Impact of Price Path on Disposition Bias*

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Abstract

Recent experimental studies have illustrated the influence of price-path, particularly the 'non-straight' price-path on several aspects of investor behaviour. The paper computes a proxy for price-path based on Cumulative Prospect Theory and with investor-level high-frequency trade data from the commodities futures market, demonstrates that the nature of the price-path significantly impacts the degree of disposition bias, after controlling for the level of returns and volatility of the commodity. We find that the experience of a favorable (unfavorable) price-path, decreases (increases) disposition bias among both long and short traders with Cumulative Prospect Theory preferences. Experience of a 'favourable' price path leads to a decline (increase) in the propensity for gain realization. However, its impact on the propensity of loss realization remains nonexistent. We conjecture that both investor preferences and beliefs about future price movement, inferred from the price-path experienced, influence their trading decisions.

Key words: Price Path, Investor Behaviour, Behavioural Finance, Disposition Bias, Futures, Commodities

JEL classifications: G110, G130, G410

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1 Introduction

It is well-known that the past prices significantly influence investor expectations about future outcomes and thus affect their trading decisions (Greenwood and Shleifer, 2014; Choi et al., 2010; De Bondt, 1993). De Bondt (1993) and Greenwood and Shleifer (2014) found that investors often expect the past return trend to be representative of the future, and irrationally expect the trend to prevail. Choi et al. (2010) found that experimental subjects are strongly influenced by past returns while forming their portfolios. Grinblatt and Keloharju (2001) found that past returns increase the propensity to sell, particularly for stocks with positive returns in the immediate past and those which touch benchmarks such as the monthly high. However, research on the impact of past prices on investor beliefs and their trading decisions investigated the role of past returns and largely ignored the possible influence of the trajectory of the price, the price path, between two-time points.

Recent research by Grosshans and Zeisberger (2018), Nolte and Schneider (2018) and Borsboom and Zeisberger (2019), experimentally examined the impact of price path on investor satisfaction level, investment decisions and risk-perception, respectively. Grosshans and Zeisberger (2018) found that after controlling for the level of returns, assets that grow in value towards the end of the holding period, generates a higher satisfaction among the traders than the assets that have declined in value towards the end. They also document that the observed price path shapes the expectation of future returns, and the subjects believe in short-term trend continuation in the price movement. Nolte and Schneider (2018) found that price paths that have the same risk-return profile but different characteristics, such as the recent returns, maximum price, minimum price, purchase price, and amplitude, attract significantly different investment amounts from the participants of the experiment. Borsboom and Zeisberger (2019) also demonstrate that statistically equivalent price paths, in terms of return and standard deviation, can induce different levels of risk-perception in the minds of the subjects.

The findings from the experimental market imply that investor experience, future expectation, and investment decisions could vary substantially, depending on the price trajectory experienced, for a given level of return. For instance, the investor could experience positive returns over a holding period, where the prices rise initially and then decline in the later period (referred to as an 'up-down' path), as shown in Path 2 of Figure 1. The same level of returns could be earned under another price trajectory, where the price could decline in the initial phase, followed by a price rise (referred to as the 'down-up' path), as shown in Path 1 of Figure 1. Holding the level of returns the same, the investor would have a substantially different experience of the subjective value from the investments under the 'up-down' and 'down-up' price paths. Despite the potential significance price path has in shaping the investor decisions, it is not examined deeply in real financial markets. We attempt to investigate the role of price path in the paper by empirically examining its influence on the trading decisions of investors.

In this study, we develop a proxy for price path and empirically examine the impact of price path on a well-known trader characteristic, disposition bias (Shefrin and Statman, 1985; Odean, 1998; Weber and Camerer, 1998; Frazzini, 2006; Choe and Eom, 2009). Specifically, we investigate whether the nature of price path, captured using behavioral decision theories such as cumulative Prospect Theory (CPT) and Salience Theory, impacts disposition bias displayed by investors. We employ a high-frequency trader-level data, from the commodities derivative market for gold (GOLD) traded at the Multi Commodity Exchange of India (MCX), to construct the price path proxy and measure disposition bias. Disposition bias refers to the higher tendency of investors to sell their winning investments compared to their losing investments. In other words, assets that have made a profit are quickly sold off, but the assets that have declined in value are held on to by the investors (Shefrin and Statman, 1985). Barber et al. (2009) find that disposition bias substantially reduces investors wealth.

It is widely documented that disposition bias increases with returns earned on the investments (Ben-David and Hirshleifer, 2012). However, if price path influences the timing and the aggressiveness of the trading decisions, then it is likely to impact the level of disposition bias in the market. For instance, if the 'down-up' price path, as shown in Path 1 of Figure 1, conveys a more optimistic signal about the future returns than Path 2, then investors may delay their selling decision, in which case, the intensity of disposition bias would decline in the market. Conversely, if an 'up-down' price path, as shown in Path 2 of Figure 1, conveys a more pessimistic signal about the future returns, relative to Path 1, then the investor may want to divest, which will intensify disposition bias. Therefore, it is reasonable to assume that the nature of price path has an incremental explanatory role for disposition bias observed in the market, in addition to the returns over a period in the account of the investor. Our paper attempts to bring out the nature of the influence price path has on disposition bias over and above the level of returns.

We contribute to the stream of literature on investor behavior by examining the impact of the price path on the level of disposition bias in the market. While most of the studies examine the influence of asset returns on disposition bias, our study differs from the previous attempts in several essential ways. First, we consider not only the impact of the previous returns but also the entire price path while the previous studies had only considered the influence of past returns. Second, the traders in the futures market have to maintain a margin account which is debited or credited daily, which makes the investor realistically feel the price trajectory, as it impacts his margin balance. Hence, the futures market offers itself as an appropriate context to examine the role of price path.

Our key results are as follows. First, the price path has a significant influence on disposition bias in the futures market, after controlling for returns, volatility, and the time left for the expiration of the contract. Second, a favourable price path (a high subjective CPT value path for long and a low subjective CPT value path for short investors) lowers disposition bias among the traders, and an unfavourable price path (a low subjective CPT value path for long and a high subjective CPT value path for short investors) accentuates it. Third, a favourable (unfavourable) price path is accompanied by a reduction (increase) in the propensity for gain realization (PGR). However, there is no influence of the price path on the propensity for loss realization(PLR). The findings confirm the significance of the price path in shaping investor decisions, observed by Grosshans and Zeisberger (2018) and Nolte and Schneider (2018) in experimental settings, in an actual market.

We employ an alternate framework to capture price path based on salience theory proposed by Bordalo et al. (2012), and find that the price path continues to influence the level of disposition bias among the traders. We find that the significance of the price path holds for traders with different holding periods and trade sizes. We also, examine the influence of price-path by varying the horizon, which is captured by the empirical proxy of the price path. The significance of the price path is not dependent on any specific time horizon over which it is measured. While we carry out the primary analysis in a precious metal commodity (GOLD contracts), we find a similar impact of price path on disposition bias of investors trading in energy markets (CRUDEOIL contracts).

Based on the findings, we conjecture that disposition bias is influenced by both the preferences and beliefs of the investors. Preference-based explanations argument is that investors are loss-averse, which makes them quickly close the winning position, thereby increasing disposition bias. On the other hand, belief-based explanations argue that after a series of gains, investors are more likely to believe that the uptrend in price would continue into future, which in turn would make them retain their winning assets and thus reduce disposition bias. While we find that consistent with the preference-based explanations, favourable contemporaneous and lagged returns intensifies the level of disposition bias, but consistent with belief-based explanations we also find that a favourable price path weakens the level of disposition bias by reducing the propensity of gain realization. Thus, we argue about the simultaneous influence of both preferences and beliefs on trade decisions of investors.

To the best of our knowledge, our study is the first attempt to empirically examine the impact of the price path on the investor level trade decisions. Our results complement the findings of the recent experimental studies (Grosshans and Zeisberger, 2018; Nolte and Schneider, 2018; Borsboom and Zeisberger, 2019), which examine the role played by price path in shaping investor decisions. We also extend the application of the CPT framework employed by Barberis et al. (2016) in the financial market to examine the investor level trade decisions. The paper also contributes to the research on the determinants of disposition bias by demonstrating how the price path shapes the trading choice of investors.

The rest of the paper is organized as follows. Section 2 discusses the literature on the various explanations for disposition bias. Section 3 describes the methodology and data. Section 4 presents the main results, Section 5 describes the robustness checks and Section 6 concludes.

2 Literature Review

Our paper is related to the strand of literature that demonstrates that traders in financial markets infer additional information from the price paths, which is not captured by return and risk. While the return captures the change in level from start to end point, it does not account for the path that the asset price follows between the points. Further, the sequence of events that occur between the start and end points is not captured by the change in the level between the two points.

Loewenstein and Prelec (1993) document that decision makers prefer sequences that increase in value and dislike the sequences that decline in value towards the end. In financial context, implication of price path has been documented to influence the satisfaction level (Grosshans and

Zeisberger, 2018), investment decision (Nolte and Schneider, 2018) as well as risk-perception (Borsboom and Zeisberger, 2019) in experimental settings.

Grosshans and Zeisberger (2018) analyse the impact of various price paths 'up-down', 'down-up', 'straight-up' and 'straight-down' on disposition bias, in an experimental market. They find that a downward trend in the past does increase the propensity to hold on to the stock, but it exists only for a 'non-straight' price path. In other words, a price path which closely resembles an 'up-down' trajectory increases the propensity to hold losers, but a 'straight-down' path decreases the same. Their research shows that price path has a significant influence on the propensity to sell, brought about by its role in shaping investor beliefs about future price movements.

Nolte and Schneider (2018) investigate the influence of certain noticeable points of the price path and heuristics on investment decisions. They find evidence that investors focus on recent trends, focus more on losses and estimate risk from the range (amplitude). Their research highlights that price path similar in terms of statistical risk and return, can have drastically different impact on the willingness of the traders to invest. Borsboom and Zeisberger (2019) experimentally find that price paths despite having identical daily and monthly return (also standard deviation) lead to varied perception of risk. Specifically, they find that high, lows and final returns are the most influential drivers of risk perception.

The overarching picture from the experimental studies is that paths with identical statistical properties but different trajectories can lead to varied investor response. While there are several studies that examine the influence of the price path in experimental settings, empirical evidence on this meagre. Barberis et al. (2016) attempt to empirically test the impact of past 5-year return distribution on the asset prices. They find that stocks with high CPT valuation of the past return distribution earn lower returns in future, as investors may overvalue assets with attractive return distribution. Their research had been motivated by the industry-wide use of price charts to elicit investor response, such as Value Line Investment Survey.

In this paper, we empirically investigate the possible influence the price path could have on investor trading decisions, by examining its influence on the level of disposition bias.

Disposition bias (Shefrin and Statman, 1985), where investors show a higher propensity to realize their gains than the their losses, adversely impacts investor wealth, as the assets investors sell outperform those which are retained (for instance, Odean, 1998). It is known to be prevalent in equity markets (for instance, Shefrin and Statman, 1985; Barber and Odean, 1999; Brown et al., 2006; Visaltanachoti et al., 2007; Grinblatt and Keloharju, 2001), in futures markets (Choe and Eom, 2009) and in real estate markets (Genesove and Mayer, 2001).

Research has offered a range of explanations for the prevalence of disposition bias, consistent with both investor preferences and their beliefs. The argument that disposition bias is an outcome of investor preference is commonly driven by the inherent dislike of the experience of losses and the preference for gains. The preference based explanations are grounded in loss-aversion (Kahneman and Tversky, 1979; Shefrin and Statman, 1985), regret aversion (Shefrin and Statman, 1985; Frydman and Camerer, 2016), cognitive dissonance (Chang et al., 2016) and realization utility (Barberis and Xiong, 2012). An alternative explanation for disposition bias based on beliefs about the future price movements is proposed by Barber and Odean (1999) and Ben-David and Hirshleifer (2012).

Belief based explanations for disposition bias suggest that investors form expectations about future price movements and may trade in a manner consistent with their expectations. Barber and Odean (1999) propose that investors might expect the prices to mean-revert, hence they may refrain from selling the assets in loss as they expect to break-even in future. Ben-David and Hirshleifer (2012), find that investors not only refrain from selling the stocks in losses, but they are also likely to buy additional units of stocks with losses in their portfolio. As the expectations about future prices movements could be impacted by the past price path (for instance, Grosshans and Zeisberger, 2018), the observed price path may also influence the level of disposition bias. For instance, on observing "down-up" price path, despite negative returns an investor may expect the trend to continue and prices to recover further. This would reduce the intensity of disposition bias.

Despite the significance price path may have in impacting disposition bias, the belief-based explanations have received very little attention. In this study, we attempt to empirically examine the role played by the nature of price path on disposition bias among investors.

3 Methodology and Data

3.1 Empirical estimation approach

We examine the significance of price path on disposition bias through a regression of disposition bias in the market on price path variable, along with other variables which are known to influence disposition bias. The detailed estimation approach is given below:

$$
\begin{aligned}
DB_t^i = \quad & \alpha + \beta_1 Days.to.Expiry_t^i + \beta_2 r_t^i + \beta_3 r_{t-1}^i + \beta_4 r_{t-2}^i \\
& + \beta_5 TK_{1,t-1}^i + \beta_6 r_{1,t}^i + \beta_7 RV_{1,t}^i \\
& + \textit{Weekday fixed effects} + \textit{Month fixed effects} \\
& + \textit{Year fixed effects} + \textit{Expiry Month fixed effects} + \epsilon_t^i
\end{aligned} \tag{1}
$$

where, DB_t^i is the market-level disposition bias prevalent among traders in contract i on day t. The construction of the DB_t^i variable is detailed in Section 3.2. $Days.to.Expiry_t^i$ is the time to expiry of contract i measured in calendar days on day t . Controlling for the influence of $Days.to.Expiry_t^i$ is crucial to the analysis as investors are more likely to close out their open positions as the contract approaches the expiry date. As the contemporaneous and near-lag returns on the contract are likely to induce trading (Grinblatt and Keloharju, 2001; Shefrin and Statman, 1985; Odean, 1998; Ben-David and Hirshleifer, 2012), we control the daily returns by employing the contemporaneous (r_t^i) and two lagged (r_{t-1}^i, r_{t-2}^i) returns . $TK_{1,t-1}^i$ is the proxy constructed to capture the nature of price path as described in Section 3.4. The cumulative returns on a contract ($r_{1,t}^i$) reflects the change in the price of the contract since its launch and it is known to influence disposition bias of investors. The trading decisions are also impacted by the volatility (Ben-David and Hirshleifer, 2012; Kumar, 2009) of prices. Hence, we control for the realized volatility ($RV_{1,t}^i$) of the contract from the date of the initiation of the contract. It is computed using intraday prices sampled at the 5-minutes interval[1]. In all the regressions, robust standard errors are computed and are clustered at the contract level. To control for any seasonality in trading patters, we add month level, year level and the month of expiration level fixed effects. Birru (2018) find evidence that cross-sectional variation in anomaly returns is

[1] $RV = \sqrt{\sum_{n=1}^{t} r_n^2}$, where r_n is the return in 5-minute interval

strongly dependent on day of the week. Further, psychology literature has documented higher mood on Fridays in comparison to Mondays (Rossi and Rossi, 1977; Watson, 2000; Young and Lim, 2014). Hence, to control for any influence on trading due to day of the week, we add weekday level fixed effects.

In our analysis, the examination of the disposition bias as impacted by the price path does not take into account the other constituents of the investor portfolios, as we do not have access to the data of any other holdings of the market participants. The individual portfolios are less important in our analysis as we are focused on disposition bias at the market level, unless the investor portfolios are substantially overlapping. If the investors hold largely non-overlapping portfolios, yet chose to trade the candidate future position in a common manner, then it could be reliably attributed to the characteristics of the futures contract, including the price path.

3.2 Measuring disposition bias

We measure the market level disposition bias for each contract on a daily basis (referred to as contract-day level analysis). To measure disposition bias at the market on a given contract-day, we rely on the approach proposed by Choe and Eom (2009) for the futures market in a certain contract-day. They define the market level disposition in a contract-day as the difference between the proportion of gain realized (PGR) and the proportion of loss realized (PLR), defined as follows.

$$DB_t^i = PGR_t^i - PLR_t^i \tag{2}$$

where,

$$PGR_t^i = \frac{N_{RG}^{i,t}}{N_{RG}^{i,t} + N_{PG}^{i,t}} \tag{3}$$

and

$$PLR_t^i = \frac{N_{RL}^{i,t}}{N_{RL}^{i,t} + N_{PL}^{i,t}} \tag{4}$$

$N_{RG}^{i,t}$ is the number of individual accounts (investors) on date t that realize a gain by selling at least a part of their open position in contract i. Similarly, $N_{RL}^{i,t}$ is the number of individual accounts (investors) on date t that realize a loss in contract i. $N_{PG}^{i,t}$ is the number of individual accounts on date t that has a gainful portfolio position, but did not realize gains (paper gain) in contract i. Analogously, $N_{PL}^{i,t}$ is the number of accounts on date t that experience a paper loss on the position in contract i.

To compute PGR_t^i and PLR_t^i, in each contract we track trades committed by individual investors on each contract-day, starting from the first day of trading until the maturity of each contract. Overall the data spans from the first trading day of January, 2012 to the last trading day of December, 2014 in one of the most liquid futures contracts, GOLD. As robustness check, we also investigate the influence among the traders of CRUDEOIL contracts. The details of the contracts are presented in subsection 3.5. The gains and losses in each individual account for each contract-day are ascertained as follows.

3.3 Computing the the gains and losses for each individual account

We first compute a high-frequency time-series of the cost corresponding to the net position observed in each commodity-maturity (referred to as contract above) pair, for each individual account. The time series of the cost is estimated by taking the contract weighted transaction (long or short) price at each point of time, when the individual account records a transaction. It gives a cost estimate of the position each time a transaction is carried out by an individual account. Particularly, in the case of an account with a net long position, we compute the cost as the contract weighted average of the purchase prices. Similarly, for an account with a net short position, we compute the cost as the contract weighted selling price. For each account, we compare the futures price of the commodity-maturity pair with its corresponding cost benchmark to ascertain the status of gains or loss in the account. For accounts having a net long position, with only one transaction in a contract on a single day, if the sale takes place at a price above (below) the cost benchmark, it will be classified as an account with a realized gain (loss) for that day. If an account executes multiple trades in a particular contract on a day and realizes gains or losses multiple times, then the net gain or loss in the contract on that day is used to classify the status of the account as either a realized gain or a realized loss.

For accounts with an open position in a contract but have no transactions in that contract on a certain day, they would be classified as either a paper gain or a paper loss in comparison with the cost benchmark. Similarly if the trades in an account have only increased the net position in a contract on a certain day, then also the account would be classified as either a paper gain or a paper loss. For instance, an individual account with a net long (short) position increases the long (short) position on a day by buying (selling) additional contracts. In all such cases, we compute the paper gain (or losses) by comparing the closing price of the contract with the corresponding cost benchmark, for each account.

However, the approach adopted to compute the paper gains and losses of individual accounts only employs the end of the day price, whereas the investor account has been exposed to price changes throughout the day. Hence, where the end of the day prices are uncharacteristic of the prices prevailed during the day, due to sharp price changes towards the market close, the classification based solely on the end of the day prices would be unreliable. To improve the reliability of the classification, we compute the proportion of time the individual account remained as a paper gain versus a paper loss throughout the day, using the intraday prices at the one minute interval. Hence, for each account that did not execute any trade, we compute the proportion of the day the account remained as a paper gain or a paper loss. If the status of an account was a paper gain (alternatively paper loss) for more than 75% of the day, then we classify the account as a paper gain (loss). In all the other cases, the classification of the paper gain (or loss) is done by comparing the cost benchmark with the end of the day prices, as described above.

3.4 Measuring the nature of price path

3.4.1 Cumulative Prospect Theory

We adopt the Cumulative Prospect Theory (CPT) framework to compute our primary measure of price path as it accommodates several departures in investor decision making in the financial markets such as the over-weighting of small probabilities and excessive aversion towards losses. CPT has been found to be more successful in an empirical context than many other frameworks of decision making, including the Expected Utility.

We build on the approach proposed by Barberis et al. (2016), to rank the historical return distribution of individual stocks using a CPT framework, for capturing the price path.

As specified by (Tversky and Kahneman, 1992) the CPT value of a stock return distribution is driven by two key facets of human decision making, the loss-aversion and distortion of the probability estimates, particularly the overestimation of low probability events. When the trading decisions of investors are induced by CPT, then the evaluation of the past price path by an investor can be captured in the CPT value of the return distribution. We apply the above logic to capture the evaluation of price path by Prospect Theory investors. The specific details of the approach are given below.

Let l be the number of days for which return observations are available, and out of the l observations, let m be the number of negative returns and let n be the number of positive returns. Then the historical return distribution in increasing order is:

$$R = (\frac{1}{l}, r_{-m}; \frac{1}{l}, r_{-m+1}; ....; \frac{1}{l}, r_{-1}; \frac{1}{l}, r_1; ....\frac{1}{l}, r_n)$$

According to Barberis et al. (2016) the CPT value of the above stock distribution will be

$$\begin{aligned} TK = \\ &\sum_{i=-m}^{-1} \upsilon(r_i)\left[w^-\left(\frac{i+m+1}{l}\right) - w^-\left(\frac{i+m}{l}\right)\right] + \\ &\sum_{i=1}^{n} \upsilon(r_i)\left[w^+\left(\frac{n-i+1}{l}\right) - w^-\left(\frac{n-i}{l}\right)\right] \end{aligned} \tag{5}$$

where, $\upsilon(.)$ is the CPT value function

$$\upsilon(x) = \begin{cases} x^\alpha & x \geq 0 \\ -\lambda(-x^\alpha) & x < 0 \end{cases} \tag{6}$$

Here λ measures the loss-aversion of the economic agent. $w^+()$ and $w^-()$ are the weighting function whose functional forms are

$$w^+(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{1/\gamma}} \tag{7}$$

$$w^-(P) = \frac{P^\delta}{(P^\delta + (1-P)^\delta)^{1/\delta}} \tag{8}$$

The value of TK as described above, gives equal weight to all the observations in the return distribution, however if investors attach higher weights to the returns observed in the immediate past and lower weights to the returns observed in the distant past, then Barberis et al. (2016) propose a modified measure, $TK(\rho)$, computed as

$$
\begin{aligned}
TK(\rho) = \\
&\frac{1}{\varrho}\sum_{i=-m}^{-1}\rho^{t(i)}\upsilon(r_i)\left[w^{-}\left(\frac{i+m+1}{l}\right)-w^{-}\left(\frac{i+m}{l}\right)\right]+ \\
&\frac{1}{\varrho}\sum_{i=1}^{n}\rho^{t(i)}\upsilon(r_i)\left[w^{+}\left(\frac{n-i+1}{l}\right)-w^{+}\left(\frac{n-i}{l}\right)\right]
\end{aligned}
\tag{9}
$$

where $\varrho = \rho + ... + \rho^l$ and $t(i)$ is the number of observations in the distribution which occurs subsequent to the realization of return r_i and $\rho \in (0,1)$. $TK(\rho)$ assigns a higher CPT value to the more recent return observations and lower CPT value to the more distant return observations.

The values of parameters used are the same as the those used in Barberis et al. (2016)

$$\alpha = 0.88, \lambda = 2.25$$

$$\gamma = 0.61, \delta = 0.69$$

In our main analysis, we have used the value of $\rho = 0.95$. However, as a robustness check, we have also carried out the same analysis with values ranging from $\rho = 0.91$ to $\rho = 0.97$

ρ controls the horizon or the number of days of observations that are relevant for computing the price path measure. Higher the value of rho, longer is the horizon and more are the number of days that are considered for assessment of price path.

The association between the price path ($TK(\rho)$) values and the trajectory of prices an asset may follow between any two time points is illustrated in Figure 1. The two sample price paths, Path 1 and Path 2, given in the figure, correspond to two distinct price realizations that may be experienced by a trader during her holding period. As given in the figure, both price paths, start at an arbitrary initial value of, 30,000 and end at 30,655, giving rise to a return of 2% over the period [2]. However, the nature of price path is significantly different. Price Path 2 follows an 'up-down' trend where the prices first increase and then decline, whereas path 1 follows a 'down-up' trend where the prices first decline and then rise.

[2]Gold prices were around the 30000 INR level in our sample period

Despite both Path 1 and Path 2 having the same total return, the TK values are substantially different owing to the occurrence of the positive returns in the latter half of path 1 and the negative returns in the latter half of path 2. Path 2 has a TK value of -0.0134 and the corresponding value for path 1 is 0.0086.

The 'up-down' path (path 2) experiences losses towards the end, hence the negative returns receive greater weights whereas the 'down-up path' (path 1) experiences positive returns towards the end which receive greater weights in the computation of TK values. The declining weights for the distant outcomes and a greater loss of value associated with the negative outcomes make the 'down-up' path relatively more appealing than an 'up-down' path to a Prospect Theory investor.

The $TK(\rho)$ values that correspond to the returns for each period in Path 1 and Path 2 of Figure 1 are plotted along with the prices in Figure 3a, Figure 3b.

The $TK(\rho)$ values in Figure 3a (Figure 3b) correspond to ρ of 0.91 (0.97). Comparison of the price paths captured by $TK(\rho)$ values indicate that though Path 2 has higher initial returns and greater price path values in the early period, the path ends up with lower $TK(\rho)$ value relative to price Path 1. The crossing of price Path 1 over Path 2 occurs due to the reversal of the trend of initial returns. The plots illustrate that the price path proxy employed here, based on CPT is able to clearly differentiate between characteristically different price trajectories that have similar returns. The figures demonstrate that the distinctive difference in the appeal of price paths, after controlling for the influence of the level of return is captured by our proxy for price path TK.

The different weighting scheme, $\rho = 0.91$ and $\rho = 0.97$, bring out the influence of horizon on the assessment of price paths. With higher weights, the horizon which is used to asses the nature of price path is higher, and subsequently the time taken for crossover between the favourableness of Path 1 and Path 2 increases as depicted in Figure 3b. Further, the magnitude of difference between the assessment of Path1 and Path 2 shrinks with $\rho = 0.97$, as compared to $\rho = 0.91$.

Figure 2 also compares two alternative price paths that could be faced by an investor who experiences negative returns over a holding period. In path 2 (path 1), the investor experiences an 'up-down' ('down-up') path. Evidently, the TK value is greater for path 1, as it experiences positive returns towards the end of the holding period. In same figure, we compare two price paths which have equal negative returns, path 3 (1) is a 'straight down' ('down-up') path. In this case again, the 'down-up' path has a greater value for the investor. A similar comparison between price paths with positive returns with 'straight-up' and 'up-down' trajectories is illustrated in Figure 1. In this case, the 'up-down' path has a lower TK value because of its negative returns.

Figures 1 and 2 illustrate that the TK values capture the essential characteristic of a history return distribution, or in other words, the 'essence' of the past price path of an asset, for investors whose decision making is coherent with Prospect Theory framework.

The distribution of $TK^{i}_{1,t-1}$ values for long traders in GOLD, given in figure Figure 8, indicates that there is a significant variation of the values within the sample period.

There are alternative frameworks for evaluating a prospect with uncertain outcomes. One of the recently proposed framework is Salience Theory (Bordalo et al., 2012) of decision making. Similar to CPT, a decision maker operating under the assumption of Salience theory, would overestimate the likelihood of re-occurrence of certain outcome compared to their objective probability. However, the degree of distortion of the probabilities is not dependent on the objective probabilities or the rank of the payoff, instead the distortion would be dependent of the salience of the outcome. We employ a Salience theory based framework as an additional proxy for price path. It would ensure that the results of the research are not driven entirely by the price path formulation based on CPT.

3.4.2 Salience Theory

Bordalo et al. (2012) proposed a model of choice under risk, in which the objective probabilities of outcomes are replaced by a weighting scheme in which the likelihood of a salient outcomes is overestimated. We use their framework to capture the nature of price path based on salience of change in daily prices.

$$V(L) = \sum_{s \in S} \pi_s \omega_s \nu(x_s) \tag{10}$$

ν is the value function that gives a subjective evaluation of the payoff of the state s. The objective probability of the state s is distorted by a factor ω_s, where

$$\omega_s = \frac{\delta^{k_s}}{\sum_r \delta^{k_r} \pi_r} \tag{11}$$

where, $\delta < 1$ and k_s is the salience ranking of state s, which depends on payoff x_s. In our analysis, for computation of price path using salience theory, we use the value of $\delta = 0.95$.

$$k_s \in \{1, ..., |S|\} \tag{12}$$

A lower k_s indicates higher salience. Therefore state with $k_s = 1$ will be the most salient state and will have the higher value of ω_s

Similar to Barberis et al. (2016), we can consider that investors observe a sequence of daily returns and evaluate the subjective value of that sequence using the salience theory preference. Similar to the measure of $TK(\rho)$ in subsubsection 3.4.1, we apply time decaying weights to capture the recency effect.

$$Saliency(\rho) = \frac{1}{\varrho} \sum_{s=1}^{n} \rho^{t(s)} \nu(r_s) \pi(r_s) \omega(r_s) \tag{13}$$

where $\varrho = \rho + ... + \rho^l$ and $t(s)$ is the number of observations in the distribution which occurs subsequent to the realization of return r_s and $\rho \in (0, 1)$.

We assign objective probability of $\frac{1}{n}$ to each return value of the series and consider $\nu(x) = x$. The expression becomes

$$Saliency(\rho) = \frac{1}{\varrho} \sum_{s=1}^{n} \rho^{t(s)} \left(\frac{r_s}{n}\right) \frac{\delta^{k_s}}{\sum_r \delta^{k_r} \pi_r} \tag{14}$$

The value is k_s comes from a salience utility function. We use the salience utility function proposed by Bordalo et al. (2012) to estimate salience ranking

Consider two lottery options $X = \{x_1, ..., x_s, ...x_S\}$ and $Y = \{y_1, ..., y_s, ...y_S\}$, the salience utility function employed by Bordalo et al. (2012) has the functional form

$$\sigma(x_s, y_s) = \frac{|x_s - y_s|}{|x_s| + |y_s| + \theta}, \theta > 0 \tag{15}$$

The payoffs of state i that has the higher value of $\sigma(x_i, y_s)$ will have the salience ranking of 1. For our empirical estimation we consider comparing the sequence of daily returns with the average daily returns that an investor can expect to earn in a day. The average daily return in commodities under consideration is 0%. Therefore for estimating salience ranking we consider $y_s = 0$. The salience function reduces to

$$\sigma(x_s) = \frac{|x_s|}{|x_s| + \theta} \tag{16}$$

One of the key differences between the CPT frame and Salience frame work is that unlike CPT framework, the probability weights assigned depend on the magnitude of the payoff and not the rank of the payoff. For example, $r_p < 0$ can be most salient if $|r_p|$ has the highest magnitude. In CPT framework the probability weights assigned to each payoff depend on its rank and not on the absolute magnitude.

3.5 Data

As it is documented that disposition bias is strongly prevalent in the futures markets (Choe and Eom, 2009), we employ investor-level data from the futures market to examine the influence of price path on disposition bias. The data of the futures markets is obtained from Multi Commodity Exchange of India Limited (MCX). MCX is the dominant non-agricultural commodities derivatives exchange in India, governed by the financial markets regulator, Securities and Exchange Board of India (SEBI). It has the dominant volume share in the futures contracts on precious metals (99%), base metals (99%) and energy commodities derivatives (99%) traded in India. We employ the trader-level, high-frequency data of the two most liquid derivatives contracts on MCX, gold (GOLD) and crude oil (CRUDEOIL). As part of the main analysis, we examine the influence of price path on the trading decision of investors in GOLD futures market and as a robustness we investigate the same in CRUDEOIL futures contract.

We employ the individual account level futures trading data of three-years from January 2012 to December 2014 of GOLD. The period covers GOLD contracts which expire between April 2012 and December 2014. The average daily value of trading in GOLD is about INR 18.1 billion with total numbers of trades reported in the database are about 36 million. A brief description of the contracts and its trading environment are described below.

GOLD contract for any target expiry has a one-year duration. New contracts are launched on the 16-th day of a month, once every two months in a year (February, April, June, August, October, and December). The detailed specification of each contract is provided in Appendix A and Table A1. In 44 % of out of the total trades, traders hold the position open for more than a trading day. Nearly 34% of the total trades are held for more than five trading days with an average holding period of 20.73 trading days. Among the trades which are open for at least one day, the average holding period is 9.86 trading days. The presence of a significant proportion of traders with long-holding periods allows us to examine the incremental impact of price path on their trading preferences.

The average returns on GOLD across all the contracts expiring both in 2012 and 2013 indicate a significant price movement. For instance, on an average, the GOLD contracts expiring in 2012, generate a return of 8.77% in the year 2012. Only GOLD contracts expiring in 2014 have mostly ended flat (average return of -0.085%). However, the average daily 5-minutes realized volatility of GOLD and spot prices as shows in Figure 4 suggest, even when the prices ended flat, there were significant price fluctuations within the maturity cycle of the contracts. The volatility of the commodity derivative combined with the high level of leverage available in the futures trading suggests that outcomes from the investment in the commodities derivatives have a significant impact on the investor wealth. Hence, an examination of the influence of price path on investor level trading behaviour such as disposition bias with trading data of derivatives market would offer interesting insights into the behaviour of investors.

We demonstrate that GOLD exhibits price trajectories which are close to each other by way of overall returns, but show significant difference in the price path values ($TK(\rho)$) in Figure 6. Figure 6 shows the box plot of cumulative returns and the corresponding price path values for all possible 30 day periods from the GOLD spot prices in Figure 4 . The figure illustrate that for most of the return buckets, there is significant variation in the $TK(\rho)$ values. For instance for the -1% to 0% return bucket the standardized values of $TK(\rho)$ values vary between -2.5 and 1.2, representing a range of movement of 3.7 standard deviation. The standard deviation (SD) of cumulative return of 30 day window is around 4.8%, making the 1% width interval equivalent to width of 0.2 SD. Within 0.2 SD of variation in cumulative returns, the values of Price Path ($TK(\rho)$) are varying in the range of 3.7 SD. This highlights the variation in the trajectory of prices that have the same level of returns in the spot market. The median of the range of variation of standardized values of $TK(\rho)$ across all the 1% window of cumulative return (which corresponds to a variation within 0.2 SD of cumulative return) displayed in Figure 6 is 2.86. Overall, the figure indicates that the price of GOLD has sufficient episodes of reaching similar level of returns with different price paths, to examine its influence after controlling for the influence of level returns and volatility.

The trade data file provided by the MCX for each contract contain the trade number, timestamp, price, quantity, unique client code, buy/sell indicator, an indicator to indicate whether the the trade is based on spread and an indicator variable to identify the algorithmic trades. We use the unique Client Code available in the data to track the trades made by a certain individual trader, in each contract throughout its maturity cycle. With a complete track of the trades made by an individual trader, we are able to re-construct their portfolio holdings and their benchmark cost for each contract at a high-frequency. We compute the losses and gains made by individual traders at each observed instance of transaction for each contract as described in Section 3.3. The traders in India have a rich exposure to futures trading as India has one of the largest single stock futures market in the world [3]

In our sample trade data of the two contracts, around 56 % of the total trades in GOLD are held for a duration of less than 1 day, indicating the widespread presence of short horizon investors in the market. To assess the impact of price path on the level of disposition bias, we need to focus on the set of trades which have a longer holding period and are closed out well before the expiry date of the contract. For our main analysis, we include trades which have a holding period of at least 5 days and that are carried out at least 15 days prior to the expiration date.

The rationale for relying on transactions that are away from the expiry date is that as the expiry approaches, investors may be forced to close out their positions irrespective of their gains

[3]WFE annual statistics guide 2017 http://w.world-exchanges.org/home/index.php/statistics/annual-statistics

or losses. As the propensity to sell may not be affected by price path, the extent of disposition bias observed near the expiry date may be independent of price path. Hence, the final sample has only trades which have been carried at least 15 calender days prior to the expiry. We combine the expiry criteria with a minimum holding criteria. We focus on the set of investor positions which are held for a duration of at least five calender days. Around 34% of the total trades in GOLD in our dataset have been held for a duration of at least 5 calender days. The reason for keeping a minimum threshold on the holding period is to let the investors be exposed to price path for a reasonably long period. It is more likely for a trader with a relatively longer holding period to be more concerned about the shape of price path than a day trader, as the day traders focus almost entirely on profits from the intraday price movements. A long horizon trader, on the other hand, will trade with an expectation of the price moving in her favor over an extended period and consequently she will monitor price path over a more extended period. Overall, the impact of price path experienced can be reliably examined with positions held for a long time.

In all the analyses, we remove the trades of the spread traders, who take a long position in one contract and an opposite position in a subsequent expiry contract, to bet on the increase in the spread. Such, traders might not be influence by the price path while making trading decisions. In our main analysis, we also exclude the set of trades carried out by algorithmic traders from the dataset as they may not be influenced by the nature of price path, but could be trading purely on programmed routines.

A natural question that arises in our analysis is "What is the duration over which an investor would examine price path?" As we are working with the futures contracts; we choose a natural starting point, price path from the initiation of the contract. Since each contract has a designated starting date, any point of time, we compute the $TK^i_{1,t-1}$ values from the initiation of the contract and measure the impact of price path from the date of initiation to previous trading day on the level of disposition bias in the contract. However, due to the declining weights given because of ρ, the influence of distant observation on the assessment of price paths declines geometrically. For instance, for a value of $\rho = 0.95$, which is used in our main analysis, the influence of observations beyond 60 trading days becomes negligible.

4 Findings and Discussion

We observe a significant prevalence of disposition bias among traders in the futures contracts of the two commodities chosen for the study. The average disposition bias over the 3-year sample period is about 4.3% in GOLD contracts, for investor who hold the position for at least 5 trading days. The figure indicate that a significantly higher proportion of the derivative traders prefer to realize their gains than the proportion who realize their losses. The level of disposition observed here is comparable to that reported by Choe and Eom (2009) in the Korean Stock Index futures markets.[4]

We find that while disposition bias increases with contemporaneous returns as commonly observed (Ben-David and Hirshleifer, 2012; Grinblatt and Keloharju, 2001), we also find that it declines with the valuation of the price path ($TK^i_{1,t-1}$).

We examine the univariate relationship between disposition bias and our price path proxy $TK^i_{1,t-1}$, for traders with net long and short positions separately. The comparison of disposition bias for traders experiencing different price paths for GOLD is presented in Figure 7. As depicted in Figure 7, the long investors exhibit lower disposition bias in the higher deciles of $TK^i_{1,t-1}$, whereas the short investors in GOLD exhibit lower levels of disposition bias in the lower deciles of $TK^i_{1,t-1}$. This indicates that broadly the level of disposition bias declines in response to favourable price paths.

In Table 5, we divide the investor accounts into two groups by the level of the attractiveness of price path they experienced during their holding period. The figures under the column overall sample, compare the trader groups formed on the median of the $TK^i_{1,t-1}$ value. The comparison of disposition bias for the overall sample suggests that a favourable price path leads to a decline in disposition bias of the traders, for both accounts with net long and short positions. For instance, when the $TK^i_{1,t-1}$ is below the median value, we observe that disposition bias more than halves from 8.1% to 3.5% in GOLD contracts among the short traders. For traders with net long positions, the nature of the influence of price path, where traders exhibit lower level of disposition bias when the $TK^i_{1,t-1}$ is above the median, again suggests that a favourable price movement leads to lower disposition bias.

Columns 3 and 4 of Table 5, presents the univariate comparisons of disposition bias, for traders

[4] Choe and Eom (2009) report disposition bias of 7.8% for the index futures. However, they have not imposed a minimum holding period by the traders and therefore, the reported figure could also include the day traders.

grouped by both the level of returns and the $TK^i_{1,t-1}$ value. The comparison would indicate whether the attractiveness of price path captured by the $TK^i_{1,t-1}$ value offer any significant incremental explanation for disposition bias after controlling for the level of returns. We find that across accounts with net long positions, when grouped based on the return quantiles of their portfolios, the level of disposition is lower among traders with a relatively higher $TK^i_{1,t-1}$ in GOLD. The disposition bias among the long traders moves inversely with $TK^i_{1,t-1}$, and for the short traders, the intensity of disposition bias varies positively with $TK^i_{1,t-1}$.

Overall univariate comparisons of disposition bias, presented in Table 5 and Figure 7, suggest that price path has a significant influence on trader behaviour. Particularly investors have significantly different preferences for disposing of their gain and losses following episodes of price movement characterized by favourable and unfavourable price paths. We examine the incremental role of price path on disposition bias in a multivariate framework, which allows us to control for the various factors which could influence the investor level disposition bias.

Estimation of the possible influence of price path on disposition bias in a the multivariate approach Equation 1 is presented in Table 6. It provides detailed estimation for traders with net long and short positions in columns $1, 2$ and $3, 4$ of Table 6 respectively. Primarily, we find that price path has an economically significant influence on the level of disposition bias observed in the market, after controlling for the other variables known to influence disposition bias.

In line with the documented evidence of the influence of returns on disposition bias, such as Grinblatt and Keloharju (2001), we find that high contemporaneous and near lag daily returns ($r_{i,t}$, $r_{i,t-1}$ and $r_{i,t-2}$) accentuate the level of disposition bias among the traders. The cumulative return ($r^i_{1,t}$) has a significant and negative coefficient in case of regressions of the disposition bias of accounts with net long positions and a positive and significant coefficient for accounts with short positions. Hence disposition bias declines (increases) with higher cumulative returns for the long (short) positions.

Our most important result is that, on experiencing price paths with high valuation, as captured by $TK(\rho)$, the propensity of the traders to realize their gains over losses declines. For instance, the coefficient estimate of $TK^i_{1,t-1}$ suggests that a standard deviation increase in the value of $TK^i_{1,t-1}$ leads to a decrease of 0.9% in disposition among traders with net long position. Given the average level of disposition in the gold derivative markets of about 4.3%, and as demonstrated in Figure 6, variation within 0.2 SD of 30 day cumulative return can lead to 3.7 SD variation in the values of $TK^i_{1,t-1}$, the marginal impact of price path has a substantial economic significance. As observed in both the regressions, the adjusted R-square of the regression increases on the inclusion of price path $TK^i_{1,t-1}$ variable (Model 2 and Model 4) in Table 6.

The price volatility does not have any significant influence on the level of disposition bias among investors (coefficient of the realized volatility). We included the number of days to expiry as an additional control variable, in the regression, as traders are likely to show a higher propensity to realize the outcome of their trades close to the contract expiry. We find that the longer the period left before expiry, the lower is disposition bias. However, this effect is again present only among long investors. The negative and significant coefficient of the days to expiry suggests the propensity to realize gains is attenuated in the early period of the expiry cycle.

We find almost analogous results for disposition bias of traders holding net short positions (Column 3 and 4). The results presented Table 6 indicate that a psychologically attractive price path attenuates disposition bias, after controlling for the influence of contemporaneous, lagged and cumulative returns. The coefficient of the $TK^i_{1,t-1}$ is economically and statistically significant in explaining the change in disposition among investors. However, the economic influence of $TK^i_{1,t-1}$ is higher among the short traders with one standard deviation increase in $TK^i_{1,t-1}$, leading to 1.9% increase in the level of disposition bias.

The significance of price path in the estimation of disposition bias, despite the role of the cumulative returns over the period and the returns in the immediately past, demonstrates that the price path independently influences disposition bias.

As research has found that there is more variation in the propensity of gain realization than propensity of loss realization (Frydman et al., 2014), we also examine the impact of price path in a multivariate framework on the dimensions of disposition effect. With this analysis, we intend to gain greater insights into the influence of price path on disposition bias. The analysis follows an approach similar to that adopted in the case of disposition bias. The results of the estimations for PGR and PLR are presented in Table 7 and Table 8 respectively.

The important finding is that the proxy of price path significantly influences PGR and not PLR. While the price path impacts PGR for both long and short investors, its influence on PLR is absent. As observed for disposition bias, a favorable price path has a negative impact on PGR for both long and short traders Table 7. For the long (short) traders, an increase (decrease) in the value of $TK^i_{1,t-1}$ lowers the propensity for gain realization among the traders and thus attenuates their disposition bias. It is possible that on observing a favourable price path, investors expect the price trend to sustain into future. As opposed to the influence of price path on PGR, its influence on the propensity for loss realization (PLR) is non-existent (Table 8).

Hence, traders refrain from selling their investments at a profit on experiencing a 'favourable' price path, however their decision to sell the investment in losses is not influenced by the nature of price path.

In contrast, cumulative returns, since initiation ($r^i_{1,t}$) of the contract, influences both PGR (only for investors with net short position) and PLR. Therefore, the level of return influences PGR and PLR, but the price path only impacts investors selling decision with respect to their investments with capital gains, as captured by PGR. Earlier research (Frydman et al., 2014) had found that activity in ventromedial prefrontal cotrex (vmPFC) is significantly correlated with PGR but not with PLR, indicating that the neurological response to capital loss is not opposite of the response to capital gains. Our findings with respect to influence of price path on PGR and PLR are in line with asymmetric neurological response of the participants in Frydman et al. (2014).

The impact of price path on disposition bias documented above can be possibly linked to investor beliefs in continuation of the observed favourable price path. A favourable price path is accompanied by a reduction in the intensity to realize gains. However, the absence of influence of price path on PLR does not allow us to strongly conclude on the expectation of trend continuation as the reason for impact of price path on disposition bias.

Among the other variables employed in the regressions, the realized volatility has a positive impact on PGR and PLR, for investors with net long position, implying that an increase in the market volatility increases the realization of gains and losses. The propensity for gain realization as well as loss realization is lower when a relatively longer horizon until expiry is available to the traders, as indicated by the coefficient of the 'Days to expiry' variable. It could be expected as investors would prefer to avoid to the realization of the outcomes when there is ample scope for future actions to improve upon the outcomes. As observed in the case of the disposition bias, the contemporaneous and lagged return have a positive (negative) impact on PGR for long (short) positions., while exhibiting an opposite influence on PLR.

In summary, the analysis of the components of disposition bias suggests that PGR is significantly influenced by the nature of price path experienced by traders in addition to the cumulative returns in the trader accounts, but not PLR. Our findings contribute to the on-going debate on the nature of disposition bias and the causal factors behind disposition bias.

Most of the explanation for disposition bias had been based on investor preferences. Among them the dominant explanation had been driven by a combination of Prospect Theory preferences (Kahneman and Tversky, 1979) and mental accounting (Thaler, 1985). Under Prospect Theory, the investors would have a higher preference to realize their gains than their losses due to the 'S-shaped' value function, which is concave for gains and convex for losses. The loss-aversive behviour induced by the Prospect Theory is accentuated through the tracking of the gains and losses of individual assets, than that of the portfolios (Shefrin and Statman, 1985; Grinblatt and Han, 2005). Barberis and Xiong (2012) argue that disposition bias is also explained by the incremental utility from selling an appreciated asset, called realization utility. Both the preference-based models, as discussed above, would lead to an increase in disposition when the value of an asset rises above its cost.

However, it is also found that in some instances, the investor preference manifested through disposition bias does not conform to simple explanations involving preferences (Ben-David and Hirshleifer, 2012; Greenwood and Shleifer, 2014; De Bondt, 1993). As per the preference view of disposition bias, a steady price rise, resulting in significant positive returns to the investors, should increase disposition bias. However, as portrayed in studies on beliefs formation driven by over-extrapolation of short-term trends (Greenwood and Shleifer, 2014; De Bondt, 1993), it is possible that the steady price rise could result in a lower disposition, contrary to the predictions of preference based explanations for disposition bias. Hence, if the price could lead to extrapolation of trends by the investors, we could find that price path has an impact on the level of disposition bias among the traders.

Our findings indicate that disposition bias is driven partly by the investor preferences, but is also significantly influenced by price path, experienced by the investors. For long (short) investors positive (negative) contemporaneous and lagged returns accentuate the disposition bias among the traders, which is consistent with the preference based arguments. In this case loss-aversive preference makes investors close out their profitable positions while holding on to the unprofitable positions. Consistent with belief based explanation, we find that for long (short) investors, an increase (decrease) in price path proxy, $TK(\rho)$, dampens the level of disposition bias among the traders. In this case, we can conjecture that if investors extrapolate price path, then after experiencing a favourable price path, investors expect the trend to continue and subsequently they refrain from closing out their profitable position, in the hope that they will increase in value further.

While we have not examined the mechanism through which price path leaves its influences on disposition bias, several research papers (Grosshans and Zeisberger, 2018; Nolte and Schneider, 2018; Greenwood and Shleifer, 2014; Choi et al., 2010; De Bondt, 1993), suggest that the past price movements heavily influence investor expectations about the future returns. The role of price path would predict that disposition bias would be attenuated (accentuated) by a favourable (unfavourable) price path for an investor. Our paper offers empirical evidence about the role of both investor preferences and beliefs in shaping the investor trading decisions.

5 Additional Measures of Price Paths and Robustness of the Results

5.1 Alternative Measures of Price Paths

The results of the influence of price path as captured using salience theory are reported in Table C1 for GOLD and Table C2 for CRUDEOIL. The economic and directional influence of price path continues to hold under the alternative framework of salience theory as well. For investors with net long position, one standard deviation increase in the price path, as captured by $Salience(\rho)$, leads to a reduction in disposition bias by 1.2%, the corresponding figure for the influence of price path as captured by $TK(\rho)$ was 0.9%. Similarly, for investors with net short position, one standard deviation increase in price path as captured by $Salience(\rho)$ leads to a decline in disposition bias by 2%. The corresponding figure for $TK(\rho)$ was 1.9%.

The comparison suggests that when price path is measured under the salience theory, the results of the impact of price path on disposition bias is qualitatively unchanged. Therefore, the results on the influence of price path on disposition bias are largely independent of the specific formulation of the price path proxy. For the remaining analysis we only focus on the price path proxy based on CPT ($TK(\rho)$).

5.2 Robustness of the results

The following section presents the results of the robustness checks on the validity of the price path proxy with alternate definition and another test asset. As a robustness check, we carry out the same analysis in another commodity traded in MCX, CRUDEOIL. The results for CRUDEOIL are reported in Table B1. We find the in response to a favourable price path, the level of disposition bias declines among the traders of CRUDEOIL as well.

As part of the main analysis, we had excluded from the analysis all the trades committed by investors with holding period less of than 5-days, trades of algorithmic traders and trades carried within 15 days to expiry, to ensure the investors have a non-trivial exposure to the price path. We examine the robustness of our major finding that the price path significantly influences the disposition bias with an alternative estimations. The first alternative sample includes all the trades, except those committed by the day traders and spread traders. The influence of the price path on disposition bias is qualitatively unchanged for the larger sample, which includes all the trades within 15 days of the expiry date as well the trades made by algorithmic traders. The results of the estimation for are given in Table B2. The second alternative sample includes all the trades that have a duration of at least 10 days, including the trades made by algorithmic traders and also the set of trades carried out within 15 days of expiration date. The results of second alternative sample are presented in Table B3. In this sample of relative longer holding period also, price path continues to have an influence on the level of disposition bias.

We also conduct robustness checks to demonstrate that the impact of price path on the level of disposition bias is prevalent across the cross-section of investors types. We split our universe of investors having a threshold holding period of five days into two categories based on their average trade value ($N_{contracts} \times Price$), above median trade value group and below median trade value group. We separately examine the impact of price paths on the level of disposition bias in both these groups for long and short traders and both the commodities. The results are presented in Table B4 for GOLD. We find a strong influence of price path on the trading decision of investors having above median trade size, while the influence on the decision of traders with below median trade size is absent. This implies that influence of price path is predominant only when the volume is trade is high. For low volumes of trade, the influence of price oath is negligible.

In our main analysis, we have used a value of $\rho = 0.95$, to compute the $TK(\rho)$ in Equation 9. With $\rho = 0.95$ observations beyond 60 days have negligible contribution to the measure. We re-examine the results presented in Table 6, by changing the values of ρ over a range. Table B5, shows the analysis with value of $\rho = 0.91$ and Table B6 shows the analysis with $\rho = 0.97$. $\rho = 0.91$ gives weightage to past 30 trading days of observation, whereas $\rho = 0.97$ gives weights to past 80 trading days of observation . The nature of price path continues to influence the level of disposition bias as found in our baseline analysis.

Overall, we demonstrate the influence of price path on disposition bias among traders with different holding periods and different trade size. We also, demonstrate that the results are robust across a large range of weighting scheme (ρ varying from 0.91 to 0.97). Overall, our results are consistent across various sub-samples of investors and across a range of weighting schemes.

Our analysis focuses on the impact of price path on market level disposition bias for two commodities separately. However, most of the research on disposition bias, examine if there is a greater likelihood to sell an asset with capital gains relative to an asset with capital loss, within each of the investor portfolio (Ben-David and Hirshleifer, 2012; Shefrin and Statman, 1985; Odean, 1998). If an investor holds multiple assets in her portfolio, then the price path of a particular asset might impact the trading decisions of other assets in her portfolio. Unfortunately, we cannot examine the influence of the price path of the other assets in the trading decisions of the two sample futures contracts with the available data.

6 Conclusion

Recently, researchers have started to examine the possible influence of price path, which reflects how investors earn the returns, on essential dimensions of investor behavior, beyond explanation offered by the returns on their portfolio. The studies so far have only examined the role of price path in the experimental settings of the financial markets. Against this backdrop, we empirically examine the incremental influence of the trajectory of prices experienced by a trader, on her disposition bias - a widely documented irrational investor trait. We develop a proxy for the price path experienced by an investor with Prospect Theory preferences, based on a framework developed by Barberis et al. (2016), and estimate the incremental role of price path in explaining disposition bias. We employ the high-frequency investor-level trade data of highly liquid commodities futures contracts to examine the relationship. The study brings forth interesting and novel results on the nature of the influence of price path on disposition bias of traders.

Our findings indicate that after controlling for the returns and volatility, the nature of price path has a significant impact on the level of disposition bias exhibited by the investors. A favourable price path (a high subjective CPT value path for long and a low subjective CPT value path for short investors) is followed by a decline in the level of disposition bias among the traders. Further, the intensity of the impact of the observed price path is significant in the case of investors with both net long and short positions. The reduction in disposition bias following a favourable price movement can be traced to the reduction in the propensity for gain realization. We do not find any influence of price path on the propensity for loss realization among the investors in the GOLD futures market. We capture the nature of price path under an alternate theory of decision making, the salience theory (Bordalo et al., 2012), and find that price path continues to have a similar influence on the disposition bias among the traders.

Our findings potentially indicate the role of both preferences and beliefs in shaping the trading decisions of the market participants. Preference based explanations argue that a series of positive returns increases disposition bias due to loss-aversion, while the belief based explanations argue that a series of positive returns leads to a decline in disposition bias as investors extrapolate the trend in the prices. Consistent with preference-based explanations, we find that favourable contemporaneous and lagged returns increase the intensity of disposition bias. Concurrently, consistent with belief-based explanations, we find that a favourable price path reduces the intensity of disposition bias. Hence, we can argue that there is an influence of both preferences and beliefs of investors on their trading decisions. Overall, our results complement the findings of experimental studies such as Grosshans and Zeisberger (2018) and Nolte and Schneider (2018) that demonstrate the impact of the observed price path on the level of satisfaction and the investment decisions.

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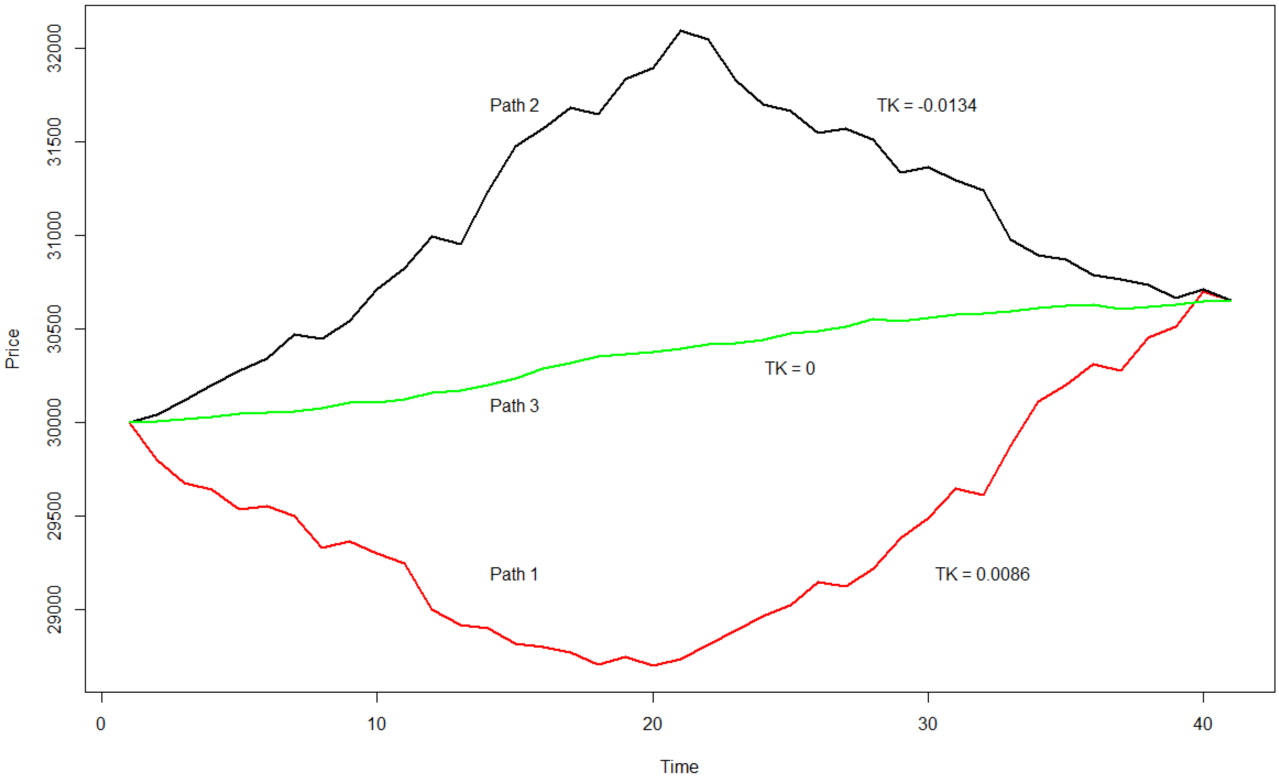


Figure 1: Positive Return: Alternative Price Paths

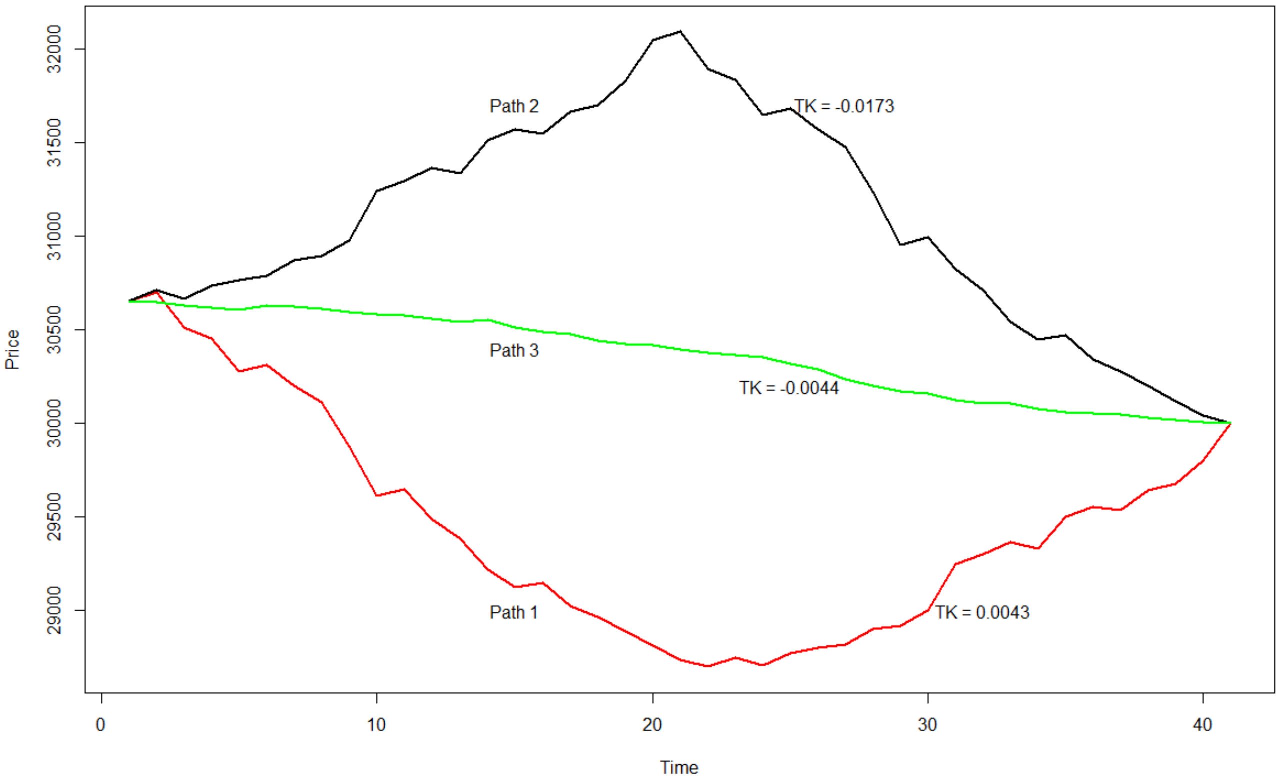
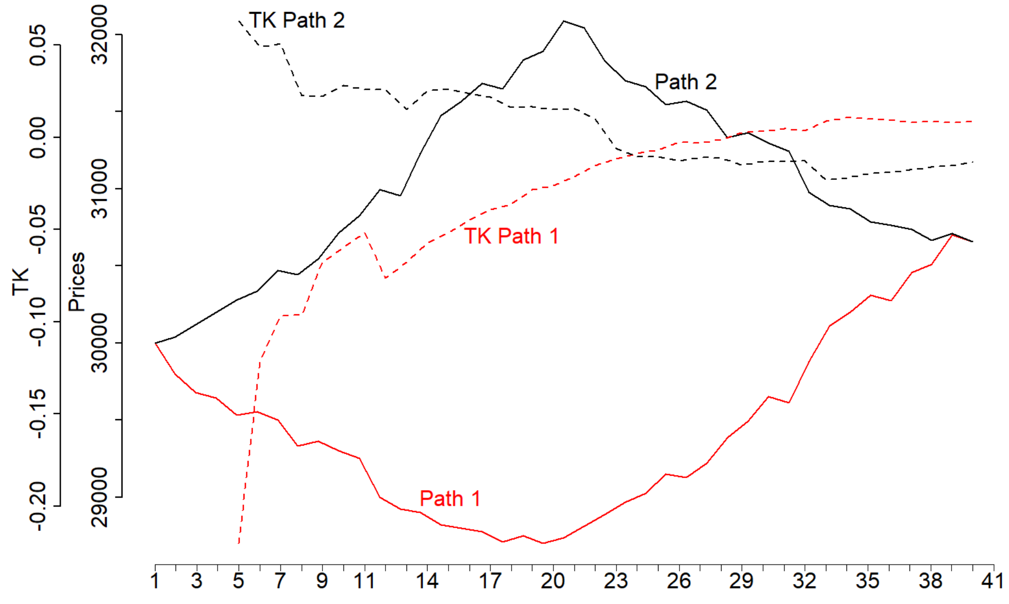
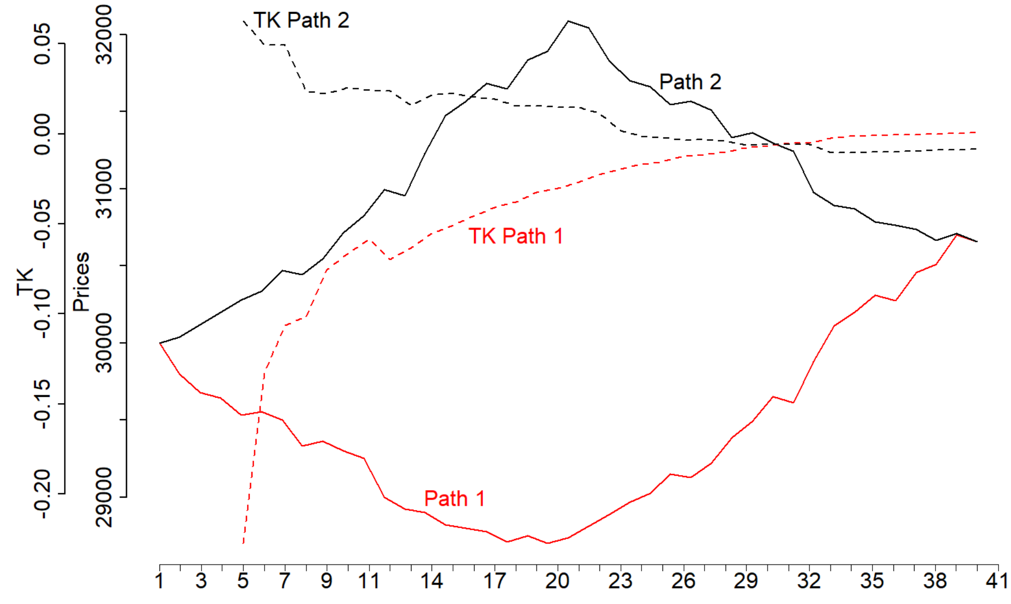


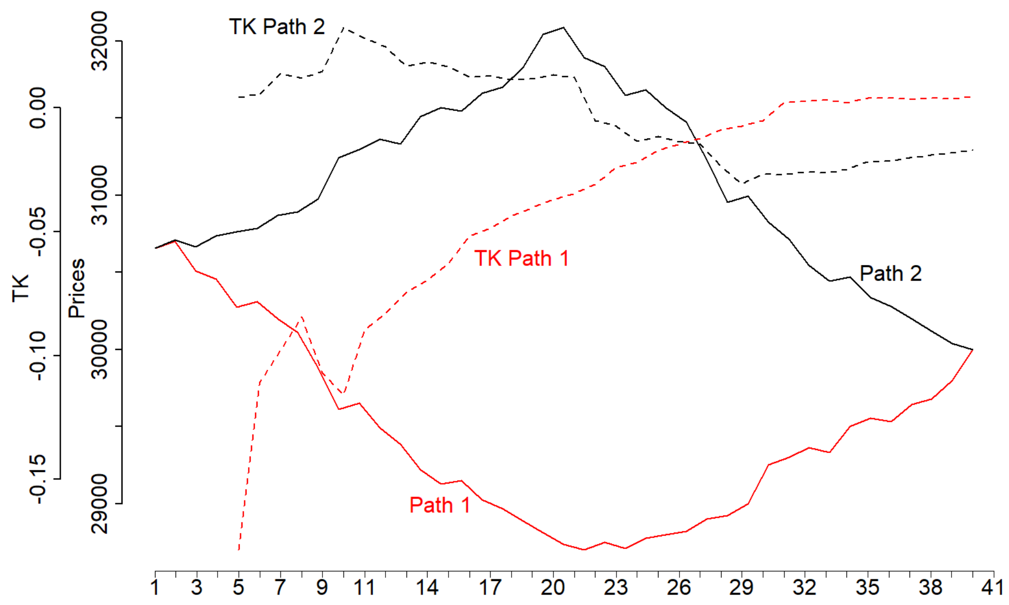
Figure 2: Negative Return: Alternative Price Paths



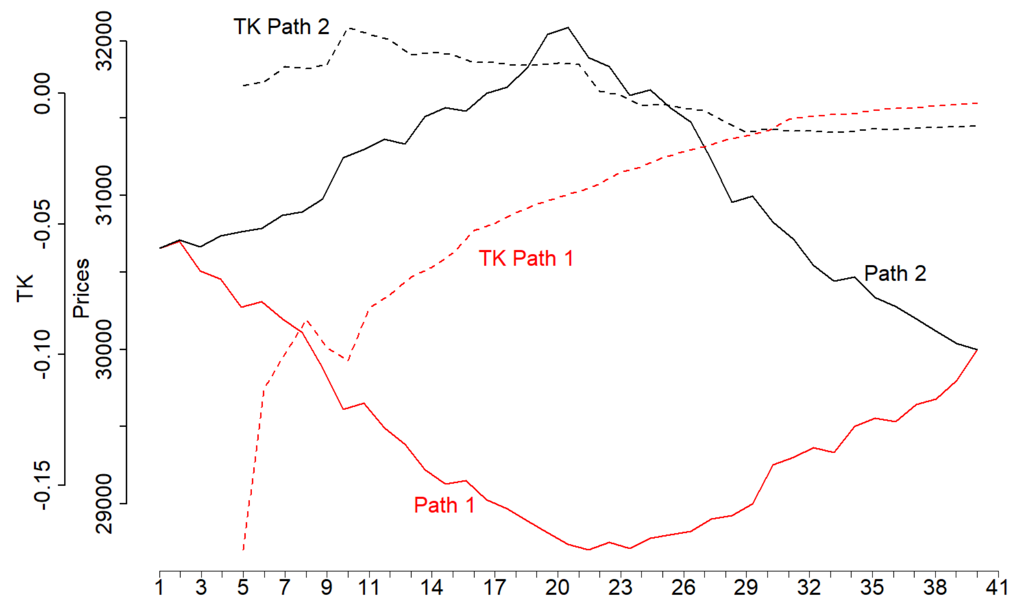
(a) Gain - Alternative Price Paths and $TK(\rho), \rho = 0.91$



(b) Gain - Alternative Price Paths and $TK(\rho), \rho = 0.97$



(c) Loss - Alternative Price Paths and $TK(\rho), \rho = 0.91$



(d) Loss - Alternative Price Paths and $TK(\rho), \rho = 0.97$

Figure 4: Spot Prices of Gold (INR)

Figure 5: Spot Prices of CRUDEOIL (INR)

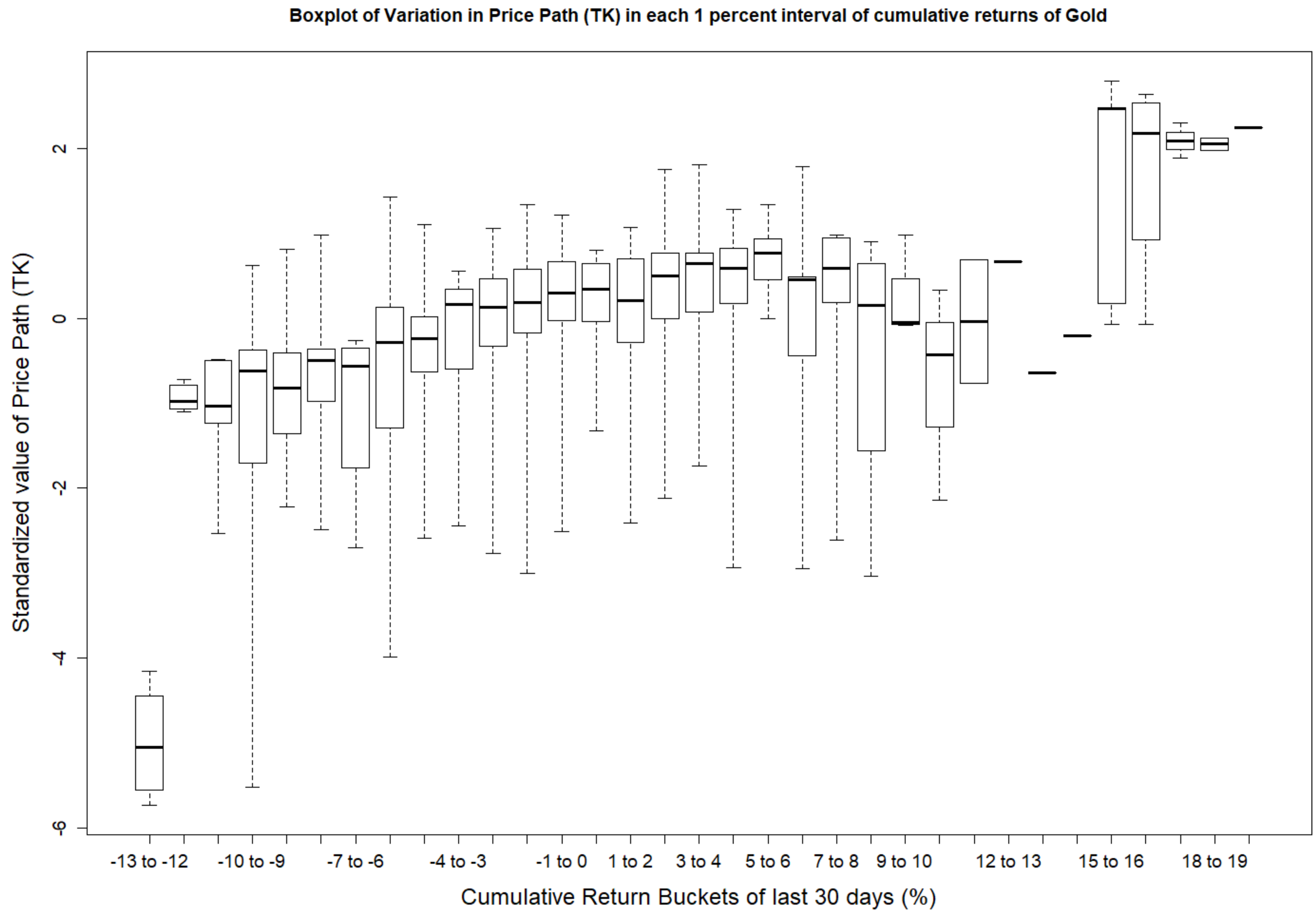


Figure 6: Box Plot

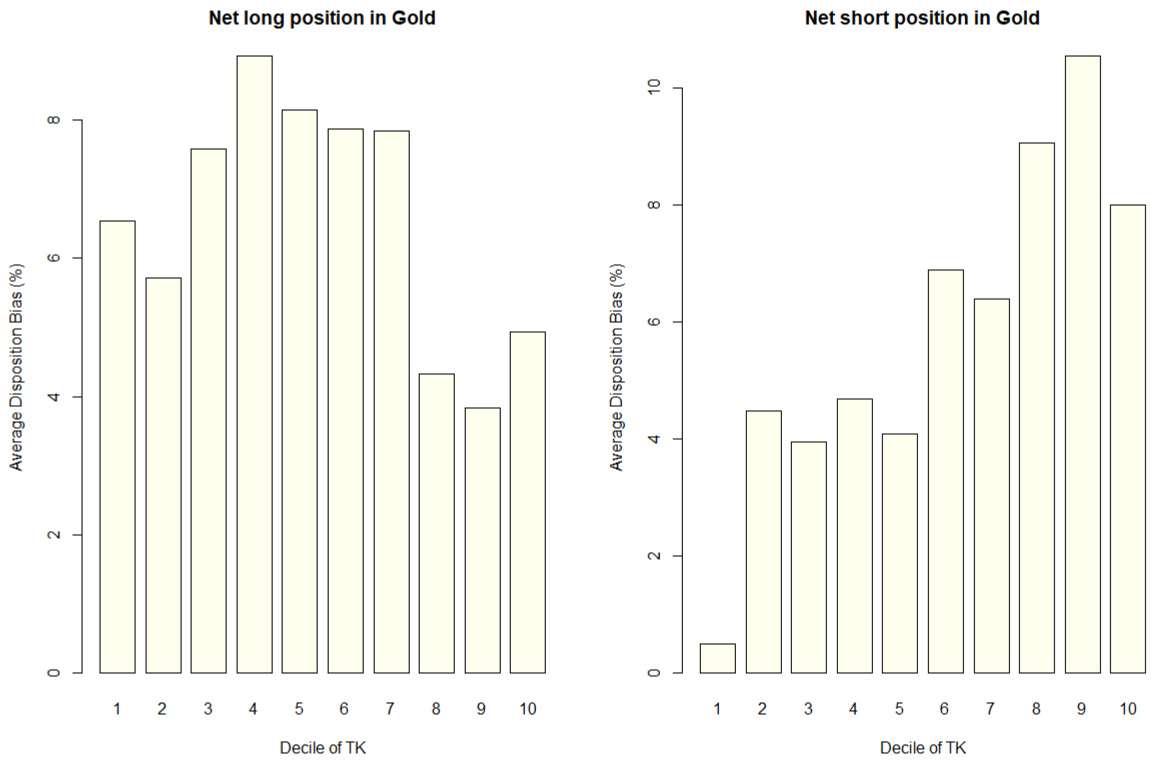


Figure 7: Disposition Bias across deciles of TK

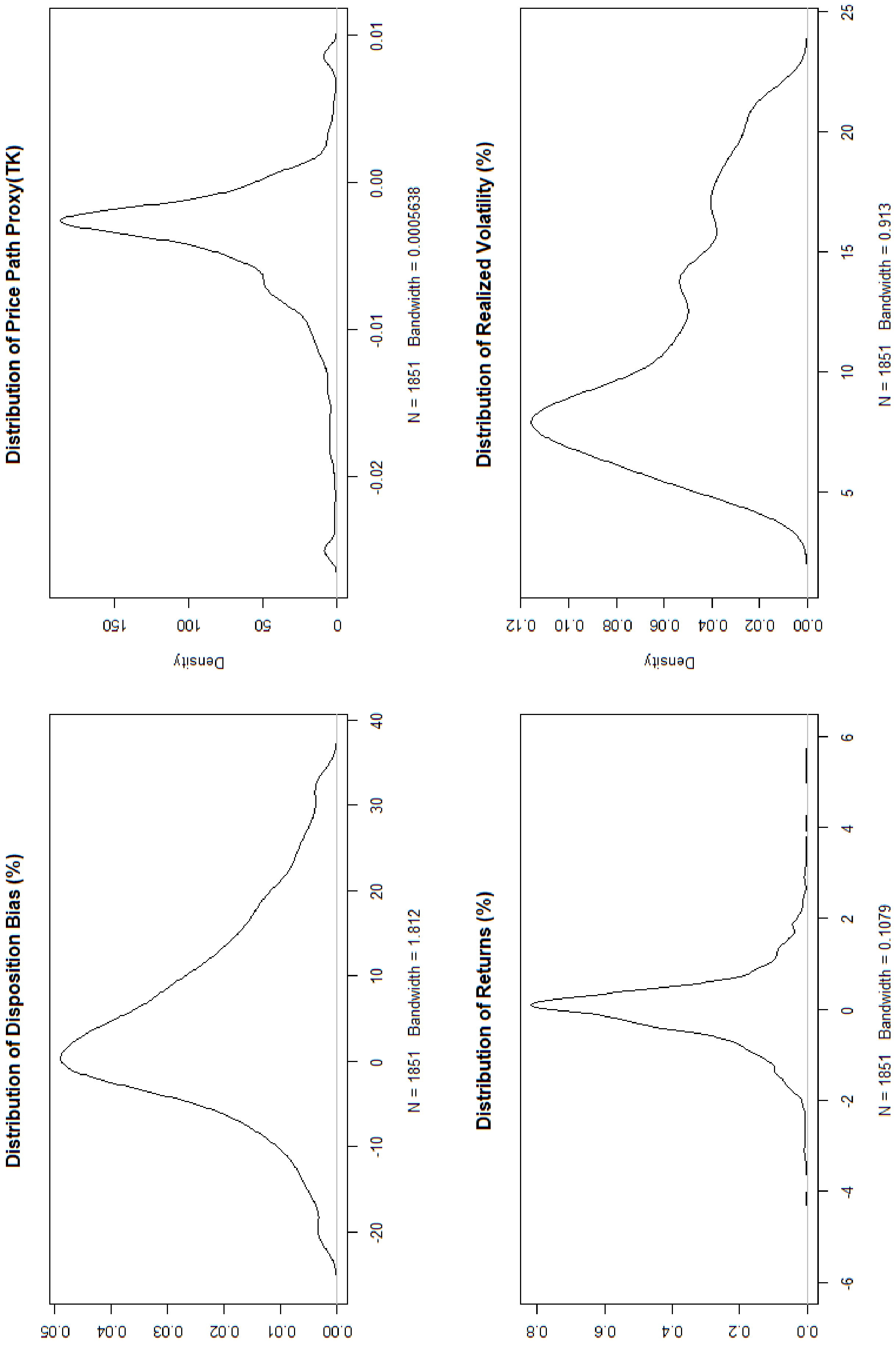


Figure 8: Density plot of Regression Variables - GOLD - Long

Table 1: Variable Description

Variable Name	Description
DB_t^i	Market-level disposition bias prevalent among traders in contract i on day t
PGR_t^i	Propensity for gain realization in contract i on day t
PLR_t^i	Propensity for loss realization in contract i on day t
$Days.to.Expiry_t^i$	Time to expiry of the derivative contract i measured in calendar days on day t
r_t^i	Return in contract i on day t
r_{t-1}^i	Return in contract i on day $t-1$
r_{t-2}^i	Return in contract i on day $t-2$
$TK_{1,t-1}^i$	Proxy constructed to capture the nature of price path of contract i till day $t-1$
$r_{1,t}^i$	Cumulative Return in contract i till day t
$RV_{1,t}^i$	Cumulative Realized volatility of contract i computed using 5-minute interval prices till day t

This table contains the variable description of the variables used in the analysis.

Table 2: Summary statistics of the trading activity - GOLD derivative contracts

	All Holding Periods				*Holding Period $\geq$ 5 Days*			
Contract Expiry	No. of Trades (000)	No. of Traders	Avg. Holding Period (days)	Avg. Trade Size	No. of Trades (000)	No. of Traders	Avg. Holding Period (days)	Avg. Trade Size
Apr 2012	2,153	25,076	1.28	1.22	854	7,087	19.08	1.25
Jun 2012	2,057	24,688	1.18	1.20	669	6,774	17.22	1.23
Aug 2012	2,344	28,004	1.31	1.20	769	8,597	18.39	1.24
Oct 2012	2,020	28,016	1.65	1.21	857	8,740	21.12	1.22
Dec 2012	1,819	27,221	1.92	1.22	774	8,390	22.79	1.24
Feb 2013	2,050	28,674	1.76	1.22	810	8,949	23.24	1.26
Apr 2013	1,950	27,364	1.55	1.24	747	7,850	21.87	1.28
Jun 2013	2,203	25,763	1.28	1.28	931	6,922	23.02	1.34
Aug 2013	1,971	25,761	1.12	1.23	620	6,172	22.61	1.30
Oct 2013	1,330	19,256	1.08	1.18	416	4,305	23.89	1.22
Dec 2013	1,132	16,378	0.84	1.17	313	2,956	23.22	1.21
Feb 2014	1,077	16,992	0.73	1.18	202	2,905	18.50	1.25
Apr 2014	966	16,240	0.77	1.20	223	2,735	17.24	1.29
Jun 2014	830	15,057	0.87	1.21	235	2,609	18.04	1.30
Aug 2014	856	15,436	1.05	1.21	244	3,071	20.50	1.26
Oct 2014	837	13,764	0.96	1.24	212	2,380	20.76	1.31
Dec 2014	737	13,431	1.07	1.28	204	2,530	20.96	1.38
Average	1,549	21,595	1.20	1.22	534	5,469	20.73	1.27

The table represents the summary statistics, for the traders in the GOLD futures contract at MCX from 2012 to 2014, for the following variables - total number of trades, total number of traders, average holding period and the average trade size. Columns 2 to 5 show the statistics for the entire dataset, and columns 6 to 9 show the same for the set of traders having a holding period of atleast five days. Contract expiry is the month in which a particular contract expires, No. of trades indicates the total number of trades carries out in the contract, no. of traders shows the total number traders who have traded in the contract, avg. holding period shows the average holding days of all traders, and avg. trade size shows the average number of contracts traded by the traders per trade by all the traders.

Table 3: Summary statistics of the trading activity - CRUDEOIL derivative contracts

	All Holding Periods				*Holding Period $\geq$ 5 Days*			
Contract Expiry	No. of Trades (000)	No. of Traders	Avg. Holding Period (days)	Avg. Trade Size	No. of Trades (000)	No. of Traders	Avg. Holding Period (days)	Avg. Trade Size
Feb 2012	3,017	60,911	1.14	1.70	939	16,767	17.06	1.84
Mar 2012	2,865	55,929	1.05	1.70	502	14,339	16.43	1.76
Apr 2012	3,163	56,576	0.79	1.75	586	11,881	14.60	1.85
May 2012	3,767	61,643	0.85	1.73	1,022	15,990	14.25	1.83
Jun 2012	4,414	67,100	0.64	1.76	917	13,887	14.37	1.93
Jul 2012	5,717	75,454	0.71	1.72	1,327	19,798	14.27	1.89
Aug 2012	4,950	76,292	1.07	1.74	1,487	23,056	16.12	1.94
Sep 2012	5,192	79,860	0.88	1.76	1,292	20,407	16.17	1.89
Oct 2012	5,004	82,039	0.88	1.76	1,244	23,738	14.35	1.88
Nov 2012	4,003	73,691	0.89	1.73	1,069	20,908	14.20	1.88
Dec 2012	4,981	81,611	0.85	1.79	1,062	22,912	13.89	1.90
Jan 2013	3,536	75,392	1.01	1.79	804	21,052	14.37	1.94
Feb 2013	3,512	71,723	0.99	1.88	882	17,568	15.14	2.09
Mar 2013	3,425	70,577	0.90	1.87	833	17,365	13.83	2.06
Apr 2013	3,581	68,495	0.78	1.91	657	16,798	12.99	2.07
May 2013	3,218	64,585	0.81	1.74	801	15,980	14.21	1.90
Jun 2013	3,954	70,793	0.87	1.73	1,123	21,742	14.01	1.88
Jul 2013	3,923	77,084	0.95	1.58	1,059	24,278	16.08	1.76
Aug 2013	3,048	68,589	1.02	1.43	761	20,155	16.80	1.56
Sep 2013	2,113	51,861	1.03	1.43	553	14,890	17.63	1.63
Oct 2013	1,727	38,575	0.69	1.35	273	6,421	22.93	1.47
Nov 2013	1,590	37,830	0.51	1.37	195	5,526	16.03	1.48
Dec 2013	1,613	42,475	0.57	1.38	173	6,125	16.13	1.50
Jan 2014	1,346	41,104	0.67	1.40	177	7,576	13.79	1.54
Feb 2014	1,554	42,622	0.49	1.39	168	5,681	14.37	1.53
Mar 2014	1,386	40,654	0.45	1.38	125	4,844	13.12	1.52
Apr 2014	1,412	39,153	0.47	1.39	127	5,190	12.01	1.53
May 2014	1,175	35,301	0.47	1.40	89	4,125	14.29	1.52
Jun 2014	1,314	39,201	0.49	1.46	125	4,888	12.31	1.64
Jul 2014	1,194	37,687	0.57	1.45	136	5,825	12.97	1.66
Aug 2014	1,286	36,240	0.55	1.47	166	5,547	13.45	1.62
Sep 2014	1,794	41,335	0.50	1.46	190	6,170	14.89	1.62
Oct 2014	1,894	41,234	0.44	1.49	215	6,965	11.82	1.65
Nov 2014	1,995	43,455	0.47	1.44	264	7,504	14.53	1.60
Dec 2014	2,557	50,501	0.51	1.50	439	10,156	15.15	1.65
Jan 2015	1,019	36,459	1.40	1.48	251	11,194	21.22	1.63
Average	2,840	56,501	0.76	1.59	612	13,257	14.99	1.74

The table represents the summary statistics, for the traders in the CRUDEOIL futures contract at MCX from 2012 to 2014, for the following variables - total number of trades, total number of traders, average holding period and the average trade size. Columns 2 to 5 show the statistics for the entire dataset, and columns 6 to 9 show the same for the set of traders having a holding period of atleast five days. Contract expiry is the month in which a particular contract expires, No. of trades indicates the total number of trades carries out in the contract, no. of traders shows the total number traders who have traded in the contract, avg. holding period shows the average holding days of all traders in the contract, and avg. trade size shows the average number of contracts traded by the traders per trade by all the traders.

Table 4: Summary statistics of regression variables - GOLD

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Panel A: Long Traders - GOLD							
DB_t^i	1,851	4.6	10.3	-20.5	-1.7	10.5	32.7
r_t^i	1,851	0.000	0.01	-0.1	-0.004	0.004	0.1
$TK_{1,t-1}^i$	1,851	-0.004	0.005	-0.03	-0.01	-0.002	0.01
$r_{1,t}^i$	1,851	-0.9	8.1	-24.2	-4.8	4.7	14.8
$\mathrm{RV}_{1,t}^i$	1,851	11.2	4.6	4.2	7.6	14.4	21.5
Panel B: Short Traders - GOLD							
DB_t^i	1,559	4.1	12.2	-22.5	-3.5	10.9	38.8
r_t^i	1,559	0.000	0.01	-0.1	-0.004	0.004	0.1
$TK_{1,t-1}^i$	1,559	-0.004	0.004	-0.02	-0.005	-0.002	0.01
$r_{1,t}^i$	1,559	-0.9	8.6	-24.2	-5.3	5.1	14.8
$\mathrm{RV}_{1,t}^i$	1,559	11.8	4.4	5.3	8.0	14.9	21.5

The table shows the summary statics of the regression variables. DB_t^i (Equation 2) is the measured disposition among the traders in contract i on date t. r_t^i is the return on contract i on date t. $TK_{1,t-1}^i$ (Equation 9) is the value of price path proxy in contract i on date $t-1$, computed using value of $\rho = 0.95$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. $\mathrm{RV}_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. DB_t^i and $TK_{1,t-1}^i$ are winsorized at 1% level. This table reports the summary statistics of the variables in the main analysis which consists of the set of trades that have a duration of atleast five days and which are carried out at least fifteen days before the expiry of the contract. The main analysis excludes all the trades carried out by algorithmic traders and spread traders.

Table 5: Comparison of disposition bias among different groups of traders - GOLD

Panel A: Net Long Positions

	Overall Sample	Return Quantile	
		Below median	Above median
Overall	6.571	6.639	6.503
$TK^i_{1,t-1}$ below median	7.380	7.493	7.229
$TK^i_{1,t-1}$ above median	5.762	5.500	5.959
Difference	1.617	1.992	1.270
t-stat.	2.551	2.186	1.423
Panel B: Net Short Positions			
Overall	5.862	4.654	7.071
$TK^i_{1,t-1}$ below median	3.544	2.396	5.112
$TK^i_{1,t-1}$ above median	8.181	7.738	8.506
Difference	-4.637	-5.342	-3.394
t-stat.	-6.080	-5.075	-3.050

The table shows the average value of DB^i_t (Equation 2) within each quantile of cumulative return ($r^i_{1,t}$) and quantile of $TK^i_{1,t-1}$ (Equation 9). In each Panel, the first row indicates the average disposition bias in the group, the second row indicates the average disposition bias among the group when $TK^i_{1,t-1}$ is below the median, the third row indicates the average disposition bias among the group when $TK^i_{1,t-1}$ is above the median, the fourth row indicates the difference in the values between the second and third row. The last row of each panel indicates the t-stats for difference between disposition bias between quantiles of $TK^i_{1,t-1}$ (computed in fourth row). In this table, we show figures for the set of trades that have a holding period of at least one day and exclude all the trades carried out by spread traders.

Table 6: GOLD - Price path and disposition bias

	DB_t^i			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_t^i$	-0.026^{***}	-0.029^{***}	-0.003	0.001
	(0.003)	(0.003)	(0.005)	(0.005)
r_t^i	0.042^{***}	0.042^{***}	-0.051^{***}	-0.050^{***}
	(0.004)	(0.004)	(0.007)	(0.007)
r_{t-1}^i	0.027^{***}	0.029^{***}	-0.035^{***}	-0.037^{***}
	(0.002)	(0.003)	(0.004)	(0.004)
r_{t-2}^i	0.010^{***}	0.012^{***}	-0.010^{***}	-0.013^{***}
	(0.002)	(0.002)	(0.004)	(0.004)
$TK_{1,t-1}^i$		-0.009^{***}		0.019^{***}
		(0.002)		(0.004)
$r_{1,t}^i$	-0.016^{***}	-0.012^{***}	0.032^{***}	0.022^{***}
	(0.004)	(0.003)	(0.006)	(0.005)
$\mathrm{RV}_{1,t}^i$	-0.001	-0.002	0.005	0.006
	(0.003)	(0.002)	(0.005)	(0.005)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	1,851	1,851	1,559	1,559
Adjusted R^2	0.337	0.340	0.320	0.331

The table reports the result from regression of DB_t^i for GOLD contract for both long and short investors. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. DB_t^i (Equation 2) is the measured disposition among the traders in contract i on date t. r_t^i is the return on contract i on date t. $TK_{1,t-1}^i$ is computed as per Equation 9 in contract i on date $t-1$, using value of $\rho = 0.95$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. $\mathrm{RV}_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. DB_t^i and $TK_{1,t-1}^i$ are winsorized at 1% level, and all the independent variables are standardized. We are considering only the set of trades that have a duration of at least five days and which are carried out at least 15 days before the expiration date. We also exclude all the trades carried out by algorithm traders and spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 7: GOLD - Price path and PGR

	PGR_t^i			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_t^i$	-0.063^{***}	-0.066^{***}	-0.050^{***}	-0.046^{***}
	(0.003)	(0.003)	(0.007)	(0.006)
r_t^i	0.036^{***}	0.035^{***}	-0.040^{***}	-0.039^{***}
	(0.005)	(0.005)	(0.007)	(0.007)
r_{t-1}^i	0.016^{***}	0.017^{***}	-0.019^{***}	-0.022^{***}
	(0.002)	(0.002)	(0.003)	(0.003)
r_{t-2}^i	0.007^{***}	0.008^{***}	-0.002	-0.005
	(0.002)	(0.002)	(0.003)	(0.003)
$TK_{1,t-1}^i$		-0.009^{***}		0.019^{***}
		(0.003)		(0.004)
$r_{1,t}^i$	-0.008	-0.004	0.023^{***}	0.012^{**}
	(0.005)	(0.005)	(0.006)	(0.005)
$\text{RV}_{1,t}^i$	0.005^{**}	0.004^{*}	0.005	0.006
	(0.002)	(0.002)	(0.004)	(0.004)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	1,851	1,851	1,559	1,559
Adjusted R^2	0.558	0.561	0.447	0.457

The table reports the result from regression of PGR_t^i for GOLD contract for both long and short investors. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. PGR_t^i (Equation 3) is the measured propensity for gain realization among the traders in contract i on date t. r_t^i is the return on contract i on date t. $TK_{1,t-1}^i$ is computed as per Equation 9 in contract i on date $t-1$, using value of $\rho = 0.95$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. $\text{RV}_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. $TK_{1,t-1}^i$ is winsorized at 1% level, and all the independent variables are standardized. We are considering only the set of trades that have a duration of at least five days and which are carried out at least 15 days before the expiration date. We also exclude all the trades carried out by algorithm traders and spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 8: GOLD - Price path and PLR

	PLR$_t^i$			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_t^i$	−0.037***	−0.037***	−0.046***	−0.046***
	(0.003)	(0.003)	(0.002)	(0.002)
r_t^i	−0.008***	−0.008***	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
r_{t-1}^i	−0.011***	−0.012***	0.016***	0.016***
	(0.001)	(0.001)	(0.002)	(0.002)
r_{t-2}^i	−0.003***	−0.003***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
$TK_{1,t-1}^i$		0.001		−0.0003
		(0.002)		(0.003)
$r_{1,t}^i$	0.008***	0.008**	−0.010***	−0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
RV$_{1,t}^i$	0.006***	0.006***	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	1,851	1,851	1,559	1,559
Adjusted R^2	0.457	0.457	0.514	0.513

The table reports the result from regression of PLR$_t^i$ for GOLD contract for both long and short investors. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. PLR$_t^i$ (Equation 4) is the measured propensity for loss realization among the traders in contract i on date t. r_t^i is the return on contract i on date t. $TK_{1,t-1}^i$ is computed as per Equation 9 in contract i on date $t-1$, using value of $\rho = 0.95$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. RV$_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. $TK_{1,t-1}^i$ is winsorized at 1% level, and all the independent variables are standardized. We are considering only the set of trades that have a duration of at least five days and which are carried out at least 15 days before the expiration date. We also exclude all the trades carried out by algorithm traders and spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Appendix

A Details of GOLD and CRUDEOIL contracts

Traders in GOLD contracts are allowed to vary their trade size between 1 kg (minimum) and 10 kg (maximum). The minimum tick size is Rs.1 per 10 grams. The contracts are traded on six days a week from 10:00 am to 11:30 pm (10:00 am to 2:00 pm on Saturdays). The contract-wise trading characteristics of GOLD is given in Table 2. The GOLD contracts are highly liquid and have no significant seasonality in the trading activity during a year. During the sample period, an average of 1.5 million trades are carried out in each contract. There are approximately 21000 unique traders in the market including the day traders. The average quantity per trade is 1.2 kg of gold. Each contract represents an underlying of 1 kg of gold.

The minimum (maximum) trade size in CRUDEOIL is 100 barrels (10000 barrels). The minimum tick size of Rs. 1 per barrel. It enjoys a high level of liquidity with approximately 2.8 million trades in each CRUDEOIL contract, carried out by about 56,000 unique traders. The average traded quantity is 1.6 contracts (corresponding to 160 barrels) per trade. The contract-wise trading characteristics of CRUDEOIL is given in Table 3.

Table A1: Comparison of GOLD and CRUDEOIL contracts

	Gold	Crude oil
Symbol	GOLD	CRUDEOIL
Trading Unit	1 Kg	100 barrels
Quotation/ Base Value	10 grams	Rs. Per barrel
Tick Size	Re. 1 per 10 grams	Re. 1
Maximum Order Size	10 Kg	10,000 barrels
Duration of Trading	1 year	6 months
Expiry Months	Feb, April, June, Aug, Oct, Dec	Every Month

B Additional robustness checks

Table B1: CRUDEOIL - Price path and disposition bias

	DB^i_t			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry^i_t	-0.011^{**}	-0.012^{***}	-0.014^{***}	-0.013^{***}
	(0.004)	(0.004)	(0.005)	(0.004)
r^i_t	0.036^{***}	0.036^{***}	-0.039^{***}	-0.039^{***}
	(0.003)	(0.003)	(0.004)	(0.004)
r^i_{t-1}	0.019^{***}	0.020^{***}	-0.017^{***}	-0.022^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
r^i_{t-2}	0.007^{***}	0.008^{***}	-0.001	-0.005^{**}
	(0.001)	(0.001)	(0.002)	(0.002)
$TK^i_{1,t-1}$		-0.005^{**}		0.018^{***}
		(0.002)		(0.003)
$r^i_{1,t}$	-0.012^{***}	-0.011^{***}	-0.001	-0.004
	(0.003)	(0.003)	(0.005)	(0.004)
$RV^i_{1,t}$	-0.006^{*}	-0.006	-0.008	-0.009^{**}
	(0.004)	(0.003)	(0.005)	(0.004)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	2,050	2,050	2,098	2,098
Adjusted R^2	0.244	0.245	0.236	0.255

The table reports the result from regression of DB^i_t for CRUDEOIL contract for both long and short investors. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. DB^i_t (Equation 2) is the measured disposition among the traders in contract i on date t. r^i_t is the return on contract i on date t. $TK^i_{1,t-1}$ is computed as per Equation 9 in contract i on date $t-1$, using value of $\rho = 0.95$. $r^i_{1,t}$ is the cumulative return in the contract i from date 1 to date t. $RV^i_{1,t}$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. DB^i_t and $TK^i_{1,t-1}$ are winsorized at 1% level, and all the independent variables are standardized. We are considering only the set of trades that have a duration of at least five days and which are carried out at least 15 days before the expiration date. We also exclude all the trades carried out by algorithm traders and spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table B2: Price path and Disposition Bias - Full Sample

	DB_t^i			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry_t^i	-0.014^{***}	-0.021^{***}	0.008	0.019^{***}
	(0.005)	(0.005)	(0.006)	(0.005)
r_t^i	0.069^{***}	0.068^{***}	-0.074^{***}	-0.073^{***}
	(0.007)	(0.007)	(0.010)	(0.010)
r_{t-1}^i	0.037^{***}	0.040^{***}	-0.045^{***}	-0.051^{***}
	(0.004)	(0.004)	(0.005)	(0.005)
r_{t-2}^i	0.004^{*}	0.007^{***}	-0.009^{**}	-0.015^{***}
	(0.002)	(0.002)	(0.004)	(0.004)
$TK_{1,t-1}^i$		-0.021^{***}		0.039^{***}
		(0.005)		(0.006)
$r_{1,t}^i$	-0.024^{***}	-0.015^{***}	0.042^{***}	0.021^{***}
	(0.007)	(0.004)	(0.008)	(0.006)
$\text{RV}_{1,t}^i$	-0.001	-0.003	0.005	0.009
	(0.004)	(0.003)	(0.006)	(0.006)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	2,096	2,096	1,822	1,822
Adjusted R^2	0.337	0.346	0.339	0.366

The table reports the result from regression of DB_t^i (Equation 2) for GOLD contracts. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. DB_t^i is the disposition bias among the traders in contract i on date t. r_t^i is the return on contract i on date t. $TK_{1,t-1}^i$ is computed as per Equation 9 in contract i on date $t-1$, using value of $\rho = 0.95$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. $\text{RV}_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. DB_t^i and $TK_{1,t-1}^i$ are winsorized at 1% level, and all the independent variables are standardized. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. In these four regressions, we are considering the full sample of traders except the trades made by the day traders. The set of trades also includes trades made by algorithmic traders and excludes the trades carried out by spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table B3: Price path and Disposition Bias - Holding Period at least 10 Days

	DB_t^i			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_t^i$	-0.014^{***}	-0.017^{***}	0.005	0.010^{*}
	(0.004)	(0.004)	(0.005)	(0.005)
r_t^i	0.039^{***}	0.039^{***}	-0.045^{***}	-0.045^{***}
	(0.004)	(0.004)	(0.006)	(0.006)
r_{t-1}^i	0.030^{***}	0.031^{***}	-0.035^{***}	-0.038^{***}
	(0.003)	(0.003)	(0.005)	(0.005)
r_{t-2}^i	0.010^{***}	0.012^{***}	-0.011^{***}	-0.014^{***}
	(0.002)	(0.002)	(0.003)	(0.003)
$TK_{1,t-1}^i$		-0.008^{***}		0.020^{***}
		(0.003)		(0.004)
$r_{1,t}^i$	-0.019^{***}	-0.015^{***}	0.029^{***}	0.017^{***}
	(0.006)	(0.005)	(0.008)	(0.006)
$\mathrm{RV}_{1,t}^i$	-0.0004	-0.001	0.007	0.009^{**}
	(0.003)	(0.003)	(0.005)	(0.004)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	2,055	2,055	1,722	1,722
Adjusted R^2	0.271	0.274	0.292	0.305

The table reports the result from regression of DB_t^i (Equation 2) for GOLD contracts. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position.DB_t^i is the disposition bias among the traders in contract i on date t. r_t^i is the return on contract i on date t. $TK_{1,t-1}^i$ is computed as per Equation 9 in contract i on date $t-1$, using value of $\rho = 0.95$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. $\mathrm{RV}_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. DB_t^i and $TK_{1,t-1}^i$ are winsorized at 1% level, and all the independent variables are standardized. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. In these four regressions, we are considering the only the trades that have a duration of at least 10 days. The set of trades also includes trades made by algorithmic traders and excludes the trades carried out by spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table B4: Gold - Comparison of disposition among investors with different trade value

	DB_t^i			
	Long		Short	
	Above Median Average Trade	Below Median Average Trade	Above Median Average Trade	Below Median Average Trade
	(1)	(2)	(3)	(4)
Days to Expiry$_{i,t}$	-0.038^{***}	-0.016^{***}	0.013^{***}	-0.009^{**}
	(0.006)	(0.004)	(0.004)	(0.004)
$r_{i,t}$	0.055^{***}	0.030^{***}	-0.055^{***}	-0.034^{***}
	(0.005)	(0.005)	(0.008)	(0.006)
$r_{i,t-1}$	0.037^{***}	0.024^{***}	-0.036^{***}	-0.018^{***}
	(0.004)	(0.003)	(0.006)	(0.003)
$r_{i,t-2}$	0.014^{***}	0.010^{***}	-0.013^{***}	-0.006^{*}
	(0.003)	(0.002)	(0.004)	(0.003)
$TK_{i,1,t-1}$	-0.017^{***}	-0.008	0.029^{***}	0.007
	(0.005)	(0.005)	(0.005)	(0.005)
$r_{i,1,t}$	-0.007	-0.025^{**}	0.016^{**}	0.041^{***}
	(0.005)	(0.011)	(0.007)	(0.012)
RV$_{i,1,t}$	0.010^{***}	-0.002	0.004	0.010^{*}
	(0.004)	(0.004)	(0.006)	(0.005)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	1,598	1,317	1,346	1,129
Adjusted R^2	0.347	0.218	0.335	0.234

The table reports the result from regression of DB_t^i for GOLD contract among the set of investors divided based on the average trade value. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. In columns 1 and 3, the sample is the set of investors whose average trade value ($N_{contracts} \times Price$) is above the median trade value. In columns 2 and 4, the sample is the set of investors whose average trade value ($N_{contracts} \times Price$) is below the median trade value. DB_t^i (Equation 2) is the measured disposition among the traders in contract i on date t. r_t^i is the return on contract i on date t. $TK_{1,t-1}^i$ is computed as per Equation 9 in contract i on date $t-1$, using value of $\rho = 0.95$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. $\mathrm{RV}_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. DB_t^i and $TK_{1,t-1}^i$ are winsorized at 1% level, and all the independent variables are standardized. We are considering only the set of trades that have a duration of at least five days and which are carried out at least 15 days before the expiration date. We also exclude all the trades carried out by algorithm traders and spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table B5: GOLD - Price path and disposition bias, $\rho = 0.91$

	DB_t^i			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_t^i$	-0.026^{***}	-0.028^{***}	-0.003	-0.001
	(0.003)	(0.003)	(0.005)	(0.005)
r_t^i	0.042^{***}	0.042^{***}	-0.051^{***}	-0.050^{***}
	(0.004)	(0.004)	(0.007)	(0.007)
r_{t-1}^i	0.027^{***}	0.029^{***}	-0.035^{***}	-0.039^{***}
	(0.002)	(0.003)	(0.004)	(0.004)
r_{t-2}^i	0.010^{***}	0.012^{***}	-0.010^{***}	-0.014^{***}
	(0.002)	(0.002)	(0.004)	(0.004)
$TK_{1,t-1}^i$		-0.008^{***}		0.017^{***}
		(0.002)		(0.003)
$r_{1,t}^i$	-0.016^{***}	-0.013^{***}	0.032^{***}	0.024^{***}
	(0.004)	(0.003)	(0.006)	(0.005)
$\mathrm{RV}_{1,t}^i$	-0.001	-0.001	0.005	0.006
	(0.003)	(0.002)	(0.005)	(0.005)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	1,851	1,851	1,559	1,559
Adjusted R^2	0.337	0.340	0.320	0.330

The table reports the result from regression of DB_t^i for GOLD contract for both long and short investors. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. DB_t^i (Equation 2) is the measured disposition among the traders in contract i on date t. r_t^i is the return on contract i on date t. $TK_{1,t-1}^i$ is computed as per Equation 9 in contract i on date $t-1$, using value of $\rho = 0.91$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. $\mathrm{RV}_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. DB_t^i and $TK_{1,t-1}^i$ are winsorized at 1% level, and all the independent variables are standardized. We are considering only the set of trades that have a duration of at least five days and which are carried out at least 15 days before the expiration date. We also exclude all the trades carried out by algorithm traders and spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table B6: GOLD - Price path and disposition bias, $\rho = 0.97$

	DB^i_t			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry^i_t	-0.026^{***}	-0.029^{***}	-0.003	0.002
	(0.003)	(0.003)	(0.005)	(0.005)
r^i_t	0.042^{***}	0.042^{***}	-0.051^{***}	-0.050^{***}
	(0.004)	(0.004)	(0.007)	(0.007)
r^i_{t-1}	0.027^{***}	0.028^{***}	-0.035^{***}	-0.036^{***}
	(0.002)	(0.003)	(0.004)	(0.004)
r^i_{t-2}	0.010^{***}	0.011^{***}	-0.010^{***}	-0.012^{***}
	(0.002)	(0.002)	(0.004)	(0.004)
$TK^i_{1,t-1}$		-0.009^{***}		0.020^{***}
		(0.003)		(0.004)
$r^i_{1,t}$	-0.016^{***}	-0.012^{***}	0.032^{***}	0.021^{***}
	(0.004)	(0.003)	(0.006)	(0.006)
$RV^i_{1,t}$	-0.001	-0.002	0.005	0.008^{*}
	(0.003)	(0.003)	(0.005)	(0.005)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	1,851	1,851	1,559	1,559
Adjusted R^2	0.337	0.340	0.320	0.330

The table reports the result from regression of DB^i_t for GOLD contract for both long and short investors. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. DB^i_t (Equation 2) is the measured disposition among the traders in contract i on date t. r^i_t is the return on contract i on date t. $TK^i_{1,t-1}$ is computed as per Equation 9 in contract i on date $t-1$, using value of $\rho = 0.97$. $r^i_{1,t}$ is the cumulative return in the contract i from date 1 to date t. $RV^i_{1,t}$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. DB^i_t and $TK^i_{1,t-1}$ are winsorized at 1% level, and all the independent variables are standardized. We are considering only the set of trades that have a duration of at least five days and which are carried out at least 15 days before the expiration date. We also exclude all the trades carried out by algorithm traders and spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

C Alternative Specifications to Capture the Price Path

The results for the influence of price path on the level of disposition bias as captured by the Salience Theory is given in the Table C1 for GOLD and in Table C2 for CRUDEOIL.

Table C1: GOLD - Price path (Salience) and disposition bias

	DB_t^i			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_t^i$	−0.026***	−0.025***	−0.003	−0.003
	(0.003)	(0.003)	(0.005)	(0.005)
r_t^i	0.042***	0.042***	−0.051***	−0.050***
	(0.004)	(0.004)	(0.007)	(0.007)
r_{t-1}^i	0.027***	0.029***	−0.035***	−0.038***
	(0.002)	(0.003)	(0.004)	(0.004)
r_{t-2}^i	0.010***	0.012***	−0.010***	−0.013***
	(0.002)	(0.002)	(0.004)	(0.004)
$Salience_{1,t-1}^i$		−0.012***		0.020***
		(0.003)		(0.004)
$r_{1,t}^i$	−0.016***	−0.008***	0.032***	0.018***
	(0.004)	(0.003)	(0.006)	(0.005)
$RV_{1,t}^i$	−0.001	0.00002	0.005	0.004
	(0.003)	(0.003)	(0.005)	(0.005)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	1,851	1,851	1,559	1,559
Adjusted R^2	0.337	0.342	0.320	0.332

The table reports the result from regression of DB_t^i for GOLD contract for both long and short investors. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. DB_t^i (Equation 2) is the measured disposition among the traders in contract i on date t. r_t^i is the return on contract i on date t. $Salience_{1,t-1}^i$ is computed as per Equation 13 in contract i on date $t-1$, using value of $\rho = 0.95$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. $RV_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. DB_t^i and $TK_{1,t-1}^i$ are winsorized at 1% level, and all the independent variables are standardized. We are considering only the set of trades that have a duration of at least five days and which are carried out at least 15 days before the expiration date. We also exclude all the trades carried out by algorithm traders and spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table C2: CRUDEOIL - Price path (Salience) and disposition bias

	DB_t^i			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry_t^i	-0.011^{**}	-0.010^{**}	-0.014^{***}	-0.019^{***}
	(0.004)	(0.004)	(0.005)	(0.004)
r_t^i	0.036^{***}	0.036^{***}	-0.039^{***}	-0.038^{***}
	(0.003)	(0.002)	(0.004)	(0.004)
r_{t-1}^i	0.019^{***}	0.021^{***}	-0.017^{***}	-0.022^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
r_{t-2}^i	0.007^{***}	0.009^{***}	-0.001	-0.005^{**}
	(0.001)	(0.001)	(0.002)	(0.002)
$Salience_{1,t-1}^i$		-0.008^{**}		0.024^{***}
		(0.004)		(0.004)
$r_{1,t}^i$	-0.012^{***}	-0.009^{**}	-0.001	-0.011^{***}
	(0.003)	(0.004)	(0.005)	(0.004)
$\text{RV}_{1,t}^i$	-0.006^{*}	-0.005	-0.008	-0.010^{***}
	(0.004)	(0.003)	(0.005)	(0.004)
Weekday Fixed effects	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
Expiry Month Fixed effects	Yes	Yes	Yes	Yes
Observations	2,050	2,050	2,098	2,098
Adjusted R^2	0.244	0.246	0.236	0.257

The table reports the result from regression of DB_t^i for CRUDEOIL contract for both long and short investors. Columns 1 and 2 depict the results for investors with net long position and columns 3 and 4 depict the results for investors with net short position. DB_t^i (Equation 2) is the measured disposition among the traders in contract i on date t. r_t^i is the return on contract i on date t. $Salience_{1,t-1}^i$ is computed as per Equation 13 in contract i on date $t-1$, using value of $\rho = 0.95$. $r_{1,t}^i$ is the cumulative return in the contract i from date 1 to date t. $\text{RV}_{1,t}^i$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. In all the models we have controlled for weekday, month, year and month of expiration fixed effects. Robust standard errors clustered at contract level are computed and are reported in parenthesis. DB_t^i and $TK_{1,t-1}^i$ are winsorized at 1% level, and all the independent variables are standardized. We are considering only the set of trades that have a duration of at least five days and which are carried out at least 15 days before the expiration date. We also exclude all the trades carried out by algorithm traders and spread traders. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.