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# JENA ECONOMIC RESEARCH PAPERS



# 2011 – 010

## **Recognition-Based and Familiarity-Based Portfolio Strategies – An Experimental Study**

by

**Linan Diao**

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# Recognition-Based and Familiarity-Based Portfolio Strategies – An Experimental Study

Linan Diao\*

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**Abstract:** Empirical evidences show that investors tend to be biased toward investing in domestic (home bias) and local (local bias) stocks. Familiarity is considered to be one of the reasons. A similar concept was proposed by Goldstein and Gigerenzer (1999, 2002), known as the recognition heuristic: “when choosing between two objects, of which only one is recognized, choose the recognized. Investors recognize or are familiar with local stocks, expect them to provide higher returns and, therefore, invest more in such stocks”. We conducted an experiment in Jena, Germany to test whether subjects show local bias and use recognition-based and familiarity-based portfolio strategies. We categorized them into an experienced and an inexperienced group; in addition, we used two data periods, i.e., bull market and bear market, to see if they behave differently in the two markets. Results show that all participants invested more of their endowments in the stock market in bull rather than bear market. All participants showed greater familiarity with local stocks. However, the experienced participants only invested more in local rather than recognized and familiar stocks; on the contrary, the inexperienced participants invested more in recognized and familiar but not local stocks. Our experiment shows no evidence that familiarity is a reason for local bias.

**Keywords:** Recognition Heuristic, recognition-based portfolio strategy, familiarity-based portfolio strategy, local bias

*JEL Classification: C91, G11, D03, D14*

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## 1. Introduction

“Familiarity breeds investments” (Huberman, 2001). Research evidences showed that investors tend to invest in familiar stocks while often ignoring the principles of portfolio theory. Familiarity is considered one of the main reasons for local bias (biased toward investing in local securities) (Coval and Moskowitz, 1999, 2001). In this paper, we experimentally test whether participants invest more in familiar stocks (familiarity-based portfolio strategies) in different markets (bull and bear markets) and whether participants from different groups (experienced and inexperienced) behave differently. In contrast to the measurement of (perceived) familiarity, which is highly ambiguous, measuring recognition (binary choice) is easier and more precise. Therefore, we additionally test if participants invest more in recognized stocks (recognition-based portfolio strategies).

Empirical evidences revealed local bias on the part of both individual investors (laypeople) and investment managers (experts). Besides information asymmetry (investors knew more about the local companies, (Coval and Moskowitz, 1999)), evidences were more in favor of familiarity. Investors had the same information about local and nonlocal companies; however, they were more familiar with the local ones, therefore they invested more in such stocks. Huberman (2001) found that customers of a U.S. company (here, the Regional Bell Operating Company (RBOC)) tend to hold more of its shares and invest more money in it than in other RBOCs’ equity. His explanation was individual investors simply prefer to invest in familiar stocks. They “root for the home team” and feel more comfortable investing their money in a business that is tangible to them. Zhu (2002) investigated U.S. individual investors’ bias toward nearby companies and found that their familiarity with local companies and a ready reaction to local information are more plausible explanations. Feng and Seasholes (2004) studied the portfolio choices of individual investors in China. They found that stocks traded near where investors live receive the highest weights in their portfolios (local bias), and all tests supported the idea that familiarity drives purchases. Hiraki et al. (2003) investigated home bias in Japan in the sample period of 1985-1998 and found that money managers’ investment behavior is consistent with the familiarity explanation.

Experimental evidences were also published in Ackert et al. (2005) and Weber et al. (2005). Ackert et al. (2005) tested home bias (investment bias toward domestic securities) (French and Poterba, 1991, Tesar and Werner, 1995) and local bias with students from the U.S. and Canada. Results demonstrated that all students showed greater familiarity with domestic compared to foreign stocks and with local compared to nonlocal stocks. They found that U.S. students invested significantly higher amounts in domestic investment opportunities when both the investments' names and locations were given, whereas Canadian students showed familiarity bias at the local level. Weber et al. (2005) found that provision of asset names made participants feel more competent and changed their behavior. They also provided evidence that participants had a greater perceived familiarity with local and domestic securities and, in turn, invested more in such securities.

The disadvantage of testing familiarity is that it is not easy for participants to precisely distinguish the level of familiarity. Recognition is distinct from familiarity in that it is binary and does not depend on the level of knowledge, which is thus irrelevant (Goldstein and Gigerenzer, 2002).

Goldstein and Gigerenzer (1999, 2002) have proposed a theory of judgment as recognition heuristic for two-alternative tasks. "If one of two objects is recognized and the other is not, then infer that the recognized object has the higher value with respect to the criterion" (in our context, the criterion is the returns of stocks). For the financial market, Merton (1987) in his theoretical model, has already argued that security value is positively related to investors' recognition. Furthermore, this was empirically testified by Lehavy and Sloan (2008). Consistent with these findings, Borges et al. (1999) and Ortman et al. (2008) found that constructing share portfolios based on simple name recognition alone often yields better returns than the market index. Therefore, according to the recognition heuristic, when choosing one of two stocks where one is recognized and the other is not, a decision maker should infer that recognized stock would bring higher returns. Investors should behave accordingly (Goldstein and Gigerenzer 1999, 2002), i.e., when choosing between two objects, of which only one is recognized, choose the recognized object. However, the above literature focused on whether investors should use the recognition heuristic or not. There is no study about whether investors use the recognition heuristic to pick up stocks. This is one of our contributions in this paper because we test whether

participants use recognition-based and familiarity-based portfolio strategies. In addition, we investigate if local bias exists.

Another contribution of this paper consists in testing our research questions in two different markets: bull and bear markets. Until now, research has shown that it is highly controversial under what market conditions the recognition heuristic should be used. Borges et al. (1999) showed that investors could obtain better-than-average returns simply by using the recognition heuristic. Boyd (2001) criticized that Borges et al.'s tests were only based on bull market. He demonstrated that the recognition heuristic performs poorly when the correlation between recognition and return is low (e.g., in bear markets), which means recognized stocks perform badly in bear market. Andersson and Rakow (2007) found no support for the claim that the recognition heuristic can be used as a simple strategy to choose stocks that yield better-than-average returns. Most recently, Ortmann et al. (2008) retested recognition in both bull and bear markets and confirmed Borges et al.'s results. However, all these works are based on hypothetical assumptions about when we should use the name recognition strategy to choose stocks. There are no tests whether participants use the recognition heuristic to choose stocks under these two market conditions. This is, therefore, one of our research questions. Newell and Shanks (2004) tested investment decisions between two fictional companies for the use of name recognition. They found that participants use the recognition heuristic only when it has positive validity. The works of Oppenheimer (2003) and Pohl (2006) showed similar conclusions, i.e., that recognition was relied on when it had a high predictive validity; when it had a low predictive validity, it was ignored. However, if recognition has positive validity, e.g., when recognized and familiar stocks have higher returns, we do not know whether participants invest more in such stocks because of name recognition or because of return advantages. Thus, for the data we used, there is no correlation between familiarity and returns in both markets. We tested whether participants would use recognition-based and familiarity-based portfolio strategies even when there was no positive correlation between recognition and validity.

Borges et al. (1999) and Ortmann et al. (2008) also showed that laypeople recognized fewer stocks than experts; however, they did recognize the stocks that were recognized by most people. When constructing portfolios by selecting only prominent stocks, laypeople were able to obtain even higher returns than experts. This raises another question: would laypeople behave the

same way as experts in trusting the recognized and familiar stocks? Grinblatt and Keloharju (2001) and Giofré (2008) showed that, compared to professional institution investors, household investors are more strongly influenced by location information, among others. Therefore, this is also one of our research questions, namely to test the difference between laypeople and experts.

In our experiment, we categorized the participants into an experienced and an inexperienced group as an approximation to experts and laypeople, respectively. The experienced participants were students from economics departments, took finance and investment courses, had investment experience and read finance magazines and newspapers quite often; the other participants belonged to the inexperienced group. We did not expect that the experienced participants would behave the same way as professional institutional investors. We just tested whether the inexperienced participants were more strongly influenced by the local and recognition /familiarity information than the experienced participants. We provided participants with German domestic stocks, including local and nonlocal ones, to test whether they showed local bias. By asking participants ex post if they recognized the stocks and, if they answered yes, how familiar they were with them, we tested whether participants showed a tendency to invest more in recognized and familiar stocks. Since the recognition heuristic is about two-alternative tasks, we designed our experiment such that investors always faced pair-wise investment tasks. As mentioned before, we tested our questions in both bull and bear markets.

In between-subject design experiments, knowledge of asset names influences portfolio behavior and shows home bias (Ackert et al., 2005, Weber et al., 2005). In our experiment, we tested the effect of name provision in a within-subject design. Participants were provided with 60 stocks paired into 30 pairs with or without ID, including name, location (of companies' headquarters), and sector. Unlike the other two experiments (Ackert et al., Weber et al.), we gave participants the possibility to keep the endowment as cash if they did not want to invest money in the stock market. We tested whether name provision would make participants feel more competent (Weber et al., 2005) so that they would invest more in the stock market and keep less cash. We expected that participants would trust the market more when stocks' names were provided and invest more in the stock market (treatment effect). For the same reason, participants should invest more in the stock market in bull market (market effect); the experienced participants should also invest more in the stock market (group effect). We also expected that

with the number of recognized stocks increasing (from 0 to 1 and 2), participants would increase their investment in the stock market.

The paper is organized as follows. Section 2 describes the experiment in detail. Section 3 presents the results. Section 4 concludes.

## 2. Research Method

### 2.1 Overview

We ran the experiment in Max Planck Institute of Economics lab in Jena, Germany. The experiment consists of two parts: the portfolio decision task and the recognition task.

The portfolio task is a repetitive individual decision making process. Participants are provided with 60 stocks from the German stock market (Deutsche Börse Group), of which 57 are Midcap market index (36 from MDAX Index, 21 from TecDAX Index) and another 3 local Jena stocks. We only choose stocks whose price data have been available since June 2004. Together with another 2 stocks in MidCap Index, there are 5 local Jena stocks in total. The information on 60 stocks is shown in Appendix A. For each participant, 60 stocks are randomly paired into 30 pairs, i.e., every participant is given different pairs.

This is a two-treatment within-subject design experiment. In both treatments, participants are given data on the development of 30 months' normalized prices and returns. Additionally, participants in the 'with ID' treatment are provided with name, location (of corporate headquarters), and sector of stocks, whereas in the 'without ID' treatment, only prices and returns information is provided. Each pair of stocks is randomly assigned to with or without ID treatment with probability 0.5.

For each pair of stocks, there are two investment periods: bull and bear market. In both investment periods, prices are stocks' monthly adjusted close prices and normalized with initial value equal to 10. Returns are calculated from prices with  $R_t = (P_t - P_{t-1}) / P_{t-1}$ . In bull market, prices date from June 2004 to November 2006 (30 months). In bear market, prices date from January 2007 to June 2009 (30 months). We use the real monthly returns of December 2006 and July



2009 as the participants' payment returns in bull and bear market, respectively.<sup>1</sup> Figure 1 shows the market prices of Midcap Stock Index which show that from June 2004 to December 2006 the market was increasing (bull market) and that from January 2007 to July 2009 it was decreasing (bear market). We remove the order effect by randomizing the order of these two investment periods, which means bull (bear) market has 0.5 probability to show up first. Participants do not know the real dates of these two investment periods; the information they are given is only the prices and returns from month 1 through month 30.

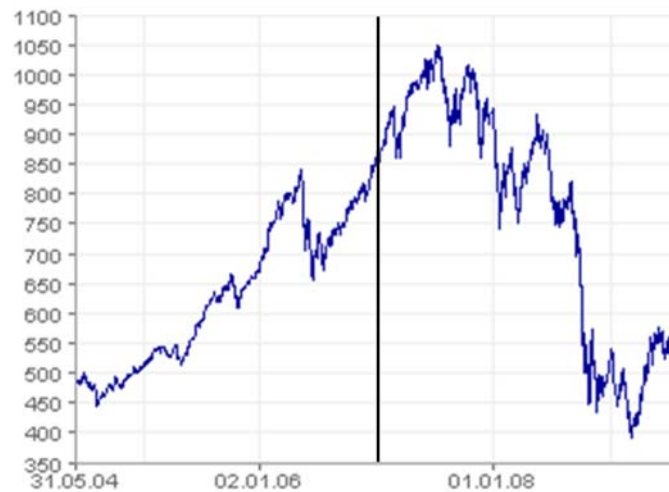


Fig. 1. Prices for Midcap Stock Index from 1 June 2004 to 31 July 2009. Data from 1 June 2004 to 31 December 2006 are bull market; whereas data from 1 January 2007 to 31 July 2009 are bear market. Figures are from Deutsche Börse website (see note 1).

Not surprisingly, the average returns in bull market are overall higher than in bear market, and the standard deviation in bull market are smaller than in bear market. Figure 2 plots the 60 stocks' average returns and standard deviation in two markets. We also see that the stocks are randomly scattered in figure 2, which means there are no systematic patterns between stocks. Therefore, participants should not use any systematic investment strategies only by observing the returns.

<sup>1</sup> All data are from Xetra, Deutsche Börse Group ([http://deutsche-boerse.com/dbag/dispatch/en/kir/gdb\\_navigation/home](http://deutsche-boerse.com/dbag/dispatch/en/kir/gdb_navigation/home)) and Yahoo! FINANCE ( <http://de.finance.yahoo.com/> )

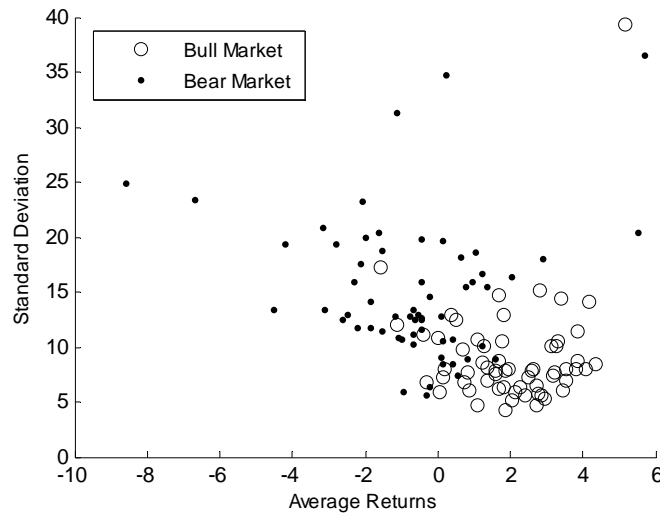


Fig. 2. Average returns and standard deviation of 60 stocks in two markets

## 2.2 Participants

Participants, who numbered 192, on average aged 25 years ( $SD = 3.6$ ), were recruited by using the online recruitment system ORSEE (Greiner, 2004). Table 1 provides detailed information about the participants. They were students of Friedrich Schiller University and University of Applied Sciences Jena and had on average completed 7.8 semesters ( $SD = 3.9$ ). The students taking finance courses had on average completed 2.38 ( $SD = 1.84$ ) courses. Of the 85 nonlocal participants (from other places), 58 claimed they had stayed in Jena for more than one year. It follows that 165 participants were local residents.

Table 1 Information about participants

	Yes	No			
Students	188	4			
Studying economics	35	157			
Taking finance courses	38*	154			
Investment experience	57	135			
	Very Often	Often	Sometimes	Rarely	Never
Reading finance literature	2	4	21	45	119
	Jena	Thuringia	Others		

	Yes	No	
Local	27	80	85

\* The number of students taking finance courses is higher than the number of students studying economics. The reason is that it is not necessary that only economics students take finance courses. Of 38 participants who claim they have taken at least one finance course, 13 claim they study other majors than economics.

### 2.3 Procedure

The experiment was conducted in German. Appendix C contains the English translation of the instructions. Since many foreign students took part in the experiment, we had to make sure they could speak German well enough to understand our instructions. For this reason, we ran a German language test before the experiment started. Only those who passed the test could take part in our experiment. After the instructions were distributed and before the experiment started, they were read aloud by an assistant of the experiment to make sure participants had understood the information clearly and correctly. The assistant did not know the purpose and hypotheses of the experiment, therefore emphasis on specific points was precluded when the instructions were read.

Before the portfolio task, participants had to fill in a preexperiment questionnaire about age, gender, major, semesters completed, hometown, in which places they had stayed for more than one year, if they had taken finance courses before, if they had real investment experience, and if they read finance newspapers and magazines (selecting from a scale with 5 values: never, rarely, sometimes, often, very often).

As mentioned above, during the portfolio task, each participant was provided with 30 pairs of stocks. For the same pair of stocks, there are two investment periods: bull and bear market. Therefore, there are 60 investment periods in total. The procedure for each investment period is as follows:

- 1) At the beginning of each investment period, participants receive 1,200 experimental currency units (ECU), which they could invest in two stocks or keep as cash.

2) In each investment period, participants are given the normalized prices and returns information for both stocks, i.e., the data from June 2004 through November 2006 (January 2007 through June 2009) if they are in bull (bear) market. They are given (not given) extra information about stocks' names, location, and sector if they are in with (without) ID treatment. Two investment periods for the same pair of stocks belong to the same treatment. Figure 3 shows the information and investment screen in without ID treatment. In with ID treatment, stocks' names, location, and sector are shown inside the boxes below "A" and "B."

3) Participants make their investment decisions by inputting 3 numbers in the text boxes on the screen, indicating how many ECU they invest in A (stock on the left), B (stock on the right) and keep as cash. The sum of these 3 numbers must be equal to 1,200.

4) After participants have made their portfolio decisions, their realized returns and earnings are revealed on the next screen. The realized returns from stocks are real monthly returns of December 2006 (July 2009) if they are in bull (bear) market. Their payoffs are calculated by

$$Payoff = (x_A + x_A r_A) + (x_B + x_B r_B) + (1,200 - x_A - x_B),$$

where  $r_A$  and  $r_B$  are realized returns of 2 stocks,  $x_A$  and  $x_B$  are the amounts of money (ECU) invested in 2 stocks.  $(1,200 - x_A - x_B)$  are the amounts of money kept as cash.

After finishing the portfolio task, participants receive the instructions for the second part on the computer screen. They are presented with the names of 60 stocks they have at their disposal during the experiment and are asked to indicate whether they recognize the stocks or not by selecting a "Yes/No" binary choice. If they select "Yes," they have to indicate how familiar they are with the stocks by selecting from a scale of 1 to 7, where 7 means very familiar and 1 not very familiar.

At the end of the experiment, one realized payoff out of 60 is chosen randomly to be paid out based on an exchange rate of 100 ECU = 1euro. The program is written in z-Tree (Fischbacher, 2007). It took on average 23.9 minutes ( $SD = 6.3$ ) for participants to finish the

portfolio task and 0.74 minutes ( $SD = 0.32$ ) to finish the recognition task. Participants on average received 12.63 ( $SD=0.7$ ) euros for taking part in the experiment.

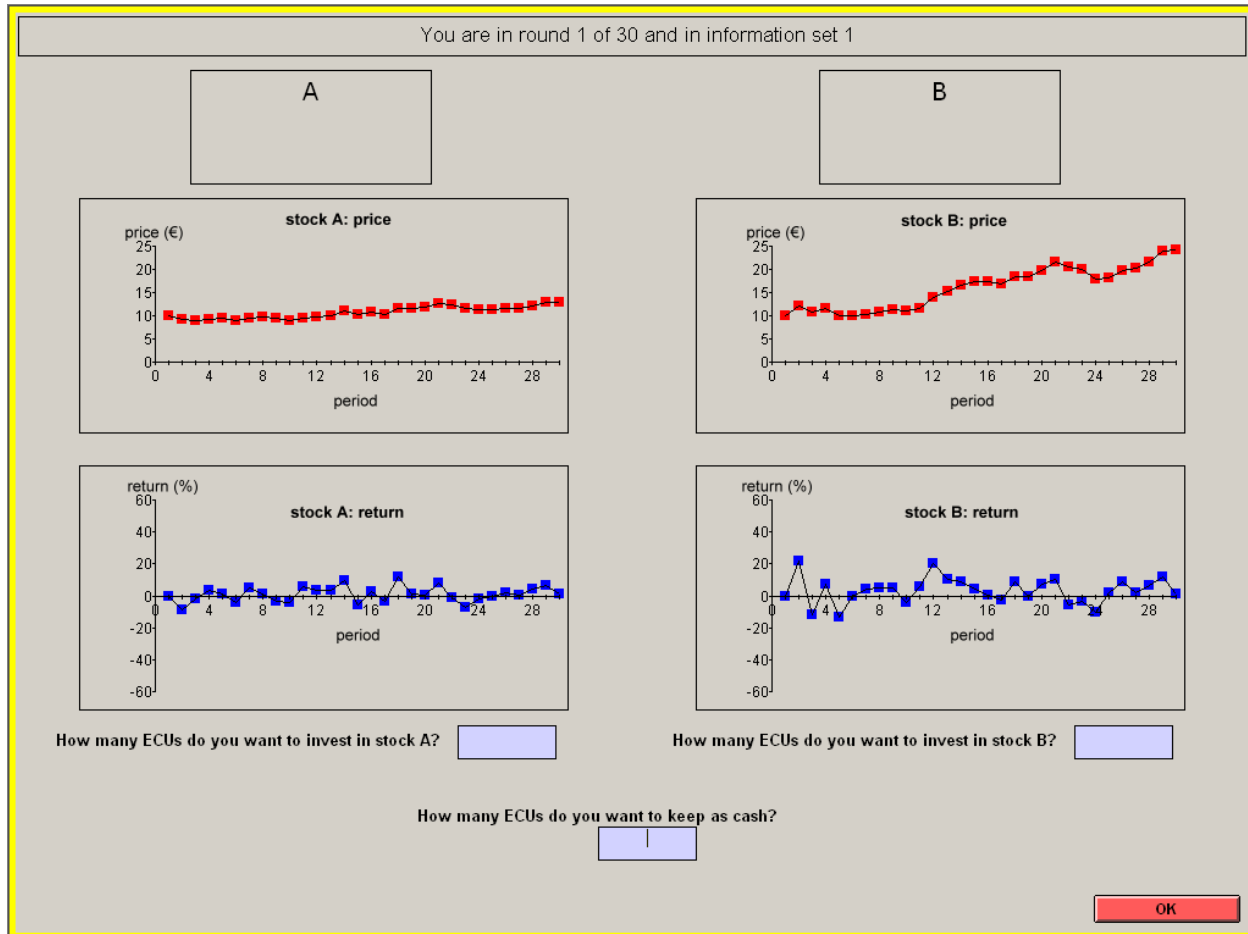


Fig. 3. Information and investment screen in without ID treatment

### 3. Results

#### 3.1 Experienced and Inexperienced Participants

We divided the participants into two groups: experienced and inexperienced. The participants in the experienced group satisfied at least one of the conditions below:

- 1) they study an economics-related major
- 2) they have taken finance, investment courses

- 3) they have real investment experience
- 4) they read finance newspapers and magazines

The participants in the inexperienced group satisfied none of the conditions. Of 192 participants, 105 participants were in the experienced and 87 in the inexperienced group.

### 3.2 Recognition Task

First, we looked at how many stocks each participant recognized. On average, each participant recognized 13.8 (sd. =10) stocks. Figure 4 shows the histogram of the number of stocks recognized by the two groups. Twenty-two participants from the experienced group and 4 participants from the inexperienced group claimed they recognized none of the 60 stocks. One participant from the experienced group claimed he recognized all 60 stocks. Most of the participants recognized between 0 and 30 stocks. The experienced participants on average recognized 17.59 ( $SD = 9.55$ ) stocks, whereas the inexperienced participants on average recognized fewer stocks, i.e., 9.14 ( $SD = 8.37$ ).

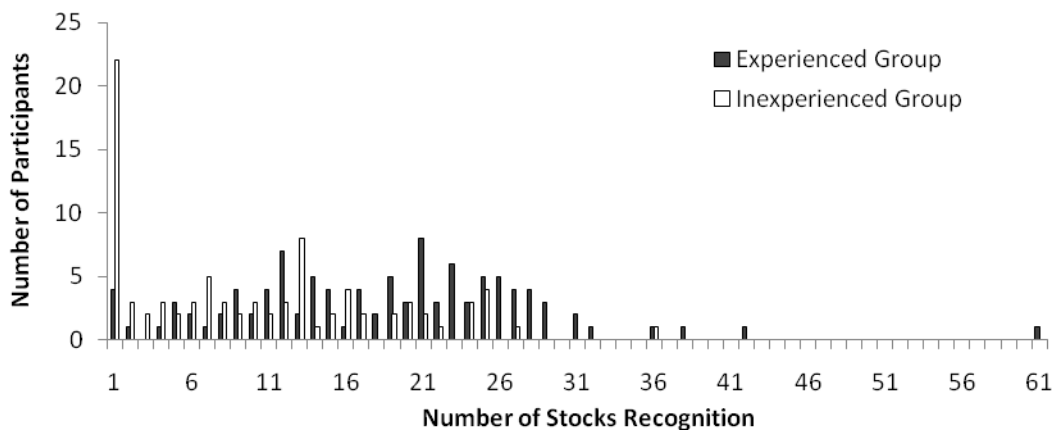


Fig. 4. Histogram of number of stocks recognized by participants

We then calculated participants' familiarity with 60 stocks. If, during the recognition task, they chose "Yes," they had to indicate their familiarity with the stocks by selecting from a scale of 1 to 7, where 7 meant recognize very well and 1 meant not very well. Figure 5 plots the familiarity with 60 stocks, which is calculated separately for the experienced and inexperienced participants. The figure indicates that, except one, all points are below the 45 degree line, which

means the experienced participants show greater familiarity than the inexperienced participants. Four out of 5 local stocks have a high familiarity score,<sup>2</sup> which means the participants are more familiar with local stocks. Detailed recognition data are given in Appendix B.

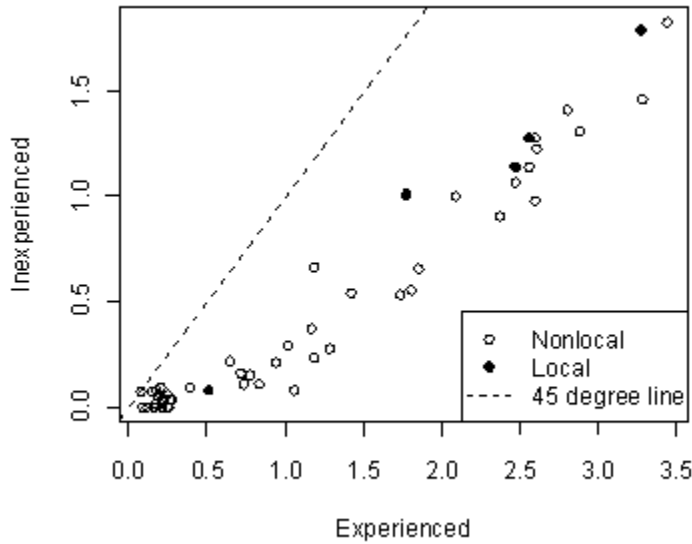


Fig. 5. Familiarity score of 60 stocks

Further tests show that there is no correlation between familiarity and the realized returns of stocks for both bull and bear market (table 2). This means that using recognition- or familiarity-based portfolio strategies would not yield more payoffs. The results in figure 2 indicate that there are no systematic patterns between the performances of 60 stocks. If participants invest more in recognized or familiar stocks, that is purely because of name recognition and familiarity, not because the stocks perform better.

<sup>2</sup> The local stock that shows a very low familiarity score belongs to a comparatively small (market capital 13.19 mill.) pharmacy and health care company.

Table 2 Spearman correlation between familiarity and returns of 60 stocks

	Experienced Group		Inexperienced Group	
	Bull Market	Bear Market	Bull Market	Bear Market
Spearman correlations	-0.0942	0.0240	-0.1324	0.0226
p-value	0.4739	0.8553	0.3133	0.8640
S value	39380.98	35124.51	40754.61	35177.62

H0: Correlation is equal to 0

### 3.3 Investment in the Stock Market / Cash Amount Participants Keep

In this subsection, we only focused on the cash participants kept and on how much participants invested in the stock market (equals to endowment minus cash). First, we tested treatment, market, and group effect. Second, we tested whether participants behaved differently when no ID information was provided compared to when the provided ID was not recognized. Finally, we tested whether participants increased their investment in the stock market according to the increase of the number of recognized stocks.

#### Treatment, Group, and Market Effects

Overall, there were 11,520 observations (192 participants, 60 decisions each) with 2 treatments (with and without ID), 2 groups of participants (experienced and inexperienced group), and 2 markets (bull and bear market). In this subsection we tested whether name provision made participants feel more competent, whether participants therefore invested more in the stock market (treatment effect), whether the experienced participants invested more in stocks market than the inexperienced participants (group effect), and whether participants invested more in the stock market in bull market than bear market (market effect).



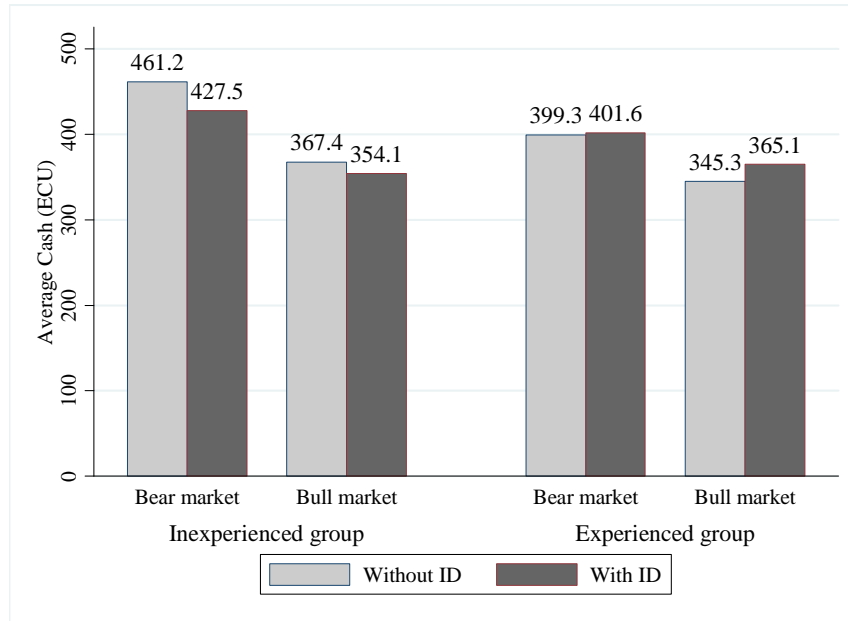


Fig. 6. Average cash (ECU) participants keep, categorized by treatments, groups, and markets

Figure 6 lists the average cash participants keep, categorized by treatment, group, and market. We used the Tobit regression model with treatments, groups, markets as the fixed effect since the cash participants kept was censored between 0 and 1,200, i.e., there were situations that participants invested all their endowments in the stock market, also situations that they kept all their endowments as cash. Furthermore, adding the subject random effect improved the model's AIC from 104070.6 to 95774.7; a likelihood ratio test showed that adding 60 stocks dummies improved the model significantly ( $p=0.0000$ ,  $\chi^2=230.98$ ). The regression model we used is as follows:

$$Cash_{ij} = \beta_0 + \beta_1 T + \beta_2 G + \beta_3 M + \beta_4 T \cdot G + \beta_5 T \cdot M + \beta_6 G \cdot M + \beta_7 T \cdot G \cdot M + \sum_{t=1}^{60} \beta_{t+7} S_t + v_i + \epsilon_{ij}$$

, where  $i=1,2,\dots,192$  is the index of subjects;  $j=1,2,\dots,60$  is the index of decisions of each subject;  $t=1,2,\dots,60$  is the index of stocks.  $S_t$  is the stock dummy variable, which equals to 1 if stock  $S_t$  is the available investment at decision  $j$ ;  $T$  is the treatment dummy variable, which equals to 1 in with ID treatment;  $G$  is the group dummy variable, which equals to 1 for an

inexperienced participant; M is the market dummy variable, which equals to with 1 for bear market. For consistency, the variables we used here have the same meaning throughout the paper.

Regression results are listed in table 3 (first column). The coefficients of treatment and the interactions with treatment are not significant. A further test about the sum of the coefficient of treatments and all the interactions with treatment are not significant either ( $\chi^2(1) = 0.45, p = 0.501$ ). Therefore, there is no treatment effect in our experiment. In other words, in a within-subject design, the provision of stocks' IDs does not make the participants invest more in the stock market.

The coefficient of market is significant, and the interaction between market and group is significant. This means all participants kept more cash in bear than in bull market. Furthermore, in bear market the inexperienced participants kept more cash than the experienced participants. Thus, a market effect can be observed; however, a group effect can only be observed in bear market.

Table 3 Tobit regression results of cash participants keep

	(1)	(2)
Intercept	-43.29	-44.46
	[83.01]	[96.19]
Treatment (with ID=1)	18.379	14.08
	[19.04]	[23.13]
Market (Bear Market=1)	92.59***	92.28***
	[19.03]	[18.72]
Group (Inexp. Group=1)	41.16	49.7
	[92.62]	[92.81]
Treatment*Group	4.2	9.28
	[28.06]	[31.87]
Treatment*Market	-24.06	-7.5
	[26.47]	[31.37]
Market*Group	72.6**	71.83**
	[27.85]	[27.37]

	(1)	(2)
Treatment*Group*Market	-12.08	-18.83
	[38.91]	[43.70]
No. of observations	11520	9204
No. of left-censored observations	4533	3523
No. of uncensored observations	5855	4744
No. of right-censored observations	1132	937
Rho	0.654	0.663

Note: The coefficients of 60 stocks dummies are not included in the table. Column 1 lists the regression results of all observations. Column 2 lists the regression results of observations in without ID treatment and observations that both stocks are not recognized in with ID treatment. \*\*\*  $p < 0.00$ , \*\*  $p < 0.01$ . Standard errors in brackets

In summary, the provision of stocks' IDs does not make participants invest more in the stock market. All participants are sensitive to bull and bear market. They are more conservative when the market is going down. In bear market, the inexperienced participants are even more conservative than the experienced participants.

### **Stocks' IDs not Provided and Stocks' Names Unrecognized**

Weber et al. (2005) and Ackert et al. (2005) argued that name provision made participants feel more competent. Therefore, the latter invested more in stocks whose names were provided (compared to the when no names were provided). However, this also raises the question if participants will trust the market when the provided names are not recognized or familiar to them. In this subsection, we examined if participants invested more in the stock market when provided names were not recognized, compared to when no names were provided. We used the observations in without ID treatment and in with ID treatment, but neither of the two stocks were recognized. Figure 7 shows the average cash participants kept under these two scenarios.

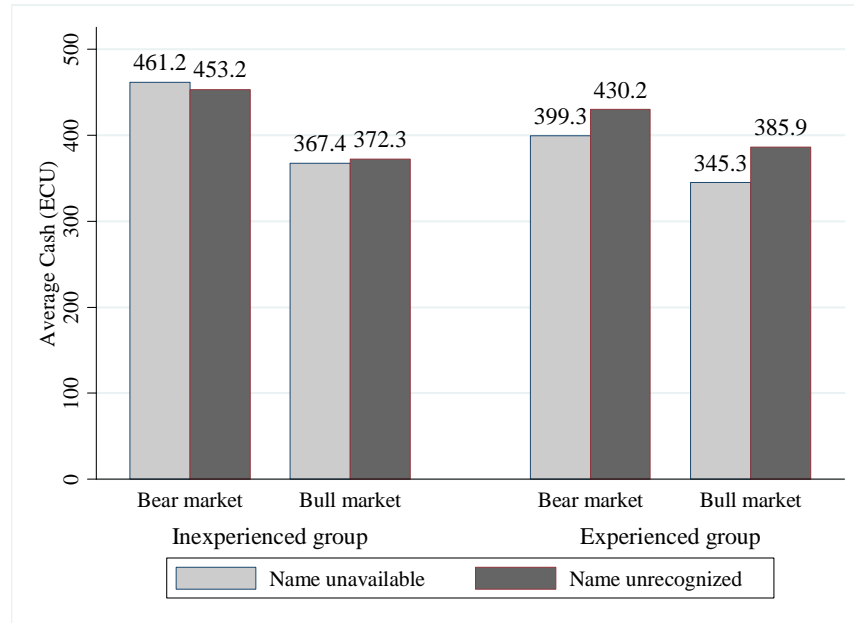


Fig. 7. Comparison of average cash (ECU) participants keep when names are not provided (unavailable) and names are not recognized (unrecognized), categorized by markets and groups of participants

We used the subject random effect model with 60 stocks dummies. Analysis showed that adding the subject random effect improved the model's AIC from 84130.67 to 77426.96. Furthermore, a likelihood ratio test showed that adding 60 stocks dummies to the random Tobit model improved the model significantly ( $p = .0004$ ,  $\chi^2 = 203.79$ ). Results are listed in table 3 (second column). We obtained similar results in the part entitled Treatment, Group, and Market Effects. The coefficients of market and the interaction between market and group are significant, which means participants kept more cash in bear than in bull market; in bear market, the inexperienced participants kept even more cash than the experienced participants. The coefficients of treatment and the interactions with treatments are not significant. A further test about the sum of the coefficients of treatment and all the interactions with treatment is not significant either ( $\chi^2(1) = 0.02$ ,  $p = 0.891$ ). Therefore, when both names are not recognized, name provision does not make participants invest more in the stock market.

### Recognition-Based Portfolio Strategy

In this subsection, we categorized the observations in with ID treatment into three groups: neither of the two stocks is recognized, only one is recognized, both are recognized. We tested whether participants increased investment in stock market according to the increase of the number of recognized stocks.

Figure 8 shows the average cash (ECU) participants kept in with ID treatment, categorized by the number of recognized stocks, group, and market. The figure shows that the average cash kept by the experienced participants decreased with an increase of the number of stocks they recognized. Nevertheless, the inexperienced participants kept least cash when only one stock was recognized, and kept most cash when no stocks were recognized. We still assume that the cash kept by the inexperienced participants decreased with the number of recognized stocks. However, since the two groups showed different patterns, we also tested them separately. Our hypothesis is that the cash participants keep will decrease with an increase of the number of stocks they recognize.

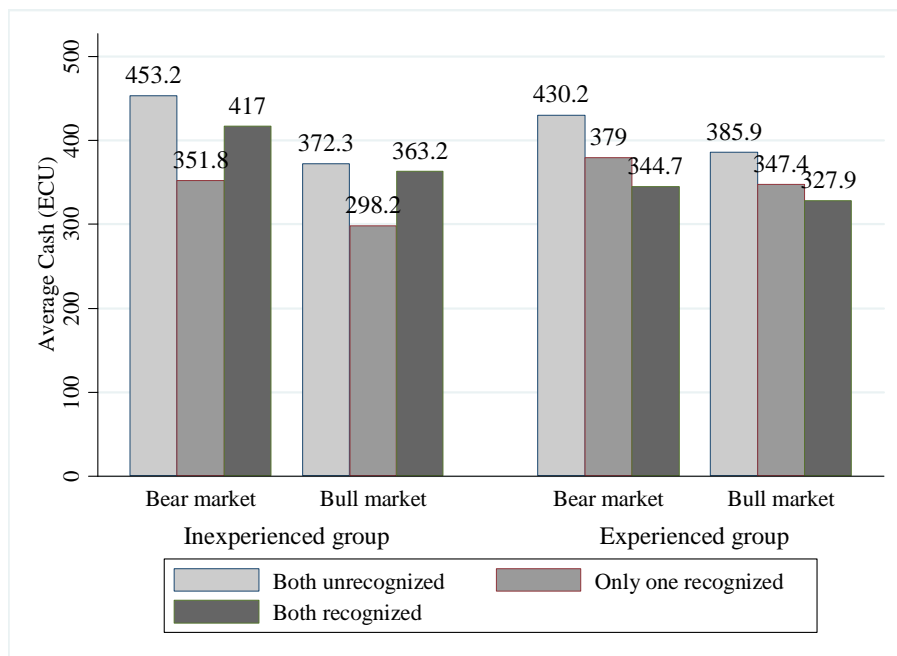


Fig. 8. Average cash participants keep (ECU) in with ID treatment, categorized by number of recognized stocks, market, and group

To test the hypothesis, we used the subject random effect Tobit model with 60 stocks dummies. By adding the random effect improved the model's AIC from 53044.82 to 49197.78, and a likelihood ratio test showed that adding 60 stocks dummies improved the regression significantly ( $p=0.000$ ,  $\chi^2=150.21$ ). The model we used is as follows:

$$Cash_{ij} = \beta_0 + \beta_1 M + \beta_2 G + \beta_3 M * G + \beta_4 REC_{ij} + \sum_{s=1}^{60} \beta_{s+3} S_s + \alpha_{ij} + v_i$$

, where  $REC$  is the recognition situation of subject  $i$  in decision  $j$ ,  $REC=0$  if no stocks are recognized,  $REC=1$  if only one stock is recognized, and  $REC=2$  if both stocks are recognized.

Results are shown in table 4 (first column). The coefficient of  $REC$  is 5.68 and is not significant ( $p=0.721$ ); separate tests with the experienced and inexperienced participants do not change the results (table 4, second and third columns). Our hypothesis that the amount of cash kept changes according to the number of recognized stocks does not hold. However, here we only tested the within-subject effect. The decrease in cash according to the number of stocks is evident in figure 8. Therefore, we subsequently tested if the cash change was due to the between-subject effect, i.e., the subjects who recognized more stocks invested more in the stock market and kept less cash. In order to measure subjects' recognition level, we separated  $REC$  into two parts,  $REC = RI + RDev$ , where  $RI = (\sum_j REC)/60$  is individual  $i$ 's average recognition score ( $0 \leq RI \leq 2$ ). The more stocks subjects recognized, the higher was the  $RI$ .  $RDev$  is the deviation of each observation from the individual average. Yet the subject random effect improved the model's AIC from 52980.03 to 49193.77, and adding 60 stocks dummies improved the model significantly ( $p=0.000$ ,  $\chi^2=150.87$ ). Therefore, the model changes to:

$$Cash_{ij} = \beta_0 + \beta_1 M + \beta_2 G + \beta_3 M * G + \beta_4 RI + \beta_5 RDev + \sum_{s=1}^{60} \beta_{s+3} S_s + \alpha_{ij}$$

Table 4 Determinant cash in with ID treatment

	Experienced	Inexperienced	
All	Group	Group	All

	All	Experienced Group	Inexperienced Group	All
Intercept	22.26 [108.70]	-227.75 [141.39]	152.63 [158.19]	460.49** [134.81]
Market (Bear Market=1)	69.56*** [18.52]	67.46*** [17.06]	135.09*** [21.84]	69.55*** [18.52]
Group (Inexp. Group=1)	36.92 [92.12]			-77.02 [100.52]
Market*Group	60.09* [27.39]			60.11* [27.39]
REC	5.68 [15.89]	27.07 [18.58]	-25.39 [29.43]	
RI				-381.58* [149.59]
Rdev				10 [15.95]
No. of observations	5892	3254	2638	5892
No. of left-censored observations	2345	1290	1055	2345
No. of uncensored observations	2983	1654	1329	2983
No. of right-censored observations	564	310	254	564
rho	0.65	0.68	0.61	0.64

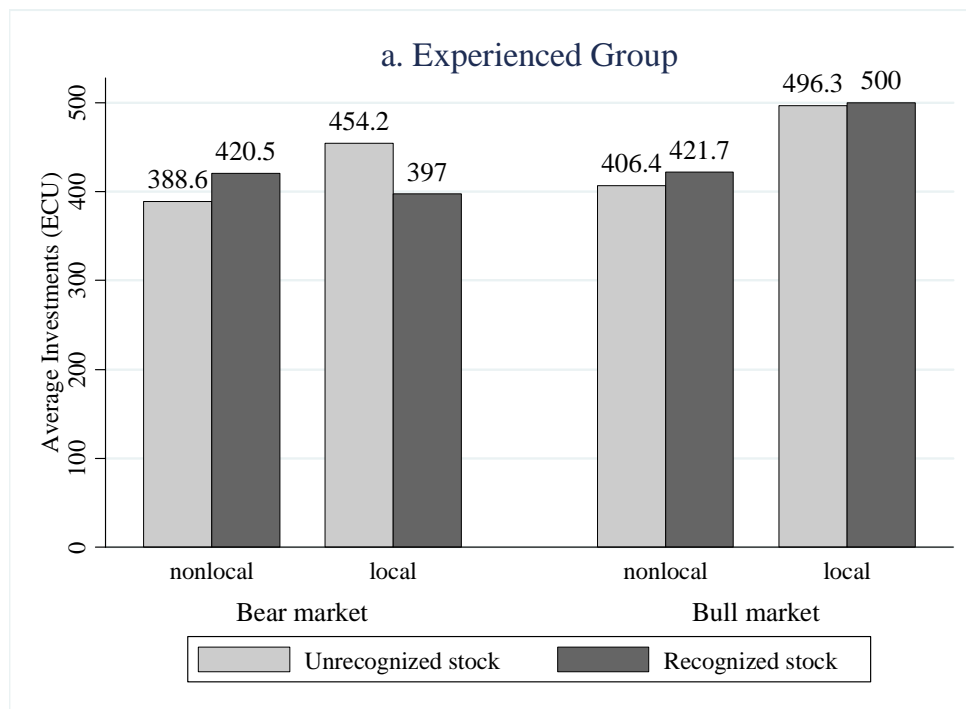
Note: The coefficients of 60 stocks dummies are not included in the table. Columns 1-3 list the regression results of within-subject effect. Column 1 is the regression for all subjects. Column 2 lists the regression for the experienced participants only. Column 3 lists the regression for the inexperienced participants only. Column 4 lists the regression results of the between-subject effect. \*\*\* p<0.00, \*\* p<0.01, \* p<0.05. Standard errors in brackets

Results are shown in table 4 (column 4). We observe that the coefficient of *RI* is negative and significant when  $p < 0.05$ . This confirms our hypothesis that participants who recognize more stocks (with higher *RI*) keep less cash. In summary, participants do not invest more in the stock market when provided with more recognized stocks (within subjects). However, those participants who recognize more stocks invest more (between subjects) in the stock market.

### 3.4 Recognition-Based, Familiarity-Based Portfolio Strategies, Local Bias

In this subsection, we analyzed the investments in stocks to see if participants invested more in recognized stocks, familiar stocks, or local stocks. We tested the recognition-based and familiarity-based portfolio strategy separately. First, we tested the recognition-based portfolio strategy together with local bias. Then, we replaced the recognition-based strategy with the familiarity-based strategy.

In figure 9, we listed the average investments in with ID treatment, categorized by market, local stock, and recognition. Results in figure 9a refer to the experienced group, those in figure 9b to the inexperienced group.





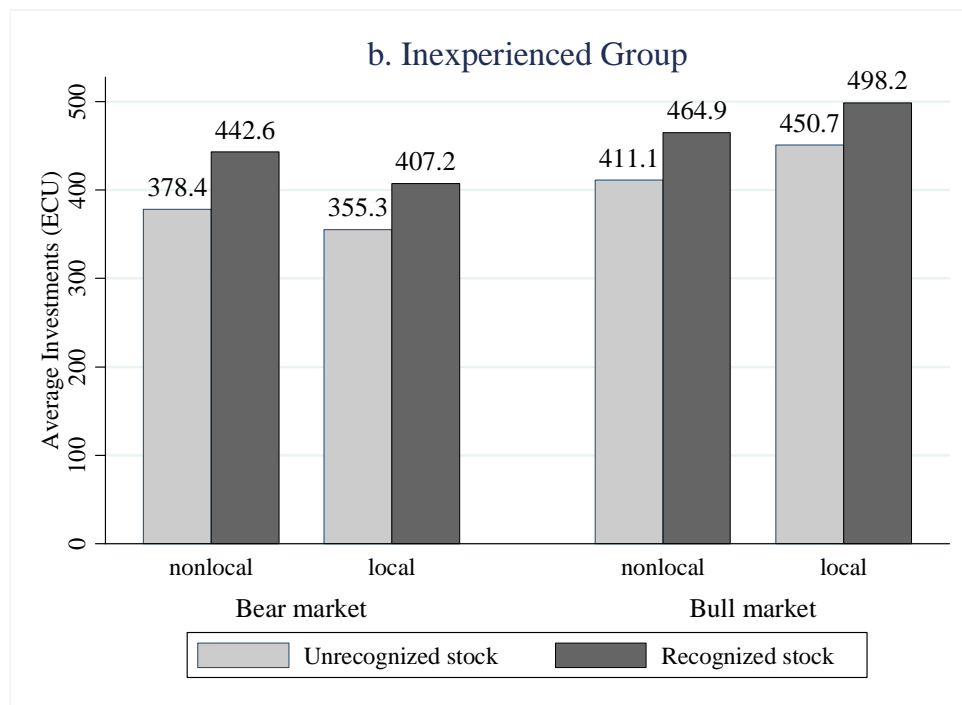


Fig. 9. Average investments (ECU) in stocks in with ID treatment, categorized by market, local stock, and recognition

Figure 9 shows different patterns for the participants from the two groups. The experienced group invested more in local stocks, whereas the inexperienced group invested more in recognized stocks. Therefore, we used the random effect Tobit model (participants' portfolios were censored between 0 and 1,200 ECU) and tested the two groups separately. It is reasonable to assume that if participants recognize only one stock of the pair, the unrecognized stock might also have a positive impact on the recognized one in the same pair, e.g., the unrecognized stock makes participants invest more in the recognized stock. The same assumption goes for the local and nonlocal stock. Therefore, we included not only the recognition dummy and the local dummy of one stock in the model, but also the recognition dummy and the local dummy of the other stock in the same pair. The model we used is as follows:

$$\begin{aligned}
 Portfolio_{i,t} = & \beta_0 + \beta_1 R + \beta_2 RP + \beta_3 Local + \beta_4 LocalP + \beta_5 M + \beta_6 R * Local + \beta_7 M * Local \\
 & + \beta_8 M * R + \beta_9 M * R * Local + \sum_{t=1}^{60} \beta_{10+t} S_t + v_t + \varepsilon_{i,t}
 \end{aligned}$$

, where  $R$  is the dummy variable for recognition and  $RP$  is the dummy variable for the recognition of the other stock in the same pair; 1 if stock is recognized, 0 if it is not recognized.  $Local$  is the dummy variable for local stock,  $LocalP$  is the local dummy for the other stock in the same pair; 1 if it is local stock, 0 otherwise.  $M$  is the dummy for market; 1 if it is bear market, 0 if it is bull market.

Table 5 (the two columns on the left) shows the regression results. The experienced participants invest significantly more in local stocks but not in the recognized stocks, whereas the inexperienced participants invest significantly more in the recognized stocks. The interaction of recognition and market is not significant, which means the inexperienced participants use the recognition portfolio strategy regardless of the current market conditions. Since there are many variables that are not significant in the model, we reduced the model to a simple form, which only includes recognition, local stocks, and market. Likelihood ratio tests show that the reduced model fits the data as well as the full model.

Table 5 Random effect Tobit model, tests recognition-based strategy and local bias

	Experienced Group	Inexperienced Group	Experienced Group	Inexperienced Group
Intercept	341.68*** [52.91]	376.87*** [69.23]	266.61*** [51.65]	359.1*** [67.97]
Recognition	-9.17 [20.75]	73.77* [33.85]	-6.22 [16.09]	73.54* [24.86]
Recognition of the other stock	-5.15 [12.47]	-27.88 [20.69]		
Local	220.18*** [67.06]	44.1 [88.79]	160.87* [64.26]	13.72 [82.92]

	Experienced Group	Inexperienced Group	Experienced Group	Inexperienced Group
Local of the other stock	-11.66 [20.35]	-16.85 [25.38]		
Market	-21.22 [12.75]	-53.98*** [15.57]	-24.26* [10.42]	-58.54*** [13.77]
R*L	-96.19 [63.17]	-72.02 [79.09]		
R*Market	17.53 [24.23]	20.12 [41.00]		
Market*L	-61.6 [58.86]	-83.02 [60.21]		
R*Local*Market	77.02 [79.32]	17.25 [105.23]		
No.of observations	6508	5276	6508	5276
No.of left-censored observations	1449	1342	1449	1342
No.of uncensored observations	4604	3473	4604	3473
No.of right-censored observations	455	461	455	461
rho	0.31	0.24	0.31	0.24

Note: The coefficients of 60 stocks dummies are not included in the table. The two columns on the left show the results of the full model. The two columns on the right show the results of the reduced model. \*\*\*  $p < 0.00$ ; \*\*  $p < 0.01$ , \*  $p < 0.05$ . Standard error in the brackets

The results of the reduced model (the two columns on the right) confirm that our results are not different from the full model. All participants invest less in bear market than in bull market. The experienced participants show local bias but ignore the recognition information. By contrast, the inexperienced participants trust the recognized stocks more and ignore the local information.

Next, we replaced recognition with familiarity. Figure 10 lists the average investments in with ID treatment, categorized by market, local stock, and familiarity; 10a indicates the results of the experienced group, 10b those of the inexperienced group. We ran the Tobit subject random effect model and replaced recognition with familiarity. The model we used is as follows:

$$\begin{aligned}
 Portfolio_{ij} = & \beta_0 + \beta_1 Fam + \beta_2 FamP + \beta_3 Local + \beta_4 LocalP + \beta_5 M + \beta_6 Fam * Local \\
 & + \beta_7 M * Local + \beta_8 M * Fam + \beta_9 M * Fam * Local + \sum_{t=1}^{60} \beta_{t+10} S_t + v_i + \epsilon_{ij}
 \end{aligned}$$

, where  $Fam=0, 1, 2, \dots, 7$  is the familiarity with stock  $j$ ;  $FamP$  is the familiarity with the other stock in the same pair.

Table 6 shows that when we replace recognition with familiarity, results do not change. The experienced participants only invest more in local stocks, whereas the inexperienced participants' investments increase with the level of familiarity.

In summary, our data indicate that the inexperienced participants do not show local bias. They have no investment experience and have no knowledge of the stock market; therefore, the local information is of no use for them, whereas recognition and familiarity with stocks matter more to them. However, the experienced participants only invest more in local stocks but do not invest more in recognized and familiar stocks. In our experiment, we find no evidence that familiarity is the reason for local bias (Feng and Seasholes, 2004, Hiraki et al., 2003, Huberman, 2001, Zhu, 2002). Even though the inexperienced participants are more familiar with local stocks, they do not invest more in them; whereas for the experienced participants, recognition and familiarity are obviously not enough to make them increase their investments. What counts for them is the local information.

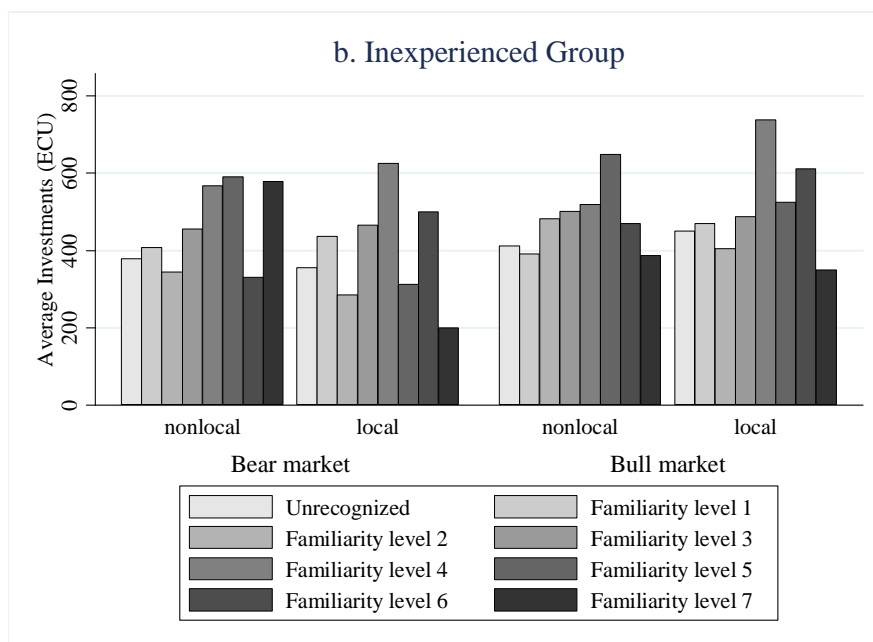
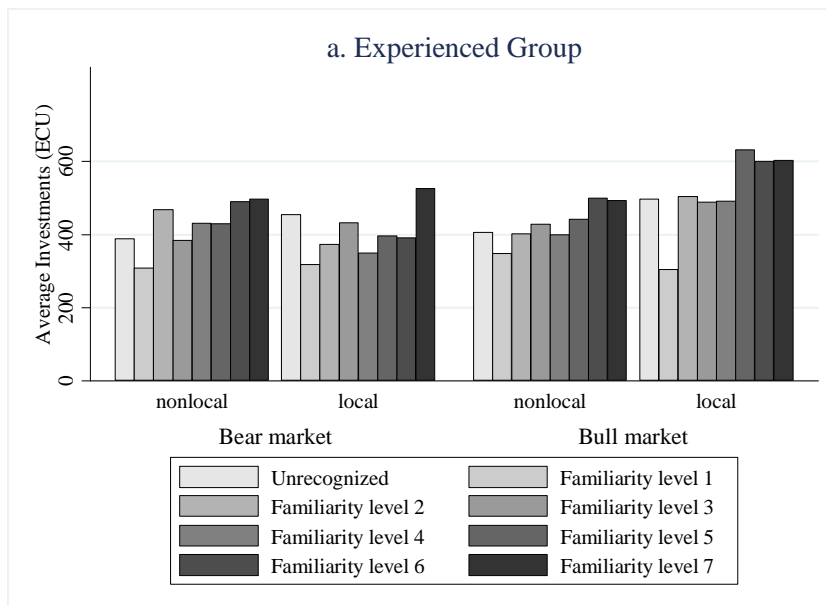


Fig. 10. Average investments (ECU) in stocks in with ID treatment, categorized by market, local stock, and familiarity. The higher the familiarity level, the more familiar participants are with the stocks.

Table 6 Random effect Tobit model, tests familiarity-based portfolio strategy and local bias

	Experienced Group	Inexperienced Group	Experienced Group	Inexperienced Group
Intercept	343.79*** [52.87]	365.62*** [68.06]	371.32*** [51.13]	361.57*** [67.92]
Familiarity	-1.03 [4.78]	25.73* [10.22]	1.69 [3.66]	25.05*** [7.25]
Familiarity with the other stock	-2.64 [2.97]	-11.70 [6.37]		
Local	96.41 [74.39]	50.12 [87.31]	162.35* [66.25]	11.74 [82.91]
Local of the other stock	-10.78 [20.22]	-15.19 [25.42]		
Market	-21.00 [12.25]	-54.45*** [15.19]	-24.26* [10.42]	-58.53*** [13.77]
Fam*L	-8.68 [12.88]	-32.54 [20.71]		
Fam*M	4.57 [5.62]	8.67 [12.52]		
M*L	-56.41 [51.80]	-69.96 [56.49]		
Fam*M*L	23.55 [16.96]	18.93 [27.92]		
No. of observations	6508	5276	6508	5276
No. of left-censored observations	1449	1342	1449	1342
No. of uncensored observations	4604	3473	4604	3473
No. of right-censored observations	455	461	455	461

	Experienced Group	Inexperienced Group	Experienced Group	Inexperienced Group
rho	0.31	0.24	0.30	0.24

Note: The coefficients of 60 stocks dummies are not included in the table. The two columns on the left show the results of the full model. The two columns on the right show the results of the reduced model. \*\*\*  $p < 0.00$ ; \*\*  $p < 0.01$ , \*  $p < 0.05$ . Standard error in the brackets

#### 4. Conclusions

Our main purpose in this paper has been to test whether participants use familiarity-based and recognition-based portfolio strategies to choose stocks and whether recognition can influence investors' portfolio behavior, e.g., whether recognition makes participants feel more competent when making investment decisions so that they invest more in the stock market (keep less cash). Since familiarity is considered to be one of the main reasons for local bias, we also tested if local bias occurred in our experiment. Local bias is a highly common phenomenon, which has been found in many countries and different investor groups of both individual (laypeople) and institutional investors (experts) (Coval and Moskowitz, 1999, Feng and Seasholes, 2004, Hiraki et al., 2003, Huberman, 2001, Zhu, 2002). Thus, we categorized our participants into two groups, experienced (experts) and inexperienced (laypeople), to test whether these two groups of investors behave differently; we tested for familiarity and recognition-based strategy in both bull and bear markets.

Not surprisingly, all participants invested more in the stock market in bull market than in bear market, even though we did not inform them explicitly about the market type. In bear market, the inexperienced participants were more conservative than the experienced participants: when the market was down, they kept even more cash than the experienced participants. Unlike in the between-subject design (Ackert (2005) and Weber (2005)), in a within-subject design the provision of stocks' IDs did not make the participants invest more in the stock market. Further tests showed that the provision of unrecognized names had the same effect as no name provision. Furthermore, we tested if the amount invested in the stock market increases with the number of recognized stocks (from 0 to 1 and 2). Analysis showed that this is not the case within subjects,

e.g., subjects do not invest more in the stock market when more stocks are recognized. However, the hypothesis holds for between subjects; e.g., those subjects who recognize more stocks in general invest more in the stock market than those who do not.

The results of our experiment show that all participants are more familiar with local stocks. Unlike the results of Giofré (2008) and Grinblatt and Keloharju (2001), the inexperienced participants are not more strongly influenced by the local and recognition / familiarity information than the experienced participants. Rather, the participants from the two groups are totally influenced by different information. The experienced participants show local bias. They do not invest more in the familiar and recognized stocks. Familiarity and recognition are not enough for the experienced participants to increase their investments. For them the local information is decisive. In contrast, the inexperienced participants invest more in the recognized and familiar stocks, regardless of the current market conditions, and ignore the local information. In our experimental settings, recognition has no correlation with a stock's returns. Therefore, unlike the results of Oppenheimer (2003), Newell et al. (2004), and Pohl (2006), the inexperienced participants do use the recognition-based strategy even when the recognition cue has no positive validity. Based on our experiment, we cannot conclude that local bias exists because of familiarity.

It may be argued that there is a big difference between the experienced participants in our experiment and the real 'experts.' But we were interested if the more experienced participants would be less influenced by the local and recognition/familiarity information than the inexperienced participants. To test our hypothesis with real 'experts' will be a topic for future study.



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**Appendix A: Detailed information on 60 stocks.**

	Trading Symbol	Reporting Instrument	ISIN	Sector	Location	Market Cap. (in Mio.) <sup>3</sup>
1	AIXA	AIXTRON AG NA O.N.	DE000A0WMPJ6	Technology	Herzogenrath	956.81
2	ARO	ARCANDOR AG O.N.	DE0006275001	Retail	Essen	50.21
3	NDA	AURUBIS AG	DE0006766504	Basic resources	Hamburg	799.09
4	BBZA	BB BIOTECH NAM. SF 1	CH0038389992	Pharma & Healthcare	Küsnacht/Zürich-Switzerland	786.40
5	BC8	BECHTLE AG O.N.	DE0005158703	Software	Neckarsulm	141.22
6	GBF	BILFINGER BERGER AG	DE0005909006	Construction	Mannheim	1,300.38
7	AFX	CARL-ZEISS MEDITEC AG	DE0005313704	Pharma & Healthcare	Jena	280.60
8	CLS1	CELESIO AG NAM. O.N.	DE000CLS1001	Retail	Stuttgart	1,404.87
9	CON	CONTINENTAL AG O.N.	DE0005439004	Automobile	Hannover	438.35
10	DEQ	DEUTSCHE EUROSHOP AG O.N.	DE0007480204	Financial services	Hamburg	619.18
11	DPB	DEUTSCHE POSTBANK AG NA	DE0008001009	Banks	Bonn	1,505.32
12	DOU	DOUGLAS HOLDING O.N.	DE0006099005	Retail	Hagen	675.66
13	DRW3	DRAEGERWERK VZO O.N.	DE0005550636	Pharma & Healthcare	Lübeck	127.89
14	ZIL2	ELRINGKLINGER AG NA O.N.	DE0007856023	Automobile	Dettingen/ Erms	346.71
15	EAD	EUROP.AERON.DEF.+SP. EADS	NL0000235190	Industrial	Schiphol Rijk, Netherlands	4,804.02
16	FIE	FIELMANN AG O.N.	DE0005772206	Retail	Hamburg	588.25
17	FRA	FRAPORT AG FFM.AIRPORT	DE0005773303	Transportation & Logistics	Frankfurt am Main	1,133.04
18	FPE3	FUCHS PETROL.AG VZO O.N.	DE0005790430	Chemicals	Mannheim	506.68
19	G1A	GEA GROUP AG	DE0006602006	Industrial	Bochum	1,774.53
20	GIL	GILDEMEISTER AG O.N.	DE0005878003	Industrial	Bielefeld	326.50
21	HDD	HEIDELBERG.DRUCKMA.O.N.	DE0007314007	Industrial	Heidelberg	317.43
22	HEI	HEIDELBERGCEMENT AG O.N.	DE0006047004	Construction	Heidelberg	519.43
23	HOT	HOCHTIEF AG	DE0006070006	Construction	Essen	1,917.05
24	BOS3	HUGO BOSS AG VZO O.N.	DE0005245534	Consumer	Metzingen	280.63
25	HRX	HYPOTHEK REAL ESTATE HLDG	DE0008027707	Banks	Unterschleißheim	181.43
26	IDS	IDS SCHEER AG O.N.	DE0006257009	Software	Saarbrücken	249.66
27	IFX	INFINEON TECH.AG NA O.N.	DE0006231004	Technology	Neubiberg	2,430.28
28	IVG	IVG IMMOBILIEN AG O.N.	DE0006205701	Financial services	Bonn	363.64
29	JEN	JENOPTIK AG O.N.	DE0006229107	Industrial	Jena	125.04
30	KBC	KONTRON AG O.N.	DE0006053952	Technology	Eching	409.96
31	KRN	KRONES AG O.N.	DE0006335003	Industrial	Neutraubling	364.03
32	KU2	KUKA AG	DE0006204407	Industrial	Augsburg	169.35
33	LEO	LEONI AG NA O.N.	DE0005408884	Automobile	Nürnberg	365.93
34	MDG	MEDIGENE NA O.N.	DE0005020903	Pharma & Healthcare	Martinsried/München	127.21
35	MLP	MLP AG	DE0006569908	Financial services	Wiesloch	345.28
36	MOR	MORPHOSYS AG O.N.	DE0006632003	Pharma & Healthcare	Martinsried/München	323.17
37	PFV	PFEIFFER VACUUM TECH.O.N.	DE0006916604	Industrial	Asslar	444.00
38	PFD4	PFLIEDERER AG	DE0006764749	Industrial	Neumarkt	196.91
39	PSM	PROSIEBENSAT.1 O.N.VZO	DE0007771172	Media	Unterföhring	362.84
40	PUM	PUMA AG	DE0006969603	Consumer	Herzogenaurach	821.80

<sup>3</sup> Market capital data are from 31 July 2009. / 31.07.2009.

# Jena Economic Research Papers 2011 - 010

	Trading Symbol	Reporting Instrument	ISIN	Sector	Location	Market Cap. (in Mio.) <sup>3</sup>
41	QIA	QIAGEN NV EO -,01	NL0000240000	Pharma & Healthcare	KJ Venlo, Netherlands	2,659.71
42	QSC	QSC AG NA O.N.	DE0005137004	Telecommunication	Köln	143.79
43	RAA	RATIONAL AG	DE0007010803	Industrial	Landsberg a. Lech	277.90
44	RHM	RHEINMETALL AG	DE0007030009	Industrial	Düsseldorf	1,179.34
45	RHK	RHOEN-KLINIKUM O.N.	DE0007042301	Pharma & Healthcare	Bad Neustadt/ Saale	1,451.84
46	RSI	ROFIN SINAR TECHS DL-,01	US7750431022	Industrial	Plymouth- USA	442.33
47	SGL	SGL CARBON SE O.N.	DE0007235301	Chemicals	Wiesbaden	1,019.13
48	SNG	SINGULUS TECHNOL.	DE0007238909	Industrial	Kahl am Main	72.89
49	SOW	SOFTWARE AG O.N.	DE0003304002	Software	Darmstadt	1,069.30
50	SOO1	SOLON SE O.N.	DE0007471195	Industrial	Berlin	81.35
51	SAZ	STADA ARZNEIMITT.VNA O.N.	DE0007251803	Pharma & Healthcare	Bad Vilbel	1,001.27
52	SZU	SUEDZUCKER MA./OCHS. O.N.	DE0007297004	Food & Beverages	Mannheim	978.20
53	TUI1	TUI AG NA	DE000TUAG000	Transportation & Logistics	Hannover	623.50
54	UTDI	UTD.INTERNET AG NA	DE0005089031	Software	Montabaur	1,031.70
55	VOS	VOSSLOH AG O.N.	DE0007667107	Industrial	Werdohl	705.23
56	WIN	WINCOR NIXDORF O.N.	DE000A0CAYB2	Industrial	Paderborn	1,245.98
57	WDI	WIRECARD AG	DE0007472060	Software	Grasbrunn	710.20
58	AJA	ANALYTIK JENA AG O.N.	DE 0005213508	industrial	Jena	24.71
59	BIB	BIOLITEC AG O.N.	DE0005213409	Pharma & Healthcare	Jena	13.19
60	ISH2	INTERSHOP COMMUNICATIONS AG	DE000A0EPUH1	Software	Jena	41.13

**Appendix B: Recognition Details and Familiarity Score of 60 stocks**

	Stocks	Nr. of participants recognize the stock	Average familiarity	Average Familiarity EG (N=105)	Average Familiarity IG (N=87)
1	Elringklinger AG	2	0.05	0.25	0.00
2	Aurubis AG	5	0.06	1.02	0.29
3	Fuchs Petrol AG	4	0.07	0.20	0.00
4	Rofin-Sinar Technologies Inc.	4	0.08	1.73	0.53
5	Morphosys AG	4	0.08	0.27	0.03
6	Wirecard AG	5	0.08	0.71	0.16
7	Vossloh AG	5	0.08	2.56	1.14
8	Solon SE	5	0.08	2.56	1.28
9	Kontron AG	4	0.09	2.09	1.00
10	GEA Group AG	7	0.10	0.94	0.21
11	Krones AG	8	0.11	1.06	0.08
12	Singulus Technology	8	0.11	1.77	1.01
13	Kuka AG	5	0.11	0.21	0.03
14	Leoni AG	7	0.11	0.25	0.06
15	SGL Carbon SE	8	0.11	0.39	0.09
16	Medigene	9	0.12	0.73	0.10
17	IVG Immobilien AG	9	0.13	0.65	0.22
18	Gildemeister AG	7	0.13	0.20	0.00
19	Deutsche Euroshop AG	9	0.13	0.17	0.08
20	Celesio AG	11	0.14	0.15	0.00
21	Aixtron AG	7	0.14	0.08	0.07
22	Pfleiderer AG	9	0.14	0.15	0.00
23	Bechtle AG	9	0.14	2.89	1.31
24	QSC AG	8	0.15	0.14	0.07
25	Rational AG	10	0.16	0.21	0.00
26	Qiagen NV	11	0.16	3.28	1.79
27	Drägerwerk AG & Co KG aA	11	0.17	0.25	0.00
28	Pfeiffer Vacuum Technology AG	15	0.26	1.80	0.55
29	Biolitec AG	22	0.31	0.15	0.00
30	Rhön-Klinikum AG	27	0.45	0.11	0.00
31	IDS Scheer AG	28	0.45	0.28	0.03
32	Software AG	29	0.46	1.86	0.66
33	United Internet AG	21	0.49	0.16	0.00
34	Heidelbergcement AG	22	0.50	2.47	1.14
35	BB Biotech AG	39	0.61	0.77	0.15
36	Heidelberger Druckmaschinen AG	28	0.61	0.15	0.00
37	Billfinger Berger AG	50	0.69	0.17	0.01
38	EADS NV	40	0.75	1.18	0.67
39	MLP AG	38	0.80	3.45	1.83
40	Stada Arzneimittel AG	52	0.83	0.18	0.05
41	Wincor Nixdorf AG	55	0.95	0.22	0.02

	Stocks	Nr. of participants recognize the stock	Average familiarity	Average Familiarity EG (N=105)	Average Familiarity IG (N=87)
42	Fraport AG	55	1.02	0.20	0.09
43	Rheinmetall AG	76	1.19	2.81	1.41
44	Douglas Holding AG	70	1.23	2.60	1.28
45	Südzucker AG	81	1.31	1.29	0.28
46	Analytik Jena AG	85	1.43	0.09	0.00
47	Hochtief AG	90	1.59	1.42	0.54
48	Tui AG	108	1.71	3.29	1.46
49	Infineon Technology AG	103	1.83	1.16	0.37
50	Intershop Communication AG	101	1.86	0.26	0.00
51	Puma AG	107	1.86	2.60	0.98
52	Hugo Boss AG	111	1.92	0.15	0.00
53	Carl Zeiss Meditec AG	112	1.98	0.83	0.10
54	Arcandor AG	113	1.98	0.20	0.01
55	Fielmann AG	115	2.00	2.47	1.07
56	Continental AG	121	2.17	2.61	1.23
57	Prosiebensat1 Media AG	113	2.18	0.22	0.03
58	Hypo Real Estate Holding AG	128	2.46	1.18	0.23
59	Jenoptik AG	141	2.60	2.37	0.91
60	Deutsche Postbank	155	2.71	0.50	0.08

## **Appendix C: Experimental Instructions**

Welcome to our lab. This experiment is about portfolio decision making, and you can earn real money based on your decisions. From now on, any communication - verbal or written - between participants is forbidden. If you have any questions, please raise your hand. A member of our staff will come to your cabin and answer your question privately. It is very important to follow these rules; otherwise we will have to exclude you from the experiment and the payment.

Before the experiment starts, please fill in a questionnaire indicating your age, gender, main field of studies, etc.

There are 2 parts in our experiment: the so-called portfolio decisions and a questionnaire.

The first part of the experiment – portfolio decision making – has 30 rounds. In every round you will make a portfolio decision under *Information set 1* and thereupon under *Information set 2*.

### **Part I. Portfolio Decisions:**

Portfolio Decision I:

1. You will receive the information about the development of the price and the returns of two stocks (A and B). The information is composed of the prices and returns of stocks A and B from the German stock market (Xetra, Deutsche Börse Gruppe), which are calculated at the end of each month. You will see this information for 30 successive months. *Information set 1.*
2. For the portfolio decision, you will receive 1,200 experimental currency units (ECU). Afterwards you will have the possibility either to invest the 1,200 ECU in the two stocks or to keep them as cash.
3. The return of the next (31<sup>st</sup>) month of stocks A and B will be revealed to you.
4. You will learn the amount of the return of your investments. The return shows the ratio of the money which you have earned or lost through your investment to the amount of money which has been actually invested. The return is a consequence of the prices: if the prices go up, the return will be positive; if the prices go down, the return will be negative.
5. Your gain during this portfolio decision will be calculated and displayed to you.

Portfolio Decision II:

1. Again, you will receive some information about the prices and returns of the same stocks (A and B). The information will tell you about the prices of the same stocks A and B (Xetra, Deutsche Börse Gruppe) at the end of the month, but this time for ANOTHER successive 30 months. *Information set 2.*
2. The same as above
3. The same as above
4. The same as above
5. The same as above

Altogether for the *Information set 1* and *Information set 2* you will make portfolio decisions in 30 rounds.

In every new round there will be different investment options. It means that there will be 30 pairs of investment possibilities during the 30 rounds. (Round 1:  $A_{(1)}$  und  $B_{(1)}$ ; Round 2:  $A_{(2)}$  und  $B_{(2)}$ ; Round 3:  $A_{(3)}$  und  $B_{(3)}$ ; ...).

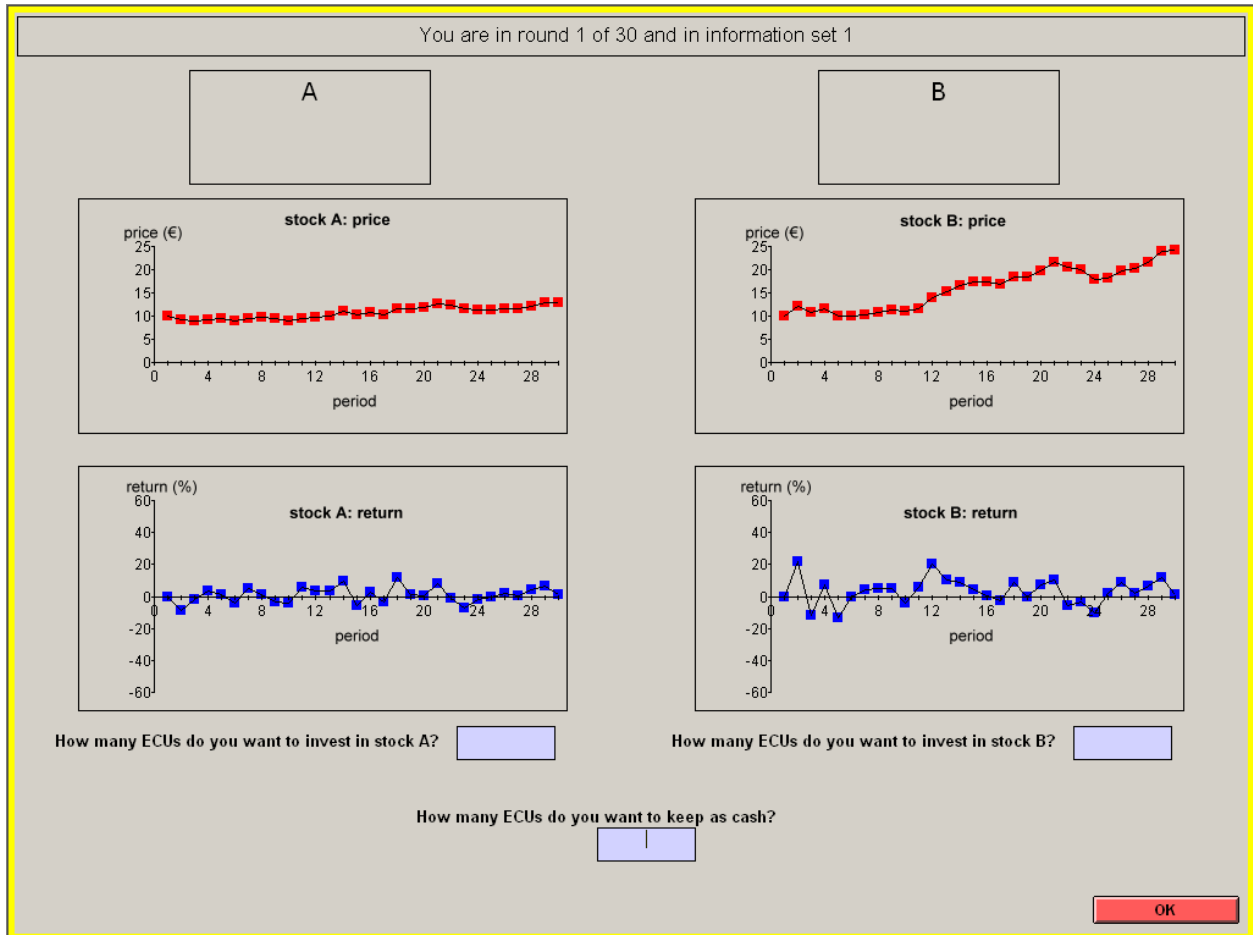
**Example:**

During one portfolio decision you will decide how many ECU you invest in the investment option and how many ECU you keep in your account. In order to do this, you have to enter 3 numbers in 3 input boxes. The sum of these numbers must be equal to 1,200 ECU.

For example, you invest 600 ECU in stock A and 500 ECU in stock B. Thus you must have 100 ECU in your account. If you invest 450 ECU in A and 750 ECU in B, you will have 0 ECU left in your account.

The figure below shows what the screen looks like.





Please note that some of the figures show additional information, e.g., the name of the company, the place of the headquarters, and the relevant economic sector.

**The Payoff:**

At the end of every portfolio decision you will be informed about the return of your investments, i.e., about your gain and loss due to your investments. Hence, your gain and loss depend on your investment decisions and the return of the stock options. If you invest a large amount of money in an investment option and it has a positive return, you will have a large gain. If you invested a smaller amount, the gain would be smaller accordingly. If the return is negative, you will even have some losses. The ECU which you do not invest will remain in your account and will cause neither gain nor loss.

To be precise, your gains/losses and payoff in every round will be calculated by

Gain/loss from stock A:  $x_A r_A$

Gain/loss from stock B:  $x_B r_B$

$$\text{Payoff} = (x_A + x_A r_A) + (x_B + x_B r_B) + (1,200 - x_A - x_B),$$

where:

- $r_A$  and  $r_B$  are realized returns of 2 stocks, which have been disclosed in the following month.
- $x_A$  and  $x_B$  are the amounts of money (ECU) you have invested in two stocks.
- $(1,200 - x_A - x_B)$  shows the amount of money which you have not invested, i.e., the amount of money you kept in your account.

## Part II. Questionnaire

After you finish the first part, you will receive/ get the instruction for the second part of the experiment on the computer screen.

Your actual **payoff** at the end of the experiment will be calculated as follows:

One session out of the 60 portfolio decisions will be randomly selected for the payoff.

Your selected portfolio decision will be converted at the exchange rate of 100 ECU = 1 euro and will be paid to you in cash.

When you are finished with the experiment, please raise your hand. A member of our staff will come to you and will pay you the money in your cabin. Please remain seated in your cabin until then and do not speak with other participants of the experiment. As soon as you have received your payoff, you are allowed to leave the laboratory.

Before starting the experiment, please answer some control questions on your computer screen. They should assure that you have fully understood the rules of the experiment.

**Control Questions:**

1. What is the difference of the portfolio decisions due to information status 1 and 2?
  - a) Different endowment of ECU.
  - b) Different information about the prices at the end of the 30 months.
  - c) Different investment option.
  
2. What is the difference between the 30 rounds?
  - a) There are other investment options in every round.
  - b) Different ECU endowment at the beginning.
  - c) Increasing amount of information about investment options.
  
3. Which of the following statements is right?
  - a) You will receive/get the sum of the whole gain in all of the rounds.
  - b) You will receive/get the sum of portfolio decision I and portfolio decision II.
  - c) You will receive/get the gain of a randomly selected round out of 60 rounds.
  
4. Which of the following statements is right?
  - a) You will receive 1,200 ECU in every information status.
  - b) You will receive 1,200 ECU in every round.
  - c) You will receive 1,200 ECU at the beginning of the experiment.