Investor Reference Points: An Investigation using Experiments and Asset-Pricing Models

Christopher Allan Riley

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The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

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Abstract

It is widely acknowledged that reference points play an important role in decision-making and that the study of reference points has application to decisions taken in a wide range of areas within Management, Marketing and Sports Analytics. Within the realm of Finance, reference points have been incorporated into models that are designed to capture the behaviour of both buyers and sellers of financial assets. Typically, the reference point within these models is assumed to be the purchase price of an asset and is not thought to move in line with the price of the asset. Our aim in this thesis is to investigate the role of reference point adaptation by investors. Specifically, we examine if prior price movements can influence the reference point of participants. Our study should be of interest, both in the academic field of reference points and more specifically in the area of reference points within financial models. We use both experiments and classical empirical methods within the thesis, utilising the advantages of both methods. Experiments are used to test for reference point adaptation within controlled conditions. We undertake two different experiments, which measure reference point adaptation across either a single chart, or across 60 months within a chart. Then we test the external validity of our findings, using three different market data models. Each of the market data models use reference points to predict mispricing in shares. The use of both experiments and market data testing within a single study is rare within the academic literature and is a key competitive edge of our approach. Our results have implications both for academics interested in reference point adjustment and investment professionals who wish to study how reference points cause mispricing in markets. The distortions in market prices caused by reference points, which we demonstrate using three different market data models, lead to profitable arbitrage opportunities which could be capitalised upon by Investment Managers.

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1 Introduction

1.1 Background

A reference point acts as a neutral basis or standard for evaluation of a decision, acting as a demarcation between a gain or a loss to the decision maker. Reference points have been shown to play a role in decision making in a wide range of fields. Within the field of management, reference points influence firm based capital investment decisions (Whyte, 1986) and strategic decisions (Bamberger and Fiegenbaum, 1996). Reference points also have wide application to behavioural marketing and in particular to the pricing of consumer products (Mazumdar et al., 2005). In more recent research, reference points have been shown to influence sporting behaviour and hence have application to Sports Analytics. Stone and Arkes (2016) show that reference points influence the behaviour of PGA golf players, inducing players to take more risk when they are below their reference point, while Bartling et al. (2015) show how reference points affect the substitution decisions of football managers and the subsequent results they achieve.

Given the broad applicability of reference points to decision-making, it is perhaps surprising that more attention has not been paid to this subject within the field of finance. One of the first major applications of reference points within finance was as part of the disposition effect, developed in Shefrin and Statman (1985). They showed that investors have a disposition, or tendency, to sell winners over losers. The authors use the purchase price, as the reference point which defines a gain or loss. Mental accounting rules are mentioned as a reason why the reference point remains fixed in their paper, as each stock is allocated a new account at the time of purchase, making the purchase price the most natural reference point for investors.

Subsequent testing on the disposition effect within an experiment (Weber and Camerer, 1998) and field data (Odean, 1998), largely chose to continue with the assumption of a fixed reference point. Weber and Camerer (1998) undertake their experiment using either a purchase price based reference point, or a last-period reference point and show that a disposition effect holds under either assumption. Odean (1998) explicitly assumes a purchase price-based reference point for the purposes of his testing, although he accepts that the price path may affect the reference point for long-term investments such as the purchase of a home. He does, however, make the case that if the purchase price is only a proxy for the true reference point then the statistical evidence would only be stronger if a more accurate proxy could be found, which is our aim in this thesis.

Investor reference point adaptation has implications, both for investor models and the asset pricing literature. Prominent models that incorporate reference points include the Capital Gains Overhang model of Grinblatt and Han (2005) and the V-Shaped Net Selling Propensity Model of Ben-David and Hirshleifer (2012), which was subsequently tested in market data in An (2016). Both models use a fixed reference point, based on the purchase price, and do not consider that reference points may move over the life of an investment. Grinblatt and Han (2005) test one alternative to the purchase price, the 52-week high, in their market data testing and find that it has greater explanatory power than the purchase price. Given the promising findings of Grinblatt and Han (2005) regarding the 52-week high as a reference point, an obvious line of inquiry is to investigate if more complex reference points can improve predictive power still further.

The Prospect Theory Value of a Stock model of Barberis et al. (2016) uses reference points within their model to predict investor preference. They assume that the reference point is the monthly return of a relevant benchmark index of stocks. Investors have also been shown to have a preference for volatile stocks (Ang et al., 2006) and stocks that exhibit high positive skewness (Ang et al., 2013), which leaves these stocks overpriced. The Barberis et al. (2016) model has the potential to explain these anomalies within a single model that also incorporates reference points. The inclusion of adjusting reference points within their model could further increase its explanatory power.

1.2 Research Questions

A number of prior studies measure the investor reference point e.g. see Baucells et al. (2011) or Arkes et al. (2008), at the point of sale, and therefore our research questions in this area focus on improving these studies, specifically in the area of external validity. In particular, there are no previous studies using realistic share price charts sampled from real market data, or using time calibrated in realistically long holding periods for investors. This makes it difficult to apply the studies in a real-world context and means that findings on time-specific reference points, such as the 52-week high (George and Hwang, 2004), cannot be incorporated into the analysis. The aim of the 1st experiment is to address these issues, within the design of the experiment, and hence improve external validity, such that coefficients from the experiment can be used in the subsequent market data analysis.

Our thesis also aims to test if the adaptation, observed within an experiment, has an impact on market prices. We achieve this using 2 different asset pricing models: the Capital Gains Overhang (CGO) model of Grinblatt and Han (2005) and the V-Shaped Net Selling Propensity model of An (2016). Both models attempt to measure the market reference price of a representative investor using turnover. The idea is that turnover (volume/shares outstanding) represents new investors coming into the market, which refreshes the aggregate reference point. A key omission of both models is that they do not take account of reference point adaptation that may occur on the part of existing holders. A more accurate reference point could improve the explanatory power of their models. To address this issue, we assess how these models perform under a regime of reference point adaptation on the part of existing holders. We examine if the predictive power of the models are improved when reference points adjust to new salient features in price charts.

Our 2nd experiment was designed to measure reference point adaptation through 60 consecutive months rather than once, at the point of sale. This is so that the results of the experiment can later be used as an input to improve the Barberis et al. (2016) model. To do this, we design an experiment with a 5-year price chart and ask participants for a neutral selling price every month. A key question to be examined is whether the reference point is the same for this experiment, as for the earlier one. Are the same salient prices the relevant ones and do they have the same weight in the determination of the reference point in both experiments? As 60 reference points are taken from participants within the same chart, this raises the possibility that the previous month's reference point may act as an anchor for the current month; something that is not possible in the earlier experiment. Therefore, we also investigate the impact of a lagged reference point on the determination of the current reference point. Finally, as reference points are measured across 60 months, this raises the possibility that time moderation effects are evident. For example, it may be the case that the purchase price matters more in the initial months than the later months as a determinant of the reference point. We investigate time moderation effects across the 60 months.

The model of Barberis et al. (2016) looks at how investor preference for stock price patterns affect their valuation. The model builds on previous work that found an investor preference for highly volatile (Ang et al., 2006) and highly skewed Ang et al. (2009) stock returns. The prior literature, however, is silent on how investors might form reference points in this context and Barberis et al. (2016) assume a reference point based on a market benchmark. In our experiment, we examine the role of the prior price path on the sequential reference point across 60 months. We investigate if this reference point has greater explanatory power when incorporated into the Barberis et al. (2016) model than the reference point based on the market benchmark. The results can also be compared to those of the previous experiment. For example, what if reference point formation is actually closer to our earlier experiment, where reference points are only measured once at the end of a chart? We explore the possibility, within the Barberis et al. (2016) model, that reference points are formed using an end-point reference point and test if this method of adjustment has more explanatory power than the adaptation approach. A final question to consider is if a reference point constructed using a lagged reference point from the previous month has explanatory power within the Barberis et al. (2016) model? Our experiment suggests that lagged reference points are a major determinant of the current period reference point and so we test if versions of TK that incorporate lagged reference points have greater predictive power than conventional TK.

1.3 Contribution

We design an experiment to measure investor reference points building on the experiment of Baucells et al. (2011). Specific modifications are made to improve external validity and measure the impact of recent highs and lows on reference point formation, which is achieved by using charts sampled from real data that go up to 5 years in length. We show that recent highs and lows are important determinants of an investor's reference point in addition to the overall high, purchase and final prices. The role of recent highs and lows in reference point formation is a new finding in the literature that was not discovered previously due to the use of short time periods or generic (nameless) time periods. The coefficients from the experiment then form a predictive function that is used as an input within the empirical analysis in Chapter 4 and Chapter 5.

The new reference point is used to modify the CGO model and VNSP models. Both models aim to predict mispricing in the equity market caused by the behaviour of investors. In the case of CGO, winners are underpriced and losers are overpriced, whereas, in the VNSP model, both extreme winners and extreme losers are underpriced. We find that composite CGO variables, based on adjusting reference points, are better predictors of future returns than the traditional CGO variable, based on the purchase price. The results suggest that investors do indeed update their reference point and that accounting for this, as the composite variables do, improves the predictive power of these models relative to models that only include traditional CGO.

In terms of VNSP, however, we do not find that VNSP based on an adjusting reference point is better than the purchase price based VNSP. Our results suggest that VNSP based behaviour may be driven by a different mechanism that does not involve reference point adjustment from the purchase price. Both Ben-David and Hirshleifer (2012) and An (2016) believe that VNSP is caused by the behaviour of speculative investors who make decisions driven by their prior beliefs. These speculative investors expect any stock they purchase to appreciate relative to the initial purchase price and are reluctant to sell if the price does not move significantly from the purchase price in either direction. Our results confirm that the speculative trading hypothesis is the most likely cause of VNSP behaviour, although we also discuss alternative hypotheses.

In terms of reconciling CGO and VNSP effects together, Hoffmann et al. (2013) show that participants place more weight on initial beliefs at the beginning of their investment but place more weight on salient features of the share price path as time invested progresses. The implication is that the VNSP effect may be predominant in the early stages of an investment, with the CGO effect becoming more important as the holding period increases.

We also examine how recent highs and lows can improve the predictive power of the CGO variable and investigate if their incorporation adds to predictive power in the presence of the previously discovered 52-week high of George and Hwang (2004), added as a control variable. We find that the strongest composite CGO variable is the one that includes recent highs and lows. When we add the 52-week high variable from George and Hwang (2004) into the regression as an additional control variable, the predictive power of the composite CGO based on recent highs and lows is still maintained. This suggests that recent highs and lows are determinants of the reference point, as suggested by our earlier analysis, and that the result is not simply a proxy for the already discovered distance from 52-week effect of George and Hwang (2004).

The Barberis et al. (2016) model requires an experimental design that can account for updating of reference points on a monthly basis. Therefore, we design an experiment that measures the adaptation of reference points across 60 months, within the context of a single 5-year chart. We find that the salient points that determine the reference point are somewhat different from those in the first experiment. In particular, we find a greater role for that of the final price and smaller role for intermediate maximums and minimums than indicated in the previous experiment.

The impact of lagged reference points is a possible explanation for the differences in reference point formation across the two experiments. In Chapter 3 participants only gave one reference point across each chart and so the previous reference point is an irrelevant anchor for the next chart, whereas in this experiment all 60 reference points are provided for the same chart. We find that the previous period's reference point is a strong anchor for the current period reference point, although the purchase and final prices still remain significant in the regression. We also explore the issue of time moderation, which the design of the experiment facilitates, measuring reference points across 60 months. There is some evidence that maximums and minimums become less important as time progresses, which is likely due to a greater weight being placed on the final price as the 60-month period progresses. The explanatory power of the model with time moderators included, however, is not much greater than without them, suggesting that time moderation does not play a large role in the determination of the reference point.

In our final empirical Chapter, we apply the results from the adapting reference point experiment to the model of Barberis et al. (2016). This model generates a variable called TK, which is the Prospect Theory Value of a stock. Barberis et al. (2016) show that high TK stocks tend to be overvalued, while low TK stocks tend to be undervalued. We show that alternative TK variables, created using composite reference points with weights developed in the last experiment, are significant when included in a model with the traditional TK variable included, but the traditional TK variable is insignificant. We also examine if TK variables with reference points generated using the process from the 1st experiment are significant. This experiment only provides one reference point for each chart, so we consider two methods of adjustment, either linear or exponential across the 60 months. Neither of these methods have as strong explanatory power as the TK variables created using the 60 reference points adapted over the months. The results suggest that our 2nd experiment provides a more valid context to generate reference points as an input to the Barberis et al. (2016) model than the 1st experiment.

We also consider the impact of lagged reference points. Results from the 2nd experiment suggest that lagged reference points are important anchors in determining the subsequent period reference point. We find TK variables that incorporate the lagged reference point are significant when included in the model with the traditional TK variable, but the traditional TK variable is insignificant. The results suggest that the alternative TK variables, with a reference point based on the prior price path or the lagged reference point, are better predictors of future equity returns than the traditional TK variable.

1.4 Structure

Chapter 2 of the thesis provides an overview of the literature in the area of reference points. Given the breadth of research in this area, the focus is on studies related to investor behaviour. We split the literature up into previous work on experiments, field data and asset pricing models in relation to investor reference points.

Chapter 3 covers the design and analysis of a new experiment to measure reference point formation. The experiment uses real share price charts for horizons up to 5 years and is the first to show that recent highs and lows play an important role in the formation of investor reference points. We generate formulas for composite reference points in this chapter, which are used in subsequent market data testing.

Chapter 4 features an extension of the Capital Gains Overhang model to account for reference point adaptation. We use coefficients from Chapter 3 to form composite CGO variables that account for movements in investor reference points. These composite based CGO variables outperform the traditional CGO variable in explaining future returns. Models that include the 2nd composite variable, built using recent highs and lows, have the highest r-squared.

Chapter 5 applies reference point adaptation to the V-Shaped Net Selling Propensity Model. In contrast to the CGO model, we do not find that incorporating reference point adaptation improves the predictive power of this model. Possible reasons why reference point adaptation is not as applicable to this model are explored, such as the role of investor beliefs in driving this effect.

In Chapter 6 we design and implement a new experiment to measure reference point formation and adaptation across a set of 60 months to act as an input into the Barberis et al. (2016) model. This experiment differs from Chapter 3 in that reference points are measured repeatedly across all 60 months within a 5-year time period, rather than just once at the end of the chart. We generate a formula for a new composite reference point based on adaptation across the 60 months, which is used in the subsequent chapter.

Chapter 7 then applies the results of the experiment in Chapter 6 to the Barberis et al. (2016) model. We find that TK variables that incorporate adjusting reference points are better predictors of future returns, than the traditional TK variable which has a reference point based on the benchmark return. We also examine time moderation across the 60 months and the impact of lagged reference points on the determination of the current month’s reference point and show that TK variables that incorporate lagged reference points are also significant predictors of future returns.

In Chapter 8 we conclude with a summary of findings and discuss limitations and future research avenues that arise from the thesis, as well as implications for the existing literature.

2 Literature Review

The following literature review is split into 4 sections: theoretical background, review of papers in experimental research, review of papers in market data testing and review of market data models. In the theoretical background section, we discuss the main building blocks of Prospect Theory and Mental Accounting with a focus on the role of the reference point.

The experimental section considers experiments carried out in reference point formation and adaptation, with a focus on studies related to share price movements. Reference-dependent preferences are not limited to share prices, but are prevalent in a range of situations, for example the behaviour of game show contestants (Post et al., 2008), PGA Tour golf players (Stone and Arkes, 2016), the behaviour of football players & managers (Bartling et al., 2015), firm based capital investment decisions (Whyte, 1986), firm based strategic decisions (Bamberger and Fiegenbaum, 1996) or behavioural pricing of consumer products (Mazumdar et al., 2005). We only consider this literature if it is of direct relevance to the work on reference points in share prices.

In the third section, we examine studies of reference points within market data. These papers may use field data to study the behaviour of investors, or the reference point may be measured indirectly from the market data using proxies. For example, changes in a metric such as share turnover could indirectly measure changes in reference points (Kliger and Kudryavtsev, 2008). The use of proxies can be problematic, however. Duxbury (2015) discusses proxies used for overconfidence and shows that they have inconsistent results, depending on the proxy chosen.

The fourth section of the literature review discusses market data models. These models are mechanisms through which reference points may affect market prices, through the action of investor preference. Typically, these models will utilise a fixed reference point based on the purchase price, but newer work is introducing the concept of a moving reference point.

2.1 Theoretical Background

The reference point is one of the central pillars of Prospect Theory, developed by Kahneman and Tversky (1979) as an alternative to Expected Utility Theory. They found that choices taken by decision makers exhibited a number of features that were not in line with those predicted by Expected Utility Theory. The three central features of prospect theory are:

1. Decisions are taken relative to a reference point.
2. Risk aversion in gains (consistent with expected utility theory), but risk seeking in losses.
3. Loss Aversion.

A key element in Prospect Theory is recognising that people make decisions based on a reference point. When making a decision, the consequences are then measured as the change relative to the reference point. One example of the reference point would be their current situation, as the status quo represents a powerful anchor by which individuals can judge changes (Samuelson and Zeckhauser, 1988). Alternative reference points could also be adopted such as an aspirational goal (Heath et al., 1999b) or an expected return (Hack and von Bieberstein, 2015). For example, if an individual expects to make a 10% return on an asset over the course of a year then a 5% return would be treated as a 5% loss relative to the 10% expected return.

The second key element of Prospect Theory is to value gains and loss from the reference point differently. Kahneman and Tversky (1979) found that decision makers were risk averse in gains above the reference point, which is not a controversial finding as it is consistent with expected utility theory. This is because individuals reach a satiation point with goods or with total wealth as the quantity of the good increases. A newer element of Prospect Theory, however, was the discovery of risk seeking in losses. An example of this would be the desire to take on a gamble to recover initial losses.

The third area of development was to measure how sensitive people are to individual gains and losses, resulting in a valuation function. Specifically, Kahneman and Tversky (1979) found that people were 2-3 times more sensitive to equivalently sized losses than to gains (the standard parameter used is 2.25x), which they termed `loss aversion'. Differential sensitivity to gains and losses was not previously considered in expected utility theory, as only changes in total wealth were considered and hence individual gains or losses could be netted out.

The key features of Prospect Theory can be observed in Figure 2-1 below. The reference point is the central point of the X-axis. Gain or loss is now measured as the change from the reference point, which is the point of indifference, rather than changes in total wealth.

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Figure 2-1: Taken from Kahneman and Tversky (1979)

The concave shape of the curve in gains is uncontroversial, as it reflects risk aversion in gains. This reflects decreasing marginal value from gains, as the size of the gain increases. A more unusual feature is the convex shape of the curve in losses, reflecting risk seeking. This suggests that people care less about each marginal unit of loss, as the size of the loss increases.

The steeper slope of the curve in losses relative to gains is also evident. Experimental evidence pinpointed the rate of loss aversion at a factor of around 2.25 times. This feature of Prospect Theory has been used to explain the endowment effect (Kahneman et al., 1990), where participants value a good more highly when it is in their possession than when they bid for it as a potential buyer. For example, if they are given a mug then their potential selling price for the mug is well above the price that they would have been willing to purchase it, had they been given cash instead. A good in their possession becomes the status quo and a sale is then considered as a loss, relative to the status quo of possessing the mug. The value of the mug as a gain, when making a purchase from cash, however, is much lower.

The reference point is key to how decisions are framed and subsequently evaluated. This framing can have a marked influence on the decisions taken. In particular, a frame that invokes a loss moves participants into the loss portion of the curve where they tend to be risk-seeking, rather than the gains portion of the curve where they tend to be risk-averse. A common example of this is the ‘Asian Disease Problem’ (Tversky and Kahneman, 1981), where participant response varies depending on how the scenario is presented to them. In the lives saved frame, they are given the option to save 200 out of 600 lives by providing a conservative treatment or choose a more speculative treatment where there is a 1/3 probability that 600 people will be saved and a 2/3 probability that no people will be saved. The reference point is therefore that all 600 lives will be lost and so any life that is saved is treated as a gain. In the expected deaths frame, the more conservative treatment will cost 400 out of the 600 lives, or the speculative treatment will ensure a 1/3 probability that nobody will die, and a 2/3 probability that 600 people will die. Therefore, the reference point in the loss frame is that all 600 people will live and so any death is treated as a loss. Although the two treatments provide the same outcome in either frame, participants prefer the conservative 1st treatment in lives saved frame and the more speculative 2nd treatment in the expected deaths frame. This demonstrates that framing problems as either gains or losses can provoke risk-averse or risk-seeking behaviour. This is because it changes the reference point.

Standard Prospect theory has difficulty explaining certain decisions. For example, the propensity of a decision maker to buy both insurance and buy lottery tickets. If the decision maker is risk-seeking in losses, then the decision to buy insurance to cover a large loss seems unlikely. Equally, risk aversion in gains should act as a disincentive to buy lottery tickets as the marginal utility from gains is decreasing. What is common across both of these decisions, however, is the low probability of the event occurring, either a disaster that brings about an insurance claim or to win the lottery. Thus, the key to unlocking this puzzle is to consider how people measure objective probabilities when calculating Prospect Theory value.

Tversky and Kahneman (1992) developed new cumulative decision weights, which could explain the issue around small probability events. In Figure 2-2 below, objective probabilities are represented by the solid black line, while decision weights for gains and losses are represented by the dotted lines w^+ and w^- respectively. Small probability events are given considerably more weight than deserved by their objective probability for both gains and losses. This explains why the same individual can both play the lottery and buy insurance, as the participant overweights the chance of having to make an insurance claim or winning the lottery. The slope of the w^+ and w^- curves then becomes flatter than the objective probability line in the middle section of the curve, reflecting a lower decision weight than warranted for these events. Finally, for very likely events the w^+ and w^- curves again become steeper than the objective probability curve. If an event is very likely to happen, decision makers may ascribe certainty to the event.

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Figure 2-2: Taken from Tversky and Kahneman (1992)

The parameters discussed in Tversky and Kahneman (1992) are relevant for decisions in which participants are aware of events and are in a calculating frame of mind. This is the case where participants are provided with a gamble with pre-defined probabilities, as this puts them in a calculating frame of mind and there is little emotion attached to the decision. Emotionally charged presentation of information can cause a bigger deviation between the objective probability and the decision weight, as well a bigger deviation between the subjective and objective value, due to scope insensitivity (Hsee and Rottenstreich, 2004). For example, the small risk of death of a child due to a disease may be greatly over exaggerated by a parent because of the feelings invoked in the decision. The probabilities of winning a gamble used in Tversky and Kahneman (1992) do not evoke as large an emotional response and are therefore likely to be considered in a more calculating way.

Participants may ignore rare events altogether if the event is not salient in their mind (Bordalo et al., 2012). This is relevant because the information for events, provided to participants in academic studies, is provided to them within an experiment so that a choice can be made. In real-life decision making, however, the attention of the individual may not be on a rare event and so it could be discounted altogether. In these cases, the individual would ascribe a lower (or zero) decision weight to the events than that warranted by the objective probability.

Presentational format also has an impact. Participants tend to view events with a probability of occurring of 0.1% as rarer than the statement `1 person in 1000', even though the two statements are mathematically equivalent (Wong and Kwong, 2005). This tendency can be used to promote an agenda, with the percentage wording used to give the impression of rarity, or the alternative wording to promote the idea that the event is common. For example, a politician looking to fund a certain social program to solve an issue could use the `1 person in 1000' type wording to describe the problem, making the issue seem larger than it really is.

Mental Accounting rules can determine how decision makers frame multiple decisions. Under expected utility theory, decision makers only consider the impact of their decision on total wealth. This is based on the idea that wealth is fungible and each unit of wealth is treated identically. In the context of mental accounting, this would be called comprehensive accounting, implying that all mental accounts are merged into one.

Topical accounting implies that related decisions may be included in the same account. For example, two gambling losses on the same day may be integrated together within the same account. The aggregation of several outcomes provides an opportunity for individuals to integrate or segregate related gains and losses depending on whether this improves their hedonic utility. Generally, utility can be maximised by segregating gains into separate accounts, while integrating losses together. The house money effect suggests that people are often risk-seeking after an earlier gain and this is linked with the idea that a loss on a second gamble could always be integrated with the earlier gain, while a second gain could be segregated to maximise utility (Thaler and Johnson, 1990).

Many of the share price models that we examine below are based on the idea of narrow framing, which implies that each stock has its own mental account within the mind of the investor. Under this framework, each stock has its own reference point and gains and losses in each account are not co-mingled with other stock transactions. Narrow framing can lead to illogical behaviour such as preference reversals (Bazerman et al., 1992). This is where one option is preferred when 2 options are shown in isolation, but the other option is preferred when the options are presented together. This may be because the single presentation makes certain features salient that are less salient when the options are presented together. Rational decision making is usually enhanced by considering decisions under a full range of options and by considering previous related decisions (Sunstein et al., 2002).

2.2 Experimental Research

In this section, we examine experimental studies that investigate the reference point of investors. An obvious starting point for experiments is to assume that the purchase price of the share is the reference point of the investor and that this reference point remains fixed over the life of the investment. This is in line with the status quo bias developed by Samuelson and Zeckhauser (1988) that is prevalent across a wide range of decisions. A problem with assuming a static, purchase-price based reference point in the context of share trading, however, is that investors may hold a share for a prolonged period of time, which is unlike the static one-shot gamble scenarios commonly used in tests of Prospect Theory. This then raises the question of whether the reference point will remain fixed or will move over time in line with the share price.

Weber and Camerer (1998) was the first experiment to try and replicate the disposition effect (Shefrin and Statman, 1985), where investors have a disposition to sell winners over losers. A virtual market was created using 6 risky assets, which moved in a random way. They found that around 60% of the shares sold were winners (Overall Gain), while only 40% sold were prior losers (Overall Loss), providing support for the disposition effect. Share D was an exception to the rule, however, and this share had an interesting pattern in that it bottomed out in period 10 before rising in period 14 when participants sold the stock. This was unlike the other losing stocks B & C that had a more uniform decline in their path. They suggested in the footnotes that the low price in period 10 may act as an alternative reference point (minimum) that enables participants to feel like they are selling at a gain. This is instructive for our purposes in that it suggests that participants may have been adjusting their reference point to movements in the path and felt some pleasure at being able to liquidate stock D away from the minimum point achieved earlier in the path.

An initial avenue of research was to assess if reference point adaptation occurred, from the purchase price, over time. Chen and Rao (2002) demonstrated adjustment in reference points and were the first to suggest that the adjustment was asymmetric in nature. They studied two different types of event: a false alarm and a dashed hope. Both scenarios start and end at the same point, but the false alarm features an improvement from an intermediate low position, whereas a dashed hope features a deterioration from a stronger intermediate position. They showed that participants are happier in the false alarm path than the dashed hope. This suggested that the maximum attained in the dashed hope and the minimum attained in the false alarm might also be acting as reference points.

Heyman et al. (2004) studied the area of adaptation and chose to focus in on maximum and minimum prices. They presented two price paths to participants which started and ended at the same point. However, one path featured a salient low leading to a smile pattern, whereas the other path featured a salient high leading to a scowl pattern. Although the satisfaction paths of participants closely followed the movement of either the smile or the scowl pattern, the ending satisfaction level was higher for the smile than for the scowl pattern. The suggestion was that the path dependency involved in the smile pattern, which involved a salient low, left participants happier at the end than the path involving a salient high. The salient high reminded participants that they could have sold at this higher price and hence they felt some regret at missing out.

While these previous two studies suggested that reference points did adjust over time and that adjustment differed between gains and losses, Arkes et al. (2008) were the first to measure the size of the adjustment. This was measured by moving the price of a single asset from $30 to either $36 or $24, representing either an increase or a decrease of 20%. Participants were then asked for the price the asset will have to move during the next month to make them just as happy as they felt the previous month. For participants in the gain position (who previously experienced a move from $30 to $36), they required a move of **$4.24** (to $40.24) to make them just as happy as last month. If these investors had fully adjusted after the first period, then their new reference point would be $36 and they would require another $6 shift to $42 in order to make them just as happy as last month. For participants in the loss position (who previously experienced a move from $30 to $24), they required a move of **-$2.51** to make them just as happy as last month. There is a weakness in their approach, however, in that a move of +/- $6 from $30 in the 1st period represents a symmetrical shift of 20%, but this symmetry is not maintained for the 2nd period. For example, when the reference point moved to $36 in the 1st period then another 20% move would imply a price of $43.20, not $42. Therefore, their approach rests on the assumption that participants think about nominal prices rather than returns in percentage returns.

Aside from the size of adjustment, other experimental studies have looked at different salient points that could influence the reference point beyond the purchase price. Gneezy (2005) provided support for a reference point based on historical peaks. Artificially generated share price patterns are shown to participants featuring either gains or losses and the propensity of participants to sell was measured. He found that a disposition effect was present i.e. a tendency to sell winners over losers and that the historical peak of a series was the key reference level that participants used to measure gain or loss.

Baucells et al. (2011) was the first study to examine how multiple salient prices may influence the reference point. Their approach to eliciting reference points is slightly different from the other studies. They displayed share price paths to participants and asked for their neutral selling price, which they take to be the reference point at that moment. When regressing the reference point against other salient points within the share price charts they found that all salient prices: purchase, final, average, maximum and minimum were significant in the determination of the reference point. Baucells et al. (2011) used artificial data to generate charts, which helped to control collinearity between the salient prices within the charts. It did, however, have the potential to introduce non-randomness in the charts, which may have been detected by the participants along with other biases such as round number bias (Bhattacharya et al., 2012). The charts were constructed using daily price movements, with a maximum of 10 days and a minimum of 3 days. Maximums and minimums may be less salient in the short-term charts used, as there is limited time for salient points to develop (Raghubir and Das, 2009) .

There has been little research on the impact of price volatility on share price reference points, but some work has been done in the area of consumer behaviour. Drechsler and Natter (2011) was the first paper to consider the impact of price history charts from online shopping sites on reference points. In the charts shown in Figure 2-3 below, charts 3 and 4 are high volatility versions of chart 1 and chart 2. Participants were asked to give an expected price at 4, 8, and 12 weeks later given the trends presented in the charts. They found that trend, variance and range (high-low) all play a part in reference point formation. Specifically, a strong trend and high variance lead to the greatest shift in reference points, relative to the price movement.

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Figure 2-3: Taken from Drechsler and Natter (2011)

Kahneman and Tversky (1979) considered that goals or beliefs might be an alternative to the status quo as a reference point in certain situations. This seems particularly relevant to share price purchases, where it is likely that an investor has a preconceived goal or positive belief regarding how the share price might develop before a purchase is made. Without a positive belief, there is little reason (beyond diversification) for a risk-averse investor to buy the share in the first place as it represents a risky gamble, with a negative Prospect Theory value (Barberis and Xiong, 2009). A number of studies have looked at the influence of beliefs on the reference point, either in the form of initial exogenous beliefs or beliefs endogenously generated by the share price pattern. The first 2 papers discussed below involve beliefs in relation to reference points in general, rather than investors specifically.

Heath et al. (1999b) were one of the first papers to consider that goals may function as reference points. Goals have always played a role in theories of motivation and can explain a wide range of empirical findings related to motivation e.g. Atkinson (1957). They combined the work on goals with the Prospect Theory value function of Kahneman and Tversky (1979) to show how goals divide outcomes into regions of good and bad i.e. it is the goal based reference point that determines the frame adopted by the participant. They suggested that people with higher goals tend to put in more effort and show more persistence when they are in the loss region of the Prospect Theory curve i.e. below their goal. Equally, when two people are above their goal, the one who is closer to the goal will exert more effort than one who is further above the goal, as they are closer to the reference point.

Marzilli Ericson and Fuster (2011) tested whether reference points are determined by the status quo in the form of an endowment, or by expectations. They provided participants with an endowment of a mug and offered them the possibility of the chance to swap it for a pen. They found that subjects who do not expect to be given the possibility of an exchange are more inclined to decline the exchange if it is offered. This provides support to the idea that their reference point is determined by their expectation rather than the status quo endowment of the mug. An expectation of continued ownership of the mug sets this as the reference point and induces a reluctance to part with it, whereas individuals who expect a transfer to be granted are more likely to subsequently allow it, as they are less impeded by loss aversion around the possession of the mug.

Moving to an application to share prices, Hack and von Bieberstein (2015) attempted to directly replicate the Arkes et al. (2008) study with the addition of beliefs. Participants were taken through the Arkes et al. (2008) framework, but also given a future expectation about the share price. They found that giving the participants an expectation encouraged adaptation in the direction of the expectation i.e. a positive belief combined with an appreciating share price encouraged further adaptation to gains.

One notable feature of Hack and von Bieberstein (2015) is that the belief is exogenous as it is given to the participants in the experiment. Research suggests that share price movements themselves may generate beliefs in investors e.g. Barberis et al. (1998) or Rabin and Vayanos (2010). Specifically, long-term trends generate a belief that the trend will continue, whereas short trends generate a belief in reversal. These belief based models have been used to explain why short-term momentum (Jegadeesh and Titman, 1993) and long-term reversal (De Bondt and Thaler, 1985) are present in market returns, although alternative explanations also exist.

Grosshans and Zeisberger (2018) measured the impact of these endogenously generated beliefs in relation to investor reference points. Using 6 different share price paths (3 winners and 3 losers) of 12 months in duration. They adapted the approach from Baucells et al. (2011) to measure reference points and they also measure participant's beliefs about the future share price path by collecting forecast estimates. They found that investors exhibited a strong belief in trend continuation and that these beliefs can enhance reference point adaptation in a trending environment. For example, in a rising trend, positive beliefs facilitated reference point adjustment to the gain which lessened or could even reverse the disposition effect.

Hoffmann et al. (2013) measured the impact of the status quo (purchase price) versus goals on the determination of reference points. The participant started with an aspiration level (goal) in addition to the starting status (purchase price) and they then examined how the relative importance of the two anchors change over time. In the early stages of a gamble, participants felt that the goal was credible and so attached a greater weight to it at this stage. The starting status, however, became the most important reference point as the gamble developed. This suggests that the new information is used to re-assess the initial goal and weakens its importance.

2.2.1.1 Summary and Research Gap

The previous experimental research into reference points suggests that there are a number of important determinants of the reference point for an investor. The status quo or purchase price of the investment remains a key determinant of the reference point. Baucells et al. (2011) suggest that the purchase price is the most important determinant of the reference point, even while other points in the share price path are also important.

Studies from Gneezy (2005), Baucells et al. (2011), as well as work on asymmetric adaptation Chen and Rao (2002), Arkes et al. (2008), suggest that intermediate maximums and minimums are important determinants of the reference point. The maximum, in particular, seems to be a key point that is salient in the mind of the investor and leads to regret if the current price falls below a maximum. Equally, rises above a minimum can lead to satisfaction in some circumstances, even if the current price is below the purchase price.

The role of recency of maximums or minimums has not been studied i.e. do more recent maximums have a greater weight than less recent maximums. This is partly due to the limitations of chart design in previous work. Studies typically either treat time in generic units or use very short time periods, such as a few days. For example, two of the most highly cited studies Arkes et al. (2008) and Baucells et al. (2011) measure time as either 3 generic periods or a maximum of 10 days. Short time periods do not provide the scope for salient maximums or minimums to be formed in charts (Raghubir and Das, 2009) and nor do they allow for the study of recency.

The work on expectations as reference points suggests a role for beliefs, but do not support the idea that reference points are based solely on beliefs. There is an issue about whether beliefs are something that is exogenous as in Hack and von Bieberstein (2015) or endogenously formed from the share price path as in Grosshans and Zeisberger (2018). Hoffmann et al. (2013) provide some middle ground, which is to assign a greater weight to exogenously determined beliefs at the beginning of the investment, but a lower weight as the share price develops over time. This is an interesting avenue of research, which may overlap with the V-shaped trading schedule (Ben-David and Hirshleifer, 2012) that we will discuss in the next section.

One final limitation of all the experimental studies is in the area of external validity. While there is a trade-off between maintaining controlled conditions and realism, the experiments tend to be fairly abstract and far removed from the real world. Artificial chart patterns are typically used, which feature round number bias and non-random share price movements, as well as charts that can only move in a pre-determined range during each period. We worry that the non-random design of the charts may influence the responses of participants. External validity can be improved by using charts sampled from real share price data.

2.3 Market/Field Data Testing

Shefrin and Statman (1985) were the first to apply Prospect Theory (PT) to the area of share price trading. They discovered a disposition effect, where investors were too keen to sell previous winners and held previous losers for too long. For a stock that has appreciated in price, the investor is now in the gains portion of the Prospect Theory value curve, which has a concave shape. Due to the shape of the curve, additional gains have a lower absolute marginal utility to the investor than losses. So, in gains, the tendency is for the investor to be risk averse and sell the security. For stocks that have depreciated, the investor is now in the convex part of the value curve. In this instance, additional losses have a lower absolute marginal utility than additional gains. In losses, the tendency is therefore for investors is to be risk seeking and hold onto the position. Loss aversion may play an additional role here, as the investor will be keen to break-even on their position, relative to the purchase-price based reference point.

Shefrin and Statman (1985) assumed that the reference point, from which gains or losses are measured, is the initial purchase price. On the other hand, a perfectly adjusting reference point would imply no disposition effect, as investors would never be in a position of gains or loss within the Prospect

Theory curve. An imperfectly adjusted reference point, where some of the gain or loss was integrated, could also generate a smaller disposition effect.

If investors are looking to maximise after-tax returns (Constantinides, 1983) then they should sell more losers than winners in the short-run and liquidate more of their winners in the long run. Using data from Schlarbaum et al. (1978), Shefrin and Statman (1985) showed that the tendency to realise winners is quite stable across all duration periods at just under 60%. This result is not consistent with the tax maximisation strategy, but it is consistent with the Prospect Theory explanation.

Further testing on the disposition effect was carried out by Odean (1998) using trading data from a large brokerage house. He measured the percentage of losers realised (PLR) versus the percentage of gainers realised (PGR) and found that for an annual horizon around 15% of winners are realised, whereas only around 10% of losers are realised. The pattern was reversed in December, perhaps for tax reasons. In addition, he demonstrated that the stocks sold subsequently outperformed the stocks that were retained. This is an important observation as one could incorrectly argue that investors were following a logical strategy of selling winners over losers.

Kaustia (2010), however, showed results that are inconsistent with Prospect Theory as a cause of the disposition effect. He measured the propensity to sell around various return intervals, using a purchase-price based reference point, from a dataset of Finnish household investors. In Figure 2-4 below, the propensity to sell was shown to jump around the level of the purchase price and be relatively flat away from the region of the purchase price. This seemed odd given the shape of the Prospect Theory curve, which would suggest that the propensity to sell should increase as returns increase above the reference point and the investor moves up the risk-averse part of the value curve. Equally, for losses, the propensity to sell seemed relatively flat or slightly increasing, whereas Prospect Theory implies that the investor should become risk-seeking in losses and hence more reluctant to sell as losses increase.

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Figure 2-4: Taken from Kaustia (2010)

The jump in the propensity to sell around the zero-return limit suggested a far greater emphasis should be placed on the position of the reference point, rather than the shape of the curve in gains or loss, which did not seem to drive behaviour. It should also be noted that the purchase price was the only reference point considered by Kaustia (2010) and hence other reference points may provide a propensity to sell function more in line with that implied by Prospect Theory.

The selling schedule from Kaustia (2010) actually has a mild V-shape for the shorter-term holding periods and this was further investigated by Ben-David and Hirshleifer (2012) who documented a V-shaped selling effect for securities. The probability of selling line, as shown in Figure 2-5 below, used data from retail investors from a large discount broker. The selling schedule is flatter in losses than gains, which explains why researchers previously found a disposition effect, but the selling schedule in losses is upward sloping rather than download sloping, as would be implied by Prospect Theory. The purchase price acts as the pivot point for the v-shaped selling schedule and is the point with the lowest probability of a sale taking place.

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Figure 2-5: Taken from Ben-David and Hirshleifer (2012)

The authors suggested that a speculative motive is responsible for the shape of the selling schedule. Investors buy with a speculative belief that the share will increase in price. If the share subsequently increases in price, then the belief has been met and it is time to sell. Big losing positions, however, force investors to re-examine their beliefs and to conclude that they were wrong, which also brings about a sale. Shares that don't move a great deal in either direction allow the speculative belief to remain in place for the time being, which reduces the chance of a sale. They showed that the V-shaped selling schedule is steeper in more active traders and males, who are more likely to be overconfident in their beliefs (Barber and Odean, 2001). They also documented the same V-shaped schedule for additional purchases of securities already held, suggesting that investors like to top-up either big winners or big losers, but avoid the stocks in the middle.

An alternative to the speculative trading motive could be the attention effect (Barber and Odean, 2008). Big losers and big winners are likely to catch the attention of potential buyers and potential sellers, which could explain the greater propensity to buy and sell these securities. The attention effect explanation is of note in that it does not involve reference points. This explanation is supported in work by Hartzmark (2014) which demonstrated a rank effect in the realisation of securities. Specifically, Figure 2-6 below shows that stocks with both a higher return ranking and a lower return ranking, within an investor's portfolio, have a greater chance to be sold. The author is able to control for stock-specific factors by analysing selling behaviour across investors. As investors buy at different times, the same stock will have a different rank within investor portfolios, but it will be identical in other regards. He found that the rank effect still has significant power. The author also suggested that the V-shaped selling schedule was eliminated once rank is taken account of.

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Figure 2-6: Taken from Hartzmark (2014)

Other work has tested the significance of alternative reference points. The importance of the high price is emphasised by George and Hwang (2004) who focused on individual share prices. They found that the 52-week high was a point of significance for investors. In particular, they showed that stocks near to their 52-week high are undervalued relative to stocks that are far from their 52-week high. This result was further expanded by Bhootra and Hur (2013) who looked at the recency of the 52-week high. Stocks that obtained their 52-week high more recently were undervalued relative to stocks that obtained their 52-week high in the more distant past, holding the size of the distance from the 52-week high constant.

A second stream of literature uses changes in trading patterns to indirectly measure reference points. Initial Public Offerings (IPOs) are interesting transactions to study in relation to reference points, as the initial float price can be studied as a reference point. Kaustia (2004) looked at trading patterns around the float price for IPOs and found increases in trading volumes for big moves away from the float price, but also when new minimums or maximums were attained. The increase in trading around new maximums or minimums suggested they are significant points for the investor that trigger trading activity. For example, stocks making new highs may be attractive to sell for the current holder if the attainment of a prior maximum is a significant reference point for them.

Heath et al. (1999a) found a similar volume effects around prior maximums in the stock options market for seven listed corporations. In the case of the options, an initial price is less likely to be the reference point as employees are given the options and they are initially worthless at the point of issuance. They studied the stock option exercise behaviour of 50,000 employees of the corporations and found that exercise roughly doubled when the stock price exceeded the maximum over the year. The findings were later replicated in equity options across all investors in Poteshman and Serbin (2003). They found that equity options are often exercised early in an irrational manner by customers of brokers, although there is no evidence of this for institutional traders. For both irrational and rational traders, there was evidence that exercise was triggered by a stock either attaining a high over the past year or high past returns.

Huddart et al. (2009) carried out similar work examining volume changes within the share market. Trading volume was greatest in the market following new 52-week highs or lows, providing further support to the idea that recent highs and lows are key reference points. Figure 2-7 plots the coefficient estimate (volume adjusted for changes in returns, volatility, and earnings announcements) against the event week after a 52-week high is achieved.

Volume is markedly increased immediately after the 52-week high is met and continues for a number of weeks after that. A similar pattern applies to 52-week lows, although the coefficient estimates are not as high as for 52-week highs. The effect is also bigger for smaller firms with more individual investor interest.

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Figure 2-7: Taken from Huddart et al. (2009)

Kliger and Kudryavtsev (2008) is another study that uses changes in trading volume to infer changes in reference points using stock market data. Their conjecture is that changes in a stock's reference point trigger trading activity reflected in higher trading volume. They then measured trading activity following unanticipated and anticipated changes in earnings and found that the unanticipated changes trigger higher trading activity, but the anticipated changes do not. They suggested that this is because a reference point change occurs in the case of an unanticipated change but does not in the case of an anticipated change. The effect is larger for smaller companies or riskier, higher beta firms. In summary, this paper suggests that expected earnings are another significant reference point for an investor.

Summary and Research Gap

The work on reference points using market data can be broadly split into two areas. The first area explores the propensity to sell stocks in relation to potential reference points such as the purchase price or 52-week high. This area of research began with Shefrin and Statman (1985)'s work on the disposition effect, which is a widely cited paper. The disposition effect was confirmed in field data by Odean (1998), but subsequent work from Kaustia (2010) and Ben-David and Hirshleifer (2012) suggests that there is not a simple linear relationship between past returns and selling behaviour.

The V-shaped selling schedule of Ben-David and Hirshleifer (2012) suggests that the initial understanding of a disposition effect between losers and winners is too simplistic. However, the V-shaped pattern is more strongly observed for shorter holding periods and only a very flat V can be observed for holding periods of 200 days or longer. If the base of the V represents the reference point, then we would expect that reference point to move around for longer holding periods and hence the shape of the V is less well defined. Alternatively, if the V is created by prior beliefs then the passage of time may act to erode the confidence of the investor in these beliefs (Hoffmann et al., 2013). The short lifespan of the V-shaped pattern could also suggest that the rank effect of Hartzmark (2014) is the most likely contender. This is because the high or low returns initially attract attention from the investor leading to action, but the attention effect diminishes over time as other return movements become salient. In summary, there is no agreed explanation for the V-shaped selling schedule within the literature, but a number of possible explanations do exist.

The second set of papers attempt to measure reference points through changes in trading activity. These papers have shown that price moves to salient points such as the 52-week high trigger an increase in trading activity by investors across a diverse range of asset classes. In addition, this work suggests that reference points are not limited to past prices and may also be influenced by fundamental factors or news flow such as earnings revisions (Kliger and Kudryavtsev, 2008).

The weakness in these studies is that reference points are not being directly observed. While it is a feasible hypothesis that price movements around reference points trigger an increase in trading, there are many other factors that could trigger volume changes. For example, Huddart et al. (2009) show that volume changes around 52-week highs and lows are caused by increased activity from buyers rather than sellers. In this regard, experimental studies are stronger in that reference points can be directly elicited from participants. This presents a gap in the literature, as there is the potential to use experiments to measure reference points by directly eliciting them from participants. The directly elicited reference points can then be used as inputs in market data models that predict asset prices. This ensures that the experimental work holds up in real-world conditions and is externally robust, provided that the design of the experiments is externally valid.

2.4 Market Data Models

In this section, we examine three market data models that incorporating reference points. We subsequently develop these models later in the thesis, by changing the reference point used. The three models: Grinblatt and Han (2005), An (2016) and Barberis et al. (2016) are not the only ones to incorporate reference points but they do present an ideal framework for us, as we are able to design experiments to capture reference points within a valid setting for these models. Predictive equations for the reference points are subsequently used as inputs into the models, in the later chapters of the thesis. We also briefly discuss some of the other models at the end of the section.

Grinblatt and Han (2005) was the first model to link Prospect Theory to price momentum (Jegadeesh and Titman, 1993) observed in share markets. The capital gain overhang (CGO) variable itself is simple. CGO for a stock is defined as the percentage deviation between the final price of a stock (P) and its reference point (R), shown in Equation 2-1. The final price is lagged by 1 week relative to the reference point to account for the bid-ask bounce in market data (Rosenberg and Rudd, 1982).

$$g_{t-1} = \frac{P_{t-2} - R_{t-1}}{P_{t-2}}$$

Equation 2-1: Taken from Grinblatt and Han (2005)

The formulation does not account for risk aversion in gains or risk seeking in losses or for loss aversion, but only the deviation between the final price of a stock and its reference point. Stocks that have positive CGO are expected to be oversold and hence underpriced. Stocks that have negative CGO are expected to be undersold and hence overpriced. In summary, the CGO variable should be negatively related to future stock price return.

The challenging element in the CGO model is how to measure the reference point of market investors, as this can not be directly elicited using market data. Grinblatt and Han (2005) assumed a purchase-price based reference point, but market investors buy at different times and hence they will all have different purchases prices. Weighting is achieved using weekly share turnover (volume/share outstanding), as shown in Equation 2-2. Every week of turnover (V) is multiplied by the share price (P) during that week and then a total of 260 weeks (5 years) is summed together to form an aggregate reference point. To account for the fact that some of the earlier purchasers will subsequently sell during the calculation period, each week's turnover number is adjusted. For example, assuming turnover is 5% on week$_{t-2}$ then the purchase price (P) of that week is given a 5% weight in the reference price (R_{t-1}). For week$_{t-3}$, the turnover for that week again reflects its weight, but some of the buyers in week $_{t-3}$ may also sell during the following week$_{t-2}$. To reflect this, if the turnover in week$_{t-3}$ is 5% then its weight will be 5% * (1 - 5%) = 4.75% to reflect that 5% of the purchases are subsequently sold in week$_{t-2}$.

$$R_{t-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right)P_{t-1-n}$$

Equation 2-2: Taken from Grinblatt and Han (2005)

The CGO variable is then added as an independent variable to a regression of one-month ahead returns as a dependent variable. Grinblatt and Han (2005) found that the traditional momentum variable of Jegadeesh and Titman (1993) is no longer significant when CGO is added to the regression. Later derivations of CGO, such as those used in An (2016) or Wang et al. (2017), used daily data rather than weekly. These papers found that while CGO is a significant predictor of one-month ahead returns, the traditional momentum variable is also significant. This suggests that CGO explains a different source of return predictability than the price momentum variable, although the two variables have a correlation of 0.48 in An (2016).

An (2016) is an attempt to apply the findings of a V-shaped selling schedule (VNSP) from Ben-David and Hirshleifer (2012) to market data. The method through which this is done is by using a modified version of the CGO variable from Grinblatt and Han (2005). Rather than calculate an aggregate reference point for all market investors, a separate reference point is calculated for each day and then these reference points are summed using turnover in a similar way to Grinblatt and Han (2005). Although the result is identical to conventional CGO when gains and losses are added together, by separating out each gain and loss on a daily basis, it allows gains and losses to be summed differently.

The gains variable, as shown in Equation 2-3 below, is calculated by multiplying each daily gain by its appropriate weight (ω). The weight itself is calculated using the turnover (V) approach of Grinblatt and Han (2005). The loss variable, shown in Equation 2-4, is calculated in the same way using the turnover weighted approach. Rather than using weekly data, daily data is used over the same 5-year horizon, which leaves 1260 trading days.

$$Gain_t = \sum_{n=1}^{\infty} \omega_{t-n}\, gain_{t-n}$$

$$gain_{t-n} = \frac{P_t - P_{t-n}}{P_t} .1\ (P_t - n\ \leq P_t)$$

$$\omega_{t-n} = \frac{1}{k} V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}]$$

Equation 2-3: Taken from An (2016)

$$Loss_t = \sum_{n=1}^{\infty} \omega_{t-n}\, loss_{t-n}$$

$$loss_{t-n} = \frac{P_t - P_{t-n}}{P_t} .1\ (P_t - n\ \geq P_t)$$

$$\omega_{t-n} = \frac{1}{k} V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}]$$

Equation 2-4: Taken from An (2016)

Field data from Odean (1998) was used to approximate the coefficients that should be used to combine gains and losses. This data suggested that the investor is approximately 4 times more sensitive to gains than losses and hence the losses are adjusted by a factor of 0.23 below to calculate VNSP, as shown in An (2016). The smaller sensitivity to losses could be caused by a greater reluctance on the part of investors to accept that their initial speculative belief was wrong and subsequently sell the security, whereas it is much easier for investors to accept that their initial belief was correct when in a position of gain. The equivalent calculation for CGO is to add gains and losses together so that they net off.

$$VNSP_t\ =\ Gain_t - 0.23Loss_t$$

$$CGO_t\ =\ Gain_t +\ Loss_t$$

Equation 2-5: Taken from An (2016)

The author finds that the traditional CGO variable is no longer significant once VNSP is included in the regression. However, traditional momentum remains significant regardless of whether CGO or VNSP is included in the regression, which is consistent with the finding of Wang et al. (2017) who also use daily data to calculate CGO. In summary, the paper suggests that investors exhibit a strong tendency to sell big winners and big losers, which leaves these securities underpriced relative to stocks that have traded sideways.

Barberis et al. (2016) focussed on investor preference and presented evidence that investors evaluate stocks using prospect theory rules. Previous research such as Ang et al. (2006) and Kumar (2009) found that investors have a preference for highly volatile, lottery-type stocks. The increased demand for these types of stocks left them overpriced and they subsequently underperformed. The model of Barberis et al. (2016) acted as a link between the work on investor preference for volatility/skewness and reference points, as potential buyers evaluated monthly returns in relation to a reference point within their model. They found that stocks with a high prospect theory value are subsequently over-valued by investors and tend to underperform relative to stocks with a lower prospect theory value.

The first stage in the process of calculating the prospect theory value of a stock (TK) was representation. This is how the investor derives utility from gains and losses in the previous price history of a share. Barberis et al. (2016) believed that investors use past monthly returns to assess the security, with the monthly return of the benchmark set as the reference point each month. The representation is based on 5 years i.e. 60 months of data, so each month has a positive value if the share price return is above the reference point (benchmark return) for that month.

The second stage was valuation where the investor evaluates the gains and losses to see if they are desirable. This step is straightforward in their view, as they used the standard parameter valuation rules from Tversky and Kahneman

(1992). Losses were given a 2.25X weight relative to gains to reflect loss aversion. The Prospect Theory value of each monthly return (v[x]) was multiplied by the probability (π) implied by Cumulative Prospect Theory (Tversky and Kahneman, 1992), as shown in Equation 2-6. In the base case, all the months had an equal weight and n is equal to 60 months (5 years). The probability weighting function (π[i]) was used with the standard parameter values and is calculated using the formula below.

$$TK = \prod_{i=-m}^{n} \pi_j \, v(x_i)$$

where

$$\pi_i = \begin{cases} \omega^+(\rho_i + \cdots + \rho_n) - \omega^+(\rho_{i+1} + \cdots + \rho_n) & 0 \le i \le n \\ \omega^-(\rho_{-m} + \cdots + \rho_i) - \omega^-(\rho_{-m} + \cdots + \rho_{i-1}) & -m \le i \le 0 \end{cases}$$

Equation 2-6: Taken from Barberis et al. (2016)

If the TK value of a stock is high then investors tilt towards these stocks in their portfolios, which leaves them overpriced. Therefore, stocks with high TK value should have low subsequent returns. They found support for this framework using regression analysis and double sorted portfolios. Positive skewness is a key driver of the result. Stocks with desirable skew characteristics are valued by investors, having high TK value, and subsequently underperform. The probability weighting function parameters are therefore the most important features of cumulative PT that drive their results.

We focus on the 3 models above in the thesis, but they are not the only ones that use reference points. The concept of realization utility developed by Barberis and Xiong (2012) is an alternative theoretical framework to Prospect Theory that can be used to explain the disposition effect. The authors previously found (Barberis and Xiong, 2009) that Prospect Theory alone cannot explain the disposition effect and so developed realization utility as an alternative. In this model, the investor only receives utility when they liquidate a position. Paper gains and losses do not produce utility as they are unrealised, which is especially significant for losses as the investor can suspend liquidation until the paper loss has been eliminated. Momentum in stock returns, in this model, is generated by realization utility investors holding onto their losers in order to avoid realising the position at a loss while selling winners to realise positive utility. This leaves prior winners underpriced and prior losers overpriced. Gains and losses are defined relative to a reference point which is set at the purchase price, but this assumption could be relaxed.

A more recent paper from Meng (2014) attempts to resurrect the Prospect Theory explanation for the disposition effect, by changing the assumption of a fixed reference point. They show that Prospect Theory can explain the disposition effect if the reference point chosen is expected final wealth (Kőszegi and Rabin, 2006). They adjust the Barberis and Xiong (2009) model by adopting a reference point based on expected final wealth and show that Prospect Theory can explain the disposition effect in some circumstances.

Summary and Research Gap

The literature has a number of financial models that incorporate investor reference points. The majority of these models aim to capture the behaviour of sellers, starting with Grinblatt and Han (2005) and later developed by An (2016) to incorporate v-shaped selling preferences. Grinblatt and Han (2005) calculate an aggregate reference point that can be applied to market prices, but they assume that the reference point remains fixed on the purchase price. A more comprehensive approach would take into account movements in the reference point in line with share prices. The same argument could be made for the V-shaped selling schedule of An (2016) that continues with the assumption of a fixed reference point that is centred around the purchase price.

There is a further weakness in the share turnover approach that is used to calculate the probability that a share is traded on a particular day in both

Grinblatt and Han (2005) and An (2016). It is implicitly assumed that a sale in particular day will be apportioned in an equally weighted way to all existing holders. For example, if turnover is 5% today then it is assumed that this 5% comes equally from holders on all previous trading days. It could be argued that more recent buyers have less chance of selling than more distant buyers, as this would minimise transaction costs for investors. This would imply that a FIFO (first in first out) approach would be more accurate than an equally weighted approach. Another alternative weighting scheme would be LIFO (last in first out), although this approach seems less credible than equally weighted.

Barberis and Xiong (2009) aim to disprove the link between Prospect Theory and the disposition effect altogether, which would undermine the claims of the Capital Gains Overhang model. The approach of Barberis and Xiong (2009) has subsequently been challenged by papers that relax its assumptions about the reference point (Meng, 2014) and have shown that Prospect Theory is still capable of explaining the disposition effect.

Turning to the Barberis et al. (2016) model that focusses on investor preference; reference points are not a core concern of their paper. They assume that the reference point is either the market return or a benchmark of zero for each month. An alternative approach adopted by Nolte and Schneider (2018) is to measure a reference point at the end of the 5 year period and then use the compounded monthly return as the reference point. A weakness with this, however, is that it does not consider how the reference point might evolve on a month-by-month basis. In order to do this, an experiment could be designed that measures reference point adjustment from month-to-month and then apply this adjustment to the TK model.

There are other arbitrary choices in the Barberis et al. (2016) model such as the choice of a 5 year evaluation period and the related issue of monthly weighting. They choose to equally weight each month in the calculation of the TK variable, but other weighting schemes are available. It may be the case that giving greater weight to more recent months will improve the predictive power of the TK variable.

2.5 Conclusion

In this section, we summarise the findings of the chapter and discuss research questions to be covered later in the thesis. Firstly, we turn to the experimental research of investor reference points. This confirms that reference points do not normally remain fixed but move over the life of an investment (Arkes et al., 2008, Arkes et al., 2010). In addition, there is support for a number of different salient prices that could determine the reference point such as the purchase, maximum, minimum, average and final prices (Baucells et al., 2011).

There are a number of avenues for us to build on previous research within the design of our first experiment in Chapter 3. The use of realistic share price charts is largely absent from the literature. While using artificial charts does improve control and internal validity, it does also have the potential to introduce non-randomness into the chart patterns and biases such as round number bias (Bhattacharya et al., 2012). In addition, there is a tendency for prior literature to use either very short-term chart patterns of a few days or use generic (nameless) time periods. This makes it difficult to explore recency effects and the saliency of important points such as the 52-week high (George and Hwang, 2004). In Chapter 3 we will address these two areas through the use of long-term charts that are constructed using real share-price data.

Turning now to the two investor models (CGO and VNSP) that address investor selling behaviour, both of these models are predictive of future returns using a purchase price-based reference point. The CGO model is solidly grounded in Prospect theory but the underlying rationale for the VNSP model is less certain. Both Ben-David and Hirshleifer (2012) and An (2016) favour an explanation based on the actions of speculative traders, who hold strong prior beliefs about the shares that they purchase.

Both of these models could be adapted to incorporate other reference points, which we subsequently undertake in Chapters 4 and 5. For example, Baucells et al. (2011) find that the maximum, minimum, average and final prices are significant determinants of the reference point in addition to the purchase price. It is also possible for a composite reference point to be formed from a mix of these reference points and then the composite could be used as an input into the models. If the composite is a better representation of the reference point than the purchase price, then the models which incorporate the composite should have greater predictive power. This will be tested using regression analysis and double sorted portfolios.

The Prospect Theory Value of a Stock Model developed by Barberis et al. (2016), focuses on investor preferences. Investors are assumed to represent the returns of stocks as a series of 60 separate months, with each month having a separate reference point based on a benchmark return. The 60 separate returns are then valued based on standard Prospect Theory parameters incorporating loss aversion, risk seeking or risk aversion and decision weights. They show that the TK variable is predictive of future returns.

Is it possible that investors form a reference point each month based on salient price features in a price chart, rather than by the return of a benchmark. This reference point could be calculated and then be incorporated into the TK model. In order to test this possibility, we design a new experiment in Chapter 6 that captures 60 monthly reference points over a 5-year period. Participants are asked for a new reference point each month as the price series develops, which differs from the earlier experiment in Chapter 3. A couple of additional insights will be available, within the framework of the new experiment, in the areas of time moderation and lagged reference points. Within the area of time moderation, it is possible to investigate the strength of various prices as time progresses over the 5 years. For example, is the strength of the purchase price as a reference point reduced as time progresses or do maximums and minimums become more important if they are more recent? It is also possible that participants may use the reference point provided the previous month as an anchor for the current month's reference point. If this is the case then how important is this anchor as a determinant of the current month's reference point?

An alternative TK variable can then be calculated using salient prices in the price chart, rather than monthly benchmark returns. We utilise a predictive equation of the reference point from the experiment in Chapter 6 and use this as an input into the TK model in Chapter 7. The predictive power of this alternative TK variable can be tested against the traditional TK variable to determine which one has the greatest predictive power. It is also possible that investors form reference points at the end of the 60-month period only (as in our first experiment) and then spread the adjustment towards this reference point (from the purchase price) evenly over the 60 months in either a linear or an exponential manner. TK variables with reference points constructed in such a manner can also be tested to see if they are better predictors of future returns than the original TK variable or the alternative TK variable based on 60 different reference points. In this way, we can establish which one of our two experiments provide a better framework to measure reference points for use in the TK model.

3 Experiment I: Examining Reference Point Adaption

Reference points are a central feature of Prospect Theory, which can be applied to a wide range of decisions. Our interest is in the role of reference points in the decisions of investors. In this chapter, we design an experiment to capture the reference points of participants in relation to prior share price movements, displayed in price charts. The role of the reference point within investment decision making is important given the presence of intermediate price momentum (Jegadeesh, 1990) in share price returns. Various arguments have been made as to why price momentum exists, with Prospect Theory preferences (Grinblatt and Han, 2005) being one such explanation. In this chapter, we examine how these reference points are formed by participants.

A number of prior studies examine investor reference points using share price charts. Weber and Camerer (1998) are able to replicate a disposition effect (tendency to sell winners over losers) in experimental conditions using the purchase price as a reference point. Heyman et al. (2004) study the role of prior maximums and minimums in reference point formation. They find that participants are happier at the end of sequences that feature a salient minimum rather than a salient maximum. Further support for the maximum is provided by Gneezy (2005) who shows that the historical peak is the key reference point adopted by participants in his experiment. Baucells et al. (2011) are the first experiment to consider the impact of multiple salient prices on reference points and they find that the purchase, maximum, minimum, average and final prices are all significant determinants of the reference point.

All of the studies above use pre-designed charts created using artificial data. This is to improve control so that the effects of each variable can be measured in isolation. The downside is that the charts may contain non-random patterns, which could bias the results. For example, pre-designed charts could inadvertently draw salience to a certain price such as the series maximum.

Pre-designed charts often also feature the round number bias (Bhattacharya et al., 2012). Participants' attention could be drawn to prices that are whole numbers such as 100. In summary, then, there appears to be a trade-off between external and internal validity, with prior studies choosing to emphasise the latter in their design.

To our knowledge, there has been no experimental work carried out into the area of recency and reference points. This is surprising as George and Hwang (2004) identify the 52-week high as an important price that drives returns in the share market. Specifically, stocks near their 52-week high tend to outperform in the future, relative to stocks that are far from their 52-week high. The mechanism for this mispricing is unknown but the authors suggest the 52-week high may be an important reference point for buyers. One reason why previous experimental studies do not examine 52-week highs is likely to do with the design of the charts used in the experiments. Prior studies tend to use either generic periods of time or very short holding periods, such as 10 days (Baucells et al., 2011) or 2 months (Arkes et al., 2008). The role of the 52-week maximum and minimum cannot be addressed when using either generic time periods or time periods that are well short of an annual holding period.

Little research has been carried out examining the impact of volatility on reference points. Drechsler and Natter (2011) study the impact of chart volatility on the reference points of consumers using 12-week charts. They find that a high variance leads to greater reference point adaptation towards the final price. This may be because the volatile movements are more salient in the minds of participants, so they pay more attention to the trend in the chart. Duxbury and Summers (2018) examine how investors perceive volatility in share price charts and they find that price volatility is a closer proxy for how investor perceive risk than return volatility. To our knowledge, no research has been carried out examining the impact of volatility on the reference points of investors.

In this chapter, we look to build on the work of Baucells et al. (2011) to measure reference point formation of participants based on multiple salient prices. We make a number of modifications to their experiment in order to increase realism and thus increase external validity. We use 30 different charts, sampled from market data, in order to maximise variation in the independent variables and minimise the risk that the charts introduce non-random bias into the experiment. The aim is for participants to relate the decisions taken in the experiment to a real-life trading context and minimize the risk that biases may be introduced by the design of the charts themselves. We show that the purchase, maximum and final prices are significant determinants of the reference point, along with the average or minimum. The average and minimum have high levels of multicollinearity within market data and so they act as substitutes for each other within the models.

Chart periods vary between 6 months and 5 years so that the impact of recency bias and specifically the role of the 52-week high and 52-week low can be examined. The impact of the 52-week high and low on reference points have not been tested previously within an experiment. We find that overall maximums and minimums have greater explanatory power than that suggested by previous studies, such as Baucells et al. (2011). In addition, we show that 52-week highs and lows are significant determinants of the reference point, lending weight to the argument that recency plays a role in reference point formation within the context of maximums and minimums.

We also consider the impact of share price volatility on reference points. We use several different proxies for volatility and show that price volatility is the one with the greatest relationship to reference point adaptation. Specifically, the charts that have the highest price volatility tend to have a greater deviation in reference point from the final price. This suggests that participants have less confidence in the share price pattern when it is highly volatile and so are less likely to adapt from the initial purchase price. We conclude that further work should be carried out in the relationship between volatility and reference point formation and adaptation.

3.1 The Experiment

In this section, we discuss the design of the experiment and its associated charts. The aim of the experiment is to examine the impact of features of the stock price path on the reference point adopted by participants. The experimental approach adopted is based on that of Baucells et al. (2011), with some adjustments that are described in the section below.

Experimental Design

The first choice was whether to follow Baucells et al. (2011) and have a balanced design or adopt an unbalanced design. A balanced design ensures that all participants go through the same treatment (experience the same chart patterns), whereas in an unbalanced design, all participants go through different treatments (different chart patterns). An advantage of balanced designs is that statistical efficiency is improved. Variability is kept within participants rather than between participants, as each participant receives the same treatments (although not in the same order). The advantage of an unbalanced design is that a greater number of treatments (charts) can be used in the experiment. This allows for a greater variation in salient chart features, which could influence reference points.

We decided to adopt a balanced, repeated-measure design with 30 different chart patterns shown to participants. This is because 30 chart patterns allow for enough variation in salient prices to maximise variation, while the balanced design eliminates variability between participants. We found that multicollinearity in independent variables typically was not reduced beyond around 20 charts. This is because there is a natural relationship in charts between the initial, maximum, minimum, average and final prices, which is achieved at around the 20 chart level.

A second major design choice is the type of charts to use in the experiment. The experimental design is based on Baucells et al. (2011) who use charts that move in a +/-50 Euro range per day. Their charts are constructed using artificial data. The benefit of artificially generated charts is that control is increased and this leads to lower multicollinearity between the independent variables (purchase, maximum, minimum, average and final prices) in Baucells et al. (2011), thus improving internal validity. The main drawback is a drop in externally validity as the charts may be viewed as artificial by participants, which may affect their responses. Patterns could be unknowingly introduced into the charts and round number bias could also affect participant responses (Bhattacharya et al., 2012). We, therefore, decided to use real share price charts sampled from a market dataset, ensuring that bias was not introduced into the experiment by the design of the charts themselves. The market dataset consisted of the dataset of all US equities from 1963-2016, which is used later in Chapter 5 for market data testing.

The next decision was to determine the mix of chart lengths shown to participants. Prior studies tend to use either generic time periods or time periods that are too short in length, which reduces ecological validity. For example, in Baucells et al. (2011) charts had a maximum length of only 10 days and some of the charts had a duration of only 3 days. We decided to use longer duration charts using real-time periods that more accurately reflect the holding periods of investors and can be used to explore recency effects (George and Hwang, 2004). Therefore, our experiment uses an equal number of charts of the following lengths: 6 months, 1 year, 2 years, 3 years and 5 years. The increase in chart length, relative to other reference point studies such as Baucells et al. (2011), enables detailed analysis of the impact of past prices on the reference point, such as 52-week highs and lows, versus overall highs and lows.

To create the charts we randomly sampled from the market dataset, using the rsample command in Stata to sample without replacement. The rsample command chooses a particular security id at a particular time. For example, the first selection that forms Chart1 was the security id for Nevada National Bancorporation (Permno 57190) at time 22-Jun-78. As this is a 6-month chart, it is formed by reading 126 trading days forward from the initial date. The sampled master file is shown in Table 3-1. A total sample of 41 points was needed to produce the 30 charts, as 11 charts had to be rejected. Charts were rejected if they failed a market cap screen for being in the bottom 10% of the total universe. This screen is applied to ensure that untradeable microcaps stocks, with unrealistic share price patterns, are not included in the sample. The second reason for rejections was because there was not enough data to produce the charts. For example, a 5-year chart selected with a start date in 2015 needs a total of 1,260 forward days to produce the chart.

In Baucells et al. (2011), each point in the graph is presented with a 3-4 second lag, reflecting the emphasis in their paper on measuring the amount of adaptation at each point of the stock price movement, which may also facilitate the participant experiencing time. We did not incorporate the lag into our experiment, as we are interested in measuring reference points formed from a previous stock price path, as an entire series, rather than as a set of lagged points. This is because the CGO model requires a single reference point, as an input into the model. The study, therefore, presents the graphs to participants without delay between points. We do revisit this issue in Chapter 6 however, for the 2nd experiment in this thesis.

In terms of capturing reference points from participants, this study uses direct elicitation to capture reference points, based on Baucells et al. (2011). An adjusted form of the question used in Baucells et al. (2011) is adopted as follows, '*at what selling price would you feel neutral about the sale of the stock, i.e. be neither happy nor unhappy about the sale?*'. The adjustment allows for the fact that participants may feel positive and negative emotions at the same time (Cacioppo and Berntson, 1994), and therefore asks participants to consider the balance of their feelings. Therefore, the question we adopt is, *"Your task will be to indicate the selling price at which you would feel neutral (i.e. feel neither predominantly positive nor negative) about selling the stock."*

Table 3-1*: Sampled Chart Master File*

permno	date	Company Name	Graph	Comment
57190	22-Jun-78	NEVADA NATIONAL BANCORPORATION	1	
74297	18-Apr-77	TOLLEY INTERNATIONAL CORP	2	
89245	22-Aug-01	ISCO INC	3	
10392	02-Oct-90	PEOPLES WESTCHESTER SAVINGS BANK	4	
85500	28-Sep-01	ROCK OF AGES CORP	5	
78875	15-Dec-99	CREE RESEARCH INC	6	
87269	27-Feb-04	CITIZENS HOLDING CO	7	
92467	30-Jun-11	ORION MARINE GROUP INC	8	
86079	21-Oct-05	M S G I SECURITY SOLUTIONS INC		Failed market cap screen
91204	16-Jul-10	PORTLAND GENERAL ELECTRIC CO	9	
66384	22-Mar-02	WESTERN DIGITAL CORP	10	
77213	01-Jul-93	EDMARK CORP	11	
43334	30-Dec-88	SYNALLOY CORP	12	
79601	19-Jun-97	KENTUCKY ELECTRIC STEEL INC	13	Less than 10% under mrk cap screen
81382	28-Apr-78	WALBRO CORP	14	
62228	22-Oct-86	FREQUENCY ELECTRONICS INC	15	
70974	13-Feb-85	SOLAR SYS BY SUN DANCE		Failed market cap screen
80236	24-Mar-16	D S P GROUP INC		Not enough data
10961	09-Dec-94	CENTENNIAL BANCORP	16	Used, Adjusted for stock split
70325	06-Jan-83	SHERWOOD DIVERSIFIED SVCS INC		Failed market cap screen
64610	20-Jan-84	M G M U A HOME ENTERTAINMEMT GP		Not enough data
50965	07-Nov-96	MAGNETIC TECHNOLOGIES CORP		Not enough data
11382	10-Jan-89	PROFFITTS INC	17	
27115	24-Aug-78	GREAT WESTERN FINANCIAL CORP	18	Used, Adjusted for stock split
40715	05-Nov-65	CHELSEA INDUSTRIES INC	19	Used, Adjusted for stock split
89419	11-Oct-04	PACER INTERNATIONAL INC TN	20	
89761	25-Mar-04	CYCLE COUNTRY ACCESSORIES CORP		Failed market cap screen
77505	06-Nov-13	ASURE SOFTWARE INC		Failed market cap screen
71554	02-Nov-90	BELVEDERE CORP		Not enough data
62586	27-Aug-74	FAIRFIELD COMMUNITIES LAND CO		Not enough data
83264	21-Dec-04	GREIF INC	21	Used, Adjusted for stock split
29912	04-May-83	DICKEY JOHN CORP	22	
83124	31-Aug-06	C S G SYSTEMS INTERNATIONAL INC	23	
42999	07-Apr-67	SANDERS ASSOCIATES INC	24	Used, Adjusted for stock split
44039	12-Aug-80	INDUSTRIAL RES INC	25	
87623	01-Aug-00	NEXTEL PARTNERS INC	26	
35238	03-Feb-87	PEP BOYS MANNY MOE & JACK	27	
89793	27-Apr-10	D T S INC	28	
75628	03-Nov-87	TESCO AMERICAN INC		Not enough data
89575	22-Jan-03	SAFETY INSURANCE GROUP INC	29	
88199	09-Jan-02	TANOX INC	30	

Notes: Table showing the randomly selected security paths from the market dataset. permno= unique security ID number from CRSP database, date=beginning date of sample, Graph=the chart number subsequently used in the experiment. Companies must be in top 90% of market cap of the universe and must have enough data to produce the chart.

Previous research has shown that beliefs about future prices can affect the reference point (Grosshans and Zeisberger, 2018, Hoffmann et al., 2013). Baucells et al. (2011) control for this by informing participants that all possible price changes between €+50 and €−50 are equally likely. The study does not use this approach because beliefs are part of the way investors form reference points in real life trading and share price patterns that investors experience can influence these beliefs (Barberis et al., 1998, Rabin and Vayanos, 2010). In addition, the use of real share price data to construct charts means that this approach can not be adopted.

The final 30 charts selected are shown in the Appendix along with the instructions for the experiment. Charts 1-6 have a 6-month duration, Charts 7-12 are of 12 months duration, Charts 13-18 are 2 years duration, Charts 14-24 are 3 years duration, and Charts 25-30 are 5 years duration. Table 3-2 shows the characteristics of the charts. The average characteristic of all 30 charts has a purchase price of around \$19, with a maximum of \$36, a minimum of \$13 and a final price of \$25. The average annualized standard deviation of the charts was quite high at 50% with a slight positive skew of 0.46. Chart 6 was atypical in that it had a very high standard deviation, moving from a purchase price of \$66 to a maximum price of \$198, and a final of \$155, all in the course of 6 months.

While we aim to capture the effects of changes in time frames on reference points, it is imperative that participants pay attention to any changes in a timeframe within the x-axis of charts presented. To ensure that participants recognised the change in time frames, all charts of the same length are presented as a group along with an introductory screen to alert them that the timeframe had changed. Each timeframe has 6 charts each and so these 6 were presented together. The timeframe was also clearly visible in the x-axis of the charts. The order of presentation of groups was randomized as well as the presentation of charts within groups, as indicated above, to counteract order effects. This ensures that participants do not all go through the charts in the same order.

Table 3-2: Chart Characteristics

Chart Number	Purchase	Maximum	Minimum	Final	STDEV	SKEW
1	13.33	14.58	10.67	11.83	31.4%	-1.35
2	3.38	3.5	2.38	2.38	46.6%	-0.18
3	7	10.3	7	10.29	41.0%	0.09
4	13.5	15.25	8.25	15.25	65.2%	0.59
5	5.9	6.72	4.76	6.6	47.5%	-0.06
6	66.13	198.19	66.13	155	104.6%	0.03
7	22	23.45	19.7	20.75	16.7%	1.33
8	9.41	9.77	5.18	6.85	56.1%	0.02
9	18.53	25.97	18.29	25.31	14.9%	-0.16
10	6.05	8.9	3.05	8.15	85.2%	0.44
11	15	15.5	9.5	10	77.3%	0.33
12	5.88	10.75	5.5	10	47.3%	2.29
13	5.63	8	2.5	3.06	93.5%	0.45
14	14.5	14.5	6.5	7	39.3%	0.35
15	20.13	29.38	9.25	10.5	49.6%	0.50
16	9.5	22.06	9.25	21.71	53.4%	0.39
17	6.88	8	5	5.5	52.4%	0.13
18	31.38	41.25	21.75	31.13	37.2%	0.06
19	10	73.06	7.38	62.54	46.3%	1.37
20	17.7	35.17	17.2	18.49	36.1%	-0.37
21	54.04	126.76	52	121.36	34.0%	0.08
22	14.25	18.88	10.38	15	32.5%	2.33
23	26.92	28.22	10.55	14.88	42.3%	0.96
24	78.38	151	22	24.5	47.5%	0.07
25	1.91	4.66	1.25	2.78	50.1%	1.29
26	30.94	34.19	2.36	26.25	77.8%	0.85
27	46.5	58.13	25.88	49.88	41.4%	-0.15
28	34.22	50.16	14.1	37.26	40.1%	-1.71
29	13.49	56.03	12.9	38.16	31.0%	0.15
30	15.51	22.74	8.03	19.81	53.1%	2.20
Average	19.5	36.1	13.0	24.9	51.0%	0.46
Median	13.9	17.2	8.8	13.4	47.4%	0.34
Max	78.4	198.2	66.1	155.0	104.6%	2.33
Min	1.9	3.5	1.3	2.4	14.9%	-1.35
STDEV	19.2	48.6	15.0	35.9	21.7%	0.79

Notes: Table showing characteristics of the 30 charts used in Experiment 1. Purchase=initial price, Maximum=maximum price, Minimum=minimum price, Final=end price, STDEV=annualised standard deviation of returns, Skew=skew of returns.

Data Collection

A data survey company, SSI International, was used to collect responses. All responses were taken from US Citizens who are resident in the United States. To ensure that no novices participated in the experiment, all participants had to confirm that they have some experience of trading in US stocks or mutual funds, even if this is infrequent. A novice was defined as an individual who does not trade at least once in a stock or mutual fund over the last year. We eliminated novices as they have no prior experience with trading.

The initial data sample consisted of 191 participants who provided 30 reference points each [5730 in total]. A number of exclusions were necessary in order to clean the data. This was because a small number of participants clicked through the charts providing invalid answers e.g. providing a reference point of 200 for every chart regardless of the chart pattern. In addition, some participants made typos for an individual chart e.g. typing 20 when they meant 200. Two methods are available to clean the data, which we discuss below. The first method is adopted in subsequent analysis.

The first data cleaning method relies on the range of the chart and establishes a feasible tolerance of +/-25% around the range of the stock price chart. To catch the participants who provided poor quality data consistently across charts, we excluded participants who gave an answer outside this range for a third or more of the charts i.e. the reference price was greater/lower than max/min price by more than 25% for a third or more of the charts. This removed 22 participants from the results [660 reference points]. To catch participants who made an individual, rather than a persistent mistake, reference points outside the feasible range of +/-25% were also removed on an individual basis, rather than excluding the whole sample of a participant. This removed an additional 65 reference points. The final data sample, after the exclusions, comprised 5005 reference points across 169 participants (109 male, 60 female) with a broad distribution of ages between 30-65 years (average = 53 years).

The second method uses the distribution of the reference points provided to identify outliers and eliminate them rather than the range of the chart. A Z-score is first calculated for each chart by subtracting the median (med) reference point, from each individual reference point (x) and divides by the median absolute deviation (MAD). Each of the 30 charts is calculated separately.

$$Z = \frac{(x - med)}{\mathrm{MAD}}$$

Equation 3-1: Z-Score Formula

Using the Outlier Sum method (OS) (Tibshirani and Hastie, 2007), the interquartile range (IQR) of the Z score is calculated as the difference between the 75th and 25th boundaries of the distribution. The maximum OS boundary is then defined as the 75th percentile of the distribution of Z-scores, plus the IQR and the minimum boundary is the 25th percentile minus the IQR, as shown in Equation 3-2. Values outside the maximum (OS_{max}) or minimum (OS_{min}) limits are excluded. The OS screening method removes a total of 697 reference points from the raw data, leaving 5033 remaining.

$$OS_{max} = p75(modfied\ z) + IQR(z)$$

$$OS_{min} = p25(modified\ z) - IQR(z)$$

Equation 3-2: Outlier Sum Exclusion Boundaries

In the remaining sections, we show results using the first screening method. As a cross-check, the main regression is shown using both the range method (Table 3-9) and the OS method (Table 3-11). We find that there is no significant difference in results when data is cleaned by either method.

3.2 Results

Descriptive Variables

The experiment includes a number of identifying variables that can be used to segment the data by demographics. We measure participant age, gender and frequency of trading. In addition, we also measure the time (duration) that participants take to complete the experiment. To measure the variation in reference points across groups of individuals, we create a variable to measure the percentage deviation between the reference point and the final price, defined in Equation 3-3. We call this variable Capital Gain Overhang (CGO), originally from Grinblatt and Han (2005), and we take the absolute of CGO to stop positive and negative values from cancelling out.

$$Abs[CGO] = ABS\ \frac{(Final\ Price - Reference\ Point)}{Final\ Price}$$

Equation 3-3: Absolute Capital Gains Overhang

We test if the 4 identifying variables: age, gender, trading frequency, and duration can explain variation in CGO using ANOVA analysis but first we show the individual impact of each variable for descriptive purposes. The following tables show reference points and Absolute CGO split by demographic variables. The reference point shown is directly elicited from participants in the experiment when they are asked for their neutral selling price. Table 3-3 shows reference points and absolute CGO split by gender. The mean and median of reference points are virtually identical by gender and the SD of both these variables is also similar. Table 3-4 shows reference points by the trading frequency of participants, which is split into 4 groups: daily, weekly, monthly, or rarely (at least once per year). The most notable feature of the table is that the mean of both reference points and absolute CGO are higher for daily traders than for the other groups that trade less frequently. The daily traders also have more variation (SD) around their reference points and absolute CGO. One possibility is that this result could be due to the overconfidence of more frequent traders, which leads to higher reference points. Table 3-5 shows reference points with participants split across 5 categories of age, broadly equal in the number of participants per category. There seems very little difference in reference points across age brackets. In the area of absolute CGO, there appears to be a decreasing absolute CGO as age bracket increases, as well as a lower standard deviation. Finally, Table 3-6 shows reference points and absolute CGO for groups split by the duration taken to complete the experiment, into 5 broadly equal groups. There appears to be no relationship between duration and reference points or absolute CGO, although we will confirm that with Anova analysis below.

Table 3-3: Reference Point/CGO by Gender

Gender	Reference Point			Absolute CGO		
	Mean	Median	SD	Mean	Median	SD
Male	26.0	15.0	30.0	31%	17%	50%
Female	25.8	15.0	29.4	34%	20%	50%

Notes: The table shows mean, median and SD of elicited reference points or Absolute CGO (defined in Equation 3.3), split by gender of the participant.

Table 3-4: Reference Point/CGO by Trading Frequency

Frequency	Reference Point			Absolute CGO		
	Mean	Median	SD	Mean	Median	SD
Daily (at least once per day)	27.4	15.0	32.1	37%	21%	60%
Weekly (at least once per week)	26.8	15.0	31.0	30%	16%	49%
Monthly (at least once per month)	25.4	15.0	28.7	33%	18%	50%
Rarely (less than once per year)	25.8	15.0	30.0	32%	18%	50%

Notes: The table shows mean, median and SD of elicited reference points or Absolute CGO (defined in Equation 3.3), split by the self-reported trading frequency of the participant.

Table 3-5: Reference Points/CGO by Age

Age	Reference Point			Absolute CGO		
	Mean	Median	SD	Mean	Median	SD
30-40	26.0	15.0	30.0	34%	20%	52%
41-50	25.8	15.0	29.9	33%	17%	52%
51-55	26.3	15.0	30.6	34%	19%	55%
56-60	26.0	15.9	29.6	31%	18%	47%
60-65	25.5	15.0	29.1	29%	15%	47%

Notes: The table shows mean, median and SD of elicited reference points or Absolute CGO (defined in Equation 3.3), split by the self-reported age of the participant.

Table 3-6: Reference Points/CGO by Duration

Duration	Reference Point			Absolute CGO		
	Mean	Median	SD	Mean	Median	SD
0-7 mins	26.2	15.0	30.9	33%	19%	52%
7-10 mins	25.4	15.0	28.9	32%	18%	48%
10-13 mins	26.5	15.1	30.4	31%	16%	51%
13-16 mins	25.9	15.0	29.9	30%	17%	51%
Above 16 mins	26.2	15.0	29.7	33%	19%	53%

Notes: The table shows mean, median and SD of elicited reference points or Absolute CGO (defined in Equation 3.3), split by the time that the participant took to complete the experiment in minutes.

Anova analysis of the four identifying variables versus the reference point is shown in Table 3-7. The analysis suggests that none of the 4 variables can explain variation in reference points. The descriptive variables do a better job of describing variation in absolute CGO, as shown in Table 3-8, reflected by the higher r-squared of this model. However, none of the variables are significant at the 5% level. The results suggest that the identifying variables cannot explain the variation in either reference points or CGO.

Table 3-7: Anova- Reference Point against Descriptive Variables

Number	of obs =	5,005		R-squared	0.0007
Root	MSE =	29.8358		Adj R-squared	-0.0017
Source	Partial SS	df	MS	F	Prob>F
Model	3276.622	12	273.0518	0.31	0.9885
Gender	15.24478	1	15.24478	0.02	0.8959
Frequency	2123.624	3	707.8748	0.8	0.4964
Age	183.9396	4	45.98491	0.05	0.995
Duration	1063.572	4	265.8931	0.3	0.8789
Residual	4,443,745	4,992	890.1732		
Total	4,447,021	5,004	888.6933		

Notes: Table showing ANOVA analysis of the reference point against descriptive variables of participants. DV=reference point, Gender=Male or Female, Frequency=frequency of trading (yearly, monthly, weekly, or daily), Age=age in years of participants, duration=time taken to complete the experiment in seconds.

Table 3-8: Anova- Absolute CGO against Descriptive Variables

Number	of obs =	5,005		R-squared	0.0034
Root	MSE =	0.505066		Adj R-squared	0.001
Source	Partial SS	df	MS	F	Prob>F
Model	4.291585	12	0.357632	1.4	0.1568
Gender	0.769315	1	0.769315	3.02	0.0825
Frequency	1.206078	3	0.402026	1.58	0.193
Age	1.851309	4	0.462827	1.81	0.1231
Duration	0.473688	4	0.118422	0.46	0.762
Residual	1273.42	4,992	0.255092		
Total	1277.711	5,004	0.255338		

Notes: Table showing ANOVA analysis of Absolute CGO against descriptive variables of participants. DV=ABSCGO defined in Equation 3-3, Gender=Male or Female, Frequency=frequency of trading (yearly, monthly, weekly, or daily), Age=age in years of participants, duration=time taken to complete the experiment in seconds.

Regression: Reference Point using Price Variables

We examine salient features in the share price path, previously identified in Baucells et al. (2011), which are the purchase, maximum, minimum, average and final prices. Baucells et al. (2011) found all the variables to be significant at the 5% level in a regression against the reference point. The regression in Table 3-9 uses the Purchase, Maximum, Minimum, Average and Final prices as independent variables (IV's), predicting the Reference Price as the dependent variable (DV) as shown in Equation 3-4 below. Linear least squares regression is used and robust standard errors are clustered by participant, to mirror the approach in Baucells et al. (2011). In this and all subsequent regressions, variables are categorised as significant if they meet the 5% threshold.

$$Reference\ Point = \beta_0 + \beta_1\ Purchase + \beta_2\ Maximum + \beta_3\ Minimum + \beta_4\ Average + \beta_5\ Final + \varepsilon$$

Equation 3-4: Regression Equation

We start with the full set of variables in Model A and then remove IV's and reduce Variance Inflation Factors (VIFs) while observing the r-squared of the reduced model. The VIF of an IV is calculated by regressing the IV against the other IVs in the model. The R-squared from this regression is then used in Table 3-10 to calculate the VIF score using Equation 3-5.

$$VIF = \frac{1}{1 - R^2}$$

Equation 3-5: Formula for VIF

Models D, E, and F of Table 3-9 replace the maximum and minimum variables with the 52-week maximum and minimum variables, as shown in Equation 3-6. Model D begins with the full set of variables, which is gradually reduced. The 52-week variables take account of the investment horizon. For example, over the 6-month charts, the 52-week maximum is the maximum over the 6-month horizon of the investor and does not take account of the remaining 6 months, where they are not invested.

$$Reference\ Point = \beta_0 + \beta_1 Purchase + \beta_2 Max52 + \beta_3 Min52 + \beta_4 Average + \beta_5 Final + \varepsilon$$

Equation 3-6: Regression Equation

In Model A, the purchase, maximum and final price are found to be significant, but the average and minimum prices are insignificant. Table 3-10 suggests the level of collinearity between the variables in Model A is high, with a mean VIF of 77.76 and with the maximum, minimum, average and final prices having high VIF scores. In Models B and C we eliminate one of the two insignificant variables. Model B removes the average variable while retaining the minimum, leaving all of the remaining variables significant. The r-squared of the model is not reduced relative to Model A, and the mean VIF falls to 10.15. Model C removes the minimum variable while retaining the average. All of the remaining variables are significant with no drop in r-squared. The mean VIF score is higher than Model B however, with both the maximum and average having high VIF scores, leaving us with a preference for Model B.

The results from Models A, B and C suggest that the purchase, maximum and final prices play a role in determining the reference point, along with the minimum or the average price. These results are in line with the findings of Baucells et al. (2011), although they also find that both the average and minimum prices play a role. We find that Models B or C, with minimum or average included, are close substitutes for each other due to the natural multicollinearity that is present in real share price data.

In Models D, E and F we replace the maximum and minimum variables with max52 and min52 respectively. In Model D, which includes all the variables, the purchase, max52 and min52 variables are significant but the final and average prices are insignificant. The average VIF score is 39.62 suggesting that we can remove variables from the regression. Model E removes the average Price from the regression. The purchase, max52, and min52 variables remain significant but the final price remains insignificant. As the average VIF score is still high at 16.93, in Model F we also remove the final Price. All of the remaining variables are significant and there is no reduction in r-squared, while the average VIF score is reduced to 4.44.

Model F is our preferred model of the three that introduce the 52-week variables. This model has the same r-squared as Model D, which includes all the independent variables and has a far lower average VIF score.

Table 3-11 replicates the analysis of Table 3-9 but with data cleaned using the OS method, rather than the range method discussed earlier. Table 3-12 shows the VIF analysis for the data cleaned using the OS method. There is no material difference in the results, regardless of which method is used to clean the data.

Table 3-9: Regression Analysis Point Variables (Range Cleaning Method)

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
Purchase	0.328**	0.328**	0.341**	0.435**	0.434**	0.431**
	(10.03)	(9.660)	(9.812)	(14.09)	(16.74)	(11.53)
Maximum	0.294**	0.292**	0.235**			
	(6.430)	(11.85)	(10.05)			
Minimum	0.138	0.135**				
	(1.847)	(4.326)				
Average	-0.00280		0.114**	-0.00286		
	(-0.0300)		(2.914)	(-0.0582)		
Final	0.232**	0.232**	0.265**	0.00440	0.00554	
	(6.768)	(7.373)	(9.420)	(0.0914)	(0.126)	
Max52				0.446**	0.444**	0.448**
				(9.903)	(12.40)	(17.59)
Min52				0.109**	0.109**	0.112**
				(3.300)	(4.077)	(4.042)
Constant	0.168	0.171	0.314**	0.101	0.103	0.116
	(1.430)	(1.459)	(3.212)	(0.994)	(0.948)	(0.702)
Observations	5,005	5,005	5,005	5,005	5,005	5,005
R2	0.837	0.837	0.837	0.836	0.836	0.836
Adjusted R2	0.837	0.837	0.837	0.836	0.836	0.836

This table reports results for predictive regressions of reference points on a set of salient prices. Dependent variable= reference point provided by participant. Purchase= purchase price shown in chart. Maximum= maximum price shown in chart. Minimum= minimum price shown in chart. Average= arithmetic average of prices shown in chart. Final= final price shown in chart. Max52=52-week high price shown in chart for charts of 12 months or longer; 6 month high otherwise. Min52=52-week low price shown in chart for charts of 12 months or longer; 6 month low otherwise. Robust t-statistics in parentheses, clustered by participant - ** p<0.01, * p<0.05.

Table 3-10: VIF Analysis

Variable	Model A	Model B	Model C	Model D	Model E	Model F
Purchase	7.46	7.34	6.68	6.57	4.96	2.92
Maximum	126.20	12.40	25.70			
Minimum	53.87	9.46				
Average	177.50		31.18	50.38		
Final	23.77	11.39	5.43	40.47	28.56	
Max52				90.68	25.99	6.17
Min52				9.63	8.43	4.23
Mean VIF	77.76	10.15	17.25	39.62	16.98	4.44

Table 3-11: Regression of Reference Point (OS Cleaning Method)

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
Purchase	0.344**	0.343**	0.350**	0.447**	0.440**	0.416**
	(11.06)	(10.49)	(10.32)	(14.81)	(17.91)	(11.40)
Maximum	0.254**	0.271**	0.225**			
	(4.801)	(12.00)	(9.429)			
Minimum	0.0674	0.103**				
	(0.767)	(3.110)				
Average	0.0364		0.0929*	-0.0222		
	(0.333)		(2.148)	(-0.397)		
Final	0.264**	0.256**	0.280**	0.0411	0.0498	
	(7.816)	(8.590)	(10.52)	(0.818)	(1.172)	
Max52				0.427**	0.411**	0.445**
				(8.679)	(12.48)	(18.20)
Min52				0.0842*	0.0792*	0.114**
				(2.134)	(2.516)	(4.036)
Constant	0.367*	0.322*	0.437**	0.252	0.271	0.393
	(2.023)	(1.995)	(3.030)	(1.631)	(1.709)	(1.855)
Observations	5,033	5,033	5,033	5,033	5,033	5,033
R^2	0.826	0.826	0.826	0.826	0.826	0.826
Adjusted R^2	0.826	0.826	0.826	0.826	0.826	0.826

This table reports results for predictive regressions of reference points on a set of salient prices. Dependent variable= reference point provided by participant. Purchase= purchase price shown in chart. Maximum= maximum price shown in chart. Minimum= minimum price shown in chart. Average= arithmetic average of prices shown in chart. Final= final price shown in chart. Max52=52-week high price shown in chart for charts of 12 months or longer; 6 month high otherwise. Min52=52-week low price shown in chart for charts of 12 months or longer; 6 month low otherwise. Robust t-statistics in parentheses, clustered by participant - ** p<0.01, * p<0.05.

Table 3-12: VIF Analysis

Variable	Model A	Model B	Model C	Model D	Model E	Model F
Purchase	7.46	7.34	6.68	6.57	4.96	2.92
Maximum	126.20	12.40	25.70			
Minimum	53.87	9.46				
Average	177.50		31.18	50.38		
Final	23.77	11.39	5.43	40.47	28.56	
Max52				90.68	25.99	6.17
Min52				9.63	8.43	4.23
Mean VIF	77.76	10.15	17.25	39.62	16.98	4.44

Regression: CGO against CGO Variables Incorporating 52-Week Highs and Lows

The next set of regressions use the CGO variable as the dependent variable, as defined in Equation 3-3. Independent variables calculated using the CGO methodology will tend to have lower VIF scores, as they are calculated using the percentage difference between the salient price and the final price, rather than the value of the price itself. The independent variable, *CGOPurchase,* is defined in Equation 3-7 as the percentage difference between the purchase and final price. Versions of the CGO using the maximum or minimum price are also defined below as *CGOMax* or *CGOMin* respectively, along with the average, *CGOAverage* and the 52-week high or 52-week low, *CGOMax52* and *CGOMin52*.

$$CGOPurchase \ = \ (Final\ Price - \ Purchase\ Price)\ /Final\ Price)$$

$$CGOMax \ = \ (Final\ Price - \ Max)\ /\ Final\ Price)$$

$$CGOMin \ = \ (Final\ Price - \ Min)\ /\ Final\ Price)$$

$$CGOAverage = (Final\ Price - Average) / Final\ Price)$$

$$CGOMax52 \ = \ (Final\ Price - \ Max52)\ /\ Final\ Price)$$

$$CGOMin52 \ = \ (Final\ Price - \ Min52)\ /\ Final\ Price)$$

Equation 3-7: Independent CGO Variables

The first 3 models (A/B/C) of Table 3-13 are based on Equation 3-8 below. These models act as alternatives for Models (A/B/C) in Table 3-9. The second 3 models (D/E/F) replace CGOMax and CGOMin with CGOMax52 and CGOMin52, as we did in Table 3-9. They are based on Equation 3-9 below.

$$CGO = \ \beta_0 + \beta_1 CGOPurchase + \beta_2 CGOMax + \beta_3 CGOMin + \beta_4 CGOAverage + \mathcal{E}$$

Equation 3-8: Regression Equation

$$CGO = \beta_0 + \beta_1 CGOPurchase + \beta_2 CGOMax52 + \beta_3 CGOMin52 + \beta_4 CGOAverage + \mathcal{E}$$

Equation 3-9: Regression Equation

Model A shows that the variables *CGOPurchase and CGOMax* are significant at the 1% level. CGOMin is significant in Model B when CGOAverage is removed and CGOAverage is significant in Model C when CGOMin is removed. This is in line with the earlier regression results, which show that the purchase, maximum and minimum or average are significant determinants of the reference point. The collinearity of the CGO variables is far lower than for the point regression reflected in the lower VIF scores shown in Table 3-14 versus Table 3-10.

The 52-week CGO variables replace CGOMax and CGOMin in Models D, E and F. In Model D all variables are significant at the 1% level. When we omit CGOAverage in Model E, CGOMin is no longer significant. Model F omits CGOMin and re-introduces CGOAverage and in this instance all the independent variables are significant.

In summary, the results seem consistent with the earlier regression analysis using the reference point and salient prices. Models B and C suggest we should include the minimum or the average, although VIFs are again lower for Model B which includes the minimum. For the models including the 52-week variables, Model D or Model F have a similar r-squared.

Table 3-13: Regression using CGO Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
CGOPurchase	0.300**	0.291**	0.311**	0.362**	0.469**	0.353**
	(10.12)	(9.687)	(10.88)	(13.60)	(20.09)	(13.10)
CGOMax	0.251**	0.309**	0.210**			
	(8.421)	(12.35)	(10.01)			
CGOMin	0.0686	0.151**				
	(1.843)	(7.689)				
CGOAverage	0.115*		0.194**	0.348**		0.310**
	(2.131)		(7.099)	(8.924)		(8.870)
CGOMax52				0.203**	0.427**	0.228**
				(9.138)	(12.41)	(9.284)
CGOMin52				-0.125**	-0.0380	
				(-5.165)	(-1.935)	
Constant	0.00482	0.00280	0.0101*	0.000243	0.0447**	-0.0268**
	(0.791)	(0.497)	(2.014)	(0.0333)	(5.076)	(-3.508)
Observations	5,005	5,005	5,005	5,005	5,005	5,005
R^2	0.673	0.673	0.673	0.668	0.661	0.667
Adjusted R^2	0.673	0.673	0.673	0.668	0.661	0.667

This table reports results for predictive regressions of CGO on a set of CGO variables. Dependent variable is the percentage difference between the reference point and final price. CGOPurchase is the percentage difference between the reference point and purchase price. CGOMax is the percentage difference between the reference point and maximum price. CGOMin is the percentage difference between the reference point and minimum price. CGOAverage is the percentage difference between the reference point and average price. CGOMax52 is the percentage difference between the reference point and 52-week maximum price. CGOMin52 is the percentage difference between the reference point and 52-week minimum price. Robust t-statistics in parentheses, clustered by participant - ** p<0.01, * p<0.05.

Table 3-14: VIF Analysis

Variables	Model A	Model B	Model C	Model D	Model E	Model F
CGO-Purchase	5.90	5.25	4.12	4.51	2.76	4.43
CGO-Max	66.18	3.70	10.61			
CGO-Min	10.42	1.87				
CGO-Average	75.65		13.59	13.91		12.87
CGO-Max52				7.64	2.31	7.20
CGOMin52				1.54	1.42	
Mean VIF	39.54	3.61	9.44	6.90	2.16	8.17

Moderation Analysis: Volatility

Danziger and Segev (2006) suggest that more volatile price patterns increase saliency, which could promote more reference point adjustment and they find that participants update their reference point more for higher volatility charts than for lower volatility charts within their experiment. In our context, the increased salience of a volatile pattern could reduce the size of the dependent variable, CGO, as the reference point adjusts closer to the current price, whereas less volatile charts may inhibit reference point adjustment to the final price. In addition, there is some controversy about the best method of volatility to adopt in experiments. Although return volatility is the most conventional measure, Duxbury and Summers (2018) show that price volatility may more accurately measure how investors truly assess volatility in price charts. In this section, we test if volatility has a moderating effect on reference point adjustment and in addition, we test if volatility has a moderating effect on the relationship between the CGO and independent variables. We use three different measures of volatility, which are defined below.

The first measure of volatility that we test is the standard deviation of daily returns (Stdev), as this is what practitioners would usually define as volatility. We also include the volatility of daily prices as the second variable (PriceDev). Although this typically is not how academics think about volatility, it could be that movements in prices are more salient i.e. more noticeable to participants than movements in returns (Duxbury and Summers, 2018).

$$Stdev = \text{standard deviation of daily returns (annualised)}$$
$$PriceDev = \text{standard deviation of daily prices (annualised)}$$

Equation 3-10: Volatility Variables

The third volatility variable, Frog-in-the-Pan (FIP), comes from Da et al. (2014). The idea behind this variable is that investors are inattentive to continuous information, arriving in small amounts. They find that continuous information, as measured by their information discreteness (ID) variable defined in Equation 3-11, indicates a strong persistent return continuation that does not reverse in the long-run, unlike traditional momentum. PRET in Equation 3-11 is equal to the return over the last year (excluding the last month), sng is a binary variable that identifies whether the return is positive (+1) or negative (-1), %neg is equal to the percentage of days that have positive returns and %pos is equal to the percentage of days that have a positive return.

$$ID = sng(PRET) * [\%neg - \%pos]$$

Equation 3-11: FIP ID variable from Da et al. (2014)

We adapt the variable somewhat as we are not looking to measure the impact on 1-year price momentum and so we do not use the sng(PRET) part of the variable, but instead, we use the overall return of the chart (which can vary between 6 months and 5 years). Therefore, we replace PRET with RET in Equation 3-12. The rest of the calculation is identical, which we use to calculate the Frog in the Pan (FIP) proxy. The variable varies from -1 to +1 depending on the discreteness of the information. A large FIP signifies discrete information, which should be more salient to participants, while a small FIP signifies continuous information which should be less noticeable to participants. More salient, discrete information should facilitate adjustment and lead to a smaller CGO variable.

$$FIP = sng(RET) * [\%neg - \%pos]$$

Equation 3-12: FIP Proxy

As well as including the three volatility proxies in the regression as independent variables, we also include moderating variables that test if the volatility proxies have a moderating effect on the other independent variables. For example, the moderating variables for StDev and the three CGO based independent variables are shown in Equation 3-13 below. We also calculating moderating variables for the other two volatility proxies in the same manner.

$$ModStDevCGOPurchase = StDev * CGOPurchase$$
$$ModStDevCGOMax = StDev * CGOMax$$
$$ModStDevCGOMin = StDev * CGOMin$$

Equation 3-13: Volatility Moderators for StDev

Table 3-15 shows the regression of CGO as dependent variable against Stdev, along with the three moderating variables. Model A is the standard model without volatility moderators included for comparison purposes. Model B includes the Stdev variable and all 3 moderating variables. The moderators for the purchase price and minimum price are significant, however, Table 3-16 reveals that multicollinearity is high with large VIFs. There appears to be a natural relationship between high volatility and pronounced maximums and minimums. To reduce the problem, we remove the moderators for the maximum and minimum variables in Model C. The moderator for the purchase price remains positive and significant. Finally, in Model D, we remove the remaining moderator variable to see the effect of Stdev on CGO in isolation. The Stdev variable is not significant when the moderators are removed, suggesting no relationship between return volatility and reference point adjustment. In summary, there is some evidence that high return volatility increases the importance of the purchase price as a reference point but return volatility itself is not a significant driver of reference point adjustment.

Table 3-17 shows the same analysis but using the price volatility variable. Model A is the standard model with no moderators included. Model B includes all the moderating variables. None of the moderating variables are significant and the VIF scores are high as before. We again remove the moderators for the maximum and minimum variables in Model C. Unlike the case with return volatility, however, the moderating variable for the purchase price is not significant, but the price volatility variable itself is significant. In Model D, we remove the CGO purchase moderator to examine the relationship between price vol and reference points in isolation and we find that the coefficient on the PriceDev variable increases with a t-statistic over 5. The results suggest that reference point maladaptation (reflected in a high CGO statistic) increases for high price volatility charts. This suggests that participants put less weight on the final price when high price volatility is present. In terms of moderating relationships, there is no evidence that high price volatility increases the salience of any particular points in the chart.

The final set of analysis uses the adjusted FIP variable, as shown in Table 3-19. The first model is the standard model shown for illustration purposes. The second model includes all the moderators along with the FIP variable itself. The results suggest that the FIP is significant, although none of the moderators are significant at the 5% level. VIF scores are again too high in Model B. Model C removes the moderators for *CGOMax* and *CGOMin*. None of the remaining variables are significant. When we remove the moderator for *CGOPurchase* in Model D, the FIP variable is insignificant. The results suggest there is no relationship between FIP and the CGO variable and no moderating effect of FIP on any particular prices in the chart series.

In summary, the only volatility variable that has a significant effect on reference point adjustment is price volatility, supporting the findings of Duxbury and Summers (2018). High price volatility increases the amount of maladjustment from the final price and leads to a higher CGO. In terms of moderating effects on specific prices, we found that return volatility has a positive moderating effect on the purchase price. Both of these results suggest that high volatility charts, in the form of price or return volatility, tend to increase the amount of maladjustment in the reference point. This would be consistent with Arena et al. (2008), who show that high return volatility is a positive moderator of price momentum. Our results show that the positive relationship between volatility and price momentum could be caused by an increase in reference point maladjustment in high volatility charts. The results of the FIP analysis show no relationship between FIP or the moderators with CGO, once multicollinearity was reduced in Models C and D. This suggests that the FIP effect is not related to reference points, but could be related to investor attention as Da et al. (2014) suggest in their article.

Table 3-15: Regression Analysis- Return Volatility

VARIABLES	Model A	Model B	Model C	Model D
cgopurchase	0.291**	0.200**	0.261**	0.292**
	(0.0300)	(0.0394)	(0.0328)	(0.0300)
cgomax	0.309**	0.354**	0.311**	0.309**
	(0.0250)	(0.0341)	(0.0250)	(0.0250)
cgomin	0.151**	0.234**	0.144**	0.145**
	(0.0197)	(0.0392)	(0.0197)	(0.0198)
modstdevpurchase		0.163**	0.0512*	
		(0.0412)	(0.0233)	
modstdevmax		-0.0837		
		(0.0426)		
modstdevmin		-0.142*		
		(0.0570)		
stdev		0.00897	0.00199	0.0114
		(0.0187)	(0.0139)	(0.0121)
Constant	0.00280	-0.00316	0.00469	-0.000855
	(0.00562)	(0.00812)	(0.00592)	(0.00533)
Observations	5,005	5,005	5,005	5,005
R-squared	0.673	0.673	0.673	0.673
F	264.8	126.9	168.0	208.8

This table reports results for predictive regressions of CGO on a set of CGO variables, with moderation using return volatility. Dependent variable is the percentage difference between the reference point and final price. CGOPurchase is the percentage difference between the reference point and purchase price. CGOMax is the percentage difference between the reference point and maximum price. CGOMin is the percentage difference between the reference point and minimum price. Robust t-statistics in parentheses, clustered by participant - ** p<0.01, * p<0.05.

Table 3-16: VIF Analysis

Variables	Model A	Model B	Model C	Model D
CGO-Purchase	5.25	47.23	14.21	5.35
CGO-Max	3.70	62.43	3.80	3.70
CGO-Min	1.87	16.72	2.30	2.30
modstdevpurchase		46.39	8.80	
modstdevmax		61.42		
modstdevmin		33.23		
stdev		7.92	1.39	1.27
Mean VIF	3.61	39.33	6.10	3.16

Table 3-17: Regression Analysis- Price Volatility

VARIABLES	Model A	Model B	Model C	Model D
cgopurchase	0.291**	0.298**	0.274**	0.274**
	(0.0300)	(0.0314)	(0.0304)	(0.0303)
cgomax	0.309**	0.304**	0.316**	0.325**
	(0.0250)	(0.0265)	(0.0253)	(0.0255)
cgomin	0.151**	0.102**	0.138**	0.135**
	(0.0197)	(0.0231)	(0.0201)	(0.0192)
modvolpurchase		-0.000260	4.25e-05	
		(0.000157)	(5.36e-05)	
modvolmax		0.000141		
		(7.72e-05)		
modvolmin		0.000335		
		(0.000232)		
pricevol		9.36e-05	8.68e-05*	0.000106**
		(9.24e-05)	(3.51e-05)	(2.11e-05)
Constant	0.00280	0.00627	0.00198	0.00605
	(0.00562)	(0.00646)	(0.00492)	(0.00559)
Observations	5,005	5,005	5,005	5,005
R-squared	0.673	0.673	0.673	0.673
F	264.8	129.7	164.5	198.9

This table reports results for predictive regressions of CGO on a set of CGO variables, with moderation using price volatility. Dependent variable is the percentage difference between the reference point and final price. CGOPurchase is the percentage difference between the reference point and purchase price. CGOMax is the percentage difference between the reference point and maximum price. CGOMin is the percentage difference between the reference point and minimum price. Robust t-statistics in parentheses, clustered by participant - ** p<0.01, * p<0.05.

Table 3-18: VIF Analysis

Variables	Model A	Model B	Model C	Model D
CGO-Purchase	5.25	18.58	6.23	6.23
CGO-Max	3.70	19.24	12.10	6.01
CGO-Min	1.87	7.92	2.08	2.03
modvolpurchase		206.24	6.04	
modvolmax		185.84		
modvolmin		71.43		
pricevol		32.70	2.58	2.00
Mean VIF	3.61	77.42	5.81	4.07

Table 3-19: Regression Analysis- FIP

VARIABLES	Model A	Model B	Model C	Model D
cgopurchase	0.291**	0.290**	0.290**	0.292**
	(0.0300)	(0.0310)	(0.0307)	(0.0301)
cgomax	0.309**	0.331**	0.308**	0.308**
	(0.0250)	(0.0262)	(0.0249)	(0.0250)
cgomin	0.151**	0.122**	0.154**	0.154**
	(0.0197)	(0.0228)	(0.0203)	(0.0206)
modFIPpurchase		-0.0654	-0.0217	
		(0.213)	(0.0863)	
modFIPmax		0.385		
		(0.211)		
modFIPmin		-0.676*		
		(0.339)		
FIP		0.366**	-0.0308	-0.0261
		(0.0812)	(0.0419)	(0.0453)
Constant	0.00280	0.0248***	0.000134	0.000304
	(0.00562)	(0.00840)	(0.00720)	(0.00711)
Observations	5,005	5,005	5,005	5,005
R-squared	0.673	0.673	0.673	0.673
F	264.8	148.7	166.5	201.9

This table reports results for predictive regressions of CGO on a set of CGO variables, with moderation using FIP. Dependent variable is the percentage difference between the reference point and final price. CGOPurchase is the percentage difference between the reference point and purchase price. CGOMax is the percentage difference between the reference point and maximum price. CGOMin is the percentage difference between the reference point and minimum price. Robust t-statistics in parentheses, clustered by participant - ** $p<0.01$, * $p<0.05$.

Table 3-20: VIF Analysis

Variables	Model A	Model B	Model C	Model D
CGO-Purchase	5.25	8.71	7.68	5.53
CGO-Max	3.70	12.78	3.92	3.91
CGO-Min	1.87	3.44	2.19	2.12
modFIPpurchase		16.85	3.07	
modFIPmax		25.77		
modFIPmin		7.51		
FIP		9.14	1.69	1.50
Mean VIF	3.61	77.42	3.71	3.27

3.3 Conclusion

Our results show that the purchase, maximum, and final prices are significant determinants of the reference point, along with the minimum or the average price. The average price or minimum prices are not significant if both are included in the model, due to multicollinearity between variables. Baucells et al. (2011) find that all 5 of the variables are significant within the context of artificially designed charts, however, our experiment uses share price paths sampled from real market data to measure investor reference points, with multicollinearity a natural feature of share price charts.

To overcome multicollinearity we perform regressions using CGO variables, where both the dependent variables and independent variables are calculated as their percentage difference from the final price. The CGO methodology original comes from Grinblatt and Han (2005). VIF scores are lower for these models, which allows individual effects to be measured in more detail. We find that this analysis largely corroborates the earlier analysis using point variables.

We find a far larger role for the maximum price than Baucells et al. (2011) in the form of a higher coefficient. This may be due to the difference in chart lengths with our study using charts of up to 5 years, whereas the Baucells et al. (2011) study uses charts up to a maximum of 10 days, which limits the scope for maximums to develop. The significance of the maximum is in line with other studies on reference point adaptation that examine the impact of highs versus lows e.g. Heyman et al. (2004). It is also possible that asymmetric adjustment to gains versus losses e.g. Chen and Rao (2002) or Arkes et al. (2008) is due to maximums having a greater role in reference point formation than minimums.

This experiment is the first to consider the impact of 52-week highs and lows on reference points. Previous work using market data (George and Hwang, 2004), suggests that the 52-week high is a key driver of momentum profits and the authors suggest that this could be because this price acts as a reference point for investors. We found that the 52-week high and 52-week low are key determinants of the investor's reference point. This insight was only possible due to the use of real share price charts with units of time-calibrated across months.

A final contribution is to explore the impact of volatility on reference point adaptation. Although the issue of share price volatility has been studied extensively in terms of its relation to future returns (Ang et al., 2006), the relationship with reference points has not previously been considered. We do not find a clear, well-defined pattern between return-based volatility and reference point adjustment. The results do suggest, however, that high price-based volatility increases reference point maladaptation, where the reference point is further away from the final price and hence CGO tends to be greater at these times. This interpretation would be consistent with the findings of Arena et al. (2008), who find that high volatility increases the price momentum premium available from stocks. In the context of our experiment, it could be that increased volatility leads to greater uncertainty, which reduces the amount of reference point adjustment from the initial price.

Limitations & Future Research

Internal validity of the experiment would be increased by comparing charts that are identical in salient features and then varying only one independent variable at a time. A mixed design that utilises market data but retains some element of control over the charts could be adopted. This would also reduce the multi-collinearity problems encountered in this chapter.

The issue of volatility and reference point adaptation is deserving of a separate study of its own. Proxies for volatility other than return vol, price vol and FIP could be considered. Graphs could also be constructed from returns rather than prices, as Sobolev and Harvey (2016) suggest participants may assess risk more accurately when graphs are constructed using returns. Although share price graphs are commonly used for individual shares, return graphs are often used for overall portfolio performance.

4 Model I: Reference Point Adaptation within the Capital Gains Overhang (CGO) Model

In the next two chapters, we apply the insights from the experiment in Chapter 3 regarding reference point adaptation to market data models using real-life data. The model that we choose for this chapter is the Capital Gains Overhang Model developed by Grinblatt and Han (2005). Our aim is to adapt this model so that it can account for updating of reference prices from the purchase price and to assess if this change improves the predictability of the model.

The CGO variable (g) in Grinblatt and Han (2005) is defined as the deviation between the final price (P) and reference price (R), divided by the final price as shown in Equation 4-1. As such, it represents the percentage difference between the investor's reference point and the current share price of the stock. The idea is that shares with a positive CGO tend to be undervalued in the market relative to their fundamental value. The reason is that these shares have a positive capital gain and investors tend to be risk-averse in gains, selling these securities too early. For shares with a negative CGO, these shares tend to be overvalued as investors tend to be risk seeking in losses and are reluctant to sell the security at a loss due to loss aversion.

Notice that the final price is lagged by an additional week, relative to the reference point, as shown in Equation 4-1. This is to avoid market microstructure events such as the bid-ask bounce that leads to short-term reversal in stock prices (Rosenberg and Rudd, 1982, Da et al., 2013). The short-term reversal effect could swamp the impact on returns of capital gains or losses if it is not adjusted for. Short-term reversal is also included in later regressions, by including the last month's return as a control variable.

$$g_{t-1} = \frac{P_{t-2} - R_{t-1}}{P_{t-2}}$$

Equation 4-1: Capital Gains Overhang

The challenging question that the model addresses is how to calculate the reference point within the context of market data. Unlike an experiment, reference points can not be directly elicited from market investors. For example, if we assume that the reference point is the purchase price then different investors are likely to have bought a security on different days and therefore have different reference points. To overcome this problem, it is necessary to calculate an aggregate reference point for the representative market investor.

By calculating the probability that a stock was traded on a particular day, it is possible to measure the purchase price on that day and then multiply by this probability. Grinblatt and Han (2005) calculate the probability using stock turnover (V) across 260 weeks of data (5 years in total), as shown in Equation 4-2. By way of example, assuming turnover is 5% on week$_{t-2}$ then the purchase price (P) of that week is given a 5% weight in the reference price (R_{t-1}). This is a straightforward week to deal with because there are no subsequent sales in the following week. For week$_{t-3}$, however, the turnover for that week again reflects its weight, but some of the buyers in week $_{t-3}$ may also sell during the following week$_{t-2.}$ To reflect this, if the turnover in week$_{t-3}$ is 5% then its weight will be 5% * (1 - 5%) = 4.75% to reflect that 5% of the purchases are subsequently sold in week$_{t-2.}$ Similar adjustments are made in subsequent weeks in an iterative fashion, such that weeks in the distant past receive a very low weight, due to a high probability that shares purchased in those weeks were subsequently sold in the more recent past.

$$R_{t-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right)P_{t-1-n}$$

Equation 4-2: Equation for Reference Point

Theoretically, the reference price would be calculated using an infinite number of weeks, but in practice Grinblatt and Han (2005) sum 5 years of weekly turnover adjusted purchase prices (260 weeks) and adjust by a constant (k) to make the weights sum to 1. This does not lead to much information loss relative to an infinite calculation, as the weight given to purchase prices beyond 5 years is typically very small given the high level of weekly turnover for most securities in the market.

While the CGO model is very adept at measuring the likely reference point of the average investor using turnover data, the model uses the assumption of a fixed, purchase price based reference point from the disposition effect (Shefrin and Statman, 1985). As such, it successfully captures external reference point updating that occurs due to turnover in the market but does not take account of internal reference point updating that may occur on the part of individual investors. Adaptation of the model to take into account both types of updating could improve its predictive power.

Prior research such as Baucells et al. (2011) or Arkes et al. (2008) suggest that internal reference point updating does occur. These studies show that other salient prices in a share price chart such as the maximum, minimum and final price are also important determinants of the reference point, in addition to the purchase price. The challenge then is to modify the CGO model in such a way that this internal reference point adaptation can be taken account of.

In this chapter, we construct alternative CGO variables based on reference points in the prior share price path for horizons up to 5 years. These are based on our findings in Chapter 3, where we used an experiment designed to elicit reference points and determined that the purchase, maximum, minimum, average, 52-week maximum and 52-week minimum are important determinants of the reference point. Therefore, we construct alternative CGO variables using these points. For example, the maximum price is used to create a CGO variable based on the maximum, called CGOMax. We find that all of alternative CGO variables based on alternative prices have explanatory power in explaining future returns, in addition to the purchase price-based CGO. This finding is in line with our earlier experiment results.

We then form composite CGO variables with references points generated from several of the salient points, with weights determined from the experiment in Chapter 3. The composite CGO variables are compared to the traditional CGO variable based on the purchase price and we demonstrate that the composite CGO variables have greater explanatory power in explaining future returns. Backtested performance analysis using double-sorted portfolios further confirms the superior predictive power of the composite CGO variables. The composite CGO variables are predictive of returns even after stocks are first sorted by CGO but CGO is rarely predictive of returns after stocks are first sorted by the CGO composites. The results suggest that that the CGO model can be improved by incorporating the updating of internal reference points.

Our best composite variable, CGOCom2, is constructed from the purchase, 52-week maximum and 52-week minimum prices. The importance of the 52-week high and low in reference point formation is a new finding in the literature. Previously it had been shown that stocks near the 52-week high are undervalued and that this could be due to reference point effects (George and Hwang, 2004), but this had never been directly demonstrated. To check that the significance of CGOCom2 is not just because of the previous empirical finding of George and Hwang (2004), we add this variable to the regression as an additional control variable. The results suggest that incorporating the 52-week high into the reference point generates additional explanatory power in addition to the standalone 52-week high variable of George and Hwang (2004).

4.1 Adjustments to the CGO Model

In order to test for the impact of reference points within the Grinblatt and Han (2005) model, we adopt the same weighting scheme as Grinblatt and Han do in Equation 4-2. That is we establish the probability that a stock is traded on a particular day using turnover information, but then we multiply this probability by the alternative salient points rather than the purchase price. Specifically, the adjustment we make in the calculation of the CGO is to replace the price variable (P) in Equation 4-2 with alternatives to the purchase price, such as the maximum or minimum price, to create new versions of the aggregate reference point based on alternative salient prices. All other elements of the CGO calculation remain identical to that of Grinblatt and Han (2005), other than we use daily turnover and price information rather than weekly and hence 1260 trading days rather than 260 weeks shown in Equation 4-2. Daily data allows the reference point to be calculated more accurately than weekly although it is more computationally intensive, and has been adopted by more recent papers that use the CGO model e.g. Wang et al. (2017). The aggregate reference point based on the purchase price is shown in Equation 4-3, along with five alternative aggregate reference points.

$$RefPurchase_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right) Purchase_{t-1-n}$$

$$RefMax_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right) Maximum_{t-1-n}$$

$$RefMin_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right) Minimum_{t-1-n}$$

$$RefAverage_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right) Average_{t-1-n}$$

$$RefMax52_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right) Max52_{t-1-n}$$

$$RefMin52_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right) Min52_{t-1-n}$$

Equation 4-3: Alternative Market Reference Points

The five alternative reference points: *RefMax, RefMin, RefAverage, RefMax52 and RefMin52* reflect the salient prices that we found to be significant in the determination of the reference point in Chapter 3. The maximum or minimum price used in *RefMax* or *Refmin,* at a given point in time*,* is a function of when the investor bought the security, proxied by the volume on that day. For example, if the investor bought the security 6 months ago then the maximum or minimum used is that over the last 6 months, as this represents the maximum or minimum over the life of their investment. *RefMax52* and *RefMin52* use the 52-week high or 52-week low respectively. These variables are also a function of when the investor bought the security and so a 6-month holder may have a lower 52-week high than an investor with a 12 month or longer holding period, as well as a higher low.

Once we have the six reference points calculated using Equation 4-3 then we plug these back into Equation 4-1 to calculate six new CGO variables: *CGO, CGOMax, CGOMin, CGOAverage, CGOMax52*, and *CGOMin52*.

In addition to exploring alternative reference points, we also consider how multiple reference points combine to create composite reference points. We, therefore, create composite aggregate reference points formed from a mix of six salient points, with weights determined by the regression results in Chapter 3. The first composite variable, *RefCom1* shown below, is created from Model B of Table 3-9, which suggests that the reference point is represented by the purchase, maximum, minimum and final prices. *RefCom2* is based on model F of Table 3-9, which suggests the reference point is represented by the purchase, 52-week maximum, and 52-week minimum prices. The reference points *RefCom1* and *RefCom2* are then fed into Equation 4-1 to create the CGO variables, *CGOCom1* and *CGOCom2*.

$$RefCom1_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right) 0.33 * Purchase_{t-1-n} + 0.29 * Max_{t-1-n} + 0.14 * Min_{t-1-n} + 0.23 * Final_{t-1-n}$$

$$RefCom2_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{t=1}^{n-1}[1 - V_{t-1-n+t}]\right) 0.43 * Purchase_{t-1-n} + 0.45 * Max52_{t-1-n} + 0.11 * Min52_{t-1-n}$$

Equation 4-4: Combination CGO Variables

4.2 Data and Method

The market data sample is all US common Stocks (Codes 10 &11) from January 1958 until Dec 2016. NYSE, Amex and NASDAQ firms are included, although NASDAQ firms have their volume cut in half to compensate for double counting of volume (Anderson and Dyl, 2007). Daily data is used to calculate the CGO variable and is then converted to monthly data for the regressions, which have 1 month forward returns as the dependent variable. The monthly data is from Jan 1963 until Dec 2016, as the CGO variable calculation requires 5 years of data. We convert to a monthly basis, rather than weekly as in Grinblatt and Han (2005) because this is a common frequency for asset pricing tests. Shares are ranked by market capitalization every month as a liquidity screen, with stocks in the bottom-decile eliminated for that month. This is to remove the impact of illiquid, untradeable stocks, which could bias the results. There is a total of 68 million firm-day cases in the daily data and around 2.7 million in the monthly data.

The following control variables are used, taken from Grinblatt and Han (2005): Mom- is price momentum defined as the percentage return over the last 12 month excluding the last month, STR- is short-term reversal defined as the percentage return last month, LTR- is long-term reversal defined as the percentage return over the last 3 years excluding the last year, AvgTurn- is the average of daily stock turnover (daily volume/shares outstanding) over last year and Mrkcap- is the log of market cap (stock price*shares outstanding) in units of millions. An additional control variable is included, BM- is the log of the book to market ratio, with a minimum lag of 6 months from the reporting date. This is a common control variable, which is included in the Fama-French 3 factor model (Fama and French, 1993).

Calculation of *CGO* and *LTR* require a minimum of 3 years (out of a maximum of 5) of data and are set to missing otherwise, as are the reference points: *RefPurchase, RefMax, RefMin, RefMax52, RefMin52, RefCom1 and RefCom2*. Prices are adjusted for stock splits when used to calculate the CGO. In the following regressions, the Fama-Macbeth (Fama and MacBeth, 1973) method is utilised, to mirror the original approach in Grinblatt and Han (2005). Standard errors are corrected using the Newey-West method (Newey and West, 1987) with a lag length of 12.

Descriptive Statistics

Table 4-1 and Table 4-2 shows descriptive statistics for the CGO variables and controls. Both *CGO* and *CGOMax* have a negative mean value, reflecting that *RefPurchase* and *RefMax* have a higher mean than stock prices. *CGOMin* has a positive mean and the lowest standard deviation of the CGO variables. The CGO variables based on 52-week high and low have similar characteristics to the CGO's based on overall highs and lows.

Figure 4-1 shows the reference point, based on the purchase price and the second composite, for the stock IBM (ticker IBM), shown for illustrative purposes. IBM has a turnover of around 80% per annum, which is fairly typical for the sample (the average stock turnover is 86% per annum across the sample). Around 80% of the weight of the reference point is provided by the first 3 years of price data.

Table 4-1: Descriptive Statistics for CGO Variables

	CGO	CGOMax	CGOMin	CGOAverage	CGOMax52	CGOMin52	CGOCom1	CGOCom2
Mean	-0.178	-0.528	0.253	-0.038	-0.310	0.200	-0.167	-0.184
SD	0.754	0.945	0.129	0.265	0.405	0.117	0.518	0.478
Median	-0.013	-0.281	0.240	0.009	-0.194	0.184	-0.044	-0.065
Max	0.665	0.030	0.799	0.564	0.031	0.718	0.322	0.331
Min	-18.841	-25.563	-0.132	-4.048	-7.682	-0.134	-13.139	-10.528
Skew	-8.944	-9.891	0.426	-3.495	-5.423	0.634	-9.107	-7.122

Notes: This table reports summary statistics for CGO variables. All number presented are the time-series average of the cross-sectional statistics. CGO calculated using turnover adjusted purchase price as shown in Equation 5. CGOMax calculated as per CGO but replacing the purchase price with the maximum price. CGOMin calculated as per CGO but replacing the purchase price with the minimum price. CGOAverage calculated as per CGO but replacing the purchase price with the average price. CGOMax52 calculated as per CGO but replacing the purchase price with the 52-week maximum price. CGOMin52 calculated as per CGO but replacing the purchase price with the 52-week minimum price. CGOCom1 calculated as per CGO but replacing the purchase price with Refcom1, calculated as per equation 6. CGOCom2 calculated as per CGO but replacing the purchase price with Refcom2, calculated as per equation 7.

Table 4-2: Descriptive Statistics for Control Variables

	Mom	STR	LTR	Avgturn	Mrkcap	BM
Mean	0.164	0.016	0.377	0.003	4.818	-0.693
SD	0.573	0.143	1.014	0.005	1.720	0.976
Median	0.077	0.004	0.187	0.002	4.584	-0.558
Max	10.520	2.379	20.004	0.126	11.603	2.991
Min	-0.866	-0.606	-0.918	0.000	2.108	-7.251
Skew	4.405	3.121	5.673	9.735	0.652	-0.949

Notes: This table reports summary statistics for control variables. All number presented are the time-series average of the cross-sectional statistics. MOM=12month momentum, excluding the last month. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. Mrkcap is the log of market capitalisation in thousands. BM is log of the book to market ratio.

Figure 4-1: IBM Price & Reference Price (RefPurchase): 1963-2016

Regression of One Month Ahead Returns against CGO Variables

In this section, we regress returns against alternative specifications of the CGO variables defined earlier. Table 4-3 shows the regression analysis for one month ahead returns as the dependent variable, with various specifications of the CGO variable as independent variables, and the control variables. Model A, shown below, uses the conventional CGO variables based on the purchase price

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 CGO_t} + \beta_2 MOM_t + \beta_3 STR_t + \beta_4 LTR_t + \beta_5 Mrkcap_t + \beta_6\, AvgTurn_t + \varepsilon$$

Equation 4-5: Regression Equation

The results show that the CGO based on purchase price is significant at the 5% level, along with some of the control variables. Whilst the dual significance of CGO and MOM is at odds with the findings of Grinblatt and Han (2005), it is consistent with a more recent study (Wang et al., 2017) that uses daily data to calculate the CGO as we do. Models B to F use the alternative CGO variables calculated using alternative reference points. All of these variables are significant at the 5% level, suggesting that these CGO variables are also predictive of future returns. All of the six models have a similar Average R^2. The results suggest that the purchase price is not the only point that is relevant in investor reference point determination, as the alternative specifications of the CGO, using alternative reference points, have similar levels of power to predict one month ahead returns.

So far we have only shown the impact of alternative CGO variables as a replacement for the traditional CGO variable. Table 4-4 introduces the CGO composite variables, *CGOCom1 and CGOCom2*. In Models A, B and C we show the effect of CGO, CGOCom1 and CGOCom2 on future returns with no control variables. The explanatory power of CGO and CGOCom1 is about the same, while the explanatory power of CGOCom2 is higher. In Model D, E, and F we introduce the controls that are formed from past returns: price momentum (Mom), short-term reversal (STR) and long-term reversal (LTR). All of the CGO variables remain significant and the explanatory power of both composite CGO variables is higher than that of traditional CGO. Finally, in Models G, H and I we introduce the full range of controls. The CGO variables continue to be significant and the explanatory power of models with the CGO composite variables are again higher than models containing traditional CGO. The results suggest that the CGO composite variables have the same or greater explanatory power than traditional CGO with any combination of controls used in the table. We will confirm the result with double sorted portfolio results in the next section.

Table 4-5 shows the regression results of models that include both the traditional CGO variable and combination CGO variables in the same model, to assess which variable retains its significance as a positive predictor of returns.

$$Ret_{t+1} = \beta_0 + \beta_1 CGO_t + \beta_2 CGOCom_t + \beta_3 MOM_t + \beta_4 STR_t + \beta_5 LTR_t + \beta_6 Mrkcap_t + \beta_7\, AvgTurn_t + \mathcal{E}$$

Equation 4-6: Regression Equation

Models B & C include the CGO combination variables along with the traditional CGO. In both cases, the combination CGO variables are positive and significant predictors of returns, while the traditional CGO has a negative coefficient. The adjusted R-squared for both Models B & C are higher than Model A, suggesting that the composites increase explanatory power when they are added to a model that already includes CGO. Model D includes both CGO combination variables *CGOCom1* and *CGOCom2*, and in this instance neither variable is significant.

Table 4-3: Regression of Monthly Returns using CGO Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
CGO	0.00511**					
	(4.429)					
CGOMax		0.00384**				
		(4.111)				
CGOMin			0.0202**			
			(5.208)			
CGOAverage				0.0167**		
				(6.305)		
CGOMax52					0.0108**	
					(5.710)	
CGOMin52						0.0189**
						(3.615)
Mom	0.00491**	0.00565**	0.00481**	0.00292	0.00485**	0.00502**
	(2.934)	(3.500)	(2.611)	(1.797)	(3.223)	(2.654)
STR	-0.0541**	-0.0542**	-0.0551**	-0.0587**	-0.0570**	-0.0554**
	(-10.01)	(-9.860)	(-9.977)	(-10.92)	(-10.25)	(-9.685)
LTR	-0.000959	-0.000769	-0.000876	-0.00106	-0.000755	-0.000518
	(-1.736)	(-1.483)	(-1.447)	(-1.798)	(-1.288)	(-0.915)
Avgturn	-0.673*	-0.777*	-0.579	-0.559	-0.650	-0.752*
	(-2.076)	(-2.285)	(-1.572)	(-1.503)	(-1.728)	(-2.238)
Mrkcap	-0.000279	-0.000344	0.000172	-0.000316	-0.000518	0.000126
	(-0.649)	(-0.818)	(0.395)	(-0.727)	(-1.232)	(0.297)
BM	0.00205**	0.00185*	0.00253**	0.00225**	0.00174*	0.00237**
	(2.682)	(2.445)	(3.685)	(3.027)	(2.325)	(3.431)
Constant	0.0144**	0.0159**	0.00697*	0.0145**	0.0175**	0.00887**
	(4.166)	(4.768)	(2.213)	(4.166)	(5.165)	(2.834)
Observations	1,749,966	1,749,966	1,749,966	1,749,966	1,749,966	1,749,966
Number of groups	647	647	647	647	647	647
Average R^2	0.0684	0.0685	0.0656	0.0677	0.0690	0.0663

This table reports results for predictive Fama and MacBeth (1973) regressions of one-month ahead returns on CGO and a set of control variables. Dependent variable= 1 month return in month t+1. CGO calculated using turnover adjusted purchase price as shown in Equation 5. CGOMax calculated as per CGO but replacing the purchase price with the maximum price. CGOMin calculated as per CGO but replacing the purchase price with the minimum price. CGOAverage calculated as per CGO but replacing the purchase price with the average price. CGOMax52 calculated as per CGO but replacing the purchase price with the 52-week maximum price. CGOMin52 calculated as per CGO but replacing the purchase price with the 52-week minimum price. MOM=12month momentum, excluding the last month. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. Mrkcap is the log of market capitalisation in thousands. BM is log of the book to market ratio. T-statistics in parentheses are Newey-West adjusted- ** p<0.01, * p<0.05.

Table 4-4: Regressions of Monthly Returns Using CGO Composite Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I
CGO	0.00543**			0.00503**			0.00511**		
	(4.975)			(3.784)			(4.429)		
CGOCom1		0.00915**			0.00873**			0.00944**	
		(5.618)			(4.342)			(5.256)	
CGOCom2			0.00901**			0.00960**			0.00947**
			(5.643)			(4.964)			(4.915)
Mom				0.00497**	0.00461*	0.00416*	0.00491**	0.00450**	0.00424**
				(2.759)	(2.565)	(2.381)	(2.934)	(2.739)	(2.727)
STR				-0.0467**	-0.0472**	-0.0498**	-0.0541**	-0.0546**	-0.0565**
				(-9.744)	(-9.689)	(-10.01)	(-10.01)	(-9.994)	(-10.36)
LTR				-0.00197**	-0.00204**	-0.00210**	-0.000959	-0.00101	-0.000996
				(-3.567)	(-3.630)	(-3.713)	(-1.736)	(-1.894)	(-1.801)
Avgturn							-0.673*	-0.674	-0.650
							(-2.076)	(-1.957)	(-1.771)
Mrkcap							-0.000279	-0.000363	-0.000415
							(-0.649)	(-0.845)	(-0.977)
BM							0.00205**	0.00202**	0.00197**
							(2.682)	(2.674)	(2.599)
Constant	0.0116**	0.0120**	0.0121**	0.0111**	0.0115**	0.0119**	0.0144**	0.0153**	0.0157**
	(5.373)	(5.680)	(5.847)	(5.229)	(5.525)	(5.786)	(4.166)	(4.453)	(4.604)
Observations	1,931,079	1,930,195	1,931,079	1,927,482	1,927,482	1,927,482	1,749,966	1,749,966	1,749,966
Number of groups	647	647	647	647	647	647	647	647	647
Average R^2	0.0162	0.0160	0.0181	0.0382	0.0384	0.0399	0.0684	0.0685	0.0692

This table reports results for predictive Fama and MacBeth (1973) regressions of one-month ahead returns on CGO and a set of control variables. Dependent variable= 1 month return in month t+1. CGO calculated using turnover adjusted purchase price as shown in Equation 5. CGOCom1 calculated as per CGO but replacing the purchase price with Refcom1, calculated as per equation 6. CGOCom2 calculated as per CGO but replacing the purchase price with Refcom2, calculated as per equation 7. MOM=12month momentum, excluding the last month. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. Mrkcap is the log of market capitalisation in thousands. BM is log of the book to market ratio. T-statistics in parentheses are Newey-West adjusted- ** $p<0.01$, * $p<0.05$.

Table 4-5: Regression of Monthly Returns using CGO Composites

VARIABLES	Model A	Model B	Model C	Model D
CGO	0.00511**	-0.0327**	-0.0103**	
	(4.429)	(-6.450)	(-3.633)	
CGOCom1		0.0562**		0.00326
		(7.414)		(0.566)
CGOCom2			0.0261**	0.00929
			(5.663)	(1.552)
Mom	0.00491**	0.00553**	0.00384*	0.00398**
	(2.934)	(3.351)	(2.428)	(2.586)
STR	-0.0541**	-0.0526**	-0.0587**	-0.0569**
	(-10.01)	(-9.665)	(-10.35)	(-10.27)
LTR	-0.000959	-0.000134	-0.000547	-0.000973
	(-1.736)	(-0.230)	(-0.923)	(-1.766)
Avgturn	-0.673*	-0.857**	-0.498	-0.533
	(-2.076)	(-2.601)	(-1.507)	(-1.509)
Mrkcap	-0.000279	-0.000514	-0.000490	-0.000450
	(-0.649)	(-1.190)	(-1.160)	(-1.072)
BM	0.00205**	0.00139	0.00178*	0.00198**
	(2.682)	(1.848)	(2.398)	(2.634)
Constant	0.0144**	0.0178**	0.0166**	0.0158**
	(4.166)	(5.205)	(4.864)	(4.668)
Observations	1,749,966	1,749,966	1,749,966	1,749,966
R-squared	0.0683	0.0710	0.0722	0.0721
Adjusted R-Squared	0.0638	0.0659	0.0671	0.0670
Number of groups	647	647	647	647

This table reports results for predictive Fama and MacBeth (1973) regressions of one-month ahead returns on CGO with CGO Composites and a set of control variables. Dependent variable= 1 month return in month t+1. CGO calculated using turnover adjusted purchase price as shown in Equation 5. CGOCom1 calculated as per CGO but replacing the purchase price with Refcom1, calculated as per equation 6. CGOCom2 calculated as per CGO but replacing the purchase price with Refcom2, calculated as per equation 7. MOM=12month momentum, excluding the last month. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. Mrkcap is the log of market capitalisation in thousands. BM is log of the book to market ratio. T-statistics in parentheses are Newey-West adjusted- ** p<0.01, * p<0.05.

These results suggest that the combination based CGO measures are better predictors of future returns than the traditional CGO variable and *CGOCom2* is the strongest predictor, in line with our earlier experimental results which show that the 52-week high and 52-week low have an influence on reference points in addition to the overall high and low. CGOCom1 and CGOCom2 add additional explanatory power to Models B & C that include the CGO variable and remain significant and positive, whereas the coefficient for CGO becomes negative and significant. We will confirm the result with double sorted portfolio results in the next section.

Double Sorted Portfolio Analysis

Grinblatt and Han (2005) analyse the performance of double-sorted portfolios, sorted by the *CGO* and *Mom* variables, where portfolios are sorted into quintiles by one variable and then by the other. This is to test if a variable has predictive power for returns after first being sorted by the other variable. Portfolio sorts are less affected by noise and outliers than regression analysis, due to individual stock diversification across quintile portfolios, and a linear relationship between the sorting variable and dependent variable does not have to be assumed.

As our primary interest is in comparing the predictive power of the traditional CGO variable versus the composite variables, we sort by *CGO* and either CGOCom1 or *CGOCom2*. Each portfolio is rebalanced every month with stocks within each quintile being equally weighted. The bottom decile of stocks by market cap is excluded from portfolio sorts due to liquidity reasons, as they are for the earlier regression analysis. In Table 4-6 stocks are first sorted by *CGO* into quintiles and then are further sorted into quintiles by *CGOCom1* and in Table 4-7 stocks are first sorted by *CGO* and then by *CGOCom2*. The lowest numbered quintile represents the lowest values of the variable in question.

When sorted first by CGO and then by CGOCom1, the average returns of portfolios increase monotonically with their *CGOCom1* quintile, except for the first quintile of CGO (CGO-1). The difference between the first and last quintile (5-1) is always significant, except in the case of the first CGO quintile (CGO-1). When stocks are first sorted by CGOCom1 and then by CGO into quintiles, returns rarely increase with CGO quintile and 4 out of 5 of the difference portfolios have a negative value.

Table 4-6A: Double Portfolio Sorts by CGO and CGO-Com1

	CGO-1	CGO-2	CGO-3	CGO-4	CGO-5
CGOCom1-1	0.76	0.59	0.78	0.90	1.07
	1.76	2.21**	3.28**	3.87**	4.97**
CGOCom1-2	0.70	0.87	1.14	1.23	1.35
	1.93	3.46**	5.15**	5.90**	6.64**
CGOCom1-3	0.82	1.00	1.19	1.31	1.63
	2.52**	4.15**	5.53**	6.69**	7.69**
CGOCom1-4	0.94	1.05	1.29	1.33	1.73
	3.13**	4.34**	6.21**	6.64**	7.96**
CGOCom1-5	1.09	1.27	1.42	1.52	2.09
	3.89**	5.53**	7.34**	7.42**	8.28**
5-1	**0.33**	**0.68**	**0.64**	**0.62**	**1.03**
	1.52	**6.06****	**5.62****	**5.48****	**6.87****

This table (Panels A & B) reports returns in double sorted portfolios based on values of CGO and CGOCom1. At the end of each month, stocks are sorted into 5 portfolios by CGO and CGOCom1. Stocks in a portfolio are equally weighted. Each portfolio is held for one month and the time series average return in reported in monthly percent. Newey-West corrected t-Statistics are shown below performance.

**=significance at the 5% level.

Table 4-6B: Double Portfolio Sorts by CGO-Com1 and CGO

	CGOCom1-1	CGOCom1-2	CGOCom1-3	CGOCom1-4	CGOCom1-5
CGO-1	0.86	1.05	1.30	1.41	1.55
	2.00**	4.14**	6.08**	7.36**	7.47**
CGO-2	0.82	0.98	1.27	1.27	1.52
	2.25**	4.00**	5.85**	6.70**	7.53**
CGO-3	0.79	0.98	1.24	1.30	1.54
	2.42**	3.91**	5.87**	6.18**	7.35**
CGO-4	0.94	0.91	1.11	1.29	1.69
	3.20**	3.78**	5.27**	6.33**	7.31**
CGO-5	0.58	0.71	0.88	1.13	1.92
	2.03**	2.83**	3.67**	5.18**	7.90**
5-1	**-0.28**	**-0.34**	**-0.42**	**-0.27**	**0.37**
	-1.29	**-2.83****	**-3.66****	**-2.70****	**3.16****

Table 4-7A: Double Sorts by CGO and CGOCom2

	CGO-1	CGO-2	CGO-3	CGO-4	CGO-5
CGOCom2-1	0.97	0.65	0.97	1.05	1.27
	2.15**	2.23**	3.70**	4.06**	5.28**
CGOCom2-2	0.83	0.86	1.12	1.32	1.45
	2.13**	3.16**	4.47**	5.75**	6.68**
CGOCom2-3	0.83	1.05	1.22	1.34	1.61
	2.49**	3.97**	5.23**	6.44**	7.40**
CGOCom2-4	0.96	1.06	1.31	1.39	1.79
	3.09**	4.25**	5.92**	6.44**	7.62**
CGOCom2-5	1.21	1.33	1.37	1.47	2.05
	4.13**	5.62**	6.63**	7.08**	7.74**
5-1	**0.24**	**0.68**	**0.40**	**0.43**	**0.79**
	0.97	**4.42****	**2.74****	**3.03****	**4.89****

This table (Panels A & B) reports returns in double sorted portfolios based on values of CGO and CGOCom2. At the end of each month, stocks are sorted into 5 portfolios by CGO and CGOCom2. Stocks in a portfolio are equally weighted. Each portfolio is held for one month and the time series average return in reported in monthly percent. Newey-West corrected t-Statistics are shown below performance.

**=significance at the 5% level.

Table 4-7B: Double Sorts by CGOCom2 & CGO

	CGOCom2-1	CGOCom2-2	CGOCom2-3	CGOCom2-4	CGOCom2-5
CGO-1	1.08	1.17	1.33	1.37	1.59
	2.41**	4.35**	5.67**	6.64**	7.27**
CGO-2	0.93	1.07	1.28	1.26	1.54
	2.48**	4.0**7	5.52**	6.45**	7.29**
CGO-3	0.81	0.81	1.18	1.34	1.57
	2.41**	3.01**	5.08**	6.27**	7.06**
CGO-4	0.93	0.95	1.15	1.39	1.78
	2.94**	3.49**	4.83**	6.27**	7.38**
CGO-5	0.66	0.93	1.10	1.30	1.97
	2.14**	3.47**	4.26**	5.37**	7.73**
5-1	**-0.42**	**-0.25**	**-0.23**	**-0.07**	**0.38**
	-1.73	**-1.58**	**-1.47**	**-0.55**	**3.06****

Table 4-7 repeats the analysis for CGO and the second composite variable, CGOCom2. Except for the first *CGO* quintile (CGO-1), the average returns of portfolios increase monotonically with their *CGOCom2* quintile. The difference between the last and first (5-1) *CGOCom2* quintiles are significant and positive, except for the first *CGO* quintile. Even in the case of this first *CGO* quintile (CGO-1), although there is no significant difference between the average *CGOCom2* quintiles as shown by t-statistic on the spread (5-1) portfolio, the average returns on the first quintile (CGO-1/CGOCom2-1) is comprised of high volatility stocks and thus has a far lower compound return than the fifth quintile (CGO-1/CGOCom2-5). This is reflected in the lower t-statistic of portfolio CGO-1/CGOCom2-1 of 2.15, versus the t-statistic of CGO-1/CGO-Com2-5 of 4.13, even though both portfolios have a similar average return.

In Table 4-7B stocks are first sorted by *CGOCom2* into quintiles. Within each quintile, stocks are sorted into further quintiles by *CGO*. When first sorting by *CGOCom2* there is not a monotonic relationship between *CGO* and future returns in any of the *CGOCom2* quintiles. The differences between the last and first *CGO* quintiles (5-1) are negative and insignificant, except in the case of the *CGOCom2-5* quintile.

The results of the double sorts suggest that the composite CGO variables are a stronger and more consistent predictor of future returns than CGO. The composite variables exhibit a monotonic relationship with returns for all the CGO quintiles, except the first CGO quintile and the composite difference portfolios are positive and significant. The reverse is not true, as CGO quintiles largely exhibit no relationship with future returns, after first sorting by the composite variables.

Moderation Analysis: Speculative Stocks

Within Grinblatt and Han (2005) investors are split into two categories: rational or PT/MA investors (short for Prospect Theory/Mental Accounting). The PT/MA investors are subject to the disposition effect and hence drive returns from the CGO variable within their model. This suggests that the predictive power of CGO and the CGO composite variables could be stronger among more speculative stocks, whose investors are more prone to PT/MA behaviour.

To test for this possibility, we adopt three proxies for speculative characteristics in stocks based on high turnover, small size or high volatility. The categorizing variables are defined as follows: Avgturn (average of daily turnover over the last year), Mrkcap (log of market capitalization), and Ivol (daily idiosyncratic volatility over the last year measured using the Fama-French 3 factor model). Table 4-8 presents Fama-Macbeth regressions that are the same as Equation 4-5, except that we add three new independent variables: CGO interacted with turnover, CGO interacted with market capitalization, and CGO interacted with idiosyncratic volatility. We repeat for both CGO composite variables; CGOCom1 and CGOCom2 to produce 9 models in total across the 3 moderating variables.

The first three models A, B and C report the coefficients on the turnover interaction term. All three of the interaction terms are positive and significant demonstrating that high turnover stocks are more subject to mispricing caused by CGO. As mispricing is caused by PT/MA investors within the Grinblatt and Han (2005) model, this suggests that high turnover stocks are more likely to be traded by the PT/MA investors. For both market capitalization (Models D, E, F) and volatility (Models G, H, I), however, none of the interaction terms are significant. This suggests that neither of these variables magnifies mispricing within the CGO model and in turn that low market cap and high volatility stocks are not more likely to be traded by PT/MA investors. In summary, only the turnover variable acts as a positive moderator of CGO or the CGO composite variables, with no significant effect from the other two proxies.

The pattern of results may have an alternative explanation suggested by the Grinblatt and Han (2005) model itself. The model suggests that expected future equity returns should be equal to the difference between the final price (P) and reference point (R), multiplied by the current period turnover (V_t), as shown in Equation 4-7. High current turnover implies that the forecast absolute return should be higher. Grinblatt and Han (2005) avoid using the product term in the main analysis of their paper and instead just use the CGO. The reason is that earlier research from Lee and Swaminathan (2000) found that high turnover is a positive moderator of the relationship between momentum and returns and so Grinblatt and Han (2005) did not want to confound the two effects.

$$E_t[P_{t+1} - P_t] = (1 - w)V_t(p_t - R_t)$$

Equation 4-7: Expected Forward Return, taken from Grinblatt and Han (2005)

In their model, high current turnover updates the reference point (R) to the current price (P) thereby reducing CGO, as more recent investors buy at the latest price. This movement in CGO is necessary to close the gap in pricing between the fundamental value of a stock and its share price. Stocks that the CGO model suggests are under-priced (positive CGO) will have a high forward return if high turnover is present, as the high turnover ensures that the valuation gap is closed when previous investors are replaced by newer investors with more recent reference points. Low turnover in the past ensures that CGO will be high in absolute terms and this provides an opportunity for reference prices to diverge from current prices, but high recent turnover is necessary to close the gap between the reference price and final price. It is this convergence between the reference point and the final share price that drives returns. In summary, the model suggests that future returns should be driven more strongly by the product term, [$CGO^* V_t$] than by *CGO* alone.

It is possible therefore that our average turnover variable, that is calculated using the average turnover over the past year, acts as a proxy for the refreshing of the reference point that occurs as older investors are recycled by new ones. Analysis using the current month's turnover as a moderator produces similar results to those presented here using the average daily annual turnover. The t-statistics of the interaction terms between monthly turnover and CGO are significant and positive in the case of all 3 CGO variables, which supports the idea that the two turnover moderators act as proxies for each other.

Table 4-8: Regressions of Monthly Returns against CGO and Turnover

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I
Avgturn*CGO	4.511**								
	(2.858)								
Avgturn*CGOCom1		7.390**							
		(2.911)							
Avgturn*CGOCom2			6.445**						
			(2.661)						
Mrkcap*CGO				0.000611					
				(1.107)					
Mrkcap*CGOCom1					0.00103				
					(1.181)				
Mrkcap*CGOCom2						0.000822			
						(1.013)			
Ivol*CGO							0.106		
							(1.018)		
Ivol*CGOCom1								0.232	
								(1.412)	
Ivol*CGOCom2									0.267
									(1.718)
CGO	0.00108			0.00489*			0.00243		
	(0.727)			(1.975)			(1.005)		
CGOCom1		0.00214			0.00894*			0.00437	
		(0.887)			(2.291)			(1.151)	
CGOCom2			0.00261			0.00943**			0.00412
			(0.926)			(2.684)			(1.046)
Mom	0.00405*	0.00384*	0.00375*	0.00442**	0.00397**	0.00378**	0.00571**	0.00519**	0.00486**
	(2.488)	(2.436)	(2.476)	(2.822)	(2.584)	(2.637)	(3.801)	(3.497)	(3.417)
STR	-0.0557**	-0.0557**	-0.0573**	-0.0551**	-0.0556**	-0.0575**	-0.0547**	-0.0552**	-0.0568**
	(-10.15)	(-10.05)	(-10.39)	(-10.28)	(-10.30)	(-10.66)	(-10.19)	(-10.18)	(-10.43)
LTR	-0.00110*	-0.00110*	-0.00105*	-0.00103	-0.00107*	-0.00102	-0.000986	-0.00106*	-0.00109*
	(-2.167)	(-2.195)	(-1.993)	(-1.899)	(-2.047)	(-1.844)	(-1.789)	(-2.062)	(-2.033)
Avgturn	-0.856**	-0.665*	-0.592	-0.522	-0.567	-0.530	-0.431	-0.494	-0.501
	(-2.869)	(-2.181)	(-1.694)	(-1.770)	(-1.736)	(-1.516)	(-1.797)	(-1.834)	(-1.680)
Mrkcap	-0.000382	-0.000449	-0.000474	-0.000366	-0.000413	-0.000464	-0.000706*	-0.000711*	-0.000708*
	(-0.892)	(-1.053)	(-1.119)	(-0.858)	(-0.961)	(-1.071)	(-2.235)	(-2.259)	(-2.250)
BM	0.00208**	0.00203**	0.00196**	0.00213**	0.00208**	0.00203**	0.00166*	0.00171**	0.00169*
	(2.730)	(2.677)	(2.586)	(2.824)	(2.780)	(2.700)	(2.552)	(2.619)	(2.580)
Ivol							-0.138*	-0.109	-0.0881
							(-2.057)	(-1.603)	(-1.232)
Constant	0.0154**	0.0160**	0.0162**	0.0146**	0.0154**	0.0158**	0.0188**	0.0188**	0.0185**
	(4.457)	(4.670)	(4.764)	(4.204)	(4.474)	(4.576)	(6.742)	(6.732)	(6.625)
Observations	1,749,966	1,749,966	1,749,966	1,749,966	1,749,966	1,749,966	1,749,177	1,749,177	1,749,177
Number of groups	647	647	647	647	647	647	647	647	647
Average R^2	0.0725	0.0727	0.0730	0.0721	0.0723	0.0732	0.0785	0.0784	0.0791

This table reports results for predictive Fama and MacBeth (1973) regressions of one-month ahead returns on CGO and a set of control variables. Dependent variable= 1 month return in month t+1. CGO calculated using turnover adjusted purchase price as shown in Equation 5. CGOCom1 calculated as per CGO but replacing the purchase price with Refcom1, calculated as per equation 6. CGOCom2 calculated as per CGO but replacing the purchase price with Refcom2, calculated as per equation 7. MOM=12month momentum, excluding the last month. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. Mrkcap is the log of market capitalisation in thousands. BM is log of the book to market ratio. Ivol is daily idiosyncratic volatility calculated over 12 months using the 3 factor Fama-French model. T-statistics in parentheses are Newey-West adjusted- ** p<0.01, * p<0.05.

Additional Control Variable: Distance from 52 Week High

The CGOMax and CGO composite variables make use of the share price high in the form of the overall maximum or the 52-week maximum. It could be argued that these alternative CGO variables have superior predictive power because they have exposure to the distance-from-52-week-high variable developed by George and Hwang (2004) and hence their superior predictive power is not down to reference point effects, but due to a previously discovered variable in the literature. In the following analysis, we add the distance-from-52-week high variable as a control to the regression to check if it eliminates the predictive power of the alternative CGO variables.

The distance from 52-week high variable, in George and Hwang (2004), is calculated by dividing the current price (P_i) by the high price over the last 12 months ($high_i$) as shown in Equation 4-8. The current month is excluded from the calculation in both cases. This is to provide comparability with the price momentum measure of Jegadeesh and Titman (1993), which also excludes the current month. We use daily data to calculate the distance from 52-week high (Disthigh) to ensure that the high price ($high_i$) is the most accurate available.

$$Disthigh_t = \frac{P_{i,t-22}}{high_{i,t-22}}$$

Equation 4-8: Taken from George and Hwang (2004)

A number of models are used below with regression results shown in Table 4-9. Model A includes only the *Disthigh* variable along with the previously used controls. This is to establish the predictive power of the *Disthigh* variable. Model B includes both the *Disthigh* and *CGO* variables to check if the *CGO* is still significant with *Disthigh* also in the model. Then Models C and D replace the *CGO* variable with *CGOMax52* and *CGOCom2* respectively, to check if they are still significant with *Disthigh* also included in the regression.

Table 4-9: Regressions of Monthly Returns with Disthigh Control Variable

VARIABLES	Model A	Model B	Model C	Model D
Disthigh	0.0125**	0.00757	-0.0130*	-0.000197
	(2.778)	(1.816)	(-2.047)	(-0.0417)
Mom	0.00625**	0.00510**	0.00668**	0.00498**
	(4.934)	(3.915)	(5.101)	(3.931)
STR	-0.0477**	-0.0538**	-0.0612**	-0.0572**
	(-8.801)	(-9.654)	(-9.300)	(-9.858)
LTR	-0.000778	-0.000954	-0.000715	-0.00117*
	(-1.459)	(-1.721)	(-1.255)	(-2.121)
Avgturn	-0.696	-0.574	-0.781*	-0.611
	(-1.911)	(-1.704)	(-2.152)	(-1.655)
Mrkcap	-0.000487	-0.000550	-0.000589	-0.000571
	(-1.205)	(-1.389)	(-1.458)	(-1.437)
BM	0.00189*	0.00189*	0.00171*	0.00194**
	(2.515)	(2.546)	(2.272)	(2.618)
CGO		0.00400**		
		(3.498)		
CGOMax52			0.0182**	
			(4.955)	
CGOCom2				0.0107**
				(4.317)
Constant	0.00426	0.00883	0.0297**	0.0162**
	(0.734)	(1.612)	(3.993)	(2.684)
Observations	1,884,620	1,749,375	1,749,375	1,749,375
Number of groups	647	647	647	647
R^2	0.0685	0.0736	0.0730	0.0737

Notes: This table reports results for predictive Fama and MacBeth (1973) regressions of one-month ahead returns on Disthigh, CGO and a set of control variables. Dependent variable= 1 month return in month t+1. Disthigh calculated as current price divided by year end, excluding the current month. CGO calculated using turnover adjusted purchase price as shown in Equation 5. CGOCom1 calculated as per CGO but replacing the purchase price with Refcom1, calculated as per equation 6. CGOCom2 calculated as per CGO but replacing the purchase price with Refcom2, calculated as per equation 7. MOM=12month momentum, excluding the last month. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. Mrkcap is the log of market capitalisation in thousands. BM is log of the book to market ratio. T-statistics in parentheses are Newey-West adjusted- ** p<0.01, * p<0.05.

$$Ret_{t+1} = \beta_0 + \beta_1 Disthigh_t + \beta_2 MOM_t + \beta_3 STR_t + \beta_4 LTR_t + \beta_5 Mrkcap_t + \beta_6 AvgTurn_t + \beta_7 BM + \mathcal{E} \quad \text{(A)}$$

$$Ret_{t+1} = \beta_0 + \beta_1 Disthigh_t + \beta_2 MOM_t + \beta_3 STR_t + \beta_4 LTR_t + \beta_5 Mrkcap_t + \beta_6 AvgTurn_t + \beta_7 BM + \boldsymbol{\beta_8\, CGO_t} + \mathcal{E} \quad \text{(B)}$$

$$Ret_{t+1} = \beta_0 + \beta_1 Disthigh + \beta_2 MOM_t + \beta_3 STR_t + \beta_4 LTR_t + \beta_5 Mrkcap_t + \beta_6 AvgTurn_t + \beta_7 BM + \boldsymbol{\beta_8\, CGOMax52_t} + \mathcal{E} \quad \text{(C)}$$

$$Ret_{t+1} = \beta_0 + \beta_1 Disthigh + \beta_2 MOM_t + \beta_3 STR_t + \beta_4 LTR_t + \beta_5 Mrkcap_t + \beta_6 AvgTurn_t + \beta_7 BM + \boldsymbol{\beta_8\, CGOCom2_t} + \mathcal{E} \quad \text{(D)}$$

Equation 4-9: Regression Equations

In Model A, we find that the distance from high is significant and a positive driver of returns in line with George and Hwang (2004). Model B shows that when both *Disthigh* and *CGO* are included in the regression, CGO is significant but Disthigh is not significant. The key results are shown in Model C and D. When *CGOMax52* or *CGOCom2* are included in a regression with Disthigh, both variables still remain significant. *Disthigh* also remains significant in Model C however.

The results suggest that the alternative CGO variables have explanatory power in addition to any exposure to the *Disthigh* variable, as they remain significant even when it is included in the regression. In addition, the Disthigh variable itself is not significant when CGO or CGOCom2 is included in the regression. This suggests that the CGO variables do not act solely as a proxy for the distance from high, but actually provides additional explanatory power.

4.3 Conclusion

In this chapter, we take the insights learnt from the experimental study of reference points in Chapter 3 and apply these to the rich and complex setting of the US stock market, using the CGO model developed by Grinblatt and Han

(2005). We show that the purchase price is not the only reference point that is predictive of one month ahead returns when plugged into the CGO model. In fact, alternative CGO variables based on the maximum, minimum, average, 52-week maximum or 52-week minimum are equally good predictors of future returns. This demonstrates that a purchase price-based reference point is not the only valid one that could be adopted in financial models and that alternatives are just as suitable within the context of the CGO model.

Secondly, we create two CGO-Combination variables formed by weighting different salient points in the stock price path, using coefficients determined in the experiment from Chapter 3. CGOCom1 is created using the purchase, maximum and minimum prices, while CGOCom2 includes the purchase, 52-week maximum and 52-week minimum prices. We then undertake regressions with the composite CGO variables and various combinations of the controls. We find that the composite variables are better or equivalent predictors of future returns than the CGO variable across all the different combinations of the controls. CGOCom2 in particular, which features the 52-week high and low, is the strongest predictor of returns, as it is the best predictor of future returns in the regression models.

We also conduct double sorts by CGO along with CGOCom1 or CGOCom2 and determine that CGO is rarely predictive of returns after stocks are first sorted by CGOCom1 or CGOCom2, but CGOCom1 or CGOCom2 are usually predictive of returns even if stocks are first sorted by CGO. The results suggest that the CGO-Combination variables, formed from a combination of salient points predicted in the experiment, are better predictors of one-month ahead returns than the traditional CGO variable. The implication of our results is that reference points are formed from multiple salient points in the stock price path, rather than the purchase price alone, and thus models using these points have additional explanatory power to predict future returns. In particular, the strong predictive power of CGOCom2, suggests that investors incorporate 52-week highs and lows into their reference point.

We also show that the explanatory power of the alternative CGO variables: CGOMax and CGOCom2 cannot be explained by the distance from high variable. Distance from high is a well-known financial variable developed in George and Hwang (2004), which the alternative CGO variables have exposure to. We show that these variables still have explanatory power even when the distance from high is included in the regression.

Thirdly, we re-examine the link between current month turnover and CGO, which is a part of the Grinblatt and Han (2005) model that has been overlooked by subsequent research. We show that turnover has a strong interaction effect, with both CGO and the CGO composites, that greatly enhances its ability to predict future returns. In the absence of high turnover, CGO has a flat or negative relationship with future returns. This result, suggests that turnover is a key mechanism to close a mispricing, which generates the abnormal return. We looked at two other moderating variables: market cap and price volatility and found that they did not have any explanatory power as moderators. Looking to future research, Lee and Swaminathan (2000) show how turnover is a key moderator of the price momentum relationship. Therefore, turnover may have a role to play as a moderating variable in a wide range of anomalies, which is worthy of further investigation.

Limitations and Future Research

We decided to change the calculation of CGO from the original weekly basis in Grinblatt and Han (2005) to a CGO calculated using daily data. This is a reflection of the increasing availability of daily data over the last 14 years. While this is in line with more modern papers that test the CGO model e.g. Wang et al. (2017), it does mean that the results are not directly comparable to Grinblatt and Han (2005). We also use a longer data sample of 53 years versus 34 in Grinblatt and Han (2005). This again reflects an improvement in data availability since Grinblatt and Han (2005) was written.

Looking to future research, many other financial models assume a fixed, purchase price based reference point such as realization utility (Barberis and Xiong, 2012), and the results suggest that the impact of adjusting reference points in other financial models is worthy of investigation. The disposition effect (Shefrin and Statman, 1985) is a popular area of study, for example, and yet the original assumption of a purchase-price based reference point has largely remained in place.

5 Model II: Reference Point Adaptation within the V-Shaped Net Selling Propensity (VNSP) Model

In this chapter, we apply reference point adaptation to the V-Shaped Net Selling Propensity Model (VNSP), first developed in Ben-David and Hirshleifer (2012) and then extended to market data in An (2016). The basis for this model is that investors have a greater tendency to sell shares that have undergone either large losses or large gains, with a smaller tendency to sell shares that have not moved in either direction. This is distinct from the disposition effect (Shefrin and Statman, 1985), where investors have a tendency to sell winners over losers. Ben-David and Hirshleifer (2012) initially discovered the effect in field data, using trades at a large discount broker, and then An (2016) found that these relationships are also present in the market data. What causes the VNSP effect is unknown, but the boundaries of the gain and loss variables are set by the position of the reference point. This raises the possibility that an adjustable reference point, formed from a composite of prices in line with the results in Chapter 3, may improve the predictive power of the VNSP model. Therefore, in this chapter, we extend the VNSP model of An (2016) to incorporate reference point adjustment.

In order to calculate the V-shaped selling schedule, it is necessary to measure the gains and losses for each individual investor in each stock. This is impossible to achieve with market data, as investors buy and sell on different days and so have different reference points. The problem is conceptually similar to that overcome by Grinblatt and Han (2005), who are able to measure an aggregate reference point using share turnover information. An (2016) adapts the Grinblatt and Han (2005) framework to measure the likely gain or loss for the average investor in each stock, with a key difference being that gains and losses are not netted out but are summed together.

To calculate VNSP, gains and losses must be calculated separately. Equation 5-1 shows how the *Gain* variable is calculated. Each trading day (n) represents a time when an investor could purchase a security. Each daily gain (*gain*) is weighted by its appropriate weight for the day (ω) to calculate the overall gain for the representative market investor (Gain). The calculation of each daily gain (*gain*) is straightforward as it is just the difference between the final price (P_t) and the price on that day (P_{t-n}), divided by the final price. The calculation of the *weight* (ω) uses the same process as the CGO from Grinblatt and Han (2005) in that each day's weight is equal to the turnover (V) for that day, with an adjustment for turnover that occurs in the future. A day that occurs in the distant past is given a lower weight than a day that occurs in the near past, as there is more chance the share will subsequently be sold in the next period.

$$Gain_t = \sum_{n=1}^{1260} \omega_{t-n}\, gain_{t-n}$$

$$gain_{t-n} = \frac{P_t - P_{t-n}}{P_t} .1\,(P_t - n \;\leq P_t)$$

$$\omega_{t-n} = \frac{1}{k} V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}]$$

Equation 5-1: Taken from An (2016)

The *loss* variable, shown in Equation 5-2, is calculated in an identical manner to that of the gain variable except for losses rather than gains. The *Loss* variable is calculated by multiplying *loss* by *weight,* again formed from turnover (v). *Loss* always takes a negative value, with a decrease in the magnitude of the loss as it approaches zero.

$$Loss_t = \sum_{n=1}^{1260} \omega_{t-n}\, loss_{t-n}$$

$$loss_{t-n} = \frac{P_t - P_{t-n}}{P_t} .1\,(P_t - n \;\geq P_t)$$

$$\omega_{t-n} = \frac{1}{k} V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}]$$

Equation 5-2: Taken from An (2016)

To calculate the VNSP variable from *Gain* and *Loss*, the *Loss* variable is subtracted from the *Gain* variable, which retains both sets of information (*Gain* has a positive sign, *Loss* has a negative sign), as shown in Equation 5-3. In addition, the *loss* variable is weighted by a factor of 0.23. This is to reflect the asymmetry in investor behaviour where the probability of sale is far greater for a gain than for an equivalent loss. The asymmetry in gains and losses was discovered in field data by Ben-David and Hirshleifer (2012) and An (2016) subsequently adopts the 0.23 factor. Incidentally, the CGO variable of Grinblatt and Han (2005) can also be calculated using the *Gain* and *Loss* variables. In the case of CGO, the *gain* and *loss* variables are simply netted off against each other, as shown in Equation 5-3. The VNSP is, therefore, a derivation of CGO that does not net off gains and losses and takes into account asymmetry in selling behaviour between gains and losses.

$$VNSP_t = Gain_t - 0.23Loss_t$$

$$CGO_t = Gain_t + Loss_t$$

Equation 5-3: Taken from An (2016)

The V-shaped selling schedule implies that stocks with both large unrealised gains and large unrealised losses are oversold and hence undervalued. Note the distinction here with both the disposition effect (Shefrin and Statman, 1985) and the Capital Gain Overhang Model (Grinblatt and Han, 2005), which imply that only stocks with large unrealised gains are oversold, while stocks with large unrealised losses are undersold and hence overvalued.

There are two possible mechanisms that could cause the VNSP effect, both of which are discussed in An (2016):

1. Rank Effect based on Limited Attention

Investors buy a stock but pay little attention to the stock after purchase due to other competing demands for their attention. Large gains and losses are successful in capturing the attention of investors (Barber and Odean, 2008), which causes belief updating and subsequent trading activity. This is consistent with the rank effect documented by Hartzmark (2014), where the biggest winners and losers in an investor's portfolio get the most attention and subsequently are more likely to be sold. This implies that large upward or downward moves could trigger more buying of such stocks due to them gaining the attention of investors and indeed, Ben-David and Hirshleifer (2012) observe a v-shaped schedule for both purchases and sales.

2. Speculative Trading Hypothesis based on Initial Beliefs

In this hypothesis developed in Ben-David and Hirshleifer (2012), selling activity is driven by changes in beliefs. When an investor first buys a security they believe that the share will do well (speculative trading motive). Big winners are subsequently more likely to be sold as the initial belief of a gain has been met, which brings about a redemption. For big losers, the initial belief of a gain has not been met, which leads to a re-adjustment in the belief and sale in the stock. Shares that perform in the middle of the V, with neither a large positive or negative move, do not undergo a change in the initial belief. These shares, therefore, tend to be held until a large upward or downward move occurs.

An investor may internalise an initial belief as a reference point at the start of their investment. During the course of the investment, salient price points in the graph may then become more important determinants of the reference point as objective information arrives, which displaces the subjective initial belief. This line of reasoning is consistent with the experimental work of Hoffmann et al. (2013) who show that beliefs are strong determinants of an investor's reference point at the beginning of the investment, but the effect of beliefs declines as the investor experiences share price movement in the investment.

If the reference point-based argument is correct then we would expect that versions of the VNSP that incorporate adjusting reference points may be better predictors of returns than the traditional VNSP variable that measures gains and losses relative to the initial purchase price. In Chapter 3, we show that internal reference points do adjust and that salient prices such as the maximum, minimum and final price also play a role in reference point formation in addition to the purchase price. The research gap, then, is to incorporate this internal reference point adaptation within the VNSP model.

In this chapter, we develop alternative versions of the VNSP that are calculated using alternative salient points such as the maximum or minimum price. We find that the alternative VNSP variables based on the maximum price are not predictive of future returns, although the VNSP variables based on minimum prices are. We also create composite VNSP variables, calculated with a reference point formed from a mix of salient points with weights determined in Chapter 3. We find that the composite VNSP variables are poor predictors of future returns and do not outperform the conventional VNSP variable that is created using the purchase price alone. The inferiority of the composite based variables relative to the conventional VNSP is confirmed through both regressions and double sorted portfolio analysis. We conclude that further research, in the form of a new experiment, will be necessary in order to confirm that the speculative trading hypothesis is, in fact, responsible for the VNSP effect.

5.1 Adjustments to the VNSP Model

An (2016) assumes a purchase price based reference point to calculate gains and losses. As in Chapter 4, where we extend the CGO model, we are interested in how alternative salient points such as the maximum or minimum may operate as alternative reference points to define how a gain or loss is identified in the mind of an investor. In order to test for the importance of alternative reference points, we retain the same weighting scheme for gains and losses as An (2016) (discussed in the prior section), but we replace the purchase price with alternative reference points as shown in Equation 5-4. A total of 4 new gains and loss variables are calculated (*gainMax, gainMin, gainMax52, gainMin52*) with *gainPurchase* calculated in an identical fashion to the original variables in An (2016).

$$gainPurchase_{t-n} = \frac{P_{t-5} - P_{t-n}}{P_{t-5}} .1\ (P_t - n\ \leq P_{t-5})$$

$$gainMax_{t-n} = \frac{P_{t-5} - PMax_{t-n}}{P_{t-5}} .1\ (PMax_t - n\ \leq P_{t-5})$$

$$gainMin_{t-n} = \frac{P_{t-5} - PMin_{t-n}}{P_{t-5}} .1\ (PMin_t - n\ \leq P_{t-5})$$

$$gain52Max_{t-n} = \frac{P_{t-5} - PMax52_{t-n}}{P_{t-5}} .1\ (PMax52_t - n\ \leq P_{t-5})$$

$$gain52Min_{t-n} = \frac{P_{t-5} - PMin52_{t-n}}{P_{t-5}} .1\ (PMin52_t - n\ \leq P_{t-5})$$

Equation 5-4: Alternative Gain Variables

The calculation for loss variables is identical as that for gain variables shown above, except done for losses rather than gains. The final price is lagged by 5 days, in both gains and losses, to maintain consistency with the CGO calculation in Chapter 4 and thus ensure that the VNSP is directly comparable. The lag is to control for the bid-ask bounce found in market data (Rosenberg and Rudd, 1982, Da et al., 2013). The gain and loss variables shown act as a replacement for those shown in Equation 5-1 and Equation 5-2. They are subsequently plugged into Equation 3 to calculate 5 VNSP variables: *VNSP, VNSPMax, VNSPMin, VNSP2Max, and VNSP52Min*. As before, the gain and loss variables associated with each reference point are added together, with the loss variable multiplied by a factor of 0.23 to incorporate asymmetry. The 0.23 factor is calculated in An (2016) using investor field data.

To investigate combinations of reference points, we also calculate two VNSP composite variables. The first composite version of VNSP (*VNSPCom1*) uses reference point RefCom1 taken from Equation 5-5, while the second VNSP composite (*VNSPCom2*) uses reference point *RefCom2*. The weights of the composite reference point are taken from the experiment in Chapter 3 and are identical to those used in the CGO composite reference points used in Chapter 4.

$$Refcom1 = 0.33 * Purchase + 0.29 * Max + 0.14 * Min + 0.23 * Final$$
$$Refcom2 = 0.43 * Purchase + 0.45 * Max52 + 0.11 * Min52$$

Equation 5-5: Composite Reference Points

5.2 Data and Method

The market data sample is identical to that used in Chapter 4, which is all US common Stocks (Codes 10 &11) from January 1958 until Dec 2016. NYSE, Amex and NASDAQ firms are included, although NASDAQ firms have their volume cut in half to compensate for double counting of volume (Anderson and Dyl, 2007). Daily data is used to calculate the VNSP variables and is then converted to monthly data for the regressions. Daily data with a conversion to monthly for asset pricing tests is the approach adopted by An (2016). The monthly data is from Jan 1963 until Dec 2016, as the VNSP require 5 years of data to calculate.

Stocks are ranked by market capitalization every month as a liquidity screen, with stocks in the bottom-decile rank eliminated for that month. This is to remove the impact of illiquid, untradeable stocks, which could bias the results. There is a total of 68 million firm-day cases in the daily data and around 2.7 million in the monthly data.

Control variables used are identical to Chapter 5 and are defined here as: Mom- is price momentum defined as the percentage return over the last 12 month excluding the last month, STR- is short-term reversal defined as the percentage return last month, LTR- is long-term reversal defined as the percentage return over the last 3 years excluding the last year, AvgTurn- is the average of daily stock turnover (daily volume/shares outstanding) over last year and Mrkcap- is the log of market cap (stock price*shares outstanding) in units of millions. An additional control variable is included, BM- is the log of the book to market ratio, with a minimum lag of 6 months from the reporting date.

Calculation of *CGO*, *LTR and all VNSP variables* require a minimum of 3 years of data (out of 5) and are set to missing otherwise. This is consistent with the approach in An (2016) where VNSP requires a minimum of 60% non-missing values from the 5-year horizon window.

Descriptive Statistics

Table 5-1 shows descriptive statistics for the 7 VNSP variables along with control variables. All VNSP variables have a positive mean as they cannot take a negative value. Looking at the 6 alternative VNSP variables, *VNSPMin* has the highest mean value. This is caused by the asymmetry in the calculation of VNSP, where gains have a value approximately 4 times the value of losses, as *VNSPMin* has the lowest reference point. Both *VNSPMax* and *VNSPMin* have larger mean values than their respective 52-week versions. This is because they both tend to take a more extreme value as a reference point, either maximum or minimum, so the difference between the current price and reference price is likely to be higher, which produces a larger value.

Figure 5-1 shows the adjusted share price of IBM and the VNSP variable. IBM has a turnover of 80%, which is very typical of stocks in the sample. VNSP tends to be the lowest when there is no movement in the share price or minor downward movement. Large upward movements (in percentage terms) cause VNSP to rise in value. This is related to asymmetry in the way that VNSP is calculated with gains having a much bigger impact than losses.

Table 5-1: Descriptive Statistics for VNSP Variables

	VNSP	VNSPMax	VNSPMin	VNSPMax52	VNSPMin52	VNSPCom1	VNSPCom2
Mean	0.194	0.122	0.253	0.072	0.200	0.102	0.103
SD	0.183	0.217	0.129	0.093	0.116	0.119	0.109
Median	0.155	0.065	0.241	0.045	0.185	0.075	0.076
Max	4.376	5.880	0.802	1.768	0.722	3.033	2.431
Min	0.015	0.000	0.001	0.000	0.000	0.002	0.008
Skew	7.236	9.889	0.525	5.420	0.740	8.417	6.615

Notes: This table reports summary statistics for VNSP variables. All number presented are the time-series average of the cross-sectional statistics. VNSP calculated using turnover adjusted purchase price as shown in Equation 3. VNSPMax calculated as per VNSP but replacing the purchase price with the maximum price. VNSPMin calculated as per VNSP but replacing the purchase price with the minimum price. VNSPMax52 calculated as per VNSP but replacing the purchase price with the 52-week maximum price. VNSPMin52 calculated as per VNSP but replacing the purchase price with the 52-week minimum price. VNSPCom1 calculated as per VNSP but replacing the purchase price with Refcom1, calculated as per equation 6. VNSPCom2 calculated as per VNSP but replacing the purchase price with Refcom2, calculated as per equation 7.

Descriptive Statistics for Control Variables

	Mom	STR	LTR	Avgturn	Mrkcap	BM
Mean	0.164	0.016	0.377	0.003	4.818	-0.693
SD	0.573	0.143	1.014	0.005	1.720	0.976
Median	0.077	0.004	0.187	0.002	4.584	-0.558
Max	10.520	2.379	20.004	0.126	11.603	2.991
Min	-0.866	-0.606	-0.918	0.000	2.108	-7.251
Skew	4.405	3.121	5.673	9.735	0.652	-0.949

Notes: This table reports summary statistics for control variables. All number presented are the time-series average of the cross-sectional statistics. MOM=12month momentum, excluding the last month. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. Mrkcap is the log of market capitalisation in thousands. BM is log of the book to market ratio.

Figure 5-1: IBM & VNSP: 1963-2016

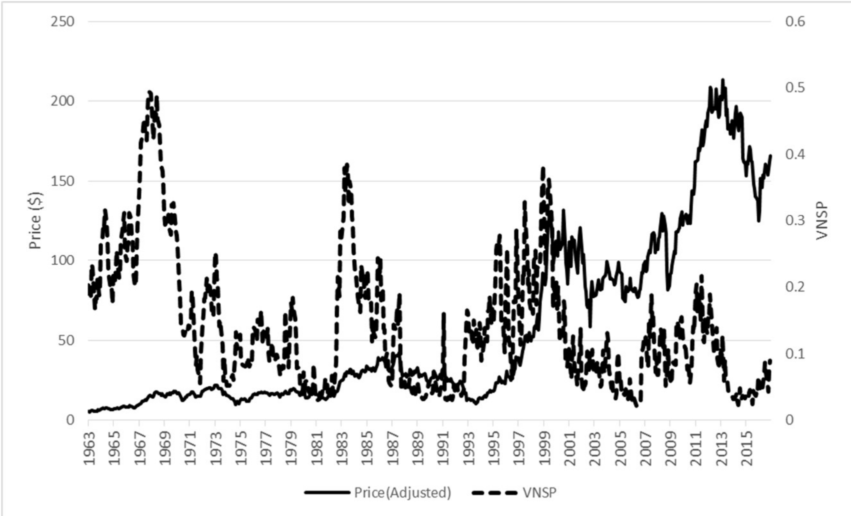


Figure 5-2 and Figure 5-3 show *VNSPMax* or *VNSPMin* respectively against the IBM adjusted share price. *VNSPMax* tends to take a low value most of the time but spikes up in value when there is a fall in share price from a previous maximum. Even then, the value of VNSPMax is rarely as high as VNSP because losses always take a smaller value than equivalent gains. *VNSPMin* tends to take a positive value most of the time but occasionally moves to a value of zero. Low values of *VNSPMin* occur when the current share price is at a minimum value. At other times the share price is above the minimum i.e. in gains, with *VNSPMin* taking a positive value.

Figure 5-2: IBM & VNSPMax: 1963-2016

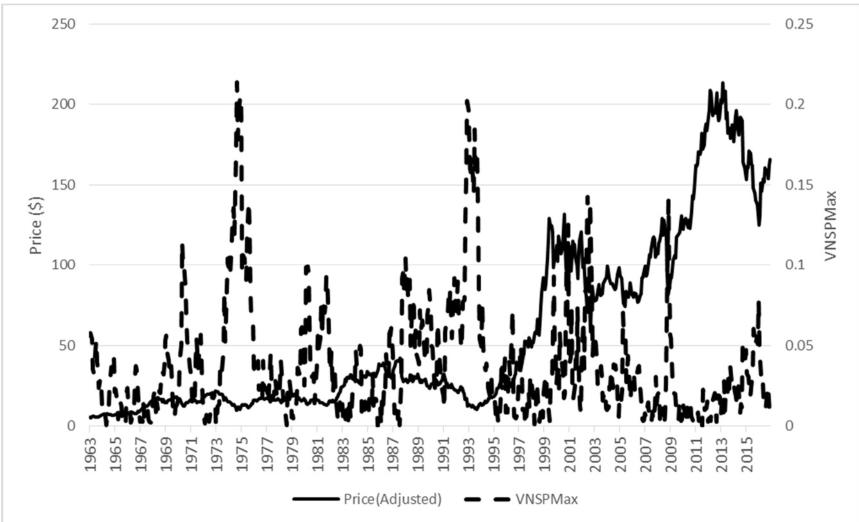
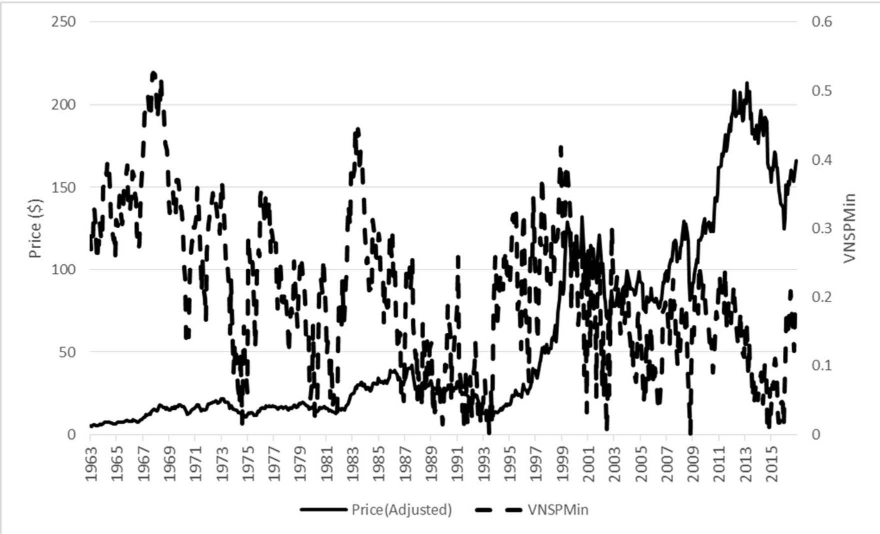


Figure 5-3: IBM & VNSPMin: 1963-2016



Regression of One Month Ahead Returns against VNSP Variables

Now that the VNSP variables are constructed, we test if the alternative VNSP variables are significant drivers of one-month look ahead returns. In the previous chapter, we found that CGO variables calculated using alternative reference points were predictive of one month look ahead returns. Table 5-2 shows regression analysis of one-month ahead returns versus the conventional and alternative VNSP variables, along with appropriate controls. Model A uses the traditional VNSP variable from An (2016) calculated using the purchase price. Models B to G replace the VNSP with alternative specifications of the VNSP variable using different reference points, as shown in Equation 5-6 .

$$\mathrm{Ret}_{t+1} = \beta_0 + \boldsymbol{\beta_1 \mathrm{VNSP}_t} + \beta_2 \mathrm{MOM}_t + \beta_3 \mathrm{STR}_t + \beta_4 \mathrm{LTR}_t + \beta_5 \mathrm{Mrkcap}_t + \beta_6 \mathrm{AvgTurn}_t + \beta_7 \mathrm{BM}_t + \mathcal{E} \quad \text{(A)}$$

$$\mathrm{Ret}_{t+1} = \beta_0 + \boldsymbol{\beta_1 \mathrm{VNSPMax}_t} + \beta_2 \mathrm{MOM}_t + \beta_3 \mathrm{STR}_t + \beta_4 \mathrm{LTR}_t + \beta_5 \mathrm{Mrkcap}_t + \beta_6 \mathrm{AvgTurn}_t + \beta_7 \mathrm{BM}_t + \mathcal{E} \quad \text{(B)}$$

$$\mathrm{Ret}_{t+1} = \beta_0 + \boldsymbol{\beta_1 \mathrm{VNSPMin}_t} + \beta_2 \mathrm{MOM}_t + \beta_3 \mathrm{STR}_t + \beta_4 \mathrm{LTR}_t + \beta_5 \mathrm{Mrkcap}_t + \beta_6 \mathrm{AvgTurn}_t + \beta_7 \mathrm{BM}_t + \mathcal{E} \quad \text{(C)}$$

$$\mathrm{Ret}_{t+1} = \beta_0 + \boldsymbol{\beta_1 \mathrm{VNSPMax52}_t} + \beta_2 \mathrm{MOM}_t + \beta_3 \mathrm{STR}_t + \beta_4 \mathrm{LTR}_t + \beta_5 \mathrm{Mrkcap}_t + \beta_6 \mathrm{AvgTurn}_t + \beta_7 \mathrm{BM}_t + \mathcal{E} \quad \text{(D)}$$

$$\mathrm{Ret}_{t+1} = \beta_0 + \boldsymbol{\beta_1 \mathrm{VNSPMin52}_t} + \beta_2 \mathrm{MOM}_t + \beta_3 \mathrm{STR}_t + \beta_4 \mathrm{LTR}_t + \beta_5 \mathrm{Mrkcap}_t + \beta_6 \mathrm{AvgTurn}_t + \beta_7 \mathrm{BM}_t + \mathcal{E} \quad \text{(E)}$$

$$\mathrm{Ret}_{t+1} = \beta_0 + \boldsymbol{\beta_1 \mathrm{VNSPCom1}_t} + \beta_2 \mathrm{MOM}_t + \beta_3 \mathrm{STR}_t + \beta_4 \mathrm{LTR}_t + \beta_5 \mathrm{Mrkcap}_t + \beta_6 \mathrm{AvgTurn}_t + \beta_7 \mathrm{BM}_t + \mathcal{E} \quad \text{(F)}$$

$$\mathrm{Ret}_{t+1} = \beta_0 + \boldsymbol{\beta_1 \mathrm{VNSPCom2}_t} + \beta_2 \mathrm{MOM}_t + \beta_3 \mathrm{STR}_t + \beta_4 \mathrm{LTR}_t + \beta_5 \mathrm{Mrkcap}_t + \beta_6 \mathrm{AvgTurn}_t + \beta_7 \mathrm{BM}_t + \mathcal{E} \quad \text{(G)}$$

Equation 5-6: Regression Equations (VNSP Variables)

In Model A, we confirm that the *VNSP* is a significant and positive predictor of look-ahead returns. All of the control variables are also significant, except Mrkcap and LTR. We replace *VNSP* with *VNSPMax* in Model B and find that *VNSPMax* is not a positive driver of returns, as the coefficient is negative and significant. *VNSPMin,* shown in Model C, is a significant and positive driver of returns. The t-statistic on the *VNSPMin* variable is greater than that for VNSP in Model A, but the r-squared of the model is lower, as this variable seems to interact more with the controls. Models D & E use the 52-week versions of the maximum and minimum and mimic the results of Models B & C, with the VNSPMax52 negative and significant and VNSPMin52 positive and significant. The final two models, F and G, include the VNSP composite variables. The first composite variable, VNSPCom1, is positive and significant driver of returns although model F has a similar R-squared to Model A. The second composite VNSPCom2 is not a significant driver of returns.

Table 5-2: Regression of Monthly Returns using VNSP Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F	Model G
VNSP	0.00860*						
	(2.499)						
VNSPMax		-0.0166**					
		(-4.088)					
VNSPMin			0.0205**				
			(5.179)				
VNSPMax52				-0.0473**			
				(-5.734)			
VNSPMin52					0.0193**		
					(3.592)		
VNSPCom1						0.0132*	
						(2.206)	
VNSPCom2							0.00959
							(1.610)
Mom	0.00630**	0.00566**	0.00479**	0.00486**	0.00500**	0.00631**	0.00664**
	(3.693)	(3.507)	(2.597)	(3.230)	(2.642)	(3.737)	(4.045)
STR	-0.0517**	-0.0543**	-0.0555**	-0.0572**	-0.0558**	-0.0516**	-0.0515**
	(-9.481)	(-9.873)	(-10.05)	(-10.30)	(-9.739)	(-9.462)	(-9.408)
LTR	-0.000665	-0.000768	-0.000876	-0.000754	-0.000512	-0.000564	-0.000542
	(-1.165)	(-1.481)	(-1.446)	(-1.286)	(-0.907)	(-1.032)	(-0.958)
Avgturn	-0.798*	-0.775*	-0.581	-0.644	-0.757*	-0.801*	-0.847*
	(-2.208)	(-2.279)	(-1.579)	(-1.710)	(-2.260)	(-2.232)	(-2.404)
Mrkcap	1.61e-05	-0.000344	0.000179	-0.000522	0.000133	-2.88e-05	-3.37e-05
	(0.0367)	(-0.818)	(0.412)	(-1.241)	(0.315)	(-0.0657)	(-0.0772)
BM	0.00212**	0.00185*	0.00255**	0.00174*	0.00238**	0.00210**	0.00204**
	(2.959)	(2.447)	(3.714)	(2.325)	(3.459)	(2.875)	(2.765)
Constant	0.0113**	0.0159**	0.00684*	0.0176**	0.00875**	0.0120**	0.0122**
	(3.373)	(4.758)	(2.168)	(5.157)	(2.788)	(3.563)	(3.641)
Observations	1,749,966	1,749,966	1,749,966	1,749,966	1,749,966	1,749,966	1,749,966
Number of groups	647	647	647	647	647	647	647
Average R^2	0.0674	0.0685	0.0656	0.0690	0.0663	0.0675	0.0679

Notes: This table reports results for predictive Fama and MacBeth (1973) regressions of one-month ahead returns on VNSP and a set of control variables. Dependent variable= 1 month return in month t+1. VNSP calculated using turnover adjusted purchase price as shown in Equation 3. VNSPMax calculated as per VNSP but replacing the purchase price with the maximum price. VNSPMin calculated as per VNSP but replacing the purchase price with the minimum price. VNSPMax52 calculated as per VNSP but replacing the purchase price with the 52-week maximum price. VNSPMin52 calculated as per VNSP but replacing the purchase price with the 52-week minimum price. VNSPCom1 calculated as per VNSP but replacing the purchase price with Refcom1, calculated as per equation 6. VNSPCom2 calculated as per VNSP but replacing the purchase price with Refcom2, calculated as per equation 7. MOM=12month momentum, excluding the last month. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. Mrkcap is the log of market capitalisation in thousands. BM is log of the book to market ratio. T-statistics in parentheses are Newey-West adjusted- ** p<0.01, * p<0.05.

In summary, the results do not suggest that all the alternative VNSP variables (Models B to E) are positive and significant drivers of returns. The most promising alternative VNSP variables are based on minimum prices. The two variables based on maximum prices: VNSPMax and VNSPMax52 are negative predictors of returns, however. This is perhaps not surprising as share prices are rarely above maximums or below minimums and so these reference points do not utilise the V-shaped selling schedule.

The results are also mixed when it comes to the composite variables (Models F & G). While VNSPCom1 is a positive and significant predictor of returns, it provides little increase in r-squared over Model A, while VNSPCom2 is not significant. To investigate the composite variables further, we carry out a number of regressions that include both the VNSP and VNSP composite in the same model in Table 5-3. Model A includes only the VNSP variable for comparison purposes, as shown in Equation 5-7. Models B and C include *VNSPCom1* or *VNSPCom2* along with the *VNSP* variables respectively. Finally, model 4 includes both of the *VNSP* composite variables, but not *VNSP*.

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 VNSP_t} + \beta_2 MOM_t + \beta_3 STR_t + \beta_4 LTR_t + \beta_5 Mrkcap_t + \beta_6\, AvgTurn_t + \beta_7\, BM_t + \mathcal{E} \qquad (A)$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 VNSP_t} + \boldsymbol{\beta_2 VNSPCom1_t} + \beta_3 MOM_t + \beta_4 STR_t + \beta_5 LTR_t + \beta_6 Mrkcap_t + \beta_7\, AvgTurn_t + \beta_8\, BM_t + \mathcal{E} \qquad (B)$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 VNSP_t} + \boldsymbol{\beta_2 VNSPCom2_t} + \beta_3 MOM_t + \beta_4 STR_t + \beta_5 LTR_t + \beta_6 Mrkcap_t + \beta_7\, AvgTurn_t + \beta_8\, BM_t + \mathcal{E} \qquad (C)$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 VNSPCom1_t} + \boldsymbol{\beta_2 VNSPCom2_t} + \beta_3 MOM_t + \beta_4 STR_t + \beta_5 LTR_t + \beta_6 Mrkcap_t + \beta_7\, AvgTurn_t + \beta_8\, BM_t + \mathcal{E} \qquad (D)$$

Equation 5-7: Regression Equations (VNSP Composites)

When we include the *VNSPCom1* variable in Model B, the variable is negative but not significant while the positive t-statistic of *VNSP* is increased. In Model

C, we include VNSPCom2 in addition to VNSP and find that the coefficient on VNSPCom2 is negative and significant while the coefficient on VNSP is positive and significant. Model D is a direct comparison of the two VNSP composite variables with both in the model. We find that VNSPCom1 is positive and significant while VNSPCom2 is negative and significant.

Table 5-3: Regression of Monthly Returns Using Alternative VNSP Variables

VARIABLES	Model A	Model B	Model C	Model D
VNSP	0.00860*	0.0289**	0.0204**	
	(2.499)	(3.381)	(4.175)	
VNSPCom1		-0.0276		0.0521**
		(-1.832)		(3.930)
VNSPCom2			-0.0204*	-0.0411**
			(-2.095)	(-3.165)
Mom	0.00630**	0.00510**	0.00571**	0.00668**
	(3.693)	(2.973)	(3.465)	(4.071)
STR	-0.0517**	-0.0533**	-0.0530**	-0.0501**
	(-9.481)	(-9.841)	(-9.588)	(-9.205)
LTR	-0.000665	-0.000700	-0.000666	-0.000593
	(-1.165)	(-1.203)	(-1.163)	(-1.079)
Avgturn	-0.798*	-0.720*	-0.703*	-0.783*
	(-2.208)	(-2.092)	(-2.077)	(-2.233)
Mrkcap	1.61e-05	-6.39e-05	-4.03e-05	-3.48e-05
	(0.0367)	(-0.147)	(-0.0934)	(-0.0805)
BM	0.00212**	0.00216**	0.00211**	0.00202**
	(2.959)	(2.933)	(2.885)	(2.772)
Constant	0.0113**	0.0110**	0.0113**	0.0119**
	(3.373)	(3.248)	(3.385)	(3.607)
Observations	1,749,966	1,749,966	1,749,966	1,749,966
Number of groups	647	647	647	647
Average R^2	0.0674	0.0697	0.0704	0.0705

Notes: This table reports results for predictive Fama and MacBeth (1973) regressions of one-month ahead returns on VNSP and a set of control variables. Dependent variable= 1 month return in month t+1. VNSP calculated using turnover adjusted purchase price as shown in Equation 3. VNSPCom1 calculated as per VNSP but replacing the purchase price with Refcom1, calculated as per equation 6. VNSPCom2 calculated as per VNSP but replacing the purchase price with Refcom2, calculated as per equation 7. MOM=12month momentum, excluding the last month. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. Mrkcap is the log of market capitalisation in thousands. BM is log of the book to market ratio. T-statistics in parentheses are Newey-West adjusted- ** p<0.01, * p<0.05.

The results suggest that neither of the VNSP combination variables are very good predictors, relative to the traditional VNSP variable based on the purchase price. The VNSPCom1 variable, that does not include the 52-week variables, appears to be a better predictor than VNSPCom2. This result differs from our analysis in the last chapter of the CGO model in that the CGO Composites were strong predictors of future returns and the composite measure that included the 52-week variables was the best predictor. To confirm the results, we perform double sorted portfolio analysis as we did in the last chapter for the CGO model.

Double Sorted Portfolios

It is possible that there is a non-linear relationship between VNSP and future returns. Double sorted portfolio analysis does not assume a linear relationship between sorting variable and dependent variable as linear regression does and so it can account for noise and outliers, which may influence the regression analysis above.

In the last chapter, we used double-sorted portfolios to contrast the ability of *CGO* versus CGO composite variables constructed from alternative reference points, to predict future returns. As the focus of this chapter is to examine the predictive power of *VNSP* versus alternative specification using other reference points, we sort by *VNSP* or *VNSP composite variables*. Each portfolio is rebalanced every month, with stocks in each quintile being equally weighted. The bottom decile of stocks by market cap is excluded from portfolio sorts due to liquidity reasons, as they are for the earlier regression analysis.

In Table 5-4 , stocks are first sorted by *VNSP* into quintiles and then are further sorted into quintiles by *VNSPCom1*. The lowest numbered quintile represents the lowest values of the variable in question. Sorting is done in this way to determine if *VNSPCom1* is predictive of returns after stocks are first sorted by *VNSP*. This is measured by the spread portfolio (5-1), which shows the difference in average return between the first and fifth *VNSPCom1* quintiles. In this instance, only one of the *VNSPCom1* spread portfolios are significant and this portfolio happens to be negative and significant. This suggests that *VNSPCom1* does not have any explanatory power after stocks are first sorted by *VNSP*.

In Panel B stocks are first sorted by *VNSPCom1* into quintiles and then by *VNSP*. The difference portfolios (5-1) now reflect the difference in average returns between *VNSP*-1 and *VNSP*-5 quintiles, after first sorting for *VNSPCom1*. In this case, two of the spread portfolios are positive and significant. The results suggest that *VNSP* still has some explanatory power even after stocks are first sorted by *VNSPCom1,* within the higher VNSPCom1 portfolios. In summary, there is little evidence to suggest that VNSPCom1 has any explanatory power after stocks are first sorted by VNSP but there is some evidence to suggest that VNSP has power even after stocks are first sorted by VNSPCom1.

Table 5-5 repeats the analysis but using VNSP and the second composite variable, VNSPCom2. In Table 5-5 stocks are first sorted into quintiles by VNSP and then by VNSPCom2. In this instance, three out of five of the spread portfolios are significant but they are all of the wrong sign. When we first sort stocks by VNSPCom2 and then by VNSP in Panel B, the spread portfolios are positive and significant for three out of the five portfolios. The significant portfolios are again amongst the higher values of the composite variable. The results suggest that VNSP often retains predictive power even after stocks are first sorted by VNSPCom2 but that VNSPCom2 is not a positive predictor of returns after stocks are first sorted by VNSP.

Table 5-4: Double Sorts by VNSP and VNSPCom1 Variables

	VNSP-1	VNSP-2	VNSP-3	VNSP-4	VNSP-5
VNSPCom1-1	1.01	0.81	0.78	1.01	1.28
	5.77**	4.02**	3.52**	4.25**	5.11**
VNSPCom1-2	0.91	0.98	1.20	1.35	1.74
	5.09**	4.59**	5.38**	5.78**	6.53**
VNSPCom1-3	0.92	1.01	1.24	1.47	1.84
	4.84**	4.66**	5.22**	5.79**	6.28**
VNSPCom1-4	0.97	1.10	1.27	1.54	1.60
	4.85**	4.82**	5.22**	5.92**	4.54**
VNSPCom1-5	0.76	0.87	0.87	1.05	1.52
	3.48**	3.56**	3.19**	3.45**	3.68**
5-1	**-0.25**	**0.06**	**0.09**	**0.05**	**0.24**
	-2.51**	**0.55**	**0.75**	**0.32**	**0.94**

This table (Panels A & B) reports returns in double sorted portfolios based on values of VNSP and VNSPCom1. At the end of each month, stocks are sorted into 5 portfolios by VNSP and VNSPCom1. Stocks in a portfolio are equally weighted. Each portfolio is held for one month and the time series average return in reported in monthly percent. Newey-West corrected t-Statistics are shown below performance.
**=significance at the 5% level.

Panel- B: Double Sorts by VNSPCom1 and VNSP Variables

	VNSPCom1-1	VNSPCom1-2	VNSPCom1-3	VNSPCom1-4	VNSPCom1-5
VNSP-1	0.97	0.85	0.91	0.90	0.97
	5.31**	4.05**	3.88**	3.36**	3.00**
VNSP-2	0.92	0.91	1.15	1.22	1.46
	5.11**	4.29**	4.89**	4.71**	5.12**
VNSP-3	0.89	1.02	1.25	1.55	1.66
	4.72**	4.52**	5.32**	6.19**	5.66**
VNSP-4	0.90	1.04	1.29	1.54	1.82
	4.51**	4.90**	5.58**	6.17**	5.42**
VNSP-5	0.87	0.83	1.06	1.37	1.72
	3.97**	3.59**	4.38**	6.01**	4.43**
5-1	**-0.11**	**-0.03**	**0.15**	**0.47**	**0.75**
	-0.84	**-0.21**	**1.29**	**3.68****	**4.08****

Table 5-5: Double Sorts by VNSP and VNSPCom2 Variables

	VNSP-1	VNSP-2	VNSP-3	VNSP-4	VNSP-5
VNSPCom2-1	1.03	1.00	1.01	1.20	1.39
	6.04**	5.09**	4.68**	5.12**	5.49**
VNSPCom2-2	0.99	1.05	1.20	1.34	1.73
	5.48**	4.94**	5.21**	5.35**	6.40**
VNSPCom2-3	0.97	1.08	1.25	1.53	1.77
	5.11**	4.92**	5.15**	6.18**	6.07**
VNSPCom2-4	0.94	0.95	1.11	1.41	1.62
	4.54**	4.15**	4.59**	5.43**	4.84**
VNSPCom2-5	0.65	0.69	0.80	0.94	1.46
	2.93**	2.78**	2.94**	3.19**	3.45**
5-1	**-0.38**	**-0.31**	**-0.20**	**-0.26**	**0.07**
	-3.01**	**-2.56****	**-1.63**	**-2.00****	**0.28**

This table (Panels A & B) reports returns in double sorted portfolios based on values of VNSP and VNSPCom2. At the end of each month, stocks are sorted into 5 portfolios by VNSP and VNSPCom2. Stocks in a portfolio are equally weighted. Each portfolio is held for one month and the time series average return in reported in monthly percent. Newey-West corrected t-Statistics are shown below performance.
**=significance at the 5% level.

Panel B- Double Sorts by VNSPCom2 and VNSP Variables

	VNSPCom2-1	VNSPCom2-1	VNSPCom2-1	VNSPCom2-1	VNSPCom2-5
VNSP-1	0.97	0.81	0.68	0.70	0.83
	5.30**	3.96**	2.97**	2.58**	2.68**
VNSP-2	0.95	0.98	1.06	1.21	1.26
	5.31**	4.48**	4.73**	4.72**	4.14**
VNSP-3	0.98	1.09	1.24	1.47	1.60
	5.35**	5.17**	5.31**	5.76**	5.38**
VNSP-4	1.02	1.10	1.28	1.59	1.76
	5.08**	4.83**	5.51**	6.21**	5.22**
VNSP-5	1.06	1.02	1.19	1.51	1.73
	5.25**	4.47**	4.78**	6.25**	4.42**
5-1	**0.09**	**0.21**	**0.51**	**0.82**	**0.91**
	0.83	**1.96**	**4.28****	**5.90****	**4.85****

5.3 Possible Underlying Mechanism of VNSP

In the previous chapter, we found that relaxing the purchase-price based reference point assumption enhanced the explanatory power of the Capital Gains Overhang model. No such effect is present for the VNSP model. The purchase price remains the most important reference point to calculate VNSP. Earlier we discussed 2 possible mechanisms that could generate the VNSP effect: attention affects based on rank or speculative trading based on beliefs.

Moving to the attention based explanation, the rank effect of Hartzmark (2014) suggests that it is the rank of the security in an investor's portfolios that is driving the propensity to sell. Stocks that are high or low in rank tend to catch the attention of an investor and are more likely to be bought or sold. This is consistent with the finding of a V-shaped propensity to buy as well as sell, found in Ben-David and Hirshleifer (2012). There are a couple of issues with the rank effect explanation, however. Firstly, it is difficult to explain why the V-shaped selling schedule tends to flatten across longer holding period using this explanation. Figure 5-4 shows the net-selling propensity across different holding periods from Ben-David and Hirshleifer (2012). There is a clear tendency for the V to flatten as the holding period increases and it tends to be almost flat by day 250. If the V-shaped propensity to sell is caused by the relative rank of a security in an investor's portfolio then it is difficult to see why a longer holding period would change the shape of the selling schedule. Stocks that appreciate over a long holding period would still occupy a high rank in an investor's portfolio and so should still have a greater tendency to be sold.

"This image has been removed by the author of this thesis for copyright reasons."

Figure 5-4: Taken from Ben-David and Hirshleifer (2012)

A second issue is the asymmetry of the selling schedule, with a flatter propensity to sell in losses than in gains, shown in Figure 5-4. This is also difficult to explain using the rank explanation. If anything, we would expect losses to attract more attention than gains given that most individuals are loss averse and yet we find the investors are more sensitive in the realm of gains, having a greater tendency to sell after gains than losses.

Taking the above into consideration, we find the speculative trading hypothesis, the idea initially advanced in Ben-David and Hirshleifer (2012), to be the most convincing argument. The speculative trading hypothesis can explain the shape of the V, in that investors tend to sell when their initial belief of a positive move is met, or they tend to sell because they drop the initial belief due to a large loss. The speculative trading hypothesis can also explain asymmetry in the gain/loss selling schedule in that a loss requires a change in belief to act as a trigger, whereas a gain only requires that a belief is met in practice through price appreciation. Finally, the speculative trading hypothesis can also explain why the V pattern tends to flatten over time. Speculative beliefs tend to be strong in the initial phase of the investment but give way to actual trading experience as the length of the investment increases. Hoffmann et al. (2013) show in an experiment that participants tend to put more emphasis on an initial belief in the earlier stages of an investment but its importance erodes as the holding period increases. Following a 250-day holding period, there is virtually no impact from speculative beliefs, according to Figure 5-4, and hence no V-shape selling schedule. Despite the reasoning here tending to support the speculative trading hypothesis, further research needs to be carried out, ideally under controlled conditions in an experiment to check if investors really do have these beliefs and how these beliefs change as prices move.

5.4 Conclusion

We began this chapter with an overview of the An (2016) model, which is a practical application of the V-shaped selling schedule discovered in Ben-David and Hirshleifer (2012). We discussed 2 competing hypothesis for the shape of the V-shaped selling schedule based on attention effects or initial beliefs incorporating reference points. The successful hypothesis must be able to explain why the V-shape tends to flatten over time and why the V-shape is asymmetric between winners and losers.

We then adapted the An (2016) *gain* and *loss* variables to incorporate alternative reference points. These 6 alternative reference points were identified in Chapter 3 as important determinants of an investor's reference point. Alternative VNSP variables were formed from the new *gain* and *loss* variables. The alternative VNSP variables were then tested for their ability to predict future returns. We found that while VNSP variables calculated using the minimum price or 52-week minimum are positive and significant predictors of returns, this is not the case for VNSP variables calculated using the maximum price or 52-week maximum. We also found that the two composite VNSP variables do not have greater predictive power than the traditional VNSP variable calculated using the purchase price.

To further check the predictive power of the composite variables, we double sorted stocks by the VNSP variable and the composite variables. We found that when stocks were first sorted by VNSP, the VNSP composite variables are not predictive of returns. When stocks are first sorted by the composite variables, however, VNSP is still predictive of returns in 2 or 3 of the quintile portfolios. The results of the double-sorted portfolios further reinforce the conclusion from the regression analysis, which is that the VNSP composite variables are not better predictors of returns than VNSP. The implication of the results is that incorporating reference point adjustment does not increase the predictive power of the VNSP variable.

We then discussed the possible mechanisms behind the explanatory power of the VNSP variable. Of the two hypotheses, attention effects and the speculative trading hypothesis, we believe there is more support for the speculative trading hypothesis. This is because the speculative trading hypothesis can explain why the V shape pattern tends to flatten over time, as previous research (Hoffmann et al., 2013) has shown that the importance of initial beliefs tends to erode over the life of an investment. The speculative trading hypothesis can also explain the asymmetry in selling behaviour between gains and losses in that winners tend to meet the prior expectation of the investor and thus have the greatest chance of being sold, whereas the rank-based explanation cannot explain these tendencies.

Limitations and Future Research

We are not able to produce direct evidence to support the speculative trading hypothesis explanation for the V-shaped trading effect. Future research could be carried out to further explore the implications of the speculative trading hypothesis. In particular, it is possible to examine the speculative trading hypothesis under experimental conditions, by measuring investor's initial beliefs and seeing how these beliefs evolve over time. Hoffmann et al. (2013) devise a very similar experiment but not in order to explore the VNSP effect. An experiment focussed on V-shaped selling behaviour could explore how an investor's tendency to sell a share is influenced by initial beliefs and look at particular patterns that might cause a subsequent reassessment in those beliefs as the share price evolves.

A further extension of our approach would be to consider if different reference points are more critical at different times, as suggested by Hoffmann et al. (2013). We only consider the formation of the reference point at the end of a chart, but the reference point formation process may differ based on how long the investor has held the stock for. We will consider the impact of time invested on the reference point formation process in Chapter 6.

6 Experiment II: Examining Reference Point Adaptation by Month

In this Chapter, we undertake the 2nd experiment of the thesis. This new experiment measures reference points from participants on a month-by-month basis, rather than based on their assessment of the chart as a whole. The new approach allows us to measure the amount of adaptation in participant reference points from one month to the next. We then undertake regression analysis to establish the determinants of the reference point under this new framework. The results are compared and contrasted with those of our earlier experiment and are subsequently used as an input into the Prospect Theory Value of a Stock framework, developed by Barberis et al. (2016), in the next chapter of the thesis.

In the model of Barberis et al. (2016), potential buyers assess the desirability of a stock based on its past 5-year history, as a set of 60 separate months. Each month has its own reference point, which is taken to be the return of the benchmark over the month. The Prospect Theory value of each of the 60 months is then summed together to form the overall Prospect Theory value of the stock (TK).

Our aim in this chapter is to measure the monthly reference points of an investor, over a 5-year investment horizon. This means that we can measure the amount of movement in the reference point from one month to the next. In this context, our first experiment does not provide an ideal framework, as the reference point is only measured once (at the end of the investment horizon), rather than on a monthly basis through the life of the investment. This one-off approach is in line with that of Baucells et al. (2011), who likewise measure the reference point only at the end of the experiment, but it does not provide an ideal input into the Barberis et al. (2016) model, which requires 60 sequential reference points.

Some prior research has been conducted that measures reference points over multiple periods of an investment. Heyman et al. (2004) is not a direct study of reference points but of satisfaction levels of participants. Nevertheless, this study does measure these satisfaction levels at each stage of an investment and they find a strong role for salient maximums and minimums. Arkes et al. (2008) and Arkes et al. (2010) only include 3 stages (time periods) and find partial adaptation between the reference points at each stage, with adaptation greater in gains than in losses. Gneezy (2005) measures the propensity to sell across a 10 stage (time period) investment and finds support for both the purchase and maximum prices acting as reference points.

A number of issues remain unsolved, from prior literature, which we aim to address in this Chapter. None of the multi-period studies above directly measure reference points except Arkes et al. (2008) & Arkes et al. (2010), but these papers only feature 3 investment periods. In our experiment, we will adopt the direct elicitation method used in Baucells et al. (2011), but we will apply this in a multi-stage way to capture reference points across 60 months.

We found, in the last experiment, that 52-week highs and lows are important determinants of the investor reference point and this result was confirmed in Chapter 4, where reference points that incorporated the 52-week variables performed well in predicting future market returns. None of the prior studies considers the role of 52-week highs or lows in the formation of the reference point. In our study, we will incorporate the 52-week variables as independent variables, thereby determining if they remain important determinants of the reference point in the context of a multi-period investment.

Finally, prior studies do not consider the role of lagged reference points within the context of a multi-period investment. If a participant is asked to provide a reference point at a previous month in the same chart, they may use this as an anchor for the next month’s reference point. Kőszegi and Rabin (2006) construct a model where the reference point is a function of lagged probabilistic beliefs about prior outcomes and then apply the model to consumer and worker decisions. We aim to investigate if lagged reference points play a role in the determination of future reference points.

In total, 25 price charts are used in our experiment to ensure adequate variation in independent variables, although individual participants only see 1 price chart, as they are asked to provide 60 reference points across a single chart. Our results show that the purchase and final prices are key salient prices which determine the reference point. There is also a role for the maximum, although this is much smaller than that discovered in Chapter 3. We argue that the final price plays a greater role in reference point formation when participants are asked for the reference point on a monthly basis, as their attention is shifted to the recent movement in the chart and they use the last reference point provided as an anchor.

We also test the role of 52-week maximum and minimum prices and find that they play less of a role in this experiment than in Chapter 3. This finding is related to the reduced importance of overall maximums and minimums within the context of the multi-stage capture of reference points, where participant attention is more focussed on the recent monthly movement in the chart.

Then we consider the impact of lagged reference points on the determination of the current month's reference point and show that a 1-month lagged reference point is a powerful predictor. The 2-month lag is also significant, but it does not add greatly to the explanatory power of the models. Our results demonstrate the importance of the lagged reference point, as suggested by the model of Kőszegi and Rabin (2006) and provide an explanation as to why the results differ from Chapter 3, where lagged reference points from the same chart were not available.

Finally, we consider how time influences the explanatory power of the independent variables on the determination of the reference point. As the experiment measures reference points across 60 months, we split the sample across months to determine if certain independent variables play a greater role at different stages. In addition, we also construct interaction variables (constructed by multiplying the number of the month that the reference point was collected by the independent variable) to assess if they are significant. We show that the purchase price becomes more important as time progresses, while the maximum and minimum prices become less important. This may be because participants start to focus on their accounting gain and loss, measured from the purchase price, as the 60-month investment horizon nears an end. The time moderators do not greatly increase the explanatory power of the models, however.

6.1 The Experiment

Experimental Design

Participants in this experiment view one of the 25 share price charts each. For each graph, participants are asked for a reference point each month, which provides 60 reference points per participant across the life of the 5-year graph. A total of 25 charts were chosen to ensure reasonable variation across independent variables, with a minimum data collection of 30 participants per chart giving a total of 750 participants. This means that the scale of the experiment is considerably bigger than that in Chapter 3, with a far greater number of participants. In addition, the number of reference points collected from each participant more than doubled from 1 across 25 charts (total 25 per participant) to 60 across 1 chart (total 60 per participant).

In Chapter 3 we used a within-subject design, whereas in this chapter we use a between-subject design. The main benefit of a within-subject design is that each subject is exposed to the same treatment (charts). This ensures that variation comes solely from chart characteristics, rather than the participants being exposed to different charts. Order effects are a danger in within-subject designs, but these can be prevented through randomisation and counter-balancing of chart order presented as was the case in Chapter 3. Given the need to collect only 1 reference point per chart in Chapter 3, a within-subject design was optimal to minimize unwanted variation.

The approach we adopt in this Chapter is a between-subjects design. In the between-subjects design, each participant receives a different treatment (chart). In the context of this chapter, there is only time to show each participant one chart, as 60 reference points have to be collected from each chart. Therefore, a between-subject design allows us to increase the number of charts from 1 to 25, which increases the variation of the independent variables.

The chart chosen for each participant is randomly selected by Qualitrics, with balancing of graph selection to ensure that each chart is shown roughly an equal number of times across the experiment as a whole. The time taken to provide a reference point is measured for each month, in addition to the total time taken to complete the experiment for each participant.

This experiment again uses direct elicitation to measure reference points. The question to elicit the reference points is unchanged from Chapter 3, "Your task will be to indicate the selling price at which you would feel neutral (i.e. feel neither predominantly positive nor negative) about selling the stock". There is no lag between points shown in the graph, although obviously there is a time delay each month as the participant must enter the reference point and click <next> to move to the next month.

In Chapter 3, around 10% of the data had to be excluded as part of the data cleaning process. The data cleaning process was based on a range of variation around the maximum and minimum prices. Analysis of excluded data from

Chapter 3 indicated there was no relationship between data quality and time taken to complete the experiment. The participants excluded in Chapter 3 took an average of 792 seconds to complete the experiment, whereas the population average was 796 seconds. This being the case it is likely that participants who provide poor quality data do so because they do not understand the instructions, but proceed through the experiment anyway in order to collect the fee from the data sampling company. In an attempt to exclude such participants before they take the experiment, an additional screen is added to ask participants if they understood the instructions and example. Participants have to self-certify that they understood what they have been asked to do. If participants indicate that they are not sure then they are not able to take the experiment.

It is important that investors have a sense of time as the share price develops rather than just viewing the graph as a sequence of 60 points that occurs at one point in time. The instructions, shown in the appendix, make clear that the timeframe is over 5 years and time in months is shown on the x-axis of every chart. In addition, the participant has to click “Next” with their mouse to proceed to the next month, after they enter the reference point (the mouse cursor is automatically placed in the text box for convenience). This is designed to reinforce the participant’s appreciation of a sense of time as the share price develops. A live screenshot from the experiment is also included in the appendix (Chart 1, Month 5). The only information provided to participants is the current price, month and the chart.

Chart Design

The final (5 year) version of each chart is shown in the appendix. A minimum of 30 participants are required for each chart to provide variation. 25 charts require a total of 750 participants for a minimum sample of 30 participants per graph. This means that the scale, cost and complexity of data collection is significantly greater than the experiment presented in Chapter 3. Specifically, as each graph had 60 monthly frames, the experiment required the design of 1500 (60 X 25) frames.

Real share price data is again used to create charts rather than artificial generation. As discussed in Chapter 3, the benefit of artificial generation is increased control, which can be used to minimise multicollinearity between salient features in the graph such as purchase, minimum, maximum and final prices. The increased control comes with a drawback, however, in that the charts presented to participants are clearly artificial and lack external validity. There is a danger that spurious, unintended, patterns are present in the data which may influence how investors form reference points. In fact, multicollinearity between salient points is a natural feature in share price charts and so it is decided to proceed with real share price charts and use statistical techniques to deal with multicollinearity later on in the results section. The primary method used is to generate differencing variables, as were used in Chapter 3.

Chart selection is undertaken on a random basis to ensure that no bias is introduced into the experiment. In this instance, data is randomly selected (without replacement) from a master file based of US stocks (share code 41 and 42) from 1926-2016. A sample of 40 points is taken and 38 of these are needed to generate the 25 charts, as 13 charts have to be excluded, as shown in *Table 6-1*. The reason some charts are excluded is because there is not a full 5-year horizon with which to generate the chart. *Table 6-2* shows the characteristics of the charts. The 25 charts provide a good range of prices and volatility characteristics.

A number of trade-offs are involved with respect to data frequency within the charts. There is a strong case to use monthly data to generate charts, as was used in Barberis et al. (2016). The rationale in Barberis et al. (2016) for using monthly data is that investors were reliant on hand-drawn charts in the pre-2000 period when internet use was not widespread. Hand-drawn charts are far less likely to make use of higher frequency data such as weekly or daily data, as this makes them more cumbersome to draw. This means that investors may not be aware of daily maximums or minimums if they do not monitor the stock on a daily basis. Barberis et al. (2016) make specific mention of the Value Line Investment Handbook, which was a very popular source of charts for investors in the pre-internet period and remains in use today.

Table 6-1: Sampled Chart Master File

Permno	Date	Company Name	Chart Number	Comment
81736	31-Jul-06	RESMED INC	1	
40635	31-Mar-75	TIMES MIRROR CO	2	
25937	30-Sep-68	UNITED STATES SHOE CORP	3	
48734	28-Feb-85	LARSEN COMPANY		Not Enough Data
63240	31-Dec-90	PLAINS RESOURCES INC	4	
92452	29-Dec-89	THERAPEUTIC TECHNOLOGIES INC		Not Enough Data
57138	29-Oct-93	PEERLESS TUBE CO		Not Enough Data
86544	26-Feb-10	INFOSPACE INC	5	
92054	31-Jan-14	TOWERSTREAM CORP		Ends 2019
31042	31-Dec-84	CROWN CENTRAL PETROLEUM CORP	6	
61023	28-Sep-84	PAN WESTERN CORP		Not Enough Data
10252	29-Apr-05	INDEPENDENT BANK CORP MA	7	
20562	29-Mar-68	MARTIN MARIETTA CORP	8	
11373	29-Feb-96	SECOM GENERAL CORP		Not Enough Data
40272	28-Mar-91	INTERNATIONAL FLAVORS & FRAG INC	9	
14795	29-Aug-97	TIMKEN COMPANY	10	
33209	30-Apr-98	ENZO BIOCHEM INC	11	
81141	28-Jun-96	AVERT INC	12	
15229	30-Nov-62	MURRAY CORP AMER	13	
86793	31-Jan-08	YADKIN VALLEY FINANCIAL CORP	14	
68814	30-Sep-94	ALPINE GROUP INC	15	
78008	30-Sep-04	EPICOR SOFTWARE CORP	16	
38842	30-Nov-70	MARLENE INDUSTRIES CORP	17	
85174	30-Apr-99	CENTENNIAL HEALTHCARE CORP		Not Enough Data
60986	30-Mar-84	NEWELL COMPANIES INC	18	
41057	31-Mar-78	KAYOT INC		Missing Data
75503	30-Apr-01	ARISTOTLE CORP	19	
90183	30-Aug-13	CORNERSTONE THERAPEUTICS INC		Ends 2018
13856	28-Feb-39	LOFT INC	20	
80943	28-Jun-02	MATTSON TECHNOLOGY INC	21	
22680	30-Sep-92	CINCINNATI MILACRON INC	22	
79027	29-Nov-96	ACCUMED INTERNATIONAL INC		Not Enough Data
16986	31-Jul-74	BARRINGER RESOURCES INC		Missing Data
16715	30-Apr-90	STANDARD COMMERCIAL CORP	23	
45736	31-May-78	INVENT INC		Not Enough Data
93113	31-Jul-95	WESTPORT BANCORP INC		Not Enough Data
69243	30-Apr-87	CENTERIOR ENERGY CORP	24	
80951	30-May-03	T E S S C O TECHNOLOGIES INC	25	
76122	30-Sep-96	SANTA FE ENERGY RESOURCES INC		
56282	30-Jan-76	ALCOLAC INC		

Notes: Table showing the randomly selected security paths from the market dataset. Permno= unique security ID number from CRSP database, date=beginning date of sample, Chart Number=the chart number subsequently used in the experiment. Companies excluded (marked in yellow) if 5 years of data not present, or data missing over the 5 year period.

Table 6-2: Chart Characteristics

Chart	Purchase	Maximum	Minimum	Max52	Min52	Average	Final	Volatility	Skew
1	23.21	35.61	14.92	35.61	29.62	24.61	30.29	31.98	7.14
2	4.44	9.91	3.66	9.91	7.03	6.32	7.88	24.15	6.42
3	0.99	2.70	0.97	2.70	1.83	1.81	2.68	22.20	-3.07
4	3.41	16.22	2.72	5.99	2.99	5.40	4.87	65.68	24.41
5	10.08	29.82	6.69	20.10	12.88	14.12	14.82	40.17	13.27
6	11.00	40.25	9.38	40.25	20.38	19.40	30.63	38.02	21.47
7	27.44	36.91	10.94	28.09	18.99	27.49	25.94	45.46	-12.22
8	3.20	4.54	1.69	3.41	2.35	3.01	2.35	27.07	4.32
9	25.58	54.88	25.42	54.88	46.63	39.03	50.25	17.48	3.26
10	26.38	29.42	8.80	19.27	8.80	14.76	12.60	38.78	21.32
11	12.03	100.37	5.35	17.41	10.45	20.75	14.63	84.55	29.69
12	5.63	31.38	3.25	26.25	10.88	10.30	21.63	67.58	18.06
13	6.59	34.09	6.59	34.09	16.57	16.16	25.28	31.47	8.19
14	45.00	52.95	4.65	10.44	6.15	16.59	10.08	86.45	19.89
15	5.96	21.88	3.38	18.69	10.06	10.37	11.88	58.75	6.07
16	12.03	16.00	2.36	8.93	2.36	10.93	6.37	50.65	-12.97
17	5.63	15.50	1.50	6.88	1.50	4.97	5.75	62.67	24.00
18	1.81	8.00	1.66	8.00	4.50	3.72	7.97	32.09	10.40
19	3.20	8.20	1.77	8.00	5.69	4.93	7.61	84.46	4.25
20	0.03	0.13	0.02	0.13	0.06	0.06	0.12	51.95	11.02
21	4.62	15.92	1.21	10.48	7.10	8.07	9.70	71.77	-6.24
22	148.75	335.00	135.00	280.63	180.00	232.72	270.00	33.21	2.37
23	9.08	31.15	6.05	16.58	10.18	17.19	12.92	40.65	7.78
24	19.75	21.00	12.38	20.00	15.00	17.15	18.38	19.99	-10.44
25	3.28	20.91	2.98	16.68	6.05	8.71	8.48	52.65	17.99
Average	16.76	38.91	10.93	28.14	17.52	21.54	24.52	47.20	8.65
Median	6.59	21.88	3.66	16.68	8.80	10.93	11.88	40.65	7.78
Max	148.75	335.00	135.00	280.63	180.00	232.72	270.00	86.45	29.69
Min	0.03	0.13	0.02	0.13	0.06	0.06	0.12	17.48	-12.97
Stdev	29.57	65.20	26.45	54.20	35.34	44.91	52.37	20.88	11.78

Notes: Table showing characteristics of the 30 charts used in Experiment 2. Purchase=initial price, Maximum=maximum price, Minimum=minimum price, Average= average price, Final=end price, Volatility=annualised standard deviation of returns, Skew=skew of returns.

Modern Value line charts, currently available on the internet, show prices on a month-by-month basis, but the maximum monthly range is also shown through a vertical line every month. Given that in Chapter 3, we demonstrate that maximums and minimums are important points used by investors to form reference points, we therefore decide to investigate further if these maximums and minimums were always present in Value Line Charts in the pre-internet period. Value Line was able to provide us with the oldest hardcopy of a chart they had available taken from 1946 and shown in Figure 6-1.

"This image has been removed by the author of this thesis for copyright reasons."

Figure 6-1: Value Line inc. Investment Survey: May 1946. [1]

In the case of the older chart, the maximum and minimum daily range is still present in the chart. In addition, the chart from 1946 uses labels to highlight salient maximums and minimums over the life of the chart. In summary, the charts have changed remarkably little between 1946 and the current day and this is particularly so in the case of the saliency of daily maximums and minimums. Given the evidence presented by Value Line, we decide to use charts constructed of daily data in the experiment. The use of daily data is consistent with the earlier experiment in Chapter 3.

Data Collection

We use the survey company, SSI International, to collect responses. All responses come from US Citizens who are resident in the United States. All participants must have previous investing experience in stocks or mutual funds. This is to exclude outright novices, who may never have looked at share

[1] **Provided by: Value Line inc.**

price charts previously. The age range is restricted to working-age adults of 18 to 64 years of age

The initial data sample consists of 767 participants who provide 60 reference points each for a total of 46,020 reference points. Participants are split broadly across the number of charts, ensuring that no individual chart has less than 30 participants. As was the case in our previous experiment, data cleaning is necessary to eliminate participants who provide unrealistic answers across the experiment.

A number of different methods are considered for data cleaning, as considered previously in Chapter 3. While reference points outside a certain range could be removed, this might prove to be objectionable as the maximum and minimum points are also explanatory variables in the subsequent analysis. An alternative method is to identify and eliminate outliers based on the distribution of the reference points themselves. Trimming or winsorising are feasible but seems inappropriate, as reference points in the tails of the distribution would be automatically removed regardless of whether they were realistic responses or not.

An alternative approach uses Z-score to assess whether reference points in the tails of the distribution are realistic, as shown in Equation 6-1 below. The Z-score (Z) is calculated below as the difference between the reference point ($x_{i,t}$) in the i^{th} chart and the t^{th} month and the mean reference point over that chart/month ($\mu_{i,t}$), divided by the standard deviation of the reference point over that chart/month ($\sigma_{i,t}$). The Z-score approach has the advantage of only removing reference points when they are out of line with the others provided in that chart/month, with the standard deviation of the distribution acting as a measure of when to remove them. Using the mean to normalise may be inappropriate, however, as each chart-month only has between 30-32 points and skewness is likely to be present within the data if outliers are present. Therefore, a modified Z-score approach is used using the median and defined in Equation 6-1. The modified Z formula subtracts the median (med) reference point from each individual reference point and divides by the median absolute deviation (MAD).

$$Z_{i,t} = \frac{x_{i,t} - \mu_{t,t}}{\sigma_{i,t}}$$

$$modified\ Z_{i,t} = \frac{(x_{i,t} - med_{i,t})}{\mathrm{MAD}_{i,t}}$$

Equation 6-1: Z-Score Formulas

One issue with both the Z-score and modified Z approaches is that reference points are removed in a symmetrical manner across the high and low boundaries, based on passing a threshold provided by the standard deviation or the MAD. If outliers across a particular chart happen to be in one tail only, they would increase the standard deviation or MAD, which could lead to the unnecessary removal of data in the other tail. A more sophisticated approach called the Outlier Sum(OS) method (Tibshirani and Hastie, 2007) is able to overcome this weakness. The OS statistic uses the modified Z approach to calculate Z scores and then bases exclusions on its distribution. The interquartile range (IQR) of the modified Z scores is calculated as the difference between the 75th and 25th boundaries of the distribution. The maximum OS boundary is then defined as the 75th percentile of the distribution of modified Z-scores, plus the IQR and the minimum boundary is the 25th percentile minus the IQR, as shown in Equation 6-2. Values with a Z-score outside the maximum (OS_{max}) or minimum (OS_{min}) limits are excluded.

$$OS_{max} = p75(modfied\ z) + IQR(modified\ z)$$

$$OS_{min} = p25(modified\ z) - IQR(modified\ z)$$

Equation 6-2: OS Score: Max and Min Boundaries

A total of 6847 reference points are removed based on the OS method. This represented just under 15% of the total sample. Removals were split evenly across charts with a minimum of 1800 and a maximum of 1920 reference points removed from each chart. In terms of exclusions by participant, Figure 6-2 below shows the cumulative distribution of removals by participant. 345 out of a total of 761 of the participants did not have any reference points excluded. 50% of the exclusions came from 63 participants (8% of the total), while 75% of the exclusions came from 121 participants (16% of the total). This reflects the fact that most exclusions were caused by a small number of individuals providing spurious responses across the whole experiment, with a small number of exclusions across a large number of participants caused by individual error across a single reference point only. The percentage and pattern of exclusions are very similar to Chapter 3, suggesting that the "do you understand" question was not entirely successful. All subsequent data analysis is carried out using the cleaned data.

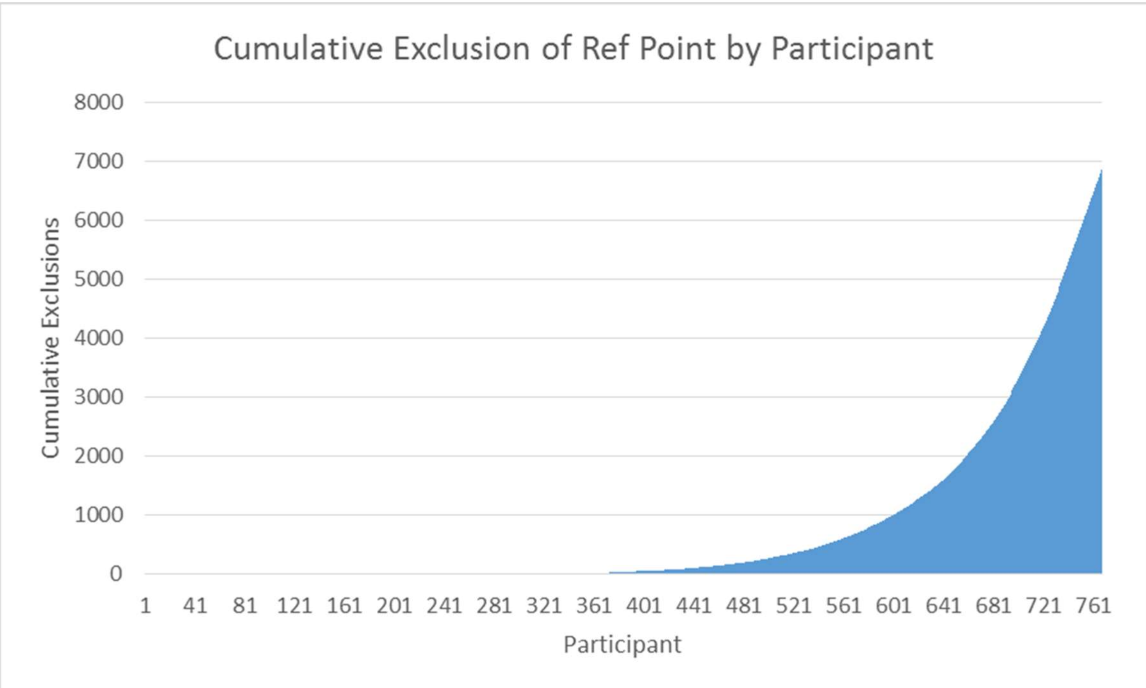


Figure 6-2: Exclusion of Reference Points by Participant

6.2 Results

Descriptive Variables

We collect a number of demographic variables, which can be used for further analysis. We look at both reference points and the amount of absolute deviation (defined below as the percentage difference between end price and reference point during each month), shown in Equation 6-3, against the descriptive statistics. The reference point shown is directly elicited from participants in the experiment when they are asked for their neutral selling price. We present a number of these variables in tabular form and then perform ANOVA at the end of the section to check if the demographic variables can explain variation in reference points. We add an additional explanatory variable to the ANOVA analysis, chart (taking a value from 1 to 25), to account for the fact that demographic characteristics may not be shared equally across charts.

$$AbsDev_t = ABS(End_t - Reference_t)/End_t$$

Equation 6-3: Absolute Deviation

There is a fairly even split of reference points provided by gender, with 60% coming from males and 40% coming from females, as shown in Figure 6-3. This shows that the sample is balanced and broadly representative of the population as a whole, based on gender.

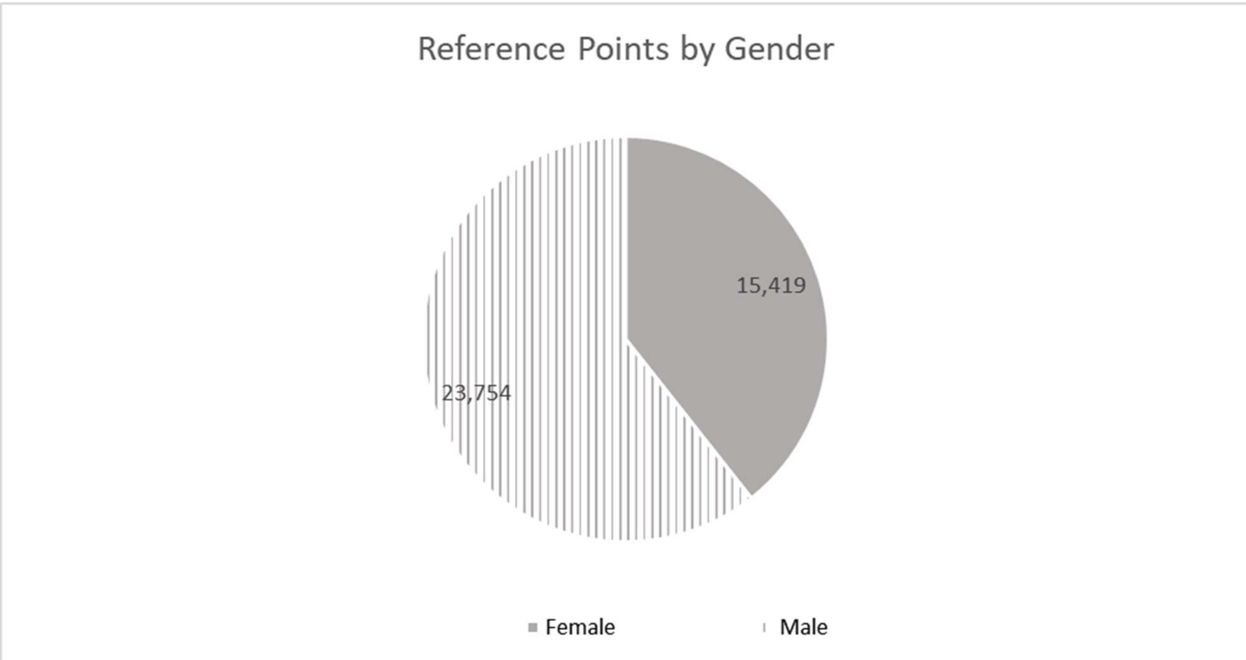


Figure 6-3: Reference Points provided by Gender

Table 6-3 shows reference points and absolute deviation split by gender. The mean of the AbsDev variable is higher for females than males, although the medians are closer. There also appears to be similar variability of AbsDev across females and males, reflected in the standard deviations.

Table 6-3: Reference Point/AbsDev by Gender

Gender	Reference Point			Absolute Deviation		
	Mean	Median	SD	Mean	Median	SD
Female	26.7	12.0	52.5	28.0%	10.0%	69.0%
Male	19.4	11.0	35.1	26.0%	9.0%	70.0%

Notes: The table shows mean, median and SD of elicited reference points or Absolute Deviation (defined in Equation 6.3), split by gender of the participant.

Table 6-4 shows reference points by the trading frequency of participants (how often they trade in real life), which is split into 4 groups: daily, weekly, monthly, or rarely (at least once per year). There does seem to be a relationship between trading frequency and absolute deviation, as it decreases in line with trading frequency. We will check if this relationship holds using ANOVA later in the section. Note, however, from Figure 6-4 that most participants are in the rarely or monthly trading category and few are in the weekly or daily categories.

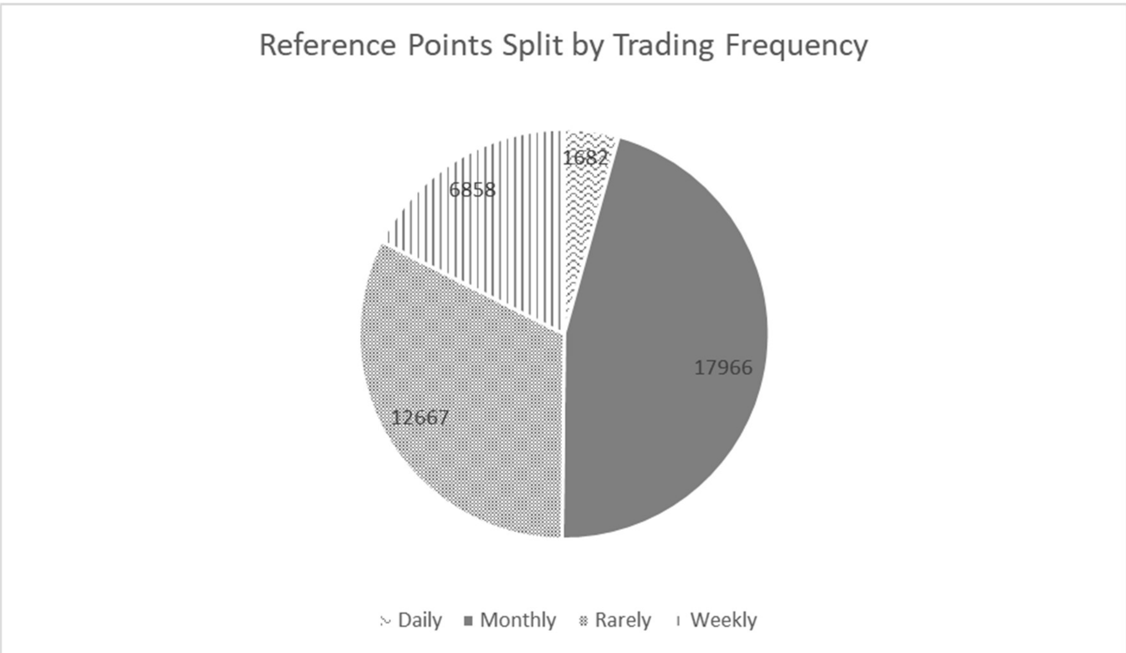


Figure 6-4: Reference Points Provided by Trading Frequency

Table 6-4: Reference Point/AbsDev by Trading Frequency

Frequency	Reference Point			Absolute Deviation		
	Mean	Median	SD	Mean	Median	SD
Rarely (less than once per year)	25.8	11.0	51.1	31.0%	11.0%	80.0%
Monthly (at least once per month)	20.0	12.0	35.3	27.0%	10.0%	72.0%
Weekly (at least once per week)	19.8	11.0	36.9	18.0%	8.0%	45.0%
Daily (at least once per day)	29.7	7.0	64.4	18.0%	8.0%	43.0%

Notes: The table shows mean, median and SD of elicited reference points or Absolute CGO (defined in Equation 3.3), split by the self-reported trading frequency of the participant.

The average time taken to complete the experiment is 16 minutes with a median time of around 10 ½ minutes. Figure 6-5 shows the mean and median response time in seconds per month. Participants take the longest time to decide in the 1st month with an average time around 45 seconds and median time of around 18 seconds. After the first couple of months, the average response time tends to lie in a range of 5-15 seconds and the median response time in a range of 5-10 seconds. This suggests that participants did take some time in analysing the charts.

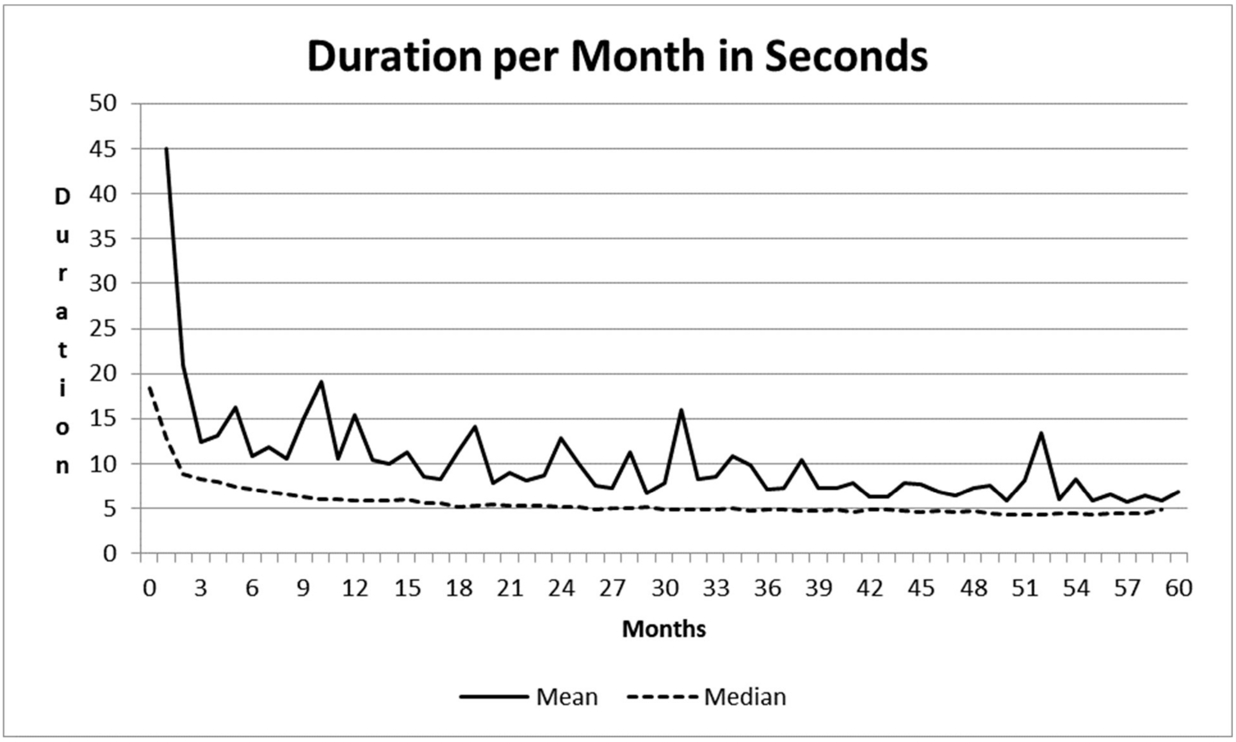


Figure 6-5: Average Duration per Month

There does not seem to be much of a relationship between total response time and absolute deviation, although the slowest participants do have a lower absolute deviation than the other groups. Table 6-5 shows reference points and absdev split by the time taken to complete the experiment. Participants are split into 5 evenly sized groups based on the total response time of the experiment (from fastest to slowest), for the purposes of this analysis.

Table 6-5: Reference Points/AbsDev by Duration

Duration	Reference Point			Absolute Deviation		
	Mean	Median	SD	Mean	Median	SD
<8 mins	17.1	9.0	32.2	25.9%	10.3%	60.6%
8-10 mins	22.2	12.0	40.4	34.6%	11.7%	86.9%
10-12mins	24.9	11.0	49.1	29.7%	9.1%	86.1%
12-17mins	24.2	12.0	45.6	24.6%	9.5%	63.1%
Over 17mins	22.9	12.0	44.8	17.6%	7.7%	40.5%

Notes: The table shows mean, median and SD of elicited reference points or Absolute CGO (defined in Equation 3.3), split by the time taken by the participant to complete the experiment.

The final variable that we consider is age. The average age of participants was 49 years and the median age was 50 years, with a minimum of 24 and a maximum of 64 years. We split participants into 5 equally sized groups based on self-reported age, shown in Table 6-6. There does not appear to be any pattern between age and absolute deviation, although the variability of reference points provided seems higher among the older age groups.

Table 6-6: Reference Points/AbsDev by Age

Age	Reference Point			Absolute Deviation		
	Mean	Median	SD	Mean	Median	SD
24-39	18.7	10.0	38.6	19.0%	8.0%	45.0%
40-47	20.3	10.0	38.4	30.0%	10.0%	76.0%
48-54	16.2	11.0	22.9	33.0%	11.0%	83.0%
55-59	29.5	14.0	54.6	19.0%	8.0%	38.0%
60-64	27.9	12.0	53.0	33.0%	10.0%	92.0%

Notes: The table shows mean, median and SD of elicited reference points or Absolute CGO (defined in Equation 3.3), split by the age of the participant.

ANOVA analysis of the four descriptive variables versus the reference point is shown in Table 6-7. As we used a between-subjects design, different groups of subjects could have been exposed to different chart characteristics, although there is no reason why this variation should be non-random. To take account on this we include an extra variable in the analysis, *Chart*, which is the chart number ranging from 1 to 25. The Chart variable is designed to capture any variation that comes from chart characteristics, rather than the descriptive variables we are interested in.

The analysis suggests that 3 of the 4 descriptive variables can explain variation in reference points. The duration variable has the highest F-statistic and the frequency variable has the 2nd highest F-statistic. The descriptive variables do a slightly worse job of describing variation in absolute deviation (AbsDev) reflected by a lower r-squared, shown in Table 6-8. In this table, the coefficient of gender is insignificant but the other 3 variables are again significant. Duration and frequency again have the highest F-statistics.

Table 6-7: Anova- Reference Point against Descriptive Variables

Number	of obs =	39,173		R^2	0.9531
Root	MSE =	9.3		Adj R^2	0.9531
Source	Partial SS	df	MS	F	Prob>F
Model	68736718	36	1909353	22104.73	0.000
Gender	294.27	1	294	3.41	0.0649
Frequency	3617.33	3	1206	13.96	0.000
Age	2695.01	4	674	7.80	0.000
Duration	7951.36	4	1988	23.01	0.000
Chart	66610338.00	24	2775431	32131.37	0.000
Residual	3,380,474	39,136	86.38		
Total	72,117,192	39,172	1841.04		

Notes: Table showing ANOVA analysis of the reference point against descriptive variables of participants. DV=reference point, Gender=Male or Female, Frequency=frequency of trading (yearly, monthly, weekly, or daily), Age=age in years of participants, duration=time taken to complete the experiment in seconds, Chart=chart number ranging from 1 to 30.

The results suggest that there is some relationship between duration and reference points. Participants who took longer to complete the experiment tended to have reference points that were closer to the final price i.e. more fully adjusted. The gender variable, however, can not explain variation in either reference points or the amount of adjustment to the final price. The analysis also suggests that the characteristics of the share price charts can explain more of the variation in reference points, or reference point adjustment, than any of the descriptive variables, as reflected in the performance of the *Chart* Variable. As the point of this Chapter is to explore the relationship between reference points and the share price charts themselves, we will now examine the relationship between reference points and salient features of the share price charts.

Table 6-8: Anova- AbsDev against Descriptive Variables

Number	of obs =	39,173		R^2	0.3505
Root	MSE =	0.563638		Adj R^2	0.3499
Source	Partial SS	df	MS	F	Prob>F
Model	6708.91	12	186.36	586.61	0.000
Gender	1.03	1	1.03	3.23	0.072
Frequency	8.53	3	2.84	8.95	0.000
Age	30.59	4	7.65	24.07	0.000
Duration	78.57	4	19.64	61.83	0.000
Chart	6361.26	24	265.05	834.32	0.000
Residual	12433.05	39,136	0.32		
Total	19141.96	39,172	0.49		

Notes: Table showing ANOVA analysis of Absolute Deviation (defined in equation 6-3) against descriptive variables of participants. DV=reference point, Gender=Male or Female, Frequency=frequency of trading (yearly, monthly, weekly, or daily), Age=age in years of participants, duration=time taken to complete the experiment in seconds, Chart=chart number ranging from 1 to 30.

Regression: Reference Point using Price Variables

The first set of regressions use the reference point as a dependent variable (DV), with salient prices in the chart as independent variables (IVs). We previously identified in Chapter 3 that the purchase, maximum, minimum, average and final prices can determine the reference point. In this section, we examine variables constructed using monthly data, in line with the approach in Barberis et al. (2016). Inter-month variables, formed from daily data, will be examined in a later section, to test if participants take account of daily highs and lows that are displayed in the charts.

The following variables are defined across the i^{th} chart (ranging from 1 to 25) and the t^{th} month (ranging from 1 to 60). The maximum and minimum at month (t) are based on the cumulative data up to month (t) i.e. the maximum at month (t) will be the maximum price attained in months 1 to t. The month-end price at time t is calculated as the last monthly price shown to the participant in month t. The end price here is defined as the end price based on the month (t) in which the reference point was collected e.g. a reference price provided in month 3 will have an end price at the end of month 3. Therefore, the purchase price is static whereas the end price is variable and depends on the month in question.

$$Purchase_{i,t} = price_{i,t=0}$$
$$Maximum_{i,t} = Max(price_{i,t})\ for\ all\ months\ 1\ to\ t$$
$$Minimum_{i,t} = Min(price_{i,t})\ for\ all\ months\ 1\ to\ t$$
$$Average_{i,t} = Avg(price_{i,t})\ for\ all\ months\ 1\ to\ t$$
$$End_{i,t} = price_{i,t}$$

Equation 6-4: Price Variable Definitions

The regression in Table 6-9 uses the Purchase, Maximum, Minimum, Average and End prices as independent variables (IV's), predicting the Reference Point as the dependent variable (DV) as shown in Equation 6-5 below. Linear least squares regression is used and robust standard errors are clustered by participant.

$$Reference\ Point_t = \beta_0 + \beta_1\ Purchase_{t=0} + \beta_2\ End_t + \varepsilon \quad \text{(A)}$$
$$Reference\ Point_t = \beta_0 + \beta_1\ Purchase_{t=0} + \beta_2\ Maximum_t + \beta_3\ End_t + \varepsilon \quad \text{(B)}$$
$$Reference\ Point_t = \beta_0 + \beta_1\ Purchase_{t=0} + \beta_2\ Minimum_t + \beta_3\ End_t + \varepsilon \quad \text{(C)}$$
$$Reference\ Point_t = \beta_0 + \beta_1\ Purchase_{t=0} + \beta_2\ Average_t + \beta_3\ End_t + \varepsilon \quad \text{(D)}$$
$$Reference\ Point_t = \beta_0 + \beta_1\ Purchase_{t=0} + \beta_2\ Maximum_t + \beta_3\ Minimum_t + \beta_4\ End_t + \varepsilon \quad \text{(E)}$$

Equation 6-5: Regression Equations

Model A suggests that both the purchase and end prices are significant, although the unstandardized coefficient for the end price is twice as high as for the purchase price. Model B adds the maximum price, which is also significant although the coefficient is lower than for the purchase and end prices and the explanatory power of the model is not increased. This result deviates from Chapter 3 where the maximum price was a key driver of the reference point, with a large coefficient, and suggests that the maximum is not as important when participants are asked to provide a reference point every month. This may be because the repeated action of providing a reference point every month focusses more attention on the last reference point provided, which acts as an anchor. We investigate this possibility further in a later section.

Model C adds the minimum price to Model A. Although the minimum price is also significant, it has the wrong sign. Table 6-10 suggests this may be down to multicollinearity with the other variables as VIF scores are high. If either the purchase or end prices are removed from the model then the coefficient on minimum becomes positive and significant with a coefficient of +0.21 or +1.05. The coefficients is therefore larger if the end price is removed.

Model D includes the average term but this is insignificant. This result is in line with the analysis in Chapter 3, which showed that the average term was the least important variable for the determination of the reference point. The r-squared of Model D again shows no improvement over Model A and VIF scores are high.

Finally, Model E adds both the maximum and minimum prices to Model A. All of the variables are significant but the minimum again has the wrong sign. The VIF scores of this model are high and it provides very little improvement in r-squared relative to Model A.

In summary, the purchase and end prices appear to be the key drivers of the reference point with the maximum playing a minor role. None of the models provide a notable increase in r-squared versus Model A and the only additional variable to be positive and significant is the maximum price. A smaller role for the maximum is in line with the findings of Baucells et al. (2011) who also presented prices in a sequenced way. The result differs somewhat from Chapter 3, however, where the maximum and minimum played a large role in the determination of the reference point. This may be because prices were presented all at once rather than sequenced in Chapter 3, with sequencing shifting the attention of the participants onto the previous reference point provided.

Table 6-9: Regression Analysis Point Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E
purchase	0.367**	0.313**	0.494**	0.374**	0.448**
	(8.591)	(8.335)	(7.618)	(6.655)	(6.913)
end	0.720**	0.667**	0.836**	0.726**	0.792**
	(23.65)	(18.44)	(33.94)	(26.23)	(26.69)
max		0.0717**			0.0457**
		(6.635)			(5.012)
min			-0.312**		-0.285**
			(-4.526)		(-4.098)
average				-0.0117	
				(-0.375)	
Constant	0.525**	0.430**	-0.00496	0.508**	-0.0200
	(3.601)	(3.021)	(-0.0233)	(3.009)	(-0.0946)
Observations	39,173	39,173	39,173	39,173	39,173
R^2	0.980	0.980	0.981	0.980	0.981
Adjusted R^2	0.980	0.980	0.981	0.980	0.981

Notes: Regression using the Purchase, Maximum, Minimum, Average and Final prices as independent variables (IV's), predicting the Reference Price as the dependent variable (DV). T-statistics in parentheses. Robust standard errors are clustered by participant. ** p<0.01, * p<0.05

Table 6-10: VIF Analysis

Variables	Model A	Model B	Model C	Model D	Model E
purchase	8.3	11.7	14.6	17.7	20.8
end	8.3	16.1	21.0	28.4	34.8
maximum		21.7			23.0
minimum			36.7		38.8
average				56.3	
Mean VIF	8.3	16.5	24.1	34.1	29.3

Regression: Reference Point Deviation against Deviation Variables

The next set of regressions use deviation variables, rather than point variables. This is to reduce multicollinearity and lower the VIF scores. The variables are defined in Equation 6-6 below. The dependent variable is deviation (Dev) and is measured as the percentage difference between the end price, for the appropriate month, and the reference point. The five IV's used in the subsequent analysis are also calculated as the percentage difference between a specific point on the chart and the end price. The method of calculation of the point variables, used to calculate the deviation variables, remain the same as in the last section.

$$Dev_t = \frac{(\mathrm{End}_t - \mathrm{Reference}_t)}{End_t}$$

$$Absdev_t = \frac{(End_t - Purchase_{t=0})}{End_t}$$

$$Maxdev_t = \frac{(End_t - Max_t)}{End_t}$$

$$Mindev_t = \frac{(End_t - Min_t)}{End_t}$$

$$Averagedev_t = \frac{(End_t - Average_t)}{End_t}$$

Equation 6-6: Deviation Variables

The following regressions, shown in Table 6-11, are based on Equation 6-7 below and use linear least squares regression. Robust standard errors are clustered by participant.

$$Dev_t = \beta_0 + \beta_1 Absdev_t + \mathcal{E} \quad \text{(A)}$$
$$Dev_t = \beta_0 + \beta_1 Absdev_t + \beta_2 Maxdev_t + \mathcal{E} \quad \text{(B)}$$
$$Dev_t = \beta_0 + \beta_1 Absdev_t + \beta_2 Mindev_t + \mathcal{E} \quad \text{(C)}$$
$$Dev_t = \beta_0 + \beta_1 Absdev_t + \beta_2 Averagedev_t + \mathcal{E} \quad \text{(D)}$$
$$Dev_t = \beta_0 + \beta_1 Absdev_t + \beta_2 Maxdev_t + \beta_3 Mindev_t + \mathcal{E} \quad \text{(E)}$$

Equation 6-7: Deviation Regression Models

Model A uses the absolute deviation variable, which our prior analysis suggests should be significant as it incorporates the purchase and end prices. Model A confirms that the Absdev variable is significant, although there is also a significant constant term. This suggests that the reference point is a fixed amount below the final price, regardless of chart characteristics. This may be caused by the fact that 19 of the 25 charts appreciated over the 5-year holding period. When the model is run on the 6 charts with a declining trend alone, the constant term is insignificant. An alternative explanation is that the constant term is significant due to missing variables.

Model B adds the MaxDev variable. We have reason to believe this will also be significant, as the maximum was shown to be a significant variable in Table 6-9. The analysis confirms that both Absdev and Maxdev are significant, although the coefficient is around 9x larger for Absdev than for Maxdev and there is little pickup in r-squared versus Model A. This result again suggests that the purchase price is far more important in determining the reference point than the maximum price when prices are presented sequentially rather than all at once.

Model C adds the minimum term, Mindev, to Model A. Once again the term involving the minimum has the wrong sign and is significant. The minimum term appears to take explanatory power away from the constant term, as the constant is only ever insignificant when the minimum is included.

Model D adds the Average deviation variable to Model A. The AverageDev variable, however, is insignificant. This result is also consistent with Table 6-9, where the average was insignificant as a point variable. Finally, Model E adds both MaxDev and MinDev terms to Model A. Both of the terms are significant, although MinDev again has the wrong sign and there is only a small increase in R-squared over Model A.

In summary, the results confirm that, as well as the end price, the purchase price is the key driver of the reference point when prices are presented sequentially. The maximum price also plays a role, although this is downplayed relative to when prices are presented all at once, such as in Chapter 3. It seems that participants are drawn more strongly to the final price when their attention is on an evolving price series. The minimum price appears to interact with other variables and has the wrong sign, although it has the correct sign on a univariate basis. Finally, the average term was insignificant in both the regression using the point variables and the deviation variables. This is consistent with Chapter 3.

Table 6-11: Regression using Deviation Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E
Abs	0.499**	0.448**	0.534**	0.500**	0.502**
	(7.760)	(7.033)	(7.245)	(5.773)	(6.227)
Max		0.0509**			0.0297*
		(4.842)			(2.506)
Min			-0.327**		-0.299**
			(-3.455)		(-2.987)
Average				-0.00156	
				(-0.0255)	
Constant	-0.153**	-0.117**	-0.0287	-0.153**	-0.0182
	(-10.87)	(-8.077)	(-1.096)	(-9.968)	(-0.746)
Observations	39,173	39,173	39,173	39,173	39,173
R^2	0.500	0.503	0.510	0.500	0.511
Adjusted R^2	0.500	0.503	0.510	0.500	0.511

Notes: Regression using the deviation variables as independent variables (IV's), predicting the Reference Price deviation as the dependent variable (DV). DV= Dev, IVs=Absolute Deviation (AbsDev), Maximum Deviation (MaxDev), Minimum Deviation (MinDev and Average Deviation (AverageDev). Variables are defined in Equation 6-6. T-statistics in parentheses. Robust standard errors are clustered by participant. ** p<0.01, * p<0.05

Table 6-12: VIF Analysis

Variables	Model A	Model B	Model C	Model D	Model E
AbsDev	1	2.61	1.24	3.86	3.33
MaxDev		2.61			2.8
MinDev			1.24		1.33
AverageDev				3.86	
Mean VIF	1	2.61	1.24	3.86	2.48

Regression: Reference Point Deviation against 52-Week Variables

Chapter 3 suggests that 52-week highs and lows are important determinants of the reference point. Versions of the deviation variables can also be calculated using the rolling 52-week maximum or minimum price, which are defined using Equation 6-8 as Max*52Dev* and *Min52Dev* respectively. Differencing variables are also included, which are calculated using the difference between the 52-week variable and the overall high or low, thereby removing the overlap between these variables and MaxDev/MinDev, while retaining any explanatory information.

$$Max52Dev_t = \frac{(End_t - High52_t)}{End_t}$$

$$Min52Dev_t = \frac{(End_t - Low52_t)}{End_t}$$

$$DiffMaxDev_t = \frac{(High52_t - Maximum_t)}{End_t}$$

$$DiffMinDev_t = \frac{(Low52_t - Minimum_t)}{End_t}$$

$$\textit{Where:}$$

$$High52_t = Max(price_t)\ for\ all\ months\ t-12\ to\ t$$

$$Low52_t = Min(price_t)\ for\ all\ months\ t-12\ to\ t$$

Equation 6-8: Further Deviation Independent Variables

In Table 6-13 we perform regressions using the 52-week variables. Equation 6-9 shows the regression models for the regressions.

$$Dev_t = \beta_0 + \beta_1 AbsDev_t + \mathcal{E} \qquad (A)$$
$$Dev_t = \beta_0 + \beta_1 AbsDev_t + \beta_2 Max52Dev_t + \mathcal{E} \qquad (B)$$
$$Dev_t = \beta_0 + \beta_1 AbsDev_t + \beta_2 Min52Dev_t + \mathcal{E} \qquad (C)$$
$$Dev_t = \beta_0 + \beta_1 AbsDev_t + \beta_2 Max52Dev_t + \beta_3 DiffMaxDev_t + \mathcal{E} \qquad (D)$$
$$Dev_t = \beta_0 + \beta_1 AbsDev_t + \beta_2 Min52Dev_t + \beta_4 DiffMinDev_t + \mathcal{E} \qquad (E)$$

Equation 6-9: Regression Models

Model A includes just the AbsDev term for comparison purposes and is identical to model A of Table 6-11. Model B adds the Max52Dev variable, which is significant, although the t-statistic and coefficient are lower than that of the Max variable shown in model B of Table 6-11. This suggests that the 52-week maximum is not as important as the overall maximum. The r-squared of model B shows little improvement over model A.

Model C includes the Min52Dev variable. This is significant, although once again it has the wrong sign. Interestingly, the constant term remains significant in Model C, whereas it is insignificant when the minimum term is added in Model C of Table 6-11. To remove the overlap between variables, we introduce the difference variables in Models D and E. Model D adds the Max52dev and Diffmaxdev to Model A. Both are significant, although the coefficients are low, with Absdev having a far higher coefficient and t-statistic and there is little improvement in r-squared. The result suggests that there is not a major improvement in the model when adding the two maximum terms. Finally, Model E adds both Min52dev and Diffmindev. Both variables are significant and again of the wrong sign. If we remove the Absdev variable then both minimum variables become significant and positive, suggesting an interaction effect with the absolute deviation. The results suggest that the minimum terms are not important determinants of the reference point with the AbsDev variable included.

In summary, our analysis does not suggest a large role for maximums or minimums and this extends to the 52-week maximum and minimum. When both of the maximum variables are included in the regression, both are jointly significant although the additional benefit of adding a second maximum variable is very small as measured by the increase in the overall explanatory power of the model. Both minimum variables are significant, but this is down to interaction effects with the absolute deviation variable, as both have the wrong sign. The results suggest that the 52-week variables are far less important when prices are viewed in a sequential manner than all at once. This is most likely related to the lessened importance of maximums and minimums, in general, when prices are viewed sequentially as participants seem more drawn to the final price.

Table 6-13: Regression Using 52-Week Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E
Abs	0.499**	0.493**	0.504**	0.448**	0.541**
	(7.760)	(7.461)	(7.589)	(7.215)	(7.265)
Max52		0.0450**		0.0509**	
		(2.810)		(3.206)	
Min52			-0.139*		-0.223**
			(-2.167)		(-2.677)
Diffmax				0.0509**	
				(3.778)	
Diffmin					-0.467**
					(-4.176)
Constant	-0.153**	-0.138**	-0.117**	-0.117**	-0.0388
	(-10.87)	(-7.877)	(-11.48)	(-7.249)	(-1.553)
Observations	39,173	39,173	39,173	39,173	39,173
R^2	0.500	0.501	0.501	0.503	0.512
Adjusted R^2	0.500	0.501	0.501	0.503	0.512

Notes: Regression using the deviation variables as independent variables (IV's), predicting the Reference Price deviation as the dependent variable (DV). DV= Dev, IVs=Absolute Deviation (AbsDev), Maximum Deviation based on 52-week high (Max52), Minimum Deviation based on 52-week low (Min52) and differencing vars (DiffmaxDev and DiffminDev). Variables are defined in Equation 6-8. T-statistics in parentheses. Robust standard errors are clustered by participant.
** p<0.01, * p<0.05

Table 6-14: VIF Analysis

Variables	Model A	Model B	Model C	Model D	Model E
AbsDev	1	1.12	1.04	2.70	1.28
Max52Dev		1.12		1.13	
Min52Dev			1.04		1.08
DiffmaxDev				2.52	
DiffminDev					1.24
Mean VIF	1	1.12	1.04	2.12	1.20

Explaining the Results using Lagged Reference Points

In general, the reference point appears to track the end price loosely with slightly more inclination to meet an increasing price (measured from the purchase price) than a decreasing price. This is in line with Arkes et al. (2008) who find that participants update their reference points more in a position of gain than loss. Figure 6-6 and Figure 6-7 show how these relationships work in practice. Chart 9, shown in Figure 6-6 has a steadily rising trend and the reference point tends to move in line with the price trend although a little below it, whereas Chart 10, shown in Figure 6-7 has a declining trend and the reference point is often well above the trend. Analysis of the charts raises the possibility that the lagged reference point may play a role in the formation of the current reference point. The lagged reference point is provided by participants in the previous month and make act as an anchor for the next reference point.

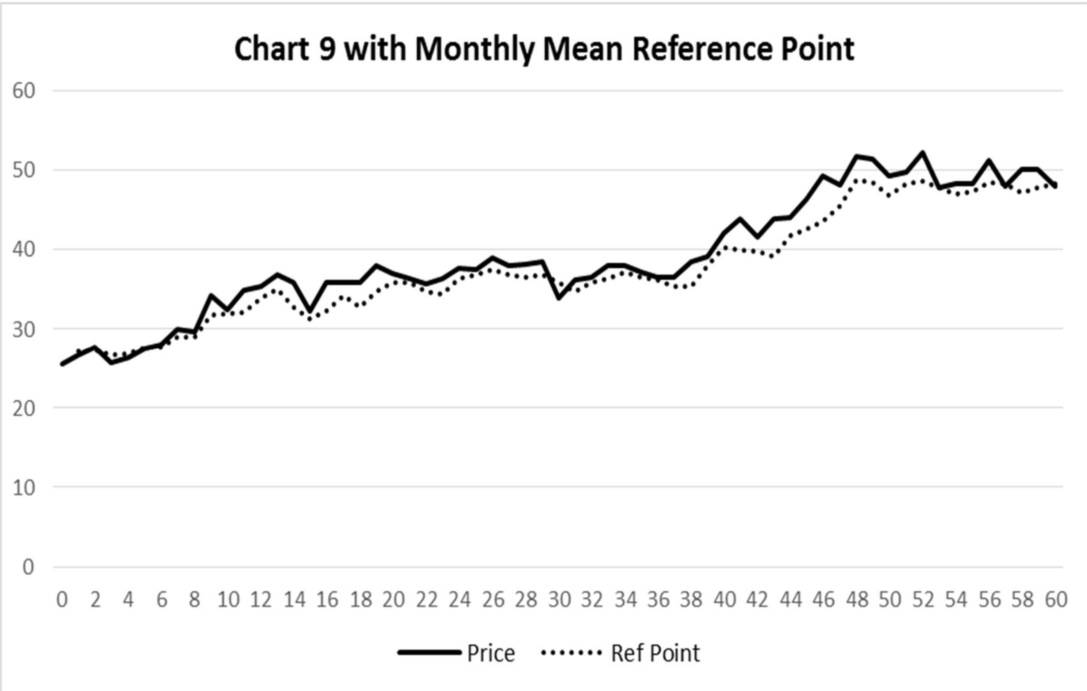


Figure 6-6: Chart 9 with Monthly Reference Point

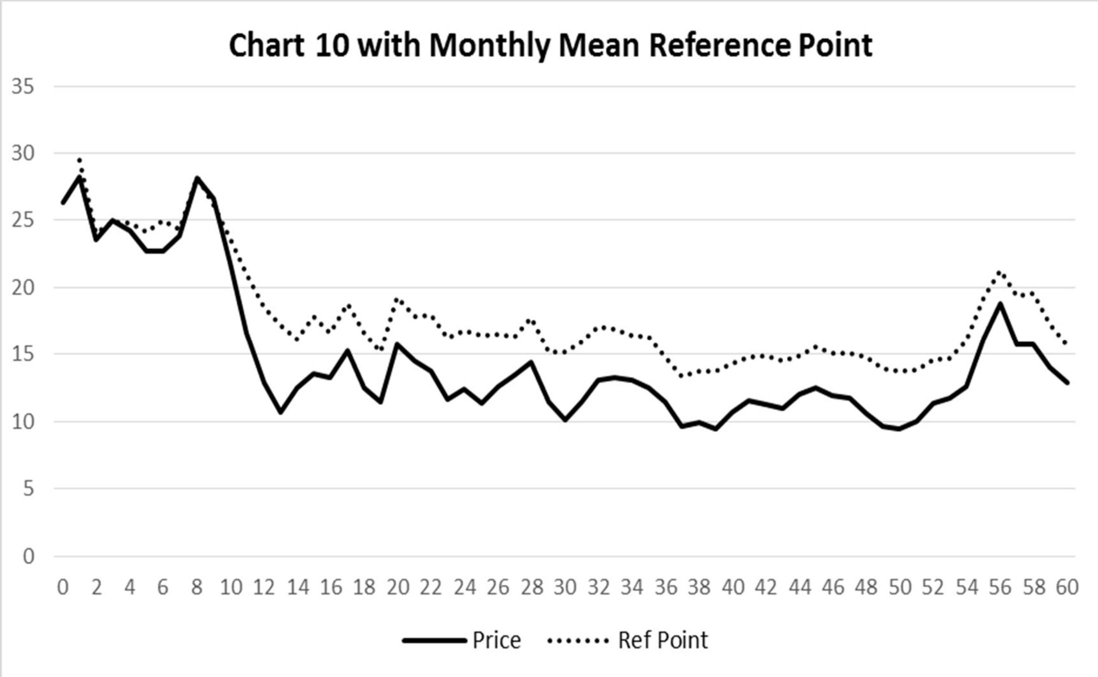


Figure 6-7: Chart 10 with Monthly Reference Point

In this section, we explore if the lagged reference point can increase the explanatory power of the models considered in Table 6-9 when it is added as independent variable. We begin with the point-based models using the reference point as the dependent variable and purchase, max and final prices as independent variables. We then add the reference point lagged by t-1 month (ref_{t-1}) or by t-2 months (ref_{t-2}) as additional explanatory variables. The regression models are shown in Equation 6-10 below.

$$Ref_t = \beta_0 + \beta_1\, Purchase_{t=0} + \beta_2\, Maximum_t + \beta_3\, End_t + \mathcal{E} \qquad \text{(A)}$$

$$Ref_t = \beta_0 + \beta_1\, Purchase_{t=0} + \beta_2\, Maximum_t + \beta_3\, End_t + \beta_4 Ref_{t-1} + \mathcal{E} \qquad \text{(B)}$$

$$Ref_t = \beta_0 + \beta_1\, Purchase_{t=0} + \beta_2\, Maximum_t + \beta_3\, End_t + \beta_4 Ref_{t-2} + \mathcal{E} \qquad \text{(C)}$$

$$Ref_t = \beta_0 + \beta_1\, Purchase_{t=0} + \beta_2\, Maximum_t + \beta_3\, End_t + \beta_4 Ref_{t-1} + \beta_5\, Ref_{t-2} + \mathcal{E} \qquad \text{(D)}$$

Equation 6-10: Regression Equation- Lagged Reference Point

The results are shown in Table 6-15. In Model A, we include the 3 point explanatory variables for comparison purposes. Then in Model B, we include the first lagged reference point. The coefficient on the first lag is positive and significant and the r-squared is increased versus Model A. Model C repeats the analysis but using the second lagged reference point. The coefficient on the second lag is again significant although it is smaller than the first lag and there is a smaller pickup in r-squared. Finally, Model D includes both the lagged variables. Both are significant, but there is no pickup in r-squared versus Model B. The results suggest that Model B, using just the first lagged reference point, is the best model. Our results are not conclusive, however, as VIF scores are high for models B, C and D. Therefore, we repeat the analysis using the difference variables used in Table 6-11, which have lower VIFs.

Table 6-15: Regression of Point Variables with Lagged Reference Points

VARIABLES	Model A	Model B	Model C	Model D
purchase	0.313**	0.132**	0.181**	0.134**
	(8.335)	(8.321)	(8.007)	(8.097)
end	0.667**	0.350**	0.480**	0.355**
	(18.44)	(8.423)	(10.71)	(8.416)
max	0.0717**	-0.0191**	-0.0258**	-0.0249**
	(6.635)	(-3.862)	(-3.418)	(-4.165)
reflag1		0.578**		0.521**
		(13.40)		(13.03)
reflag2			0.420**	0.0598**
			(9.238)	(2.816)
Constant	0.430**	0.295**	0.400**	0.292**
	(3.021)	(4.774)	(4.746)	(4.688)
Observations	39,173	37,181	36,350	35,634
R^2	0.980	0.990	0.987	0.990
Adjusted R^2	0.980	0.990	0.987	0.990

Notes: Regression using the Purchase, Maximum, Final and lagged reference prices as independent variables (IV's), predicting the Reference Price as the dependent variable (DV). DV= ref, IVs=Purchase, max and final prices, reflag1-1=1 month lagged ref, reflag2=2 month lagged ref. T-statistics in parentheses. Robust standard errors are clustered by participant. ** p<0.01, * p<0.05

Table 6-16: VIF Analysis

Variables	Model A	Model B	Model C	Model D
purchase	11.7	37.7	13.6	13.7
end	16.1	28.5	22.3	28.2
maximum	21.7	23.6	25.4	25.1
reflag1		37.7		89.9
reflag2			29.9	69.6
Mean VIF	16.5	25.8	22.8	44.9

We construct the following two independent variables, as shown in Equation 6-11. The variables are now calculated as the percentage difference between the reference point and the end price during the month in which the reference point is calculated. The independent variables, Abs and Max, are again calculated using Equation 6-6.

$$diffref1_t = \frac{(end_t - Ref_{t-1})}{end_t}$$

$$diffref2_t = \frac{(end_t - Ref_{t-2})}{end_t}$$

Equation 6-11: Diffref Independent Variables

The regression models run are shown in Equation 6-12 below, with results presented in Table 6-17.

$$Dev_t = \beta_0 + \beta_1\, Abs_t + \beta_2\, Max_t + \mathcal{E} \qquad \text{(A)}$$

$$Dev_t = \beta_0 + \beta_1\, Abs_t + \beta_2\, Max_t + \beta_3\, diffref1_t + \mathcal{E} \qquad \text{(B)}$$

$$Dev_t = \beta_0 + \beta_1\, Abs_t + \beta_2\, Max_t + \beta_3 diffref2_t + \mathcal{E} \qquad \text{(C)}$$

$$Dev_t = \beta_0 + \beta_1\, Abs_t + \beta_2\, Max_t + \beta_3\, diffref1_t + \beta_4 diffref2_t + \mathcal{E} \qquad \text{(D)}$$

Equation 6-12: Regression Equation

Model A includes just the Abs and Max variables for comparison purposes. Model B includes the diffref1 variable, which is positive and significant. There is a large increase in r-squared from Model A to Model B. Model C includes the diffref2 variable, which is again positive and significant with a large increase in r-squared but smaller than that provided by Model B. Finally, Model D includes both of the diffref variables. Both of the variables are positive and significant, although there is not a large increase in R-squared versus Model B, which is the model that just includes diffref1.

The results from Table 6-15 and Table 6-17 suggest that both the first lagged reference point and second lagged reference point are significant determinants of the reference point. There is only marginal gain, however, from including the second lagged reference point, when the first is already included, with only a small increase in r-squared. If monthly lagged end prices are used instead of lagged reference points then these variables are insignificant. The results suggest that the first lagged reference point could improve the explanatory predictions of our models.

Table 6-17: Regression of Deviation Variables with Lagged Reference Points

VARIABLES	Model A	Model B	Model C	Model D
Abs	0.448**	0.0392**	0.0584**	0.0340**
	(7.033)	(4.607)	(5.838)	(5.897)
Max	0.0509**	-0.0114**	-0.0212**	-0.0163**
	(4.842)	(-6.947)	(-8.555)	(-12.10)
diffref1		0.925**		0.683**
		(50.11)		(11.84)
diffref2			0.888**	0.257**
			(39.29)	(5.052)
Constant	-0.117**	-0.0189**	-0.0314**	-0.0201**
	(-8.077)	(-8.609)	(-11.18)	(-10.42)
Observations	39,173	37,181	36,350	35,634
R^2	0.503	0.937	0.911	0.942
Adjusted R^2	0.503	0.937	0.911	0.942

Notes: Regression using the deviation variables and lagged deviation variables as independent variables (IV), predicting the Reference Price deviation as the dependent variable (DV). DV= Dev, IVs=Absolute Deviation (Abs), Maximum Deviation (Max). Variables are defined in Equation 6-6 Diffref1=(end-1 month lagged ref)/end, Diffret2=(end-2 month lagged ref)/end. Robust standard errors are clustered by participant. T-statistics in parentheses.
** p<0.01, * p<0.05

Table 6-18: VIF Analysis

Variables	Model A	Model B	Model C	Model D
Abs	2.6	3.5	3.5	3.5
Max	2.6	2.7	2.7	2.8
diffref1		2.1		16.2
diffref2			2.1	16.5
Mean VIF	2.6	2.7	2.8	9.8

6.3 Additional Analysis

Additional Analysis- Regression: Reference Point using Variables Constructed from Daily Data

In this section, we use daily variables to calculate the independent variables. This is because, as we discussed earlier in the Chapter, ValueLine charts include a range, each month, which shows the maximum and minimum price over the month based on daily data. This raises the possibility that daily maximums and minimums over a month may play in a role in reference point formation. Each chart was produced using daily data, which means that intra-month maximums and minimums may be higher or lower than the monthly variables used in the earlier section.

Equation 6-13 shows the new variables used in this section. For each ith chart and tth month, the initial price is calculated as the beginning of each month when the reference point is requested e.g. day 0, day 22, day 44 etc. MonthMax and MonthMin are calculated as the daily maximum or minimum over the tth month in which the reference point is measured. MonthAverage is the average daily price over the tth month in which the reference point is requested. Finally, the End price is the last daily price at the end of the month in which the reference point is requested.

$$Initial_{i,t} = price_{i,t}\ for\ day\ d = 1$$
$$MonthMax_{i,t} = Max\left(price_{i,t}\right)\ for\ all\ days\ within\ month\ t$$
$$MonthMin_{i,t} = Min\left(price_{i,t}\right)\ for\ all\ days\ within\ month\ t$$
$$MonthAverage_{i,t} = Avg\left(price_{i,t}\right)\ for\ all\ days\ within\ month\ t$$
$$End_{i,t} = price_{i,t}\ for\ day\ d = 22$$

Equation 6-13: Daily Price Variable Equations

The new variables tend to be correlated with each other, as they all come from the same month. This means that VIF scores are high for point regressions.

Therefore, in order to test the relationship of the variables with reference points we use deviation variables to reduce multicollinearity. The transformed variables are shown in Equation 6-14. The dependent variable, Dev, remains the same as in the previous section. The AbsDev variable is now replaced by Absmonth, which is calculated using the initial price over the latest month rather than the purchase price. MonthmaxDev and MonthminDev are calculated using the daily maximum (monthmax) or minimum (monthmin) over the month, rather than the running maximum or minimum. Finally, MonthaverageDev is calculated using the daily average over the month (monthaverage), rather than the running average across the whole price chart.

$$Dev_t = \frac{(\mathrm{End}_t - \mathrm{Reference}_t)}{End_t}$$

$$Absmonth_t = \frac{(End_t - Initial_t)}{End_t}$$

$$MonthmaxDev_t = \frac{(End_t - monthmax_t)}{End_t}$$

$$MonthminDev_t = \frac{(End_t - monthmin_t)}{End_t}$$

$$MonthaverageDev_t = \frac{(End_t - monthaverage_t)}{End_t}$$

Equation 6-14: Deviation Variables

The following regressions (Models A-E) use combinations of variables from the regression equation shown in Equation 6-15. The final model, Model F, also includes the Absdev and Maxdev variables from the previous section to test if the new variables are still significant when these variables are added to the regression. This is to explore whether the daily variables have explanatory power when the original variables are included in the regression.

$$Dev_t = \beta_0 + \beta_1 Absmonth_t + \mathcal{E} \quad \text{(A)}$$

$$Dev_t = \beta_0 + \beta_1 Absmonth_t + \beta_2 MonthmaxDev_t + \mathcal{E} \quad \text{(B)}$$

$$Dev_t = \beta_0 + \beta_1 Absmonth_t + \beta_2 MonthminDev_t + \mathcal{E} \quad \text{(C)}$$

$$Dev_t = \beta_0 + \beta_1 Absmonth_t + \beta_2 MonthaverageDev_t + \mathcal{E} \quad \text{(D)}$$

$$Dev_t = \beta_0 + \beta_1 Absmonth_t + \beta_2 Monthmax_t + \beta_3 Monthmin_t + \beta_4 Monthaverage_t + \mathcal{E} \quad \text{(E)}$$

$$Dev_t = \beta_0 + \beta_1 Absmonth_t + \beta_2 Monthmax_t + \beta_3 Monthmin_t + \beta_4 Monthaverage_t + \beta_5 AbsDev_t + \beta_6 MaxDev_t + \mathcal{E} \quad \text{(F)}$$

Equation 6-15: Regression Equation

Referring to Table 6-19, Model A includes the Absmonth variable which is positive and significant. The r-squared of the model is lower, however, than the equivalent model using the AbsDev variable in Table 6-11. This suggests that the purchase price is more important than the initial monthly price, as a reference point. Model B adds the MonthmaxDev term which is also positive and significant, although the r-squared remains low. Model C adds the MonthMinDev term. This is negative and significant, which is in line with the point and deviation regressions where the minimum had a negative sign. Model D adds the MonthAverage term. This is significant at the 5% level, which is the first time that a variable using the average is significant. Model E puts all the daily variables together. All 4 of the daily variables are significant, although the MonthminDev variable still has a negative sign. The r-squared of this model is lower than the r-squared of models in the previous sections, however.

To test if the daily variables are significant when including some of the monthly variables, we add the AbsDev and MaxDev variables from the previous section in Model F. None of the daily variables are significant when AbsDev and MaxDev are added to the model. AbsDev and MaxDev are significant, however, and the r-squared of the model is greatly improved. This suggests that the daily variables don't have any explanatory power when the Abs and Max variables are included in the model.

Table 6-19: Regression using Daily Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
Absmonth	0.507**	0.0318	0.747**	0.419**	0.255**	0.0540
	(11.37)	(0.674)	(9.348)	(9.079)	(5.843)	(1.229)
Monthmax		0.757**			0.351**	0.0396
		(5.877)			(3.102)	(0.792)
Monthmin			-0.725**		-0.613**	-0.0632
			(-6.028)		(-5.803)	(-0.773)
Monthaverage				0.180*	0.481**	-0.0480
				(2.425)	(3.727)	(-0.508)
AbsDev						0.449**
						(7.053)
MaxDev						0.0492**
						(4.570)
Constant	-0.163**	-0.102**	-0.107**	-0.163**	-0.0874**	-0.110**
	(-7.472)	(-6.870)	(-6.526)	(-7.469)	(-5.960)	(-7.174)
Observations	39,173	39,173	39,173	39,173	39,173	39,173
R^2	0.011	0.016	0.015	0.011	0.017	0.503
Adjusted R^2	0.011	0.016	0.015	0.011	0.017	0.503

Notes: Regression using the daily deviation variables as independent variables (IV), predicting the Reference Price deviation as the dependent variable (DV). DV= Dev, IVs=Price change over month (Absmonth), max over month (Monthmax), min over month (Monthmin), average over month (Monthaverage). Variables are defined in Equation 6-14. AbsDev and MaxDev are defined in Equation 6.6. T-statistics in parentheses. Robust standard errors are clustered by participant.
** p<0.01, * p<0.05

Table 6-20: VIF Analysis

Variables	Model A	Model B	Model C	Model D	Model E	Month F
Absmonth	1	2.77	1.57	5.13	6.67	6.67
MonthMaxDev		2.77			9.08	9.13
MonthMinDev			1.57		5.89	5.9
MonthAverageDev				5.13	13.31	13.32
AbsDev						2.62
MaxDev					1.24	2.7
Mean VIF	1	2.77	1.57	5.13	8.74	6.72

In summary, although all the daily variables were significant, the models tend to have low explanatory power, as evidenced by the low r-squared, relative to models that use monthly variables. This suggests that the explanatory power of the daily version of the variables is not great when combined into an overall model. Furthermore, when two variables, Absdev and Maxdev, are added from the previous section, none of the daily variables remained significant. This suggests that the daily variables add little to our models. The results show that investors pay more attention to overall maximums and minimums and their purchase price than to intra-month maximums and minimums or the initial monthly price. It could be that participants view any intra-month activity as noise and choose to focus their attention on month-end prices only.

Additional Analysis- Reference Points across the 60 Months

One of the design features of the experiment is that reference points are collected across 60 months in sequential order. So far, we have treated all reference points in the same way, regardless of the month (t) that they were collected in. It is possible that some of the independent variables may have greater explanatory power depending on the month that the reference point was collected in. This would influence the calculation of the reference point within the Barberis et al. (2016) model, as different months would require a different formula to obtain the reference point.

In order to test this possibility, we construct a number of interaction variables, as shown in Equation 6-16 below. The month variable represents the month in which the reference point was collected, which ranges from 1 to 60, with later months having a higher value. So if the reference point was collected in month 15 (out of a total of 60) then the month variable would be equal to 15. To calculate the interaction variables we multiple the independent variable by the month in which it was measured.

The first 2 interaction variables are based on the point regression model using the purchase and end prices. We begin with this model, as it allows us to perform the analysis for both the purchase and the end prices, whereas the deviation model does not. One drawback of this model, however, is the high level of multicollinearity. Therefore, to test the interaction of the remaining variables, we switch to the deviation model. The last three time-interaction variables in Equation 6-16 represent interactors for AbsDev, MaxDev or MinDev respectively.

$$Modpurchase_t = month_t * purchase_{t=0}$$

$$Modend_t = month_t * end_t$$

$$ModAbs_t = month_t * AbsDev_t$$

$$ModMax_t = month_t * MaxDev_t$$

$$ModMin = month_t * MinDev_t$$

Equation 6-16: Interaction Variables

The first set of regressions are shown in Table 6-21. Model A includes the purchase and final prices along with the time variable, month, as a standalone variable. The month variable has a positive and significant coefficient, which suggests that the reference point increases as time progresses in the chart. This could reflect a general upward movement in the majority of the charts, which is reflected in the market data from which the charts were taken. When we repeat the analysis only using charts with a downward trend, from purchase to final price, the month variable takes on a negative and significant coefficient of -0.0198.

Model B adds the time interactor for the end variable only, while Model C adds the time interactor for the purchase price only. Both of the interaction variables are positive and significant. This suggests that both purchase and end prices become more important in reference point determination as time progresses. This seems a bit counter-intuitive for the purchase price, as we would expect that this may become less important as time progresses. Model D includes both interactors in the regression. The end interactor is no longer significant, but the purchase interactor is still significant and positive. One issue with this model is the high level of VIFs, which is a good reason to switch to the deviation variables for the next set of regressions. It is also worth noting that there is no pickup in r-squared across the model, or for the equivalent model shown in

Table 6-11 that do not have time interactors, which suggests that the time interactors do not add explanatory power to the model.

Table 6-21: Regression of Point Variables with Time Moderation

VARIABLES	Model A	Model B	Model C	Model D
purchase	0.370**	0.376**	0.337**	0.321**
	(8.636)	(8.736)	(8.469)	(8.974)
end	0.718**	0.692**	0.716**	0.728**
	(23.50)	(21.43)	(23.50)	(23.44)
month	0.0325**	0.0179**	0.0132**	0.0123**
	(6.707)	(4.273)	(3.550)	(3.455)
modend		0.000705**		-0.000339
		(4.899)		(-0.653)
modpurchase			0.00114**	0.00161*
			(5.119)	(2.031)
Constant	-0.464*	-0.0455	0.112	0.149
	(-2.252)	(-0.247)	(0.708)	(1.105)
Observations	39,173	39,173	39,173	39,173
R^2	0.980	0.980	0.980	0.980
Adjusted R^2	0.980	0.980	0.980	0.980

Notes: Regression using point variables as independent variables (IV), predicting the Reference Price as the dependent variable (DV). DV= ref, IVs=Purchase and end prices, month=month from 1 to 60, modend=end*month, modpurchase=purchase*month. Moderation variables are defined in equation 6-16. T-statistics in parentheses. Robust standard errors are clustered by participant. *** p<0.01, ** p<0.05.

Table 6-22: VIF Analysis

Variables	Model A	Model B	Model C	Model D
purchase	8.34	8.48	11.04	49.23
end	8.34	13.66	8.36	56.65
Month		1.24	1.35	1.39
modend		5.1		51.56
modpurchase	1		4.47	45.15
Mean VIF	5.89	7.12	6.3	40.79

Table 6-23 uses the deviation variables with reference point deviation (Dev), as the dependent variable. Model A includes the variables: AbsDev, MaxDev, MinDev along with the time variable, month. The time variable is again positive and significant, suggesting that the percentage deviation between the final price and reference point increases through time. Models B, C and D gradually add time interactors to the regression. Model B adds the AbsDev interactor based on the purchase price. The AbsDev interactor is positive but not significant at the 5% level. Models C and D add time interactors for the MaxDev and MinDev variables, which are both negative and significant. This result suggests that both maximum and minimum variables become less important in reference point determination as the months progress. Model D does suffer from high VIF score, however, so the insignificant AbsDev interactor is removed in Model E. The MaxDev and MinDev interactors remain negative and significant, while VIF scores are reduced. One issue to note in all models is that r-squared scores are again little changed from deviation models that do not include time interactors. This suggests that the time interactors add little explanatory power.

In summary, the strongest evidence for time interaction comes in the form of reduced importance for the maximum and minimum, as the month that the reference point is collected increases. This makes sense in that intermediate points achieved in the past may be less important to the participant as the investment is coming to an end. This result is unlikely to be caused by when maximums or minimums are generated in the sample because the purchase price is always at the beginning of the sample and yet becomes more important as months progress. This may be because investors begin to focus on their break-even profit as the 5-year investment horizon is drawing to a close.

The addition of time interaction variables does not lead to big increases in r-squared. This suggests that the benefit of adding time interactor variables is limited within the context of the whole model. Figure 6-8 shows the coefficients for the purchase, max and end variables when regressions are performed individually across the 60 different months, using these 3 variables as independent variables. The end and purchase variable coefficients are fairly stable across months, with a slight increase in both as time progresses. The maximum coefficient, however, tends to peak around the 2-year area and then declines to almost zero by the end of the 5-year period. This suggests that the model is fairly stable over time, although there is some drop-off in the importance of the maximum variable, as confirmed by the time interaction regressions, to where it has almost no explanatory power by the end of the investment horizon.

Table 6-23: Regression of Deviation Variables with Time Moderation

VARIABLES	Model A	Model B	Model C	Model D	Model E
Abs	0.499**	0.448**	0.371**	0.412**	0.499**
	(6.244)	(8.402)	(9.201)	(7.156)	(6.225)
Max	0.0403**	0.0452**	0.138**	0.147**	0.0983**
	(3.453)	(3.807)	(4.681)	(5.180)	(5.048)
Min	-0.362**			-0.0814	-0.172*
	(-3.094)			(-1.260)	(-1.964)
month	0.00178**	-0.000665	-0.00159*	0.00416**	0.00394**
	(2.959)	(-1.432)	(-2.425)	(3.557)	(3.569)
modAbs		0.000136	0.00196	0.00208	
		(0.191)	(1.820)	(1.959)	
modMax			-0.00219**	-0.00239**	-0.00124**
			(-3.352)	(-3.794)	(-3.264)
modMin				-0.00913**	-0.00680**
				(-3.779)	(-4.182)
Constant	-0.0405*	-0.101**	-0.0671**	-0.0850**	-0.0794**
	(-2.125)	(-9.931)	(-5.704)	(-6.441)	(-5.674)
Observations	39,173	39,173	39,173	39,173	39,173
R^2	0.512	0.503	0.504	0.515	0.514
Adjusted R^2	0.512	0.503	0.504	0.514	0.514

Notes: Regression using deviation variables as independent variables (IV), predicting the Reference Price Deviation as the dependent variable (DV). DV= Dev, IVs=ABS, Max and Min defined in Equation 6-6, month=month from 1 to 60, modAbs=Abs*month, modMax=Max*month, modMin=Min*month. Moderation variables are defined in equation 6-16. T-statistics in parentheses. Robust standard errors are clustered by participant.
** p<0.01, * p<0.05

Table 6-24: VIF Analysis

Variables	Model A	Model B	Model C	Model D	Model E
AbsDev	3.34	15.6	27.91	42.88	3.36
MaxDev	3.12	3.13	32.54	40.27	19.6
MinDev	1.75			7.72	5.19
Month	1.57	1.2	1.69	4.89	4.81
modAbsDev		14.43		40.4	
modMaxDev			33.44	40.87	17.91
modminDev				14.84	10.64
Mean VIF	2.45	8.59	24.51	27.41	10.25

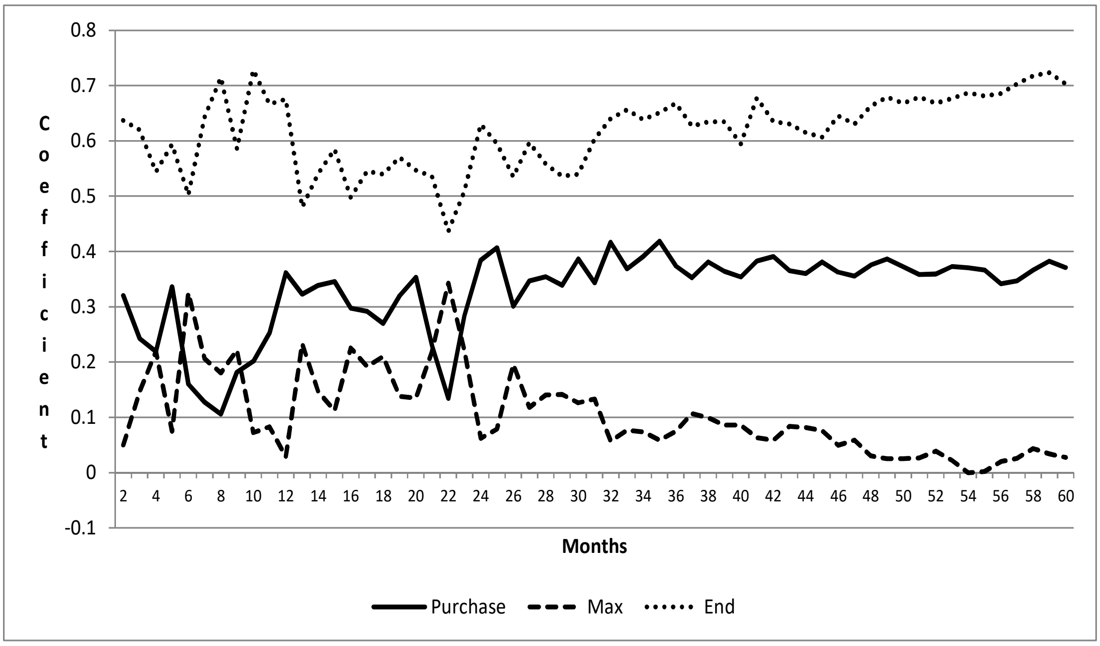


Figure 6-8: Coefficients of Independent Variables across Months

Notes: The figure shows the coefficients based on split sample regression by month. For example, for month m=1, the coefficients represent the beta values for a regression of purchase, maximum and month-end prices against the reference point.

6.4 Conclusion

This is the first experiment to consider reference point adjustment across individual months, within a multi-period setting, which uses realistic share price charts. Charts were constructed through sampling of real market data and daily data was used to replicate the charts available to investors over the internet and through the Value Line Investment Handbook. Data collection was handled by a survey company and proceeded well. Subsequently, data cleaning was necessary in order to remove unrealistic data. The OS method (Tibshirani and Hastie, 2007) was chosen after evaluating a number of alternatives. A key advantage of the OS method is that it does not rely on any of the independent variables to screen the data.

Anova analysis suggests that three descriptive variables (age, duration and frequency of trading) can explain variation in reference points. This is an interesting result that differs from Chapter 3, where the same descriptive variables could not explain variation in reference points. This opens up the possibility that demographics may be able to partly explain reference points and reference point adjustment, although the results should be treated with caution as we found no impact of demographics on reference points in Chapter 3. In related findings, Dhar and Zhu (2006) show that the scale of the disposition effect is related to demographic variables. While not the purpose here, future research could look to explore the impact of demographics, with salient prices in the chart held constant across participants.

Regression results using the point and deviation variables suggest that the purchase, end, maximum and minimum prices are significant. The average price is not a significant determinant of the reference point, which is consistent with the findings in Chapter 3. A difference with Chapter 3 is that maximums and minimums appear to play a smaller role when prices are presented in a sequential manner rather than all at once. The month-end price has a greater weight when participants are being asked to provide a reference point every month. Their memory for the initial purchase price, however, seems unaffected by the sequential nature of prices displayed in the graphs. The results suggest that intermediate maximums and minimum are less important to an investor when they are providing sequential reference points.

The next section examined the impact of 52-week maximums and minimums, which were found to play a significant role in reference point formation in Chapter 3. Work from George and Hwang (2004) also suggests the 52-week maximum is an important reference point in market data, which affects the pricing of securities. Our results, however, suggest little role for the 52-week variables when prices are presented in a sequential manner. Intermediate prices play less of a role when reference points are requested on a regular basis and in this experiment both overall maximums & minimums and 52-week maximums & minimums play less of a role in the determination of the reference point. This is again likely caused by an increased emphasis on the current (end) price when reference points are requested sequentially.

Another reason for the smaller influence of maximums and minimums may be to do with lagged reference points. Arkes et al. (2008) studied the amount of adaptation from one reference point to the next and found that adaptation was less than complete, especially when prices were moving in a downward direction. We found that models that included both a 1-month lag and 2-month lag were improved over the baseline case, although there was little incremental benefit from adding the 2-month lag variable if the 1-month lag variable was also present in the model. The results suggest that participants use their last reference point as an anchor to form the next reference point. This would reduce the cognitive load for them, within the context of a 60 reference point experiment.

The design of the experiment allowed for additional intra-month variables to be formed using daily data. When these regressions were performed, we found that the intra-month variables were significant predictors of the reference point. The explanatory power of these models, however, was lower than the earlier models, using monthly data, and none of the variables were significant once the earlier variables were added to the regression. The results suggest that participants were less concerned with intra-month starting prices and maximums & minimums than with the overall pattern of the chart.

We also examined if the month that the reference point was collected had an impact on reference point formation. A reasonable initial assumption was to consider that the purchase price may become less important as the number of the month increased, on the basis that its salience may lower as time progresses. We did not find any evidence consistent with this hypothesis, however, and in fact, the purchase price appeared to become slightly more important as months progressed. Intermediate highs and lows became less important as months progressed, especially after the 24-month mark. This could be because maximums and minimums made earlier in the 5-year period tended to be older as months increased, which lessened their importance to investors. If this was the case, however, then we might reasonably expect 52-week maximums and minimums to be more important than overall maximums and minimums, which was not the case. It is also possible that as the 5-year period progressed, participants became more focused on the final price that they could actually sell at, while keeping the purchase price in mind (but not highs or lows).

A formula for the reference point, taken principally from our main regression table of point variables (Table 6-9) will now be taken forward to the next chapter, where was will explore if the Prospect Theory Value of a Stock from Barberis et al. (2016) can be improved by taking into account a dynamically adjusting reference point over a 5 year evaluation period. An improved variable should lead to greater predictability in future share price returns than the existing variable.

6.4.1 Limitations and Future Research

In this experiment we collected reference points from participants on a monthly basis in line with the approach adopted in Barberis et al. (2016). It is possible, however, that the reference point collection frequency could affect the results. Future research could look to explore how reference point formation is affected by the frequency over which participants are requested for a reference point across an identical chart e.g. monthly versus quarterly versus annual to see if this affects the results.

We undertook some initial analysis to explore if reference points differed across the month in which the reference point was collected, but further work, in the form of a new experiment, would be necessary to expand the analysis. Why participants maintained focus on the initial purchase price, but not maximums or minimums, is an interesting question for future research, but it is possible that they start to think about their accounting gain or loss as the investment horizon is coming to an end (participants know beforehand that the investment horizon is 60 months in length).

7 Model III: Reference Point Adaptation within the Prospect Theory Value of a Stock (TK) Model

In this chapter, we investigate how different reference points perform with the Prospect Theory Value of a Stock Model developed by Barberis et al. (2016). The model assumes that a prospective investor evaluates a stock based on 60 months of returns (5 years) relative to a benchmark return, which is the reference point of the model. We explore how the Prospect Theory Value of a Stock model can be improved by introducing new reference points into the model. Specifically, we use the equation for monthly sequential reference points, developed in Chapter 6, and evaluate if the TK model can be enhanced such that its predictive power is improved.

Prior research on the role of reference points in investor preferences has focussed on the sell decision, the most notable development being the disposition effect outlined in Shefrin and Statman (1985). There has been some work, however, that could also be applied to the buy or sell decision. For example, George and Hwang (2004) suggest that the 52-week high is a key reference point for investors, with shares near their 52-week high being underpriced. This was later extended by Bhootra and Hur (2013) who show that more recent highs within the 52-week period have a more powerful influence on returns than less recent highs. Both papers suggest that stocks near the 52-week high attract attention from investors.

Another related stream of literature looks at the relationship between reference points and volume (trading) in the market. The first of these, Ferris et al. (1988), is motivated as a test of selling behaviour. The authors detect abnormal trading volume which is higher for winning stocks and lower for losing stocks, in line with that predicted by the disposition effect. A later paper from Huddart et al. (2009) measures abnormally high trading volume when stocks make a new 52-week high or low. The implication is that the 52-week high and low are key reference points for investors and the authors suggest that much of the abnormal volume is driven by the buying behaviour of small investors, as a stock making a new high attracts buyer attention and subsequent trading activity (Barber and Odean, 2008). This is in line with Duxbury and Yao (2017) who show that investors exhibit momentum behaviour when buying stocks and hence stocks making new highs are attractive to them.

Looking more broadly at investor preference, there is some coverage in the literature regarding how stock characteristics themselves (not specifically the reference point) might influence the decisions of an investor. Ang et al. (2006) show that stocks with high idiosyncratic volatility in the US market, within the context of the CAPM model, have low subsequent returns and vice versa. A later paper from them (Ang et al., 2009), extends the analysis to all major developed markets and finds a similar effect. Mispricing is also found in the case of stocks that have lottery type characteristics. Kumar (2009) finds that investors have a preference for lottery-type stocks, with skewed returns, that offer a small probability of extremely high returns. The increased demand for these types of stocks causes them to be overpriced, which leads to subsequent underperformance in the future. The effect is even stronger in non-market traded, over-the-counter stocks, which tends to have extremely high positive skew combined with negative future returns (Eraker and Ready, 2015). The model of Barberis et al. (2016) acts as a link between the work on investor preference for volatility/skewness and reference points. In their model, investors evaluate monthly returns in relation to a reference point and then evaluate subsequent gains or losses using Prospect Theory rules. High volatility in the form of past gains are favoured by investors but high volatility caused by large losses are undesirable due to investor loss aversion.

The prior literature does not mention the role of reference points in the formation of investor preference in any detail. The lack of attention on the investor preference of investors, in general, and the role of reference points specifically is surprising, as the majority of anomalies discovered in markets (for a review see Subrahmanyam (2010)), could plausibly be caused by the preferences of investors. Equally, when reference points are addressed more specifically, in the case of selling behaviour, it has been usual to assume a static reference point, which is fixed on the purchase price. This assumption is used in Shefrin and Statman (1985)'s initial work and then is largely continued through the literature.

In this chapter, we examine the role of investor reference points in the formation of investor preferences by modifying the reference point assumption of the Prospect Theory Value of a Stock model developed by Barberis et al. (2016). In the first section, we describe their model and show how the reference point assumption can be changed to develop alternative Prospect Theory values for stocks. We create 5 new versions of the Barberis et al. (2016) variable, using the purchase, maximum, minimum, 52-week maximum and 52-week minimum as reference points, as well as two combination variables that are formed from a combination of the above points. The weights for the combination variables are taken from the coefficients of the experiment in Chapter 6, which was designed to measure sequential reference point formation.

Then we perform regression analysis using the Barberis et al. (2016) and alternative variables and show that the alternative variables, based on composite reference points (TK_Com1 & TK_Com2), retain significance at the 5% level, even when the original TK variable is added into the regression. The explanatory power of the original TK variable is removed, however, and it becomes insignificant. The result suggests that the buyer's reference point is formed from salient points in the prior price path.

In the remainder of the chapter, we test different mechanisms by which the reference point may be formed and thereby improve the predictive power of the Barberis et al. (2016) model still further. Firstly, we look at the case of an investor who forms only a single reference point at the end of the chart (as in Chapter 3) and then applies this reference point across months. This is to check that the reference point formula provided by Experiment 2 is superior to Experiment 1 for the purposes of the TK model. The change in the reference point, from the initial purchase price, is adjusted in either a linear fashion or exponential fashion across the months. We find that the linear adjustment model works best, although it is no more predictive than the TK_Com1 and TK_Com2 variables discussed earlier. Secondly, we look at the case of an investor who uses the lagged reference point to form the reference point in the current month. In Chapter 6, we discovered that last month's reference point is a strong predictor of the current month reference point and this insight is confirmed in our subsequent regression analysis. We find that versions of the Barberis et al. (2016) model that incorporate lagged reference points are predictive of future returns, although no more so than the TK composite variables.

In summary, our results show that reference points do affect the investor preferences of investors and we show for the first time that these reference points are partly determined by salient points in the prior price path that is experienced by the investor.

7.1 The Prospect Theory Value of a Stock Model

The Barberis et al. (2016) model is an attempt to calculate the value of a prior share price pattern using Prospect Theory. The idea is that investors find some share price patterns more attractive than others. The attractive patterns have a high prospect theory value (TK) and are subsequently overvalued, relative to stocks with a low TK value. Barberis et al. (2016) find that stocks with a high TK value underperform relative to stocks with a low TK value. The model adds nicely to the prior literature, which shows a preference for volatility (Ang et al., 2006) and skew (Kumar, 2009), but which did not previously considered how these preferences could be brought together using Prospect Theory into a single model.

The first step in calculating the TK value of a stock in Barberis et al. (2016) is representation i.e. how does the investor represent a past return distribution. In their view, the easiest way for an investor to learn about a stock's past return distribution it to look at a chart of historical prices. In the pre-internet era, these charts were available in print form, such as those in the Value Line Investment Handbook. Of the sources that they review, a 5-year price chart was a common horizon in which to represent past price movements. They, therefore, assume that an investor represents a past return distribution as a series of 60 separate months. Other alternative representations are possible and may be the subject of further work, although for the purposes of this Chapter we choose to stick with this assumption in order to make the results comparable with the Barberis et al. (2016) paper.

The second step is valuation, where the investor evaluates the monthly gains and losses to assess if they are desirable. The key elements of Prospect Theory come into play here. Firstly, gains or losses are measured relative to a reference point. The reference point that Barberis et al. (2016) choose is the return of the benchmark over the month (value-weighted index from CRSP), with the idea being that investors regard returns that are above the benchmark for that month as a gain and below the benchmark as a loss (we subsequently change this reference point to see if it improves the predictive power of the model). The second element of Prospect Theory that comes into play is loss aversion. Barberis et al. (2016) use the standard loss aversion parameter of 2.25 to magnify the impact of losses on the Prospect Theory value.

The third element of Prospect Theory that is used to calculate TK is decision weighting, which is used to replace probabilities, as outlined in Tversky and Kahneman (1992). These decision weights are used to replace objective probabilities, with small probability events given considerably more weight than is deserved by their objective probability. The standard parameters are again adopted, as Barberis et al. (2016) find these to be the most accurate.

The Prospect Theory value of a stock is given the abbreviation TK, as the calculation of probabilities is based on Tversky and Kahneman (1992). The prospect theory value of each monthly return (v[x]) is multiplied by the decision weight (π_i) defined by cumulative prospect theory, as shown in Equation 7-1, to calculate TK

$$TK = \prod_{i=-m}^{n} \pi_j \, v(x_i)$$

where

$$\pi_i = \begin{cases} \omega^+(\rho_i + \cdots + \rho_n) - \omega^+(\rho_{i+1} + \cdots + \rho_n) & 0 \le i \le n \\ \omega^-(\rho_{-m} + \cdots + \rho_i) - \omega^-(\rho_{-m} + \cdots + \rho_{i-1}) & -m \le i \le 0 \end{cases}$$

Equation 7-1: Taken from Barberis et al. (2016)

Each month's return is ranked in order and given a probability of 1/60. Each decision weight (π_i) is calculated by subtracting the total cumulative probability [$\omega^+(\rho_i + \cdots + \rho_n)$] from the remaining cumulative probability excluding the specific month [$\omega^+(\rho_{i+1} + \cdots + \rho_n)$]. For example, if we are talking about the third highest return month out of a return distribution with 20 positive months (n=20, i=18) then the decision weight is calculated as the cumulative probability of the 1st, 2nd and 3rd highest months (i=18, 19 & 20) minus the cumulative probability of the 1st and 2nd months (i=19 & 20).

Both the values (v) and the decision weights (ω) are calculated using the standard parameters, as shown in Equation 7-2 and Equation 7-3. For the value function (v), positive and negative values are calculated differently. Positive values are scaled by the alpha adjustment of 0.88 (the standard parameter in Tversky and Kahneman (1992)). This is to reflect risk aversion in gains. Losses are first made positive and then scaled again by the same alpha parameter. This is to reflect risk seeking in losses. This value is then multiplied by the negative value of λ=2.25. The value of lambda reflects loss aversion for negative months, such that they take a larger absolute value than equivalent gains.

$$v(x) = \begin{cases} x^{\alpha} & for\ x \geq 0 \\ -\lambda(-x)^{\alpha} & for\ x \leq 0 \end{cases}$$

Equation 7-2: Taken from Barberis et al. (2016)

The decision weights ω+ and ω- are also constructed using the standard parameters shown in Equation 7-3, which are taken from Tversky and Kahneman (1992) as γ=0.61 and δ=0.69. Barberis et al. (2016) experiment with other parameter values but find that the standard parameters work as well as any others.

$$\omega^{+}(\mathrm{P}) = \frac{P^{\gamma}}{(P^{\gamma} + (1-P)^{\gamma})^{1/\gamma}}$$

$$\omega^{-}(\mathrm{P}) = \frac{P^{\delta}}{(P^{\delta} + (1-P)^{\delta})^{1/\delta}}$$

Equation 7-3: Taken from Barberis et al. (2016)

7.2 Adjustments to the Model

The adjustment that we make to the model is through the value function (v[x]) and specifically in the calculation of x. In Barberis et al. (2016), x is calculated as the stock return (r) for the month minus the return of the benchmark for the month (b). As a robustness check, they also use a version of TK with x calculated using raw returns or returns minus a risk-free rate and find similar results to the benchmark return version.

In our model, we calculate x as the percentage difference between the current monthly price and the reference point, as shown in Equation 7-4. This reference point could take a number of different values of which we will explore further below. In essence then, we replace the benchmark return with alternative reference points.

$$x_t = \frac{(p_t - ref_t)}{p_t}$$

Equation 7-4: Calculation of value using reference point

In addition to the standard TK variable as calculated in Barberis et al. (2016), we create 5 additional TK variables based on alternative reference points (ref) shown in Table 7-1. The first salient point is the average price, which is used to calculate TK_Average. TK_Max and TK_Min are calculated using the running maximum or minimum price up to that month in the 60-month series. TK_52max and TK_52min are calculated using the running maximum or minimum over the last year only. For the first 12 months, they will be the same as TK_Max and TK_Min.

TK Variable	Reference Point
TK_Average	Average price
TK_Max	maximum price
TK_Min	minimum price
TK_52max	52-week maximum
TK_52min	52-week minimum

Table 7-1: Alternative TK Variables

In addition to the alternative TK variables, calculated using a single reference point, we also calculate alternative TK variables using a combination of reference points. This is because Chapter 6 demonstrated that a number of salient points are relevant in the formation of the reference point. In Chapter 6, we show that the purchase and final prices are the most important determinants of the reference point, in a context where investors are evaluating a sequential reference point every month. To reflect this, Ref_Com1 shown in Equation 7-5, uses a mix of the purchase and final price with a greater weight given to the final price. The experiment also showed that the maximum plays a small, but significant, role in reference point formation. To take account of the role of the maximum, Ref_Com2 gives a small weight to the maximum price. Ref_Com1 and Ref_Com2 are used to calculate two combination based

TK variables, TK_Com1 and TK_Com2 with weights taken from Table 6-9 of Chapter 6.

$$Ref\_Com1 = 0.33 * purchase + 0.66 * final$$
$$Ref\_Com2 = 0.3 * purchase + 0.65 * final + 0.05 * maximum$$

Equation 7-5: Combination Reference Points

7.3 Data and Method

The market data sample comprises all US common Stocks (stock codes 10 &11 from CRSP) from 31 July 1931 until 31 Dec 2010. NYSE, Amex and NASDAQ firms are included (exchange codes 1, 2 and 3). No liquidity screening is carried out in this section, as it is not undertaken in Barberis et al. (2016). Calculation of TK and all the alternative TK variables require a full 60 months of data.

We include the following controls from the paper Barberis et al. (2016): *Mom-* is price momentum defined as the percentage return over the last 12 month excluding the last 2 months, Size- is the log of market capitalisation (stock price*shares outstanding) in units of millions, *Rev-* is short-term reversal defined as the percentage return last month, Ltrev- is long-term reversal defined as the percentage return over the last 5 years excluding the last year, Ivol- is idiosyncratic volatility calculated using the Fama-French 3 factor model with 1 year of daily data (min 6 months to be reported non-missing) and Beta- calculated using Fama-French 3 factor model with 1 year of daily data (min 6 months to be reported non-missing).

Mom, Rev and Ltrev are the standard variables constructed using past returns to explain future returns. Size is included as a control variable for firm size. Ivol and Beta are included as two common measures of firm volatility. It has been demonstrated that share price returns have a negative relation to return volatility (Ang et al., 2006) and Beta (Frazzini and Pedersen, 2014). The two volatility controls are there to ensure that the TK variable is not simply acting as a proxy for volatility either in the form of idiosyncratic volatility or volatility that is correlated to the market return in the form of beta.

Descriptive Statistics

Table 7-2 shows descriptive statistics for the independent TK variables and the control variables: Mom, Rev, Ltrev, Size, Beta and Ivol. TK_max can only ever take a negative value as each month's price is subtracted from the running maximum over the 5-year period. Conversely, the TK_min variable can only take a positive value. The combination TK variables, TK_com1 and TK_com2, have negative mean values, along with the original TK variable.

Figure 7-1 shows the stock IBM (ticker IBM) during a rising market. Over the 5-year period, June 94-June 99, the adjusted share price of IBM increased from under $20 per share to around $130. For this 5-year horizon period, the original TK variable takes a value of -0.02. TK_min takes on a positive value of 0.50, however, as the share price never falls below its purchase price, which is also the minimum. The lowest value is provided by TK_Max, with a negative value of -0.15. This is because the share price is constantly making new highs due to the rising trend in the price but it sometimes dips below these highs in subsequent months. The combination variables, TK_Com1 and TK_Com2, are in the middle of the range, with TK_com1 taking a value of 0.20 and TK_Com2 taking a value of 0.17.

Table 7-2: Descriptive Statistics for Returns and Control Variables

	TK	TK_Average	TK_Max	TK_Min	TK_52Max	TK_52Min	TK_Com1	TK_Com2	Mom	Rev	Ltrev	Size	Ivol	Beta
Mean	-0.052	-0.486	-1.761	0.289	-0.752	0.192	-0.307	-0.384	0.140	0.014	0.803	11.008	0.023	1.003
Max	0.167	0.338	-0.086	0.672	-0.083	0.399	0.258	0.214	5.866	1.411	26.833	17.159	0.262	3.939
Min	-0.180	-24.441	-90.239	0.056	-7.083	0.050	-25.961	-28.387	-0.724	-0.474	-0.880	6.049	0.002	-1.432
SD	0.029	1.018	3.150	0.103	0.541	0.056	0.935	1.017	0.424	0.118	1.597	1.835	0.019	0.535

Notes: Descriptive statistics for independent and control variables. All number presented are the time-series average of the cross-sectional statistics. TK=Prospect Theory value of a stock (Barberis et al., 2016), TK_average=TK value calculated using average price, TK_max=TK value calculated using maximum price, TK_min=TK value calculated using minimum price, TK_yearmax=TK value calculated using 52-week maximum, TK_yearmin=TK value calculated using 52-week minimum, TK_com1=TK value calculated using 33% purchase price & 66% final price, TK_com2=TK value calculated using 30% purchase price/65% final price & 5% max price. Mom=12month momentum excluding latest 2 months, Rev=return past month, Ltrev=5 year return excluding the last year, Size=market capitalisation in log (millions), Beta=beta calculated using 3 factor returns over last year, Ivol=Idiosyncratic volatility calculated using 3 factor model over the last year.

	TK	TK_Average	TK_Max	TK_Min	TK_52Max	TK_52Min	TK_Com1	TK_Com2	Mom	Rev	Ltrev	Size	Ivol	Beta
TK	1.00	0.62	0.52	0.45	0.53	0.28	0.56	0.57	0.31	0.11	0.56	0.36	-0.31	-0.02
TK_Average	0.62	1.00	0.91	0.31	0.78	0.10	0.86	0.89	0.11	0.01	0.45	0.34	-0.38	-0.09
TK_Max	0.52	0.91	1.00	0.09	0.85	-0.11	0.83	0.87	0.10	0.01	0.30	0.38	-0.44	-0.13
TK_Min	0.45	0.31	0.09	1.00	-0.04	0.88	0.33	0.31	0.10	0.00	0.62	0.03	0.05	0.28
TK_52Max	0.53	0.78	0.85	-0.04	1.00	-0.30	0.65	0.69	0.14	0.02	0.29	0.47	-0.52	-0.25
TK_52Min	0.28	0.10	-0.11	0.88	-0.30	1.00	0.14	0.12	0.20	0.01	0.48	-0.14	0.22	0.37
TK_Com1	0.56	0.86	0.83	0.33	0.65	0.14	1.00	1.00	0.04	0.00	0.42	0.28	-0.31	-0.04
TK_Com2	0.57	0.89	0.87	0.31	0.69	0.12	1.00	1.00	0.05	0.00	0.42	0.30	-0.33	-0.05
Mom	0.31	0.11	0.10	0.10	0.14	0.20	0.04	0.05	1.00	0.02	-0.01	0.11	-0.10	-0.01
Rev	0.11	0.01	0.01	0.00	0.02	0.01	0.00	0.00	0.02	1.00	-0.01	0.04	0.13	0.00
Ltrev	0.56	0.45	0.30	0.62	0.29	0.48	0.42	0.42	-0.01	-0.01	1.00	0.20	-0.13	0.03
Size	0.36	0.34	0.38	0.03	0.47	-0.14	0.28	0.30	0.11	0.04	0.20	1.00	-0.49	0.10
Ivol	-0.31	-0.38	-0.44	0.05	-0.52	0.22	-0.31	-0.33	-0.10	0.13	-0.13	-0.49	1.00	0.05
Beta	-0.02	-0.09	-0.13	0.28	-0.25	0.37	-0.04	-0.05	-0.01	0.00	0.03	0.10	0.05	1.00

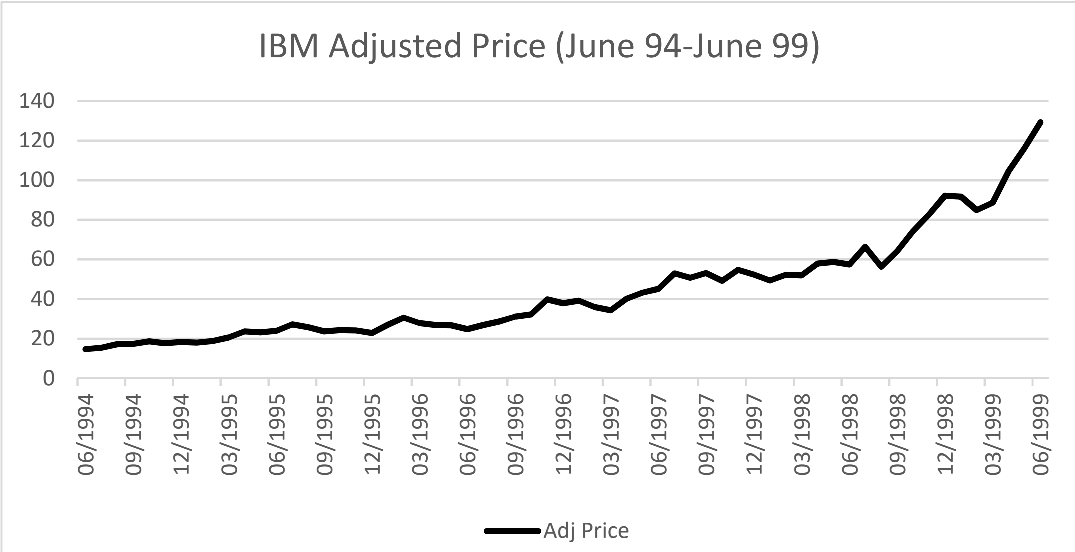


Figure 7-1: IBM Adjusted Price- Rising Market

Figure 7-2 shows the IBM share price during a falling share price. TK_Min is now the TK variable with the highest value of 0.18, and TK_max takes a value of -0.9. The combination variables, TK_com1 and TK_com2, are again the middle of the range with values of -0.27 and -0.32 respectively. The original TK variable of Barberis et al. (2016) takes a value of -0.06, as there is a mix of positive and negative returning months.

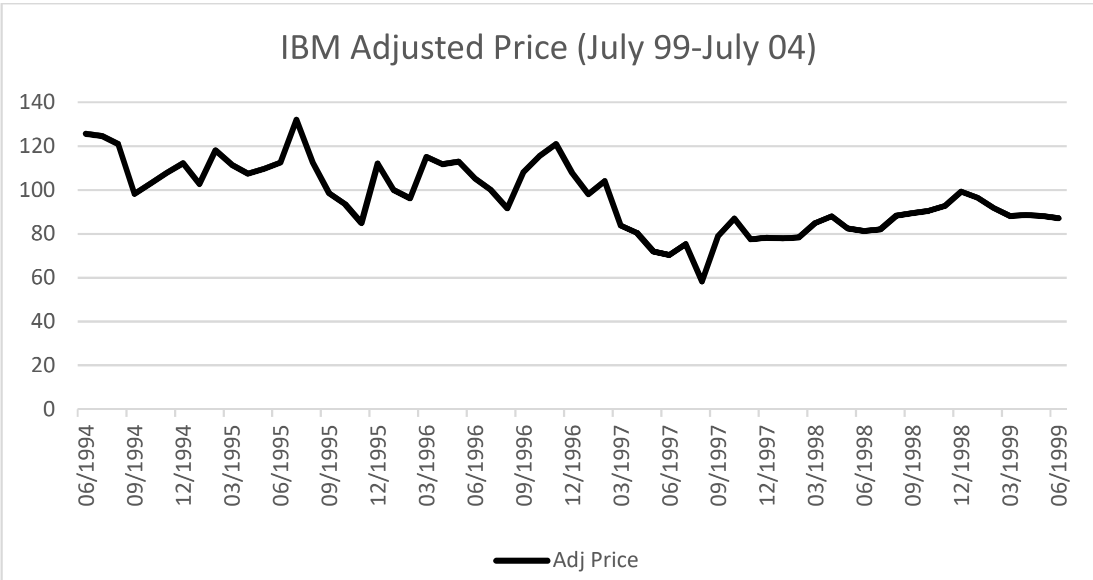


Figure 7-2: IBM Adjusted Price- Falling Market

Regression of One-Month Ahead Returns against TK Variables

In this section, we regress one month ahead returns against the original TK variable and the alternative TK variables, to see if the alternative TK variables have more predictive power. The Fama-Macbeth method (Fama and MacBeth, 1973) of regression is used and standard errors are corrected using the Newey-West method (Newey and West, 1987) with a lag length of 12. This parameter is chosen to mirror the approach in Barberis et al. (2016).

The following 6 regressions in Table 7-3 using 1 month ahead returns as the dependent variable and various specifications of the TK variables, along with the control variables, as shown in Equation 7-6. Model A uses the original TK variable, calculated using the same method as in Barberis et al. (2016), while the remaining 5 models use the alternative TK variables calculated using different reference points.

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \varepsilon \quad \text{(A)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Average_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \varepsilon \quad \text{(B)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Max_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \varepsilon \quad \text{(C)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Min_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \varepsilon \quad \text{(D)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_52max_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \varepsilon \quad \text{(E)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_52min_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \varepsilon \quad \text{(F)}$$

Equation 7-6: Regression Equations- TK Models

Table 7-3: Regression of 1 Month Ahead Returns using TK Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
TK	-0.0626***					
	(-3.104)					
TK_Average		-0.00275***				
		(-2.814)				
TK_Max			-0.000777			
			(-1.308)			
TK_Min				-0.000215		
				(-0.0432)		
TK_52Max					-0.00171	
					(-1.055)	
TK_52Min						-2.54e-05
						(-0.00221)
Rev	-0.0789***	-0.0799***	-0.0800***	-0.0808***	-0.0806***	-0.0812***
	(-15.00)	(-14.68)	(-14.77)	(-15.12)	(-14.94)	(-15.27)
Mom	0.0101***	0.00884***	0.00846***	0.00842***	0.00890***	0.00822***
	(6.536)	(5.162)	(4.729)	(4.583)	(5.593)	(4.387)
Ltrev	-0.000512	-0.000732	-0.000962	-0.00171**	-0.00108**	-0.00172**
	(-0.842)	(-1.419)	(-1.842)	(-2.078)	(-2.381)	(-2.266)
Size	-0.0014***	-0.00149***	-0.0015***	-0.0016***	-0.0015***	-0.0017***
	(-4.438)	(-4.501)	(-4.585)	(-4.664)	(-4.836)	(-4.896)
Ivol	-0.0343	-0.0504	-0.0547	-0.0247	-0.0416	-0.0307
	(-0.870)	(-1.389)	(-1.623)	(-0.621)	(-1.299)	(-0.840)
Beta	0.000896	0.000527	0.000370	0.000809	0.000296	0.000745
	(1.020)	(0.602)	(0.411)	(0.878)	(0.369)	(0.894)
Constant	0.0232***	0.0272**	0.0270***	0.0290***	0.0268***	0.0297***
	(5.604)	(6.115)	(6.250)	(6.615)	(6.496)	(7.113)
Observations	1,880,175	1,880,175	1,880,175	1,880,175	1,880,175	1,880,175
Number of groups	953	953	953	953	953	953
Average R^2	0.0827	0.0850	0.0854	0.0827	0.0872	0.0865

Regression of 1 month forward returns against TK variables and control variables. DV= 1 month ahead returns, TK= convention TK variable, TK_Average= TK calculated using average price, TK_Max= TK calculated using maximum price, TK_Min= TK calculated using the minimum price, TK_52Max= TK calculated using the 52-week maximum, TK_52Min= TK calculated using the 52-week minimum. Rev=1 month reversal, Mom=12month return excluding last month, Ltrev= 5 year return excluding last year, Size= market cap in log(millions), Ivol= Idiosyncratic volatility, Beta= 3 year beta calculated using Fama-French 3 factor model. T-statistics in parentheses, calculated using Newey-West Standard Errors.
*** p<0.01, ** p<0.05.

Model A shows that the original TK variable is significant at the 1% level, along with the Rev, Mom and Size control variables. In Model B, the TK variable is replaced by TK_Average, which is calculated using the average price. TK_Average is significant at the 1% level and the r-squared of this model is higher than Model A. In the remaining Models C to F, none of the alternative TK variables, using Max/Min or 52max/52min, are significant although they all have negative coefficients. In summary, the results suggest that as a standalone variable, the original TK variable and TK variable based on the average price, TK_Average, are the ones that are predictive of future returns. In may be the case, however, that alternative TK variables have more explanatory power when they are used in combination, which we explore in the next table using the TK composite variables.

Table 7-4 uses the composite TK variables as independent variables in the regressions, as shown in Equation 7-7. Model A uses the original TK variable for comparison purposes. Model B replaces TK with TK_com1, while Model C replaces TK with TK_com2. Model D adds the TK_Com1 independent variable to Model A. This is to check if it is a more important predictor than TK. Model E adds the TK_Com2 variable instead of TK_Com1 to Model A. Finally, Model F features both TK combination variables in the model to check which one is the dominant predictor of future returns.

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6 Ivol_t + \beta_7 Beta + \mathcal{E} \quad \text{(A)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Com1_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6 Ivol_t + \beta_7 Beta + \mathcal{E} \quad \text{(B)}$$

$$Ret_{t+1} = \beta_0 + \beta_1 \boldsymbol{TK\_Com2_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6 Ivol_t + \beta_7 Beta + \mathcal{E} \quad \text{(C)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK_t} + \boldsymbol{\beta_2 TK\_Com1_t} + \beta_3 Rev_t + \beta_4 Mom_t + \beta_5 LTRev_t + \beta_6 Size_t + \beta_7 Ivol_t + \beta_8 Beta + \mathcal{E} \quad \text{(D)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK_t} + \boldsymbol{\beta_2 TK\_Com2_t} + \beta_3 Rev_t + \beta_4 Mom_t + \beta_5 LTRev_t + \beta_6 Size_t + \beta_7 Ivol_t + \beta_8 Beta + \mathcal{E} \quad \text{(E)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Com1_t} + \boldsymbol{\beta_2 TK\_Com2_t} + \beta_3 Rev_t + \beta_4 Mom_t + \beta_5 LTRev_t + \beta_6 Size_t + \beta_7 Ivol_t + \beta_8 Beta + \mathcal{E} \quad \text{(F)}$$

Equation 7-7: Regression Equations

Table 7-4: Regressions of Monthly Returns Using Combination TK Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
TK	-0.0626**			-0.0348	-0.0317	
	(-3.104)			(-1.816)	(-1.678)	
TK_Com1		-0.00312*		-0.00260*		0.00397
		(-2.391)		(-2.019)		(0.279)
TK_Com2			-0.00311*		-0.00270*	-0.00644
			(-2.388)		(-2.053)	(-0.450)
Rev	-0.0789**	-0.0804**	-0.0803**	-0.0800**	-0.0800**	-0.0801**
	(-15.00)	(-14.71)	(-14.70)	(-14.84)	(-14.82)	(-14.87)
Mom	0.0101**	0.00847**	0.00849**	0.00941**	0.00935**	0.00845**
	(6.536)	(4.772)	(4.790)	(6.029)	(5.999)	(4.725)
Ltrev	-0.000512	-0.000864	-0.000816	-0.000346	-0.000337	-0.000846
	(-0.842)	(-1.701)	(-1.612)	(-0.686)	(-0.672)	(-1.645)
Size	-0.00141**	-0.00155**	-0.00153**	-0.00144**	-0.00143**	-0.00148**
	(-4.438)	(-4.558)	(-4.556)	(-4.596)	(-4.595)	(-4.535)
Ivol	-0.0343	-0.0445	-0.0475	-0.0469	-0.0492	-0.0546
	(-0.870)	(-1.214)	(-1.309)	(-1.299)	(-1.375)	(-1.587)
Beta	0.000896	0.000929	0.000844	0.000884	0.000817	0.000345
	(1.020)	(1.034)	(0.942)	(1.011)	(0.935)	(0.361)
Constant	0.0232**	0.0276**	0.0274**	0.0249**	0.0249**	0.0270**
	(5.604)	(6.139)	(6.138)	(5.974)	(5.992)	(6.198)
Observations	1,880,175	1,878,930	1,878,930	1,878,930	1,878,930	1,878,930
Number of groups	953	953	953	953	953	953
Average R^2	0.0827	0.0835	0.0838	0.0871	0.0873	0.0884
Adjusted R^2	0.0773	0.0781	0.0784	0.0809	0.0811	0.0822

Notes: Regression of 1 month forward returns against TK variables and control variables. DV= 1 month ahead returns, TK= convention TK variable, TK_com1 & TK_com2 calculated using the composite reference points Ref1 or Ref2. Rev=1 month reversal, Mom=12month return excluding last month, Ltrev= 5 year return excluding last year, Size= market cap in log(millions), Ivol= Idiosyncratic volatility, Beta= 3 year beta calculated using Fama-French 3 factor model. T-statistics in parentheses, calculated using Newey-West Standard Errors.
** p<0.01, * p<0.05.

In Models B and C, both TK_Com1 and TK_Com2 are significant predictors of returns when they are included in the regression and both models have a higher r-squared than Model A. When the TK_Com1 variable is added to Model A in Model D, the original TK variable is no longer significant. The coefficient on TK_Com1, however, is significant at the 5% level. The story is the same for Model E which features TK_Com2. When TK_com2 is added to Model A it is significant at the 5% level, but TK again moves from being significant at the 1% level to be insignificant. Both Models D and E have a higher r-squared and higher adjusted R-squared than Model A. Model F includes both TK_Com1 and TK_Com2 together in the same regression to check which one of them is the best predictor of returns but its results are inconclusive. Neither of the TK_Com variables are significant when both are included in the same regression suggesting shared variance between them, although TK_Com2 does retain the expected sign. The results suggest that the TK Com variables are better predictors of returns than the TK variable. Next as an extra check, we look at how TK, TK_Com1 and TK_Com2 perform when used to sort portfolios into deciles in the next section.

Decile Sorted Portfolio Analysis

In this section, we perform decile sorts across the TK and composite TK variables. The purpose of the sorts is to confirm that the variables are predictive of returns when used to select stocks. Portfolio sorts are less affected by noise and outliers than regression analysis, due to individual stock diversification across quintile portfolios, and a linear relationship between the sorting variable and dependent variable does not have to be assumed.

In Table 7-5 stocks are sorted each month based on their TK values. High TK stocks are placed into TK Decile 10 and the lowest decile stocks based on TK are placed into TK Decile 1. There are a broadly equal number of stocks placed into each decile and stocks are equally weighted. The associated t-statistics are calculated using Newey-West adjustment to mirror the previous analysis. The difference portfolio (10-1) reflect the performance of a portfolio of stocks that go long Decile 10 stocks and short Decile 1 stocks.

We see an almost monotonic relationship between TK and portfolio returns in practice, although the relationship is not linear as shown in Figure 7-3. There is a big premium for investing in stocks with a low TK value in TK Decile 1, with a shallow rate of decline after that. The difference portfolio calculated as the difference between TK deciles 10 and 1 is negative and significant, with a t-statistic close to 4.

Table 7-5: Decile Portfolios Sorted by TK

	ret	t	obs
1(loser)	0.024808	5.375287	189311
2	0.016075	4.98956	189785
3	0.014717	5.248637	189684
4	0.013925	5.262194	189794
5	0.012944	5.51676	189887
6	0.013012	5.602316	189597
7	0.012315	5.796171	189696
8	0.012217	5.880676	189783
9	0.011984	5.582943	189686
10(winner)	0.011073	4.597516	190164
diff(10-1)	-0.01374	-3.89312	

Table showing monthly average returns of sorted stocks. Portfolios sorted into 10 equal groups every month by TK. Stocks equally weighted and rebalanced monthly. T-statistics use Newey-West adjustment (1 lag).

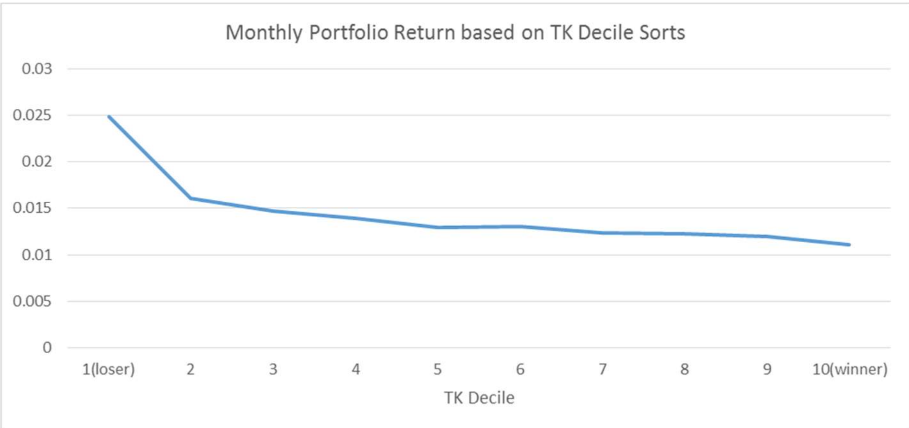


Figure 7-3: Monthly Portfolio Returns by TK Decile

Notes: Figure shows the monthly average returns of stocks sorted by TK decile. Stocks are equally weighted and rebalanced monthly. Data is taken from Table 7-5 above.

Now turning to decile sorts involving the alternative TK variables, TK_Com1 and TK_Com2, both Table 7-6 and Table 7-7 show that the alternative TK variables have a similar relationship with returns as the original TK variable.

Both sets of portfolios display a similar pattern of returns with the first 2 decile portfolios having the highest return and then a slower decline in return through the remaining decile portfolios. The difference portfolios between deciles 10 and 1 sorted by both TK_Com1 and TK_Com2 are again significant with a high t-statistic.

Table 7-6: Decile Portfolios Sorted by TK_Com1

	ret	t	obs
1(loser)	0.022521	5.311208	189184
2	0.017003	5.036573	189651
3	0.014608	5.04048	189566
4	0.013824	5.281447	189666
5	0.013377	5.525383	189762
6	0.013416	5.522731	189467
7	0.012649	5.773025	189564
8	0.012879	5.983459	189668
9	0.012292	5.8831	189549
10(winner)	0.010435	4.619904	190046
diff(10-1)	-0.01209	-3.76304	

Table showing monthly average returns of sorted stocks. Portfolios sorted into 10 equal groups every month by TK_Com1. Stocks equally weighted and rebalanced monthly. T-statistics use Newey-West adjustment (1 lag).

Table 7-7: Decile Portfolios Sorted by TK_Com2

	ret	t	obs
1(loser)	0.022757	5.325572	189184
2	0.016811	4.850588	189651
3	0.014894	4.924374	189566
4	0.013816	5.287848	189666
5	0.013465	5.399635	189762
6	0.013517	5.587727	189467
7	0.012371	5.793716	189564
8	0.013013	6.052531	189668
9	0.012068	5.972855	189549
10(winner)	0.010315	4.827663	190046
diff(10-1)	-0.01244	-3.69994	

Table showing monthly average returns of sorted stocks. Portfolios sorted into 10 equal groups every month by TK_Com2. Stocks equally weighted and rebalanced monthly. T-statistics use Newey-West adjustment (1 lag).

The results suggest that both the original TK variable and the alternative TK variables are predictive of future returns. This suggests that both a benchmark based reference point used in the original TK variable and a reference point based on the prior price path, used in the combination TK variables, are valid ways of sorting portfolios. In all three cases, we see a non-linear relationship with a big premium for investing in the worst looking stocks in Decile portfolio 1 and the rate of change slows down after passing the 2^{nd} decile portfolio, suggesting that a big component of the TK premium is driven by high returns from undesirable stocks (as proxied by a low TK value).

TK Using a Lagged Reference Point

In Chapter 6 we explore the idea of lagged reference points where each reference point is a function of the last period (lagged) reference point. The aim of this section is to check if a lagged reference point model has superior predictive power than the original TK variable.

We use the coefficients from the last Chapter to create two new TK variables, with values being partly dependent on the lagged reference point. The reference points for the two new variables are shown below in Equation 7-8. The Ref_Lag variable uses weights derived from the point regression (Table 6-15) in Chapter 6, which gives a large weight to the final price and previous reference point and a smaller role to the purchase price. The reference point based on the percentage model (Table 6-17), Ref_Difflag, gives a large weight to the difference between the final reference point and the previous price and only a small weight to the difference between the final price and the purchase price. For both equations, we have no lagged reference point during the first month, so we use the first price available as the lagged reference point for this month, which is the purchase price. The two lagged reference points are then used to calculate two new alternative TK variables, TK_Lag and TK_Difflag, by placing the reference points into Equation 7-4.

$$Ref\_Lag_m = 0.1 * Purchase_{m=1} + 0.55 * Ref_{m-1} + 0.35 * Final_m$$

$$Ref\_Difflag_m = 1.011 * Final_m - 0.923 * (Final_m - Ref_{m-1}) - 0.03 * (Final_m - Purchase_{m=1})$$

$$where\ Ref_0 = Purchase$$

Equation 7-8: Reference Point Equations

Now that the TK variables based on the lagged reference points have been defined, we undertake regressions with the new variables. Table 7-8 shows the results of the four regression equations shown below. Model A uses the TK_Lag variable to check if it is significant, while Model B uses the TK_Difflag variable. Then Models C and D check whether the TK_Lag and TK_Difflag variables are still significant when the original TK variable is added to the regression.

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Lag_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \mathcal{E} \quad \text{(A)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Difflag_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \mathcal{E} \quad \text{(B)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Lag_t} + \boldsymbol{\beta_2 TK_t} + \beta_3 Rev_t + \beta_4 Mom_t + \beta_5 LTRev_t + \beta_6 Size_t + \beta_7\, Ivol_t + \beta_8\, Beta + \mathcal{E} \quad \text{(C)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Difflag_t} + \boldsymbol{\beta_2 TK_t} + \beta_3 Rev_t + \beta_4 Mom_t + \beta_5 LTRev_t + \beta_6 Size_t + \beta_7\, Ivol_t + \beta_8\, Beta + \mathcal{E} \quad \text{(D)}$$

Model A shows that the TK_Lag variable is significant at the 5% level, while Model B suggests that TK_Difflag is also significant at the 5% level. Both models have a similar r-squared. Only Models C and D can tell us if they are significant when the original TK variable is added to the regression. In Model C the TK_Lag variable is still significant when TK is added to the regression and TK is insignificant. Finally, Model D suggests that neither TK_Difflag nor TK is significant when they are both included in the model.

Table 7-8: Regressions of Monthly Returns against TK Variables using Lagged Reference Points

VARIABLES	Model A	Model B	Model C	Model D
TK_Lag	-0.00442**		-0.00380**	
	(-2.475)		(-2.043)	
TK_Difflag		-0.00190**		-0.00152
		(-2.400)		(-1.838)
TK			-0.0330	-0.0341
			(-1.701)	(-1.802)
Rev	-0.0803***	-0.0803***	-0.0800***	-0.0800***
	(-14.71)	(-14.71)	(-14.84)	(-14.83)
Mom	0.00853***	0.00866***	0.00940***	0.00948***
	(4.816)	(4.936)	(6.021)	(6.052)
Ltrev	-0.000826	-0.000765	-0.000326	-0.000295
	(-1.631)	(-1.541)	(-0.648)	(-0.596)
Size	-0.0015***	-0.0015***	-0.0014***	-0.0014***
	(-4.554)	(-4.557)	(-4.596)	(-4.577)
Ivol	-0.0459	-0.0453	-0.0480	-0.0476
	(-1.264)	(-1.245)	(-1.339)	(-1.326)
Beta	0.000875	0.000824	0.000832	0.000793
	(0.979)	(0.927)	(0.953)	(0.909)
Constant	0.0274***	0.0270***	0.0248***	0.0245***
	(6.141)	(6.105)	(5.979)	(5.938)
Observations	1,878,930	1,878,930	1,878,930	1,878,930
Number of groups	953	953	953	953
Average R^2	0.0837	0.0839	0.0872	0.0874

Notes: Regression of 1 month forward returns against TK variables with lag and control variables. DV= 1 month ahead returns, TK= convention TK variable, TK_Lag & TK_Difflag= TK variables calculated using a lagged ref point shown in Equation 7-8, Rev=1 month reversal, Mom=12month return excluding last month, Ltrev= 5 year return excluding last year, Size= market cap in log(millions), Ivol= Idiosyncratic volatility, Beta= 3 year beta calculated using Fama-French 3 factor model. T-statistics in parentheses, calculated using Newey-West Standard Errors.
*** p<0.01, ** p<0.05.

The results suggest that TK_Lag, from Models A and C, is the best variable for modelling lagged reference points. There is little evidence, however, to suggest that the TK lag variable is better than the composite TK variables, TK_Com1 and TK_Com2. Comparing the results here to those in Table 7-4, TK_Lag as a standalone variable does not have a higher R-squared than the composites used as standalones (shown in Models B & C), nor does the model including both TK_Lag and TK have a higher r-squared than those including the composites and TK (shown in Models E & F). In summary then, our composite variables: TK_Com1 and TK_Com2 have the same or stronger explanatory power than the models including lagged reference points and in addition, they are easier to calculate.

TK using an End Period Reference Point

The result from the first experiment in Chapter 3 assumes that investors only form one reference point from the entire chart presented to them, rather than one reference point every month. It is, therefore, possible that investors do not form 60 monthly reference points when assessing the desirability of a stock, as we assumed in Chapter 6, but only a single reference point formed by observing the price chart as a whole. If the single reference point assumption is valid then we would expect TK variables formed from these points to be superior to the multi-stage ones we tested in Table 7-4.

The best predictor of the single reference point, based on the results of Chapter 3, is shown in Equation 7-9. The CGO variable is calculated as the percentage deviation between the reference point in question and the final price e.g. CGOMax52 is the percentage deviation between the final price and the 52-week maximum. Therefore, we can multiply both sides by the final price and re-arrange the equation to produce a predictor for the reference point using a mix of final, max, min, max52 and min52 prices. The re-arranged version is shown in Equation 7-9, where the reference point can be calculated using a mix of final, purchase, max, min, max52 and min52 variables, taken from the final month (t=60).

$$CGOCom2 = (26\% * CGO) + (28\% * CGOMax52) + (13\% * CGOMin52) + (24\% * difCGOMax) + (9\% * difCGOMin)$$

$$Reference = Final_{t=60} - 26\% * (Final_{t=60} - Purchase_{t=0}) - 28\% * (Final_{t=60} - Max52_{t=60}) - 13\% * (Final_{t=60} - Min52_{t=60}) - 24\% * (Max52_{t=60} - Max_{t=60}) - 9\% * (Min52_{t=60} - Min_{t=60})$$

Equation 7-9: Reference Point Equation from Chapter 3

While we can calculate the end reference point for each chart, at month (t=60), this raises the question of how the investor applies the reference point across the whole 60 months within the chart? There are 2 possible ways to spread the reference point across the months, either using a linear method or compounding. The linear method assumes a linear increase in the reference point, starting at the purchase price, from months (t) 1 to 60, shown in Equation 7-10. The reference point begins at the purchase price and gradually moves towards the end reference point in a linear manner. Each month moves the reference point an additional 1/60 of the way from the purchase price to the reference point.

$$Reference_m = \frac{60-t}{60} * Purchase_{t=0} + \frac{t}{60} * Reference_{t=60}$$

Equation 7-10: Linear Reference Point Adjustment

The other alternative is that the reference point adjusts in an exponential manner. Equation 7-11 reflects how the reference point would move if the investor moved in a geometric manner from the purchase price to the final reference point across the 60 months. This method is consistent with the one used by Nolte and Schneider (2018).

$$Reference_m = Purchase_{t=0} * \left[1 + \left(\frac{Reference_{t=60} - Purchase_{t=0}}{Purchase_{t=0}}\right)\right]^{t/60}$$

Equation 7-11: Exponential Reference Point Adjustment

With the equation for the end month reference point now defined and two possible mechanisms for how the reference point may adjust over the 60 months, we now repeat the regressions of the last section using the TK variables that are calculated using the end period reference points, rather than separate reference points every month. We define two new variables: TK_Linear, which uses the linear method of reference point adjustment and TK_Exp, which uses the exponential method of adjustment.

The following four regressions in Table 7-9 are based on the four equations in Equation 7-12. Model A uses TK_Linear, while Model B replaces TK with TK_Exp. Models C and D check the significance of the original TK variable when the alternative TK variables are added to the regression. Therefore, Model C adds the original TK variable to Model A and Model D adds the original TK variable to Model B.

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Linear_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \mathcal{E} \qquad \text{(A)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Exp_t} + \beta_2 Rev_t + \beta_3 Mom_t + \beta_4 LTRev_t + \beta_5 Size_t + \beta_6\, Ivol_t + \beta_7\, Beta + \mathcal{E} \qquad \text{(B)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Linear_t} + \boldsymbol{\beta_2 TK_t} + \beta_3 Rev_t + \beta_4 Mom_t + \beta_5 LTRev_t + \beta_6 Size_t + \beta_7\, Ivol_t + \beta_8\, Beta + \mathcal{E} \qquad \text{(C)}$$

$$Ret_{t+1} = \beta_0 + \boldsymbol{\beta_1 TK\_Exp_t} + \boldsymbol{\beta_2 TK_t} + \beta_3 Rev_t + \beta_4 Mom_t + \beta_5 LTRev_t + \beta_6 Size_t + \beta_7\, Ivol_t + \beta_8\, Beta + \mathcal{E} \qquad \text{(D)}$$

Equation 7-12: Regression Equations- Single Point Reference Prices

Turning now to the results, Model A shows that the TK_Linear variable is significant at the 5% level, but Model B suggests that TK_Exp is not significant. This provides some evidence that the linear adjustment method works better than exponential, which is perhaps down to the complexity of compounding. To check how good the variables are at explaining returns relative to the original TK variable, we turn to Models C and D. When TK is included in the regression with TK_Linear in Model C, TK_Linear is no longer significant but TK is significant at the 5% level. It is a similar story in Model D where TK_Exp is no longer significant but TK is significant at the 5% level. The results suggest that the TK variables using an end period reference point are not very good predictors relative to the original TK variable. They perform poorly in comparison with the alternative TK variables calculated using monthly adjusting reference points, as they are not significant when original TK is added to the regression. The results suggest that our earlier models TKCom1 and TKCom2 that use reference points calculated every month, as assumed in Chapter 6, are a better approximation of true TK than the TK variables that use only a single reference point, as calculated in Chapter 3.

Table 7-9: Regressions of Monthly Returns against TK Variables using End Reference Point

VARIABLES	Model A	Model B	Model C	Model D
TK_Linear	-0.00129**		-0.000987	
	(-2.062)		(-1.555)	
TK_Exp		-0.00128		-0.000906
		(-1.881)		(-1.309)
TK			-0.0401**	-0.0409**
			(-2.160)	(-2.208)
Rev	-0.0808***	-0.0808***	-0.0801***	-0.0801***
	(-14.75)	(-14.73)	(-14.84)	(-14.80)
Mom	0.00814***	0.00816***	0.00921***	0.00925***
	(4.573)	(4.587)	(5.825)	(5.864)
Ltrev	-0.00100**	-0.000950	-0.000439	-0.000391
	(-1.969)	(-1.858)	(-0.878)	(-0.780)
Size	-0.0015***	-0.0015***	-0.0014***	-0.0014***
	(-4.571)	(-4.579)	(-4.535)	(-4.543)
Ivol	-0.0438	-0.0448	-0.0476	-0.0485
	(-1.218)	(-1.248)	(-1.343)	(-1.367)
Beta	0.000790	0.000780	0.000745	0.000741
	(0.881)	(0.870)	(0.854)	(0.850)
Constant	0.0274***	0.0274***	0.0243***	0.0243***
	(6.160)	(6.170)	(5.904)	(5.887)
Observations	1,878,930	1,878,930	1,878,930	1,878,930
Number of groups	953	953	953	953
Average R^2	0.0841	0.0841	0.0875	0.0875

Notes: Regression of 1 month forward returns against TK variables with end period reference point and control variables. DV= 1 month ahead returns, TK= convention TK variable, TK_Linear & TK_Exp= TK variables calculated using end point reference point shown in Equation 7-10 or Equation 7-11, Rev=1 month reversal, Mom=12month return excluding last month, Ltrev= 5 year return excluding last year, Size= market cap in log(millions), Ivol= Idiosyncratic volatility, Beta= 3 year beta calculated using Fama-French 3 factor model. T-statistics in parentheses, calculated using Newey-West Standard Errors.
*** p<0.01, ** p<0.05.

7.4 Conclusion

Prior literature has shown that investor preference for skewness and high volatility stocks can produce mispricing e.g. Ang et al. (2006) or Kumar (2009). The Prospect Theory Value of a Stock Model developed by Barberis et al. (2016) is able to bring this literature together, by showing that investors evaluate stocks according to Prospect Theory rules. One consequence of the use of Prospect Theory is that returns must be measured relative to a reference point with Barberis et al. (2016) selecting the benchmark return as the relevant reference point. In this chapter, we explore how the Prospect Theory Value of a Stock model can be improved by introducing new reference points into the model.

The composite TK variables we formed, TK_Com1 and TK_Com2, have weights that are grounded in the experiment of Chapter 6. We carry out empirical testing of the new TK variables as predictors of future returns, which suggests that they are good predictors of future returns on a standalone basis. In addition, when the original TK variable is added to the regression, they remain significant at the 5% level while the original TK variable is insignificant. Our results, therefore, suggest that the TK variables calculated using a reference point from the prior price path can be used to replace the original TK variable.

We then examine the influence of lagged reference points. In Chapter 6, we found that lagged reference points play a role in the determination of the current reference point when participants are asked to provide sequential reference points across months. Under these circumstances, it seems that participants use the prior reference point as an anchor to form their current reference point. We form two models to replicate how an investor may use lagged reference points and create two new TK variables from the models. We find that the TK_Lag variable, which has a high weight to the lagged reference point and final price, is the most predictive. It remains significant at the 5% level, even when the TK variable is added to the regression. There was no evidence, however, that it performs better as a predictor than TK_Com1 and TK_Com2 and the composite reference points are easier to calculate. The results suggest that the composite based TK variables and the TK_lag variable are close substitutes for each other. Future research could examine the role of lagged reference points in more detail.

In the final section, we examine how the reference point formation process itself could influence the TK variable. A central assumption of Barberis et al. (2016) is that an investor evaluates a 5-year price chart as a series of 60 separate months. Our earlier experiment, however, in Chapter 3, looked at the formation of a single reference point formed from an entire chart, rather than a series of 60 separate months. We create two different TK variables based on the final-month reference point rather than 60 separate reference points and tested the significance of these variables. We find that neither variable is significant once the original TK variable is added to the regression. The results suggest that investors evaluate reference points across each of the 60 months separately, in line with Barberis et al. (2016) model.

Our previous work, using the CGO model, found that the single end-point model worked well within the context of that model and this is not necessarily a contradictory finding. The CGO model is attempting to model the behaviour of investors, who are looking to sell at a particular point in time and thus perform a one-time evaluation at that time, whereas the Prospect Theory of a Stock Model is attempting the model the preferences of an investor who is evaluating the return stream of a stock using 5 years of past price information. Therefore, it is possible that both approaches, monthly evaluation and end-point evaluation, are valid within their appropriate context.

7.4.1 Limitations and Future Research

Our results suggest that investors may form reference points based on both the prior price path and benchmark returns. However, we are not able to determine the weights that investors might assign to the different components under the current experimental framework. Future research could look to form reference points that incorporate both the benchmark return as Barberis et al. (2016) and the prior price path. A new experiment would be helpful in this regard to determine the amount of weight investors place in the benchmark return relative to past price information in their calculation of reference points.

Duxbury and Yao (2017) show that an investor's trading strategy differs based on whether they are a buyer or a seller and different reference point formation processes could play a role in these results. We have considered the case of an existing holder who holds a stock for 5 years and evaluates the investment on a monthly basis, but the results may not be universal to other situations. Future research could look to investigate if investors choose a different evaluation method for different contexts.

8 Conclusion

8.1 Discussion of Results

In this thesis, we use both experimental and empirical methods to examine the reference point adaptation of investors. Prior research in finance tends to adopt the purchase price as the reference point of investors and incorporates this assumption into financial models. We identify how reference points are formed from a composite of salient prices within the controlled conditions of two experiments and then the predictive power of these reference points are tested using several different asset pricing models.

Reference points of sellers are modelled using the Capital Gains Overhang (CGO) model of Grinblatt and Han (2005) and the V-Shaped Net Selling Propensity (VNSP) Model of An (2016), which require an experiment to be designed to capture the reference point of sellers at the point of sale. The reference points of investors assessing the desirability of a stock are modelled using the Prospect Theory Value of a Stock Model of Barberis et al. (2016), which requires an experiment that measures the reference points of investors across a 60 month period. Both experiments are designed to meet the specific criteria of the market data model in question.

In the first experiment, we study the formation of reference points when price sequences are viewed as a whole, rather than one price at a time, across a series of months. This design is adopted to mimic the environment that a seller might face in the market at the time of sale and hence provide a useful input into the CGO (Grinblatt and Han, 2005) and VNSP (An, 2016) models. We find that the purchase, maximum, minimum and final prices are significant determinants of the reference point, in line with the findings of Baucells et al. (2011). When we add 52-week variables into the model, we find that the purchase, 52-week high and 52-week low are significant determinants of the reference point. The importance of the 52-week variables is a new finding that is only possible because we use charts that are longer than a year in length; a method that is rare in the experimental literature. This reflects our emphasis on external validity within the design of the experiment. Our research shows that the recency effect discovered by George and Hwang (2004) is important for sellers, as we show that the 52-week variables are key prices that determine their reference point.

We also explore the effect of share price volatility on reference points and show that high volatility may inhibit reference point adaptation to the final price. The amount of maladaptation of the reference point to the final price is greater for share price charts which have higher volatility, in the form of higher price volatility. The emphasis on price, rather than return volatility, corroborates the findings of Duxbury and Summers (2018). These results may also shed light on Arena et al. (2008) who show that high volatility increases the magnitude of price momentum in share prices. The increase in momentum could be caused by a greater amount of reference point maladaptation in shares with higher volatility, although alternative hypotheses are also possible. For example, Da et al. (2014) suggest that more volatile price patterns attract more attention than less volatile ones, which could also drive price momentum.

In Chapters 4 & 5 we apply the results of the first experiment to two different asset pricing models. We show in Chapter 4 that the purchase price is not the only important salient reference point to consider within the context of the CGO model, as is commonly assumed. We construct alternative CGO variables formed from the maximum, minimum, 52-week maximum and 52-week minimum and show that these variables are just as predictive of future returns as the traditional CGO variable that uses the purchase price as a reference point. We then construct composite reference points using the weights determined in the previous experiment and plug these into the CGO model. We show that the CGO variables based on the composite reference points are better predictors of returns than the traditional CGO variable. Our results suggest that the reference points based on a composite of salient points in the experiment are a more accurate reflection of investor reference points than the purchase price, within the context of the CGO model, and this is why the composite variables are better predictors of future returns.

The role of turnover as a moderating variable is also examined. Grinblatt and Han (2005) suggest that current turnover is a key moderator of the CGO variable, which increases its predictive power. They construct a moderating variable, which is calculated by multiplying CGO by current week turnover and show that this has greater predictive power than CGO alone. We show that turnover improves the predictive power of both the traditional CGO and composite CGO variables. Future research could look to further examine the role of turnover as a moderator within the CGO model. Grinblatt and Han (2005) suggest that turnover works as a moderator because old investors, who bought at older reference points, are recycled out of the market, which brings the market price back in line with its fundamental value. It is possible, however, that high turnover stocks are more sensitive to the reference point for other reasons, such as high turnover stocks having a higher prevalence of overconfident investors (Statman et al., 2006). The interaction between turnover and volatility, within reference point adaptation, could also be considered within this context.

In Chapter 5, we apply the results of Experiment 1 to the VNSP asset pricing model devised in An (2016). In contrast to Chapter 4, we do not find that alternative VNSP variables, calculated with alternative reference points, are predictive of future returns. In addition, VNSP variables calculated using a composite based reference point were not better predictors of future returns than the VNSP variable calculated using the purchase price. The results suggest there is a different mechanism that drives returns in the case of the CGO model versus VNSP. In the case of CGO, returns are driven by existing holders of the security who find themselves in a position of gain or loss relative to a reference point. In the case of the VNSP, the most popular theory is the speculative trading hypothesis explained in Ben-David and Hirshleifer (2012). The idea is that a buyer purchases a security expecting it to rise in price and is thus likely to sell if the security does rise in price as the security performed as expected, or if it falls greatly in price as this erodes their prior expectation or proves that it was false. In the case of these speculative, short-term traders it seems that the purchase price is the most valid reference point. This is consistent with the V-shaped trading schedule only existing for short holding periods, with Ben-David and Hirshleifer (2012) showing a flattening of the V-shaped selling schedule for holding periods longer than 30 days. An (2016) also shows that the VNSP effect is highest among stocks with speculative characteristics such as high volatility, high turnover and low liquidity. Future research could examine if the VNSP applies to long-term holders, as well as short-term holders and further examine the competing hypotheses for why this effect holds in the market data.

In Chapter 6 we design and implement a new experiment to measure reference point adaptation on a month-by-month basis across a chart, rather than at the end of a chart. The reason for the change, in the design from Experiment 1, is to have an experiment that more closely matched the parameters necessary to measure reference points within the Prospect Theory Value of a Stock Model of Barberis et al. (2016). Within this model, share price charts of 5 years are represented as a set of 60 different months with a different reference point every month. The results show that the purchase, final, maximum and minimum are significant determinants of the month-by-month reference point. Although these are the same salient points that are significant in Experiment 1, we find less of a role for the maximum and minimum prices and more of a role for final monthly prices. The results suggest that frequent monthly evaluation of reference points, within the context of a 5-year chart, may promote more adjustment to the final price than less frequent evaluation explored in the earlier experiment. This may be caused by an anchoring effect, where participants use the last provided reference point as an anchor for the next (Kőszegi and Rabin, 2006). We show that models using a lagged reference point are also highly predictive of future returns.

The charts from the experiment are constructed using daily data, which allows us to measure the impact of daily highs and lows within the month, as well as monthly highs and lows. We find little impact of daily highs and lows, however. We also find that 52-week highs and lows are not significant determinants of the reference point, in contrast with Experiment 1. This is likely to do with the increased importance of the final (month-end) price in this experiment, as the final price is closely correlated with the 52-week variables. In general, participants are far more focussed on the final price in Experiment 2 than Experiment 1 and time moderation analysis suggests that the impact of the final price increases as time progressed through the 5-year charts.

In Chapter 7 we explore how the Prospect Theory Value of a Stock Model (TK) developed in Barberis et al. (2016) can be improved by considering alternative reference points. We use the coefficients from the previous chapter to form these composite reference points that are used to replace the monthly benchmark return reference points used in Barberis et al. (2016). We find that when including both the traditional TK and alternative TK variables in a model used to predict future returns, the alternative TK variables are significant at the 5% level but the traditional TK variable is insignificant. The results suggest that the composite based reference points are a good predictor of the reference points of potential buyers, which would explain why they increase explanatory power when included in the model. Future research could examine if investors place some weight on benchmark returns as a significant salient point in addition to points within a share price chart. This could be achieved by modelling the returns of a benchmark within an experiment and determining if the benchmark return adds explanatory power to the model beyond salient points displayed in the share price chart.

We also examine if the composite reference points measured in Experiment 1 are more accurate than those measured in Experiment 2 when used in the Prospect Theory model. When we test the composite reference points from

Experiment 1 within the TK model, we find that the new TK variables are not significant predictors of returns. The results suggest that the monthly representation of 60 separate months of share price returns is indeed a more accurate representation of how investors value a security, within the context of the Barberis et al. (2016) model. We explore one reason for this in the form of lagged reference points. We find that composite reference points formed of lagged reference points are also significant predictors of future returns within the TK model and may explain why the final price is given a greater weight within these models, in that investors tend to use the previous month's reference point as a base for the next reference point as suggested in Kőszegi and Rabin (2006).

In summary, this research shows that reference points other than the purchase price can be usefully considered for financial models incorporating seller behaviour and investor preference and the incorporation of these reference points can enhance the explanatory power of the models.

8.2 Limitations and Future Research

In Chapter 3, we use long-term charts and real share price data. This allows for the study of recency affects in reference point formation and real share price charts are free from indirect biases caused by artificial construction. One limitation with using real share price data is that multicollinearity is naturally high between salient prices, which makes the subsequent regression analysis more challenging.

It may be possible to retain the advantages of real share price data with the extra control of artificial charts by sampling from the market data for charts with certain characteristics e.g. comparing 2 charts with one up by 10% and one down by 10%. Multiple manipulations would be required to prevent participants from noticing any patterns. Care must be taken in such an approach, however, to ensure that non-randomness is not introduced into the design, which could affect subsequent responses. It could be particularly useful to explore the impact of share price volatility, using the semi-controlled approach, if reference point adaptation could be investigated in identical charts, except for higher volatility in one chart versus the other. Our results suggest that price volatility, rather than return volatility, would be the most interesting variable to manipulate.

In Chapter 4, we were able to show how the composite reference points improved the predictive power of the CGO model, but we were not able to show that the predictive power of the VNSP model was improved in Chapter 5. We suggest that VNSP trading behaviour is down to the speculative trading hypothesis, but we have no direct evidence for this. In this regard, a new experiment to measure the prior beliefs of traders, and how these prior beliefs evolve through time, would be informative and a good complement to the existing research carried out using asset pricing models. Participants could be further segmented into speculative (short-term) versus buy-hold (long-term) investors to clarify if a more speculative outlook drives this anomaly.

In Chapter 6, we chose to measure the reference point on a monthly basis across a 5-year horizon to match the Barberis et al. (2016) model. However, it is possible that other measurement frequencies, such as weekly or quarterly, produce a different set of reference points. Future research could look to examine the link between trading frequency and reference point adjustment. Our results suggest that high-frequency traders have a reference point that is closer to the final price than less-frequent traders. This could be because they are more willing to sell at any given point and so focus more on the current price that they would achieve. A future experiment could be designed specifically to isolate the difference in adjustment between more-frequent and less-frequent traders.

Finally, in Chapter 7, we used a composite reference point that was based on the vantage point of an existing holder of the security. It is possible, however, that the reference point creation process of buyers differs from sellers. Nolte and Schneider (2018) measure the reference point of buyers by asking for the buying price at which the investor would be neutral. In our experiment, we continued with the tradition of asking for a neutral selling price, as this has been the most common way to elicit reference points in the past. Future research could examine the differences between buyer and seller reference points in more detail and explore if the buyer focussed reference point further enhances the predictive power of financial models, especially given the findings of the endowment effect in Thaler (1980).

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Appendix A: Instructions and Charts used in Experiment I

Survey Instructions

Assume that you purchased a stock in a particular month, which we will label as month 0 in the graphs that follow. Since then you have monitored the share price closely. Today, you are considering selling the stock.

Your task will be to indicate the selling price at which you would feel neutral (i.e. feel neither predominantly positive nor negative) about selling the stock.

On the following screens, you will be shown a series of 30 share price graphs. The graphs will range in duration from 6 months to 5 years. Assume that you purchased the stock in a particular month, which we will label month 0 in the graphs that follow, and you are now considering selling the stock at the latest point shown on the graph.

This task is not about your maths skills and there are no right or wrong answers. We are just interested in your personal opinion, so just answer as honestly as you can giving an intuitive price.

A progress bar will show your progress through the survey.

You will be able re-read these instructions in the experiment.

Chart 1

Chart 2

Chart 3

Chart 4

Chart 5

Chart 6

Chart 7

Chart 8

Chart 9

Chart 10

Chart 11

Chart 12

Chart 13

Chart 14

Chart 15

Chart 16

Chart 17

Chart 18

Chart 19

Chart 20

Chart 21

Chart 22

Chart 23

Chart 24

Chart 25

Chart 26

Chart 27

Chart 28

Chart 29

Chart 30

Appendix B: Instructions and Charts used in Experiment II

Survey Instructions

Assume that you purchased a stock in a particular month, which we will label as month 0 in the graphs that follow. You plan to hold the stock for 5 years (60 months) and monitor it on a monthly basis. At the end of each of the 60 months, you will review your investment and consider how you would feel about selling the stock.

On the following screens, you will be shown how the stock price develops over the next 5 years, at monthly intervals. Your task will be to indicate the selling price at which you would feel neutral (i.e. feel neither predominantly positive nor negative) about selling the stock at the end of each month. In total you will provide 60 selling prices, which is one at the end of every month.

This task is not about your maths skills and there are no right or wrong answers. We are just interested in your personal opinion, so just answer as honestly as you can.

You will be able re-read these instructions during the experiment.

Please click <Next> to proceed to the example. The example covers the first 3 months only.

Example

Current Stock Price: $18.15, Month (1/60)

You purchased the stock in month 0 for $15.45. Since then the stock rose in price to $18.15 by the end of the month.

Your task is to indicate the <u>selling price at which you would feel neutral</u> (neither predominantly positive, nor negative) about selling.

Choose the price for which you would feel exactly neutral by entering it in the text box below.

Current Stock Price: $22.30, Month (2/60)

During month 1, the stock price moved from $18.15 to $ $22.30 by the end of the month.

Your task is to indicate the <u>selling price at which you would feel neutral</u> (neither predominantly positive, nor negative) about selling.

Choose the price for which you would feel exactly neutral by entering it in the text box below.

Current Stock Price: $23.33, Month (3/60)

During month 2, the stock price moved from $22.30 to $ $23.33 by the end of the month.

Your task is to indicate the selling price at which you would feel neutral (neither predominantly positive, nor negative) about selling.

Choose the price for which you would feel exactly neutral by entering it in the text box below.

Example Screenshot Used in the Experiment (Chart 1, Month 5)

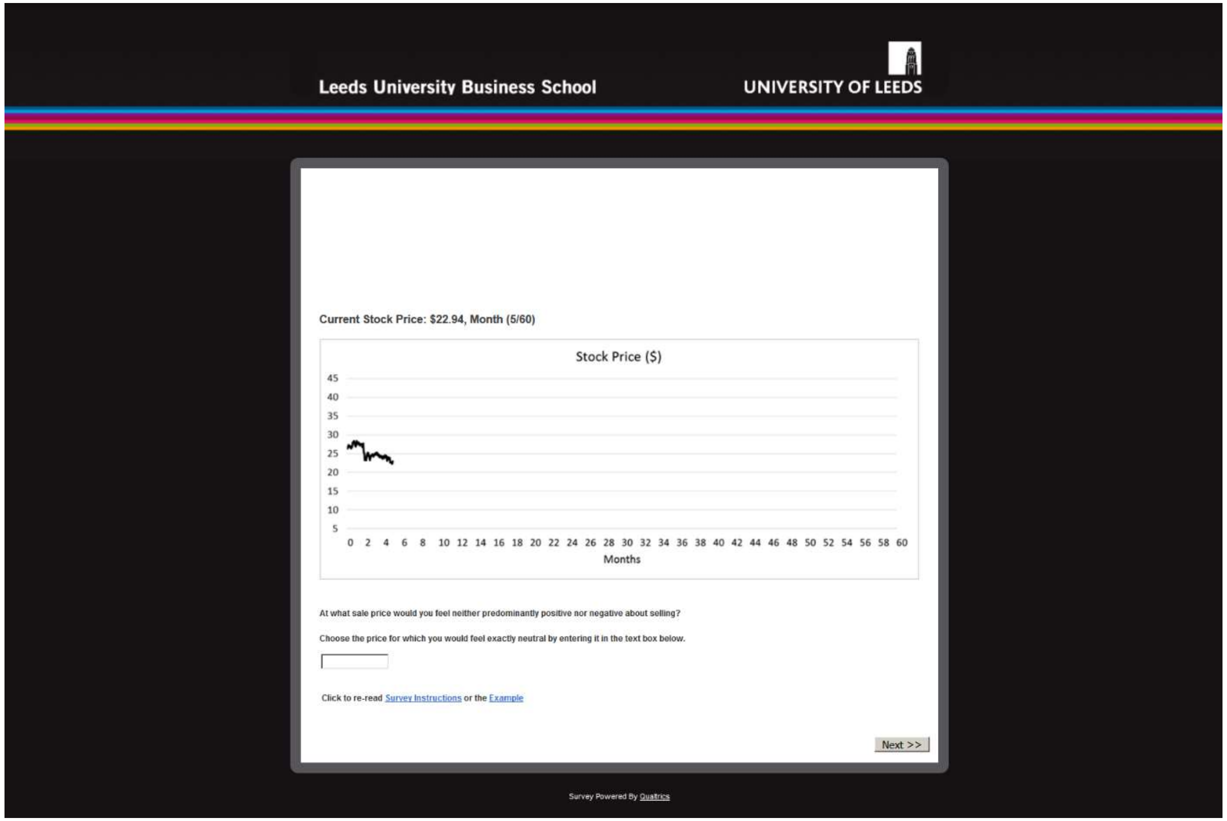

Chart 1

Chart 2

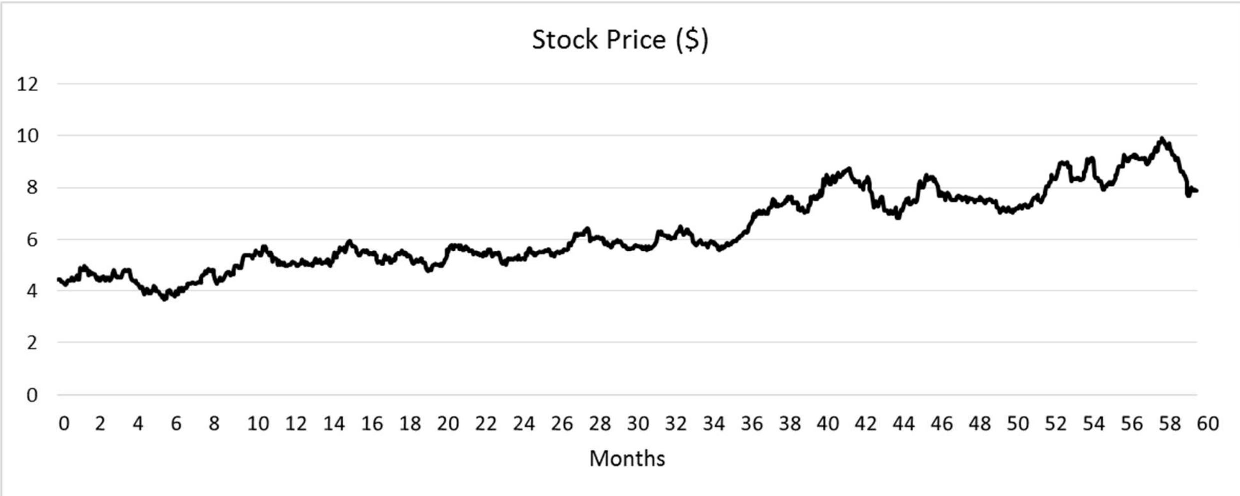

Chart 3

Chart 4

Chart 5

Chart 6

Chart 7

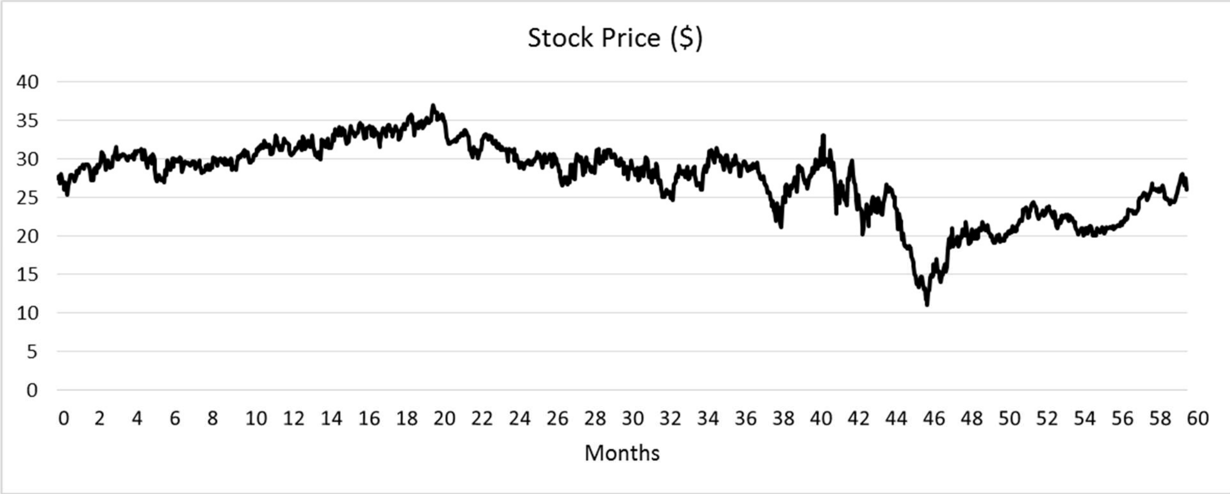

Chart 8

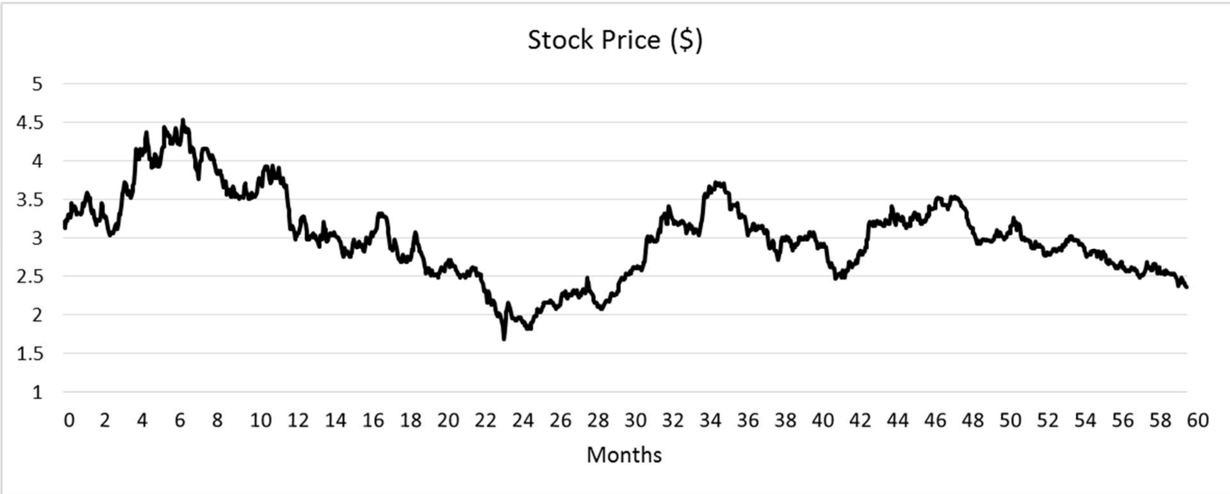

Chart 9

Chart 10

Chart 11

Chart 12

Chart 13

Chart 14

Chart 15

Chart 16

Chart 17

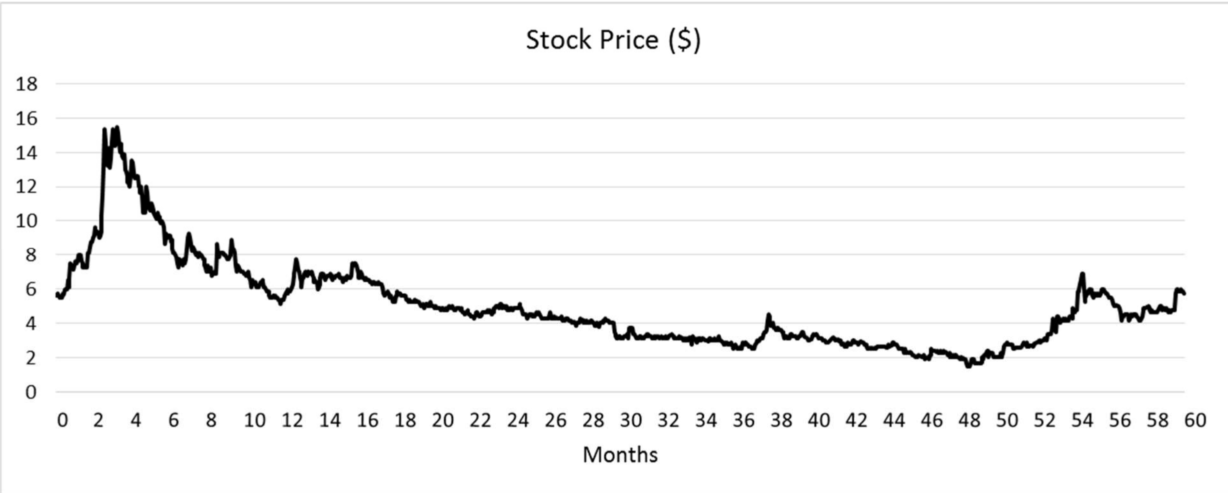

Chart 18

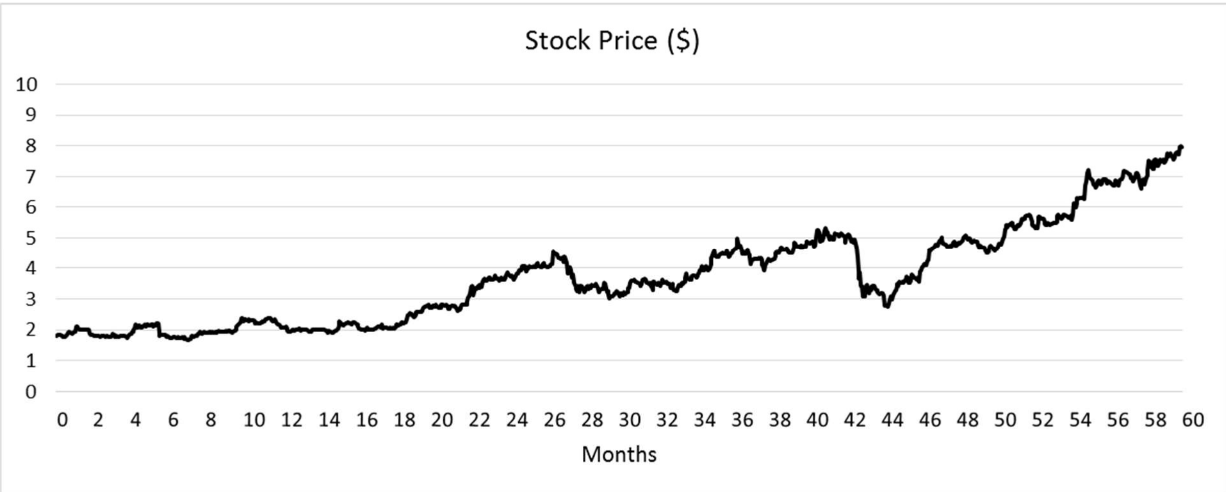

Chart 19

Chart 20

Chart 21

Chart 22

Chart 23

Chart 24

Chart 25


Stock Price ($)
25
20
15
10
5
0
0 2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50 52 54 56 58 60
Months