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Capital Gains Overhang with a Dynamic Reference Point

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Abstract. Financial models incorporating a reference point, such as the Capital Gains Overhang (CGO) model, typically assume it is fixed at the purchase price. Combining experimental and market data, this paper examines whether such models can be improved by incorporating reference-point adjustment. Using real stock prices over horizons from 6 months to 5 years, experimental evidence demonstrates that a number of salient points in the prior share price path are key determinants of the reference point, in addition to the purchase price. Market data testing is then undertaken by using the CGO model. We show that composite CGO variables, created by using a mix of salient points with weights determined in the experiment, have greater predictive power than the traditional CGO variable in both cross-sectional U.S. equity-return analysis and when analyzing the performance of double-sorted portfolios. In addition, future trading volume is more sensitive to changes in the composite CGO variables than to the traditional CGO, further emphasizing the importance of adjusting reference points.

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1. Introduction

The reference point is a central feature of Prospect Theory (Kahneman and Tversky 1979), but it has received less attention than other aspects of the theory, such as the differing shape of the value function when in a position of gain or loss. The choice of reference point has direct implications for the determination of gains and losses; hence, it impacts all kinds of financial behavior, ranging from firm-based capital investment (Whyte 1986) and strategic decisions (Bamberger and Fiegenbaum 1996) to stock investor behavior (Shefrin and Statman 1985). A key motivation for our study is to place the spotlight back on the role of the reference point, to show that it adjusts as investors experience movements in the stock price[1] and to demonstrate how incorporating this adjustment can improve financial models. To achieve this, we combine experimental and market data methods, by identifying how reference points adapt in an experiment and then using the derived parameters to test the predictive power of the model in market data. We demonstrate that treating the reference point of an investor as something that changes over time, rather than remaining fixed at the purchase price, can improve the predictive power of the Capital Gains Overhang (CGO) model developed by Grinblatt and Han (2005).

The first aim of our study is to explore the role of alternative salient prices, in addition to the purchase price, in the formation of the reference point. Prior literature, such as work on the disposition effect (Shefrin and Statman 1985), suggests that investors adopt the purchase price as the reference point, which is then fixed over the life of the investment. A purchase-price-based reference point is consistent with the tendency of investors to exhibit a status-quo bias, which is prevalent across a wide range of decisions (Samuelson and Zeckhauser 1988). A number of field-data-based studies also provide support for a purchase-price-based reference point, such as Kaustia (2010), who shows that the investor's propensity to sell a stock jumps at the purchase price but is constant or only slightly increasing across a range of gains and losses relative to the purchase price, and Ben-David and Hirshleifer (2012), who show that the propensity to sell follows a V-shaped pattern around the purchase price.

In the context of stock trading, the issue in assuming a static, purchase-price-based reference point is that stocks can be held for a prolonged period of time. As the stock price moves, the question then becomes: Will the investor update their reference point in response to the new price information, or will the reference point remain fixed at the purchase price? Papers from Chen and Rao (2002) and Arkes et al. (2008) suggest that investors do indeed update their reference point as new price information arrives. Arkes et al. (2008) show that just over half of the gain is adjusted for in the new reference point and slightly less for losses.

A number of different salient points could play a role in the reference-point-updating process. Both Heyman et al. (2004) and Gneezy (2005), using experimental methods, find that historic highs are key determinants of the reference point, and there is further evidence for the importance of the high price within studies using market data. Kaustia (2004) suggests that maximums and minimums, attained over the prior month, are key price points for investors in new initial public offerings, with stock-price moves to these points triggering higher trading activity. Both Heath et al. (1999) and Poteshman and Serbin (2003) find that exercise of stock options greatly increases when the stock price exceeds the maximum over the year. There is also support for the 52-week high in addition to the historic high. Huddart et al. (2009) find volume increases for stock prices close to the 52-week high, whereas George and Hwang (2004) find that stocks near to their 52-week high, in percentage terms, tend to be underpriced and subsequently outperform, relative to stocks that are far from the 52-week high. The authors suggest that at price levels close to the 52-week high, traders are reluctant to bid the stock price higher, as it is a key reference point in the minds of investors. This work on different reference points indicates that studies exploring how multiple salient prices influence reference-point formation would be informative.

Baucells et al. (2011) measure the impact of several of these salient points on the reference point and find that it is determined by a mix of the purchase, maximum, minimum, average, and final prices. In our study, we adapt the Baucells et al. (2011) framework by using stock-price charts created from real market data, which are up to 5 years in length, giving a greater time range than those in Baucells et al. (2011). The results of our experimental study suggest that intermediate highs and lows are important in reference-point formation, in addition to the purchase and final prices, in line with the findings in Baucells et al. (2011). In addition, we show the impact of 52-week highs and lows in the determination of investor reference points when longer time periods are considered. This is a new result that is only observed by using long-term charts, whereas previous experimental studies using shorter time periods have not identified the effect. This is not only of conceptual importance, but is also important practically, given the use of longer-term price charts in the real world.

The second aim of our paper is to demonstrate the effect of alternative reference points within a market-data model, which uses reference prices to predict future stock-price returns. If investor reference points are fixed at the purchase price, then it would be surprising if some of the alternative salient points, discussed above, do also have predictive power for future returns. The specific model that we adopt is the CGO model developed by Grinblatt and Han (2005), who show that *CGO* is a key variable that generates the underlying profitability of a momentum trading strategy (Jegadeesh and Titman 1993). Stocks that have positive *CGO* (final price above reference point) tend to be underpriced and subsequently outperform, whereas stocks that have negative *CGO* (final price below reference point) tend to be overpriced and subsequently underperform. A purchase-price-based reference point is assumed, while the probability that a stock is bought on a particular day, establishing a new purchase price, is approximated by using a stock's turnover ratio. As such, the Grinblatt and Han (2005) CGO variable takes into account external reference-point updating, which occurs due to the sale of the stock and purchase by a new stockholder. Under conditions of zero turnover, however, no updating occurs at all in their model, as the stock is not changing hands between investors.

Our contention is that internal reference-point updating on the part of existing stockholders also occurs, even if no stocks are traded, responding to developments in the stock price over time. Internal reference-point updating cannot be directly detected in market data, however, and so our experimental framework is vital in identifying important salient prices. Our experimental results suggest that prices such as the maximum, minimum, and 52-week variables are important determinants of the reference point, in addition to the purchase price. We then apply the concept to market data by calculating alternative CGO variables using the salient points identified in the experiment (the *maximum*, *minimum*, *average*, and *52-week* variables) and comparing them to the standard model. We show that these alternative CGO variables are just as predictive of 1-month-ahead returns as the traditional *CGO* variable, calculated by using the purchase price.

The third aim of our paper is to investigate whether CGO variables that use more accurate reference points, formed by using a mix of salient points, are better predictors of returns than the traditional *CGO* that uses the purchase price alone. This would demonstrate the reality of reference-point adjustment in real-world stock-price data and confirm the earlier experimental results. We use the coefficients from the experiment to create composite-CGO variables, formed by weighting a number of salient points in a price chart to create a more accurate reference point. Our first composite variable, *CGOCom1*, uses the purchase, maximum, and minimum prices, whereas the second variable, *CGOCom2*, includes the 52-week prices in place of the maximum and minimum. In cross-sectional regressions of U.S. equity returns where both the composite-CGO variables and the traditional *CGO* variable are present, we find that the composite-CGO variables are better predictors of future returns than the traditional variable, with the traditional *CGO* variable no longer a positive predictor of returns when either of the CGO-composite variables are included in the regression. Furthermore, we carry out double sorts of portfolios, mirroring the approach in Grinblatt and Han (2005), by both traditional *CGO* and our preferred CGO-composite variable incorporating 52-week prices, *CGOCom2*. We find that that *CGO* is rarely predictive of returns after stocks are first sorted by *CGOCom2*, whereas *CGOCom2* is usually predictive of returns, even if stocks are first sorted by *CGO*.

Our fourth aim is to subject our findings to a broader test premised on the implication that if reference points adjust and composite reference points are predictive of returns, then trading volume should also be more sensitive to composite reference points than to the purchase prices.[2] To this end, we complement the returns analysis by carrying out volume tests and find that the composite-CGO variables are also stronger predictors of future trading volume, thus extending the implications of our findings. Specifically, we find that future weekly volume increases almost monotonically in line with *CGOCom1* or *CGOCom2* when stocks are sorted into deciles based on these variables and volume is more sensitive to the composites than to the traditional *CGO* variable. The results suggest that future volume as well as future returns are more responsive to CGO variables based on a composite reference point than *CGO* based on a purchase-price-based reference point.

We also test whether retail investors are more sensitive to reference-point effects than institutional traders.[3] If retail investors are more likely to be the irrational traders, then the predictive power of *CGO* and the CGO composite variables should be stronger among the more speculative stocks that are more likely to be traded by these retail investors (Han and Kumar 2013). We find that, in two out of three of the proxies used for speculative stocks, both the *CGO* and CGO composites are robust across the different investor segments. In the case of the third proxy for speculative stocks, however, we do find that both the *CGO* and CGO composites have stronger predictive power among high-turnover stocks. An explanation for this may lie in the workings of the CGO model itself, where high turnover tends to refresh the aggregate reference point and temporarily raise returns to the CGO variable.

The implication of our results is that investors take multiple points into consideration when forming a reference point, so that reference points do adjust over time, and adjusted CGO variables are therefore a better predictor of future returns and trading volume than the traditional *CGO* variable. Aside from the purchase price, key determinants of the reference point are intermediate points of interest, such as recent highs and lows. The findings have wider significance, as the CGO model is not the only one that utilizes the concept of a fixed reference point, and, thus, applying adjusted reference points may improve other models. Understanding reference-point adjustment is also important for many other concepts in finance, such as the disposition effect. The results also have importance more generally in the management literature, where reference-point updating is important, but difficult to examine experimentally within an ecologically valid setting and also empirically in light of both the limited (relative) frequency and the potentially widely varying economic contexts within which managerial activities such as capital budgeting and strategic investment decisions are undertaken.

2. Experimental Examination of Reference-Point Determination

2.1. Data and Method

In the experiment, we examine the impact of features of the stock-price path on the reference point adopted by participants. A repeated-measure design is adopted with 30 different chart patterns shown to participants. Order effects are controlled for by randomizing the order of presentation of charts across participants. A data-survey company is used to collect online responses. All responses are taken from U.S. citizens who are residents in the United States. To ensure that no novices participate in the experiment, all participants are required to have some experience (self-reported) of trading in U.S. stocks or mutual funds, even if this is infrequent. The instructions and example chart for the experiment are available in the appendix.

The experimental approach adopted is based on that of Baucells et al. (2011), with some adjustments to accommodate the longer time frame required for the CGO model, which we use in testing reference-point adjustment, as suggested by our experiment, in a market context. An equal number of charts are used with the following lengths: 6 months and 1, 2, 3, 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 recent points on the reference point, such as 52-week highs and lows, as well as overall highs and lows.[4] To ensure that participants recognized the change in time frames, all charts of the same length were presented as a group along with an introductory screen to alert them that the time frame had changed. The time frame 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.

In Baucells et al. (2011), each point in the graph is presented with a 3- to 4-second lag, reflecting the later 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. Our focus is on determining the likely position of the reference point based on prior stock-price movements, which then feeds into the CGO calculation. Given that investors and traders look at a previous stock-price path as an entire series rather than as a set of lagged points, our study presents the graphs to participants without delay between points, and we elicit one reference point per stock-price chart.

The stock-price charts were formed from real stock-price data using random sampling of equities from the data set of all U.S. equities from 1963 to 2016, which is used later in the market-data-testing section. The use of real stock-price data differs from previous experimental studies and most closely replicates the stock-price path that investors will observe in real markets. It also avoids bias that may come from artificially generated price series and round numbers that may act as an anchor for participants (Bhattacharya et al. 2012). One drawback to using real stock-price data is that multicollinearity between the variables is likely to be high, as it is a natural feature of stock-price movements. More rigidly designed charts ensure that multicollinearity can be controlled, but would reduce realism and could bias the result in a predictive context, such as that used here, if they are perceived as nonrandom by participants. We, therefore, use approaches to reduce multicollinearity rather than artificial data.

In terms of capturing reference points from participants, this study uses an adjusted form of the question used in Baucells et al. (2011): "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*." In our study, participants are asked for their reference point without any actual sale being involved, allowing for a wider perspective to avoid promoting anchoring on the final price.

Previous research has shown that beliefs about future prices can affect the reference point (Hoffmann et al. 2013, Grosshans and Zeisberger 2018). Baucells et al. (2011) control for this by informing participants that all possible price changes between €+50 and €−50 are equally likely. Our study did not use this approach because beliefs are part of the way investors form reference points in real-life trading, and stock-price patterns that investors experience can influence these beliefs (Barberis et al. 1998, Rabin and Vayanos 2010). Thus, we look to avoid issues with ecological validity in the CGO calculation.

A feasible range of maximum +25% and minimum −25% around the range of the stock-price chart was adopted as a limit to establish participant understanding of the experiment. A total of 22 participants, who gave an answer outside this range for a third or more of the charts, were excluded from the results. As an additional check, reference points outside the feasible range of ±25% were also removed on an individual basis, rather than excluding the whole sample of a participant. These reference points may be invalid due to participant error in one specific chart, but not across the whole experiment. This removed an additional 65 reference points. The final data sample, after exclusions, comprised 169 participants (109 male, 60 female) with a broad distribution of ages between 30 and 65 years (average = 53 years).

As an additional check, the regression models in Section 2.2 are replicated for data screened by using the Outlier Sum method (Tibshirani and Hastie 2007), which uses the distribution of reference points alone to remove outliers. Results are shown in the electronic companion in Tables A and B, and there is no material difference in the final results between screening based on the range of the charts or by the distribution using the Outlier Sum method.

2.2. Results

Table 1 shows the characteristics of the 30 charts, along with the average, median, and standard deviation of reference points from all participants. All charts are constructed by random sampling from the market data set used in Section 3, so that real price sequences are used.

Regression: Reference Point Using Price Variables. To understand the salient prices that determine the reference price and to provide unbiased coefficient estimates for use in the market-data testing to follow, our approach to modelling is to begin with a broad set of explanatory variables so as to obtain the highest explanatory power attainable and then to remove variables in such a way that explanatory power is maintained, but multicollinearity is reduced to acceptable levels. It is important to do this, as we want reliable

Table 1. Summary of Reference Points and Price Sequences

Chart number	*Mean reference*	*Median reference*	*Standard deviation reference*	*Purchase*	*Maximum*	*Minimum*	*Average*	*Final*
1	13.14	13	0.96	13.33	14.58	10.67	13.08	11.83
2	3.09	3	0.34	3.38	3.5	2.38	2.9	2.38
3	8.87	9	1.33	7	10.3	7	8.64	10.29
4	13.51	14	1.73	13.5	15.25	8.25	11.04	15.25
5	6.11	6	0.61	5.9	6.72	4.76	5.69	6.6
6	123.9	125	42.55	66.13	198.19	66.13	128.26	155
7	21.64	22	1.11	22	23.45	19.7	21	20.75
8	8.23	8	1.17	9.41	9.77	5.18	6.9	6.85
9	22.29	22	2.85	18.53	25.97	18.29	22.42	25.31
10	7.12	7	1.23	6.05	8.9	3.05	5.96	8.15
11	12.95	13	1.89	15	15.5	9.5	11.29	10
12	8.68	9	1.55	5.88	10.75	5.5	8.81	10
13	5.27	5	1.38	5.63	8	2.5	4.85	3.06
14	11.39	12	2.58	14.5	14.5	6.5	9.22	7
15	18.55	20	5.15	20.13	29.38	9.25	17.64	10.5
16	16.57	16	4.37	9.5	22.06	9.25	14.34	21.71
17	6.52	6.5	0.82	6.88	8	5	6.46	5.5
18	32.93	32	4.06	31.38	41.25	21.75	30.4	31.13
19	40.22	40	21.57	10	73.06	7.38	21.64	62.54
20	23.13	22	5.87	17.7	35.17	17.2	26	18.49
21	90.74	95	24.35	54.04	126.76	52	78.41	121.36
22	14.85	15	1.75	14.25	18.88	10.38	13.99	15
23	21.46	20	4.75	26.92	28.22	10.55	18.79	14.88
24	78.98	80	31.78	78.38	151	22	84.08	24.5
25	2.97	3	0.8	1.91	4.66	1.25	2.61	2.78
26	27.08	30	6.63	30.94	34.19	2.36	13.05	26.25
27	48.7	50	5.58	46.5	58.13	25.88	40.87	49.88
28	35.13	34.5	7.54	34.22	50.16	14.1	28.17	37.26
29	33.04	35	11.94	13.49	56.03	12.9	31.91	38.16
30	17.74	18	3.09	15.51	22.74	8.03	14.34	19.81

Notes. This table reports summary statistics for the charts we use in the experiment. Chart number 1–6: 6 months; 7–12: 12 months; 13–18: 2 years; 19–24: 3 years; and 25–30: 5 years. *Reference* is the mean or median reference point provided by participants across the chart. *Purchase* is the purchase price of the chart. *Maximum* is the maximum price of the chart. *Minimum* is the minimum price of the chart. *Average* is the average price of a chart. *Final* is the final price of a chart.

coefficients for market data testing. Models A, B, and C in Table 2 use the *purchase*, *maximum*, *minimum*, *average*, and *final prices* as independent variables (IVs), predicting the *reference point* as the dependent variable (DV), as shown in Equation (1).

$$Reference\ Point = \beta_0 + \beta_1 Purchase + \beta_2 Maximum + \beta_3 Minimum + \beta_4 Average + \beta_5 Final + \varepsilon. \qquad (1)$$

We start with the full set of variables in Model A and then remove IVs while observing the R^2 of the reduced model. The variance inflation factor (*VIF*) of an IV is calculated by regressing the IV against the other IVs in the model. The R^2 from this regression is then used to calculate the *VIF* score using Equation (2).

$$VIF = \frac{1}{1 - R^2}. \qquad (2)$$

Models D, E, and F of Table 2 replace the *maximum* and *minimum* variables with the *52-week maximum* and *minimum* variables, as shown in Equation (3). Model D begins with the full set of variables, which is gradually reduced by removing IVs. 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 observed and does not take account of prices in the prior 6 months. This distinction is maintained in subsequent market data testing in Section 3.

$$Reference\ Point = \beta_0 + \beta_1 Purchase + \beta_2 Max52 + \beta_3 Min52 + \beta_4 Average + \beta_5 Final + \varepsilon\,. \qquad (3)$$

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 taken to be significant if they exceed the 5% significance threshold.

In Model A, the *purchase*, *maximum*, and *final price* are found to be significant, but the *average* and

Table 2. Regression Analysis Using Price Variables

Variable	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
R^2	0.837	0.837	0.837	0.836	0.836	0.836
Adjusted R^2	0.837	0.837	0.837	0.836	0.836	0.836

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

minimum prices are insignificant. Table 3 suggests that the level of collinearity between the variables in Model A is high, with a mean *VIF* of 78, 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, which has the largest *VIF*, while retaining the *minimum*, and all of the remaining variables are then significant. The R^2 of the model is not reduced relative to Model A, and the mean *VIF* falls to 10. Model C removes the *minimum* variable while retaining the *average*. All of the remaining variables are significant, with no drop in R^2. 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 found that the average price plays a role, as there is no collinearity in their constructed data. We find that Models B and 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. As the *VIF* scores are lower in Model B, however, we construct our first composite reference point, *RefCom1*, using the weights in Model B.

Table 3. *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

Note. VIF analysis shown for models in Table 2.

This will be used in the subsequent market-data-testing section.

In Models D, E, and F, we replace the *maximum* and *minimum* variables with the 52-week maximum (*max52*) or the 52-week minimum (*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 40, 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 close to 17, in Model F, we also remove the final price. All of the remaining variables are significant, and there is no reduction in R^2, while the average *VIF* score is reduced to 4.

Model F is our preferred model of the three that introduce the 52-week variables. This model has the same R^2 as Model D, which includes all the independent variables and has a far lower average *VIF* score. Therefore, coefficients from Model F are used to calculate our second composite reference point, *RefCom2*, which will be used in the subsequent market-data-testing section.

In the electronic companion, we replicate Table 2 and Table 3 using difference variables, shown as Tables C and D. Each variable is calculated as the percentage deviation of the variable from the final price, rather than the price itself. This reduces multicollinearity between the variables and leads to lower *VIF* scores. The results are in line with those in Table 2.

3. Market-Data Testing of CGO

The CGO (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). The final price is lagged by 1 week, relative to the reference point, to avoid market microstructure events, such as the bid–ask bounce, that lead to short-term reversals in stock prices (Rosenberg and Rudd 1982, Da et al. 2013).

$$g_{t-1} = \frac{P_{t-2} - R_{t-1}}{P_{t-2}}. \tag{4}$$

It is impossible to calculate the reference point for a given investor directly by using market data, as holders buy on different days and therefore have different reference points. To overcome this problem, it is necessary to calculate the probability that a stock, currently under ownership, was traded on a particular day. Grinblatt and Han (2005) calculate this probability using stock turnover across 260 weeks of data (5 years in total). By way of example, assuming turnover is 5% on $week_{t-2}$, then the purchase price 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% × (100% − 5%) = 4.75% to reflect that 5% of the purchases are subsequently sold in $week_{t-2}$.

Theoretically, the reference price is calculated by using an infinite number of weeks, but in practice, Grinblatt and Han (2005) sum 5 years of weekly turnover-adjusted purchase prices and adjust by a constant 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.

The actual adjustment we make to the calculation of the CGO in this study is to exchange the price variable used to calculate the reference point. Equation (5) shows the reference-point calculation using the purchase price, as in Grinblatt and Han (2005), to form *RefPurchase*. All other elements of the CGO calculation remain identical to that of Grinblatt and Han (2005); other than that, we use daily turnover (V) and daily price information rather than weekly, and hence 1,260 trading days rather than 260 weeks. Daily data allow the reference point to be calculated more accurately than weekly, although it is more computationally intensive. This approach has been adopted by more recent papers that use the CGO model—for example, Wang et al. (2017) or An et al. (2019).

$$RefPurchase_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}\left[1 - V_{t-1-n+t}\right]\right)Purchase_{t-1-n}, \tag{5}$$

where turnover (V) = daily trading volume/shares outstanding; k = constant that makes the weights on past prices sum to one; and n = number of trading days from 1 to 1,260.

In addition to *RefPurchase*, we use five alternative reference points to create the following: *RefMax*, *Refmin*, *RefMax52*, *RefMin52*, and *RefAverage*, to reflect the salient points that we found to be important in reference point formation. Using Equation (4), the reference points are used to calculate six CGO variables: *CGO*, *CGOMax*, *CGOMin*, *CGOMax52*, *CGOMin52*, and *CGOAverage*. 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. 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. This mirrors the approach used in the experiment.

We also create two composite reference points formed from a mix of salient points, with weights determined by the experiment. The first composite variable, *RefCom1*, shown in Equation (6), is created from Model B of Table 2, which suggests that the reference point is represented by the *purchase*, *maximum*, *minimum*, and *final* prices. *RefCom2* is based on Model F of Table 2, which suggests that 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) to create the CGO variables, *CGOCom1* and *CGOCom2*.

$$RefCom1_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}[1-V_{t-1-n+t}]\right)(0.33^{*}Purchase_{t-1-n} + 0.29^{*}Max_{t-1-n} + 0.14^{*}Min_{t-1-n} + 0.23^{*}Final_{t-1-n}), \tag{6}$$

$$RefCom2_{t-1} = \frac{1}{k}\sum_{n=1}^{1260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}[1-V_{t-1-n+t}]\right)(0.43^{*}Purchase_{t-1-n} + 0.45^{*}Max52_{t-1-n} + 0.11^{*}Min52_{t-1-n}). \tag{7}$$

3.1. Data and Method

The market-data sample is all U.S. common stocks (Codes 10 and 11) from January 1958 until December 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 are used to calculate the *CGO* variable and are then converted to monthly data for the regressions. The monthly data are from January 1963 until December 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 and a more common holding period and evaluation period for investors. 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 are a total of 68 million firm-day cases in the daily data and around 2.2 million in the monthly data.

The following control variables are used, taken from Grinblatt and Han (2005): *Mom* is the momentum factor defined as the percentage return over the last 12 months, excluding the last month; *STR* is the short-term reversal factor defined as the percentage return last month; *LTR* is the long-term reversal factor 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 the 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.

Calculations of *CGO* and *LTR* require a minimum of 3 years of data (out of a possible of 5 years) and are set to missing otherwise, as are the reference points: *RefPurchase*, *RefMax*, *RefMin*, *RefMax52*, *RefMin52*, *RefAverage*, *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 utilized, 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 for all variables are provided in the electronic companion in Tables E and F.

Figure 1 shows how the reference point, based on the purchase price or the second composite, compares to the stock price for the firm 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). This means that around 80% of the weight of the reference point is provided by the first 3 years of price data, with older data playing less of a role.

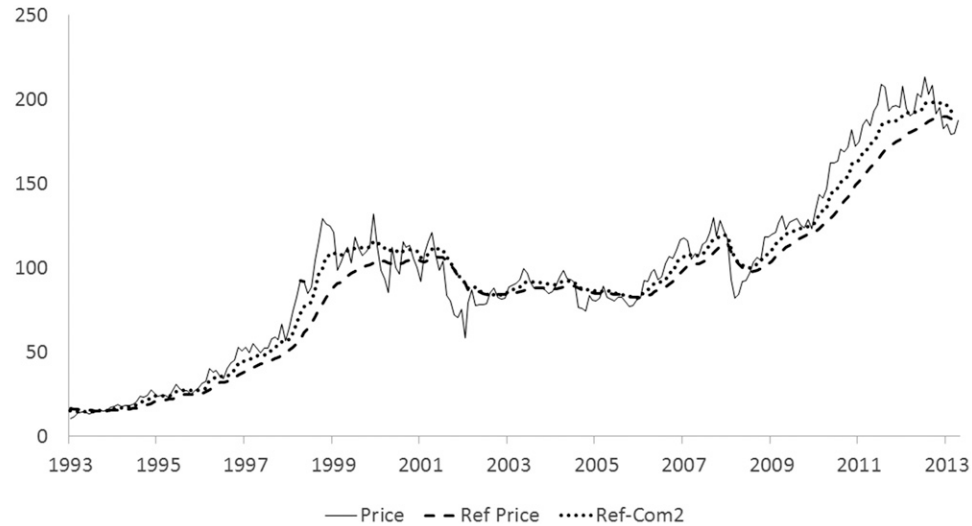
3.2. Regression of 1-Month-Ahead Returns Against CGO Variables

Table 4 shows regression analysis for 1-month-ahead returns as the dependent variable, various specifications of the CGO variable as independent variables, and the control variables.

$$Ret_{t+1} = \beta_0 + \beta_1 CGO_t + \beta_2 Mom_t + \beta_3 STR_t + \beta_4 LTR_t + \beta_5 Avgturn_t + \beta_6 Mrkcap_t + \beta_7 BM + \varepsilon. \tag{8}$$

Model A features the traditional *CGO* variable, calculated by using the purchase price alone. The results show that the *CGO* based on purchase price is significant at the 5% level, along with some of the control variables. While 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

Figure 1. IBM Price and Reference Prices: 1993–2013



we do. Models B–F use the alternative CGO variables calculated by using the 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 1-month-ahead returns.

Table 5 shows the regression results of models that include both the traditional CGO variable and composite CGO variables in the same model, to assess which variable retains its significance as a positive predictor of returns. Models B and C include the CGO composite variables along with the traditional *CGO*. In both cases, the composite CGO variables are positive and significant predictors of returns, whereas the traditional *CGO* has a negative coefficient. Both the average R^2 and the adjusted R^2 of Models B and C are greater than Model A, reflecting an increase in predictive power that the addition of the composite variables provide. This result suggests that the composite-based CGO measures are better predictors of future returns than the traditional *CGO* variable. *CGOCom2* has more explanatory power than *CGOCom1*, suggesting that the 52-week high and 52-week low have an important influence on reference points. Model D includes both CGO composite variables *CGOCom1* and *CGOCom2*, and in this instance, neither of them is significant due to collinearity. We will confirm the result with double-sorted portfolio results in the next section.

We also conduct a series of tests to check the robustness of our results in the electronic companion.[5] Grinblatt and Han (2005) find that CGO becomes a negative predictor of returns in the month of January due to tax-loss selling behavior. In Table G in the electronic companion, we perform subsample analysis across the January and February–December months to consider seasonality effects. The results show that our composites exhibit the same seasonality in returns as the original CGO variable, with negative coefficients during the month of January due to tax-loss selling.[6] In Table H in the electronic companion, we consider three additional control variables (also used in Wang et al. (2017)) accounting for market risk (beta), stock risk (idiosyncratic return volatility) measured by using the Fama–French 3 factor model, and analyst forecast dispersion. We find that our results are robust to the addition of these control variables.[7] Finally, in Table I, we repeat our analysis in Table 5, replacing the Fama–MacBeth procedure with the double-clustered standard-error regression model approach of Thompson (2011). In order to make Table I comparable with our earlier results, we perform a couple of adjustments. First, we decile-rank all independent and control variables over the month and use the decile-ranked variables in the regression. This is to ensure that extreme values in one month do not have undue influence on the results (in the Fama–MacBeth procedure, coefficients are averaged across months, and so this is less of a concern). Second, we perform a weighted regression, where observations within a month are weighted to ensure that each month receives an equal weight (in the Fama–MacBeth procedure, each month is equally weighted, regardless of the number of observations in the month). We find that the results using the double-cluster regression method are in line with those obtained by using the Fama–MacBeth procedure.

Table 4. Regression of Monthly Returns Using CGO Variables

Variable	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*** (2.934)	0.00565*** (3.500)	0.00481*** (2.611)	0.00292 (1.797)	0.00485*** (3.223)	0.00502*** (2.654)
STR	−0.0541*** (−10.01)	−0.0542*** (−9.860)	−0.0551*** (−9.977)	−0.0587*** (−10.92)	−0.0570*** (−10.25)	−0.0554*** (−9.685)
LTR	−0.000959 (−1.736)	−0.000769 (−1.483)	−0.000876 (−1.447)	−0.00106 (−1.798)	−0.000755 (−1.288)	−0.000518 (−0.915)
Avgturn	−0.673** (−2.076)	−0.777** (−2.285)	−0.579 (−1.572)	−0.559 (−1.503)	−0.650 (−1.728)	−0.752** (−2.238)
Mrkcap	−0.000279 (−0.649)	−0.000344 (−0.818)	0.000172 (0.395)	−0.000316 (−0.727)	−0.000518 (−1.232)	0.000126 (0.297)
BM	0.00205*** (2.682)	0.00185** (2.445)	0.00253*** (3.685)	0.00225*** (3.027)	0.00174** (2.325)	0.00237*** (3.431)
Constant	0.0144*** (4.166)	0.0159*** (4.768)	0.00697** (2.213)	0.0145*** (4.166)	0.0175*** (5.165)	0.00887*** (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

Notes. This table reports results for predictive Fama and MacBeth (1973) regressions of 1-month-ahead returns on *CGO* and a set of control variables. Dependent variable is 1-month return in month $t+1$. *CGO* was calculated by using turnover-adjusted purchase price as shown in Equation (5). *CGOMax* is calculated as per *CGO*, but replacing the purchase price with the maximum price. *CGOMin* is calculated as per *CGO*, but replacing the purchase price with the minimum price. *CGOAverage* is calculated as per *CGO*, but replacing the purchase price with the average price. *CGOMax52* is calculated as per *CGO*, but replacing the purchase price with the 52-week maximum price. *CGOMin52* is calculated as per *CGO*, but replacing the purchase price with the 52-week minimum price. *Mom* is the 12-month momentum, excluding the last month. *STR* is short-term reversal, calculated as the return of the last month *t*. *LTR* is long-term reversal, calculated as the return over the last 3 years, excluding the last year. *AvgTurn* is average daily turnover over the 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.

$^{**}p < 0.05$; $^{***}p < 0.01$.

3.3. Double-Sorted Portfolios: Return Analysis

Grinblatt and Han (2005) also analyze 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 whether a variable has predictive power for returns after 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 6A stocks are first sorted by *CGO* into quintiles and then are further sorted into quintiles by *CGOCom1*, and in Table 6B stocks are first sorted by *CGOCom1* and then by *CGO*. The lowest-numbered quintile represents the lowest values of the variable in question.

When sorted first by *CGO* and then by *CGOCom1* in Table 6A, the average returns of portfolios increase

Table 5. Regression Using CGO Composite Variables

Variable	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
Average R^2	0.0683	0.0710	0.0722	0.0721
Adjusted R^2	0.0638	0.0659	0.0671	0.0670
Number of groups	647	647	647	647

Notes. This table reports results for predictive Fama and MacBeth (1973) regressions of 1-month-ahead returns on *CGO* with CGO composites and a set of control variables. Dependent variable, 1 month return in month $t + 1$. *CGO* is calculated by using turnover-adjusted purchase price as shown in Equation (5). *CGOCom1* is calculated as per *CGO*, but replacing the purchase price with *Refcom1*, calculated as per Equation (6). *CGOCom2* is calculated as per *CGO*, but replacing the purchase price with *Refcom2*, calculated as per Equation (7). *Mom* is 12-month momentum, excluding the last month. *STR* is short-term reversal, calculated as the return of the last month *t*. *LTR* is long-term reversal, calculated as the return over the last 3 years, excluding the last year. *AvgTurn* is average daily turnover over the 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.

**$p < 0.05$; ***$p < 0.01$.

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*). Table 6B shows the analysis when stocks are first sorted by *CGOCom1* and then by *CGO* into quintiles. Stocks rarely increase with *CGO* quintile, and 4 out of 5 of the difference portfolios have a negative value.

Tables 7A and 7B repeat 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, except for the first *CGO* quintile, ranging from 0.24% to 0.79% per month. Even in the case of the first *CGO* quintile (*CGO-1*), although there is no significant difference between the average *CGOCom2* quintiles, as shown by *t*-statistics on the spread (*5-1*) portfolio, the average returns on the first quintile (*CGO-1*/*CGOCom2-1*) comprises 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 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 difference between the last and first *CGO* quintiles (*5-1*) is 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

Table 6A. Double Portfolio Sorts by *CGO* and *CGO-Com1*

Variable	*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**

Notes. Tables 6A and 6B report returns in double-sorted portfolios based on values of *CGO* and *CGOCom1*. At the end of each month, stocks are sorted into five portfolios by *CGO* and *CGOCom1*. Stocks in a portfolio are equally weighted. Each portfolio is held for 1 month, and the time-series average return is reported in monthly percent. Newey–West-corrected *t*-statistics are shown below performance.
$^{**}p < 0.05$.

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. For those interested, a comparison between the two composite variables: *CGOCom1* and *CGOCom2*, is available in the electronic companion in Tables J and K. This suggests that neither one of the composite variables dominates the other.

3.4. Regression of 1-Week-Ahead Volume Against CGO Variables

Prior literature suggests that trading volume may also be sensitive to the reference point. Kliger and Kudryavtsev (2008) examine the extent to which company-specific events—namely, earnings announcements—cause investors to adjust their reference points with a resulting impact on trading behavior. They find that when a stock crosses a new reference point, formed by the price level the day following unanticipated earnings news, it triggers higher trading volume. Huddart et al. (2009) show that weekly volume is strikingly higher when a stock price crosses either the upper or lower limit of its past trading range over the year and suggest that these limits are important reference points for investors. An alternative perspective offered by Baucells et al. (2011) asserts that increases in volume around historic price highs need not be reflective of such prices impacting investor reference points directly; rather, that peak prices tend to be above the reference point for most investors, resulting in increased volume because investors, experiencing paper gains, tend to succumb to the disposition effect and sell.

Following Baucells et al. (2011), if our CGO composites reveal the percentage capital gain or loss from the reference point, then we would expect them to be related to future trading volume. Specifically, higher levels of CGO should be associated with higher trading activity, as disposition-prone investors look to dispose of these stocks, whereas stocks with low CGO should be associated with low volume (Shefrin and Statman 1985). If our CGO composite variables more accurately represent the reference points of market investors than CGO, then we would expect them to have a stronger relationship with trading volume than CGO. By examining the predictive ability of CGO composites comprising reference points based on, amongst other things, historic highs/lows (*max*/*min*) and 52-week highs/lows (*max52*/*min52*), in the

Table 6B. Double Portfolio Sorts by *CGO-Com1* and *CGO*

Variable	*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****

Notes. Tables 6A and 6B report returns in double-sorted portfolios based on values of *CGOCom1* and *CGO*. At the end of each month, stocks are sorted into five portfolios by *CGOCom1* and *CGO*. Stocks in a portfolio are equally weighted. Each portfolio is held for 1 month, and the time-series average return is reported in monthly percent. Newey–West corrected *t*-statistics are shown below performance.
$^{**}p < 0.05$.

Table 7A. Double Sorts by *CGO* and *CGOCom2*

Variable	*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****

Notes. Tables 7A and 7B report returns of double-sorted portfolios based on values of *CGO* and *CGOCom2*. At the end of each month, stocks are sorted into five portfolios by *CGO* and *CGOCom2*. Stocks in a portfolio are equally weighted. Each portfolio is held for 1 month, and the time series average return is reported in monthly percent. Newey–West-corrected *t*-statistics are shown below performance.
$^{**}p < 0.05$.

context of volume, we are able to analyze the extent to which such prices shift reference points and, by doing so, impact trading volume. An increased predictive ability of our CGO composites over the original CGO would provide direct support for the view that salient historic highs/lows shift reference points and impact trading volume.

The following analysis converts our earlier data set into weekly data (Wednesday to Wednesday) to examine the predictive power of *CGO* and CGO composites on future volume. The weekly approach mirrors Huddart et al. (2009), although our data set is far larger. We define the dependent variables as follows: *VOL* is the average daily number of firm shares traded as a percentage of firm shares outstanding in the observation week, and *ABNVOL* is the residual from firm-by-firm ordinary least-squares (OLS) regressions of *VOL* on market volume, where market volume is measured as the average daily number of shares traded on the exchange where the stock is listed (NASDAQ or NYSE/Amex), expressed as a percentage of the number of shares outstanding for issues listed on that exchange in the observation week. Control variables are also taken from Huddart et al. (2009) and calculated as follows: *MAX* (*MIN*) is an indicator variable that takes the value 1 if the closing stock price for the observation week is above (below) the highest (lowest) price attained in the 48-week period ending 20 trading days before the last day of the observation week. *DIV* and *EARNANN* are indicator variables taking the value 1 if a dividend record date (from the Center for Research in Security Prices (CRSP)) or an earnings announcement (from COMPUSTAT), respectively, occurs during the observation week. *SDVOL* is the annualized standard deviation of stock returns computed from the 126 daily observations prior to the observation week. For $i \in \{1,2,3,4\}$, RET_i is the stock return in week $-i$ relative to the event. RET_5 is the return over weeks −26 to −5, inclusive. The returns are split by sign, so the returns regressors are $PRET_i = \max(RET_i, 0)$ and $NRET_i = \min(RET_i, 0)$ for $i \in \{1,2,3,4,5\}$. Descriptive statistics for all variables are shown in Table 8. *PRET* 2–5 and *NRET* 2–5 are omitted in the following regression results for reason of brevity.

In Table 9, we regress raw weekly volume (*VOL*) against *CGO* and the CGO composites in Models A, B, and C as shown in Equation (9). The results show that, whereas all of the CGO variables are predictive of

Table 7B. Double Sorts by *CGOCom2* and *CGO*

Variable	*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**	4.07**	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****

Notes. Tables 7A and 7B report returns of double-sorted portfolios based on values of *CGOCom2* and *CGO*. At the end of each month, stocks are sorted into five portfolios by *CGOCom2* and *CGO*. Stocks in a portfolio are equally weighted. Each portfolio is held for 1 month, and the time series average return is reported in monthly percent. Newey–West-corrected *t*-statistics are shown below performance.
$^{**}p < 0.05$.

Table 8. Descriptive Statistics for Volume Analysis

Statistic	*VOL*	*ABNVOL*	*MAX*	*MIN*	*DIV*	*EARNANN*	*SDVOL*	*PRET1*	*NRET1*
Mean	0.317	0.003	0.159	0.110	0.035	0.048	0.484	0.026	−0.021
Standard deviation	0.595	0.003	0.337	0.272	0.178	0.172	0.282	0.119	0.035
Median	0.180	0.002	0.001	0.020	0.000	0.000	0.424	0.005	−0.006
Maximum	18.036	0.043	1.000	0.999	1.000	0.846	4.649	5.549	0.000
Minimum	0.000	−0.007	0.000	0.000	0.000	0.000	0.036	0.000	−0.453
Skew	11.516	2.609	2.607	3.838	5.668	6.152	3.218	12.557	−3.730

Notes. This table reports summary statistics for variables used in volume analysis. All numbers presented are the time-series average of the cross-sectional statistics. *VOL* is the average daily number of firm shares traded as a percentage of firm shares outstanding in the observation week. *ABNVOL* is the residual from firm-by-firm OLS regressions of *VOL* on market volume, where market volume is measured as the average daily number of shares traded on the exchange where the stock is listed (NASDAQ or NYSE/Amex), expressed as a percentage of the number of shares outstanding for issues listed on that exchange in the observation week. *MAX* (*MIN*) is an indicator variable that takes the value 1 if the closing stock price for the observation week is above (below) the highest (lowest) price attained in the 48-week period ending 20 trading days before the last day of the observation week. *DIV* and *EARNANN* are indicator variables taking the value 1 if a dividend record date (from CRSP) or an earnings announcement (from COMPUSTAT), respectively, occurs during the observation week. *SDVOL* is the annualized standard deviation of stock returns computed from the 126 daily observations prior to the observation week. For $i \in \{1,2,3,4\}$, *RETi* is the stock return in week $-i$ relative to the event. *RET5* is the return over weeks −26 to −5, inclusive. The returns are split by sign, so the returns regressors are *PRETi* = max(*RETi*, 0) and *NRETi* = min(*RETi*, 0) for $i \in \{1,2,3,4,5\}$.

future trading volume, the CGO composite variables in Models B and C have higher coefficients than *CGO* and the explanatory power of these models is higher in the form of R^2 than Model A. This suggests that the composite variables are stronger predictors of raw weekly volume than *CGO*.

$$\begin{aligned} VOL_t = {} & \beta_0 + \beta_1 CGO_{t-1} + \beta_2 MAX_t + \beta_3 MIN_t + \beta_4 DIV_t \\ & + \beta_5 EARNANN_t + \beta_6 SDVOL_{t-1} + \beta_7 PRET1_t \\ & + \beta_8 PRET2_t + \beta_9 PRET3_t + \beta_{10} PRET4_t \\ & + \beta_{11} PRET5 + \beta_{12} NRET1_t + \beta_{13} NRET2_t \\ & + \beta_{14} NRET3_t + \beta_{15} NRET4_t + \beta_{16} NRET5 + \varepsilon. \end{aligned} \tag{9}$$

This result is mirrored in Models D, E, and F, which show the relationship between *CGO* and future abnormal volume (*ABNVOL*). Although all three CGO variables are predictive of future abnormal trading volume, the CGO composites have larger coefficients than *CGO*, and Models E and F have more explanatory power to predict future abnormal volume than Model D.

In summary, the results suggest that future volume is more sensitive to the CGO composite variables than for *CGO*. This is in line with our earlier analysis on future returns, where we show that 1-month-forward returns are more sensitive to the CGO composites than to *CGO*. Both results suggest that the composite reference points used in *CGOCom1* or *CGOCom2* are more accurate reference points than the purchase price used in *CGO*. Given that these composite reference points are formed with input from historic highs/lows (*max*/*min*) and 52-week highs/lows (*max52*/*min52*), respectively, we provide direct support to the view that such prices impact investors' reference points, as discussed in Kliger and Kudryavtsev (2008) and Huddart et al. (2009). At the same time, our use of composite CGO measures supports the view in Baucells et al. (2011) that observed volume increases around historic highs is reflective of the peak price being above the reference point for most investors, thus placing them in a gain situation and so under the influence of the disposition effect.

3.5. Moderation Analysis: Speculative Stocks

In this section, we examine whether retail investors are more sensitive to reference-point effects than institutional traders. Dhar and Zhu (2006) suggest that nonprofessionals exhibit a higher disposition effect, which supports the idea that these nonprofessionals may be more sensitive to reference points than professional institutional traders. If this is the case, then we would expect *CGO* and the CGO composites to have greater predictive power among the stocks in which retail investors are more likely to trade.

Within the Grinblatt and Han (2005) model, investors are split into two categories: either rational or prospect theory/mental accounting (PT/MA) investors. The PT/MA investors are subject to the disposition effect and, hence, drive the abnormal returns from the *CGO* variable. If retail investors are more likely to be the irrational PT/MA traders, then the predictive power of *CGO* and the CGO composite variables could be stronger among the more speculative stocks that are more likely to be traded by these retail investors (Han and Kumar 2013).

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 10 presents Fama–MacBeth regressions that are the same as Equation (8), except that we add three

Table 9. Weekly Regression of Volume Using *CGO* and Control Variables

Variable	Model A	Model B	Model C	Model D	Model E	Model F
CGO	0.0743***			0.000297***		
	(7.022)			(4.675)		
CGOCom1		0.153***			0.000733***	
		(8.151)			(6.614)	
CGOCom2			0.171***			0.000829***
			(8.104)			(6.606)
MAX	0.141***	0.140***	0.139***	0.000163***	0.000155***	0.000156***
	(11.86)	(11.78)	(11.72)	(4.778)	(4.582)	(4.500)
MIN	0.0603***	0.0640***	0.0688***	−0.000189***	−0.000165***	−0.000139***
	(9.632)	(10.05)	(10.17)	(−7.106)	(−6.187)	(−5.255)
DIV	0.00915***	0.00850***	0.00848***	−0.000164***	−0.000168***	−0.000169***
	(3.456)	(3.286)	(3.309)	(−8.301)	(−8.617)	(−8.705)
EARNANN	0.132***	0.132***	0.132***	7.50e-05***	7.76e-05***	7.76e-05***
	(13.17)	(13.17)	(13.16)	(6.436)	(6.646)	(6.661)
SDVOL	0.121***	0.135***	0.140***	0.000836***	0.000926***	0.000950***
	(8.753)	(9.507)	(9.653)	(9.965)	(11.02)	(11.22)
PRET1	1.593***	1.646***	1.630***	0.00131***	0.00159***	0.00151***
	(15.60)	(15.68)	(15.64)	(13.09)	(13.23)	(13.59)
NRET1	−1.290***	−1.245***	−1.277***	−0.00252***	−0.00231***	−0.00246***
	(−15.70)	(−15.85)	(−15.84)	(−14.46)	(−14.32)	(−14.59)
Constant	0.0754***	0.0721***	0.0679***	0.00211***	0.00208***	0.00205***
	(10.35)	(9.910)	(9.734)	(19.61)	(19.52)	(19.83)
Observations	10,123,143	10,123,143	10,123,143	10,134,527	10,134,527	10,134,527
Number of groups	2,687	2,687	2,687	2,687	2,687	2,687
Average R^2	0.139	0.141	0.142	0.108	0.109	0.110

Notes. This table reports results for predictive Fama and MacBeth (1973) regressions of *VOL* (Models A, B, and C) or *ABNVOL* (Models D, E, and F) on *CGO*, CGO composites, and a set of control variables. Refer to Table 8 for definitions of dependent and control variables. *CGO* is calculated by using the turnover-adjusted purchase price as shown in Equation (5). *CGOCom1* is calculated as per *CGO*, but replacing the purchase price with *Refcom1*, calculated as per Equation (6). *CGOCom2* is calculated as per *CGO*, but replacing the purchase price with *Refcom2*, calculated as per Equation (7). All *CGO* variables are lagged by 1 week relative to the dependent variables. *t*-statistics in parentheses are Newey–West-adjusted.
$^{**}p < 0.05$; $^{***}p < 0.01$.

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 nine models in total across the three moderating variables. The control variables are omitted from the regression results for the sake of brevity.

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, suggesting that high-turnover stocks are more likely to be subject to mispricing caused by PT/MA investors.[8] For both market capitalization (Models D, E, and F) and price volatility (Models G, H, and I), however, none of the interaction terms are significant.[9] 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 a stock's expected return is monotonically increasing in both CGO and high current turnover. This is because high current turnover closes the mispricing caused by PT/MA investors, which shifts the aggregate demand function closer to rational pricing, as earlier investors liquidate their holding. They show that the predictive power of CGO is increased when it is multiplied by the turnover of the current week, in line with the prediction of their model. It is possible, therefore, that our average turnover variable, which is calculated by 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, supporting this idea.

4. Discussion

The literature on reference-point adaptation is still developing, but research such as Baucells et al. (2011) has shown that intermediate prices can affect the reference point of the investor. Our first contribution is to expand on these earlier studies, using real stock-price graphs over longer horizons, to investigate the likely reference point for an investor in an externally valid setting.

Table 10. Regression of Monthly Returns using CGO Variables and Moderators

Variable	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)
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

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

$^{**}p < 0.05$; $^{***}p < 0.01$.

Our experimental results suggest the importance of highs and lows, in addition to the purchase and final prices, in line with earlier studies such as Baucells et al. (2011), but we also extend previous findings by demonstrating that highs and lows attained during the last 52 weeks play a strong role in reference-point formation over longer time periods. This finding is consistent with George and Hwang (2004), who demonstrate that the distance from the 52-week high is a key driver of future stock returns. The implication of our results is that further research should be carried out into the 52-week high as a reference point; for example, Bhootra and Hur (2013) have discovered a recency effect that magnifies the impact of a 52-week high. The 52-week low has received scant attention in the literature and is also worthy of further investigation. Arkes et al. (2008) and Chen and Rao (2002) suggest that reference-point adaptation is greater in gains than losses. This asymmetric adjustment may be caused by the greater saliency of recent highs than recent lows, as we demonstrate in our experiment.

Our second contribution is to take the insights we learn from the controlled conditions of the experiment and apply these to the rich and complex setting of the U.S. 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 1-month-ahead returns when plugged into the CGO model. In fact, alternative CGO variables based on the maximum, minimum, 52-week maximum, or 52-week minimum are equally good predictors. This may seem a surprising result given the common use of a purchase-price-based reference point in financial models such as the CGO, but demonstrates the benefits of exploring more complex models in a controlled environment and then applying in the real-world context.

Third, we create two CGO-composite variables formed from weighting different salient points in the stock-price path, using coefficients determined in the experiment. *CGOCom1* is created by using the purchase, maximum, and minimum prices, whereas *CGOCom2* includes the purchase and 52-week maximum and minimum prices. The traditional CGO variable is no longer a positive predictor of returns when either of the CGO-composite variables are included in the regression. We also conduct double sorts by both *CGO* and CGO composites and determine that *CGO* is rarely predictive of returns after stocks are first sorted by the composites, but the composites are generally predictive of returns even if stocks are first sorted by CGO.

Fourthly, we find that the CGO-composite variables have a stronger relationship with future trading volume than *CGO*. Both 1-week-ahead raw volume and abnormal volume are more sensitive to changes in the CGO composites than to changes in *CGO*. The results suggest that our CGO-composite variables, formed from a composite of salient points predicted in the experiment, are better predictors of forward returns and forward volume than the traditional CGO variable. The implication 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. Finally, our results are robust to investor segment analysis, using proxies for speculative stocks to measure the influence of CGO across different groups of investors.

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 the market-data model, lead to profitable arbitrage opportunities, which could be capitalised upon by investment managers.

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 our results suggest that the impact of adjusting reference points in other financial models is worthy of investigation. The disposition effect is a popular area of study, for example, and yet the original assumption of Shefrin and Statman (1985) regarding the reference point has largely remained in place. Reference-point adjustment is a subjective process that is challenging to model, being subject to many variables. The response to these variables may vary by individual characteristics (Dhar and Zhu 2006), environmental factors, and emotions (Summers and Duxbury 2012). Investigation of the influence of these additional factors could provide new insights into investor behavior and allow the potential development of more accurate reference-point predictions.

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Appendix

Figure A.1. Instructions

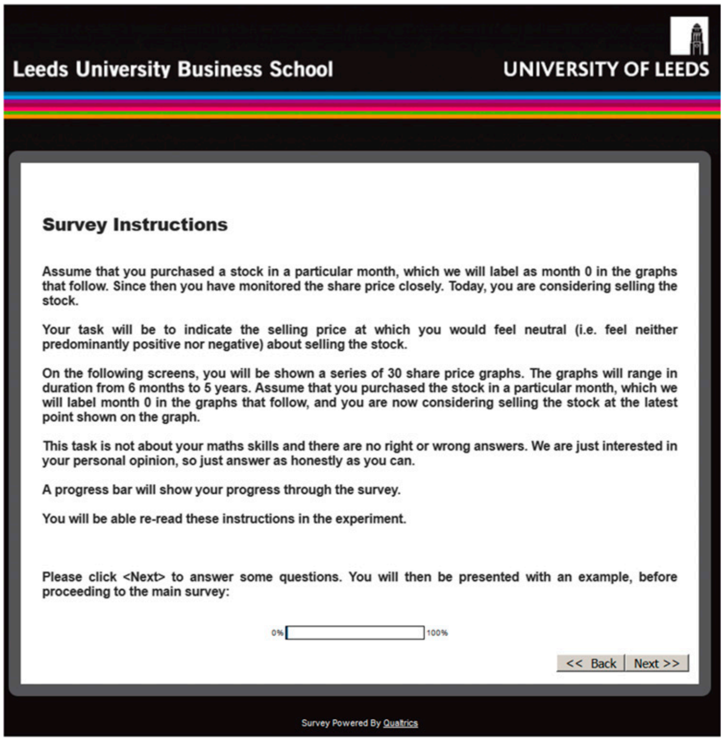
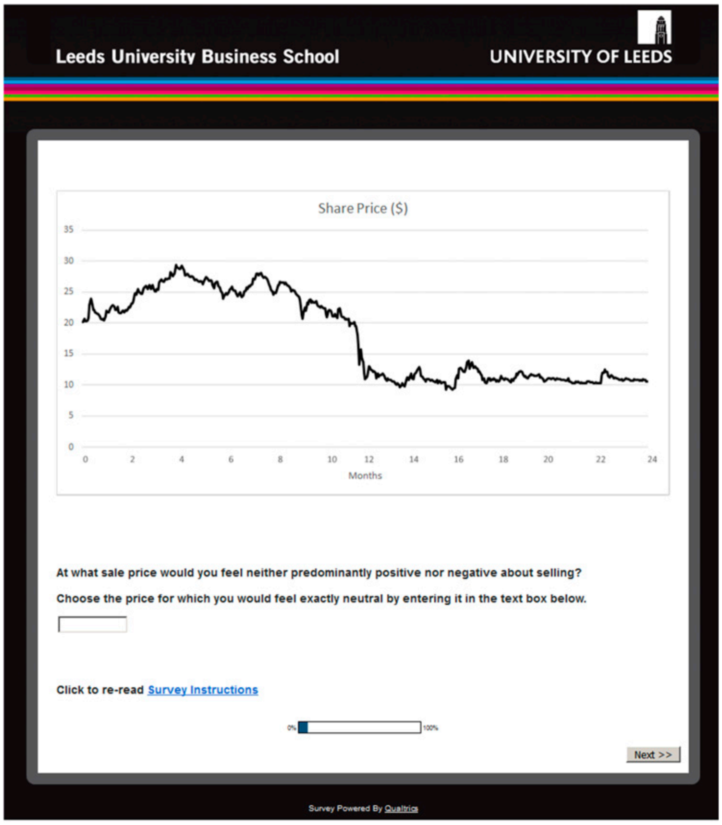


Figure A.2. Example Chart



Endnotes

[1] Investor behavior is an ideal setting in which to investigate reference-point adjustment due to the higher frequency with which stock markets feed back information (stock-price changes) on prior decisions (trading decisions) relative to other decision contexts such as capital budgeting or strategic investment.

[2] We thank an anonymous reviewer for suggesting this additional line of enquiry.

[3] We thank an anonymous reviewer for suggesting this additional line of enquiry.

[4] Indeed, Baucells et al. (2011) note the provocative nature of the conclusion reported therein, that historical peaks seem to matter little for reference points (with historic troughs even less), and calls for further exploration in this regard. We duly provide such exploration in the context of longer price sequences, thus allowing an examination of both historic highs/lows and recent (52-week) highs/lows.

[5] In addition to the tests mentioned here, we follow recent literature testing the CGO model (Wang et al. 2017, An et al. 2019) and also perform subsample tests by excluding NASDAQ stocks or by splitting the sample in half by date and running a regression on the two subsamples. Our results are robust to these additional tests.

[6] For the January subsample, Model A produces a higher average R^2 than models B and C, whereas for the February–December subsample, the CGO composite variables once more provide superior explanatory power, as is the case in the full-sample analysis. Grinblatt and Han (2005) interpret the negative *CGO* variable in the January subsample in the context of tax-loss selling in relation to the purchase price. The composite reference points entering the computation of *CGOCom1* and *CGOCom2* comprise additional salient points above and beyond the purchase price, which might account for the relative performance of the composite CGO variables in the January subsample.

[7] The inclusion of the analyst forecast dispersion variable leads to a reduction in sample size. To limit sample-size reduction, we run the models in Table H in the electronic companion with only the first two risk controls (i.e., excluding the analyst forecast dispersion variable), so as to limit sample size reduction. Again, our CGO-composite results (untabulated) remain robust.

[8] High-frequency trading has been shown to impact market performance and price discovery. To further examine the robustness of our results, we also run a subsample regression for high-frequency-trading stocks, which are ranked in the highest 20% quintile of turnover over the prior month. We find that our results in Table 5 are robust within this subset of stocks.

[9] Following Wang et al., (2017), we also ran value-weighted regressions, with weights given by the square root of market capitalisation over the prior month. We find that our results in Table 5 are robust to the change in weighting.

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