The role of extrema-locations in price paths: application to reference prices

Master's thesis

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Abstract:

Price paths are often used to visually represent information about financial products. The path that follows the initial price systematically influences individuals' self-reported reference prices. Due to the recency bias, individuals often overweight information in the latter part of the path. I therefore study the effect of extrema-locations within up-down and down-up paths in an online controlled experiment. I conclude that individuals are unaffected by the location of the maximum, but report lower reference prices for down-up paths with a late minimum relative to down-up paths with an early minimum.

Contents

1. Introduction

Since the introduction of prospect theory by Kahneman and Tversky (1979), a large stream of literature has stressed the importance of reference points. The frequently used prospect theory predicts decision making under risk and emphasises changes in wealth relative to a reference point, rather than final wealth levels such as in expected utility theory. As a consequence, when analysing decision making under risk, one might recognize the importance of how reference points are formed.

Within finance, reference points or rather prices are highly relevant as illustrated by the disposition effect: the tendency to sell 'winner' stocks too early and 'loser' stocks too late (Shefrin and Statman, 1985). The most popular explanation is that investors become risk-averse when their reference price is outperformed and risk-seeking when the price of an asset falls below their reference price (Odean, 1998). Hence, the reference price plays an important role in explaining the disposition effect.

A frequently used assumption is that the purchase price serves as a reference price (Shefrin and Statman, 1985). However, reference prices are more dynamic than assumed and are sensitive to price changes following the initial purchase price (Arkes et al. 2008). When considering price paths, individuals observe a starting price and to a certain extent adapt their reference price according to the sequence that follows (Baucells et al., 2011; Grosshans and Zeisberger, 2018; Nolte and Schneider;). Aforementioned papers all find higher reference prices for up-down paths compared to down-up paths, keeping purchase price and final price fixed. This effect is driven by a combination of higher average prices for up-down paths and a quicker adaptation to gains compared to losses (Arkes et al., 2008).

I further explore the role of the location of the minimum (maximum) price within down-up (up-down) price paths. Given the importance of reference prices in financial decision making, it is fruitful to gain a better understanding of how reference prices are formed in context of price paths. Hence, the main research question for this paper is: '*To what extent does the timing of extrema in price paths influence reference prices?*'

Empirical research has stressed the importance of the location of the 52-week high/low to stock-decision making, and find that a recent 52-week high/low has more impact on trading activity relative to a more distant 52-week high/low (Bhootra and Hur, 2013; Lin, 2018). Both suggest a higher adjustment of the reference price for recent extrema to influence trading activity or stock recommendations. Accordingly, in context of up-down (down-up) sequences, the reference price is expected to be higher (lower) when the high (low) occurs more recently.

I contribute to the field by directly eliciting reference prices of participants in a controlled experiment, where price paths are carefully constructed to isolate the effect of extrema-locations on reference prices. Baucells et al. (2011) also consider the effect of extrema-locations by using sequences of at most seven prices. However, this paper is the first to explore such effect through price paths, which have higher external validity as they are frequently used to present information about financial assets (Nolte and Schneider, 2018). Baucells et al. (2011) measure the impact of several salient prices within a price sequence, and find that reference prices are determined by the purchase price, final price, average price, maximum price and minimum price. Within down-up and up-down paths, these prices are held constant to isolate the effect of early versus late turning point on the reference price.

I test for differences in reference prices between down-up and up-down paths, and find significantly higher reference prices for up-down paths, consistent with previous literature (Baucells et al. 2011; Grosshans and Zeisberger; 2018; Nolte and Schneider, 2018). In addition, reference prices are found to be formed in accord to the final price for stocks with positive returns, in line with Arkes et al. (2008) and Grosshans and Zeisberger (2018). To test for extrema-location effects, the sample is split into two groups: down-up and up-down. Regressions are run on both samples, with the dependent variable being the reference price. The independent variable of interest is the timing dummy, aside from some controls acquired by the survey after the experiment. For the down-up sample, the late turning point treatment has a significantly lower average reference price compared to the early turning point treatment. Surprisingly, there is no timing effect found in the up-down treatment.

The remainder of this paper is structured as follows. Literature related to this topic is discussed in section 2. In section 3, the experimental design and procedure are described. Section 4 presents the main results of the experiment. At last, section 5 contains a discussion and conclusions.

2. Literature review

2.1 Reference price candidates

Reference points are highly dependent on context (Kahneman, 1992), and this section serves to narrow down the possible determinants of reference points related to this paper. In context of price paths, individuals face multiple prices over a period of time and compare those with some reference point, or rather reference price (Bell and Lattin, 2000; Baucells et al., 2011; Nolte and Schneider, 2018; Grosshans and Zeisberger, 2018). In the following, a distinction is made between start and end prices which are independent of any sort of pattern, and intermediate prices that do influence the reference price through patterns.

2.1.1 Start and end prices

The well-known disposition effect: selling winning stocks too early and losing stocks too late, is explained under the assumption that investors act to new information relative to the purchase price (Shefrin and Statman, 1985). When faced with a price path, this would imply that individuals have a static, purchase-price-based reference price (Riley et al., 2019). The purchase price is a status quo reference price in that sense, where gains and losses are compared to the status quo (Kahneman, 1992).

However, previous literature has already stressed the dynamic nature of reference points, implying that individuals adapt their reference price over time and do not necessarily stick their reference price to the purchase price (Chen and Rao, 2002; Arkes et al., 2008).

In line with adaptation to new information, the final path price is another candidate for individuals to anchor their reference price on (Baucells et al., 2011; Grosshans and Zeisberger, 2018; Riley et al., 2019). The reference price is especially formed in accord to the final price when individuals face a positive return at the end of the path, whereas individuals stick their reference price to the purchase price when they are faced with a path showing a negative return (Grosshans and Zeisberger, 2018). The difference stems from Arkes et al. (2008), who find that individuals adapt their reference point more quickly to gains compared to losses. The current price is also the best estimation of the future price (Baucells et al., 2011). Hence, when individuals have a reference price close to the current price, this might be due to having some expectations about the future value of the stock (Köszegi and Rabin, 2006).

2.1.2 Intermediate reference prices

Facing price paths, individuals receive an abundancy of information about the development of the price from start to end. For this paper, the information presented within this duration is more relevant than the start and end price-levels. Within a price path, three salient prices are relevant to consider: the minimum price, maximum price and average price (Baucells et al., 2011).

Kaustia (2004) finds that maximum and minimum prices are focal price points for investors in new initial public offerings, showing higher trading activity for prices close to the minimum or maximum. Using experimental methods, Heyman et al. (2004) and Gneezy (2005) find that historic highs are important when forming reference points. In addition, stock options significantly increase when the stock price exceeds the maximum over the past year (Heath et al., 1999; Poteshman and Serbin, 2003), providing evidence for a role of the maximum price in reference price formation.

Baucells et al. (2011) propose a model where the reference price depends on the purchase price, final price, average price, maximum price and minimum price, decreasing in weight in that order. In fact, an insignificant weight is assigned to the minimum price. However, intermediate prices influence the reference price through the 'dashed hope' versus 'false alarms' patterns (Chen and Rao, 2002; Baucells et al., 2011). In terms of price paths, a dashed hope refers to an up-down path that first increases in price and later drops in price, and a false alarm refers to a down-up path first decreases in price and later recovers. Both Chen and Rao (2002) and Baucells et al. (2011) find higher reference prices for dashed hope sequences compared to false alarm sequences. In accord, in context of price paths, both Grosshans and Zeisberger (2018) and Nolte an Schneider (2018) find higher reference prices for up-down paths. A part of this is explained by the higher average price for up-down paths (Baucells et al., 2011; Nolte and Schneider, 2018). Moreover, when faced with an up-down path, individuals first face a gain and then a loss. The maximum price serves as a focal price which at that point can be perceived as a gain relative to the purchase price, which is the most probable reference price at the start. Due to quicker adaptation to gains compared to losses (Arkes et al., 2008), the reference price is likely to be higher for up-down paths compared to down-up paths, even when keeping purchase price and final price constant. To conclude, individuals systematically form higher reference prices for up-down paths compared to down-up paths.

2.1.3 Extrema locations

The main focus of this paper is to what extent the timing of extrema within down-up and up-down paths influence reference prices. Baucells et al. (2011) consider early versus late turning points and do not find an effect of the location of extrema, by using sequences of at most seven prices. The use of price paths is beneficial for mainly two reasons. First, price paths are frequently used to present information about financial assets (Nolte and Schneider, 2018). Hence, the use of price paths in context of reference prices leads to a higher external validity compared to sequences of at most seven prices. Second, peaks and troughs are more salient when visually presented by a price path (Diacon and Hasseldine, 2007). Consequently, the lack of timing effect in case of Baucells et al. (2011) could become present in context of price paths.

Recency effect

The hypothesized relevance of extrema-timing stems from the recency bias: the tendency to overweight information close to the present relative to distant information and underweight information prior to the present (Murdock, 1962). If the extremum is close to the current price, its presence receives a higher weight compared to a larger distance from the current price. Bhootra and Hur (2013) empirically find such recency effect for the maximum price, by sorting portfolios based on the recency ratio[1] of the 52-week high. The high recency ratio portfolio has a raw return two times higher than the low recency ratio portfolio. In addition, Lin (2018) tests the recency effect of the 52-week high and low on analyst stock recommendations and finds an increase in recommendations when the price gets near the high or low. Interestingly, the effect of the nearness of the high/low compared to the current price disappears when the timing of the high/low is considered, indicating a more important role for the timing of the high/low relative to the proximity. Both Bhootra and Hur (2013) and Lin (2018) state that summed up differences are due to anchoring[2] on the high/low (Tversky and Kahneman, 1975), especially when extrema occur more recently. Accordingly, the reference price is likely to be positively (negatively) influenced by the recency of the maximum (minimum) price.

[1] The recency ratio $RR = 1 - \frac{number\ of\ days\ since\ 52\ weeks\ high\ price}{364}$ (Bhootra and Hur, 2013)

[2] Anchoring on the high/low refers to forming a reference price in accord to the maximum or minimum price as discussed by Baucells et al. (2011)

2.2 Hypotheses

H1: Reference prices are higher for up-down paths than for down-up paths.

Consistent with Grosshans and Zeisberger (2018) and Nolte and Schneider (2018), the reference prices for up-down paths are expected to be higher relative to down-up paths. The aforementioned average price effect speaks in favour of the up-down paths. Furthermore, individuals update their reference price slower for losses than for gains. Hence, the decrease in price after the maximum in case of up-down paths is expected to drive the reference price down by a small margin. Finally, the maximum price that is being focalized within the up-down paths might serve an anchor, such that reference prices stay closer to the maximum, which in turn drives up reference prices (Tversky and Kahneman, 1975).

H2: Reference prices are formed in accord to the final price.

Participants face a positive return, ie. the final price is higher than the current price. In line with Arkes et al. (2008) and Grosshans and Zeisberger (2018), the reference price is on average expected to be formed in accord to the final price rather than the purchase price, as reference prices are dynamic over time for gains especially.

H3: Reference prices within down-up paths are lower for late turning points compared to early turning points.

Consistent with literature on the recency effect (Murdock, 1962; Bhootra and Hur; Lin, 2018), the reference price is expected to be lower for down-up paths with a late turning point compared to paths with an early turning point. The minimum price serves as a focal price, especially when the minimum price occurs more recent. Moreover, in context of a down-up price path with a single trough, the recent average price is significantly lower for paths that contain late turning points.

H4: Reference prices within up-down paths are higher for late turning points compared to early turning points.

For up-down paths, the effect of the maximum price on the reference price is again expected to be stronger in case of a late turning point due to the recency effect, ie. the focal maximum price is overemphasized when its location is near the final price. In addition, the average price in the latter part of the path is higher for up-down paths with a late turning point compared to up-down paths with an early turning point. Hence, the reference price is expected to be higher for a late peak relative to an early peak.

3. Experimental design

3.1 Price paths

This paper embraces the finding of Baucells et al. (2011) that the reference price is a function of the initial price, the final price, the average price, the highest price, and the lowest price. These determinants are held constant within up-down paths and down-up paths, to isolate the effect of extrema locations on reference point formation. If such significant effect is found it implies that the determinants of the reference point found by Baucells et al. (2011) are incomplete and can be improved by incorporating extrema locations. Price paths are often used to visually present information about financial assets, so it is relevant to know how individuals form reference prices in context of price paths.

Similar to Nolte and Schneider (2018), paths are constructed by simulating prices based on a Geometric Brownian Motion. 2520 price changes are plotted per path, corresponding to 10 ticks per day in a year with 252 trading days. The choice for a one-year time frame stems from the observation that for many internet platforms the default time frame is one-year (Grosshans and Zeisberger, 2018; Nolte and Schneider, 2018).

The Geometric Brownian Motion provides a base path for both up-down and down-up samples. Each base path is then split into ten periods of equal length (252 ticks) to rearrange them into two paths for each samples. In total, four paths are created: down-up early, down-up late, up-down early and up-down late. Figure 1 illustrates the four different price paths. Turning points are symmetrically rearranged to ensure equal distance from start to peak and peak to end within up-down and down-up treatments. In this case it means the turning point either occurs three months after the start or three months before the end. The initial price is fixed at €100 across the four price paths (Nolte and Schneider, 2018), and the final price is €110 for all four paths. The final price is deliberately set higher than the initial price, as otherwise it is unclear whether individuals form their reference price in accord to the initial price or the final price. Peak and trough sizes are equal compared to the starting price of €100 (- €40 for minima and + €40 for maxima). Note that the price difference between the minimum price and end price in down-up paths is larger than the price difference between the maximum price and end price in up-down paths. However, in this context the starting price also functions as purchase price. Since the purchase price is the strongest influencer on reference price formation according to Baucells et al. (2011), the choice is made to determine equal peak and trough sizes based on the starting price instead of the end price.

Further characteristics are displayed in table 1. Annual drift and volatility are held constant at 2% and 10% respectively[3], such that neither differences in drift nor annual volatility can disturb the results (Grosshans and Zeisberger, 2018; Nolte and Schneider, 2018). Due to fixed initial and final

[3] Drift and volatility is deliberately set lower compared to Nolte and Schneider (2018) and Grosshans and Zeisberger (2018), to either get a clear single peak or trough.

price, average prices are higher for up-down paths than down-up paths: €111.44 and €87.42 respectively. Table 1 illustrates that within up-down and down-up treatments only the turning points vary. To sum up, differences in individuals' reference points within up-down or down-up treatments cannot be explained by the initial price, average price, final price, annual volatility, annual drift and peak or trough sizes, but are due to differences in extrema locations. Appendix A shows the decision screen participants face including one of the four paths with the reference price elicitation question.

Figure 1

Price paths as shown to participants. Reported reference prices are denominated in euros.

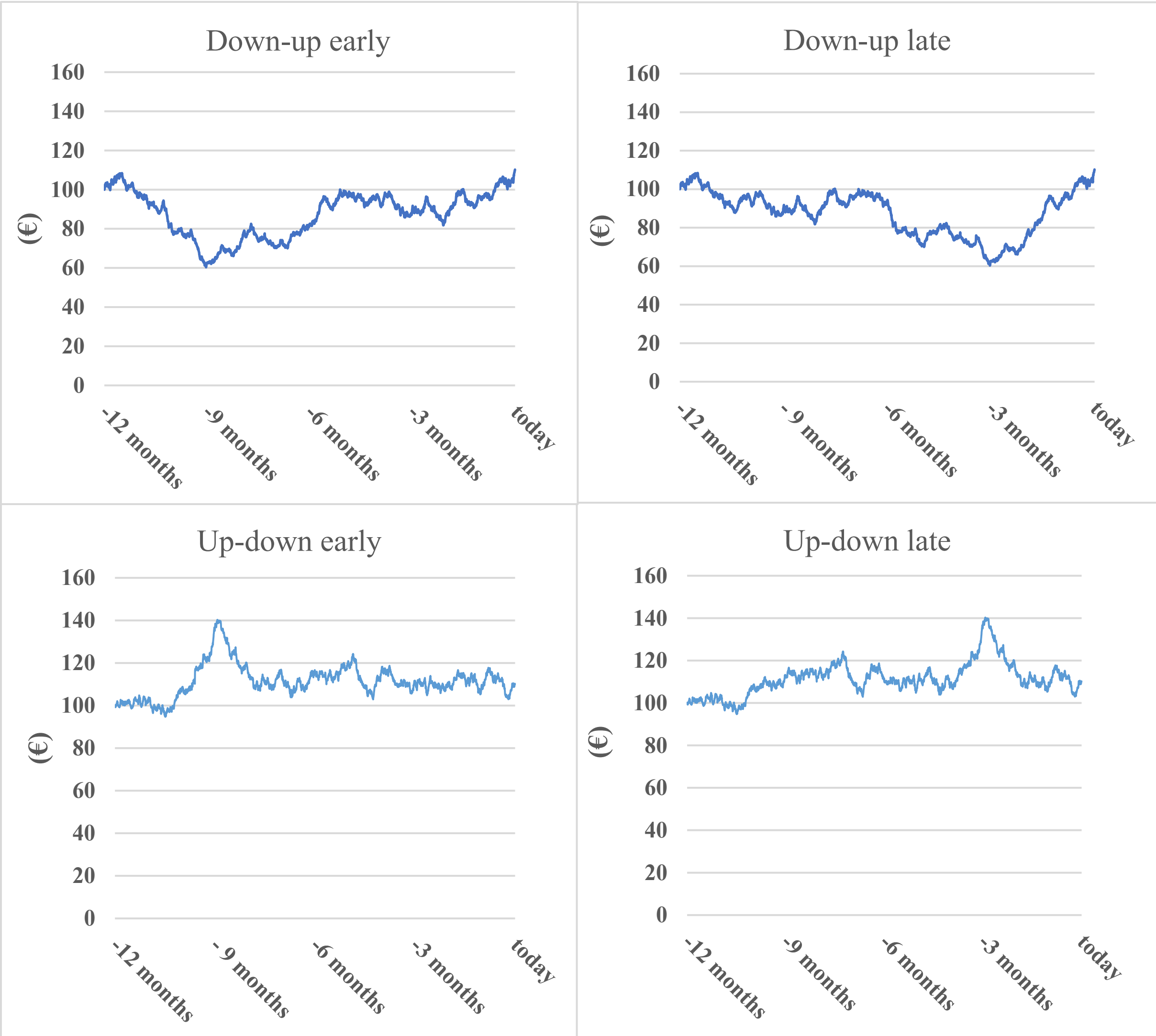


Table 1

This table reports constant average prices within the down-up and up-down sample. Annual volatility and drift is kept constant as well. Turning point occurs either after 3 or 9 months.

	Average price	Annual volatility (%)	Annual drift (%)	Turning point
Down- up early	€87.42	10	2	-9 months
Down-up late	€87.42	10	2	-3 months
Up-down early	€111.44	10	2	-9 months
Up-down late	€111.44	10	2	-3 months

3.2 Experimental procedure

The experiment consists of three parts. First, subjects are introduced to the main elements of the experiment (Appendix A). Second, subjects are randomly distributed to one of the four treatments and asked for their self-stated reference price. A between-subject design is chosen over a within-subject design for two reasons. First, subjects might notice what is being tested if they are treated with all four paths, especially in this context where only two base paths are used to create four turning point treatments. Within up-down and down-up treatments, the paths look very similar except for the location of the turning point. When respondents act in accord with some pattern, results may become biased (Charness et al., 2012). Second, being faced with a single decision requires less effort and attention, which therefore may lead to less biased results.

Subjects unconsciously reveal their reference price by answering the following question after they are faced with one of the paths: “Imagine you invested 10000 monetary units in the asset at the beginning of the period. At which hypothetical price would you neither be happy nor unhappy to sell the asset at the end of the period?”. The formulation of this question is an adoption of the questions used by Baucells et al. (2011), Grosshans and Zeisberger (2018) and Nolte and Schneider (2018) to elicit the reference point of participants[4]. The underlying assumption is that this reveals a price that corresponds with zero utility for the participants (Arkes et al., 2008), implying a neutral feeling about selling the hypothetical asset for that particular price.

Third and last, subjects are asked to fill in a short questionnaire covering questions concerning investment experience, financial literacy and socio-demographics: age, education and gender. Investment experience and financial literacy are measured through 5-point Likert scale questions (see Appendix B1). Both are relevant in this context as subjects with more financial knowledge and

[4] Both Baucells et al. (2011) and Grosshans and Zeisberger (2018) use a hypothetical selling scenario to elicit reference prices of subjects. Contrary, Nolte and Schneider (2018) consider a hypothetical buy scenario in context of investment behaviour. As for this paper, the sole focus is on reference prices and therefore uses the same approach as Baucells et al. (2011) and Grosshans and Zeisberger (2018).

experience are expected to be less exposed to the recency bias (Shefrin and Belotti, 2007). The socio-demographics serve as further controls.

3.3 Participants

In total 258 participants were recruited, from which 200 were recruited from Amazon Mechanical Turk (MTurk), an online platform to acquire workers to perform surveys in exchange for money. Mturk is appropriate to acquire subjects as in general behavior of Mturk participants is similar to that of student populations (Goodman et al., 2013). Appendix B shows that this holds for this paper as well. Participants were close to equally distributed across the four treatments (see figure 3). The mean age of the full sample was 32 years, and roughly 35% of the participants were female. Further details on the sample are reported in Appendix B. The experiment was run through Qualtrics.

4.Results

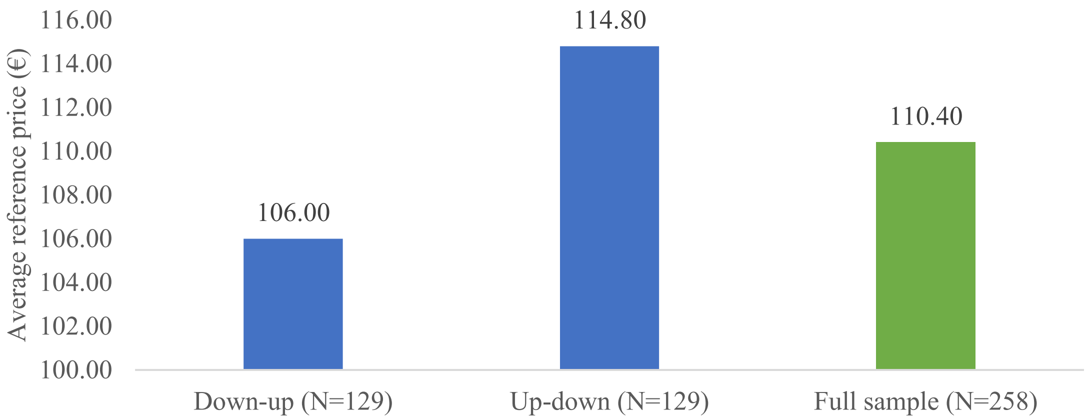
4.1 Average reference price

To test the first hypothesis, average reference prices for down-up and up-down samples are compared. Figure 2 illustrates average self-reported reference prices for the down-up, up-down and full sample, which are 106.00, 114.80 and 110.40 respectively. Appendix B2 contains distribution plots of the full sample (figure 6) and down-up and up-down samples separately (figure 7). The self-reported reference price is close to normally distributed for all samples. Hence, a two-sample t-test is appropriate to test the first hypothesis: "*Reference prices are higher for up-down paths than for down-up paths*".

The two-sample t-test indeed indicates a significantly higher average reference price for up-down paths compared to down-up paths. The difference of 8.80 is significant at a 1% significance level. The result is in line with previous literature which offer two explanations (Arkes et al., 2008; Baucells et al., 2011; Grosshans and Zeisberger, 2018; Nolte and Schneider, 2018). First, individuals are more likely to adapt their reference price to gains in wealth compared to losses (Arkes et al., 2008; Grosshans and Zeisberger, 2018). As a consequence, when faced with a price path that first goes up (wealth increase) and finally goes down (wealth decrease), reference prices turn out higher compared to down-up paths. Second, reference prices are positively influenced by the average price (Baucells et al., 2011; Nolte and Schneider, 2018). As figure 1 illustrates, the average price for up-down paths (111.44) is remarkably higher than for down-up paths (87.42), resulting in higher average reference prices for up-down paths than down-up paths.

Figure 2

Average stated reference price for down up paths, up-down paths and full sample of paths



4.2 Reference price formation

This section focusses on the extent to which reference prices are dynamic for this experimental setting, where all participants face a positive return regardless of which pattern they face. Recall the second hypothesis: "*Reference prices are on average formed in accord to the final price*". Similar to Grosshans and Zeisberger (2018), I compute t-statistics to test whether the stated average reference prices of the down-up, up-down an full sample are significantly different from the final price of 110. If the average stated reference price is insignificantly different from 110, this then implies that the average stated reference price is formed in accord to the final price.

Table 2 indicates that self-stated reference prices for both down-up paths and up-down are significantly different from 110, -4.00 and +4.80 respectively. The close to equal magnitude of those signs leads to a statistically insignificant difference of +0.40 to the final price when the full sample is considered, supporting the second hypothesis. Under consideration of the full sample, the insignificant difference to the final price is backed up by Grosshans and Zeisberger (2018). However, Grosshans and Zeisberger (2018) find a positive difference for the up-down sample and a negative difference for the down-up sample, opposing the results for this paper.

The findings of this section and section 4.1 have two major implications. First, individuals do not have a static reference price as assumed by Prospect Theory, but dynamically increase their reference price following a winning sequence[5]. Assuming static reference prices, individuals become more risk averse following a gain (Kahneman and Tversky, 1979). If individuals however adapt their reference price upwards following a gain, their decrease in risk tolerance might be smaller (Grosshans and Zeisberger, 2018). Second, individuals end up with significantly higher reference prices when they

[5] The final price being the anchor for forming reference prices holds in context of 'winning' paths. Baucells et al. (2011) report the first price to be of most importance for individuals when forming reference prices. Under consideration that only 'winning' paths are used, there is not enough evidence to reject this finding as Grosshans and Zeisberger (2018) find that the first price is most important in context of 'losing' paths

are faced with an up-down path compared to a down-up path. Hence, facing equal positive returns, individuals' risk tolerance is likely to be influenced by the path that precedes the current price. For instance, in a scenario where an individual has been faced with an up-down path, (s)he will have a higher reference price and therefore likely more tolerance towards risk in the period to come. Hence, it is fruitful to analyze to what extent reference prices are influenced by path-shape differences within down-up and up-down paths, as is done in the next section.

Table 2

This table reports differences between the average reported reference price and final price for down-up, up-down and full sample. Standard errors are reported in parentheses. Unpaired t-tests are performed to test whether differences from final price are statistically significant from zero.*,** and *** correspond to significance levels of 10%, 5% and 1% respectively.

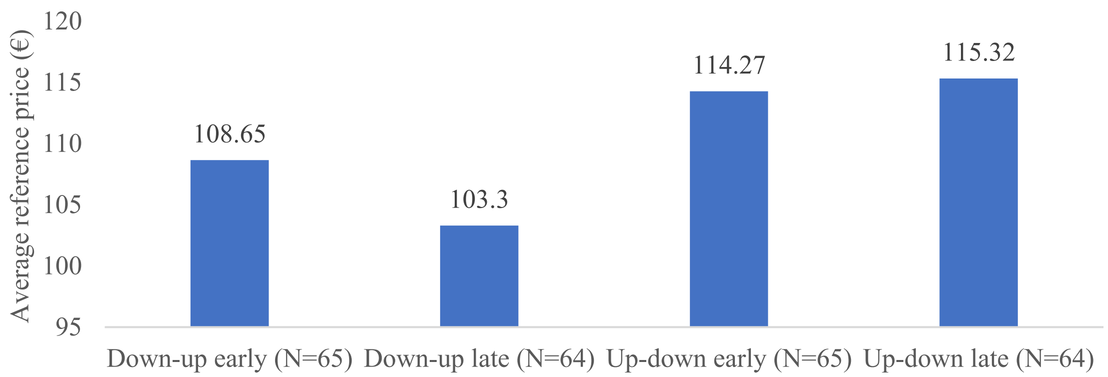
	Down-up	Up-down	Full sample
Difference to final price	-4.00***(1.25)	+4.80*** (1.30)	+0.40 (0.94)

4.3 Early versus late effects

The analysis now shifts to the main focus of this paper: the role of extrema-locations within down-up paths and up-down paths. Figure 3 visualizes the average reference price for down-up early, down-up late, up-down early and up-down late, which are 108.65, 103.30, 114.27 and 115.32 respectively. A first glance indicates that a timing effect is only present for down-up paths.

Figure 3

This figure displays the average stated reference price for early and late turning points. The number of participants per path is reported in parentheses.



In order to test for extrema-timing effects, I split the sample into two groups: down-up and up-down. Recall that the effect of extrema-timing is isolated when the maximum or minimum price, the average price, the purchase price and the final price are held constant. This is the case when the down-up and up-down samples are analysed separately (see figure 1).

For both samples, cross-sectional regressions are run with the dependent variable being the reference point and the independent variable of interest: the turning point. Cross-sectional regressions are used to be able to control for potential confounding factors and are captured in equation (1):

$$Reference\ price_{du,ud} = \beta_{du,ud} + \beta_2 * late_{du,ud} + \boldsymbol{\beta} * controls_{du,ud} + \epsilon_{du,ud} \quad (1)$$

Where du and ud denote down-up and up-down samples respectively. $late$ is a dummy variable that takes value 1 if the turning point occurs late in the price path, that is 9 months after hypothetical purchase. The potential confounding factors are captured by $controls$, containing age, gender, education, financial literacy and investment experience to remove the data from noise (Appendix B1).

Table 3

Ordinary Least Squares regressions on down-up and up-down paths focussed on turning points. The dependent variable is the average reported reference price. Table 5 in Appendix B2 includes all control variables. Standard errors are reported in parentheses.

	Down-up	Up-down
Late	-5.28** (2.49)	0.25 (2.55)
Constant	104.37*** (6.85)	120.56*** (6.75)
Controls	Yes	Yes
Adjusted R^2	0.0306	0.0498
N	129	129

* p < .1, ** p < .5, *** p < .01.

4.3.1 Down-up

Table 3 reports results from both regressions. Dummy variable $late$ has a statistically significant coefficient of -5.28 for the down-up treatment, implying that after taking controls into account, the average reference price was 5.28 lower for participants who faced the late treatment. In other words, when the trough is closer to the current price, individuals require a lower amount of money to have a neutral feeling about selling the hypothetical asset. Recall from Baucells et al. (2011) that for down-up paths the reference price is a function of the purchase price, current price, average price and minimum price, which in this case are held constant within down-up paths. Hence, differences in reported reference prices are due to the location of the minimum price which are attributed to two possible explanations.

First, the average price of the early treatment (94.62) is substantially higher in the last three months compared to the late treatment (84.77). Baucells et al. (2011) find a significant effect of the average price on the reference price. In general, many individuals are susceptible to the recency bias and overweight information close to the current price (Shefrin and Belotti, 2007; Bailey et al., 2011, Bhootra and Hur, 2013; Lin, 2018). This in turn implies that individuals consider the average price of the asset in different segments rather than just the average price of the full path, where the last piece of information is most important when forming reference prices. The combination of a lower average reference price in the last three months and the overweighting of that information could cause reference prices to be significantly lower for individuals who face a down-up path with a late turning point.

Second, the timing of the turning point influences the time to adapt the reference point in accord to the final price. In context of a down-up path, individuals first experience a loss and then a gain. Although individuals adapt their reference price rather quickly following a gain (Arkes et al., 2008), the lower reference price for the late treatment could be attributed to the lower amount of time individuals have to adapt to the final price. The early treatment has a longer and thus more stable rising pattern.

The significant lower reference price for down-up paths with an early turning point supports the third hypothesis: "*Reference prices within down-up paths are lower for late turning points compared to early turning points"*. This result implies that reference prices are lower for a late-timed minimum price, which leads to a higher probability of outperforming the reference price in the next period. Accordingly, individuals that face a down-up path with a late turning point are likely to be less tolerant towards risk in the next period, compared to individuals that face a down-up path with an early turning point.

4.3.2 Up-down

Surprisingly, $Late$ has an insignificant coefficient of 0.25 for the up-down treatment (table 3). The absence of a timing effect contradicts the fourth and final hypothesis: "*Reference prices within up-down paths are higher for late turning points compared to early turning points"*. This result is surprising, as the potential factors that drive the timing effect in the down-up treatment could be relevant for the up-down treatment too, if not, more.

Recognize that the distance from the extremum to the final price is equal across the two treatments. Hence, the argument that individuals have less time to adapt the final price when they are faced with the late treatment could work for the up-down sample as well. Even more so because Arkes et al. (2008) find that individuals adapt their reference price slower for up-down sequences compared to down-up sequences. Individuals were therefore expected to put more weight to the maximum price when faced with the late treatment, however, the results do not support this belief.

Moreover, the last three-months average price is higher for the late treatment (115.90) compared to the early treatment (110.62). Although this difference is smaller relative to the down-up sample, one would expect a significant timing effect in the up-down sample as well if individuals overweight recent information relative to distant information.

This paper offers two explanations for an absent timing effect in the up-down treatment, given the present timing effect in the down-up treatment. First, the up-down paths are shaped quite differently in comparison to the down-up paths with respect to extrema (figure 1). The peaks are significantly sharper than the troughs, as the up-down paths are characterized with a relatively straight path aside from the salient peak. As a result, the peak itself is more relevant in forming reference prices than the location of the peak. Conversely, down-up paths have broader troughs, making them less salient relative to the rest of the path. Second, the hypothesized argument inspired by Arkes et al. (2008) - asymmetric reference price updating drives the timing effect especially for up-down paths – is ambiguous. One could also argue that due to the stickiness of the reference price in context of up-down paths, the focal maximum price itself is more important than its location, such that individuals are more likely to stick their reference price in accord to the maximum price regardless of when the maximum price occurs.

5. Discussion and Conclusions

This paper contributes to the vast literature on reference prices by analysing extrema-timing effects within price paths in an experimental setting, in which paths are carefully constructed to isolate the effect of extrema-timing on reference prices. The analysis on the effect of those path characteristics on reference prices produces four main results.

First, individuals report significantly higher reference prices for up-down paths compared to down-up paths, consistent with Baucells et al. (2011), Grosshans and Zeisberger (2018) and Nolte and Schneider (2018). Second, reference prices are on average formed in accord to the final price and do not stick to the purchase price as traditionally assumed when analysing the disposition effect (Shefrin and Statman, 1985). Since only paths with positive returns are considered, this result implies that the upward updating is relatively larger than the downward updating, providing additional robustness to previous findings by Arkes et al. (2008), Baucells et al. (2011), Grosshans and Zeisberger (2018) and Nolte and Schneider (2018). Recall the main research question: '*To what extent does the timing of extrema in price paths influence reference prices?* The third and fourth result contain timing effects and deserve some extra attention.

This paper is the first to explore the effect of extrema-timing on reference price formation in context of price paths. Previously, Baucells et al. (2011) used sequences of at most seven prices and did not find a timing effect regardless of any pattern. Relative to the use of price sequences (Baucells et al., 2011), price paths have a higher external validity as they are frequently used in practice to graphically represent product information (Nolte and Schneider, 2018). I conjecture that price paths enable the timing effect by increasing the focality of both the extremum and its timing. The first hypothesized underlying driver of this effect is a combination of overweighting recent information and a different average reference price in the final part relative to the first part. Second, assuming that individuals derive implicit reference prices from the extremum, one could argue that when the extremum occurs more recently, individuals have less time to readapt the reference price to information that follows the extremum. However, the analysis shows ambiguous results with respect to timing. In context of price paths with a positive return, individuals report reference prices that are sensitive to the location of the minimum price, but insensitive to the location of the maximum price. To conclude, the timing of extrema influences reference price formation within down-up paths, but does not influence reference price formation within up-down paths

There are numerous implications to be derived from this paper. Trading decisions are largely influenced by return beliefs and risk preferences (Grosshans and Zeisberger, 2018). Reference prices determine the latter, as investors tend to act risk-averse when the reference price is outperformed, whereas they are risk-seeking when prices are below their reference price (Odean, 1998). Keeping returns and volatility constant, risk preferences are largely influenced by the path that precedes the current price. Higher (lower) reference prices for up-down (down-up) paths imply that individuals are more likely to become risk-seeking (risk-averse). In addition, within down-up paths, individuals are more likely to become risk-averse when the minimum price has occurred more recently, and ultimately less likely to invest.

Next, Lin (2018) finds an increase in stock recommendations if the stock's 52-week high or low occurred in the recent past relative to the distant past. The author suggests that investors anchor on the 52-week high and low, especially when the high/low occurs more recently. Surprisingly, in this paper's experimental setting, individuals anchor on the 52-week high but not significantly more when the 52-week high occurs more recent. One could then argue that anchoring on the 52-week recent high might not entirely explain the increase in stock recommendations around that period. The up-down paths are however constructed in a way that the maximum price stands out to an extent that the location of the peak could become irrelevant.

For future research, it would be beneficial to use price paths with negative returns as well, as price path characteristics in that context are found to be less influential in reference price formation (Grosshans and Zeisberger, 2018). Moreover, to rule out that the timing-effect is ambiguous due to extrema-width differences, future research should compare extrema with equal width. All in all, the field would benefit from a further exploration on the effect of price path characteristics on reference prices, given the importance of reference prices in financial decision making and the frequent use of price paths to inform investors.

Appendix A. Experiment

This section contains screenshots from both the introduction to the experiment (Figure 4) and the decision round (Figure 5).

Figure 4

This figure is a screenshot of the introduction to the experiment.

Dear participant,

Welcome to this online experiment! In the following, you will be presented with the price development of a single stock. After the price path is plotted, you will be asked to indicate at which selling price you would feel neither happy nor unhappy about selling the stock.

Please take your time and imagine this was your own stock. There are no right or wrong answers. It does not matter whether you actually invest in shares or not, the questions can be answered by everyone.

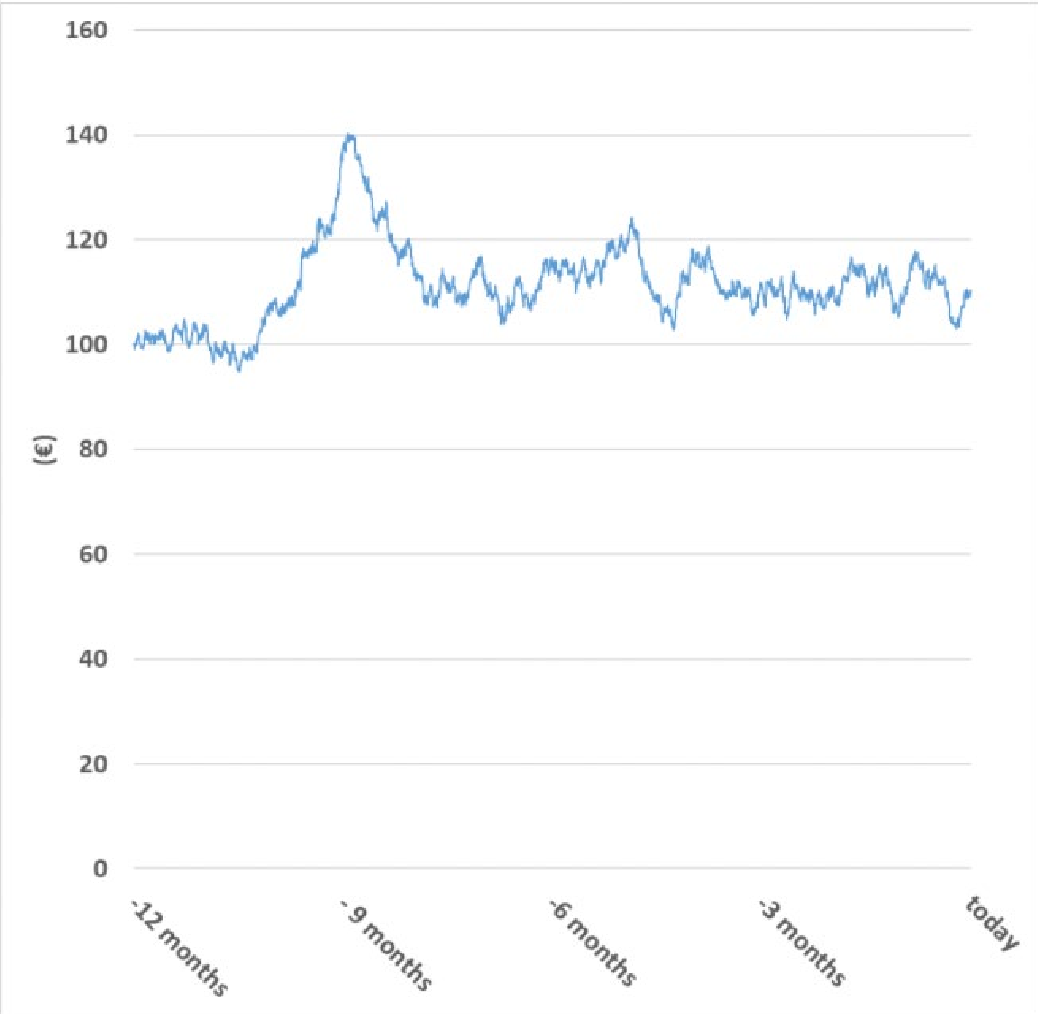
At the end, I would like you to fill in a short questionnaire. Overall, this study will approximately take 2-3 minutes of your time.

In case of any questions or remarks, you can contact me at: h.kurz@student.ru.nl

Your feedback and time is appreciated.

Figure 5

This figure is a screenshot of the decision screen participants saw when faced with the up-down early treatment. The other treatments are displayed identically in terms of scaling and question.



Please take a look at the graph above. It displays the price development of a stock over the past year. The presented information is not related to the current real financial market situation.

Imagine you purchased this stock exactly a year ago. At which hypothetical price would you neither be happy nor unhappy to sell the asset tomorrow?

Appendix B. Analyses

B1. Summary statistics

Table 4

This table reports the averages of the self-stated reference price and control variables: investment experience, financial literacy, age, education and male for the non-Mturk sample, Mturk sample and full sample.

	Non-Mturk[6]	Mturk	Full sample
Reference price	108.21	111.03	110.40
Investment experience	2.59	3.06	2.95
Financial literacy	3.29	3.19	3.21
Age	27.71	33.82	32.45
Education	4.52	4.30	4.34
Male	0.76	0.63	0.66
N	**58**	**200**	**258**

Table 4 shows that both the reference price and control variables are not shockingly different for the non-Mturk sample and Mturk sample. With 200 participants, a large portion of the total sample (N=258) is represented by Mturk participants. As table 6 shows, the timing effect of extrema (captured by $\boldsymbol{Late}$) is indifferent between the Non-Mturk and Mturk group. Hence, the regression results of table 3 are not qualitatively influenced by distinghuishing among the non-Mturk and Mturk group.

Investment experience and financial literacy are measured by asking participants to rate their own investment experience/financial literacy compared to the average person (Borsboom and Zeisberger, 2020). The questions are answered on a 5-point Likert scale, ranging from much lower to much higher. Education contains seven levels: primary school, secondary school, the Intermediate Vocational Education (IVE), the Higher Vocutional Education (HVE), university bachelor, university master and PHD. For all samples, the average level of education is therefore somewhere between HVE and university bachelor.

[6] Non-Mturk sample is acquired via distribution of survey link through social media.

B2. Reference price analyses

Figure 6

Distribution of the reference price for the full sample.

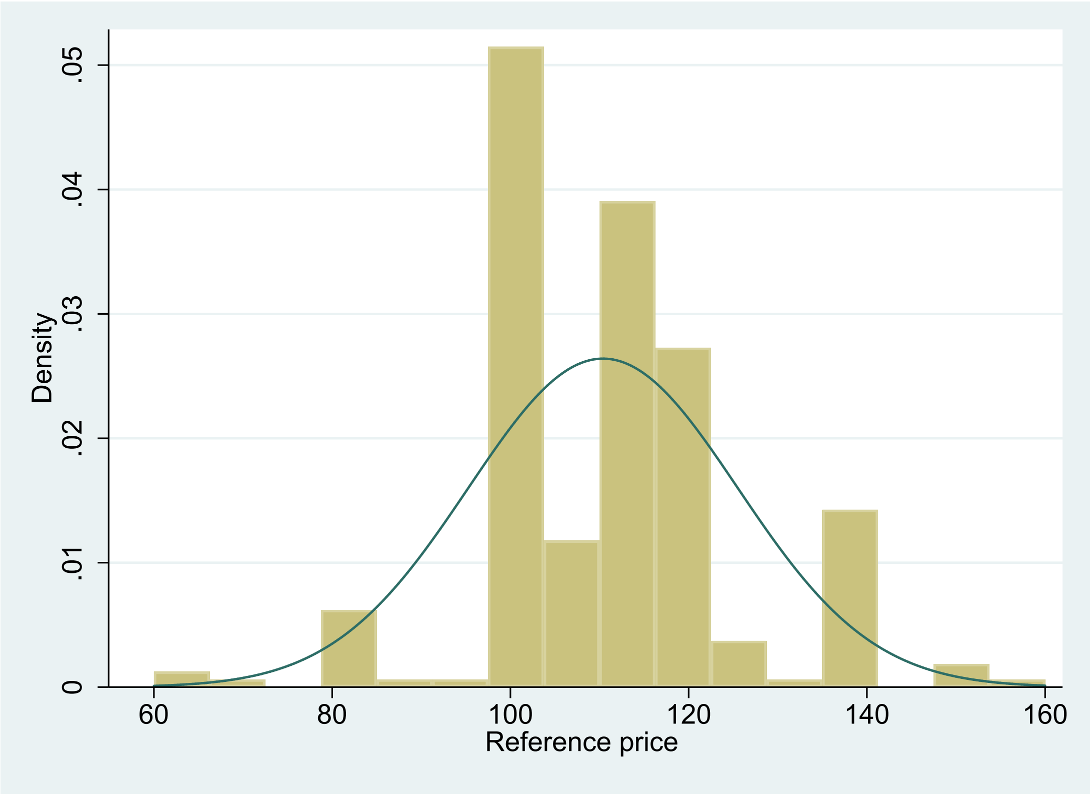


Figure 6 shows the distribution of the self-reported reference price for the full sample (N=258), to show whether it is normally distributed and to spot potential outliers. The reference price is close to normally distributed. The observations range from 60 to 160, the modus is 100 (hypothetical purchase price) and the mean is 110.40 (close to final price). Figure 7 shows the separate distributions of the reported reference price for the down-up and up-down samples.

Figure 7

Distribution of the reference price for the down-up and up-down samples separately

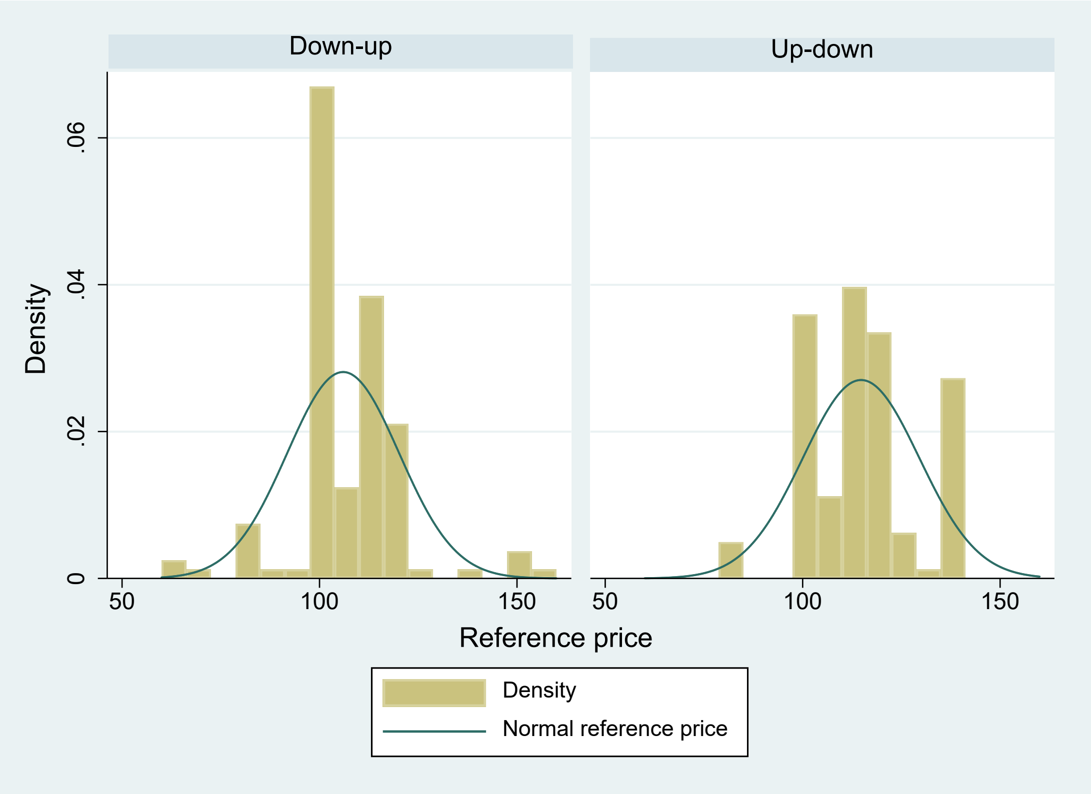


Figure 7 shows that he self-reported reference price is close to normally distributed for both samples. As for potential outliers, none of these reported reference prices are considered to be insensible, as reference prices reflect a gut feeling on which participants feel neutral about selling the hypothetical asset, ie. there is no right or wrong gut feeling. Hence, all observations are included in the analysis. The modus of 100 depicted in figure 6 is mostly driven by the high choice frequency of 100 in the down-up sample.

Table 5

OLS regressions on both samples including control variables. The dependent variable is the reported reference price. Standard errors are reported in parentheses.

	Down-up	Up-down
$\boldsymbol{Late}$	-5.28** (2.49)	0.25 (2.55)
Investment experience	2.51 (1.71)	4.85*** (1.60)
Financial literacy	-1.33 (1.86)	-3.80* (2.01)
Age	-0.10 (0.12)	-0.24* (0.13)
Education	1.04 (0.95)	0.21 (0.93)
Male	-0.57 (2.70)	-1.46 (2.85)
Constant	104.37*** (6.85)	120.55*** (6.75)
Adjusted R^2	0.0306	0.0498
N	**129**	**129**

* $p < .1$, ** $p < .5$, *** $p < .01$.

Table 5 shows that none of the control variables significantly affect the reference price for the down-up sample. Hence, the found timing effect captured by $\boldsymbol{Late}$ (-5.28**) holds when control variables are included. As for the up-down sample, $\boldsymbol{Late}$ (0.25) is insignificant, indicating zero effect of timing on the reported reference price.

Table 6

This table reports OLS regressions for both samples including an interaction term: ***Late****Mturk. The dependent variable is the reported reference price. Standard errors are reported in parentheses.

	Down-up	Up-down
Late	0.03 (4.96)	3.89 (5.89)
Mturk	4.44 (4.22)	3.88 (4.60)
Late * Mturk	-7.17 (5.71)	-4.61 (6.55)
Investment experience	2.35 (1.82)	4.56*** (1.70)
Financial literacy	-1.06 (1.92)	-3.55* (2.08)
Age	-0.12 (0.13)	-0.25* (0.13)
Education	1.08 (0.96)	0.29 (0.754)
Male	-0.90 (2.72)	-1.12 (2.90)
Constant	101.41*** (7.30)	117.16*** (7.83)
Adjusted R^2	0.0279	0.0400
N	**129**	**129**

* p < .1, ** p < .5, *** p < .01.

To test whether the Mturk sample behaves differently compared to the non-Mturk sample, an interaction term is included: *Late* * Mturk. For both samples, there is no interaction effect found, implying that their characteristics (Table 4) and results are qualitatively indifferent.

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