Decomposing Unrealized Returns into Adapted and Unadapted Components Using Reference Points

Previous research shows that realized and unrealized outcomes influence subsequent risk-taking behavior, albeit in opposite ways. We further decompose unrealized outcomes into adapted and unadapted components, which have distinct implications for risk-taking. Adapted returns are internalized as individuals adjust their reference point, while unadapted returns remain externalized. Our empirical evidence shows that adapted and unadapted returns exert opposing influences on future stock returns. Notably, the highest-performing stocks have a distant past return that is low (reflecting an adapted loss) paired with a recent past return that is high (reflecting an unadapted gain).

Declarations of interest: none.

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JEL: G1, G4

1.0 Introduction

A substantial body of evidence indicates that prior gains and losses influence individuals' decisions. Research supports the existence of a disposition effect, wherein investors tend to retain prior unrealized losers. This behavior aligns with the principles of prospect theory (Kahneman and Tversky, 1979), which suggests that individuals are more inclined to take risks following prior losses. Additionally, there is distinct evidence of investment behavior reflective of the snake-bite effect, which suggests less inclination to take risks after prior losses. According to Imas (2016), this discrepancy arises because investors treat realized losses differently from unrealized ones. Unrealized losses elicit risk-seeking behavior consistent with the disposition effect while realized losses elicit risk-averse behavior consistent with the snake-bite effect.

Our study advances this understanding of investor behavior by introducing a novel decomposition of unrealized returns into adapted and unadapted components, based on reference point adjustments. Whilst maintaining the distinction between realized and unrealized returns, we demonstrate that investors internalize portions of their unrealized returns over time, affecting their subsequent risk preferences and trading decisions. We establish that the internalized portion of unrealized returns elicits risk-taking behavior similar to realized returns. With this component removed from unrealized returns, it becomes a purer expression of the disposition effect than total unrealized returns. Consequently, distinguishing between the internalized and externalized components of unrealized returns, as defined by an adjusting reference point, is crucial for understanding individuals' risk preferences. Hence, our

decomposition offer practical implications for investing and more nuanced predictors of future stock performance.

Throughout the paper, we refer to the internalized component of unrealized return as adapted return, reflecting the investor's adaptation to this component through their reference point. The externalized component of unrealized return is referred to as unadapted return. Figure 1 shows the decomposed components at time t_n: an adapted return, which represents the difference between the investor's reference point and initial purchase price (at time t_0), and an unadapted return, which represents the difference between the current price of an asset and the investor's reference point. The investor perceives the adapted return similarly to a realized return, which are both internalized. In contrast, the unadapted return is viewed as a potential gain or loss, as the investor has not internalized this segment of the unrealized return. The key mechanism to isolate the two return components is the investor's reference point and to account for how it adjusts away from the initial purchase price during the holding period. Studies such as Baucells, Weber and Welfens (2011) and Riley, Summers and Duxbury (2020) indicates that the reference point does not remain fixed at the stock's purchase price; rather, it partially adjusts to new prices throughout the holding period. To ascertain the position of the reference point, we employ the composite reference point formulas derived from the aforementioned studies.

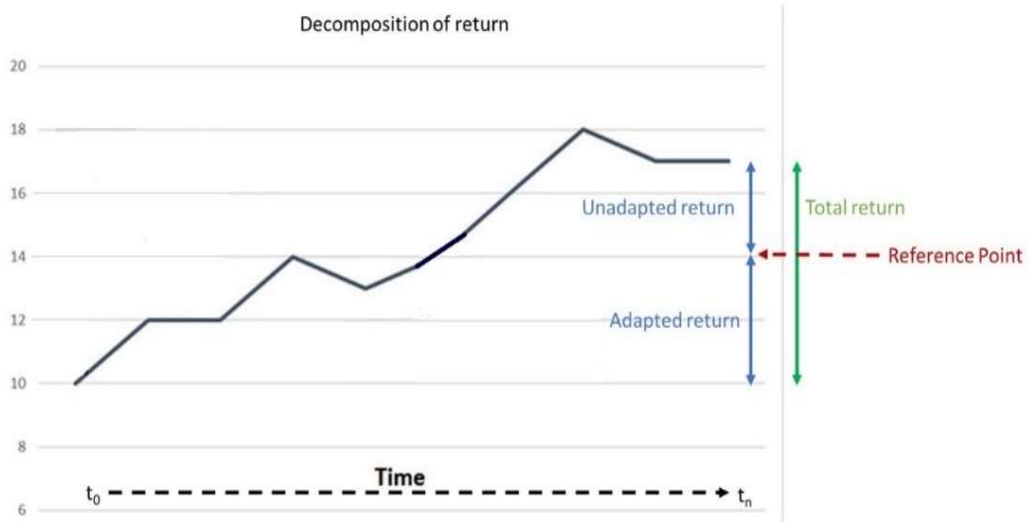


Figure 1: Stock Price over time showing Adapted and Unadapted returns *at time* t_n

To test these ideas empirically across all holders of a stock in the market, we use the volume weighting formula from Grinblatt and Han (2005) to calculate aggregate purchase prices and reference points. The aggregate purchase price, in conjunction with the stock's current price, is used to calculate the total unrealized return of the aggregate investor. While similar to the CGO variable, our total return variable is distinct in that its divisor is the reference point rather than the current price. This provides less distortion when calculating gains or losses relative to an initial purchase price. The next step is decomposing the total return into adapted and unadapted components. To do this, we incorporate reference point adjustment, specifically utilizing the composite reference point formula from Riley et al. (2020), or from Baucells et al. (2011). We use reference point formulas from two distinct sources to demonstrate the robustness of our result. The volume weighting from Grinblatt and Han (2005) is again used to calculate the aggregate reference point. Finally, the aggregate total return is decomposed into aggregate adapted and unadapted components using the aggregate reference point.

Using regression analysis, we test our total return, adapted return and unadapted return variables as predictors of future returns. We demonstrate that the total return variable is a positive and significant predictor of future returns. When we include both the *CGO*, *MOM*, and total return variables in a regression model, we find that *CGO* and *MOM* lose significance. In contrast, total return remains a positive and significant predictor of future returns, suggesting it is a better proxy for measuring the aggregate unrealized return than *CGO* or *MOM*. Then, we examine the adapted and unadapted components of total return. We find that adapted return is a negative and significant predictor of future return, as would be expected if losses cause selling due to risk aversion. Unadapted return is a positive and significant predictor of future return, as would be expected if losses cause retention due to risk seeking. This supports the notion that adaptive returns cause behavior similar to realized returns, while unadapted returns become a purer expression of unrealized returns.

In this section, we also include the V-shaped Selling Schedule (VNSP) of An (2016) as a control variable. We find that VNSP is insignificant as a predictor of future returns when adapted and unadapted returns are included in the regression. The insignificance of *VNSP* is particularly notable, as the contrasting effects of adapted and unadapted returns on investor risk preferences suggest a potential explanatory mechanism for the V-shaped selling schedule first outlined in (Ben-David and Hirshleifer, 2012). They found that investors have an increased tendency to sell unrealized winners (as predicted by the disposition effect) and an increased tendency to sell

unrealized losers (as predicted by the snake-bite effect), thus forming a V-shaped selling pattern. Our decomposition of unrealized returns into an adapted component, subject to the snake-bite effect, and an unadapted component, subject to the disposition effect, is a previously unexplored explanation for their results.

We subsequently examine these return patterns using decile-sorted portfolio analysis, confirming the earlier regression analysis. As illustrated in Figure 2, adapted returns exhibit a negative relationship with future returns, whereas unadapted returns display a positive relationship. While the relationship between unadapted returns and future returns is broadly monotonic, this is not true for the relationship between adapted returns and future returns, which is heavily influenced by low (portfolio 1-3) adapted returns stocks. The asymmetry in the relationship between adapted returns and future returns, alongside the fact that this relationship is smaller in absolute size compared to that of unadapted returns and future returns, further supports the case that our decomposition is a mechanism for V-shaped selling behaviors (Ben-David and Hirshleifer, 2012). Our findings remain robust across across sub-samples and are not caused by low price, low market cap, or NASDAQ stocks, as we demonstrate in our robustness analyses. The implication is that adapted returns have an influence similar to realized returns on investor behavior, consistent with the snake-bite effect. Investors are risk-averse in adapted losses. In contrast, unadapted returns lead to risk-seeking behavior (averse) in unadapted losses (gains), consistent with the disposition effect.

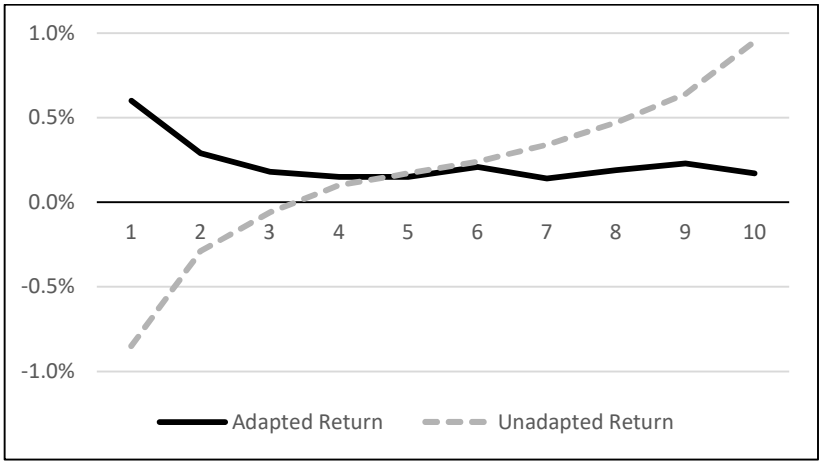


Figure 2: Relationship Between Adapted/Unadapted Returns and Future Returns (1963-2016)

If adapted and unadapted returns influence future stock returns through changes in investor risk preferences, we would expect that they act as moderators of the relationship between risk and future returns, albeit in opposing directions. Risk is widely accepted as a negative predictor of future return (Ang, Hodrick, Xing and Zhang, 2006), in contrast to the predictions of asset pricing models. However, Wang, Yan and Yu (2017) demonstrate that the CGO variable positively moderates the relationship between risk and future return. Investors tend to become risk-averse in stocks with a positive capital gains overhang, leading to low-risk stocks becoming overpriced and subsequently underperforming. Conversely, they become risk-seeking in stocks with a negative capital gains overhang, resulting in low-risk stocks being underpriced and outperforming. Consequently, we expect adapted returns to negatively moderate the relationship between risk and future returns, as investors become risk-averse in the context of losses. In contrast, unadapted returns are expected to positively moderate this relationship, as investors display increased risk aversion in gains and risk-seeking behavior in losses.

We use regression analysis to test the moderating relationship of our return variables using three proxies for risk: *total volatility, idiosyncratic volatility* and *beta*. We show that adapted return is a negative and significant moderator for all three risk proxies, while unadapted return is a positive and significant moderator for all the proxies. As shown in Figure 3, stocks with low adapted returns exhibit a positive risk-return relationship, whereas those with high adapted returns exhibit a negative risk-return relationship. For unadapted returns, the pattern is reversed. Stock with a low unadapted return exhibit a negative risk-return relationship, whereas those with high unadapted returns exhibit a positive risk-return relationship. Thus, the results align with our apriori expectations, supporting the notion that adapted and unadapted returns influence future returns by altering investors' risk preferences. Alternative explanations for the relationship between decomposed return components and future return are, of course, possible. However, the empirical evidence strongly supports the notion that investors treat adapted and unadapted returns differently and that changes in investors' risk preferences drive the disparity.

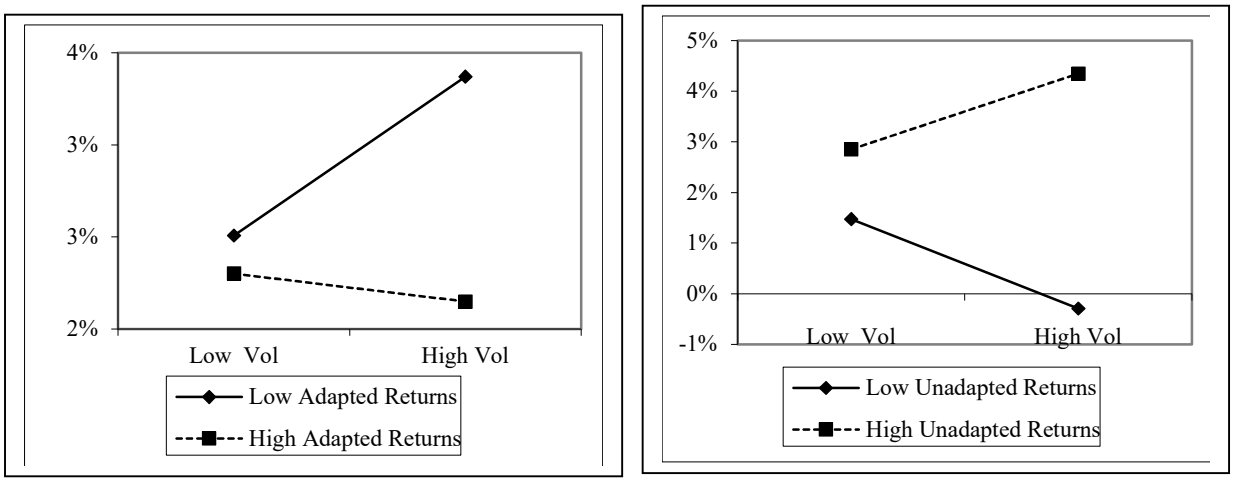


Figure 3: Moderating Relationship Between Volatility andf Future Returns

To explain our results, we note that the prior literature already distinguishes between realized and unrealized outcomes. Duxbury, Hudson, Keasey, Yang and Yao (2015) document investors simultaneously exhibiting heightened risk seeking and risk aversion following prior gains and losses, with the disposition effect associated with unrealized returns and the house money/snake-bite effects associated with realized returns. Imas (2016) distinguishes between unrealized and realized losses and finds that a prior outcome leads to lower risk-taking in the presence of realized losses, but not in the case of unrealized ones. Likewise, using field data from casino gambling, Flepp, Meier and Franck (2021) demonstrate the differential impact of unrealized outcomes versus realized outcomes on subsequent risk-taking behavior, with realized losses significantly decreasing risk-taking. Implicit in the literature is the assumption that reference points do not adjust away from the purchase price until a mental account is closed via a realization and that once a realization takes place, the mental account is closed and the reference point reset.[1] For example, Imas (2016, p.2092, emphasis added) suggests that "the realization of a loss serves as a natural point for an individual to *internalize* the negative outcome, update the reference point and close the associated mental account". Hence, investors chase unrealized losses (risk-seeking behavior), where the mental account remains open and the reference point is not reset, while avoiding risk when the mental account closes and a reset occurs following the realization of losses.

[1] An exception here is Frydman, Hartzmark and Solomon (2018). They find that mental accounts and associated reference points can roll across assets when reinvestment closely follows realization of the prior investment. Likewise, Meyer and Pagel (2022) find that reinvestment amounts differ between realized gains and losses, following a forced sale.

While it seems likely, in some contexts, that mental accounts close and reference points reset only at specific points in time, such as at the end of the day in horse race betting (Suhonen and Saastamoinen, 2018) or on leaving a casino in the case of gambling (Flepp et al., 2021), this is not so obvious in the context of stock market investing. Indeed, there is compelling evidence in the reference point literature, including Chen and Rao (2002), Arkes, Hirshleifer, Jiang and Lim (2008), Baucells et al. (2011), and Riley et al. (2020), that investors update their reference points based on past price sequences. Notably, partial adjustment of the reference point occurs during the holding period of an asset, not just at the point of sale and closure of the mental account.[2] Partial reference point adjustment of this kind suggests the possibility, therefore, that investors might therefore partially internalize unrealized returns prior to selling the stock. This is supported by the notion of reference points as a point of indifference or neutrality as per Baucells et al. (2011) and Riley et al. (2020), whereby the current reference point represents the price at which an investor would feel neutral (i.e., neither happy nor unhappy) about the sale of the stock at the current price. At this reference point, the investor has partially internalized the "happiness" associated with a stock that has gone up in value or the "unhappiness" associated with a stock that has gone down in value.

[2] In their examination of rolling mental accounts, Frydman et al. (2018) evidence the important distinction between closing a mental account and realizing a position, particularly when reinvestment closely follows realization of the initial or prior investment. That the two need not be viewed as one and the same contrasts the view in Imas (2016) that reference points are updated when a mental account closes.

In the context of stocks that have fallen in value, Kahneman and Tversky (1979, p.287) state that an investor "who has not made peace with [their] losses is likely to accept gambles that would be unacceptable to [them] otherwise" and, by extension, conversely in the case of gains. The reference to *making peace* is directly comparable with our notion of *internalization*; a loss that an investor has `made peace with' has been internalized. Absent a realization, partial adaptation to prior gains or losses renders it possible to decompose the total unrealized return into two components; an internalized component whereby the investor has adapted to some portion of the gain or loss (e.g., is at peace with a portion of the loss) and an unadapted component which the investor has yet to internalize. We show that these two components prompt differential risk-taking behavior, with unadapted returns treated like unrealized gains and losses. In contrast, internalized returns are more akin to realized gains and losses. As the point of neutrality, we propose the adapted reference point as the ideal means to separate the two components.[3] Thus, the difference between the reference point and the current price represents the purest form of the unrealized return of the transaction. In contrast, the difference between the reference point and purchase price is implicitly realized in the investor's mind, as they have already internalized (and adapted to) this portion of return. So, for any future transaction, we show these two return components play distinct roles, with significant implications for how under or over-priced the security might be and how risk is priced in the stock.

[3] Conceptually, our approach is similar to that of Baucells and Hwang (2017) They model mental accounting and reference point adaptation in the context of consumption goods. In their model, they decompose profit derived from a consumption good (revenue less cost) by way of reference point (psychological book value) to obtain the net hedonic benefit. We differ in that we allow reference point adaptation in the context of stock investing to decompose total return into internalized/adapted return and unadapted return.

We also add to the ongoing debate regarding which reference point investors use to define a gain or loss. The literature adopts several reference points, including backward-looking ones such as zero return (i.e., based on the original or average purchase price) (Odean, 1998), the risk-free return (Barberis and Huang, 2001), list-price for the housing market (Andersen, Badarinza, Liu, Marx and Ramadorai, 2022), or results of the prior trading session (Coval and Shumway, 2005). Reference points based on forward-looking beliefs about future outcomes (Kőszegi and Rabin (2006); Meng and Weng (2018)) are also common. The inherent uncertainty associated with stock markets makes such expectation-based reference points challenging to implement (Barberis, 2018) and they are not always well-supported in the literature (Baillon, Bleichrodt and Spinu, 2020). We empirically demonstrate the important asset pricing implications of reference point updating, using a backward-looking reference points from Riley et al. (2020) and Baucells et al. (2011) to decompose total unrealized return. Our work also complements studies documenting the influence of historical return patterns (Barberis, Mukherjee and Wang (2016); Cosemans and Frehen (2021)) and historic price sequences (Grosshans and Zeisberger, 2018) on investor behavior.

Our work also has important implications for the field of asset pricing. Our total return variable subsumes the CGO (Grinblatt and Han, 2005) and the price momentum (Jegadeesh, 1990) variables as a predictor of future returns, suggesting it captures aggregate unrealized returns more accurately. Furthermore, we demonstrate the importance of decomposing unrealized returns into adapted and unadapted components. The unadapted return is the purest expression of unrealized return in the mind of the investor and this is reflected in our empirical results. We

argue throughout that adapted and unadapted returns elicit different risk preferences in investors and we are able to directly test this conjecture in our moderation analysis. The unadapted component of unrealized return is a purer positive moderator of the relationship between risk and return than the unrealized return itself, while the adapted return is a negative moderator. Our results have important implications for investor trading behavior and suggest that investors should buy stocks that have a negative adapted return and a positive unadapted return. These stocks will likely have a V-shaped price chart with negative distant returns combined with positive recent returns. As Ben-David and Hirshleifer (2012) suggest, these stocks are the most likely to be sold and thus be underpriced.

Our work also has implications for the literature examining investor utility, with associated implications for investor risk preferences, differentiating paper gains/losses (e.g., Barberis and Huang (2001) from realized gains/losses (e.g., Barberis and Xiong (2009); Barberis and Xiong (2012)). We are the first to examine how investors' updating of their reference points, without the assumption of mental account closure following a sale, leads them to partially adapt to paper gains and losses. In doing so, we show by decomposing returns into adapted and unadapted components that paper gains and losses can have differing influences on risk preferences depending on the extent to which investors adapt, with the unadapted component of returns continuing to be treated like paper gains/losses (i.e., risk-averse/seeking) as per prospect theory. In contrast, the adapted component of returns is treated more like realized gains/losses (i.e., risk-seeking/averse) as per the snake-bite effect. This happens even though no realization following a sale occurs; rather, all that is required is the internalization of a part of the return due to

hedonic adaptation (Helson, 1964). Hedonic adaptation shifts perceptions of positive or negative stimuli so that what an investor initially perceives as positive or negative becomes neutral. Hence, affective responses are dampened over time. For example, accident victims have shown remarkable levels of adaptation to disability, such that their happiness levels quickly return to pre-accident levels (for a review, see Frederick and Loewenstein (1999)).

In summary, we propose to decompose unrealized returns into adapted and unadapted components. To empirically examine this decomposition, we introduce a new variable in our paper called total return, which captures the unrealized return of a stock for the aggregate investor in the market more accurately than *CGO* or price momentum. We subsequently decompose the total return variable into its adapted and unadapted components by using an adjusting reference point to identify the separation threshold. Our findings reveal that adapted returns exhibit a negative relationship with future returns, whereas unadapted returns exhibit a positive relationship with future returns. Further moderation analysis indicates that investor risk preferences drive the differences observed in future returns.

2.0 Variable Definitions and Data

2.1 Calculation of Total, Adapted and Unadapted Returns Using Volume Weighting

We first define the total return for the *aggregate* investor in a stock. For a given stock, *i*, total return (*Tot_Return*) is represented by the percentage difference between the current price (P)

and the purchase price of the aggregate investor (Pur), as shown in Equation 1. All prices are lagged by one calendar week to compensate for the bid-ask bounce observed in stock prices (Rosenberg and Rudd, 1982)[4]. The purchase price will differ by investor, as they may invest on different days. Therefore, to measure the purchase price of the aggregate investor (Pur), we volume-weight prices using a formula based on the Capital Gain Overhang (CGO) model of Grinblatt and Han (2005), as shown in Equation 2. We use daily turnover (*V*) and daily prices (*P*) and hence 1825 calendar days (*n*). Theoretically, the aggregate purchase price is calculated using an infinite number of days, but in practice, we can sum five years' worth of days and adjust by a constant (*k*) to make the weights sum to 1[5]. We calculate turnover (*V*) by dividing daily trading volume by the total shares outstanding. Each price is weighted by the turnover traded on that day. By way of example, if turnover is 5% on day_t for $stock_i$, then the price ($P_{i,t}$) on that day is given a 5% weight in the aggregate purchase price ($Pur_{i,t}$). For day_{t-1}, assuming its turnover is again 5%, then it will receive a weight of 5% × (100% - 5%) = 4.75% to reflect that 5% of holdings would be subsequently sold in day_t.

$$Tot_Return_{i,t} = \frac{P_{i,t-7} - Pur_{i,t-7}}{Pur_{i,t-7}}$$

Equation 1: Calculation of Total Return Variable

[4] If this price is un-available then the next available price in the following week (t-8 to t-14) is used. If no price is available then the variable is reported as missing.
[5] As do Grinblatt and Han (2005).

$$Pur_{i,t} = \frac{1}{k_i} \sum_{n=0}^{1824} \left(V_{i,t-n} \prod_{\tau=1}^{n} [1 - V_{i,t-n+\tau}] \right) P_{i,t-n}$$

Equation 2: Calculation of Aggregate Purchase Price[6]

We note three differences between *CGO* and our total return variable (*Tot_Return*). Firstly, the divisor in CGO is the current price (*P*) rather than the aggregate purchase price (Pur). Using the current price as a divisor distorts the calculation of returns, as gains look smaller than they would appear to an investor who used the purchase price as their divisor, and losses look larger. Secondly, the *CGO* variable uses data grouped into weeks rather than days. This is due to the limited availability of daily data at the time of Grinblatt and Han (2005), but this is no longer a limitation. More recent papers using the CGO model, such as Riley et al. (2020) or An (2016), adopt daily calculation. Thirdly, while Grinblatt and Han (2005) lag the current price (*P*) by one week to account for the bid-ask bounce, they do not lag the aggregate purchase price (*Pur*) in unison. In our total return calculation, we lag the current (*P*) and aggregate purchase prices (Pur) by one week to maintain consistency. All the changes in calculating *Tot_Return* improve its predictive power, which we test in the following section.

We then decompose the total return (*Tot_Return*) into adapted return (*Adapt*) and *un*adapted return (*UnAdapt*) components, as shown in Equation 3. The adapted part of the total return is the percentage difference between the aggregate reference point (*Ref*) and the aggregate purchase price (*Pur*), while the unadapted return is the percentage difference between the

[6] Note, our measure of the purchase price of the aggregate investor (Pur) is the same as the reference price (R) in Grinblatt and Han (2005).

current price (*P*) and the aggregate reference point (*Ref*). While many representations of the aggregate reference point are possible, Riley et al. (2020) show, using both an experiment and market data testing, that the most accurate reference point is a composite of the purchase price and 52-week maximum (*Max52*) and minimum (*Min52*). To perform the decomposition, we must calculate the aggregate reference point shown in Equation 4. We use the same turnover-weighted approach as the aggregate purchase price in Equation 2. To capture the reference point for each trading day we use formulas for the reference point taken from Riley et al. (2020) throughout the paper, or Baucells et al. (2011) in our main regression table only, as shown in Equation 5.

$$Tot_Return_{i,t} = Adapt_{i,t} + UnAdapt_{i,t}[7]$$

$$\frac{P_{i,t-7} - Pur_{i,t-7}}{Pur_{i,t-7}} = \frac{Ref_{i,t-7} - Pur_{i,t-7}}{Pur_{i,t-7}} + \frac{P_{i,t-7} - Ref_{i,t-7}}{Pur_{i,t-7}}$$

Equation 3: Decomposition of Total return into Adapted and Unadapted return

$$Ref_{i,t} = \frac{1}{k_i} \sum_{n=0}^{1824} \left(V_{i,t-n} \prod_{\tau=1}^{n} [1 - V_{i,t-n+\tau}] \right) ref_{i,t-n}$$

Equation 4: Calculation of Aggregate Reference Point

$$ref_{i,t}\,(Riley) = 0.437P_{i,t} + 0.444Max52_{i,t} + 0.119Min52_{i,t}$$

[7] This equation assumes investors decompose total returns arithmetically, which we assume for simplicity. Geometric decomposition does not materially alter the forthcoming results.

$$ref_{i,t}(Baucells) = 0.52P_{i,t} + 0.075Max_{i,t} - 0.04Min_{i,t} + 0.30Final_{i,t} + 0.15Average_{i,t}$$

Equation 5: Reference Point Equations

2.2 Data and Method

The market data sample is all US common Stocks (Codes 10 &11) from January 1958 until Dec 2016. NYSE, Amex, and NASDAQ firms are included, although NASDAQ firms have their volume cut in half to compensate for double counting of volume (Anderson and Dyl, 2007). Daily data is used to calculate the total, adapted and unadapted returns and is then converted to monthly data for the regressions, while the CGO variable requires weekly data that is likewise converted into monthly for testing. The monthly data is from Jan 1963 until Dec 2016, as total, adapted and unadapted return variables require five years of data (1825 calendar days), along with *CGO*. Stocks are ranked by market capitalization every month as a liquidity screen, with stocks in the bottom-decile eliminated for that month. This removes the impact of illiquid, untradeable stocks, which could bias the results.

Independent variables are *Total_Ret*, *Adapt*, *UnAdapt*, *CGO and VNSP* of An (2016). An (2016) found that the CGO variable could be improved by accounting for the v-shaped selling schedule of Ben-David and Hirshleifer (2012). We use the following control variables: *Mom*- defined as the percentage total return over the last 12 months excluding the previous month; *STR*- is short-term reversal defined as the percentage return previous month; *LTR*- is long-term reversal defined as the percentage return over the last three years excluding the previous year; *AvgTurn*-

is the average of daily stock turnover (daily volume/shares outstanding) over the previous year; *Mrkcap*- is the log of market cap (stock price*shares outstanding) in units of millions; and *BM*- is the log of the book to market ratio, with a minimum lag of 6 months from the reporting date. In the moderation section, we use the following volatility proxies to test our return variables as moderators: *Beta*- calculated using daily data over the last year, *Total Vol*- calculated as the daily return volatility calculated over the previous year, and *Idiosyncratic Vol*- calculated as the daily idiosyncratic volatility over the last month calculated using the Fama-French 3 factor model.

Calculation of the three return variables (*Tot_Return*, *Adapt*, and *UnAdapt*), *CGO* and *VNSP* require a minimum of 2 years of data (out of a possible of 5 years) and are set to missing otherwise. Prices are adjusted for stock splits when used to calculate these variables. In the following regressions, the Fama-Macbeth (Fama and MacBeth, 1973) method is utilized and 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 in Table 1 and Table 2. While the mean for total return is close to zero, the mean for adapted return is positive, while the mean for unadapted return is negative. This reflects investors' tendency to adjust their reference points more to gains than losses (Arkes et al., 2008); hence, their adaptive return tends to be positive.

3.0 Results

3.1 Total Return as a Predictor of Future Returns

In this section, we investigate how the total return variable performs as predictor of future returns, relative to CGO or the traditional momentum variable. Table 3 shows regression models for 1 month ahead return (Ret_{t+1}) as the dependent. Model A features the price momentum variable as shown in Equation 6. The results show that the price momentum variable is a positive and significant predictor of future returns, as we would anticipate. Model B shows that the traditional CGO variable is also a positive and significant predictor of future returns. Model C includes both price momentum and CGO and both are positive and significant predictors of future returns. This suggests that *CGO* is not able to explain the price momentum effect in share prices and this finding is consistent with other studies using CGO that is calculated with daily data, such as Riley et al. (2020), or CGO calculated using weekly data such as Wang et al. (2017). In model D, we include both the total return variable, *Tot_Return,* and price momentum, to compare them as predictors. Our results show that while the total return variable remains positive and significant at the 1% level, while *MOM* variables become insignificant. Likewise in model E, we include both *Tot_Return,* and *CGO*, to compare them as predictors. The results again show that only Tot_Return is a significant predictor of future returns. Finally, Model F includes total returns, CGO and price momentum. Only total returns is a significant predictor of future returns. The results suggest that total return is a robust predictor of future returns and subsumes price momentum and CGO as predictors of future returns, which are no longer significant.

$$Ret_{t+1} = \beta_0 + \beta_1 MOM_t + \beta_2 Mrkcap_t + \beta_3 STR_t + \beta_4 LTR_t + \beta_5 Avgturn_t + \beta_6 BM_t + \mathcal{E}_t$$

Equation 6: Regression Equation for Table 3, Model A

3.2 Adapted and Unadapted Returns as Predictors of Future Returns

In this section, we explore the predictive power of the adapted and unadapted return variables, which are arrived at by decomposing the total return variable. In Model A of Table 4 we test the predictive power of the adapted and unadapted variables together with traditional price momentum. Adapted return is negative and significant at the 1% level, while unadapted return is positive and significant at the 1% level, while price momentum is insignificant. This suggests that investors are risk-averse in their unadapted gains and risk-seeking in their unadapted losses, as we anticipated. In Model B we include the CGO variable and find that it is insignificant, while adapted and unadapted returns remain significant at the 1% level. Finally, in Model C we replace *CGO* with the *VNSP* variable. We find that *VNSP* is also insignificant, while adapted and unadapted returns remain significant at the 1% level. To check for robustness we repeat the above process in models D-F using the Baucells reference point rather than the Riley reference point and find the same pattern of results.

In summary, our results suggest that adapted and unadapted returns have disparate implications for future returns, consistent with the idea that low adapted returns lead to risk aversion, while low unadapted returns lead to risk-seeking behavior. This is consistent with investors treating adapted returns like realized returns and experiencing a snake-bite effect after making a loss. In contrast, investors continue to treat unadapted returns like unrealized returns and experience the disposition effect. When combined together, our two variables also subsume the VNSP

variable as a predictor of future returns, reflecting that our variables can capture a V-shaped selling schedule. Specifically, both unadapted losses and adapted gains can trigger selling behavior.

3.3 Residual Sorts Analysis

In Table 5 and Table 6, we use residual sorts to confirm the findings of our regression analysis and explore the pattern of returns. Stocks are sorted each month based on their return variable: total return, adapted return, or unadapted return. To account for the influence of the control variables, we first regress our return variables against the control variables using a Fama-Macbeth regression. For example, we show the residual sort equation for total returns in Equation 7. We also remove the controls' variability from the 1-month forward return *(Ret_{t+1})*, as shown in Equation 8. To account for their multicollinearity, the residual sort regression equation for adapted returns includes unadapted returns as a control and vice versa for unadapted returns.

$$Tot_Return_t = \beta_0 + \beta_1 STR_t + \beta_2 LTR_t + \beta_3 Avgturn_t + \beta_4 Mrkcap_t + \beta_5 BM_t + \mathcal{E}_t$$

Equation 7: Residual Sort Regression Equation for Independent Variable

$$Ret_{t+1} = \beta_0 + \beta_1 STR_t + \beta_2 LTR_t + \beta_3 Avgturn_t + \beta_4 Mrkcap_t + \beta_5 BM + \mathcal{E}_t$$

Equation 8: Residual Sort Regression for the Dependent Variable

We use the residuals to sort stocks into ten monthly decile portfolios for all three return variables (Tot_Return, Adapt and UnAdapt). We then measure the 1-month forward return of the decile portfolio as the residual of Equation 8 (not the forward return itself). These portfolio returns are then averaged across months and checked to see if the average returns significantly differ. Stocks are either equally weighted or market value-weighted within the portfolios. The difference portfolio (10-1) reflects the performance of a portfolio of stocks that go long Decile 10 stocks and short Decile 1 stocks. We calculate the associated t-statistics using Newey-West adjustment with a lag of 12 months to mirror the previous analysis.

Table 5 shows the results for equally weighted portfolios. For the total return variable, the portfolio with the highest decile of total returns outperforms the portfolio with the lowest decile of total returns by 1.81% per month. The difference is significant at the 1% level. We would expect high adapted returns to be negatively associated with future returns. This is indeed the case with a difference of -0.43% per month, which is significant at the 1% level. Finally, the highest decile portfolio based on unadapted returns has a higher average return than the lowest by 1.81% per month, which is also significant at the 1% level. While total returns and unadapted returns have a positive and monotonic relationship with future returns, the relationship between adapted returns and future returns is more complex. Figure 2 (in the introduction) shows that the first three deciles predominantly drive the negative relationship between adapted returns and future returns. The relationship between adapted returns and future returns is broadly flat from decile portfolio four. The implication is that low adapted returns (previous losses) drive decreased risk-taking and subsequent undervaluation, but high adapted returns (previous gains) do not drive

increased risk-taking and subsequent overvaluation to the same degree. Table 6 shows that the results are mirrored when stocks are weighted by market value rather than equally weighted each month, demonstrating that the results are not driven solely by small-cap stocks. The positive relationship between total returns, unadapted returns and future returns is still present and significant. The negative and non-monotonic relationship between adapted returns and future returns is unchanged.

The results confirm and enhance our earlier regression analysis, demonstrating that while the total return is positively related to future returns, the adapted component of this return is negatively related to future returns. In contrast, the unadapted component of the return is positive. Our decile sorts suggest a monotonic relationship for both total and unadapted returns with future returns with a sign predicted by the disposition effect. We also show that the relationship between adapted returns and future returns is non-monotonic with a sign predicted by the snake-bite effect.

3.4 Adapted and Unadapted Returns as Risk Moderators

Wang et al. (2017) demonstrate that high-risk stocks outperform low-risk stocks within the subset of positive CGO stocks. This is unusual as low-risk stocks usually outperform high-risk stocks (Ang et al., 2006) for the market as a whole. For stocks with negative CGO, this negative relationship between risk and future return is restored; hence, low-risk stocks outperform high-risk ones. Wang et al. (2017) suggest that the negative relationship between risk and future returns is

inverted in positive CGO stocks because investors become risk-averse in stocks where they have positive prior gains, reflected by a positive CGO. As investors become risk-averse in gains, they prefer low-risk stocks, which leaves low-risk stocks overpriced relative to high-risk stocks. Equally, for stocks with a negative CGO, investors become risk-seeking in these stocks, which can explain why low-risk stocks tend to outperform high-risk stocks.

We will explore how our adapted and unadapted return variables moderate the relationship between risk and future return. In testing our return variables as moderators, the first thing we will do is establish that the total return variable exhibits the same moderation effect as the CGO variable with regard to risk. In addition, we expect investors to be risk-averse in adapted losses due to the influence of the snake-bite effect. Thus, we should observe an inverse moderating relationship to that observed using total return or CGO as moderators. Then for stocks with unadapted gains, investors should be risk-averse, while for those stocks with unadapted losses, investors should become risk-seeking due to the influence of the disposition effect. Therefore, unadapted returns should show the same moderation effect as CGO and total return.

To undertake the analysis, we use three risk variables: total volatility (*Tvol),* idiosyncratic volatility *(Ivol)* and beta (*Beta*) across the three return variables (*Tot_Return, Adapt*, and *UnAdapt*) to create a total of nine new variables. For example, we show the interaction variable for total returns and total volatility in Equation 9. We then test for the sign and significance of the nine interaction variables.

$$Tot_Return * Proxy_t = Tot_Returns_t * TVOL_t$$

Equation 9: Interaction Variable- Total Returns & Total Volatility

We undertake the analysis in Table 7, beginning with the total volatility risk proxy. In Model A, the interaction variable (*Tot_Return**Tvol) is positive and significant at the 1% level. We show the relationship in Figure 4 below. The dashed line represents stocks with the highest total return per calendar month (90th decile per month) and the solid line is the lowest total return (10th decile per month). The highest total return stocks have a positive relationship between total volatility and futures returns, whereas the opposite is true for firms with the lowest total returns. This is the same moderating relationship that CGO evokes, observed by Wang et al. (2017).

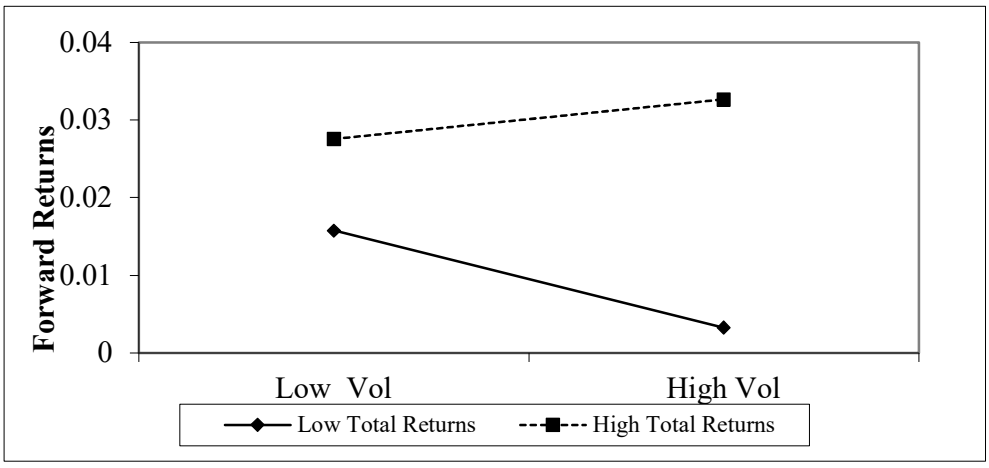


Figure 4: Moderation Analysis- Total return

In Model B, we carry out the same analysis using the adapted and unadapted return variables instead of the total return. We observe that the coefficient of the interaction variable for adapted

returns is negative and significant at the 5% level. In comparison, the coefficient for the interaction variable for unadapted returns is positive and significant at the 1% level. We plot the moderation relationship for adapted returns in Figure 3 (shown in the introduction). We observe that low-adapted return stocks have a positive relationship between risk and return and high-adapted return stocks have a negative relationship between risk and return. This finding backs up our earlier analysis that investors are risk-averse in negative adapted gains due to the influence of the snake-bite effect.

We also show the moderation relationship involving unadapted returns in Figure 3. We observe the same moderation pattern for unadapted returns and risk as we do for total returns: high unadapted return stocks exhibit a positive relationship between risk and future return and low unadapted return stocks exhibit a negative relationship between risk and future return. This result reaffirms our earlier analysis that investors become risk-averse in unadapted gains as they are in the gains portion of the prospect theory curve and risk-seeking in losses. We then perform the identical analysis for idiosyncratic volatility in Models C and D. We observe the same moderating relationships between risk and return as we did for total volatility. All the moderating variables are significant at the 1% level and all have the anticipated signs. Finally, we consider the beta variable as a risk proxy in Models E and F and find the same relationships again.

In summary, the moderation analysis suggests the mechanism behind our earlier results. Investors tend to be risk-averse in prior adapted losses due to the influence of the snake-bite effect, but equally, they are risk-seeking in their prior unadapted losses due to the influence of

the disposition effect. We expect stocks with a low adapted return to manifest a positive relationship between risk and return, which we observe. Equally, we would expect stocks with a low unadapted gain to have a negative relationship between risk and return and this is indeed the case for all three risk proxies.

3.5 Robustness Tests

In this section, we undertake robustness tests using the total, adapted, *and un*adapted return variables. In the first test, shown in Table 8, we split the sample into two halves based on the calendar month, with the first half in models A & B and the second half in models C & D. Our results show that all three variables are significant with the anticipated sign across both sub-samples. In the 2nd test (models E & F), we check to ensure that low-priced stocks do not drive our results. To do this, we exclude all stocks with a price under $2 in the relevant calendar month and our results show that all three of our return variables are still significant with the anticipated signs. In models G & F, we control for small-cap stocks by excluding stocks in each month's bottom two market deciles of the dataset. Given that the bottom decile is already excluded, this means that we exclude the bottom quintile of stocks each calendar month. Our results show that all variables are significant with the anticipated sign, so these low-priced stocks do not drive the results. Finally, in models I & J, we exclude NASDAQ stocks and all three variables remain significant with the anticipated signs. In summary, the results show that our return variables are robust to different sub-samples, with the predictive power of the variables not being driven by small stocks, low-priced or Nasdaq stocks.

4.0 Conclusion

We define a new variable, total return, that captures the return for the aggregate investor in a stock. It is a better proxy for unrealized returns than CGO, subsuming both CGO and the 1-year price momentum variables when used to predict future returns. To demonstrate this, we show that both *CGO* and *MOM* are insignificant drivers of future returns when we include total return in the regression model. We then decompose total return into two components: adapted return, the percentage difference between the investor's reference point and initial purchase price, and unadapted return, which is the percentage difference between a stock's current price and the investor's reference point. The adapted return captures the gain or loss that investors have internalized, making these outcomes susceptible to the snake-bite effect. This effect results in investors exhibiting risk-averse behavior in the presence of losses. In contrast, the unadapted return represents the gain or loss that investors have not internalized and is influenced by the disposition effect. Investors affected by the disposition effect tend to be risk-averse with gains and risk-seeking with losses.

We would, therefore, expect that the most undervalued stocks will exhibit a negative adapted return and a positive unadapted return. This situation occurs when a stock initially declines, which lowers the reference point relative to the purchase price, but then experiences a recent increase that raises the current price above this reference point. In these cases, we observe a smile or V-shaped pattern in the returns. Our findings indicate that these stocks are indeed the

most underpriced, showing the highest potential for future returns. Ben-David and Hirshleifer (2012) previously detected that investors have an increased tendency to sell both extreme winners and extreme losers and our decomposition provides an explanation for why this occurs. Investors do have a tendency to sell losers in addition to winners, but only if they have adopted their reference point to the loss.

We then investigate if our return variables can moderate the relationship between risk and return. It is well established that stocks with lower risk tend to underperform stocks with higher risk (Ang et al., 2006), but Wang et al. (2017) suggest that this relationship reverses for stocks with a positive capital gains overhang. Our findings reveal a similar moderating effect when we use the total return variable instead of capital gains overhang. If investors become risk averse following adapted losses and risk-seeking during unadapted losses, we would expect these variables to be moderators of the risk-return relationship, but with an inverse sign. We show that both variables are significant moderators of the relationship between risk and return, with adapted returns having the anticipated negative sign and unadapted returns the anticipated positive sign. These results suggest that the mechanism by which adapted and unadapted returns influence future returns is through changes in risk preference.

Our results suggest that academics should consider the role of the reference point when measuring past returns, as investors will react differently to internalized returns than externalized returns. One area explored in more detail is the distinction between realized and unrealized returns (Barberis and Xiong, 2012). Closing a mental account is a crucial feature of

Barberis and Xiong's (2012) realization utility. In evaluating gains and losses, Barberis and Xiong (2012) assume the reference point[8] to be the amount of money the investor put into the stock at the time of purchase, scaled up by the risk-free return (i.e., a purchase price-based reference point). Looking at the prior literature, we understand that past returns have never been decomposed into adapted and unadapted components, chiefly because there has been little attention on the reference point and its manner of adjustment from the initial purchase price. Therefore, the scope for future research into the decomposition of total returns into adapted and unadapted components is broad.

[8] Which they refer to as the cost basis, with gain/loss computed as selling price less cost.

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Statistical Tables

Table 1: Descriptive Statistics for Variables

	Tot_Return	Adapt	UnAdapt	CGO	Mom	Mrkcap	STR	LTR	Avgturn	BM
Mean	0.010	0.076	-0.066	-0.191	0.164	11.726	0.016	0.377	0.003	-0.693
Max	3.154	2.080	1.351	0.689	10.520	18.510	2.379	20.004	0.126	2.991
Min	-0.879	-0.437	-0.916	-21.189	-0.866	9.015	-0.606	-0.918	0.000	-7.251
SD	0.315	0.146	0.200	0.786	0.573	1.720	0.143	1.014	0.005	0.976

Notes: *Tot_Return* (total return), *Adapt* (adapted return) and Un*Adapt* (unadapted return) are the 3 dependent variables defined in Equation 1 and Equation 3. CGO is capital gains overhang of Grinblatt and Han (2005). MOM=12month momentum, excluding the last month. Mrkcap is the log of market capitalization in thousands. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. BM is log of the book to market ratio.

Table 2: Correlation Table for Variables

	Tot_Return	Adapt	UnAdapt	CGO	Mom	Mrkcap	STR	LTR	Avgturn	BM
Tot_Return	1.000									
Adapt	0.869	1.000								
UnAdapt	0.942	0.658	1.000							
CGO	0.759	0.665	0.712	1.000						
Mom	0.547	0.434	0.543	0.413	1.000					
Mrkcap	0.306	0.200	0.330	0.304	0.084	1.000				
STR	0.217	0.063	0.293	0.138	0.000	0.020	1.000			
LTR	0.260	0.368	0.150	0.217	-0.026	0.117	-0.021	1.000		
AvgTurn	-0.031	-0.005	-0.045	0.011	0.142	0.144	-0.006	0.167	1.000	
BM	-0.365	-0.368	-0.310	-0.296	-0.317	-0.279	-0.098	-0.295	-0.168	1.000

Notes: *Tot_Return* (total return), *Adapt* (adapted return) and Un*Adapt* (unadapted return) are the 3 dependent variables defined in Equation 1 and Equation 3. CGO is capital gains overhang of Grinblatt and Han (2005). MOM=12month momentum, excluding the last month. Mrkcap is the log of market capitalization in thousands. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. BM is log of the book to market ratio.

Table 3: Regression Table of 1 Month Ahead Returns and Return Variables

VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
Tot_Return				0.0175***	0.0210***	0.0190***
				(7.857)	(7.177)	(7.035)
Mom	0.00893***		0.00576***	0.000778		0.000798
	(4.183)		(2.883)	(0.393)		(0.406)
CGO		0.00995***	0.00646***		-0.00172	-0.000997
		(6.438)	(4.942)		(-0.720)	(-0.403)
Mrkcap	7.90e-06	-0.000414	-0.000248	-0.000570	-0.000630	-0.000542
	(0.0165)	(-0.902)	(-0.561)	(-1.304)	(-1.438)	(-1.266)
STR	-0.0507***	-0.0581***	-0.0560***	-0.0620***	-0.0636***	-0.0625***
	(-8.869)	(-10.43)	(-9.847)	(-10.52)	(-11.28)	(-10.67)
LTR	-0.000866	-0.00257***	-0.00148**	-0.00310***	-0.00339***	-0.00304***
	(-1.088)	(-3.341)	(-2.055)	(-3.606)	(-4.188)	(-3.617)
Avgturn	-0.944**	-0.443	-0.695*	-0.394	-0.116	-0.322
	(-2.379)	(-1.028)	(-1.818)	(-0.969)	(-0.296)	(-0.859)
BM	0.00243***	0.00147*	0.00240***	0.00268***	0.00242***	0.00267***
	(3.115)	(1.797)	(3.115)	(3.513)	(3.077)	(3.524)
Constant	0.0124*	0.0185***	0.0157**	0.0194***	0.0200***	0.0190***
	(1.836)	(2.867)	(2.521)	(3.138)	(3.234)	(3.147)
Observations	1,885,249	1,885,389	1,885,066	1,884,581	1,884,873	1,884,553
Average R^2	0.064	0.066	0.070	0.069	0.070	0.073
Groups	647	647	647	647	647	647

Notes: Tot_Return (total return), Adapt (adapted return) and UnAdapt (unadapted return) are the 3 independent variables defined in Equation 1 and Equation 3. CGO is capital gains overhang of Grinblatt and Han (2005). MOM=12month momentum, excluding the last month. Mrkcap is the log of market capitalization in thousands. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. BM is log of the book to market ratio. All independent and control variables are winsorized at the 1% and 99% levels. T-statistics in parentheses are Newey-West adjusted. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Regression of 1-Month Ahead Return Against Adapted and Unadapted Returns

	Riley Ref Point			Baucells Ref Point		
VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
Adapted Return	-0.0126***	-0.0106***	-0.0111***	-0.0660***	-0.0686***	-0.0797***
	(-4.205)	(-3.527)	(-2.991)	(-5.076)	(-5.401)	(-5.501)
Unadapted Return	0.0398***	0.0414***	0.0406***	0.0690***	0.0762***	0.0781***
	(11.22)	(10.05)	(12.18)	(7.235)	(7.740)	(8.330)
CGO		-0.00121			-0.00274	
		(-0.509)			(-1.089)	
VNSP			0.00372			0.00817
			(0.839)			(1.597)
Mom	-0.00133	-0.00126	-0.00120	0.000166	0.000136	7.77e-05
	(-0.655)	(-0.624)	(-0.600)	(0.0831)	(0.0686)	(0.0394)
Mrkcap	-0.000926**	-0.000893**	-0.000838**	-0.000859**	-0.000819*	-0.000758*
	(-2.165)	(-2.134)	(-2.088)	(-2.019)	(-1.957)	(-1.889)
STR	-0.0710***	-0.0716***	-0.0725***	-0.0676***	-0.0684***	-0.0694***
	(-11.72)	(-11.87)	(-11.95)	(-11.13)	(-11.32)	(-11.52)
LTR	-0.00177**	-0.00178**	-0.00170**	-0.00233***	-0.00216***	-0.00197**
	(-2.227)	(-2.213)	(-2.134)	(-2.747)	(-2.608)	(-2.466)
Avgturn	-0.233	-0.177	-0.187	-0.520	-0.448	-0.479
	(-0.542)	(-0.452)	(-0.481)	(-1.252)	(-1.155)	(-1.269)
BM	0.00223***	0.00220***	0.00222***	0.00224***	0.00223***	0.00227***
	(3.031)	(3.022)	(3.097)	(3.069)	(3.057)	(3.138)
cons	0.0264***	0.0258***	0.0246***	0.0277***	0.0273***	0.0259***
	(4.372)	(4.394)	(4.488)	(4.761)	(4.753)	(4.796)
Observations	1,884,581	1,884,553	1,884,228	1,884,580	1,884,552	1,884,227
Average R^2	0.072	0.077	0.077	0.072	0.076	0.077
Groups	647	647	647	647	647	647

Notes: Tot_Return (total return), Adapt (adapted return) and UnAdapt (unadapted return) are the 3 independent variables defined in Equation 1 and Equation 3. CGO is capital gains overhang of Grinblatt and Han (2005). MOM=12month momentum, excluding the last month. Mrkcap is the log of market capitalization in thousands. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. BM is log of the book to market ratio. All independent and control variables are winsorized at the 1% and 99% levels. T-statistics in parentheses are Newey-West adjusted. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Residual Sorts for Return Variables (Equally Weighted)

	Total returns		Adapted Returns		Unadapted Returns	
	ret	t	ret	t	ret	t
1(low)	-0.76%	-2.16**	0.60%	2.03**	-0.85%	-2.72***
2	-0.35%	-1.23	0.29%	1.28	-0.29%	-1.03
3	-0.12%	-0.48	0.18%	0.86	-0.06%	-0.22
4	-0.03%	-0.12	0.15%	0.71	0.10%	0.41
5	0.00%	0.01	0.15%	0.74	0.17%	0.76
6	0.15%	0.71	0.21%	0.98	0.24%	1.11
7	0.23%	1.07	0.14%	0.64	0.34%	1.63
8	0.38%	1.67*	0.19%	0.81	0.47%	2.13**
9	0.60%	2.55**	0.23%	0.88	0.64%	2.86***
10(High)	1.05%	3.99***	0.17%	0.62	0.95%	3.67***
diff (10-1)	1.81%	8.49***	-0.43%	-2.74***	1.81%	9.96***

Notes: Table showing monthly average returns of residual sorted stocks. The 3 return dependent variables are first regressed against the control variables and then the residual is used to sort stocks into deciles. Portfolios sorted into 10 equal groups every month by residuals. Stocks are equally weighted and rebalanced monthly. T-statistics use Newey-West adjustment (12 lags). *Tot_Return* (total return), *Adapt* (adapted return) and Un*Adapt* (unadapted return) are the 3 dependent variables defined in Equation 1 and Equation 3. CGO is capital gains overhang of Grinblatt and Han (2005). MOM=12month momentum, excluding the last month. Mrkcap is the log of market capitalization in thousands. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. BM is log of the book to market ratio. All independent and control variables are winsorized at the 1% and 99% levels. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Residual Sorts for Return Variables (Market Value Weighted)

	Total returns		Adapted Returns		Unadapted Returns	
	ret	t	ret	t	ret	t
1(low)	-0.74%	-2.14**	0.58%	1.98**	-0.83%	-2.71***
2	-0.35%	-1.29	0.27%	1.24	-0.27%	-0.99
3	-0.13%	-0.55	0.17%	0.83	-0.05%	-0.19
4	-0.03%	-0.13	0.14%	0.71	0.10%	0.44
5	0.00%	-0.01	0.15%	0.74	0.16%	0.73
6	0.14%	0.69	0.21%	1.00	0.23%	1.10
7	0.21%	1.00	0.15%	0.69	0.32%	1.59
8	0.36%	1.60	0.20%	0.83	0.45%	2.10**
9	0.58%	2.52**	0.23%	0.89	0.62%	2.83***
10(High)	1.04%	3.99***	0.18%	0.65	0.94%	3.64***
diff (10-1)	1.78%	8.40***	-0.39%	-2.52**	1.77%	9.94***

Notes: Table showing monthly average returns of residual sorted stocks. The 3 return dependent variables are first regressed against the control variables and then the residual is used to sort stocks into deciles. Portfolios sorted into 10 equal groups every month by residuals. Stocks are market value weighted and rebalanced monthly. Market cap is the log of market capitalization in thousands. T-statistics use Newey-West adjustment (12 lags). *Tot_Return* (total return), *Adapt* (adapted return) and Un*Adapt* (unadapted return) are the 3 dependent variables defined in Equation 1 and Equation 3. CGO is capital gains overhang of Grinblatt and Han (2005). MOM=12month momentum, excluding the last month. Mrkcap is the log of market capitalization in thousands. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. BM is log of the book to market ratio. All independent and control variables are winsorized at the 1% and 99% levels. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Regression Table of one-month ahead Returns and Moderation Variables

Risk Proxy=	Total Vol		Idiosyncratic Vol		Beta	
VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F
Tot_Return	0.00726**		0.00655**		0.0147***	
	(2.333)		(2.054)		(5.453)	
Adapt		0.00215		0.00754		-0.00960***
		(0.353)		(1.271)		(-3.077)
UnAdapt		0.00736		0.00240		0.0305***
		(1.283)		(0.424)		(6.943)
Tot_Return *Proxy	0.383***		0.415***		0.00388***	
	(3.915)		(4.796)		(3.621)	
Adapt*Proxy		-0.537**		-0.849***		-0.00239**
		(-2.118)		(-2.592)		(-2.001)
UnAdapt*Proxy		1.090***		1.428***		0.00794***
		(5.057)		(5.193)		(3.947)
Proxy	-0.0500	0.102	-0.115***	0.0663	0.00306	0.00436
	(-0.776)	(1.203)	(-2.999)	(1.150)	(1.124)	(1.620)
Mrkcap	-0.000781**	-0.000851***	-0.000962**	-0.00101***	-0.000587	-0.000900**
	(-2.311)	(-2.605)	(-2.448)	(-2.634)	(-1.261)	(-1.978)
STR	-0.0660***	-0.0745***	-0.0633***	-0.0735***	-0.0623***	-0.0703***
	(-11.42)	(-12.51)	(-10.99)	(-12.36)	(-11.28)	(-12.55)
LTR	-0.00360***	-0.00190***	-0.00351***	-0.00195***	-0.00336***	-0.00179**
	(-4.603)	(-2.682)	(-4.349)	(-2.658)	(-4.306)	(-2.520)
Avgturn	-0.178	-0.145	0.0532	0.0788	-0.177	-0.109
	(-0.539)	(-0.438)	(0.150)	(0.213)	(-0.437)	(-0.261)
BM	0.00218***	0.00198***	0.00210***	0.00188**	0.00243***	0.00206***
	(3.237)	(3.020)	(2.796)	(2.538)	(2.993)	(2.615)
Constant	0.0232***	0.0229***	0.0262***	0.0252***	0.0162***	0.0211***
	(4.735)	(4.898)	(4.729)	(4.712)	(2.914)	(3.828)
Observations	1,884,747	1,884,747	1,883,435	1,883,435	1,839,708	1,839,708
Average R^2	0.076	0.081	0.073	0.078	0.065	0.069
Number of groups	647	647	647	647	630	630

Notes: *Tot_Return* (total return), *Adapt* (adapted return) and Un*Adapt* (unadapted return) are the 3 moderating variables defined in Equation 1 and Equation 3. Proxy is one of three risk proxies: Tvol=total volatility over last year, Ivol= idiosyncratic volatility over the last month, Beta=beta calculated over the last year. Controls variables used: Mrkcap is the log of market capitalization in thousands. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. BM is log of the book to market ratio. All independent and control variables are winsorized at the 1% and 99% levels. T-statistics in parentheses are Newey-West adjusted.

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Robustness Tests

	First Half		Second Half		Exclude Low Price		Exclude Small		Exclude Nasdaq	
VARIABLES	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I	Model J
Tot_Return	0.0198***		0.0113***		0.0193***		0.0188***		0.0154***	
	(6.363)		(2.774)		(8.370)		(7.308)		(5.260)	
Adapt		-0.00981**		-0.0285***		-0.00953***		-0.0119***		-0.0215***
		(-2.118)		(-6.173)		(-3.344)		(-3.881)		(-4.835)
UnAdapt		0.0392***		0.0375***		0.0382***		0.0384***		0.0387***
		(7.437)		(7.215)		(10.15)		(9.904)		(9.126)
Mrkcap	-0.00182**	-0.00200***	-0.00116**	-0.00165***	-0.000758*	-0.00103**	-0.000600	-0.000899**	-0.00121***	-0.00151***
	(-2.466)	(-2.766)	(-2.177)	(-3.089)	(-1.761)	(-2.443)	(-1.379)	(-2.128)	(-2.783)	(-3.524)
STR	-0.0972***	-0.105***	-0.0478***	-0.0570***	-0.0602***	-0.0679***	-0.0584***	-0.0661***	-0.0672***	-0.0760***
	(-13.79)	(-15.49)	(-8.148)	(-8.994)	(-10.84)	(-12.22)	(-10.68)	(-11.87)	(-11.01)	(-12.41)
LTR	-0.00376***	-0.00154	-0.00320***	-0.00158	-0.00330***	-0.00190***	-0.00319***	-0.00174**	-0.00301***	-0.00116
	(-2.989)	(-1.494)	(-2.951)	(-1.566)	(-4.211)	(-2.601)	(-4.054)	(-2.386)	(-3.647)	(-1.644)
Avgturn	-0.474	-0.331	0.00757	0.0683	-0.172	-0.116	-0.0845	-0.0328	-0.167	-0.0819
	(-0.621)	(-0.419)	(0.0280)	(0.248)	(-0.435)	(-0.282)	(-0.206)	(-0.0777)	(-0.430)	(-0.203)
BM	0.00315***	0.00288**	0.00310***	0.00264**	0.00246***	0.00211***	0.00247***	0.00208***	0.00220***	0.00196***
	(2.768)	(2.584)	(2.737)	(2.392)	(3.206)	(2.838)	(3.127)	(2.754)	(3.061)	(2.784)
Constant	0.0357***	0.0403***	0.0283***	0.0377***	0.0218***	0.0274***	0.0194***	0.0256***	0.0275***	0.0340***
	(3.555)	(4.110)	(3.614)	(4.775)	(3.579)	(4.637)	(3.103)	(4.255)	(4.435)	(5.645)
Observations	711,275	711,275	1,357,110	1,357,110	1,854,153	1,854,153	1,705,031	1,705,031	1,063,814	1,063,814
R-squared	0.081	0.084	0.043	0.046	0.065	0.068	0.068	0.072	0.069	0.073
Groups	324	324	323	323	647	647	647	647	647	647

Notes: *Tot_Return* (total return), *Adapt* (adapted return) and Un*Adapt* (unadapted return) are the 3 dependent variables defined in Equation 1 and Equation 3. CGO is capital gains overhang of Grinblatt and Han (2005). MOM=12month momentum, excluding the last month. Mrkcap is the log of market capitalization in thousands. STR=Short term reversal, calculated as the return of the last month t. LTR=Long-term reversal, calculated as the return over the last 3 years excluding the last year. AvgTurn is average daily turnover over last year. BM is log of the book to market ratio. All independent and control variables are winsorized at the 1% and 99% levels. T-statistics in parentheses are Newey-West adjusted. Model A/B: 1st half of sample, Models D:E: 2nd half of sample, Models E/F:=exclude low price with prices below $2 in the previous month, Models G/H: excludes stocks in the bottom decile ranked by market cap over the previous month, Models I/J: exclude Nasdaq stocks.
*** p<0.01, ** p<0.05, * p<0.1.