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Reference point formation by market investors

Doron Kliger *, Andrey Kudryavtsev [1]

Department of Economics, University of Haifa, Haifa 31905, Israel

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Abstract

The *disposition effect* [Shefrin, H., Statman M., 1985, The disposition to sell winners too early and ride losers too long. Journal of Finance, 40, 777–790], investors' tendency to sell gaining assets and hold on to loosing assets, relies on the notion of a *reference point* distinguishing between losses and gains. While literature using aggregated market data documented the existence of such a reference point affecting investors' decisions, it had not pinpointed it. The main goal of our work is to shed light on the mechanism of reference point formation. We hypothesize that salient events taking place during a stock's holding period influence investors' perceptions and make them update the stock's reference point. Using analysts' earnings forecasts, stock price data, and firms' quarterly earnings announcements, we document that company-specific events indeed affect the reference points. We discover that the earnings announcements played a role in reference point formation when they were not anticipated, i.e., when (i) analysts' earnings forecasts failed to provide accurate predictions; and (ii) the earnings announcements were followed by market price reactions. Moreover, the reference points were affected more profoundly for low market capitalization, high beta firms, pointing that the reference point updating process is more reactive to events when information flow is low and prices are sensitive to market fluctuations. Our results also corroborate the attention hypothesis, i.e., the observation that agents facing numerous alternatives may consider primarily those that have caught their attention.

JEL classification: D01; D81; D84; G11

Keywords: Behavioral finance; Disposition effect; Mental accounting; Prospect theory; Reference point

1. Introduction

Empirical studies have documented that various regularities in investors' behavior seem to be at odds with the neoclassical expectations paradigm. One of the most striking patterns is the tendency of investors to sell "winners" (stocks that gained value) and to hold on to "losers" (stocks that lost value). Shefrin and Statman (1985) were the first to draw attention to the potentially substantial impact of this kind of investor behavior in capital markets, dubbing it the *disposition effect*. The behavioral explanation they offered to the disposition effect incorporates the notion of loss aversion (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) into a theoretical framework extending the behavioral model presented in Shefrin and Statman (1984). Four elements, namely prospect theory; mental accounting (Thaler, 1985); regret aversion; and self-control, contribute to the analysis. In essence, the disposition effect is a reflection of investors keeping a separate mental account for each stock and, according to prospect theory, maximizing an S-shaped, reference-level based, value function within that account. Aversion to regret explains why investors may have difficulty realizing gains and losses, and self-control provides the rationale for methods investors use to force themselves to realize losses.

The disposition effect is well documented in several studies using aggregate market-wide data (Lakonishok and Smidt, 1986; Ferris et al., 1988; Bremer and Kato, 1996,

* Corresponding author. Tel.: +972 54 428 4268; fax: +972 4 824 0059.
E-mail addresses: kliger@econ.haifa.ac.il (D. Kliger), kud.andrey@gmail.com (A. Kudryavtsev).
[1] Authors' names appear in alphabetical order.

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to name but a few), data from individual investors' accounts (e.g., Odean, 1998; Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Coval and Shumway, 2005), and also in studies using an experimental questionnaire design (Weber and Camerer, 1998; Oehler et al., 2002). The literature discusses a number of profitable investment strategies, emanating from the disposition effect. For example, Jegadeesh and Titman (1993) find that strategies which involve purchasing stocks that have performed well and selling stocks that have performed poorly generate significant positive returns. Similarly, Odean (1998) argues that the winners that people sell subsequently outperform the losers they hold.

The commonly practiced reference point distinguishes between winners and losers relatively to the asset's original purchase price. In the present work, we argue that investors may modify their view on a financial asset upon the arrival of new information, such as firms' earnings announcements. An earning announcement may make the investors acknowledge the asset's return resulting from the arrival of the information embedded in it and, therefore, reset the mental account they allotted to investing in the firm's stocks. Subsequently, they may evaluate the asset relatively to the market price established after the incorporation of the information update. To elaborate, when a firm reveals new information by announcing an unexpected earnings figure, some market participants may perceive the firm's stocks as having new, altered, attributes and, therefore, evaluate their holding position in the stocks relatively to the performance from that point on.

It is worthwhile to note here that two types of testable hypotheses emanate from the above. First, unexpected earnings announcements should be followed by investors updating the reference points of their investments, and second, such reference point updates should not be detected when the announced earning figures were expected by the investors. We investigate the latter by employing two proxies for investors' expectations with respect to the firms' earnings: (i) analysts' consensus earnings per share (EPS) figures, and (ii) the stock price reactions to the firms' earnings announcements.

The main goal of our work is to contribute to the literature shedding light on the formation of investors' reference points using aggregate market-wide data. In aggregate data analysis, where purchase prices are neither common, nor easily identified, historical stock prices, somewhat arbitrarily lagged, are often applied. Our hypothesis that salient firm-specific events may influence investors' attitudes and modify the reference points may be used to sharpen the reference points' identification. In this context, we empirically test the hypothesis that such events drive the investors to update their view on firms' stocks. As an example of firm-specific events, we employ firms' earnings announcements. For a large sample of stocks, we use market prices and trading volumes to check if the disposition effect is exhibited with respect to the stocks' prices at the firms' earnings announcements. In other words, we empirically test the hypothesis that investors compare (in their "mental accounts") contemporaneous stock prices with the prices established at the market as a reaction to the underlying firms' earnings announcements. Our approach for analyzing the disposition effect employs the trading volume at the crossing of the hypothesized reference level. This approach is fitted for revealing the investors' attitude to a specific price level.

We conjecture that if investors update the stock's reference point when the issuing firm announces its earnings, then the tendency of selling winning stocks and holding losing stocks should be reflected in a higher trading volume at upward crossings of the newly established price than at downward crossings of this price. Furthermore, we hypothesize that such a trading-volume differential should not be detected in cases where the announced earning figure was expected by the investors.

In support of our research hypothesis, we find empirical evidence that unexpected company-specific events influence investors' perceptions, causing them to record the post-event stock prices in their mental accounts. Our results also corroborate the attention hypothesis (cf. Odean, 1999; Barber and Odean, 2007), i.e., the observation that agents facing numerous alternatives may consider primarily those that have caught their attention.[2] Specifically, we find support to the hypothesis that investors' attention to the stocks is amplified at the first post-announcement price crossing. Nevertheless, the reference point updating hypothesis is established also after controlling for the sequence of the stock price crossings.

Importantly, we discover that firm-specific events play a role in cases where they were not anticipated, i.e., when (i) analysts' earnings forecasts failed to provide accurate predictions; and (ii) earnings announcements were followed by stock price reactions. These results suggest that investors update the stocks' reference points after observing events which they perceive to be surprising.

The paper is structured as follows. In Section 2, we review the existing literature. Sections 3–5 describe the dataset, define the hypotheses, perform the empirical tests, and analyze the results. Section 6 summarizes our findings.

2. Literature review

Recent literature pays much attention to documenting the disposition effect. Three different kinds of data are applied for studying the disposition effect: aggregate (on the level of stock exchanges), individual (on the level of individual investors) and experimental.

The first to employ aggregate data are Lakonishok and Smidt (1986). Using historical stock prices as possible reference points, they find that winners tend to have higher abnormal volume than losers. A similar technique is

[2] We wish to thank an anonymous referee for pointing out the possible role of the attention hypothesis in the interpretation of our findings.

employed by Ferris et al. (1988) and Bremer and Kato (1996), yielding comparable results. Huddart et al. (2003) find that a significantly higher volume when stock prices are above (below) their fifty-two week highs (lows). Kaustia (2004) uses the price and volume information on US initial public offerings (IPOs) to find that for negative initial return IPOs, trading below the offer price (which is assumed to be the reference point) is suppressed in comparison to trading above the offer price, and that there is an increase in trading volume as their stock prices reach new record highs. Yet, for positive initial return IPOs, Kaustia documents an increase in trading volume on the day the stock price first falls below the offer price, the finding which is not necessarily consistent with the disposition effect. Szyszka and Zielonka (2007) show for a sample of Polish IPOs that a higher turnover volume on the first trading day is associated with a positive initial rate of return and a lower turnover volume is associated with a negative initial rate of return.

The second major group of papers studying the disposition effect is based on individual data. The reference point in these studies is taken to be the stocks' purchase prices. In a comprehensive research, Odean (1998) takes the average purchase price (for each investor and stock) as a reference point and then distinguishes between paper, vs. realized, gains and losses. For each day and investor, he calculates the Proportion of Gains Realized (PGR) and the Proportion of Losses Realized (PLR), taking the ratio of PGR to PLR as a measure of the disposition effect. Odean's main findings include the observation that individual investors demonstrate significant preferences for selling winners and holding losers. In line with Odean, and applying similar technique, Chen et al. (2007) show that Chinese investors are also susceptible to the disposition effect, individual investors being more affected by this bias than institutional ones. Ranguelova (2001) documents a strongly pronounced disposition effect for high capitalization stocks, and a reversed effect for low capitalization stocks. Dhar and Zhu (2002) find that the disposition effect is mainly pronounced by low-income and non-professional investors. Brown et al. (2002) find that the disposition effect gradually diminishes over the holding period and traders instigating larger investments tend to be less, if not entirely unaffected by the disposition bias. Goetzmann and Massa (2003) argue that investors' disposition bias affects the firms' returns. Grinblatt and Han (2005) were the first to connect the disposition effect and momentum, showing, both theoretically and empirically, that the disposition effect may account for the tendency of past winning stocks to subsequently outperform past losing stocks. Frazzini (2006) finds that in the presence of disposition-prone investors, prices under-react to news, generating thereby a post-event price drift. Importantly, Frazzini's (2006) work indicates that mutual fund managers, i.e., professional investors, are susceptible to the disposition effect, and that losing managers exhibit the effect to the same degree as individual investors. Cici (2005) contends that there exists a negative relation between the disposition effect and mutual funds performance both in the short term and over intermediate intervals. Weber and Welfens (2006) argue that loss realization aversion is a more common mistake across investors, while there is strong heterogeneity concerning the realization of winners. Furthermore, investors who realize their winners too early are found to be not the same investors who hold their losers too long. Coval and Shumway (2005) analyzing intra-daily trading behavior, find traders to appear highly loss-averse, regularly assuming above-average afternoon risk to recover from morning losses.

Another body of papers analyzing individual data compares the holding periods of gaining and losing positions, rather than the ratios of realized gains and losses. Locke and Mann (2005) find that the average holding period for losing trades is longer than for winning trades. They argue that, while all traders hold losers longer than winners, the least successful traders hold losers the longest, while the most successful traders hold losers for the shortest time. Shapira and Venezia (2001) compare the duration of winning and losing round trips and document the disposition effect for all groups of accounts, finding that it is less pronounced for managed, than for independent, accounts. Garvey and Murphy (2005) analyze the behavior of a professional proprietary stock-trading team, and document that the mean duration of a losing round trip is 268 s, while the mean duration of a winning round trip is only 166 s. They also show that closing profitable positions early and holding losing positions longer is not optimal since it reduces the global profitability of the team. Grinblatt and Keloharju (2001) run Logit regression of the dummy variable "sell-not sell" on a large number of regressors and, consistently with the disposition effect, find that past returns, historical high and low prices and size of holding period capital gain or loss are all determinants of trading. In order to quantify the magnitude of the disposition effect, Feng and Seasholes (2005) combine the traditional Logit analysis with survival time analysis to measure the disposition effect. Their approach has the advantage of incorporating the stocks' typical holding and providing an interpretation to the probability of selling. They find that neither investor sophistication nor trading experience alone eliminates the disposition effect, while together these may eliminate the reluctance of investors to realize losses.

The third group of papers that sheds light on the disposition effect consists of papers employing experimental design. Weber and Camerer (1998) carry a multi-stage experiment examining different characteristics and determinants of the disposition effect and find that subjects tend to sell fewer shares when the price falls than when it rises and also sell less when the price is below the purchase price than when it is above. Similarly to Weber and Camerer (1998) and Oehler et al. (2002) use the purchase price and the last period price as alternative reference points. The disposition effect is found to be stronger when the purchase price is taken as a reference point.

To summarize, existing research is consistent with the disposition effect. Yet, the possibility that some real company-specific events affect investors' perspective on a specific stock, thus affecting the reference point, was not considered.

3. Data

The main data source for our work is the dataset of quarterly earnings announcements of companies listed on NYSE, NASDAQ, and AMEX, as provided by Thomson First Call. This dataset defines a firm's earnings surprise as the difference between its actual quarterly EPS and consensus EPS (an average of the estimates by all analysts following the company). The earnings surprises in the dataset are updated following firms' earnings publications and are classified into three basic categories: *upside surprises* (*US*; actual EPS > consensus EPS), *met expectations* (*ME*; actual EPS = consensus EPS), and *downside surprises* (*DS*; actual EPS < consensus EPS).

The goal of our research is to empirically test whether firm-specific salient events drive investors to update the reference levels they attribute to the prices of the firms' stocks. Specifically, we focus on the possible effect of firms' earnings announcements. The basic idea of the proposed tests is to compare the trading volumes at upward and downward crossings of the hypothesized reference level, measured by the closing stock price on the day following the announcement.

For the empirical analysis, we take all the earnings surprises provided by Thomson First Call for the first 6 months of the year 2007. We record the trading volumes at the above defined price crossings for each event in our sample, provided that they took place (i) before the firm's subsequent quarterly earnings announcement, as published by Thomson First Call; and (ii) within 70 days from the firm's earnings announcement day. One upward and one downward crossing are recorded for each stock. Stocks without such data over the specified time period are excluded from the analysis. Furthermore, we exclude stocks with less than one year of trading data available prior to the earnings announcement and stocks without information on the value of the respective firm's market capitalization. In this way, we obtain our working sample of 4517 earnings surprises for 3126 distinct firms. Table 1 provides basic descriptive statistics of our sample. Panel A of the table describes the reported EPS and Panel B the firms' market capitalization (MCap). The firms in our sample belong to nine sectors of the economy. The number of earnings surprises (firms) in the sectors varies from 20 (12) to 938 (637). Reported EPS (market capitalization) figures range from 0.049 (4265) to 0.698 (19,101) Dollars per share (millions of Dollars), with a standard deviation of 0.605 (22,870).

For assessing the news content in the earnings announcements, we divide the sample according to two "news" proxies (i) earnings surprise: the surprise relatively to the analysts' opinion (i.e., *US*, *ME* and *DS*), and (ii) market reaction: the market-model adjusted (MMA) stock price reaction to the earning announcement. For the latter, the events are classified into three roughly equally sized categories: *positive return* (*PR*) if the MMA abnormal stock return around the event is higher than 1.36%; *intermediate return* (*IR*) in case the MMA abnormal return is between −2.09% and 1.36%; and *negative return* (*NR*) if the MMA abnormal return is lower than −2.09%.[3] Table 2A depicts the working sample distribution according to the two partitions.[4]

A trading pattern consistent with the disposition effect implies a higher trading volume on days of upward crossings than on downward crossings. Yet, the employed tests should control for the possibility that the trading volume may normally be different on days of negative and positive returns. For this purpose, we adjust the employed tests for an estimated return-related volume pattern. To estimate the volume pattern, we use price and trading volume data for the 251 trading days preceding each earnings announcement, by running the following regressions:

$$\ln(V_{it}) = \delta_i + \gamma_i^* \text{dir\_dummy}_{it}, \tag{1}$$

where $\ln(V_{it})$ is the natural logarithm of the stock's trading volume on day t for firm-specific (earnings-announcement) event i; dir_dummy_{it} is a dummy variable taking the value 1 if the day-t return on the stock for which event i took place, was positive, and 0 otherwise. The γ_i coefficients provide estimates for the (natural log) volume differences between days with positive and negative stock returns. Table 3A presents descriptive statistics of the γ_i estimates for the total sample and surprise categories partition, as defined by the analysts' and market proxies, respectively.[5]

The regressions yield positive γ_i estimates for the majority of the events, suggesting that the trading volume at positive return days is generally higher than at negative return days. To control for the influence of this return-related volume pattern, we compute adjusted volumes at upward crossings, according to the following equation:[6]

$$V_{\text{adj}}(U_i) = \mathrm{e}^{[\ln(V(U_i) - \hat{\gamma}_i)]}, \tag{2}$$

where $V(U_i)$ is event i's trading volume at the upward price crossing. As an additional robustness check, we also

[3] The MMA abnormal returns are measured between days −1 and +1, where "day 0" is the announcement day.

[4] We perform many of the tests presented subsequently also on return differences from the S& P 500 index (market adjusted returns), as well as on raw returns. Table 2B depicts the working sample distribution according to these two return benchmarks.

[5] Table 3B presents the descriptive statistics of the γ_i estimates for the market proxy constructed on market adjusted returns, as well as on raw returns.

[6] Note that adjusting the statistics by a positive estimate of γ_i (the majority of the estimates are positive) reduces the power of the tests for detecting the disposition effect. Thus, the fact that we do find the effect while employing the adjustment procedure strengthens the validity of the results.

Table 1
Working sample: descriptive statistics

Sector	Number of events	Reported EPS, $			
		Average	St. Dev.	Maximum	Minimum
Panel A: Reported EPS descriptive statistics for the working sample					
1. Basic materials	394	0.473	0.513	2.68	−1.15
2. Conglomerates	20	0.698	0.410	1.54	−0.12
3. Consumer goods	359	0.354	0.395	2.26	−0.81
4. Financial	938	0.543	0.688	10.62	−1.57
5. Healthcare	602	0.049	0.431	2.72	−2.00
6. Industrial goods	304	0.336	1.013	12.96	−5.65
7. Services	907	0.342	0.629	9.20	−2.31
8. Technology	864	0.165	0.356	4.13	−2.46
9. Utilities	129	0.553	0.463	2.87	−0.60
Total sample	*4517*	*0.330*	*0.605*	*12.96*	*−5.65*
Sector	Number of firms	Market capitalization, $ millions			
		Average	St. Dev.	Maximum	Minimum
Panel B: Market capital (MCap) descriptive statistics for the firms making up the working sample					
1. Basic materials	281	12,103	44,401	508,900	19.4
2. Conglomerates	12	19,101	25,231	74,600	345.7
3. Consumer goods	250	8848	25,972	201,400	9.4
4. Financial	637	6273	22,886	361,600	39.9
5. Healthcare	421	5583	20,531	183,700	26.6
6. Industrial goods	211	4265	9118	80,200	22.2
7. Services	623	4661	13,058	201,900	17.2
8. Technology	599	5555	20,452	285,300	8.5
9. Utilities	92	6903	9108	52,600	44.3
Total sample	*3126*	*6384*	*22,870*	*508,900*	*8.5*

Table 2A
Sample partition according to the two "news" proxies

News proxy	Earnings surprise			Market reaction			Total
News category	*US*	*ME*	*DS*	*PR*	*IR*	*NR*	
Number (percent) of events in sector and news categories							
Sector:							
1. Basic materials	183(46.4)	39(9.9)	172(43.7)	116(29.4)	144(36.5)	134(34.1)	394(8.7)
2. Conglomerates	14(70.0)	0(0.0)	6(30.0)	12(60.0)	3(15.0)	5(25.0)	20(0.4)
3. Consumer goods	197(54.9)	53(14.8)	109(30.3)	135(37.6)	118(32.9)	106(29.5)	359(7.9)
4. Financial	412(43.9)	122(13.0)	404(43.1)	245(26.1)	457(48.7)	236(25.2)	938(20.8)
5. Healthcare	326(54.2)	77(12.8)	199(33.0)	204(33.9)	148(24.6)	250(41.5)	602(13.3)
6. Industrial goods	173(56.9)	25(8.2)	106(34.9)	145(47.7)	77(25.3)	82(27.0)	304(6.7)
7. Services	453(49.9)	151(16.6)	303(33.5)	315(34.7)	264(29.1)	328(36.2)	907(20.1)
8. Technology	452(52.3)	144(16.7)	268(31.0)	317(36.7)	203(23.5)	344(39.8)	864(19.1)
9. Utilities	56(43.4)	13(10.1)	60(46.5)	21(16.3)	84(65.1)	24(18.6)	129(2.9)
Total sample	2266(50.2)	624(13.8)	1627(36.0)	1510(33.4)	1498(33.2)	1509(33.4)	4517(100.0)

perform the statistical tests after adjusting each firm's volume by the grand average of the point estimates, and get similar results (see Appendix).[7]

4. Testable hypotheses and results

If investors update the reference point on the event day, then the tendency of selling winners should drive the trading volume at upward crossings to be abnormally high, that is

$$V_{\mathrm{adj}}(U_i) > V(D_i), \tag{3}$$

where $V(D_i)$ is event i's trading volume at the downward price crossing. We hypothesize that surprising events drive the investors to update the reference levels. That is, we expect to find significant evidence for the disposition effect when (i) reported EPS values are in discrepancy with analysts' forecasts, i.e., within the *US* and *DS* categories, of the earnings surprise news proxy, but not within the *ME* category; and (ii) the market reacted to the earnings

[7] Tests based on unadjusted volume (not reported here) yield qualitatively similar results. As the majority of the point estimates on dir_dummy in regression (1) are positive, these results are, in fact, stronger.

Table 2B
Sample partition by the market reaction proxy according to market adjusted and raw returns

News proxy	Market adjusted			Raw returns			Total
News category	*PR*	*IR*	*DS*	*PR*	*IR*	*NR*	
Number (percent) of events in sector and news categories							
Sector:							
1. Basic materials	121(30.7)	141(35.8)	132(33.5)	117(29.7)	140(35.5)	137(34.8)	394(8.7)
2. Conglomerates	12(60.0)	4(20.0)	4(20.0)	11(55.0)	3(15.0)	6(30.0)	20(0.4)
3. Consumer goods	135(37.6)	118(32.9)	106(29.5)	140(39.0)	109(30.4)	110(30.6)	359(7.9)
4. Financial	241(25.7)	456(48.6)	241(25.7)	248(26.4)	449(47.9)	241(25.7)	938(20.8)
5. Healthcare	203(33.7)	155(25.7)	244(40.6)	197(32.7)	171(28.4)	234(38.9)	602(13.3)
6. Industrial goods	144(47.4)	78(25.7)	82(26.9)	150(49.3)	72(23.7)	82(27.0)	304(6.7)
7. Services	310(34.2)	270(29.8)	327(36.0)	313(34.5)	259(28.6)	335(36.9)	907(20.1)
8. Technology	320(37.0)	194(22.5)	350(40.5)	322(37.3)	202(23.4)	340(39.3)	864(19.1)
9. Utilities	23(17.8)	83(64.4)	23(17.8)	19(14.7)	84(65.1)	26(20.2)	129(2.9)
Total sample	1509(33.4)	1499(33.2)	1509(33.4)	1517(33.6)	1489(33.0)	1511(33.4)	4517(100.0)

Table 3A
Empirical return-related volume pattern: descriptive statistics of the γ_i estimates

	Earnings surprise			Market reaction			Total
	US	*ME*	*DS*	*PR*	*IR*	*NR*	
Mean	0.046	0.052	0.040	0.046	0.040	0.047	0.044
Median	0.036	0.039	0.028	0.035	0.031	0.033	0.033
Standard deviation	0.100	0.115	0.114	0.102	0.109	0.113	0.108
Maximum	0.684	0.816	0.762	0.638	0.762	0.816	0.816
Minimum	−0.404	−0.433	−0.418	−0.404	−0.433	−0.418	−0.433
Kurtosis	7.144	8.661	5.762	5.999	7.090	7.258	6.914
Percent of positive estimates	68.491	66.506	62.077	67.748	64.553	65.408	65.907

Table 3B
Empirical return-related volume pattern: descriptive statistics of the γ_i estimates by the Market Reaction proxy according to market adjusted and raw returns

	Market adjusted			Raw returns			Total
	PR	*IR*	*NR*	*PR*	*IR*	*NR*	
Mean	0.045	0.041	0.047	0.044	0.042	0.047	0.044
Median	0.036	0.031	0.033	0.034	0.033	0.032	0.033
Standard deviation	0.101	0.109	0.113	0.101	0.111	0.111	0.108
Maximum	0.638	0.762	0.816	0.638	0.762	0.816	0.816
Minimum	−0.404	−0.434	−0.433	−0.404	−0.433	−0.418	−0.433
Kurtosis	6.010	7.016	7.286	5.948	6.895	7.418	6.914
Percent of positive estimates	67.860	64.510	65.341	67.172	65.212	65.321	65.907

announcements, i.e., within the *PR* and *NR* categories of the market reaction news proxy, but not within the *IR* category. We test pattern (3) using the parametric and non-parametric tests. For the parametric analysis, we construct the volume ratio test statistic:

$$VR_i = \ln\left(\frac{V_{\text{adj}}(U_i)}{V(D_i)}\right), \tag{4}$$

a measure which takes into consideration the size of the trading volume differential for each stock. Under the null hypothesis of no earnings-surprise-related update in investors' reference level, the mean of VR_i, $\mu(VR_i)$ should be close to zero. According to our conjecture, however, we expect the $\mu(VR_i)$ to be significantly greater than zero within the *US* and *DS* earnings surprise categories of the earnings surprise news proxy, as well as within the *PR* and *NR* categories of the Market Reaction news proxy.

For the non-parametric analysis, we construct the volume indicator statistic:

$$VI_i = I[V_{adj}(U_i) > V(D_i)], \tag{5}$$

where VI_i is an indicator function returning the value 1 whenever the condition is true, and zero otherwise. The test is based on comparing the proportion of observations for which the condition is true with the proportion under the null hypothesis, of 0.5. We conjecture that the proportion of VI_i equaling 1 would be greater than half within the *US* and *DS* categories of the Earnings Surprise news proxy, as well as within the *PR* and *NR* categories of the market

Table 4
Tests results based on the surprise relatively to analysts' opinion

Surprise category	$\mu(VR_i)$	$Sd(VR_i)$	t statistic	2-tailed p-value
Parametric test				
US	0.0375	0.0140	2.67	0.76%
ME	0.0073	0.0335	0.22	82.75%
DS	0.0802	0.0207	3.87	0.01%
Total sample	0.0487	0.0112	4.33	0.00%

Surprise category	Number of observations (percent of total)			t statistic	2-tailed p-value
	#($VIi = 1$)	#($VIi = 0$)	Total		
Non-parametric test					
US	1185(52.29)	1081(47.71)	2266(100)	2.16	3.05%
ME	311(49.84)	313(50.16)	624(100)	0.04	96.81%
DS	872(53.60)	755(46.40)	1627(100)	2.88	0.40%
Total sample	2368(52.42)	2149(47.58)	4517(100)	3.24	0.12%

reaction news proxy, but not within the news proxies' respective *ME* and *IR* categories.

4.1. Tests based on the surprise relatively to analysts' opinion

Table 4 reports the results of the tests for the total sample and for the *US*, *ME* and *DS* categories.[8] For each category, we report the basic test statistics, as well as t-statistics and the 2-tailed p-values for rejecting the implicit "no disposition effect" hypothesis.

The results of both parametric and non-parametric tests are consistent with our research hypotheses. Specifically, the parametric test provides significantly different from zero $\mu(VR_i)$ values within the *US* and *DS* categories and a negligible value within the *ME* category, and the non-parametric test yields significantly more than half volume indicators (VI_i values) equaling unity within the *US* and *DS* categories and an almost even proportion of positive and negative indicators within the *ME* category. The evidence for the disposition effect tested over the whole sample is strongly significant by both tests, that is, both the population mean of VR_i is significantly positive and the proportion of the events for which pattern (3) holds is significantly higher than 0.5.

4.2. Tests based on stock price reactions

The tests results reported in the preceding subsection are based on the comparison between the analysts' earnings forecast and actual earnings announcements. Yet, analysts' opinion might not reflect correctly the market expectations. Thus, we analyze another proxy for investors' expectations – the market proxy measured by initial abnormal stock returns, as defined above. We hypothesize that only the events that caused a relatively strong market reaction drive investors to update their reference levels. That is, we expect to find significant evidence for the disposition effect within the positive and negative initial return categories (that is, *PR* and *NR*), but not within the *IR* category.

Tables 5A–5C report the results with respect to the market-based division of the stocks.[9] As hypothesized, both tests significantly corroborate the disposition effect, similarly to the results based on the analysts' proxy. The results based on the market reaction are consistent with the

Table 5A
Tests results based on stock price reactions (market-model adjusted returns)

Surprise category	$\mu(VR_i)$	$Sd(VR_i)$	t statistic	2-tailed p-value
Parametric test				
PR	0.0664	0.0191	3.48	0.05%
IR	0.0016	0.0200	0.08	93.77%
NR	0.0778	0.0194	4.01	0.01%
Total sample	0.0487	0.0112	4.33	0.00%

Surprise category	Number of observations (percent of total)			t statistic	2-tailed p-value
	#($Vii = 1$)	#($VIi = 0$)	Total		
Non-parametric test					
PR	814(53.91)	696(46.09)	1510(100)	3.01	0.26%
IR	725(48.40)	773(51.60)	1498(100)	−1.21	22.46%
NR	829(54.94)	680(45.06)	1509(100)	3.81	0.01%
Total sample	2368(52.42)	2149(47.58)	4517(100)	3.24	0.12%

Table 5B
Tests results based on stock price reactions (market adjusted returns)

Surprise category	$\mu(VR_i)$	$Sd(VR_i)$	t statistic	2-tailed p-value
Parametric test				
PR	0.0577	0.0192	3.00	0.28%
IR	0.0088	0.0200	0.44	65.74%
NR	0.0794	0.0194	4.10	0.00%
Total sample	0.0487	0.0112	4.33	0.00%

Surprise category	Number of observations (percent of total)			t statistic	2-tailed p-value
	#($VIi = 1$)	#($VIi = 0$)	Total		
Non-parametric test					
PR	803(53.21)	706(46.79)	1509(100)	2.47	1.34%
IR	734(48.97)	765(51.03)	1499(100)	−0.77	43.84%
NR	831(55.07)	678(44.93)	1509(100)	3.91	0.01%
Total sample	2368(52.42)	2149(47.58)	4517(100)	3.24	0.12%

[8] The results of the test based on the alternative method of the trading volume adjustment are presented in Table 6 and discussed in Appendix.

[9] For robustness, we performed the tests on market-model adjusted return (Table 5A); market adjusted returns (Table 5B); and raw returns (Table 5C). As seen in the tables, results with these alternative return benchmarks are very similar to the results with market model adjusted returns. The results of similar tests based on the alternative method of the trading volume adjustment are presented in Tables 7A–7C and discussed in Appendix.

Table 5C
Tests results based on stock price reactions (raw returns)

Surprise category	$\mu(VR_i)$	$Sd(VR_i)$	t statistic	2-tailed p-value
Parametric test				
PR	0.0621	0.0187	3.33	0.09%
IR	0.0124	0.0207	0.60	54.92%
NR	0.0711	0.0191	3.73	0.02%
Total sample	0.0487	0.0112	4.33	0.00%

Surprise category	Number of observations (percent of total)			t statistic	2-tailed p-value
	$\#(VIi=1)$	$\#(VIi=0)$	Total		
Non-parametric test					
PR	816(53.79)	701(46.21)	1517(100)	2.93	0.34%
IR	728(48.89)	761(51.11)	1489(100)	−0.83	40.70%
NR	824(54.53)	687(45.47)	1511(100)	3.50	0.05%
Total sample	2368(52.42)	2149(47.58)	4517(100)	3.24	0.12%

Table 6
Tests results based on the surprise relatively to analysts' opinion: Adjusting each firm's volume by the grand average of the point estimates

Surprise category	$\mu(VR_i)$	$Sd(VR_i)$	t statistic	2-tailed p-value
Parametric test				
US	0.0390	0.0140	2.78	0.55%
ME	0.0145	0.0330	0.44	66.06%
DS	0.0753	0.0205	3.67	0.03%
Total sample	0.0487	0.0112	4.35	0.00%

Surprise category	Number of observations (percent of total)			t statistic	2-tailed p-value
	$\#(VIi=1)$	$\#(VIi=0)$	Total		
Non-parametric test					
US	1160(51.19)	1106(48.81)	2266(100)	1.11	26.55%
ME	303(48.56)	321(51.44)	624(100)	−0.68	49.62%
DS	872(53.60)	755(46.40)	1627(100)	2.88	0.40%
Total sample	2335(51.69)	2182(48.31)	4517(100)	2.26	2.37%

intuition that only salient "surprising events" drive the investors to update their perceptions. The investors update their reference point following the events that caused a relatively strong market reaction around the event day, assuming that these events were perceived as "news" by the market, while there is no significant effect, implicitly assuming no reference point update, for the stocks that had not reacted strongly to the earnings announcements.

5. Further empirical analysis

5.1. Market capitalization and stock beta

The hypothesis that investors update the reference points only subsequently to salient "surprising events" yields the conjecture that the reference points updating process would be more reactive to events for firms characterized by low information flow and market scrutiny. Thus, we expect to find stronger effects for stocks of firms with low market capitalization. Additionally, we expect the reference points updating process to be more responsive to events for cases where the stock prices are sensitive to market fluctuations, i.e., have high market model betas. Thus, we hypothesize that, ceteris paribus, there would be a more pronounced evidence for the disposition effect for firms with (i) low MCap, and (ii) high betas.

Table 8 provides the parametric test results on a 3×3 partition of the sample by MCap and beta according to cutoff points splitting the sample into thirds by each dimension. First, looking at the rightmost column and the bottom row, we note that the hypotheses are corroborated. That is, $\mu(VR_i)$ values within low, medium, and high MCap thirds are 0.0813, 0.0555, and 0.0092, respectively, and $\mu(VR_i)$ values within low, medium, and high beta thirds

Table 7A
Tests results based on stock price reactions: adjusting each firm's volume by the grand average of the point estimates (market-model adjusted returns)

Surprise category	$\mu(VR_i)$	$Sd(VR_i)$	t statistic	2-tailed p-value
Parametric test				
PR	0.0678	0.0190	3.57	0.04%
IR	−0.0029	0.0207	−0.14	88.54%
NR	0.0808	0.0193	4.18	0.00%
Total sample	0.0487	0.0112	4.35	0.00%

Surprise category	Number of observations (percent of total)			t statistic	2-tailed p-value
	$\#(VIi=1)$	$\#(VIi=0)$	Total		
Non-parametric test					
PR	801(53.05)	709(46.95)	1510(100)	2.34	1.92%
IR	718(47.93)	780(52.07)	1498(100)	−1.58	11.50%
NR	816(54.08)	693(45.92)	1509(100)	3.14	0.17%
Total sample	2335(51.69)	2182(48.31)	4517(100)	2.26	2.37%

Table 7B
Tests results based on stock price reactions: adjusting each firm's volume by the grand average of the point estimates (market adjusted returns)

Surprise category	$\mu(VR_i)$	$Sd(VR_i)$	t statistic	2-tailed p-value
Parametric test				
PR	0.0586	0.0192	3.06	0.22%
IR	0.0053	0.0196	0.27	78.71%
NR	0.0819	0.0193	4.25	0.00%
Total sample	0.0487	0.0112	4.33	0.00%

Surprise category	Number of observations (percent of total)			t statistic	2-tailed p-value
	$\#(VIi=1)$	$\#(VIi=0)$	Total		
Non-parametric test					
PR	790(52.35)	719(47.65)	1509(100)	1.80	7.15%
IR	728(48.57)	771(51.43)	1499(100)	−1.08	27.80%
NR	817(54.14)	692(45.86)	1509(100)	3.19	0.14%
Total sample	2368(52.42)	2149(47.58)	4517(100)	3.24	0.12%

Table 7C
Tests results based on stock price reactions: adjusting each firm's volume by the grand average of the point estimates (raw returns)

Surprise category	$\mu(VR_i)$	$Sd(VR_i)$	t statistic	2-tailed p-value
Parametric test				
PR	0.0617	0.0186	3.32	0.09%
IR	0.0104	0.0206	0.51	61.30%
NR	0.0734	0.0190	3.87	0.01%
Total sample	0.0487	0.0112	4.35	0.00%

Surprise category	Number of observations (percent of total)			t statistic	2-tailed p-value
	$\#(VIi = 1)$	$\#(VIi = 0)$	Total		
Non-parametric test					
PR	802(52.87)	715(47.13)	1517(100)	2.21	2.72%
IR	721(48.42)	768(51.58)	1489(100)	−1.19	23.32%
NR	812(53.74)	699(46.26)	1511(100)	2.88	0.39%
Total sample	2335(51.69)	2182(48.31)	4517(100)	2.26	2.37%

are 0.0227, 0.0358, and 0.0879, respectively. Eyeballing the table by the columns and rows, respectively, we establish that the results hold for MCap and beta also under the ceteris paribus requirement.

Table 9 delves a little deeper into the data, showing that the result relating to MCap holds as expected also within all the surprise categories as defined by both news proxies. For example, $\mu(VR_i)$ values for US within low, medium, and high MCap thirds are 0.0565, 0.0377, and 0.0257, respectively.

Tables 10–12, and 13–15 present separate 3 × 3 partition results for the earnings surprise and market reaction categories, respectively. The picture we get is consistent with that we have got for the total sample (Table 8). Thus, the analysis we perform provides strong support for this subsection's hypotheses.

5.2. Controlling for the crossing sequence

The tests for the disposition effect we perform in this paper are based on the comparison of the trading volumes at upward and downward price crossings. Yet, assuming that firms' earnings announcements grab investors' attention, the trading volume may be amplified at the first

Table 8
Parametric test results by market capitalization and beta groups

Beta / Market capitalization	Low	Medium	High	Total
$\mu(VR_i)$ (2-tailed p-value) (No. of events)				
Low	0.0452(27.67%) (711)	0.0539(26.58%) (375)	0.1670(0.02%) (419)	0.0813(0.19%) (1505)
Medium	0.0233(50.17%) (404)	0.0461(7.66%) (542)	0.0876(0.08%) (565)	0.0555(0.07%) (1511)
High	−0.0192(50.29%) (390)	0.0149(45.64%) (594)	0.0240(32.90%) (517)	0.0092(50.60) (1501)
Total	0.0227(32.24%) (1505)	0.0358(3.66%) (1511)	0.0879(0.00%) (1501)	0.0487(0.00%) (4517)

Table 9
Parametric test results by market capitalization (MCap) and surprise categories

Surprise category	Low MCap	Medium MCap	High MCap	Total
$\mu(VR_i)$ (2-tailed p-value) (No. of events)				
Earnings surprise				
US	0.0565(13.77%) (567)	0.0377(9.12%) (780)	0.0257(13.42%) (919)	0.0375(0.76%) (2266)
ME	0.0342(64.96%) (229)	0.0236(59.77%) (210)	−0.0447(22.87%) (185)	0.0073(82.75%) (624)
DS	0.1163(0.33%) (709)	0.0951(0.09%) (521)	−0.0040(89.08%) (397)	0.0802(0.01%) (1627)
Market reaction				
PR	0.0915(6.30%) (439)	0.0877(0.18%) (538)	0.0242(26.95%) (533)	0.0664(0.05%) (1510)
IR	0.0526(31.20%) (440)	0.0004(98.84%) (467)	−0.0355(12.15%) (591)	0.0016(93.77%) (1498)
NR	0.0943(1.25%) (626)	0.0722(0.93%) (506)	0.0579(3.42%) (377)	0.0778(0.01%) (1509)
Total	0.0813(0.19%) (1505)	0.0555(0.07%) (1511)	0.0092(50.60%) (1501)	0.0487(0.00%) (4517)

Table 10
Parametric test results by market capitalization and beta groups (US)

Beta / Market capitalization	Low	Medium	High	Total
$\mu(VR_i)$ (2-tailed p-value) (No. of events)				
Low	0.0058(91.56%) (278)	−0.0415(54.57%) (127)	0.2203(0.41%) (162)	0.0565(13.77%) (567)
Medium	0.0496(32.51%) (197)	0.0355(29.65%) (284)	0.0320(36.76%) (299)	0.0377(9.12%) (780)
High	0.0050(88.98%) (230)	0.0505(3.99%) (378)	0.0107(72.91%) (311)	0.0257(13.42%) (919)
Total	0.0178(53.11%) (705)	0.0303(13.42%) (789)	0.0629(1.06%) (772)	0.0375(0.76%) (2266)

Table 11
Parametric test results by market capitalization and beta groups (ME)

Beta / Market capitalization	Low	Medium	High	Total
$\mu(VR_i)$ (2-tailed p-value) (No. of events)				
Low	0.0182(88.31%) (113)	0.0310(80.34%) (54)	0.0662(59.16%) (62)	0.0342(64.96%) (229)
Medium	0.0074(94.52%) (47)	0.0243(75.52%) (74)	0.0315(61.26%) (89)	0.0236(59.77%) (210)
High	0.0230(79.89%) (47)	−0.0743(16.57%) (66)	−0.0616(28.65%) (72)	−0.0447(22.87%) (185)
Total	0.0169(82.12%) (207)	−0.0074(87.98%) (194)	0.0111(80.99%) (223)	0.0073(82.75%) (624)

Table 12
Parametric test results by market capitalization and beta groups (DS)

Beta / Market capitalization	Low	Medium	High	Total
$\mu(VR_i)$ (2-tailed p-value) (No. of events)				
Low	0.0890(17.75%) (320)	0.1228(10.06%) (194)	0.1548(0.87%) (195)	0.1163(0.33%) (709)
Medium	−0.0044(93.46%) (160)	0.0712(12.67%) (184)	0.2098(0.00%) (177)	0.0951(0.09%) (521)
High	−0.0862(11.64%) (113)	−0.0358(40.40%) (150)	0.1010(6.16%) (134)	−0.0040(89.08%) (397)
Total	0.0304(44.53%) (593)	0.0598(8.00%) (528)	0.1598(0.00%) (506)	0.0802(0.01%) (1627)

Table 13
Parametric test results by market capitalization and beta groups (PR)

Beta / Market capitalization	Low	Medium	High	Total
$\mu(VR_i)$ (2-tailed p-value) (No. of events)				
Low	−0.0168(81.91%) (202)	0.0943(32.33%) (117)	0.2711(0.33%) (120)	0.0915(6.30%) (439)
Medium	0.1077(11.79%) (129)	0.1604(0.04%) (201)	0.0052(89.53%) (208)	0.0877(0.18%) (538)
High	0.0123(81.34%) (115)	0.0442(12.28%) (221)	0.0088(82.54%) (197)	0.0242(26.95%) (533)
Total	0.0267(51.34%) (446)	0.0984(0.08%) (539)	0.0673(2.62%) (525)	0.0664(0.05%) (1510)

Table 14
Parametric test results by market capitalization and beta groups (IR)

Beta / Market capitalization	Low	Medium	High	Total
$\mu(VR_i)$ (2-tailed p-value) (No. of events)				
Low	0.0538(46.95%) (253)	0.0225(81.11%) (99)	0.0829(43.05%) (88)	0.0526(31.20%) (440)
Medium	−0.0032(95.19%) (150)	−0.0428(31.89%) (177)	0.0590(30.49%) (140)	0.0004(98.84%) (467)
High	−0.0387(34.77%) (195)	−0.0376(28.43%) (234)	−0.0288(52.16%) (162)	−0.0355(12.15%) (591)
Total	0.0093(79.88%) (598)	−0.0277(32.97%) (510)	0.0279(44.35%) (390)	0.0016(93.77%) (1498)

Table 15
Parametric test results by market capitalization and beta groups (NR)

Beta / Market capitalization	Low	Medium	High	Total
$\mu(VR_i)$(2-tailed p-value) (No. of events)				
Low	0.0857(20.78%) (256)	0.0439(52.71%) (159)	0.1429(1.00%) (211)	0.0943(1.25%) (626)
Medium	−0.0321(58.50%) (125)	0.0021(96.34%) (164)	0.1852(0.00%) (217)	0.0722(0.93%) (506)
High	−0.0172(78.70%) (80)	0.0565(17.16%) (139)	0.0972(2.65%) (158)	0.0579(3.42%) (377)
Total	0.0359(39.76%) (461)	0.0328(29.50%) (462)	0.1462(0.00%) (586)	0.0778(0.01%) (1509)

post-announcement price crossing.[10] In this section, we would like to control for this possibility. We hypothesize that the trading volume at the first price crossing is higher than at the second one, and note that for the events with the upward crossings coming first, the disposition and the sequence effects act in the same direction, while for the complementary group of events they are in opposite directions. Based on this distinction, we run the following restricted multiple regressions:

$$\begin{aligned} VR = {} & \alpha^*_{11}up^*US + \alpha^*_{12}up^*ME + \alpha^*_{13}up^*DS + \alpha^*_{14}(1-up)^*US \\ & + \alpha^*_{15}(1-up)^*ME + \alpha^*_{16}(1-up)^*DS \\ s.t. \quad & \alpha_{11} = D_{US} + S_{US} \\ & \alpha_{12} = D_{ME} + S_{ME} \\ & \alpha_{13} = D_{DS} + S_{DS} \\ & \alpha_{14} = D_{US} - S_{US} \\ & \alpha_{15} = D_{ME} - S_{ME} \\ & \alpha_{16} = D_{DS} - S_{DS} \end{aligned} \tag{6}$$

and:

$$\begin{aligned} VR = {} & \alpha^*_{21}up^*PR + \alpha^*_{22}up^*IR + \alpha^*_{23}up^*NR + \alpha^*_{24}(1-up)^*PR \\ & + \alpha^*_{25}(1-up)^*IR + \alpha^*_{26}(1-up)^*NR \\ s.t. \quad & \alpha_{21} = D_{PR} + S_{PR} \\ & \alpha_{22} = D_{IR} + S_{IR} \\ & \alpha_{23} = D_{NR} + S_{NR} \\ & \alpha_{24} = D_{PR} - S_{PR} \\ & \alpha_{25} = D_{IR} - S_{IR} \\ & \alpha_{26} = D_{NR} - S_{NR} \end{aligned} \tag{7}$$

where: *up* is an indicator taking the value 1 when the first price crossing is upward and 0 otherwise; *US, ME, DS, PR, IR, NR* are indicators of the respective surprise categories; and $D_{[.]}$ *and* $S_{[.]}$ are the coefficients measuring the magnitudes of the disposition and attention (sequence) effects.

With respect to the attention hypothesis, we expect the $S_{[.]}$ coefficients to be positive and significant for all surprise categories. Regarding the disposition effect, we expect the $D_{[.]}$ coefficients to be positive and significant for the *US, DS, PR, NR* categories (i.e., for the "surprising events"), while insignificant for the *ME* and *IR* categories.

Tables 16 and 17 report the regression results for the analyst-based and market-based expectations proxies, respectively. As hypothesized, the coefficients measuring the magnitude of the attention effect are positive and

[10] The attention hypothesis (cf. Odean, 1999; Barber and Odean, 2007) asserts that agents facing numerous alternatives may consider primarily those that have caught their attention.

Table 16
Multiple regression results based on the surprise relatively to analysts' opinion

Coefficient	Estimate	t statistic	2-tailed p-value
D_{US}	0.0358	2.28	2.29%
D_{ME}	−0.0019	−0.06	95.06%
D_{DS}	0.0627	3.35	0.08%
S_{US}	0.0831	5.28	0.00%
S_{ME}	0.1236	4.12	0.00%
S_{DS}	0.1286	6.87	0.00%

Table 17
Multiple regression results based on stock price reactions (market-model adjusted returns)

Coefficient	Estimate	t statistic	2-tailed p-value
D_{PR}	0.0572	2.97	0.30%
D_{IR}	0.0066	0.34	73.60%
D_{NR}	0.0594	3.08	0.21%
S_{PR}	0.1079	5.61	0.00%
S_{IR}	0.0782	4.02	0.01%
S_{NR}	0.1304	6.75	0.00%

significant for all the surprise categories, suggesting that investors' attention to the stocks is amplified when the prices cross the post-announcement price for the first time. Moreover, the $D_{[.]}$ coefficients reconfirm the disposition effect hypothesis, being positive and significant only for the "surprising events". Thus, the reference point updating hypothesis is established also after controlling for the sequence of the stock price crossings.

6. Conclusions

The psychological concept of a reference point is well-known and widely discussed in the economic literature. Yet, the mechanism of reference point formation is not thoroughly explored. Numerous empirical research applications make a simplifying assumption, taking assets' purchase prices as a reference point. In light of the aforesaid, the main goal of our research is to test the hypothesis that company-specific events drive investors to update their reference level, consequently influencing their behavior.

As an example of "company-specific events" we use quarterly earnings announcements, taking the stock price fixed at the day following the "event day" as a benchmark, that is, a potential reference point.

Our major finding is that investors update the reference level assigned to stocks subsequently to news regarding their values. Moreover, this evidence is significant after the adjustment of the statistics to an estimated return-related volume relation. These findings suggest that investors indeed update their perceptions following company-specific events, and use the new market price as a reference point. We are able to show that our findings are robust to the specification of the expectations proxy: both the "analysts' proxy" and the "market proxy" provide similar results. Importantly, only the events that are perceived as surprises lead to the empirical trading volume pattern defined in the hypotheses. Thus, our results do not stem from investors' tendency to overpredict reversals. Moreover, we detect that the reference points are affected more profoundly for low market capitalization and high beta firms, pointing that the reference point updating process is more reactive to events when information flow is low and prices are sensitive to market fluctuations. Our results also corroborate the attention hypothesis, i.e., the observation that agents facing numerous alternatives may consider primarily those that have caught their attention.

Our research yields a series of noteworthy results. First, we obtain additional evidence for the existence of the disposition effect as a psychological bias characterizing investors' behavior. This is a valuable result, as we manage to detect the disposition effect, employing new empirical tests. Second, we document the influence of the surprise component of company-specific events, as defined by the analysts' and the market proxy, on the salience of these events from the investors' viewpoint. Finally and mostly important, our research provides valuable information concerning the process of reference point formation. The significant evidence we get for the disposition effect allows us to conclude that investors indeed compare in their "mental accounts" the current stock price with the price level fixed at the day following the firm's earnings announcement. It means that the latter becomes a relevant reference point for the investors. Investors are not static in their perceptions and update their reference levels following different company-specific events. While firms' earnings announcements represent an obvious and generally used example of such events, our results suggest that other company-specific events may also drive the investors to change their reference point. A possible direction for further research may include testing and comparing the degree of influence of different company-specific events on the reference point formation.

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Appendix. Adjusting each firm's volume by the grand average of the point estimates

In Section 3, we have introduced a method of adjustment based on the empirical return-volume relation determined for each stock, i.e., we implicitly assumed a unique pattern for each stock. Another potential approach is to adjust the statistics on the basis of the average point estimate on *dir_dummy* in regression (1), of 0.0444 (mean of total sample, at the rightmost column of Table 3):

$$V_{\text{adj}}^{1}(U_i) = e^{[\ln(V(U_i)-0.0444)]} \tag{A.1}$$

Tables 6 and 7A present the results based on the above defined adjustment. They are very much the same as the results presented in the text of the paper: the t statistics for all the categories of stocks have the same sign and are significant approximately at the same levels. For robustness, we also perform the tests on market adjusted returns (Table 7B), as well as on raw returns (Table 7C). As seen in the tables, results with these alternative return benchmarks are very similar to the results with market model adjusted returns.

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