Stock Price Level Effect

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Abstract

Companies actively manipulate stock price ranges through IPOs, stock splits, and repurchases. Indeed, empirical results suggest that the stock's price range, whether at a high or low price level, affects market performance. Unfortunately, archival data does not allow us to test the effect of stock price levels on investor behavior due to uncontrolled confound effects. We thus conduct a controlled online experiment with 900 US retail investors to test whether a difference in stock price levels affects the investor's risk perception, the price forecast, and the investment. Even though we find no differences in risk perception and forecasts, our results show significantly higher investments in high-priced stocks in comparison to low-priced stocks. This effect disappears when we allow fractional share purchases or restrict naive trading strategies.

Keywords— stock price, nominal stock price puzzle, stock splits, number processing, fractional share purchases, naive trading strategies, numerosity

JEL: C9, D14, G11, G41

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1 Introduction

Previous research provides compelling evidence that stock price levels have a significant impact on investor behavior (Costa, 2020; Roger, Bousselmi, Roger, & Willinger, 2018) and market performance (Brennan & Copeland, 1988a; Desai & Jain, 1997). However, despite inflation, the average nominal share price at New York Stock Exchange is around \$35 for decades (Weld, Michaely, Thaler, & Benartzi, 2009), a phenomenon which is observed globally on other stock exchanges (Bae, Bhattacharya, Kang, & Rhee, 2019; Dyl & Elliott, 2006). These findings provide evidence for companies' active manipulation of their stock price levels, usually done by setting specific prices in IPOs and executing stock splits and share repurchases. For instance, after the euro conversion in the euro area, stock splits decreased in countries with higher conversion rates, leading to lower stock price levels, such as in Italy (Bae et al., 2019).

This study examines a stock price level effect, which we describe as the impact of stock price levels on investor behavior related to risk perception, future price forecasts, and investment decisions. We test whether the stock price level effect explains variations in trading behavior when comparing two price levels of substantial distance. For example, do traders invest differently when the share price is \$2.35 compared to \$235, holding other factors constant? If so, it would imply that the stock price level itself already biases the investment decision neglecting the reasons why some stock are substantially higher priced then others. We investigate the stock price level effect under controlled conditions in an online experiment. 900 US retail investors evaluate stocks in a low price environment or a high price environment under various conditions. The high price equals 100 times the low price while the returns in both environments remain the same; imagine the same company with 100 million or one million shares outstanding. We then test whether this treatment manipulation affects risk perception, forecasts, and investments. We opted for an experiment to control the environment allowing for high internal validity using between-subjects designs. Archival data analysis might show aggregated differences in trading behavior but not why individuals behave differently. Furthermore, archival data contains confounding factors that we cannot control for (Bloomfield & Anderson, 2010). Due to our treatment manipulation, we can carve out under what conditions stock price levels play a role.

Companies seem to be interested in maintaining their stock price range via IPOs, executing stock splits, or share repurchases. Dyl and Elliott (2006) illustrate that the average stock price on the three major US equity markets was \$18.23 during 2001 and that approximately 50% of all stocks traded in the price range between \$10 and \$30. Several arguments on why price ranges remain constant apply. Retaining stock prices within a narrow range could be due to decade-old norms (Weld et al., 2009). As described in the trading-range hypothesis, transaction costs and round-lot constraints lead to preferred stock price levels by managers. In particular, stock splits aim to increase trading liquidity by retaining the stock price in a specific range, usually between \$20 and \$35 (Baker & Powell, 1993), and to achieve tick sizes that are optimal relative to the stock price (Angel, 1997). As described by the marketability hypothesis, specific price ranges increase attractiveness (Baker & Gallagher, 1980). Splitting a mutual fund to decrease its price leads to an increase in net assets and shareholders (Fernando, Krishnamurthy, & Spindt, 1999). Moreover, the range of prices helps to attract certain investor types. Schultz (2000) explains that stock splits increase the number of retail investor shareholders, which in turn might be caused by higher bid-ask spreads and hence more promotion for the stock by brokers as transaction costs increase. Institutional investors often use block trades resulting in higher volume (Griffin, Harris, & Topaloglu, 2003). Amini, Buchner, Cai, and Mohamed (2020) show the existence of an institutional ownership premium based on stock prices. IPO pricing depends on the underwriter's reputation and the goal to attract a larger share of institutional investors (Fernando, Krishnamurthy, & Spindt, 2004). A fourth explanation is managers' signaling of future performance. Managers use stock splits as a costly signal to communicate private information such as positive expected performance (Brennan & Copeland, 1988b). Share repurchases might be a result of desired changes in the capital structure, to increase earnings per share, or to signal that the stock is undervalued in the manager's opinion (Grullon & Ikenberry, 2000).

Green and Hwang (2009) illustrate that stocks of similar price range exhibit high co-movement, indicating that investors categorize stocks based on their prices. Stock price levels seem to influence risk, abnormal returns, forecasts, trading volume, informed trading, price informativeness, and order aggressiveness; the *risk* is higher for lower-priced stocks. Seguin and Smoller (1997) examine stocks listed on the NYSE between 1974 and 1988 and find that low-priced stocks face a higher mortality rate compared to high-priced stocks, while the market capitalization has no impact on mortality rates. A reduction in share price by 50% associates with an increase in the stock's beta by around 20% (Brennan & Copeland, 1988a), and of even 30% of the return standard deviation post-split (Ohlson & Penman, 1985). Shue and Townsend (2019) confirm that lower-priced stocks indeed possess higher market betas, idiosyncratic risk, and higher return standard deviation and that stock prices of lower-priced companies react stronger to firm-specific news compared to higher-priced stocks. A doubling in the stock price is associated with a decrease of 20-30% in these risk measures. The evidence on *abnormal returns* is more dispersed. While Fama, Fisher, Jensen, and Roll (1969), Grinblatt, Masulis, and Titman (1984) and Desai and Jain (1997) find abnormal returns during the stock split announcement periods until two years after the actual split of up to 30%, Geertsema and Lu (2019) examine US equity markets and find higher returns for low-priced stocks up to the 1970's to 1980's, and an opposite pattern after that. However, recent evidence suggests that high-priced stocks obtain better Sharpe ratios (Hammerich, Fieberg, & Poddig, 2018), but a lower return of 4.88% after one year (Disli, Inghelbrecht, Schoors, & Stieperaere, 2020). *Forecasts* are more extreme in both an optimistic and a pessimistic direction for lower-priced stocks. Analysts' forecasts are higher for lower-priced stocks in an optimistic forecast, and lower for lower-priced stocks in a pessimistic forecast (Roger, Roger, & Schatt, 2018). Furthermore, individuals frequently overestimate the skewness of lower-priced stocks, potentially because they believe that lower-priced stocks have more "room to grow" (Birru & Wang, 2016). The monetary *trading volume* is lower for low-priced stocks, in particular after stock splits (Dyl & Elliott, 2006; Shue & Townsend, 2019). Chan, Li, Lin, and Lin (2017) find that for higher-priced stocks, *informed trading* is increased while *price informativeness* about future earnings is lower. The *order aggressiveness*, defined as the difference between the order price and the best opposite limit of the order book, is less pronounced for low-priced stocks than for high-priced stocks (Métais & Roger, 2021). Overall, these variations in market performance induced by stock price levels attract different types of investors. The proportion of retail and institutional investors' shareholdings differs across high and low-priced stocks. Kumar and Lee (2006) and Kumar (2009) identify that shareholdings of retail investors decrease with stock prices, while the opposite holds for institutional investors. One possible explanation is that retail investors are attracted to lottery-like stocks, which are typically low-priced (Kumar, 2009). There might be several reasons for these potential stock price level effects, such as differences in investors type, differences in company types, or differences in the behavior of investors.

Five potential drivers might explain the existence of the stock price level effect: humans' number processing, the lack of proportional thinking, numerical anchoring, naive trading strategies/numerosity bias, and the lack of fractional share trading. Roger, Roger, and Schatt (2018) describe that individuals process small numbers on a linear and large numbers on a logarithmic scale, leading to more extreme analysts' forecasts for lower-priced stocks. Individuals potentially perceive that lower-priced stocks have more "room to grow", leading to distortions in the estimation of return skewness (Birru & Wang, 2016). Furthermore, individuals experience difficulties when transforming absolute to relative values, as they frequently apply non-proportional thinking (Shue & Townsend, 2019), leading to incorrect perceptions of performance. Investors exhibit numerical anchoring as they base their beliefs on current prices, resulting in a forecasting bias. A consequence is lower forecasts for higher-priced stocks, and increased asset demand for higher-priced stocks of about 24.5% after relative gains are described in absolute terms (Costa, 2020). In line with numerical anchoring, Disli et al. (2020) describe that stock prices anchor investors' stock valuations, as higher-priced stocks have higher market-to-book ratios. Another critical factor, in particular in the case of retail investors, is the implementation of naive trading strategies (Shue & Townsend, 2019). In this trading strategy, investors mainly focus on the number of shares instead of the investment amount. Consequently, individuals would invest less in lower-priced stocks, as for an equal investment amount, the number of shares in lower-priced stocks is significantly higher than in high-priced stocks. West, Azab, Ma, and Bitter (2020) describe the numerosity heuristic, which implies that individuals focus on large numbers and prefer to receive a higher number of shares, even though the underlying economic value is equal.

Another driver of the stock price level effect could be the lack of fractional share purchases. Most brokers restrict traders from purchasing entire units of shares. Only recently, an increasing number of online brokers started to allow fractional share purchases, such as Fidelity, Robinhood and Vanguard. Without fractional share purchases, small retail investors cannot purchase an entire share of an expensive stock. Thus, restricting fractional share purchases leads to a skewed distribution of investor types in different price range as high-priced stocks are more targeted by institutional than retail investors (Kumar & Lee, 2006; Schultz, 2000). Subsequently, investment volume for higher-priced stocks could be inflated due to their purchase price, as individuals have to invest at least the amount corresponding to the current stock price.

Only a few experimental studies investigated how price levels affect investor behavior. Noussair, Richter, and Tyran (2012) investigate exogenous nominal shocks in the continuous double auction asset market. That shock rescaled the nominal values (inflated or deflated), while the assets' fundamental value remained constant. The price shock led to distortions in the valuation of the asset yielding an asymmetric response. The adjustment of prices appeared quickly during an inflationary shock but slowly during a deflationary shock. Such a response can be related to money illusion. In an individual decision-making experiment, Svedsäter, Gamble, and Gärling (2007) illustrate that buyers and sellers are more willing to trade following a stock split. [1] Although these previous experimental studies provide fruitful insights, we are the first to examine the stock price levels and their effect on investor behavior in an individual decision-making experiment examining the existence and potential drivers of the stock price level effect.

In an experiment among 900 US retail investors, we ask participants to assess the risk of a stock in line with Zeisberger (2020), elicit their beliefs in line with Glaser, Iliewa, and Weber (2019), and ask their actual investment decision similar to Nosić and Weber (2010) and Bradbury, Hens, and Zeisberger (2015). We compare two stock price levels (High vs. Low) and seven different stocks. We control the possibility of executing fractional share purchases and the display format of the investment decisions (investment amount, with and without the number of shares).

Our results illustrate that even though there is no difference in risk perception and forecasts across treatments, facing high compared to low stock prices leads to an average increase of 25% of the investment amount. This effect disappears when allowing fractional purchases or when the number of shares corresponding to the investment amount is not displayed. Overall, our findings on forecasts are not in line with previous research (Birru & Wang, 2016; Roger, Roger, & Schatt, 2018), indicating that the stock price level effect might not only driven through the belief channel. Instead, the differences in investment amounts, as observed in previous studies (Dyl & Elliott, 2006; Shue &

[1] Roger, Bousselmi, et al. (2018) conduct an experimental asset market in which two markets differ in the fundamental value (6 vs. 72). The low-fundamental value market experienced higher mispricing.

Townsend, 2019), significantly depend on the possibility to execute fractional share purchases and naive trading strategies.

Our findings emphasize relevant implications for the theoretical debate surrounding stock price levels and the practice of investing. We find that the stock price level effect is foremost driven by restrictions in fractional share purchases and naive trading strategies. An adjustment of trading opportunities and facilities would help to improve investment decisions without such stock price level distortions.

2 Experimental Design

2.1 General Set-up

In an online experiment, our participants invested in seven different stocks. We requested the participants to evaluate each stock on three aspects: (i) the perceived risk, (ii) the three-month future price forecast, and (iii) the investment amount. For every stock, we equipped the participants with an endowment of $10,000. In line with real-life investment conditions, we prohibited fractional share purchases. To examine the stock price level effect, we employed a between-subject design by creating the treatments Low and High. These treatments varied in their stock price levels as for the first five stocks the prices in High were 100 times the prices in Low ($Price_{High} = Price_{Low} * 100$) while for the last two stocks the prices in High were ten times the prices in Low ($Price_{High} = Price_{Low} * 10$). Table 1 presents an overview of the seven stocks in this study.

Table 1: Stock prices at time $t = 0$

Stock	$Price_{Low}$	$Price_{High}$	Trend
1	2.31	231	Upward-sloping
2	4.29	429	Downward-sloping
3	5.25	525	Stable
4	7.94	794	Upward-sloping
5	9.26	926	Downward-sloping
6	100	1000	Stable
7	10	100	Stable

This table presents an overview of the seven stocks used in the experiment. The price in High is based on the price in Low, multiplied by 100 for the first five stocks, and by 10 for the last two.

The first five stocks served as the baseline experiment to determine the existence and the drivers of the stock price level effect. As individuals both use logarithmic (Nieder, 2005) as well as linear processing of numbers (Siegler & Opfer, 2003; Viarouge, Hubbard, Dehaene, & Sackur, 2010), we implemented the price factor of 100 between treatments to activate both the linear (particularly numbers < 10) as well as the logarithmic thinking (numbers > 100). We included the last two stocks as a replication and extension of a design implemented by Glaser et al. (2019).

We adopted uneven numbers for the first five stocks to circumvent individuals' biases towards even numbers and portray real-life investment conditions. The asset prices ranged between \$0 and \$10 for LOW, and \$100 to \$1000 for HIGH. Table 1 illustrates the stock prices at time t = *0*. Using a price chart, the participants saw the price development from t = *-12* to t = *-1*, the actual price t = *0*, and three further periods t = *1* to t = *3*, containing no values corresponding to the estimation window. Figure 1 exemplifies the price charts for the prices \$5.25 and \$525. The design of the chart is in line with the experimental design of Glaser et al. (2019). We provide the current price at the top right. To avoid design or scale effects, the price development for each pair of stocks was consistent across treatments. Therefore, the two charts only differ in the scale of the y-axis. We account for the influence of price patterns on investor behavior by illustrating diverse price paths for the seven stocks. We simulated the asset price development using a normal return distribution with characteristics mimicking the performance of the S&P 500 from 1927 to 2020 ($\mu = 8\%, \sigma = 18\%$). Although these values represent yearly S&P 500 returns, we applied them in our experiment on a monthly basis to induce substantial price variations.

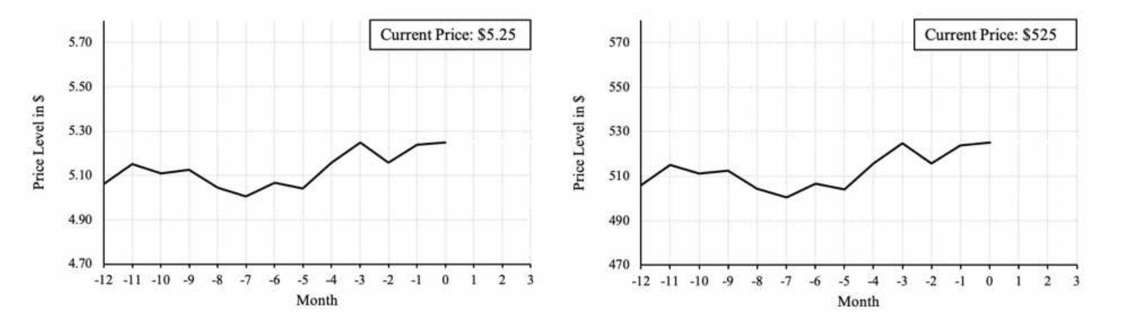

Figure 1: Example price chart in Low (left) and High (right). The price chart design is in line with earlier studies, e.g. Glaser et al. (2019). It illustrates the development of the last 12 months and is blank for the next three months in accordance with the requested forecast. We display the current price at the top right. Relative scaling is equal across treatments. The rest of the price charts is presented in Table 5.

When investing in LOW and HIGH, the participants only purchased full shares. Hence, an investment of \$5,250 means buying 1,000 shares in LOW and ten shares in HIGH. Now suppose an investor would like to invest \$5,500. In LOW, it would mean buying about 1,047 shares. What would an investor do in HIGH? Either s/he could purchase ten shares for \$5,250 or eleven shares for \$5,775. Hence, this design choice has an important implication when considering treatment effects. The investment in HIGH changes not only the price level but also restricts the investment amount. Consequently, we cannot inconclusively determine which factor prompts the stock price level effect.

To account for this circumstance, we added the HIGH-FRACTIONAL treatment permitting fractional share purchases. While participants in HIGH solely purchased whole units of shares, they could acquire fractions of shares in HIGH-FRACTIONAL. Of course, these fractions perfectly match the prices in Low. For instance, participants could buy 5.35 shares at a total of $5.35 \times \$231 = \$1,235.85$ in High-Fractional which corresponds to buying 535 shares in Low. We solely varied the opportunity to execute fractional share purchases, while all other factors are constant across treatments.

Brokers generally prohibit fractional share purchases in real-life investment decisions. However, more recently online brokers offer such opportunities at low scale. The experimental literature remains silent about such investment designs.

2.2 Experimental Procedure

Preceding research identified variations in the shareholder composition across stock price levels. Low-priced stocks seem to attract retail investors, while the opposite holds for institutional investors with High-priced stocks (Kumar & Lee, 2006; Schultz, 2000). We concentrated on retail investors listed at Amazon MTurk. Altogether, we recruited 900 US retail investors via CloudResearch;[2] 150 participants in each of the three specified treatments (High, Low, High-Fractional) plus another 450 participants in a robustness check.[3] The landing page informed the participants about the study's terms and conditions. We included an attention check similar to Oppenheimer, Meyvis, and Davidenko (2009). After completing the attention check successfully, the participants proceeded to the experimental instructions. We required them to answer three comprehension questions about the instructions correctly before continuing with the main task[4].

In the main task, for each of the seven stocks, the participants evaluated the stock on three aspects. The first question was about the stock's perceived risk. We asked: "How risky do you perceive this stock to be?", and assessed their evaluation on a scale from 1 (Not risky) to 7 (Very risky), comparable to Zeisberger (2020). The second question concerned the stock's future potential. We asked the participants to provide a future median price forecast for three months in the future, related to the design in Glaser et al. (2019). Using a slider starting with the respective stock price at time $t = 0$, they could pick any price between \$0 and twice that stock price. We calibrated the sliders in steps of \$0.01 in Low and High-Fractional, and \$1 in High to resemble the treatments' price dimensions. Lastly, we obtained the participant's willingness to invest. By employing a slider ranging from \$0 to \$10,000, the participants indicated the amount they want to invest in the illustrated stock similar to Nosić and Weber (2010). The investments involved no transaction costs. During the investment decision, we displayed the amount to invest next to the number of shares. In High and Low, we prohibited fractional share purchases such that the investment steps were fixed to the

[2] CloudResearch is an online participant recruitment platform. It screens Amazon MTurk workers on a variety of criteria to increase data quality. Furthermore, it implements strict mechanisms, such as blocking low-quality or inconsistent participants, to ensure well-qualified participation.

[3] We conducted a pilot trial with 20 participants to test the experimental progress. They only evaluated the first five stocks. After that, we extended our analysis to seven stocks. We included the data of the pre-test in all analyses.

[4] We used this strict mechanism consisting of the attention check and comprehension questions to warrant high data quality.

prices, i.e. the number of shares times price. In HIGH-FRACTIONAL, we provided the opportunity to purchase fractional shares corresponding to the proportion of LOW, hence the steps of the slider in this treatment are identical to LOW while the number of shares had two digits after the comma. Consequently, participants in LOW and HIGH-FRACTIONAL were able to invest an equal amount at any point, while this was not the case in HIGH. We randomized the order of the first five stocks and afterwards the order of the two remaining stocks. We implemented an additional attention check comparable to the previous one between the two sets of stocks.

After the main experimental task, we employed general questions to obtain control variables for the regressions, i.e. participant characteristics that were found to co-move with risk-taking. We asked for their self-assessed investment experience compared to the general population (Likert scale, 1-5), statistical knowledge compared to the general population (Likert scale, 1-5), risk tolerance (Likert Scale, 1-10), and for their year of birth and gender. We additionally elicited the participants' understanding of the experiment (Likert scale, 1-5) and provided an opportunity to enter comments on the study[5]. Appendix A presents screenshots of the survey.

Upon completion, the participants received a fixed fee of \$0.5 and a bonus corresponding to the choices made in the experiment. Therefore, we simulated each stock's three months' development by extracting returns from the initial return distribution used to generate the price charts ($\mu = 8\%; \sigma = 18\%$). We randomly selected one of the participant's choices to determine the total payoff ($Endowment - Investment_t + Investment_{t+3}$). We divided this total pay-off by 10,000 and paid the corresponding amount as a bonus. Overall, the average duration spent to complete the study was 8.32 minutes. The average payment was \$1.56, resulting in an hourly wage of \$11.25.

3 Results

The 450 US retail investors in the main experiment were mostly males (63%) and on average 43 years old. The participants rated their statistical knowledge and their investment experience slightly higher than the general population, while their risk tolerance was moderate with an average of 5.5 (1-10 scale). The mean score of understanding the study was 4.6 (out of 5), confirming that participants understood the questions well.

In this section, we present an overview of the results. We begin with a general section on the variations in investment decisions, forecasts, and risk perception across stock price levels in the treatments HIGH and LOW. Next, we extend our analysis to the possibility of executing fractional share purchases. Afterwards, we report experimental results on the stock price level's dependence when manipulating the display format, i.e., we faded out the number of shares associated with a

[5] The comments indicate that most participants either did not have specific comments or did understand the survey well.

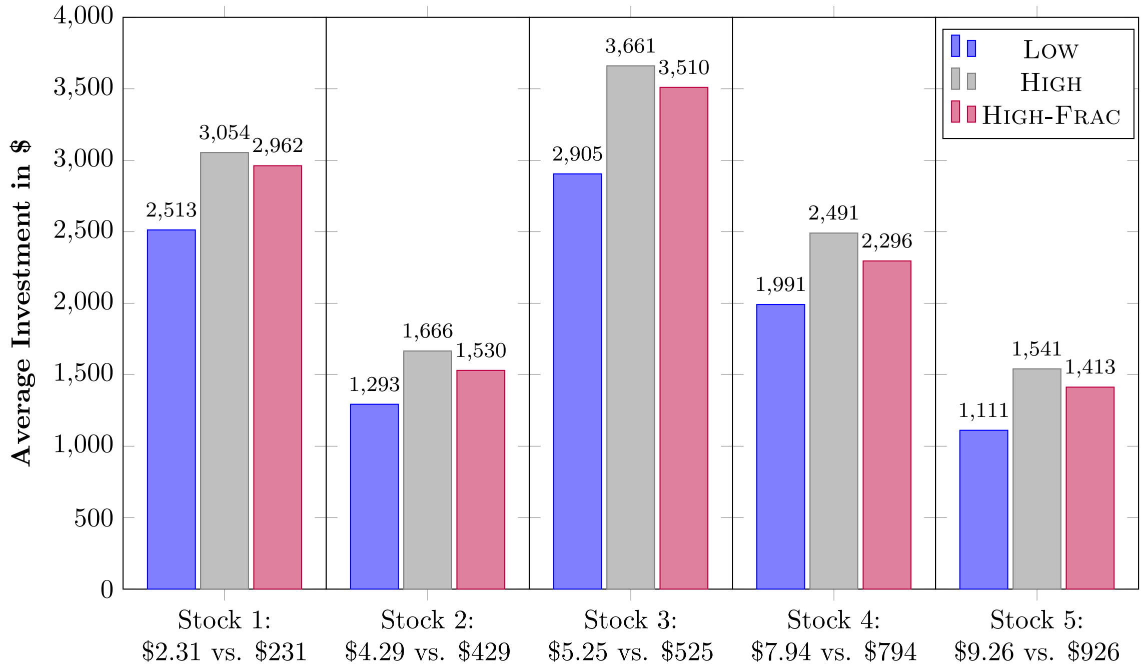

Figure 2: Average Investment Amounts in Low, High and High-Fractional. The participants had an initial endowment of $10,000 for each stock to invest, while the remainder was deposited at a 0% interest rate. The stocks differed in their prices and the displayed price path. We multiplied the stock prices in Low by 100 in High. In High-Fractional, individuals could execute fractional share purchases with a factor of 0.01, while participants in High could only buy entire shares.

specific investment amount.

3.1 Stock Price Levels

3.1.1 Investment Decisions

Figure 2 depicts the investment decisions for the first five stocks. For each stock, the investment amount in treatment High exceeds the amount in Low. This excess is substantially different across stocks. We assume that the displayed price path plays an important role. For instance, Stock 1 and Stock 4 show upward-sloping price trends, while Stock 2 and Stock 5 show downward-sloping price trends. On the other hand, stock 3 exhibited a stable trend. The variations in investment amounts between high- and low-priced stocks range from $373 in Stock 2 to $756 in Stock 3. Recall that participants in High could only purchase whole shares, i.e., the design prohibited fractional share purchases.

Table 2 presents a statistical analysis that corroborates these first insights. We employ a random-effects regression on the investment amount for the first five stocks. Model (1) purely considers the treatment effect by considering the treatment dummy $High$ (we discuss $High-Fractional$ in a later section). Model (2) controls for subject-specific factors. Our results indicate that the amount invested is significantly higher in treatment High; the treatment difference is approximately $500 compared to low-priced stocks. We thus find an investment increase of about 25% for high-priced stocks related to the average investment of $1963 in Low. Our findings reveal a substantial variation in investment decisions depending on stock price levels, hence providing evidence for the stock price level effect. Among the subject-related characteristics, we find risk tolerance to positively correlated with investment levels, while all other characteristics do not exhibit statistical significance. One problem in the regression analysis might be the difference in the dependent variable as the scaling between Low and High differs, i.e., individuals in High had lower flexibility of choosing particular investment amounts. For instance, in High stock 5 had ten possible investment levels: $926, $1,852, $1,948,..., and $9,290. Instead, the investment levels in Low were $9.26, $18.52, $19,48,..., and $9,991, i.e., 1,076 possibilities. In Appendix B, we report a robustness check where we 'round' the dependent variable *investment* in Low to the closest High price. The results are comparable to the main analyses.

Observation 1 We observe a stock price level effect for the amount invested: investments in high-priced stocks rise by 25% compared to low-priced stocks.

Assume an investor is willing to invest about $6,000 in stock 4. In Low, the investor could buy 755 or 756 shares investing $5,994.70 or $6,002.64, respectively. In High, the investor could buy either seven or eight shares investing $5,558 or $6,352. The question for the investor is now what amount to invest in High. Our results suggest that even though investors are expected to be rather risk-averse, they opt for the higher amount.

3.1.2 Risk Perception and Forecasts

Figure 3 presents the average risk perception and the average forecast across treatments, comparing the treatments High and Low. The figure does not illustrate a pronounced trend in risk perception across stock price levels. While for stocks 1 and 3, the risk perception is higher for the lower-priced stocks, the opposite holds for the other stocks. Regarding the forecasts, we observe that the forecast is slightly higher for low-priced stocks. Overall, however, the forecasts are relatively similar across treatments.

Table 3 presents the results of random-effects models for risk perception and forecasts. None of the models shows a significant treatment effect. We acknowledge potential variations in forecasts based on stock price levels in line with previous studies. Nevertheless, the effect size might be limited, and we cannot detect it in our experiment.

Observation 2. We observe no stock price level effect in the perception of risk nor for the forecasts. Risk perception and expectations seem to not explain investment differences.

Table 2: Random-Effect Regression Analyses on Investment Amount for Stock 1 to 5.

	(1) Investment Amount	(2) Investment Amount
High	519.9*	488.2*
	(2.46)	(2.38)
High-Fractional	379.6	334.5
	(1.81)	(1.65)
Investment experience		-161.0
		(-1.26)
Statistical knowledge		-165.7
		(-1.29)
Risk tolerance		256.2***
		(5.82)
Gender		-31.62
		(-0.17)
Age		1.215
		(0.19)
Understanding		114.6
		(0.96)
Constant	1962.5***	1634.2*
	(13.25)	(2.29)
Observations	2250	2250
R^2	0.01	0.14
Controlled for Stocks?	Yes	Yes

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The endowment was $10,000 for each stock. High is a treatment dummy with the value of 1 for participants assigned to High and 0 in Low (we applied the same principle to High-Fractional). We assessed investment experience and statistical knowledge compared to the general population on a scale from 1 (much lower) to 5 (much higher); risk tolerance on a scale from 1 (low) to 10 (high); and understanding ranges from 1 (low understanding) to 5 (high understanding).

3.2 Fractional Share Trading

When comparing treatments, we cannot determine whether Observation 1 results from the differences in stock prices or the limited opportunities of investment levels in High. The deficiency of fractional share trading might thus be one reason for the existence of the stock price level effect, as investors potentially take higher risks for high-priced stocks than they usually would in the absence of this constraint. As a consequence, we included the treatment High-Fractional to control for the possibility of executing fractional share purchases. In this treatment, participants can invest the same amount as in Low, i.e., we admit fractional share purchases with a factor of 0.01. Related to the stock 4 example above, an investor could buy 7.55 shares in High-Fractional, investing the same amount

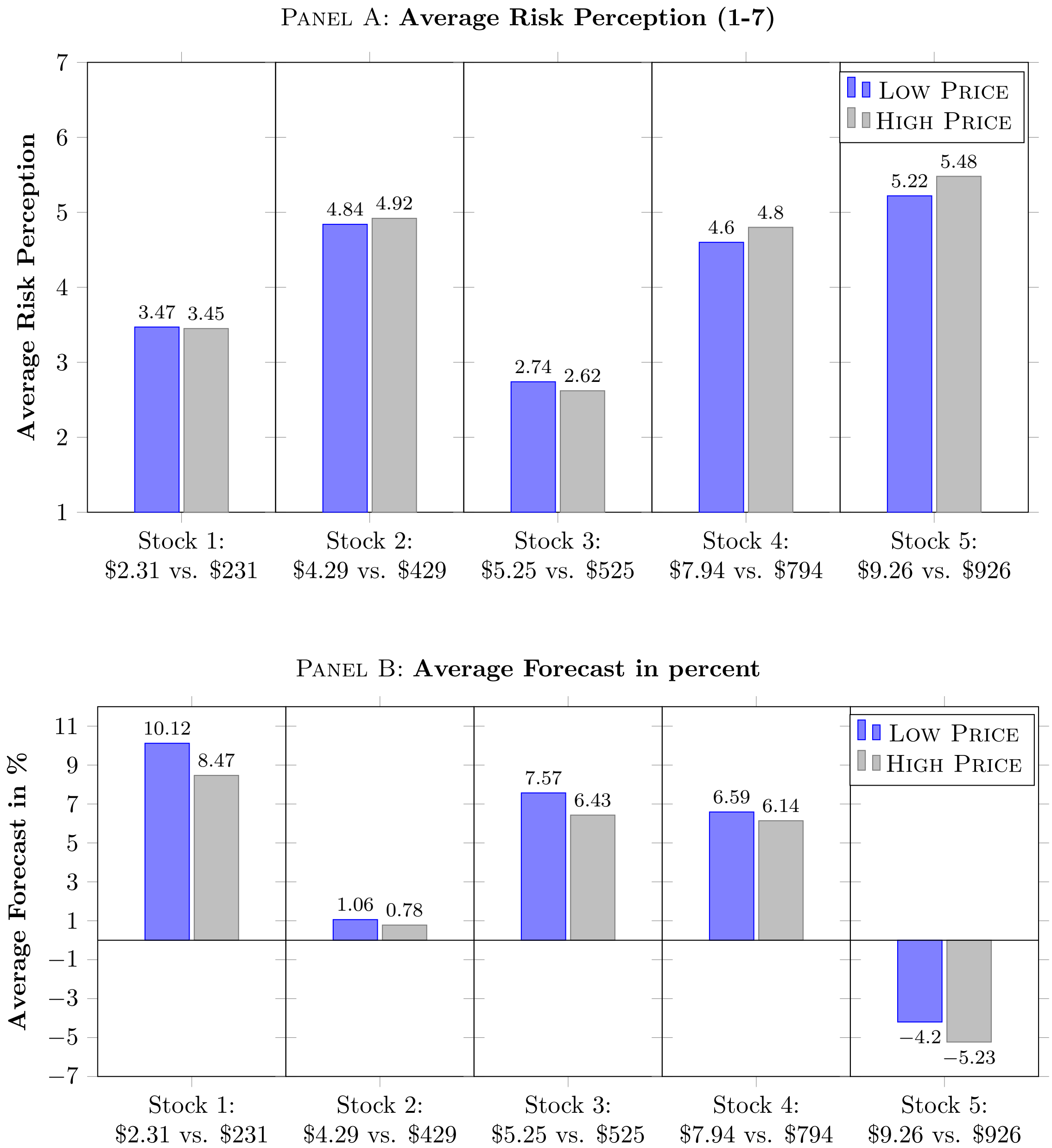

Figure 3: Overview of the results on risk perception and forecasts. The results show the score of risk perception (Panel A) and forecasts in % (Panel B) in Low and High. We measured risk perception on a scale from 1 (Not risky) to 7 (Very Risky) and forecasts using a slider with the default value on the current price and a range of $0 to two times the current price, the forecast calculated as a percentage.

as purchasing 755 shares in Low. Note that brokers generally restrain the possibility of executing fractional share trades. However, technical advancements result in an increasing proportion of brokers permitting fractional share trading.

Figure 2 also illustrates the average investment amount in High-Fractional. In High-Fractional, individuals invest more than in Low, but less than in High. Generally, the investment amounts in High-Fractional lean more towards the ones in High. The discrepancies in invest-

Table 3: Random-Effect Regression Analyses on Risk Perception and Forecasts.

	(1) Risk perception	(2) Risk perception	(3) Forecast in %	(4) Forecast in %
High	0.0824	0.0916	-0.914	-0.974
	(0.87)	(0.96)	(-0.78)	(-0.83)
Investment experience		0.0230		-0.680
		(0.32)		(-0.77)
Statistical knowledge		-0.00979		-0.123
		(-0.14)		(-0.14)
Risk tolerance		0.0000870		0.670*
		(0.00)		(2.15)
Gender		0.185		1.112
		(1.73)		(0.84)
Age		0.00456		0.0317
		(1.23)		(0.70)
Understanding		-0.0922		-1.200
		(-1.36)		(-1.44)
Constant	4.172***	3.532***	4.229***	12.41*
	(62.86)	(8.49)	(5.16)	(2.40)
Observations	1490	1490	1490	1490
R^2	0.00	0.38	0.00	0.08
Controlled for Stocks?	Yes	Yes	Yes	Yes

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. We measured risk perception on a scale from 1 (Not risky) to 7 (Very Risky) and forecasts using a slider with the default value on the current price and a range of $0 to two times the current price, and the forecast calculated as a percentage. High is a treatment dummy with the value of 1 for participants assigned to High and 0 in Low. We assessed investment experience and statistical knowledge compared to the general population on a scale from 1 (much lower) to 5 (much higher); risk tolerance on a scale from 1 (low) to 10 (high); and understanding ranges from 1 (low understanding) to 5 (high understanding).

ments between Low and High-Fractional range from $237 in Stock 2 to $605 in Stock 3. The biggest variation in investments between High and High-Fractional is $195 in Stock 4. Overall, the visual evidence suggests that the stock price level effect is diminished under the presence of fractional share purchases, even though it does not vanish entirely.

We examine the stock price level effect between Low and High-Fractional in a random-effects analysis, presented in Table 2. The results illustrate that the variation in investment amounts between Low and High-Fractional is not statistically significant. Hence, even though Figure 2 suggests that there might be a stock price level effect even when fractional share trading is permitted, the effect size appears to be rather confined. We argue that investors often have to choose between two numbers of shares in High, e.g., three or four, as fractional share purchases are prohibited. Frequently, they appear to choose the one that includes purchasing a higher number of shares, leading to increased investment amounts. As a result, when we permit fractional share trading, they invest less on average. Generally, our findings imply that the possibility to execute fractional share purchases diminishes the stock price level effect. However, the visual evidence implies that there might be a distinction between low- and high-priced stocks even when fractional share purchases are allowed.

Observation 3. The possibility to execute fractional share purchases diminishes the presence of the stock price level effect.

3.3 Number of Shares

In the three treatments, the investors decide on the amount to invest by using a slider. The intermediate steps are multiples of the stock price. This amount to invest is accompanied by the number of shares necessary to buy the stock. Of course, this number is relatively high for low-priced stocks and low for high-priced stocks. Previous studies identified naive trading strategies concerning the number of shares (Shue & Townsend, 2019) or the numerosity bias (West et al., 2020). Those strategies can play an essential role in the stock price level effect. In a follow-up experiment, we reduced such bias by letting the participants concentrate on the investment amount only, as we did not display the number of shares anymore. We again invited 450 US retail investors, while keeping all other factors constant.

Figure 4 reports the average investment amounts in the treatments not displaying the number of shares. The variations in investments are less pronounced than in the main experiment. The variations between Low and High-Fractional are minor, and for Stock 1 the investment in Low is even slightly higher than in High-Fractional. We run a random-effects analysis illustrated in Table 4. Its results corroborate these observations as neither treatment dummy High or High-Fractional is significant. Hence, displaying the number of shares in addition to the investment amounts seems to trigger the stock price level effect.

Observation 4. The stock price level effect disappears when we solely disclose the amount invested but not the number of shares.

3.4 Lower Price Distance and Prominent Numbers

We implemented Stock 6 and 7 referring to Glaser et al. (2019). In contrast to Stocks 1 to 5, they possess a lower price distance (factor 10 instead of 100 between low and high prices) and consist of prominent numbers (10, 100, and 1000). Glaser et al. (2019) compare investors' forecasts for stock prices of \$100 versus \$1000 and find no statistical differences in these forecasts. We examine risk perception, forecasts, and investment decisions for the original task with Stock 6 priced at \$100 in Low and at \$1000 in High and High-Fractional. Those are relatively high prices, which might activate logarithmic number processing. Hence, we also compare stocks priced at \$10 and at

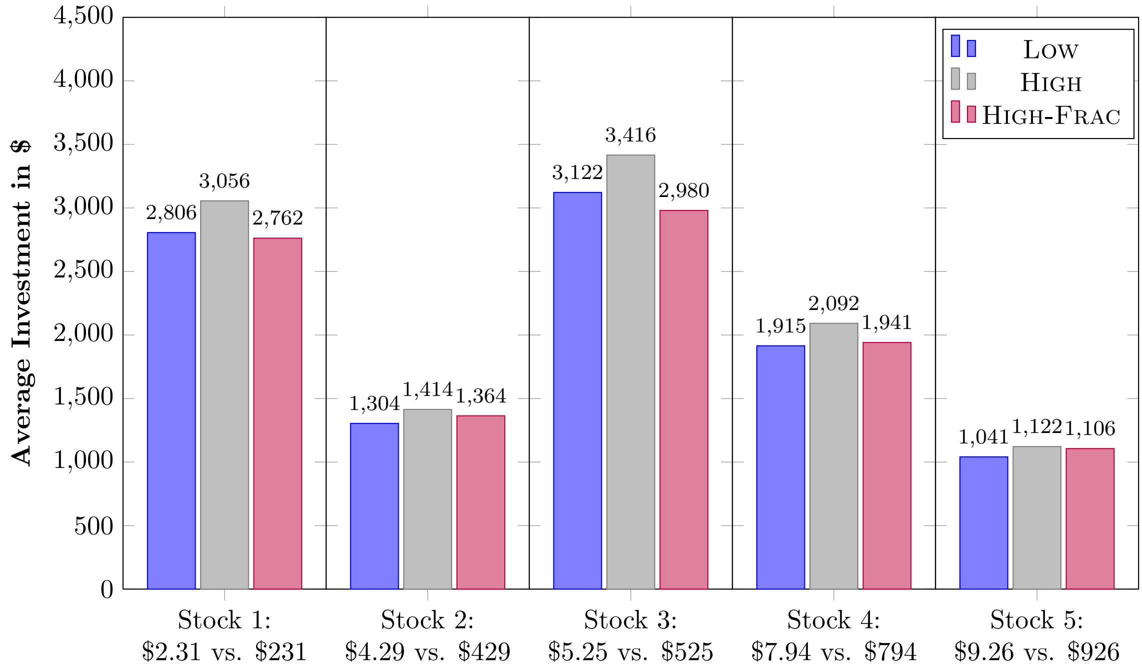

Figure 4: Average Investment Amounts in Low, High and High-Fractional, without displaying the number of shares. The participants had an initial endowment of $10,000 for each stock to invest, while the remainder was deposited at a 0% interest rate. The stocks differed in their prices and the displayed price path. We multiplied the stock prices in Low by 100 in High. In High-Fractional, individuals could execute fractional share purchases with a factor of 0.01, while participants in High could only buy entire shares.

$100. We further investigate the influence of fractional share purchases and the display format of the investment decision on the stock price level effect for these two stocks.

We consider a detailed analysis in Appendix C. The results are comparable to our previous findings. We find no differences in risk perception or forecasts, but a substantial variation in investment amounts between Low and High. Glaser et al. (2019) solely examine future price forecasts and could not detect a connection between stock price levels and the magnitude of the forecast, which is in line with our findings. However, stock price levels substantially influence investment decisions. Again, the stock price level depends on fractional share trading and information disclosure.

> **Observation 5.** We detect the stock price level effect for lower distances between prices (factor of 10 instead of 100), in higher price ranges ($100 vs. $1000) and for prominent numbers (10, 100 and 1000).

4 Discussion

This study presents experimental evidence on the effect of stock price levels on investor behavior. We report an increase of investments by 25% in high- compared to low-priced stocks, holding all other factors constant. We demonstrated that the lack of fractional share purchases and individuals'

Table 4: Random-Effects Regression Analyses on Investment Amount (no number of shares displayed).

	(1) Investment Amount	(2) Investment Amount
HIGH	187.4	148.0
	(0.90)	(0.72)
HIGH-FRACTIONAL	84.54	82.71
	(0.40)	(0.40)
Investment experience		-9.903
		(-0.08)
Statistical knowledge		-266.6*
		(-2.12)
Risk tolerance		65.35
		(1.51)
Gender		-508.3**
		(-2.73)
Age		-18.13**
		(-2.82)
Understanding		-114.0
		(-0.97)
Constant	2417.5***	4806.6***
	(16.15)	(6.86)
Observations	3150	3150
R^2	0.00	0.16
Controlled for Stocks?	Yes	Yes

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The endowment was $10,000 for each stock. HIGH is a treatment dummy with the value of 1 for participants assigned to HIGH and 0 in LOW. We assessed investment experience and statistical knowledge compared to the general population on a scale from 1 (much lower) to 5 (much higher); risk tolerance on a scale from 1 (low) to 10 (high); and understanding ranges from 1 (low understanding) to 5 (high understanding). We do not display the number of shares.

anchoring on share numbers contribute to this stock price level effect. Note that experimental methodology allowed us to test what elements cause the stock price level effect.

Companies seem to establish optimal stock price ranges to expand the diversity in shareholders, in particular, to increase the share of individual investors among shareholders (e.g. Dyl & Elliott, 2006; Schultz, 2000). This investor type might not be able to trade high-priced shares as they cannot such high prices. When different investment types trade at different price levels, an endogeneity bias will occur when running regressions on archival data. Consequently, a stock price level effect could be detected, which might be due to different investor types rather than the stock price level itself. In our experimental set-up, the endowment was sufficient to obtain multiple shares of the high-priced stocks, thereby eliminating this uncontrollable real-world effect. Yet, we still observe an elevated investment amount, hinting at an increase in risk-taking if investors' preferred level of risk lies between two numbers of shares. In some cases, however, the difference in investment amounts across treatments was higher than the price of one share, speaking in favor of further psychological explanations. Permitting fractional share purchases diminishes the stock price level effect but does not eliminate it.

An additional robustness check illustrates that displaying the number of shares causes the stock price level effect. When we stopped providing the number of shares, we observed a meaningful convergence of investments across all treatments. These results imply that individual investors naively focus on the number of shares without considering the actual investment amounts. Shue and Townsend (2019) explain that after a split the trading volume of a stock decreases, consistent with an explanation that individual investors trade a fixed number of shares naively. For a low-priced stock, the number of shares is significantly higher as for high-priced stocks, given the same absolute investment amount. West et al. (2020) demonstrate that individuals exhibit the numerosity bias, implying that individuals prefer to receive more than fewer shares in a stock split, even though the aggregate economic value is identical. This bias has also been observed in other contexts, as individuals prefer bonus packs over discounted prices, even though the discounts yield higher economic value (Chen, Marmorstein, Tsiros, & Rao, 2012). We argue that the number of shares largely influences individual investors and that they prefer more to fewer shares, especially when the number of shares is low. Our results might be explained by the fact that humans process small numbers on a linear and large numbers on a logarithmic scale (Nieder, 2005; Roger, Bousselmi, et al., 2018). Such behavior results in a higher desire to acquire more shares in the treatment of the high-priced stock, as the number of shares is generally relatively low compared to the treatment of the low-priced stock. As a consequence, investors increase risk-taking in high-priced stocks.

In our experiments, we do not discern a variation in investor risk perception or future forecasts. Birru and Wang (2016) indicate that individuals overestimate the skewness of lower-priced stocks, as they believe that lower-priced stocks have more "room to grow", potentially leading to higher forecasts for low-priced stocks. Additionally, Roger, Roger, and Schatt (2018) consider the stock price level effect elaborating on analysts' forecasts. They conclude that optimistic analysts issue more optimistic target prices for small price stocks than for large price stocks and vice versa for pessimistic analysts. Overall, we find no effects on forecasts independent on the stocks' pattern (increasing, decreasing). However, to find support for their empirical result in our experimental data, we test whether for stock 1 (most optimistic outlook) forecasts are higher in treatment LOW while in stock 5 (most pessimistic outlook) forecasts are higher in HIGH.[6] Considering all 900 observations for stock 1, we get an average forecast of 10.93% forLOW and 9.74% for HIGH. A

[6] Panel B in Figure 3 shows the highest (positive) forecasts for stock 1 and the lowest (negative) forecasts for stock 5. Hence, we can assume stock 1 to have an optimistic outlook while stock 5 has a pessimistic outlook.

simple t-test shows not significant difference ($p = 0.378$). For stock 5, the averages are -4.45% and -4.71%, respectively, and not significantly different ($p = 0.852$). The direction is even against the result from Roger, Roger, and Schatt (2018). Hence, our results do not confirm the results of Roger, Roger, and Schatt (2018). Of course, we used controlled experiments with a different environment, in particular they consider price ranges up to $40, while we consider much higher price differences. Furthermore, our design was not implemented to test for such an effect. Hence, our results are not directly comparable. We do not find evidence that variations in future forecasts drive the stock price level effect in our setting. Our results are thus in line with Glaser et al. (2019). They do not find a difference in forecasts between a stock priced at $100 and another one at $1000.

5 Conclusion

Companies around the globe manage their stock prices in IPOs and through stock splits or stock repurchases to retain their stock price within a particular range (e.g. Bae et al., 2019; Dyl & Elliott, 2006; Weld et al., 2009). Some studies consider the effect of stock price levels on investment behavior. Previous research mainly focused on empirical data, for instance, on periods surrounding stock splits, and determined that stock price levels influence investor behavior (Costa, 2020; Roger, Bousselmi, et al., 2018) and market performance (Brennan & Copeland, 1988a; Desai & Jain, 1997). Our study contributes to these previous studies by conducting a controlled online experiment on the existence and potential drivers of the stock price level effect. Based on the data of 900 US retail investors, we illustrate that investments are increased by 25% when stock prices are high compared to low. We identify two potential drivers of the stock price level effect. Our results demonstrate that the implementation of fractional purchases diminishes the effect. Additionally, the findings indicate that individuals' investment decisions depends on the number of shares and not only on the amount to invest. Erasing the number of shares during the investment decision eliminates the stock price level effect.

Our findings have relevant implications both on a theoretical as well as on a practical level. We contribute to the theoretical debate by showing that preferences alone do not shape investment behavior, as we illustrate the stock price level effect under controlled conditions. Hence, we establish the connection between psychological biases and investor behavior dependent on stock price levels. This relationship seems fundamental and is not necessarily caused by specific events, such as stock splits. On a practical level, we report that design elements in choice architecture play an important role. Simply displaying the number of stocks has a relevant effect on the amount to invest. We think that financial regulators should take such effects into account when examining providers of financial services. Even more, executing fractional share purchases seem to accommodate the investors' preferences. Hence, our treatment manipulations potentially lead to a more appropriate representation of investors' risk preferences.

Our experiment aimed to compare decisions between treatments in a static environment. One possible extension of our research is introducing a dynamic trading environment where we could test how changes in prices affect investments at different stock levels. Additionally, based on a previous experiment by Glaser et al. (2019), the influence of diverse presentation formats, for instance, by promoting return bar charts instead of price charts, can provide essential insights on the robustness of the stock price level effect. Furthermore, researchers can consult brokerage data to examine the stock price level effect in real-life investment decisions of retail investors.

We thus advocate for future research on design elements in financial decision making. We think that experiments can help carve out optimal investment designs that accurately reflect the investors' preferences without distorting decisions due to psychological biases.

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A Appendix A

A.1 All price charts

Table 5: All price charts 1-4

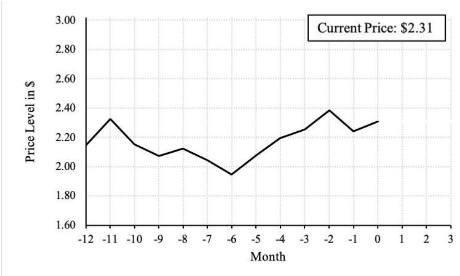
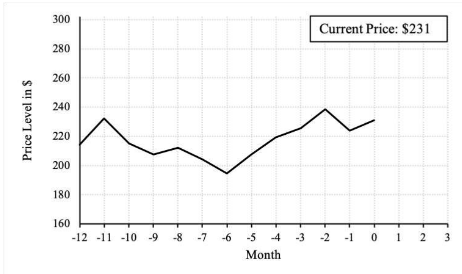
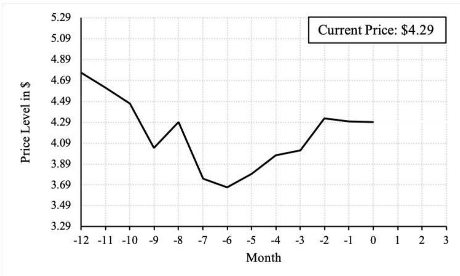
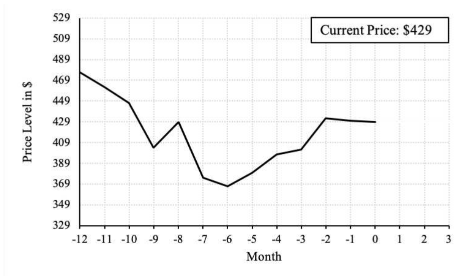
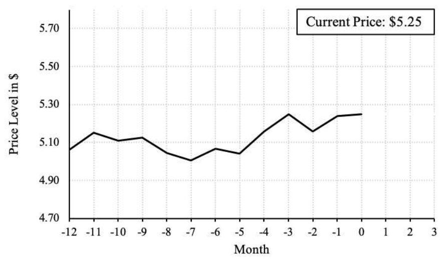
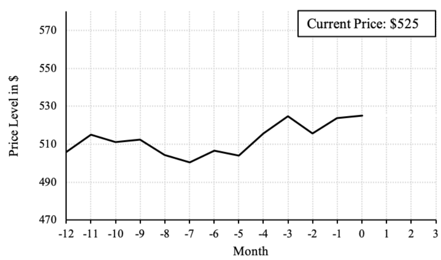
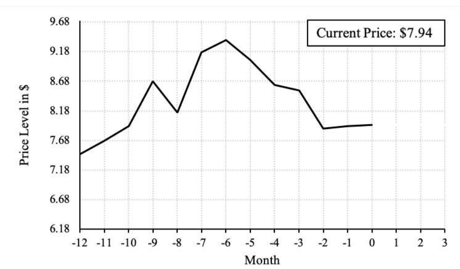
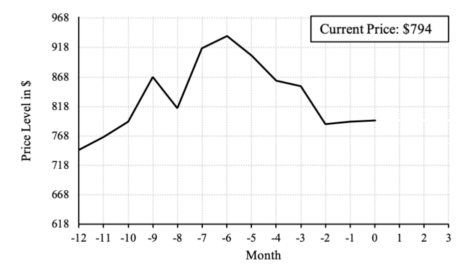
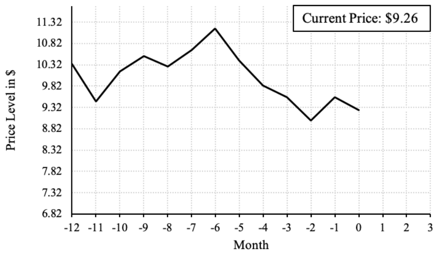
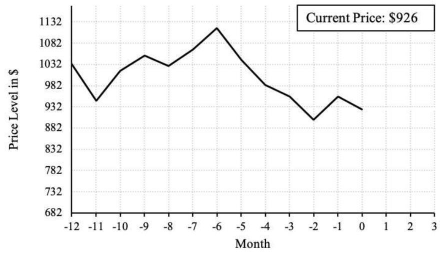
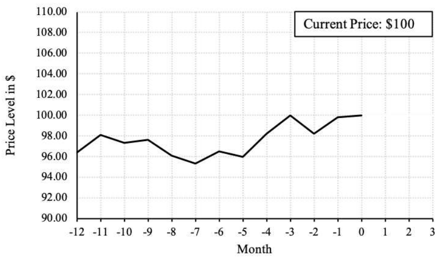
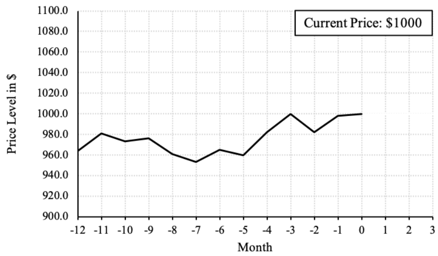
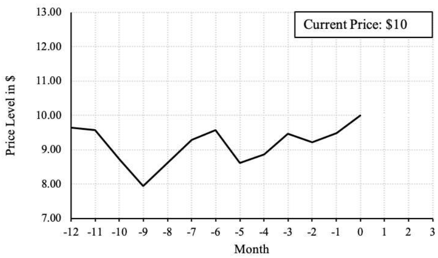
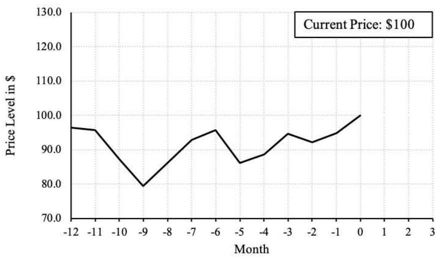
Stock	Low	High
1		
2		
3		
4		

Table 6: All price charts 5-7

Stock	Low	High
5		
6		
7		

A.2 Screenshots of the experiment

INFORMATION AND CONSENT

You are invited to participate in a research study about investment decisions.
The procedure involves filling out an online survey. The questions concern your perception and willingness to invest in a financial asset. Filling out the survey will take approximately 10 minutes. Risks are minimal for involvement in this study, it is very unlikely that answering these questions will affect you emotionally or otherwise.

What will happen to my data?
The research data we collect during this study will be used by scientists as part of data sets, articles and presentations. The anonymized research data is accessible to other scientists for a period of at least 10 years. When we share data with other researchers, these data cannot be traced back to you.

Voluntary participation
Your participation in this research is voluntary. This means that you can withdraw your participation and consent at any time during the survey, without giving a reason. All data we have collected from you will be deleted permanently. If you desire to withdraw, please simply close your internet browser.

More information?
This study is conducted by Charlotte Borsboom (Radboud University Nijmegen, Netherlands) and Prof. Dr. Sascha Füllbrunn (Radboud University Nijmegen, Netherlands). Should you want more information or have any complaints on this research study, please contact Charlotte Borsboom (email: c.borsboom@fm.ru.nl).

Should you have any complaints regarding this research, please contact the researcher.

CONSENT: Please select your choice below.

Checking "Agree" below indicates that:
• you have read the above information
• you voluntarily agree to participate
If you do not wish to participate in the research study, please decline participation by checking "I do not want to participate".

◯ I agree with the above, and I would like to proceed to the survey

◯ I do not agree, and I do not want to participate

Please enter your workerID here:

→

Proceed by clicking on the second and the sixth option. Do not select any of the other choices. This is only an attention check.

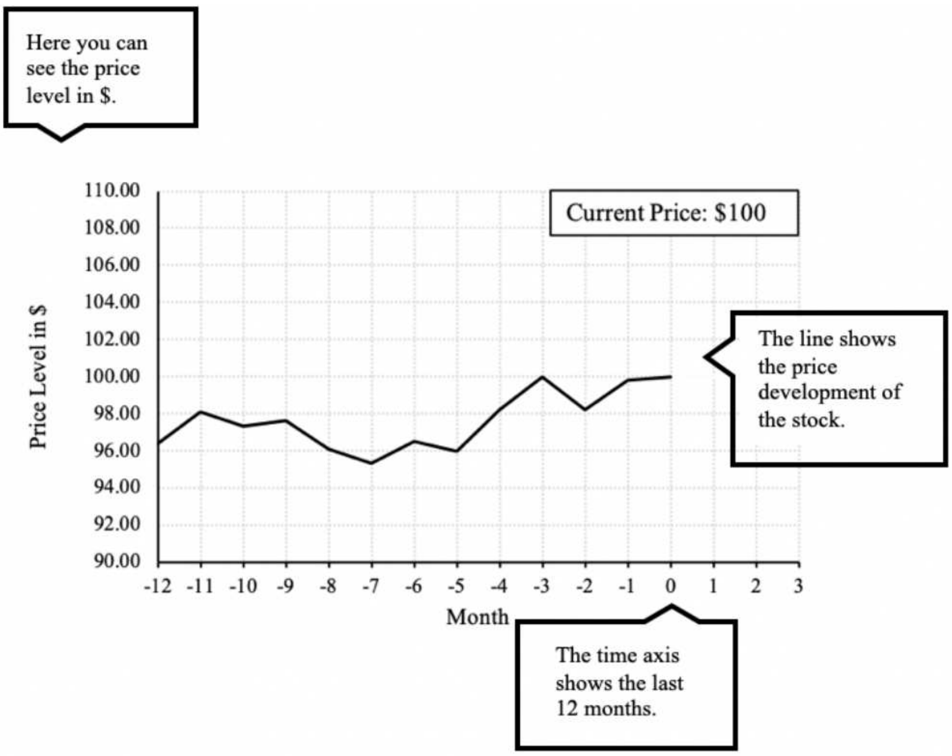
1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

→

Please read the following instructions carefully. Answer the three comprehension questions correctly to proceed to the main part of the study.

Set-up of the study

In the following tasks, you decide how much to invest in a stock (which pays no dividends). For each decision, a line chart indicates the development of the stock price over the last 12 months. The line chart below explains how to read such information.



You participate in seven separate tasks. In each task you

1) Evaluate the stock's riskiness on a scale from “Not risky” to “Very risky”.
2) Judge the stock’s potential by indicating the price level that is most likely to be achieved in three months.
3) Decide how much to invest in the stock over three months. You receive an endowment of $10000. The amount not invested is yours to keep (0% interest rate).

Afterwards, we kindly ask you to provide details about your background.

Monetary compensation

Your compensation for the experiment depends on the decisions you make.
The program will randomly pick one of your investment decisions and derive the value after three months.
Your pay-off equals the amount not invested plus the sale of your investment evaluated in three months, divided by 10,000.
(e.g. total value of 12,345 yields $1.2345)
Also, you will receive a fixed reward of $0.5 for completing the study.

How many months of stock price developments are displayed in the line chart?

- ◯ 1 month
- ◯ 3 months
- ◯ 6 months
- ◯ 12 months

You need to provide a price forecast of the stock's price in ... month(s) from now.

- ◯ 1
- ◯ 3
- ◯ 6
- ◯ 12

The amount not invested yields ...% interest rate.

◯ -1

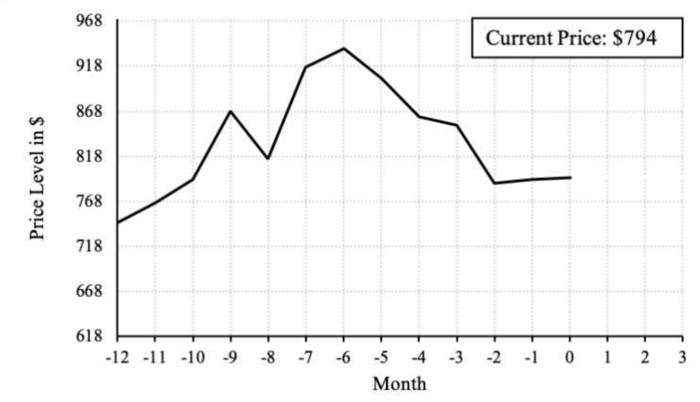
◯ -0.5

◯ 0

◯ 0.5

→

Investment opportunity 1

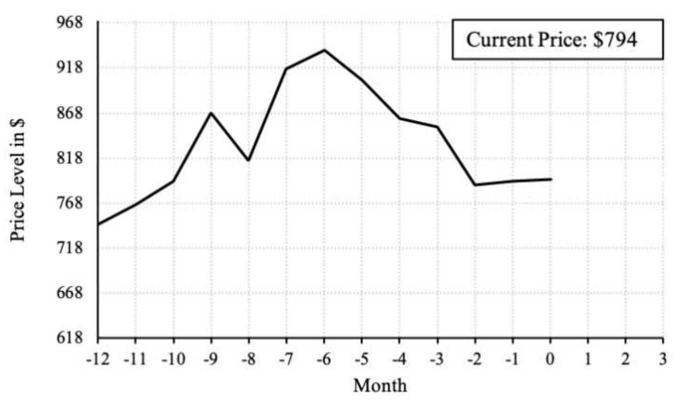


How risky do you perceive this stock to be?

	Not risky						Very risky
Perceived risk	◯	◯	◯	◯	◯	◯	◯

→

Investment opportunity 1



Please forecast the price in three months from now. Submit a forecast such that the realized price lies with equal probability above or below your forecast. Use the blue dot to adjust your forecast.

0 1588

Forecast $794

→

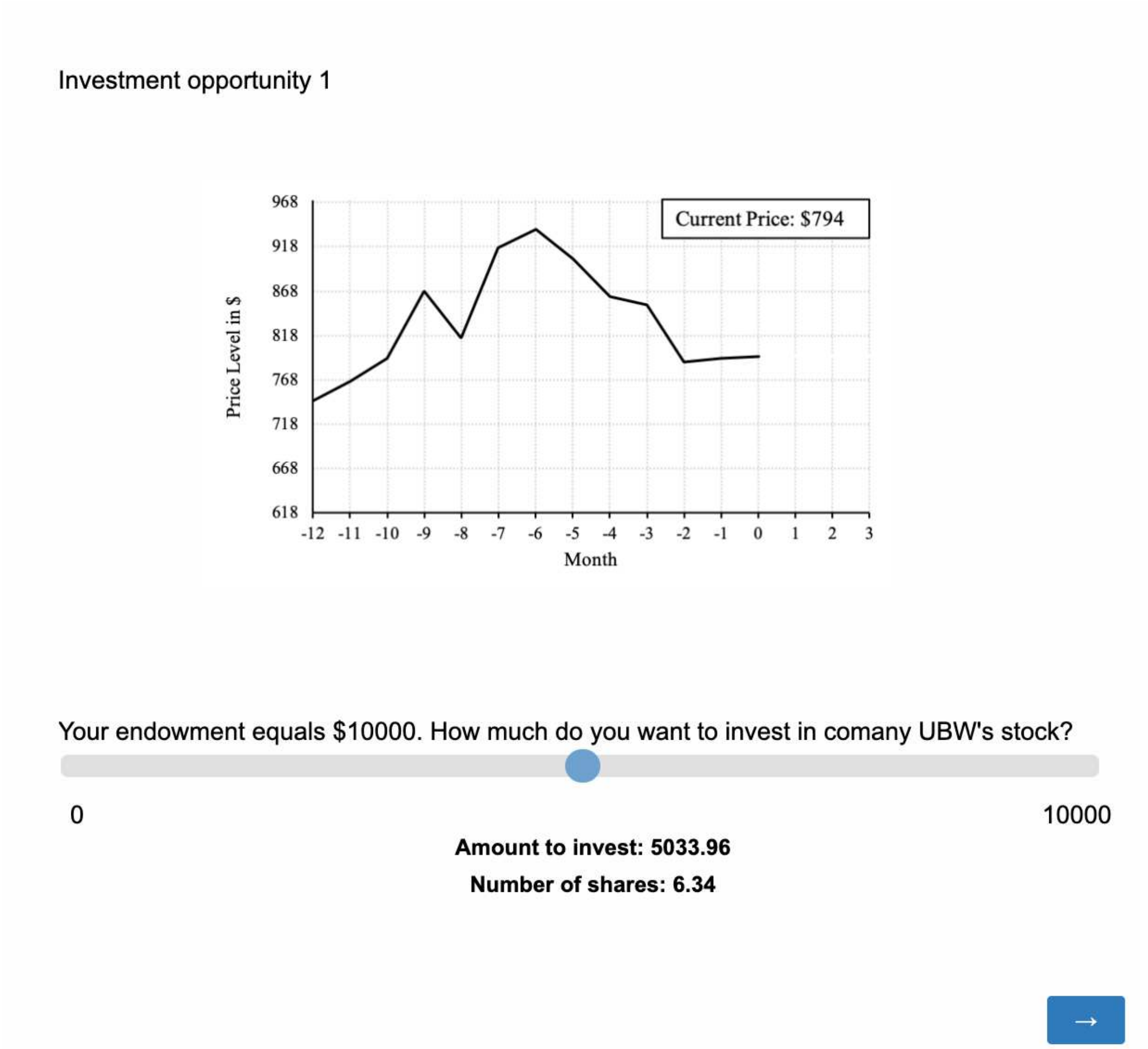


Figure 5: ***Explanation:*** *This is an investment task in the treatment* High-Fractional *because there was the possibility to purchase shares in fractions of 0.01, which was not possible in* High*. The participants saw seven different investments. We placed an attention check similar to the first between the first five and the last two decisions. After participants evaluated all investment opportunities regarding riskiness, future potential, and investments, the participants proceeded to the general questions.*

To finish, some general questions:

Do you currently invest money in stocks, bonds, mutual funds or other financial instruments?

- ◯ Yes
- ◯ Not currently, but I used to invest.
- ◯ No

How do you rate your own investment experience, compared to the average population?

- ◯ Much lower
- ◯ Slightly lower
- ◯ About the same
- ◯ Slightly higher
- ◯ Much higher

How do you rate your own statistical knowledge, compared to the average population?

- ◯ Much lower
- ◯ Slightly lower
- ◯ About the same
- ◯ Slightly higher
- ◯ Much higher

On a scale of 1 to 10, how willing are you to take financial risks?

	Not willing to take risks	2	3	4	5	6	7	8	9	Very willing to take risks
Willingness to take financial risks	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

What is your gender?

- ◯ Male
- ◯ Female
- ◯ Other

In which year were you born?

Year

I did understand the questions in this study well.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

Do you have any comments about the study?

→

B Appendix B

B.1 Variations in the dependent variable

Table 7 illustrates the analysis of the stock price level effect when we adjust the dependent variable. In the experiment, the investment flexibility for respondents in High was limited due to the higher prices and lack of fractional share purchases. To rule out any effects arising from this limitation, we adjusted the investment amount for Low, by rounding it to the closest corresponding High investment amount. We find that the stock price level effect is comparable in significance and magnitude to the original model.

Table 7: Random-Effects Regression Analyses on Investment Amount, with adjusted dep. var.

	(1) Investment adjusted	(2) Investment adjusted
High	515.5*	483.6*
	(2.43)	(2.36)
High-Fractional	375.1	330.2
	(1.79)	(1.63)
Investment experience		-161.4
		(-1.26)
Statistical knowledge		-161.3
		(-1.25)
Risk tolerance		255.6***
		(5.80)
Gender		-35.55
		(-0.19)
Age		1.305
		(0.20)
Understanding		113.2
		(0.95)
Constant	1967.0***	1630.8*
	(13.27)	(2.28)
Observations	2250	2250
Controlled for Stocks?	Yes	Yes
R^2	0.01	0.14

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. We adjusted the dependent variable, investment as Investment(adjusted) = round(Investment(Low)/Price(High))*Price(High). The endowment was $10,000 for each stock. High is a treatment dummy with the value of 1 for participants assigned to High and 0 in Low. We assessed investment experience and statistical knowledge compared to the general population on a scale from 1 (much lower) to 5 (much higher); risk tolerance on a scale from 1 (low) to 10 (high); and understanding ranges from 1 (low understanding) to 5 (high understanding).

Table 8 illustrates the same adjustment in the dependent variable as in Table 7, but for the sample without displaying the number of shares. Again, the results do not differ substantially from the previous analyses in Table 4.

Table 8: Random-Effects Regression Analyses on Investment Amount, with adjusted dep. var. and no number of shares.

	(1) Investment adjusted	(2) Investment adjusted
HIGH	230.3	192.4
	(1.07)	(0.91)
HIGH-FRACTIONAL	127.5	125.6
	(0.58)	(0.58)
Investment experience		-23.26
		(-0.17)
Statistical knowledge		-242.9
		(-1.86)
Risk tolerance		65.14
		(1.45)
Gender		-548.4**
		(-2.85)
Age		-17.82**
		(-2.68)
Understanding		-119.7
		(-0.98)
Constant	2374.5***	4771.2***
	(15.36)	(6.58)
Observations	3150	3150
Controlled for Stocks?	Yes	Yes
R^2	0.00	0.14

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. We adjusted the dependent variable, investment as Investment(adjusted) = round(Investment(LOW)/Price(HIGH))*Price(HIGH). The endowment was $10,000 for each stock. HIGH is a treatment dummy with the value of 1 for participants assigned to HIGH and 0 in LOW. We assessed investment experience and statistical knowledge compared to the general population on a scale from 1 (much lower) to 5 (much higher); risk tolerance on a scale from 1 (low) to 10 (high); and understanding ranges from 1 (low understanding) to 5 (high understanding).

C Appendix C

C.1 Robustness of Previous Studies

Table 9 displays the analysis of the stock price level effect for Stocks 6 and 7, which are a replication and extension of a study by Glaser et al. (2019). We detect the stock price level, hence an increase in the investment amount for high priced stocks, also for these stocks.

Table 9: Random-Effects Regression Analyses on Investment Amount for Stock 6 and 7.

	(1) Investment Amount	(2) Investment Amount
High	735.1*	655.2*
	(2.36)	(2.17)
High-Fractional	386.5	331.2
	(1.26)	(1.11)
Investment experience		163.3
		(0.88)
Statistical knowledge		-452.4*
		(-2.38)
Risk tolerance		315.0***
		(4.88)
Gender		-353.9
		(-1.30)
Age		-5.439
		(-0.57)
Understanding		-167.8
		(-0.97)
Constant	3127.9***	3489.0***
	(14.37)	(3.36)
Observations	860	860
R^2	0.01	0.07

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The endowment was $10,000 for each stock. High is a treatment dummy with the value of 1 for participants assigned to High and 0 in Low. We assessed investment experience and statistical knowledge compared to the general population on a scale from 1 (much lower) to 5 (much higher); risk tolerance on a scale from 1 (low) to 10 (high); and understanding ranges from 1 (low understanding) to 5 (high understanding).

Regarding the investor risk perception and forecasts, Table 10 illustrates that the forecast and the risk perception do not differ substantially between stock price levels for stocks 6 and 7. This is in line with previous research which shows that forecasts do not depend on stock price levels (Glaser et al., 2019).

Table 11 repeats the previous analysis displayed in Table 9, but then solely for the sample in

Table 10: Random-Effects Regression Analyses on Risk Perception and Forecasts for Stock 6 and 7.

	(1) Risk perception	(2) Risk perception	(3) Forecast in %	(4) Forecast in %
High	-0.0849	-0.0830	1.351	1.296
	(-0.69)	(-0.67)	(0.77)	(0.74)
Investment experience		0.0114		1.048
		(0.12)		(0.80)
Statistical knowledge		-0.00538		-1.777
		(-0.06)		(-1.33)
Risk tolerance		0.00730		0.508
		(0.22)		(1.10)
Gender		0.129		1.092
		(0.93)		(0.55)
Age		0.00467		0.0813
		(0.97)		(1.19)
Understanding		-0.115		-1.704
		(-1.32)		(-1.38)
Constant	3.283***	3.497***	6.761***	10.23
	(38.34)	(6.64)	(5.53)	(1.37)
Observations	568	568	568	568
Overall R^2	0.00	0.01	0.00	0.02

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. We measured risk perception on a scale from 1 (Not risky) to 7 (Very Risky), and the forecast using a slider with the default value on the current price and a range of $0 to two times the current price, calculated as a percentage. High is a treatment dummy with the value of 1 for participants assigned to High and 0 in Low. We assessed investment experience and statistical knowledge compared to the general population on a scale from 1 (much lower) to 5 (much higher); risk tolerance on a scale from 1 (low) to 10 (high); understanding ranges from 1 (low understanding) to 5 (high understanding).

which no number of shares were displayed. The results are similar to the ones obtained for stocks 1 to 5 in Table 4.

Table 11: Random-Effects Regression Analyses on Investment Amount for Stock 6 and 7, without the number of shares.

	(1) Investment Amount	(2) Investment Amount
HIGH	200.0	149.5
	(0.67)	(0.51)
HIGH-FRACTIONAL	313.1	316.7
	(1.03)	(1.06)
Investment experience		138.5
		(0.75)
Statistical knowledge		-381.5*
		(-2.10)
Risk tolerance		44.78
		(0.72)
Gender		-726.6**
		(-2.72)
Age		-25.22**
		(-2.73)
Understanding		61.81
		(0.36)
Constant	3367.3***	4975.2***
	(15.73)	(4.97)
Observations	900	900
R^2	0.00	0.04

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The endowment was $10,000 for each stock. HIGH is a treatment dummy with the value of 1 for participants assigned to HIGH and 0 in LOW. We assessed investment experience and statistical knowledge compared to the general population on a scale from 1 (much lower) to 5 (much higher); risk tolerance on a scale from 1 (low) to 10 (high); understanding ranges from 1 (low understanding) to 5 (high understanding).