELINE, implying that copy trading makes ex ante welfare reducing choices of investors more likely.

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 7 shows logit regressions to explain the probability of becoming a copier. In all three regressions, the more risk averse subjects are (i.e., the lower the lottery number), 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. Specifications (A.1), (A.2), and (A.3) imply that subjects with one lottery class lower exhibited a 33%, 28%, and 26% higher probability to copy, respectively.

Neither the chosen asset in Block 1 nor the realized earnings from Block 1 have a significant effect.[25] In regression (A.2), we add variables gathered from the questionnaire. None of them has a significant effect. Finally, in regression (A.3) we add the "crash

Table 7. Probability of Becoming a Copier: Logit Regressions

Regression specification	(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

Notes. "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. "Field of study" is dummies for field of study with the missing category being economics. "Asset crash in Block 1" is 1 if the subject experienced a crash in Block 1. "% of simulations crashed asset *D*" is the percentage of crashes this subject experienced in his simulations of asset *D*. "Viewed only top 5" is 1 if the subject only looked at the first page of the ranking table. Standard errors are in parentheses.

*10% level of significance; **5% level of significance.

experience" of subjects—that is, whether they experienced a crash in Block 1, or what percentage of their simulations with assets 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 fields other 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 Claim 1 with respect to the holding periods for the respective assets. Claim 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.[26]

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

7. 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 may be further exacerbated when investors are allowed to directly copy other traders. Imitation through either of these channels may lead to a reduction of investors' welfare, as judged from 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 detrimental to consumer welfare. Moreover, even outside of the domain of copy trading, information on the success of others may lead to excessive risk taking and reduced welfare.

We hope that this paper will trigger more research in the near future in order to better understand behavior in copy-trading platforms. For example, future research should be conducted in order to understand what are the reasons that lead to copy trading or to more risk-taking behavior in the INFO and COPY treatments. One possibility is that copiers attribute higher skills to copied investors. Although the design of our experiment made the role of luck very salient, future work should systematically study this possibility. Also, it has been shown that cognitive abilities or personality traits are related to risk-taking behavior (see, e.g., Harbaugh 2006, Dohmen et al. 2010, Eisenbach and Schmalz 2016). In this respect, it seems relevant to explore whether these characteristics may prompt some subjects to copy others or to be more affected by the performance of others. Moreover, although 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. Whether the welfare consequences of investors on copy-trading platforms are larger or lower than in the student population is another open question that should be addressed in future research.

One should, of course, be very cautious at extrapolating conclusions from the laboratory to the field, in particular, before a good deal of laboratory and field research has been conducted on the subject matter. However, there are reason to believe that the implications of copy trading on risk taking may be even stronger on real-world copy-trading platforms. For example, in the real world, investors' beliefs on the skills and information of leaders might be even more optimistic than in our laboratory setting. In addition, whereas our experimental setup, by way of the simulator, allowed subjects to easily assess how risky previous investments of other investors were, such an assessment is much more difficult in the real world. Finally, 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.

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Appendix. Proof of Claim 1

Suppose the investor has a CRRA utility function $v(x) = x^{1-r}/(1-r)$ for $r \neq 1$ and $v(x) = \log x$ otherwise, where the parameter r represents the (relative) risk aversion coefficient.

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

$$v(S(t)) = (1-p)v(S(t)(1+u)) + pv(S(t)(1+d)),$$

that, given the CRRA functional form, is equivalent to solve:

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

Note that the equality is independent of the actual value of the asset $S(t)$. Hence, the investor sells if and only if $r \geq r^*$.

Suppose we have shown that there is a $t+1 \in \{3, \ldots, 40\}$, such that for every $t' \geq t+1$ the investor sells at t' if and only if $r \geq r^*$. We now show it for t. By the inductive argument, when evaluating the decision to be made at time t, the investor sells at $t+1$ if $r \geq r^*$. If $r < r^*$, the level of risk aversion that makes the investor indifferent between selling asset B at t, or holding it until the end is the one solving the following equality that uses the CRRA functional form:

$$1 = \left[(1-p)(1+u)^{1-r} + p(1+d)^{1-r}\right]^{40-t+1}. \qquad (A.2)$$

The critical risk aversion value of (A.2) is r^*, and, hence, we conclude that the investor 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 because the sure value of asset A coincides with the starting value of asset B, this also represents the risk-aversion level where the investor 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 to hold asset C for one more period depends on the current value of the asset, because the relative size of the crash $S(t) - 50$ is increasing in $S(t)$. Consider asset C in the final period 40. Given a level of relative risk aversion r, the critical value $\bar{S}(40, r)$ such that for all $S > \bar{S}(40, r)$ the investor sells the asset is defined by

$$v\left(\bar{S}(40,r)\right) = (1-q)\left(pv\left(\bar{S}(40,r)(1+d)\right.\right. \\ \left.\left. + (1-p)v\left(\bar{S}(40,r)(1+u)\right)\right) + qv(50). \qquad (A.3)$$

In period 39, the investor has more options. He can sell the asset at the current value, 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 more attractive and leads to $\bar{S}(39, r) > \bar{S}(40, r)$. By the same logic, $\bar{S}(t, r) > \bar{S}(40, r)$ for all $t < 40$. Thus, given r, $\bar{S}(40, r)$ is a lower bound for the selling price.

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

$$\sum_{i=0}^{40} \binom{40}{i} p^i (1-p)^{40-i} \left[u\left(S(0)(1+d)^i(1+u)^{40-i}\right)(1-q)^{40}. \\ + \left(1-(1-q)^{40}\right)v(50)\right]. \qquad (A.4)$$

Using (A.4) and our parameters, we find (using *Mathematica*) that an investor with $r = 0.34$ prefers asset C and with $r = 0.35$ prefers asset B. Also, using (A.3), we obtain $\bar{S}(40, 0.34) = 546$, proving the claim that an investor with $r = 0.34$ does not sell below 546. Because $\bar{S}(t, r)$ is decreasing in r, investors with lower r have even higher critical values, proving the claim.

Comparison of *C* versus *D*. The proof of this case follows the same logic as in the previous case. For $r < 0.5$ and asset D, the critical $\bar{S}(t, r)$ are never binding. [There are no rational solutions to (A.3).] Thus, we can again use (A.4) and our parameters for asset D to calculate the r where an investor would switch from C to D. We find that the critical value is -0.17. □

Endnotes

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

[2] Examples include rankings of stock market traders or investment funds and less formal exchange of information among traders working in the same investment firm.

[3] See also Hopkins and Kornienko (2004) for the influence of rankings on consumption choices and Trautmann and Vieider (2012) for a survey.

[4] Carbone and Duffy (2014) show that providing information on the average consumption of others moves individuals further away from the optimal path in a deterministic, intertemporal life-cycle consumption optimization problem.

[5] Heimer (2016) shows that this holds also for traders who can be observed on a social trading platform. However, Gemayel and Preda (2018) observe the opposite.

[6] When deciding whether to copy a leader, 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.

[7] Pelster and Hofmann (2018) show that about 85% of transactions on *eToro* take place on FOREX markets.

[8] See https://www.etoro.com/en/popular-investor/ and https://www.zulutrade.co.uk/trader-program, accessed October 31, 2019.

[9] See https://uk.reuters.com/article/us-tech-etoro-fundraising/israeli-social-trading-firm-etoro-raises-100-million-in-private-funding-idUKKBN1GZ15S, accessed October 31, 2019, and 09:24 in an interview with *eToro* CEO Yoni Assia at https://www.youtube.com/watch?v=P2yRjHAAPeU&vl=en, accessed October 31, 2019.

[10] Data were obtained by using a Python script to automatically collect publicly available information on investors in copy-trading platforms.

[11] That is, the Bernoulli utility function used is $v(x) = x^{1-r}/(1-r)$ for $r \neq 1$ and $v(x) = \log x$ otherwise, where the parameter r represents the (relative) risk aversion coefficient. Other often-used utility functions, like expected utility with constant absolute risk aversion or mean-variance utility, give the same ranking of lotteries in terms of riskiness.

[12] For example, asset D would crash in 80% of cases if held for all 40 periods. This is very noticeable in the simulations (see online appendix) and in the ranking list tables of treatments COPY and INFO.

[13] Because the process reaches a price of 546 only very rarely, the investor in the third case of the claim keeps asset C for all periods with a very large probability.

[14] For reference, note that if a risk-neutral expected utility maximizer were to choose for whatever reason asset B (or asset D), he would, applying a similar argument as in the proof of Claim 1, hold it until the end (as long as the price of asset D is below 312.5, respectively).

[15] For illustrative purposes, we report a number of simulations in the online appendix.

[16] Note that subjects in INFO or COPY received no information on the Block 2 decisions of the BASELINE participants before their Block 2 decisions. Copiers were subsequently informed of the asset choice, the selling period, and the obtained payoffs of their chosen leader.

[17] Note that this design feature excluded the possibility that subjects might end up copying each other.

[18] For example, Apesteguia and Ballester (2018), using the data set of Andersen et al. (2008), find that the mean population CRRA risk-aversion level estimated using structural methods is 0.752, which falls within the range of levels implied by lottery 2. This data set involves a representative sample of 253 subjects of the adult Danish population, making a total of 7,928 lottery choices in Holt–Laury tasks.

[19] All p-values reported in this paper refer to two-sided tests, except when stated otherwise.

[20] All but one subject used this tool at least once. On average, subjects used simulations 15.2 times with a standard deviation of 13.0 and a maximum of 61. However, probit regressions show no significant effect of the number of simulations on the probability of being consistent between lottery and asset choice.

[21] 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 across domains, although they identify a general risk component operating across domains.

[22] See also Table 8 in the online appendix, which reports the corresponding distributions of Block 1 and Block 2 asset choices.

[23] Our directional Hypothesis 2 would allow us to use a one-sided t-test, which would yield $p = 0.045$. There is no significant difference between COPY, excluding the copiers, and INFO (MWU, $p = 0.89$).

[24] To prove this point, subjects in our COPY treatment actually received the highest average payoffs (134 versus 117 of noncopiers in COPY and 109 in BASELINE). 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.

[25] If subjects decide to copy according to the "proportional imitation rule" of Schlag (1998), they would copy with a probability that is increasing in the difference between the leader's payoff and their own Block 1 earnings. However, own earnings are not significant in Table 7.

[26] 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 2019).

References

Alós-Ferrer C, Schlag K (2009) Imitation and learning. Anand P, Pattanaik P, Puppe C, eds. *The Handbook of Rational and Social Choice* (Oxford University Press, Oxford, UK), 271–297.

Andersen S, Harrison GW, Lau MI, Rutström EE (2008) Eliciting risk and time preferences. *Econometrica* 76(3):583–618.

Apesteguia J, Ballester MA (2018) Monotone stochastic choice models: The case of risk and time preferences. *J. Political Econom.* 126(1): 74–106.

Apesteguia J, Huck S, Oechssler J (2007) Imitation theory and experimental evidence. *J. Econom. Theory* 136:217–235.

Apesteguia J, Huck S, Oechssler J, Weidenholzer S (2010) Imitation and the evolution of Walrasian behavior: Theoretically fragile but behaviorally robust. *J. Econom. Theory* 145(5):1603–1617.

Bikhchandani S, Hirshleifer D, Welch I (1992) A theory of fads, fashion, custom, and cultural change as informational cascades. *J. Political Econom.* 100(5):992–1026.

Bock O, Baetge I, Nicklisch A (2014) hroot: Hamburg registration and organization online tool. *Eur. Econom. Rev.* 71:117–120.

Bohnet I, Greig F, Hermann B, Zeckhauser R (2008) Betrayal aversion: Evidence from Brazil, China, Oman, Switzerland, Turkey, and the United States. *Amer. Econom. Rev.* 98(1):294–310.

Bolton GE, Ockenfels A (2010) Betrayal aversion: Evidence from Brazil, China, Oman, Switzerland, Turkey, and the United States: Comment. *Amer. Econom. Rev.* 100(1):628–633.

Bursztyn L, Ederer F, Ferman B, Yuchtman N (2014) Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions. *Econometrica* 82(4):1273–1301.

Carbone E, Duffy J (2014) Lifecycle consumption plans, social learning and external habits: Experimental evidence. *J. Econom. Behav. Organ.* 106:413–427.

Cooper DJ, Rege M (2011) Misery loves company: Social regret and social interaction effects in choices under risk and uncertainty. *Games Econom. Behav.* 73(1):91–110.

Cox JC, Ross SA, Rubinstein M (1979) Option pricing: A simplified approach. *J. Financial Econom.* 7(3):229–263.

De Long JB, Shleifer A, Summers LH, Waldmann RJ (1990) Noise trader risk in financial markets. *J. Political Econom.* 98(4):703–738.

Dijk O, Holmen M, Kirchler M (2014) Rank matters—The impact of social competition on portfolio choice. *Eur. Econom. Rev.* 66: 97–110.

Dohmen T, Falk A, Huffman D, Sunde U (2010) Are risk aversion and impatience related to cognitive ability? *Amer. Econom. Rev.* 100(3): 1238–1260.

Duffy J, Hopkins E, Kornienko T, Ma M (2019) More is better? Information choice in a social learning experiment. *Games Econom. Behav.* 118:295–315.

Eckel C, Grossman P (2002) Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution Human Behav.* 23(4):281–295.

Einav L, Finkelstein A, Pascu I, Cullen MR (2012) How general are risk preferences? Choices under uncertainty in different domain. *Amer. Econom. Rev.* 102(6):2606–2638.

Eisenbach T, Schmalz M (2016) Anxiety in the face of risk. *J. Financial Econom.* 121(2):414–426.

Ensthaler L, Nottmeyer O, Weizsäcker G, Zankiewicz C (2017) Hidden skewness: On the difficulty of multiplicative compounding under random shocks. *Management Sci.* 64(4):1693–1706.

Fischbacher U (2007) z-Tree: Zurich Toolbox for ready-made economic experiments. *Experiment. Econom.* 10(2):171–178.

Frydman C, Wang B (2019) The impact of salience on investor behavior: Evidence from a natural experiment. *J. Finance*, ePub ahead of print October 21, https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12851.

Gemayel R, Preda A (2018) Does a scopic regime erode the disposition effect? Evidence from a social trading platform. *J. Econom. Behav. Organ.* 154:175–190.

Goeree JK, Yariv L (2015) Conformity in the lab. *J. Econom. Sci. Assoc.* 1(1):15–28.

Gortner PJ, van der Weele JJ (2019) Peer effects and risk sharing in experimental asset markets. *Eur. Econom. Rev.* 116:129–147.

Harbaugh R (2006) Prospect theory or skill signaling. Working paper, Indiana University, Bloomington, IN.

Heimer R (2016) Peer pressure: Social interaction and the disposition effect. *Rev. Financial Stud.* 29(11):3177–3209.

Hopkins E, Kornienko T (2004) Running to keep in the same place: Consumer choice as a game of status. *Amer. Econom. Rev.* 94(4): 1085–1107.

Huck S, Normann H-T, Oechssler J (1999) Learning in Cournot oligopoly—An experiment. *Econom. J.* 109(45):C80–C95.

Kirchler M, Lindner F, Weitzel U (2018) Rankings and risk-taking in the finance industry. *J. Finance* 73(5):2271–2302.

Liu YY, Nacher JC, Ochiai T, Martino M, Altshuler Y (2014) Prospect theory for online financial trading. *PLoS One* 9(10), e109458.

Magnani J (2015) Testing for the disposition effect on optimal stopping decisions. *Amer. Econom. Rev.* 105(5):371–375.

Offerman T, Schotter A (2009) Imitation and luck: An experimental study on social sampling. *Games Econom. Behav.* 65(2):461–502.

Oprea R, Friedman D, Anderson ST (2009) Learning to wait: A laboratory investigation. *Rev. Econom. Stud.* 76(3):1103–1124.

Pan W, Altshuler Y, Pentland A (2012) Decoding social influence and the wisdom of the crowd in financial trading network. *Proc. 2012 ASE/IEEE Internat. Conf. Social Comput.* (IEEE Computer Society, Washington, DC), pp. 203–209.

Pelster M, Hofmann A (2018) About the fear of reputational loss: Social trading and the disposition effect. *J. Banking Finance* 94: 75–88.

Sandri S, Schade C, Musshoff O, Odening M (2010) Holding on for too long? An experimental study on inertia in entrepreneurs' and non-entrepreneurs' disinvestment choices. *J. Econom. Behav. Organ.* 76(1):30–44.

Scharfstein DS, Stein JC (1990) Herd behavior and investment. *Amer. Econom. Rev.* 80(3):465–479.

Schlag KH (1998) Why imitate, and if so, how?: A boundedly rational approach to multi-armed bandits. *J. Econom. Theory* 78(1):130–156.

Shefrin H, Statman M (1985) The disposition to sell winners too early and ride losers too long: Theory and evidence. *J. Finance* 40(3): 777–790.

Trautmann ST, Vieider FM (2012) Social influences on risk attitudes: Applications in economics. Roeser S, Hillerbrand R, Sandin P, Peterson M, eds. *Handbook of Risk Theory: Epistemology, Decision Theory, Ethics and Social Implications of Risk* (Springer, Dordrecht, Netherlands), pp. 575–600.

Vega-Redondo F (1997) The evolution of Walrasian behavior. *Econometrica* 65(2):375–384.

Weber EU, Blais A-R, Betz NE (2002) A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *J. Behav. Decision Making* 15(4):263–290.