
THE IMPORTANCE OF PRICE PATHS

HOW HISTORICAL PRICE PATHS CAN INFLUENCE INVESTMENT DECISIONS



Radboud University Nijmegen

Master Thesis

Author: Leon Bruggers (s4597443)

Supervisor: prof. dr. S.M. Zeisberger

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ABSTRACT

We show that investor buying decisions are significantly influenced by the shape of historical price paths. By conducting an experimental survey, we find that the shape of a price path can influence investment behaviour. Investors are willing to invest most when the price path goes down first and up later and least when the price path goes up first and down later. We furthermore show that this effect is stronger when the final return is negative. Our results provide important insights that can be applied in the investment industry.

Keywords: Historical price paths, willingness to invest, investment decisions, reference points, recency bias, cumulative prospect theory, confirmation bias, behavioural finance

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1. INTRODUCTION

Every day assets are bought and sold on the market. A lot of information is available to investors to help them make these decisions. For instance volatility, expected returns and loss probability, but also historical price paths. Historical price paths are charts visualizing the historical return of an asset (Nolte & Schneider, 2018). According to the efficient market hypothesis (EMH), historical returns have no influence on future returns (Basu, 1977). Therefore, keeping all other factors constant, historical price paths should not influence the investors decision to buy a stock.

However, there is literature proving that historical price paths do influence investor risk perception (Barbaris et al, 2016; Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018). Even if the final return is kept constant, the shape of a price path can influence investment behaviour (Nolte & Schneider, 2018). As a consequence, investment decisions can be influenced by the shape of an asset's price path (Nolte & Schneider, 2018).

So far, only a few papers have been written on the importance of how returns are achieved (Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018). Grosshans & Zeisberger (2018) have found that investor satisfaction is higher with "down-up" paths than with "up-down" paths. This can be explained by a combination of 3 theories that have their roots in behavioural finance. The first theory is the cumulative prospect theory (CPT). CPT states that people are loss averse and have decreasing marginal utility when gaining or losing money (Tversky & Kahneman, 1992). The second theory is reference point shifting. This is the observation that people change their reference point to a different price than the starting price, most often the highest historical prize (Arkes et al, 2008). Therefore an "up-down" movement causes the reference point to shift upwards, whilst the reference point after a "down-up" movement barely changes (Arkes et al, 2008). Last, the recency bias. The recency bias is the tendency to overweight the importance of more recent events relative to less recent events (Shefrin & Belotti, 2007). Taking these theories together, the findings of Grosshans & Zeisberger (2018) can be explained.

However, Grosshans & Zeisberger (2018) only focussed on investor satisfaction and ultimately sell/hold decisions. This paper on the other hand, will focus on the investors willingness to buy an asset, presenting investors with the opposite situation

compared to the experiment of Grosshans & Zeisberger (2018).

Nolte & Schneider (2018) found similar effects as Grosshans & Zeisberger (2018) while analysing investor buying decisions. Although they have corresponding results, their methodology is quite different. Nolte & Schneider (2018) for instance did not analyse the differences between positive and negative final returns. On top of that Nolte & Schneider (2018) provided investors with future returns distributions whilst Grosshans & Zeisberger (2018) did not. This paper will combine elements from both Nolte & Schneider (2018) and Grosshans & Zeisberger (2018) to provide a more comparable insight between sell and buy decisions based on the effects of historical price paths.

In this paper, we analyse if the shape of a historical price path can influence the investors willingness to invest in to a risky asset. The main question that is answered in this paper is: “What is the effect of the shape of historical price paths on investor buying decisions?”. We conduct a survey with an experimental design in which the respondents are faced with one out of six carefully constructed price paths. These paths have comparable returns, but different shapes.

Our results demonstrate that historical price paths indeed do influence investor buying decisions. Investors are willing to invest most when the price path goes down first and up later (“down-up path”) and least when the price path goes up first and down later (“up-down path”).

Next to the main question that is mentioned above, this paper looks in to several other topics, which are all related to the main question. The first sub-topic that is answered in this paper, is whether there is a difference in the effect of price paths between positive and negative final returns. Grosshans & Zeisberger (2018) found that the satisfaction gap, the gap between the satisfaction level of “down-up” shaped paths versus “up-down” shaped paths, is higher when the final returns are negative. We also look in to this, and show whether this difference is also present with buy decisions.

Nolte & Schneider (2018) found that participants were more willing to invest when no price path was shown. This paper also looks in to this by adding treatments to the survey where only the final return, but no price path is shown. By doing so, this paper is able to answer whether historical price paths increase or decrease the overall willingness to invest.

This paper also shows whether inexperienced investors are influenced more by the shape of historical price paths. Shefrin (2002) found that inexperienced investors tend to suffer more from the cognitive bias called representativeness.

Representativeness is the tendency of investors to make decisions based on patterns where none exist (Singh, 2012).

Last, this paper analyses whether there are gender differences among investors. Even though Nolte & Schneider (2018) and Grosshans & Zeisberger (2018) have not looked in to the differences between men and women, there is literature suggesting that these differences exist. Charness & Gneezy (2012) have found that women are more risk averse. On top of that Da Costa Jr et al. (2008) found that women are less sensitive to reference point switching.

2. THEORETICAL BACKGROUND

This chapter will give an overview of the most relevant findings on the effects of historical price paths. First, the papers of Grosshans & Zeisberger (2018) and Nolte & Schneider (2018) will be discussed. Thereafter, the three theories as stated in chapter 1, paragraph 3 will be explained one by one. In the end, the papers that are an addition to the sub-topics will be reviewed.

2.1 THE FOUNDATION

For a long time, research in the field of behavioural finance only focused on simple upward and downward price movements (Grosshans & Zeisberger, 2018). The influence of historical price paths however, has barely been taken in to account. Grosshans & Zeisberger (2018) were among the first to study the effect of historical price paths on investor satisfaction and trading decisions. Grosshans & Zeisberger (2018) conducted an experiment in which participants were presented with a historical price path that was shaped like one of the six price paths in appendix A. Grosshans & Zeisberger (2018) found that there is a significant difference in investor satisfaction between the various price paths, they call this the satisfaction gap. In particular, investors are more satisfied with a down-up path than an up-down path. This satisfaction gap is even bigger when the asset's final return is negative (Grosshans & Zeisberger, 2018). In line with the investor satisfaction, investors were more likely to hold an asset with a down-up shaped price path.

A second innovative paper on the effects of historical price paths, is that written by Nolte & Schneider (2018). Like Grosshans & Zeisberger (2018), Nolte & Schneider (2018) also conducted an experiment in which they presented investors with various historical price paths. Nolte & Schneider (2018) however, did not focus on investor satisfaction, but rather focussed on the investors willingness to invest in to the asset. Their findings are in line with Grosshans & Zeisberger (2018) as they found that participants would rather invest in to an asset with a down-up path than an up-down path. Even when participants were told that the historical price path contained no relevant information, participants reacted on the shape of it (Nolte & Schneider, 2018).

Next to that, Nolte & Schneider (2018) found that participants were on average more willing to invest when no price path was shown. This has major implications for

e.g. fund managers, because by showing the historical price path, they are on average influencing their investors in a negative way. But on the other hand, they could also use it to their advantage by picking a time interval in which the price path shows a down-up movement (Nolte & Schneider, 2018).

The next sub-chapter will discuss various theories from the field of behavioural finance, which together can substantiate the findings of Grosshans & Zeisberger (2018) and Nolte & Schneider (2018).

2.2 IMPORTANT THEORIES

2.2.1 REFERENCE POINTS

Reference point shifting is the observation that people change their reference point to a price different from the original price (Arkes et al, 2008). When the price of an asset changes, people most often shift their reference point to a price that is closer to the new price (Arkes et al, 2008). This effect is more persistent when the price is going up, compared to a situation in which the price is going down (Arkes et al, 2008; Grosshans & Zeisberger, 2018). As a consequence, an up-down movement will cause the reference point to shift upwards, whilst a down-up movement will cause the reference point to shift downwards. When the asset prices eventually end at the same price, the reference point of those with an down-up movement is lower and therefore they will be more satisfied with the final price. Because they are more satisfied, they are also willing to invest more in to this asset (Nolte & Schneider, 2018).

Baucells et al. (2011) found that reference points are mainly depending on five factors; original price, current price, average price, highest price and lowest price. Because in our experiment, but also the experiments of Grosshans & Zeisberger (2018) and Nolte & Schneider (2018), the original price and the current price are constant, reference points can only shift because of the other three factors. Of those three factors, the average price has the strongest effect, whilst the lowest price has the weakest effect (Baucells et al., 2011).

2.2.2 RECENCY BIAS AND MOMENTUM

The recency bias is the tendency to overweight the importance of more recent events relative to less recent events (Shefrin & Belotti, 2007). Recency implies that the prior information does not receive enough weight in the updating process (Offerman & Sonnemans, 2004). Therefore, investors overvalue assets that recently raised in value, whilst they undervalue assets that recently made a drop in value. If the above holds true, this favours down-up paths.

The recency bias is closely connected to the belief of momentum. Momentum is the observation that past winners outperform past losers (Chan et al, 1996). This effect has been widely observed in financial literature (Conrad & Yavuz, 2017; Jegadeesh & Titman, 1993). When the momentum theory is combined with the recency bias, this leads to a situation, in which investors only look at the most recent price movements of the asset and expect this trend to continue in the near future.

Another valuable addition are the findings of Loewenstein & Prelec (1993). They show that people have a preference for the sequence of outcomes. People prefer to have a utility pattern that is increasing over time. In the case of historical price paths, this would again favour down-up shaped paths whilst disfavours the up-down shaped paths.

2.2.3 CUMULATIVE PROSPECT THEORY

The last theory of importance is the cumulative prospect theory (CPT) created by Tversky & Kahneman (1992). The CPT is built on three important pillars; 1) Losses provide more pain than the pleasure gained by a win of the same magnitude. 2) decreasing marginal utility. 3) Small chances are overweighted, whilst big but not certain chance are underweighted. Especially point one is valuable for explaining the effect of historical price paths.

Grosshans & Zeisberger (2018) already stated that the CPT alone is not able to explain their results. However, when CPT is combined with both reference point shifting and the recency bias, CPT is able to explain their findings. What is important, is that the reference point taken in to account in the CPT calculation, is not the starting price, but a price closer to the maximum/minimum price. Next to that, the recent part of the price

path must be overweighted. Only if this is the case, CPT will favour down-up paths (Grosshans & Zeisberger, 2018).

2.3 ADDITIONAL THEORIES

This sub-chapter will discuss additional theories that help formulating the hypotheses on the sub questions as stated in chapter 1 paragraph 6-9.

2.3.1 POSITIVE VS NEGATIVE FINAL RETURNS

Grosshans & Zeisberger (2018) found that the satisfaction gap, the gap between the satisfaction level of “down-up” paths versus “up-down” paths, is higher when the final returns are negative. Grosshans & Zeisberger (2018) argue that this can be caused CPT. When the final return is negative, the path is located mostly on the negative side. CPT states that losses are perceived heavier than an equally sized gain (Tversky & Kahneman, 1992). If investor satisfaction is mostly based on the shape of the most recent part of the price path, and this part is a loss on the negative side, then this loss is perceived heavier compared to an equally sized loss on the positive side.

On the other hand, Grosshans & Zeisberger found that investors were more willing to hold an asset that lost value. This is caused by the disposition effect. The disposition effect is the tendency to sell assets that have gained value and keep assets that have lost value (Weber & Camerer, 1998). So even though people are more satisfied with winner stocks, they are more willing to hold loser stocks (Grosshans & Zeisberger, 2018).

However, as said before, Grosshans & Zeisberger (2018) analysed sell/hold decisions, whilst this paper is analysing buy decisions. Because the disposition effect is only present when somebody already owns the stock, it will not affect buy decisions. Therefore is it doubtful whether the CPT alone can show a gap in the willingness to invest between positive and negative returns.

2.3.2 GRAPHICAL FRAMING

Next to the “up-down”, “down-up” and straight line price paths, Nolte & Schneider (2018) also asked participants how much they would invest when only the final return was given and no accessory price path was shown. Nolte & Schneider (2018) found that

on average, participants were more willing to invest when no price path was shown.

Meyvis & Janaszewski (2002) found that when people are presented with only little information about a product, they systematically take in to account irrelevant information, even if they are aware the information is irrelevant. This finding, called representativeness (Singh, 2012) was also confirmed by Nolte & Schneider (2018).

On top of that, this finding can also be explained by the fact that investors adapt their reference point when the current asset price is above the starting asset price (Arkes et al, 2008). So when a price path is shown, the reference point most often shifts towards the highest historical stock price, and not the starting price (Arkes et al, 2008; Heath et al, 1999). In most price paths, the maximum price is higher than the starting price, therefore on average, the reference point is higher than the starting price. However, when no price path is shown, investors can only use the starting price as a reference point.

2.3.3 INVESTOR EXPERIENCE

Shefrin (2002) found that inexperienced investors tend to suffer more from the cognitive bias called representativeness. This means that inexperienced investors would attach more value to the historical price path than experienced investors would. Consequently, this would result in to inexperienced investors being more satisfied with the down-up path and less with the up-down path. Subsequently, this would cause a bigger gap in the willingness to invest between these paths.

Da Costa Jr. et al. (2013) found that the disposition effect, which was also present in the data from Grosshans & Zeisberger (2018), is largely reduced if only experienced investors take part in an experiment. The human brain is always subject to cognitive biases, but knowledge about a subject can help reduce the effect of these biases (Da Costa Jr. et al., 2013).

On top of that Agnew & Szykman (2005) found that individuals with little to no financial knowledge tend to get easily overwhelmed when presented with investment information. Therefore, they might make a decision that is not in line with their rational thoughts.

2.3.4 GENDER EFFECT

It is commonly known that when it comes down to personality and characteristics, men and women differ from each other (Lippa & Arad, 1999). Also when looking at pure financial characteristics, they differ (Charness & Gneezy, 2012). Women are more risk averse and less sensitive to reference point switching (Charness & Gneezy, 2012; Da Costa Jr et al., 2008). This last finding can have an impact on how women respond to historical price paths. If women switch their reference points less often, this would mean that historical price paths have less influence on their investment decisions.

Women on average also tend to invest less than men when the outcome is ambiguous (Gysler et al., 2002). In that case, the overall willingness to invest should be lower for women than for men, independent of the shape of the historical price path.

2.4 HYPOTHESES

The hypotheses of this paper are mainly based on the findings of Nolte & Schneider (2018) and Grosshans & Zeisberger (2018) in combination with the various theories discussed in chapter 2.

In line with the Nolte & Schneider (2018), this paper expects to find that historical price paths can influence investment decisions. When comparing an “up-down”, “straight line” and a “down-up” movement, we expect that an “up-down” movement induces the worst willingness to invest and that a “down-up” movement induces the highest willingness to invest. Next to that, we expect to find that people believe in short term momentum and therefore have higher future expectations about “down-up” paths whilst having lower future expectations about “up-down” paths.

Hypothesis 1: Historical price paths influence investment decisions.

Hypothesis 2: Down-up price paths lead to more willingness to invest than up-down price paths.

Hypothesis 3: Down-up price paths lead to higher future price expectations than up-down price paths.

On top of that and in line with Grosshans & Zeisberger (2018), we expect the effect in hypotheses two to be stronger when the final returns are negative. Even though the “disposition effect” can have no influence in buying decisions, we expect that

CPT alone can lead to a significant difference between positive and negative final returns.

Hypothesis 4: The gap in the willingness to invest is bigger when the final return is negative.

Also we expect the overall willingness to invest to be lower when a price path is shown, compared to a situation in which the final return is equal, but no price path is shown. This would be in line with the finding of Nolte & Schneider (2018) and the theories about reference point shifting by Arkes et al. (2008) and Heath et al, (1999).

Hypothesis 5: Showing historical price paths has a negative influence on the willingness to invest.

This paper also expects to find that, based on the papers of Shefrin (2002) and Agnew & Szykman (2005), inexperienced investors attach more value to historical price paths. Even though these price paths provide no valuable information about the future. Therefore the gap in the willingness to invest, is higher for inexperienced investors.

Hypothesis 6: The gap in the willingness to invest is bigger for inexperienced investors.

Last, this paper expects to find significant differences between men and women. First, that the gap in the willingness to invest is bigger for men than for women. This is based on the findings of Da Costa Jr. et al. (2008) and Charness & Gneezy (2012) that women change their reference point less often. Second we expect to find that on average, women on average are less willing to invest, even though they have the same price expectations about the future. This is based on the findings of Gysler et al. (2002).

Hypothesis 7: Women on average invest less than men.

Hypothesis 8: The gap in the willingness to invest is smaller for women.

3. DATA & METHODS

3.1 METHODS

The methods of this paper are a combination of elements in the papers from Nolte & Schneider (2018) and Grosshans & Zeisberger (2018).

3.1.1 HISTORICAL PRICE PATHS

The graphs we use in our experiment are shown in appendix C and are copied from and created by Grosshans & Zeisberger (2018). There are three types of graphs, both with a negative and positive final return, adding up to a total of six different graphs. The three graph types differ on how the final return is achieved. This can be either “down-up”, “up-down” or “straight”. As the name suggest, the “down-up” path firstly declines and value and goes up later. The “up-down” path rises first and declines afterwards. “Straight” represents a monotonous price development.

These historical price paths have been constructed very carefully using a total of 2520 ticks. This corresponds to 10 ticks a day, in a year with 252 trading days. Next to that the peak points of the non-straight price paths are either at 30% or -30% representing a realistic situation. The peak and trough prices of all price paths occur at the same point of time, namely after seven months. This guarantees that the slopes of the price paths before and after the turning point are not too different from each other (Grosshans & Zeisberger, 2008). Grosshans & Zeisberger (2018) deliberately refrained from a turning point after 6 months, because that looks to artificial. All charts start at 53 euro and move over a one year time horizon to either 58.3 euro (+10%) or 47.7 euro (-10%).

Next to the six graphs created by Grosshans & Zeisberger (2018), we have also added two text messages. These are only describing the historical return, but are not accompanied by a graph. The text messages can be found in appendix D.

3.1.2 EXPERIMENTAL PROCEDURE

At the start of the experiment, All participants are faced with the following scenario:

“Imagine that you have 10,000 euros which you can either put in to a bank account that earns you nothing, or that you can invest in to a risky asset of which the 1 year historical return is shown below.”

The full introduction message can be found in appendix B. Subsequently, participants are faced with either one of the six historical price paths in appendix C, or one of the two text messages describing their historical return, which can be found in appendix D. Participants in the experiment are randomly assigned to one out of the eight experimental treatments. Participants were subsequently asked what they expected the price of the risky asset to be in one year from now. We further asked them how much of the 10,000 euros they would invest in to the risky asset. Afterwards participants were asked about their age, gender, nationality and investor experience. This is necessary to answer the sub-questions as well as for controlling whether the respondents represent a realistic reflection of society.

The choice for a one year time frame, both historical and future, has been made because one year is a widely used standard format in financial markets (Grosshans & Zeisberger, 2018).

We do not show any terminal return distribution like Nolte & Schneider (2018) did. Distributions like this are not realistic, since historical returns are not a good predictor of future returns (Rotblut & Sharpe, 2014).

Participants are monetarily incentivised to increase the response rate. This payment however, is not depending on the answers given in the survey. This choice is made because Read (2005) found that monetary incentives based on performance only have an effect when the experiment is highly realistic, which also involves a realistic payment based on the situation. This is not possible for the experiment conducted in our research. To increase the response rate, three randomly drawn participants are payed 10 euros.

A carefully constructed Dutch translation of the survey was provided for those unable to answer the questions in English.

3.1.3 STATISTICAL PROCEDURE

The survey data is analysed to test whether the hypotheses are correct. For the data analyses, the statistics program STATA is used. To compare whether groups with a different treatment differ from each other, we conduct a Mann-Whitney U test. Grosshans & Zeisberger used unpaired t-statistics for their analysis. This however requires the data to have a Gaussian distribution, which is not the case with our data. The Mann-Whitney U test is the most used alternative when the data does not have a Gaussian distribution.

Next to that, the gap in willingness to invest is calculated and compared amongst the different groups and treatments. The willingness to invest is calculated as the average percentage that is invested in the risky asset. In the survey, participants answered on a scale from 0-10000. Therefore these numbers are divided by 100 to have percentages. The willingness to invest is subsequently measured on a scale from 0-100. The gap in the willingness to invest is calculated in a comparable way that Grosshans & Zeisberger (2018) calculated their satisfaction gap.

Gap in the willingness to invest = Difference in willingness to invest between up-down and down-up paths with the same final return

3.2 DATA

The data for this research is collected with an experimental survey. This survey has been spread online in a digital form between April 29, 2019 and May 20, 2019. In total, 350 individuals took part in the experiment. Of these 350 observations, 11 are dropped because of non-serious responses. These respondents have filled in expected growth rates which were higher than 100% or lower than -50%, which is highly unlikely in this scenario. After dropping these observations, 339 observations are left for data analysis.

Participants have not been recruited based on personal information and voluntarily decided to participate in the experiment. From the respondents, 47.5% was a man and 52.5% was a woman. The average age of the respondent is 33, ranging from 15 to 81. 72.8% of the respondents are Dutch, whilst the other 27.2% are spread over 27 different nationalities. All data has been collected with the use of Qualtrics survey software.

4. RESULTS

We start with the overall results where no distinction is made between positive and negative final returns. These results are able to provide an answer to hypothesis one, two and three. We tested whether the shape of a price path was able to influence the investors willingness to invest. We conducted a Mann-Whitney U test of which the results can be found in table 1. Table 1 provides significant evidence that the shape of a price path can influence the willingness to invest. More specific, down-up price paths lead to more willingness to invest than up-down price paths. Therefore we can say that both hypothesis 1 and 2 are true.

	Down-up	Up-down	Straight	Gap in the willingness to invest
Overall	27.76	21.35	26.88	6.4** (-2.35)

P= *0.1 **0.05 ***0.01

Table 1. Means of reported willingness to invest, reported on a scale from 0-100, with 0 indicating no willingness to invest and 100 indicating full willingness to invest. Z-statistics are reported in parentheses. The gap in the willingness to invest measures the gap between the down-up path and the up-down path.

We also tested whether the shape of a price path could influence the future price expectations of investors. These results are shown in table 2. The results show that the shape of a price path does not significantly influence the expectations of the future price. This means that hypothesis 3 is false. To extend this analysis, we also tested whether future price expectations influence the amount invested in to that asset. We found that when the price expectation goes up by 1 euro, on average 35.5 euro more is invested in to the asset (See appendix E).

	Down-up	Up-down	Straight	Expectation gap
Overall	56.02	54.20	55.36	1.82 (0.17)

P= *0.1 **0.05 ***0.01

Table 2. Means of reported future price expectations, reported as the expected price in euros after 1 year. Z-statistics are reported in parentheses. The expectation gap measures the gap between the down-up path and the up-down path.

4.1 POSITIVE VS NEGATIVE FINAL RETURNS

In line with Grosshans & Zeisberger (2018) we also checked whether the gap in the willingness to invest is bigger when the final return is negative. The test results can be found in table 3. What stands out is that there is a highly significant difference on the negative side, whilst on the positive side there is no significant difference at all. This

means that in line with Grosshans & Zeisberger (2018) the effect of price paths is stronger when the final return is negative. However, Grosshans & Zeisberger (2018) still found a significant effect on the positive side, whilst we did not. Nevertheless hypothesis 4 is true. A possible explanation lies in the fact that Grosshans & Zeisberger (2018) analysed investor satisfaction, whilst this paper analyses buy decisions. Investors might be less satisfied with the up-down shaped path, but willing to buy an asset anyway because it shows positive final return, whilst when it shows a negative final return, they do care about the recent price movements.

What states out, is that the straight path is showing the most extreme values on both the positive and negative side. This indicates that volatility is pulling the willingness to invest towards the mean. With a straight path, investors are convinced that the future price movements are in line with the historical ones, whilst with the more volatile paths (up-down & down-up), investors are way less certain and therefore pull towards the mean.

	Down-up	Up-down	Straight	Gap in the willingness to invest
Positive	28.2	27.57	37.44	0.63 (-0.112)
Negative	27.38	15.13	12.19	12.25*** (-3.026)

P= *0.1 **0.05 ***0.01

Table 3. Means of reported willingness to invest, reported on a scale from 0-100, with 0 indicating no willingness to invest and 100 indicating full willingness to invest. Z-statistics are reported in parentheses. The gap in the willingness to invest measures the gap between the down-up path and the up-down path. Results are split up based on final return.

4.2 GRAPHICAL FRAMING

Like Nolte & Schneider (2018) did, we also checked what the effect of showing no price path is. The results can be found in table 4. We made a distinction between positive and negative final return, but also show the overall results. Table 4 shows that overall, there is no significant difference between showing a price path or not. However, when the results are split up between positive and negative final returns, we see that there is a significant effect of showing no price path when final returns are positive. But when this is compared to the findings of Nolte & Schneider (2018), the effect has reversed. Nolte & Schneider (2018) concluded that showing no price path has a positive effect on the willingness to invest, that is also what was hypothesized in this paper. However, we found that showing no price path has a significant negative influence on the willingness to invest. Therefore, hypothesis 5 is false. This could be caused by the fact that investors

are reticent about investing in to an asset that they do not have much information about. We are however not the first that fail to find a difference between showing price path or not. Beshears et al. (2017) analysed the difference between showing daily returns (showing a price path in our experiment) and showing only final returns (showing no price path in our experiment) on investment behaviour. They found that there is no significant difference in the total amount invested between these two treatments. Beshears et al. (2017) conclude that prior research on this topic was abstracted away from real-world investments and therefore was able to find an effect. However the more realistic the experiment is, the less likely an effect like this exists.

	Price path shown	No price path shown	Gap in the willingness to invest
Overall	25.51	19.32	6.19 (1.563)
Positive	31.46	22.52	8.94* (1.935)
Negative	19.28	16.67	2.61 (0.164)

P= *0.1 **0.05 ***0.01

Table 4. Means of reported willingness to invest, reported on a scale from 0-100, with 0 indicating no willingness to invest and 100 indicating full willingness to invest. Z-statistics are reported in parentheses. The gap in the willingness to invest measures the gap between price path shown and no price path shown. Results are split up based on final return.

4.3 INVESTOR EXPERIENCE

Literature in behavioural finance suggests that experienced investors are less affected by the shape of historical price paths when making investment decisions. (Da Costa Jr. et al., 2013; Agnew & Szykman, 2005). To confirm this, we created a dummy variable that splits the experienced investors (at least moderate investment experience) from the inexperienced investors (less than moderate investment experience). The results from this analysis can be found in table 5. Table 5 shows that the gap in the willingness to invest is significant for both groups, but bigger for the experienced investors. This is the opposite of what we expected to find. As said before, literature suggested that investors with little experience should be more influenced by the shape of historical price paths when making investment decisions. Our results however, show that experienced investors are the ones that are influenced more by the shape of historical price paths. Therefore hypothesis 6 is false. We do have to make a side note, that our sample size for the experienced investors was rather low (N=48).

	Down-up	Up-down	Straight	Gap in the willingness to invest
Low exp	27.69	22.05	26.00	5.64** (-2.008)
High exp	28.20	14.07	33.55	14.13* (-1.744)

P= *0.1 **0.05 ***0.01

Table 5. Means of reported willingness to invest, reported on a scale from 0-100, with 0 indicating no willingness to invest and 100 indicating full willingness to invest. Z-statistics are reported in parentheses. The gap in the willingness to invest measures the gap between the down-up path and the up-down path. Results are split up based on investor experience.

4.4 GENDER EFFECT

Last we checked for possible differences in investment behaviour between men and women. First we checked whether men on average invest more than women. The results can be found in table 6. We see that men on average invest more than women, this difference however, is not significant. Therefore hypothesis 7 is false.

	Men	Women	Gap in the willingness to invest
Overall	25.96	22.43	3.53 (-0.729)

P= *0.1 **0.05 ***0.01

Table 6. Means of reported willingness to invest, reported on a scale from 0-100, with 0 indicating no willingness to invest and 100 indicating full willingness to invest. Z-statistics are reported in parentheses. The gap in the willingness to invest measures the gap between men and women.

Secondly we checked whether the gap in the willingness to invest is smaller for women. These results can be found in table 7. The results show that the gap in the willingness to invest is bigger for men. However, when we look at the significance of these results, we see that the gap in the willingness to invest is only significant for women and not for men. Therefore we have to state that according to our data, the gap in the willingness to invest only exists for women. Subsequently we state that hypothesis 8 is false.

	Down-up	Up-down	Straight	Gap in the willingness to invest
Men	30.71	23.55	29.54	7.16 (-1.089)
Women	25.04	19.89	24.08	5.15** (-2.243)

P= *0.1 **0.05 ***0.01

Table 7. Means of reported willingness to invest, reported on a scale from 0-100, with 0 indicating no willingness to invest and 100 indicating full willingness to invest. Z-statistics are reported in parentheses. The gap in the willingness to invest measures the gap between the down-up path and the up-down path. Results are split up based on gender.

4.5 FURTHER EXPLANATIONS

This sub-chapter will compare our findings with existing literature and theories. Our results show that investors are more willing to invest in down-up shaped price paths than up-down shaped price paths. This result can be explained by a combination of reference point shifting and the recency bias.

Let us assume that the investor splits the historical price path in to two parts when making decisions, the upward part and the downward part. The reference point that is taken in to account when looking at the final return, will then be a combination of the starting price, the final price and the price at the end of the first part (Baucells et al., 2011). I.e. when the price goes up first, the reference point will shift upwards, whilst the opposite will happen with a down-up shaped price path. With a down-up path, the final price will then be higher than the reference point. On the other hand, with an up-down path, the reference point will be higher than the final price. People are more willing to invest in assets when the reference point is lower, therefore, people are more willing to invest in to the asset with a down-up shaped price path. Hence, reference point shifting would be a possible explanation of our findings.

Our results can also be explained by the recency bias. Again, we assume that the investor splits the historical price path in to two parts. Shefrin & Belotti (2007) found that investors overvalue the most recent (second) part, whilst the less recent (first) part is undervalued. So with a down-up shaped price path, the upwards movement is overvalued, whilst with an up-down shaped price path, the downwards movement is overvalued. Therefore investors are more willing to invest in to the asset that recently raised in value, which is the asset with a down-up shaped price path.

As table 3 shows, our results are mainly driven by the respondents of which the final return was negative. We found that, in line with Grosshans & Zeisberger (2018), the gap between down-up and up-down paths is bigger when the final return is negative. However, we did not find a significant effect on the positive side, whilst Grosshans & Zeisberger (2018) did. Our results suggest that there is an effect that is only present when the final return is negative. A possible explanation would be that investors first look at the final return and only look at the historical price path when the final return is negative. This can be related to the findings of Park et al. (2010). They found that investors keep looking for information that confirms their beliefs and ignore information that contradicts their beliefs (confirmation bias). Investors are always

looking for opportunities to make money. In our experiment, investors are looking for information that confirms the belief that the asset can earn them money. There are at least two things that can be classified as positive information in our experiment: a positive final return and a positive return on the most recent part of the price path. When the final return is positive, investors see this as a positive sign and invest in to the asset, ignoring other relevant info. When the final return is negative, investors start looking for more information. If then the most recent part of the price path has a positive return (down-up path), investors are still willing to invest in to the asset. However, when also the recent part of the price path has no positive return, they do not have any information that confirms their beliefs and are therefore less willing to invest in to the asset.

This theory is further supported by our results in table 3. We see that the willingness to invest in the “down-up positive” path (28.2%), the “up-down positive” path (27.57%) and the “down-up negative” path (27.38%) is very close to each other, whilst the willingness to invest in the “up-down negative” (15,13%) path is much lower.

Park et al. (2001) on top of that found that the confirmation bias is more pronounced for experienced investors. This explains our results that experienced investors are more influenced by the shape of historical price paths.

We also observed that when the results were split between positive and negative final returns, the straight path always comes up as the most extreme outcome. This is not in line with the results of Grosshans & Zeisberger (2018). In their results, the straight price path was always in-between the up-down and down-up outcomes. This was surprising because if investors only cared about variance, the straight price path should always come out on top (Grosshans & Zeisberger, 2018). While our results show that the straight price path is not in-between the other two price paths, it is also not the case that it is in every situation preferred over the other price paths. According to financial literature, the investors willing to invest goes down when the assets variance goes up (Aizenman & Marion, 1995). So *ceteris paribus*, investors would always prefer the price path with the least variance, which is the straight path. We observe on the other hand, that the straight price path has the lowest willingness to invest when the final return is negative. Therefore standard variance preferences as described by Aizenman & Marion (1995) cannot explain our results. However, looking at our results, it becomes clear that variance influences the willingness to invest somehow. An

alternative explanation would be that volatility causes uncertainty among investors. Literature on loss aversion states that on the gain domain, investors prefer more certain outcomes. However on the negative domain, they prefer uncertain outcomes (Kahneman & Tversky, 1979). Therefore investors are very willing to invest in the straight asset when the return is positive, but are very reticent to invest in the straight asset when the return is negative. This would explain why the straight path is the most extreme outcome on both the positive and negative side.

5. CONCLUSION AND DISCUSSION

So far, only few papers have studied the effects of historical price paths on investment behaviour. This study combines aspects from these papers to come to new insights. In line with previous literature, we document significant differences in the willingness to invest between investors that are shown price paths with equal final returns, but different shaped price paths. In particular we find that down-up price paths provide more willingness to invest than up-down paths. This effect is best visible when the final return is negative. On top of that, we show that straight price paths cause more extreme values in the willingness to invest, indicating that investors are more certain about the future price movements when there is less volatility. These findings demonstrate that when analysing investment behaviour based on returns, we should not only take in to account the final return, but also how these returns are achieved.

Additionally, we document that showing no price path leads to a lower willingness to invest when the final return is positive. We further show that both women and experienced investors are more likely to be influenced by historical price paths.

Our findings demonstrate that investors take in to account both past prices and volatility when making investment decisions based on historical price paths. Especially when the final return is negative, we see that investors care about the shape of historical price paths.

We see various business implications and future research possibilities of our work, especially for the investment industry. We demonstrate that showing investors a historical price path has a positive influence on the willingness to invest. Next to that, investment companies should pick a time frame where the historical price path shows a down-up movement.

Even though our findings present clear evidence towards the effects of historical price paths, there is still space for improvement and extension of our research. Improvements can be made on the aspect of our sample size. Our sample size of 339 individuals is relatively small, especially when taking in to account that the population was divided in to 8 different treatments, resulting in 8 groups of 42 individuals. On top of that, the percentage of respondents with investor experience was low. Only 14% of the respondents had at least a moderate amount of investor experience, this might have influenced the outcome of our research. Future research can extend this paper by conducting a similar experiment with a bigger sample size. This allows for integrating

more treatments, for instance, different starting prices, like Grosshans & Zeisberger (2018) did. Next to that, repeating the experiment in a more realistic setting can help to increase the external validity of our results. Especially because Beshears et al. (2017) showed that effects can disappear when the realism of the experiment is increased. By conducting a real world experiment instead of an internet survey, the external validity is improved. Furthermore it would be interesting to extend the experiment to a multiple period setting, to check what the effect of historical price paths is over multiple periods.

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APPENDIX A



APPENDIX B

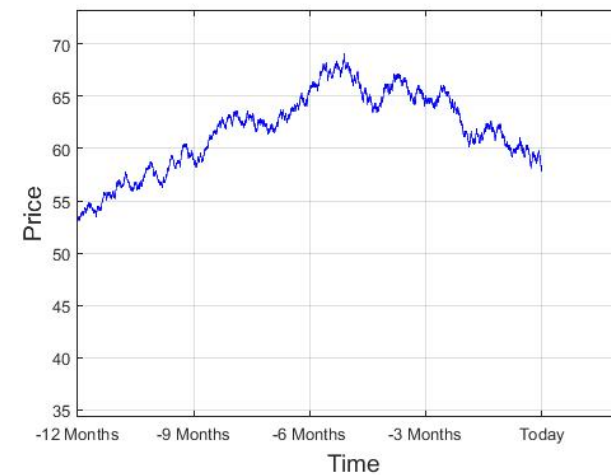
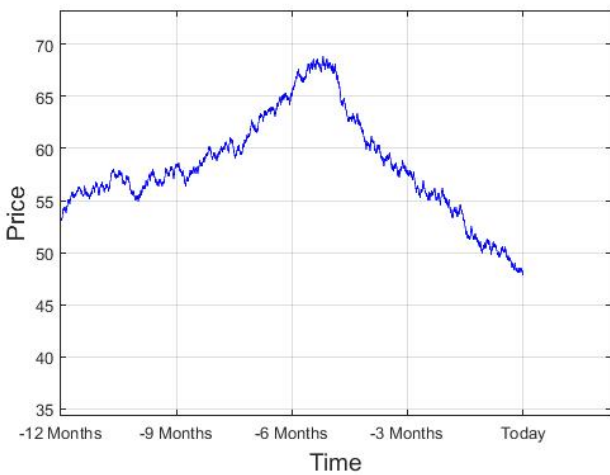
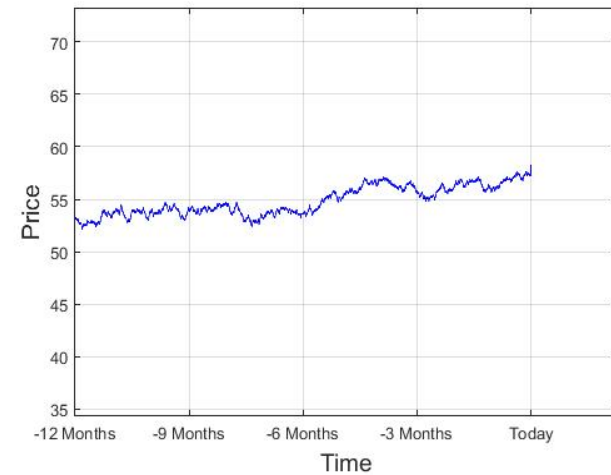
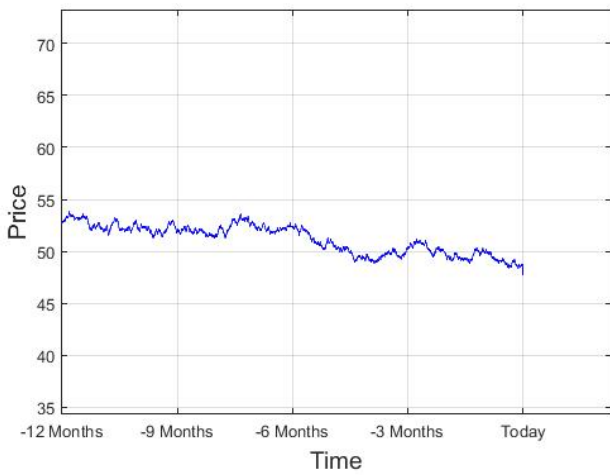
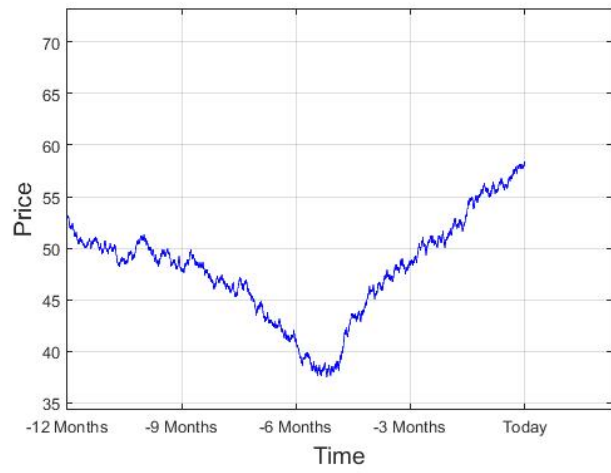
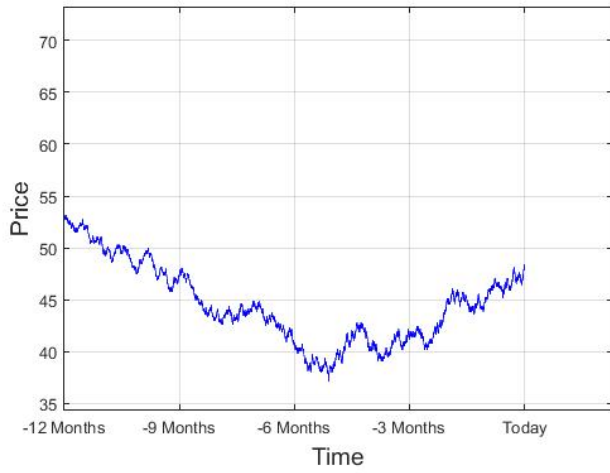
Dear Participant!

In the following you will be presented with an historical asset price path. Imagine that you have 10,000 euros which you can either put in to a bank account that earns you nothing, or that you can invest in to a risky asset of which the 1 year historical return is shown below. The future stock performance is not related to the current real world market situation. On average, the risky asset will earn between -30% & +30%

Please take your time, imagine you own this amount of money and ask yourself how much you would invest in to the risky asset. Be aware that there are no right or wrong answers. Your responses are saved anonymously. Overall, this study will take you approx. 4-5 minutes.

3 randomly chosen participants will be payed 10 euros.

APPENDIX C



APPENDIX D

Positive return:

Last year, the risky asset went from 53 to 58.3 and earned 10%
What do you expect the asset price to be in 1 year?

Negative return:

Last year, the risky asset went from 53 to 47.7 and lost 10%
What do you expect the asset price to be in 1 year?

APPENDIX E

Hypothesis 2

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummieduvsud	obs	rank sum	expected
1	80	6288.5	7080
2	96	9287.5	8496
combined	176	15576	15576

unadjusted variance 113280.00

adjustment for ties -156.72

adjusted variance 113123.28

Ho: $\text{invested}(\text{dummie} \sim d == 1) = \text{invested}(\text{dummie} \sim d == 2)$

z = -2.353

Prob > |z| = 0.0186

Hypothesis 3

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummieduvsud	obs	rank sum	expected
1	80	7137	7080
2	96	8439	8496
combined	176	15576	15576

unadjusted variance 113280.00

adjustment for ties -1148.76

adjusted variance 112131.24

Ho: $\text{estimate}(\text{dummie} \sim d == 1) = \text{estimate}(\text{dummie} \sim d == 2)$

z = 0.170

Prob > |z| = 0.8648

Hypothesis 4

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummiedup~p	obs	rank sum	expected
1	40	1687.5	1700
2	44	1882.5	1870
combined	84	3570	3570

unadjusted variance 12466.67

adjustment for ties -7.07

adjusted variance 12459.60

Ho: invested(dummie~p==1) = invested(dummie~p==2)

z = -0.112

Prob > |z| = 0.9108

. ranksum invested, by(dummiedunvsudn)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummiedunv~n	obs	rank sum	expected
1	40	1476.5	1860
2	52	2801.5	2418
combined	92	4278	4278

unadjusted variance 16120.00

adjustment for ties -57.14

adjusted variance 16062.86

Ho: invested(dummie~n==1) = invested(dummie~n==2)

z = -3.026

Prob > |z| = 0.0025

Hypothesis 5

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummieline~e	obs	rank sum	expected
1	262	45719	44540
2	77	11911	13090
combined	339	57630	57630

unadjusted variance 571596.67

adjustment for ties -2362.54

adjusted variance 569234.12

Ho: invested(dummieline==1) = invested(dummieline==2)

z = 1.563

Prob > |z| = 0.1181

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummieline~s	obs	rank sum	expected
1	134	11888.5	11390
2	35	2476.5	2975
combined	169	14365	14365

unadjusted variance 66441.67

adjustment for ties -51.79

adjusted variance 66389.88

Ho: invested(dummieline~s==1) = invested(dummieline~s==2)

z = 1.935

Prob > |z| = 0.0530

. ranksum invested, by(dummielinevsnolineneg)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummieline~g	obs	rank sum	expected
1	128	10989	10944
2	42	3546	3591
combined	170	14535	14535

unadjusted variance 76608.00

adjustment for ties -1075.85

adjusted variance 75532.15

Ho: invested(dummieline~g==1) = invested(dummieline~g==2)

z = 0.164

Prob > |z| = 0.8699

Hypothesis 6

low

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummieduvsud	obs	rank sum	expected
1	73	5165.5	5730.5
2	83	7080.5	6515.5
combined	156	12246	12246

unadjusted variance 79271.92

adjustment for ties -116.14

adjusted variance 79155.77

Ho: invested(dummie~d==1) = invested(dummie~d==2)

z = -2.008

Prob > |z| = 0.0446

High

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummieduvsud	obs	rank sum	expected
1	7	51.5	73.5
2	13	158.5	136.5
combined	20	210	210

unadjusted variance 159.25

adjustment for ties -0.12

adjusted variance 159.13

Ho: invested(dummie~d==1) = invested(dummie~d==2)

z = -1.744

Prob > |z| = 0.0812

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Hypothesis 7

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

gender	obs	rank sum	expected
Female	178	29604.5	30260
Male	161	28025.5	27370
combined	339	57630	57630

unadjusted variance 811976.67

adjustment for ties -3356.09

adjusted variance 808620.58

Ho: $\text{invested}(\text{gender}==\text{Female}) = \text{invested}(\text{gender}==\text{Male})$

z = -0.729

Prob > |z| = 0.4660

Hypothesis 8

Women

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummieduvsud	obs	rank sum	expected
1	48	2060.5	2376
2	50	2790.5	2475
combined	98	4851	4851

unadjusted variance 19800.00

adjustment for ties -14.14

adjusted variance 19785.86

Ho: $\text{invested}(\text{dummie~d}==1) = \text{invested}(\text{dummie~d}==2)$

z = -2.243

Prob > |z| = 0.0249

Men

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummieduvsud	obs	rank sum	expected
1	32	1157	1264
2	46	1924	1817
combined	78	3081	3081

unadjusted variance 9690.67

adjustment for ties -28.31

adjusted variance 9662.36

Ho: $\text{invested}(\text{dummie} \sim d=1) = \text{invested}(\text{dummie} \sim d=2)$

z = -1.089

Prob > |z| = 0.2764

OTHER

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummiesnvs~u	obs	rank sum	expected
1	92	6505.5	5934
2	36	1750.5	2322
combined	128	8256	8256

unadjusted variance 35604.00
 adjustment for ties -458.72

adjusted variance 35145.28

Ho: invested(d~nvsu~u==1) = invested(d~nvsu~u==2)
 z = 3.048
 Prob > |z| = 0.0023

. ranksum invested, by(dummiespvsuddu)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

dummiespvs~u	obs	rank sum	expected
1	84	5115	5670
2	50	3930	3375
combined	134	9045	9045

unadjusted variance 47250.00
 adjustment for ties -27.93

adjusted variance 47222.07

Ho: invested(d~pvsu~u==1) = invested(d~pvsu~u==2)
 z = -2.554
 Prob > |z| = 0.0106

Source	SS	df	MS	Number of obs	=	339
Model	78982859.8	1	78982859.8	F(1, 337)	=	15.66
Residual	1.6993e+09	337	5042309.24	Prob > F	=	0.0001
Total	1.7782e+09	338	5261068.26	R-squared	=	0.0444
				Adj R-squared	=	0.0416
				Root MSE	=	2245.5

invested	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
estimate	35.54928	8.982125	3.96	0.000	17.88118 53.21737
_cons	461.382	507.408	0.91	0.364	-536.7039 1459.468

Syntax-file

```
*HYPOTHESIS 2
ranksum invested, by(dummieduvsud)
*HYPOTHESIS 3
ranksum estimate, by(dummieduvsud)
*HYPOTHESIS 4
ranksum invested, by(dummiedupvsudp)
ranksum invested, by(dummiedunvsudn)
*HYPOTHESIS 5
ranksum invested, by(dummielinevsnoline)
ranksum invested, by(dummielinevsnolinepos)
ranksum invested, by(dummielinevsnolineneg)
*HYPOTHESIS 6
*load dataset with only low exp investors
ranksum invested, by(dummieduvsud)
*load dataset with only high exp investors
ranksum invested, by(dummieduvsud)
*HYPOTHESIS 7
*standard dataset again
ranksum invested, by(gender)
*HYPOTHESIS 8
*load dataset with only women
ranksum invested, by(dummieduvsud)
*load dataset with only men
ranksum invested, by(dummieduvsud)
*OTHER
ranksum invested, by(dummiesnvsuddu)
ranksum invested, by(dummiespvsuddu)
regress invested estimate
```