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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 behavior. 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 the traders with Prospect Theory preferences. The decline (increase) in disposition bias is an outcome of the decline (increase) in the propensity for gain realization, accompanied by a concurrent increase (decline) in the propensity for loss realization among the traders. 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 the 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 a monthly high. However, most of the papers, which examined the impact of past prices on investor beliefs and their trading decisions, had focused typically on the role of the magnitude of past returns and had not considered the possible role of price path.

Recent research by Grosshans and Zeisberger (2018) and Nolte and Schneider (2016), experimentally examined the impact of price path on investor satisfaction level and investment decisions, 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 (2016) found that paths that have the same risk-return profile but different characteristics, such as the recent returns, maximum price, minimum price, purchase price, and variability, attract significantly different investment amounts from the participants of the experiment. The findings from the experimental market, as above, clearly imply that for a given level of return earned by the investor, their experience, expectation and decisions could vary substantially depending on the price trajectory experienced. 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 A 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 B 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, there is almost no empirical study that examines it. We attempt to investigate this in our paper by empirically examining the influence of price path on the trading decisions.

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 impacts disposition bias displayed by investors with Cumulative Prospect Theory (CPT) preferences. We employ a high-frequency trader-level data 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 reduces investors wealth by around 2.8%.

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 B of Figure 1, conveys a more optimistic signal about the future returns than Path A, 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 A of Figure 1, conveys a more pessimistic signal about the future returns, relative to Path B, 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 influence price path has on disposition bias over and above the level of returns.

We contribute to the stream of literature on investor behaviour by examining the impact of 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 important ways. First, we not only consider the impact of the previous returns but also the entire price path by the using the method proposed in Barberis et al. (2016), 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 on a daily basis, which makes the investor realistically feel the price trajectory, as it impacts his margin balance. Hence the futures market offers itself as a more appropriate context to examine the role of price path, than the stock market. Finally, most of the studies on disposition bias in the stock markets examined it only from the long investor's point of view as shorting is difficult and rare. However, in the futures market, there is no asymmetry in establishing short and long positions, and it gives us the opportunity to study the impact of price path on investors with both net long and short positions.

Our key results are as follows. First, after controlling for returns, volatility, and the time left for the expiration of the contract, price path has a significant influence on disposition bias in the futures market. 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) and an increase (reduction) in the propensity for loss realization (PLR) among traders with both net long and net short positions. The findings confirm the significance of price path in shaping investor decisions, observed by Grosshans and Zeisberger (2018) and Nolte and Schneider (2016) in experimental settings, in an actual market.

Finally, we conjecture that disposition bias is influenced by both 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 (price trend) weakens the level of disposition bias. 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 price path on the investor level trade decisions. Our results complement the findings of existing experimental studies (Grosshans and Zeisberger, 2018; Nolte and Schneider, 2016) 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 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 and provides directions for future action.

2 Literature Review

Disposition bias, where investors show a higher propensity to realize their gains than the their losses, was proposed by Shefrin and Statman (1985). It adversely impacts investor wealth, as studies (for instance, Odean, 1998) have found that the assets investors sell outperform those which are retained. Disposition bias is known to be prevalent in equity markets worldwide (for instance, Shefrin and Statman, 1985; Barber and Odean, 1999;

Brown et al., 2006; Visaltanachoti et al., 2007; Grinblatt and Keloharju, 2001). It is also prevalent in the futures markets (Choe and Eom, 2009) and real estate markets (Genesove and Mayer, 2001). Though disposition bias is documented to be more widespread among the retail investors, it is also documented to significantly influence the trading decisions of the institutional investors (Barber and Odean, 2007) and professional traders (Shapira and Venezia, 2001).

Research so far has offered a range of explanations for the prevalence of disposition bias, consistent with both irrational and rational investor behaviour. The explanations based on irrational behaviour include those founded on Prospect Theory (Shefrin and Statman, 1985; Kahneman and Tversky, 1979; Thaler, 1985), regret aversion (Shefrin and Statman, 1985; Frydman and Camerer, 2016), self-control (Shefrin and Statman, 1985; Fischbacher et al., 2017), selective attention (Schmidt, 2016; Karlsson et al., 2009), cognitive dissonance (Chang et al., 2016) and investor expectations driven by prior prices (Grinblatt and Keloharju, 2001; Grosshans and Zeisberger, 2018). The rational explanations for disposition bias include mean-reversion of prices (Barber and Odean, 1999) and realization utility (Barberis and Xiong, 2012).

The link between disposition bias and Prospect Theory preferences lies in the shape of the value function. The 'S-shaped' value function of Prospect Theory (Kahneman and Tversky, 1979) implies that investors would be expected to quickly realize their gains and hold on to their losses. Disposition bias, induced by the 'S-shaped' value function, would be aggravated by the mental accounting (Shefrin and Statman, 1985) preference of the investors, where gains and losses are tracked for each individual asset rather than for the portfolio of assets. Disposition bias is further magnified by the manner in which investors judge the gains and losses of their investments relative to a reference price. While the cost of the investment is the initial reference price, investors are known update the reference price as the prices continue to evolve. Wang et al. (2017) found that investors are reluctant to update their reference price when they experience a price decline, but are prompt to do so when they experience a price rise. The investor perception of gains is dampened when they update the reference price with the high prices as it brings the reference price and the current price close to each other. On the other hand, the reluctance to incorporate the low prices into the reference price intensifies investors' perception of losses. Thus, the asymmetry in integrating the recent low prices while updating the reference price accentuates disposition bias.

As a decline in the value of an investment contradicts the initial belief held by the investor about the asset, it creates a cognitive dissonance (Chang et al., 2016). Investors attempt cope with the dissonance, by trying to convince themselves that the losses are only temporary. This makes them hold on to their losing assets and induces a disposition bias.[1] Disposition bias can also be triggered by regret aversion (Shefrin and Statman, 1985), where investors attempt to avoid the regret by not selling an asset that has suffered a capital loss. Schmidt (2016) found that distracted investors, who fail to correctly assess the negative signals tend to exhibit a greater disposition bias. The explanations for disposition bias offered by cognitive dissonance, regret aversion and distraction suggest that disposition bias is a coping mechanism where investors attempt to protect their gains and at the same time attempt to speculate on their losing positions to recoup their losses. Lack of self-control is also cited as a reason for the reluctance to realize losses among investors Shefrin and Statman (1985). For instance, Fischbacher et al. (2017) found that the use of 'stop-loss' and 'take-gain' options in trading sessions reduce disposition bias in an experimental market.

While most of the studies categorize disposition bias as a sign of departure from rationality, the relatively higher rate of selling winners than losers can be rational, if the asset prices were expected to mean revert. Ben-David and Hirshleifer (2012) argue that disposition may be an outcome of the trading on private information. Traders may sell following a price increase on the belief that the underpricing in the asset has been eliminated. However, after a price decline, a trader confident about her private information may refrain from selling as it reinforces the undervaluation of the asset. The investor might even increase the investment in the asset in line with her private information. Hence, disposition pref-

[1] A reversal of disposition bias is observed, when a loss is suffered in a mutual fund investment. In mutual funds, the investors can blame the fund managers for the poor outcome and absolve themselves of any blame. Therefore, poor performance by a mutual fund leads to substantial redemption from the funds.

erences exhibited by investors could be rational. Another rational argument in support of disposition bias is realization utility (Barberis and Xiong, 2012). Barberis and Xiong (2012) argue that investors experience utility not only from the the final consumption of wealth but also from selling their appreciated financial assets, called realization utility. Analogously, when an asset is sold at a loss it leads to a negative realization utility. Hence, as per the realization utility argument, investors would be reluctant to sell investments with capital losses.[2] Several arguments, as presented above, suggest that the observed disposition bias is not entirely an irrational investor behaviour but it is a outcome of investor preferences which departs from the expected utility framework.

Most of the above explanations offered for disposition bias are routed in investor preferences such as Prospect theory and realization utility. However, as indicated by the possible influence of the mean-reversion expectations and private information held by investors, disposition bias is also influenced by investor beliefs about the future price movements. As the expectations about future prices movements could be impacted by the past price trends (for instance, Grinblatt and Keloharju, 2001; Grosshans and Zeisberger, 2018), the observed price path may also influence the level of disposition bias.

Grinblatt and Keloharju (2001) find that the probability of selling a stock is positively impacted by the returns observed in the past. Particularly, positive (negative) returns in the immediate past increases(decreases) the investor propensity to sell the stock. Further, they also find that, the returns observed beyond the immediate past month have a negligible impact of the decision to sell.

While the influence of the level of past returns on trading decision has been somewhat well studied, how the returns are earned as reflected in price path, might also influence the trading decisions. For instance, on observing a price rise, despite the high negative returns an investor may have, she may expect the trend to continue and prices to recover further. This would reduce the intensity of disposition bias. In a recent study, Grosshans and Zeisberger (2018) analyse the impact of various price paths 'up-down', 'down-up', 'straight-

[2] Frydman et al. (2014) conducts an experimental analysis by monitoring brain activity using fMRI and finds that the observed neural activity is consistent with the neural predictions of the realization utility model.

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.

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:

$$\begin{aligned} DE_{i,t} = \quad & \alpha + \beta_1 Days.to.Expiry_{i,t} + \beta_2 r_{i,t} + \beta_3 r_{i,t-1} + \beta_4 r_{i,t-2} \\ & + \beta_5 TK_{norm_{i,1,t-1}} + \beta_6 r_{i,1,t} + \beta_7 RV_{i,1,t} + \epsilon_{i,t} \end{aligned} \tag{1}$$

where, $DE_{i,t}$ is the market-level disposition bias prevalent among traders in contract i on day t. The construction of the $DE_{i,t}$ variable is detailed in Section 3.2. $Days.to.Expiry_{i,t}$ is the time to expiry of contract i measured in calendar days on day t . Controlling for the influence of $Days.to.Expiry_{i,t}$ 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 ($r_{i,t}$) and two lagged ($r_{i,t-1}$, $r_{i,t-2}$) returns . $TK_{norm_{i,1,t-1}}$ is the proxy constructed to capture the nature of price path as described in Section 3.4. The cumulative returns on a contract ($r_{i,1,t}$) 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 ($RV_{i,1,t}$) of the contract from the date of the initiation of the contract. It is computed using intraday prices sampled at the 5-minutes interval[3]. In all the regressions, heteroskedasticity and autocorrelation consistent robust standard errors are computed.

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.

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

$$DE_{i,t} = PGR_{i,t} - PLR_{i,t} \tag{2}$$

where,

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

and

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

$N_{RG}^{i,t}$ 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 $PGR_{i,t}$ and $PLR_{i,t}$, 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 two of the most liquid futures contracts, GOLD and CRUDEOIL. 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

The Cumulative Prospect Theory (CPT) framework is known to accommodate several departures in investor decision making in the financial markets such as the over-weighting of small probabilities and excessive aversion towards losses. It is found to be more successful in an empirical context than many other frameworks of decision making, including the Expected Utility. Hence we adopt the CPT framework to compute a measure of the price path.

We capture the nature of price path of an asset, by building on an approach proposed by Barberis et al. (2016). They link Cumulative Prospect Theory (CPT) preferences (Tversky and Kahneman, 1992) to the cross-section of expected stock returns. Barberis et al. (2016) ranked stocks on the CPT value of the return distribution and found that the high-ranking stocks have lower expected returns, implying their overpricing in the market. 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

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

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

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

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.

However, $TK(\rho)$ reflects the magnitude of the returns and is not a normalized measure of the nature of price path. Therefore, to construct a measure of price path that is independent of the magnitude of returns, we construct a normalized version of $TK(\rho)$

$$TK_{norm} = \frac{TK(\rho)}{|TK|} \tag{10}$$

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 $\rho = 0.99$

The reasoning behind employing TK_{norm} is as follows. $TK(\rho)$ is a function of the series of returns experienced and despite the fact it captures the nature of price path, it is not independent of the magnitude of return of price path. However, we want a measure of the character of price path which is independent of the level of returns, as we are interested to examine the impact of the nature of price path after controlling for the level of returns. Hence, to disentangle nature of price path and the level of returns, we create a normalized measure that only captures the trajectory of prices and not the magnitude of returns.

$TK(\rho)$ uses time-varying weights, and TK uses equal weights, however both are functions of the same time series of returns. Hence their ratio (TK_{norm}) gives a measure that removes the influence of the magnitude of returns and gives us a variable that captures only the nature of price path.

The association between the TK_{norm} values and the trajectory of price path an asset may follow between any two time points is illustrated in Figure 1. The two sample price paths, A and B, 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, A and B, start at an arbitrary initial value of, 30,000 and end at 30,655, giving rise to 2% returns over the period. However, the nature of price path is significantly different. Price path A follows an 'up-down' trend where the prices first increase and then decline, whereas path B follows a 'down-up' trend where the prices first decline and then rise. Path A has a TK_{norm} value of -1.27 and the corresponding value for path B is -0.604. Both A and B have negative TK_{norm} values as the negative returns part of either price path is penalized with the loss aversion coefficient (assumed as 2.25). Despite both A and B having the same total return, the TK_{norm} values are substantially different owing to the occurrence of the positive returns in the latter half of path B and the negative returns in the latter half of path A. The 'up-down' path (path A) experiences losses towards the end, hence the negative returns receive greater weights whereas the 'down-up path' (path B) experiences positive returns towards the end which receive greater weights in the computation of TK_{norm} 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 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_{norm}.

In Figures 2 - 4 we compare additional pairs of price paths that have the same periodic returns but have very different price trajectories. Figure 2 compares two alternative price paths that could be faced by an investor who experiences negative returns over a holding period. In path A (path B), the investor experiences an 'up-down' ('down-up') path. Evidently, the TK_{norm} value is greater for path B, as it experiences positive returns towards the end of the holding period. In Figure 3 we compare two price paths which have equal negative returns, path A (B) 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 4. In this case, the 'up-down' path has a lower TK_{norm} value because of its negative returns.

Figures 1 - 4 illustrate that the TK_{norm} 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_{norm} values for long traders in GOLD, given in figure Figure 7, indicates that there is a significant variation of the values within the sample period. As displayed in Table 4, the summary statistics of TK_{norm} for long traders in GOLD are - mean of -1.0 with a standard deviation is 0.9. The maximum is 1.7 and the minimum is -4.0. The distribution of TK_{norm} is approximately normal as indicated by Figure 7. TK_{norm} for CRUDEOIL also shows significant variation in the values, as indicated in Table 4. However, its distribution is moderately left skewed.

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). While our primary objective is to examine the impact of price path on disposition bias of investors, the employment of the futures market data would also allow us to separately examine its impact on traders with net long and short positions. In the stock markets, establishing a short position is significantly more expensive than a long position, making it more difficult and rare.

We employ the individual account level futures trading data of three-years from January 2012 to December 2014 of GOLD and CRUDEOIL contracts. The period covers GOLD (CRUDEOIL) contracts which expire between February (January) 2012 and February 2015. The average daily value of trading in GOLD is about INR 18.1 billion and that in CRUDEOIL is about INR 11.5 billion. The total numbers of trades reported in the database are about 36 million for GOLD and 130 million for CRUDEOIL. 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 40 % of out of the total trades, traders hold the position open for more than a trading day. Nearly 25% of the total trades are held for more than five trading days with an average holding period of 14.6 calendar days. Among the trades which are open for at least one day, the average holding period is 6.68 calendar 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 crude-oil contracts at MCX (CRUDEOIL) are traded for a maximum maturity of six months, and new contracts are launched every month as per a pre-specified contract launch calendar. At the aggregate level, 28.5% of the CRUDEOIL trades are held open for more than one day with an average holding period of 5.18 calendar days. Around 15.6% of the trades are held open for at least 5 days and its average holding period is 11.3 calendar days.

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 5 suggest, even when the prices ended flat, there were significant price fluctuations within the maturity cycle of the contracts. Relative to GOLD, the CRUDEOIL contracts have higher volatility. The volatility of the two commodities derivatives 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.

The trade data file provided by the MCX for each contract contain the trade number, timestamp, price, quantity, unique client code, buy/sell indicator, 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 [4]

In our sample trade data of the two contracts, around 60 % of the total trades in GOLD and about 70% of total trades in CRUDEOIL are held for a duration of less than 1 day,

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

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 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 25% of the total trades in GOLD and 15.6% total trades in CRUDEOIL, 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 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_{norm} 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.

4 Findings and Discussion

We observe a widespread prevalence of disposition bias among traders in the futures contracts of the two sample commodities chosen for the study. The average disposition bias over the main sample period of 3-years is about 2.4% in GOLD and 3% in the CRUDEOIL contracts. The figures indicate that a significantly higher proportion of the derivative traders prefer to realize their gains than their losses. The level of disposition observed here is somewhat comparable to that reported by Choe and Eom (2009) in the Korean Stock Index futures markets.[5]

We find that overall disposition bias increases with returns as observed elsewhere (Ben-David and Hirshleifer, 2012; Grinblatt and Keloharju, 2001). We examine the univariate relationship between disposition bias and our price path proxy $TK_{norm_{i,1,t-1}}$, for traders with net long and short positions separately. The comparison of disposition bias for traders facing different price paths for both the commodities is presented in Table 5. We divide the 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 $TK_{norm_{i,1,t-1}}$ 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 $TK_{norm_{i,1,t-1}}$ is above the median of $TK_{norm_{i,1,t-1}}$, we observe that disposition bias more than halves from 3.4% to 1.5% in GOLD contracts among the long traders. For traders with net short positions, the nature of the influence of price path, where traders exhibit lower level of disposition bias when the $TK_{norm_{i,1,t-1}}$ is below the median, again suggests that a favourable price movement leads to lower disposition bias. Almost the

[5] 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.

same pattern of trader behavior is observed among both the long and short traders in the CRUDEOIL contracts. The only exception is that the difference in the level of disposition bias is not significantly different among the long traders when grouped by the median of the $TK_{norm_{i,1,t-1}}$ value.

Columns 3-6 of Table 5, presents the univariate comparisons of disposition bias, for traders grouped by both the level of returns and the $TK_{norm_{i,1,t-1}}$ value. The comparison would indicate whether the attractiveness of price path captured by the $TK_{norm_{i,1,t-1}}$ 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 quartiles of their portfolios, the level of disposition is significantly lower among traders with a relatively higher $TK_{norm_{i,1,t-1}}$ value, except for one group (Quartile 2) in GOLD. As observed in the case of the univariate comparisons, which did not control for the level of returns, disposition bias among the long traders moves inversely with $TK_{norm_{i,1,t-1}}$, and for the short traders, the intensity of disposition bias varies positively with $TK_{norm_{i,1,t-1}}$. Almost a similar pattern emerge from the comparison of the CRUDEOIL contracts, when they are grouped by their returns (Panels C and D of the Table 5). The univariate analysis of the observed disposition bias, presented in Table 5, demonstrates that a favourable price movement dampens disposition bias among the traders, and its impact persists even after controlling for the level of the returns. The findings suggest that it is not just the level of returns, but how the investors earn the returns, represented by price path also has a significant influence on the trading decisions.

Having observed a significant difference in disposition bias between trader groups which faced relatively favourable and unfavourable price paths, we examine their realization preferences for gains and losses separately, in order to gain more insights into the observed behaviour. We separately examine the influence of price path for the two components of disposition bias, the propensity for gain realization (PGR) and the propensity for loss realization (PLR). A comparison of the PGR and PLR for traders who face relatively favourable and unfavourable price paths is given in Table 6 for both the commodities.

As given in Panel B (Panel A) of Table 6, the PGR is significantly lower for traders, after experiencing a favourable price path, as indicated by the below (above) the median $TK_{norm_{i,1,t-1}}$ of price path. For instance, while 9.5% of the traders with net short positions dispose at least some of their gains following a favourable price path, the corresponding number following a less attractive price path is about 12.5%, in the case of GOLD contracts. A similar lower propensity for gain realization is also observed among traders with net long positions (Panel A of Table 6), following an episode of a psychologically attractive price path ($TK_{norm_{i,1,t-1}}$ above the median). However, for traders with net long positions, the difference is not statistically significant for both GOLD and CRUDEOIL contracts, at least in the univariate comparisons. Overall, we find that the traders have a lower propensity to realize their gains following a favourable price path. It is possible that traders expect a continued price momentum into the future as argued in the literature. At the least, the results in Table 6 imply that price path influences the propensity to close out trader positions with gains.

In Panel C and Panel D of Table 6, we similarly examine the propensity for loss realization (PLR) following relatively favourable and unfavourable price paths. The results suggest that both long and short traders have a higher preference to realize their losses following a favourable price path than an unfavourable price path, in both GOLD and CRUDEOIL contracts. However, the PLR is significantly lower only among the traders with net long positions in GOLD. For instance, among the long traders in GOLD, while 7.5% of the traders realize at least some of their loss positions, after experiencing price paths with relatively high $TK_{norm_{i,1,t-1}}$ value, the corresponding figure for the below median $TK_{norm_{i,1,t-1}}$ value is only 5.8%. The break-even effect could possibly drive the trader behaviour to dispose more of their losses on experiencing a favourable price path.

The univariate comparisons of PGR and PLR against the $TK_{norm_{i,1,t-1}}$ value suggest that while the PGR is lower on experiencing an attractive price path by the traders, the PLR is higher following an attractive price path. Taken together, the observed association between price path and the components of disposition bias, suggest that both attenuate the overall disposition in response to a favourable price movement.

Overall the univariate comparisons suggest that price path has a significant influence on trader behaviour, and it possibly induces differences in disposition bias exhibited by the traders. Particularly investors have significantly different preferences for disposing of gain and loss positions 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.

The estimation results of the multivariate approach Equation 1 for traders with net long and short positions are presented in Table 7 for GOLD and in Table 8 for the CRUDEOIL contracts.

Our primary result is 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. Notably, on experiencing price paths similar to the uptrending ('down-up' and 'straight-up') price paths, as represented by Path B in Figures 1 - 4 by traders, has an influence on the propensity of the traders to realize their gains. The significance of price path despite the role of the cumulative returns and returns in the immediately prior trading days demonstrates the influence it has on disposition bias.

The detailed results of the estimation for long and short investors in the GOLD contract is presented in the model $1, 2$ and $3, 4$ of Table 7 respectively. The cumulative return 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. We also find that higher price volatility lowers the gain realization preferences among investors (coefficient of the realized volatility). Possibly, the increased uncertainty about the future price movements dampens the selling propensity of trader positions. The contemporaneous and the two lagged daily returns have a significant positive impact on disposition bias of investors in line with the findings of other studies, which examine the impact of past returns on disposition bias such as Grinblatt and Keloharju (2001). We included the number of days to expiry as a 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. 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. As observed in both the regressions, the adjusted R-square of the regression significantly increases on the inclusion of price path $TK_{norm_{i,1,t-1}}$ variable (Model 2 and Model 4) in Table 7. For instance, the adjusted R-square increases from 17.2% (Model 1) to 22.3% (Model 2) on the inclusion of price path variable, $TK_{norm_{i,1,t-1}}$, in the case of regressions for the long positions. The incremental influence of price path is evident from the coefficient of the $TK_{norm_{i,1,t-1}}$ value, which proxies price path. For Model 2, it is -0.023 as compared to -0.018 of the cumulative return. Specifically, the coefficient estimate of $TK_{norm_{i,1,t-1}}$ suggests that a unit increase in the value of $TK_{norm_{i,1,t-1}}$ leads to a decrease of 2.3% in disposition. Given the average level of disposition in the gold derivative markets of about 2.4%, the marginal impact of price path estimated here, has a substantial economic significance.

We find almost analogous results for disposition bias of traders holding net short positions (Model 3 and Model 4). The results presented Table 7 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 $TK_{norm_{i,1,t-1}}$ is economically and statistically significant in explaining the change in disposition among investors.

We also have almost similar findings on the significance of price path variable in explaining disposition bias of traders with both long and short positions in CRUDEOIL contracts. The details of the estimation are presented in Table 8. The coefficients of price path variable are uniformly significant across all the regressions, and the adjusted R-square of the regressions increase significantly on the inclusion of price path variable for the CRUDEOIL contracts.

We also examine the impact of price path in a multivariate framework on the dimensions of disposition effect, in order to gain greater insights into the relationship between price path and disposition bias. The analysis follows an approach similar to that adopted in the case of disposition bias. The results of the estimations are presented in Table 9 and Table 10 for PGR and PLR separately.

The important finding is that the proxy of price path significantly influences both the PGR and the PLR. As observed for disposition bias, a favorable price path has a negative impact on the PGR for both long and short traders Table 9, which is consistent across both the commodities. For the long (short) traders, an increase (decrease) in the value of $TK_{norm_{i,1,t-1}}$ 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 could be expected, the impact of price path on the propensity for loss realization (PLR) is of the opposite direction as that of PGR Table 10. A favourable price path has a positive and significant impact on traders with net long positions in both the commodities (columns 1 and 3 of Table 10). Hence, the traders attempt to sell-off their losses on experiencing a price path dominated by positive returns. The traders with net short positions, on experiencing a price path high $TK_{norm_{i,1,t-1}}$ value show a lower propensity for the realization of their losses. It can be argued on the investor beliefs in trend continuation. Hence, a favourable price path is accompanied by a reduction in the intensity to realize gains and an increase in the intensity to realize losses for both types of traders in both the commodities. Hence, the combined impact of decrease (increase) in PGR and increase (decrease) in PLR leads to a reduction (increase) in the level of disposition bias in response to favourable (unfavourable) price movement.

Among the other variables employed in the regressions, the realized volatility has a positive impact throughout on PLR, implying that an increase in the market volatility increases the realization of losses. However, the impact on PGR is mixed. 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 returns have a negative (positive) impact on PGR for long (short) positions.

In summary, the analysis of the components of disposition bias suggests that both the PGR and PLR are significantly influenced by the nature of price path experienced by traders in addition to the cumulative returns in the trader accounts. 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 a increase (decrease) in price path proxy, TK_{norm}, dampens the level of disposition bias among the traders . In this case, we can conjecture that if investors extrapolate price trends, 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, 2016; 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 Robustness of the Results

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. 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 A2. 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 A3. 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 A4 and Table A5 for GOLD and CRUDEOIL respectively. In both the groups, the nature of the directional impact of price path on disposition bias remains consistent with our main results. However, the influence of price path on the level of disposition bias, as captured by the magnitude of the coefficient of $TK_{norm_{i,1,t-1}}$, is stronger among the investors belonging to the above median trade value group in both long and short traders and both the commodities. A possible explanation for this might be that the holding period of above median the trade value investors is longer than the below median trade value investors. Hence they are exposed to price path for a longer duration and subsequently there is a higher degree of influence of price path on their trading decisions.

In our main analysis, we have used a value of $\rho = 0.95$, to compute the TK_{norm} in Equation 10. With $\rho = 0.95$ observations beyond 60 days have negligible contribution to the measure. We re-examine the results presented in Table 7, by changing the values of ρ over a range. Table A6, shows the analysis with value of $\rho = 0.91$ and Table A7 shows the analysis with $\rho = 0.99$. The nature of price path continues to influence the level of disposition bias as found in our baseline analysis.

We also run the analysis in Table 7, with contract and year fixed effects to control for any seasonality in the contracts. The results are in Table A8. The impact of price path on the level of disposition bias continues to hold.

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 0.99). 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 and future directions

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 have empirically examined 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. The reduction in disposition bias following a favourable price movement can be traced to the reduction in propensity for gain realization and an increase in the propensity for loss realization. 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.

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 trend reduces the intensity of disposition bias. Hence, we can argue that their is 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 (2016) that demonstrate the impact of the observed price path on the level of satisfaction and the investment decisions.

While we have used the framework developed by Barberis et al. (2016) to capture how a Prospect Theory investor will evaluate the price path, it will be an interesting extension to explore alternative formulations to capture the nature of the price path. We also intend to examine the other dimensions of known investor behaviour that could be impacted by price path. For instance, we can examine the aggressiveness of the investors in placing the limit order after experiencing a favorable price path.

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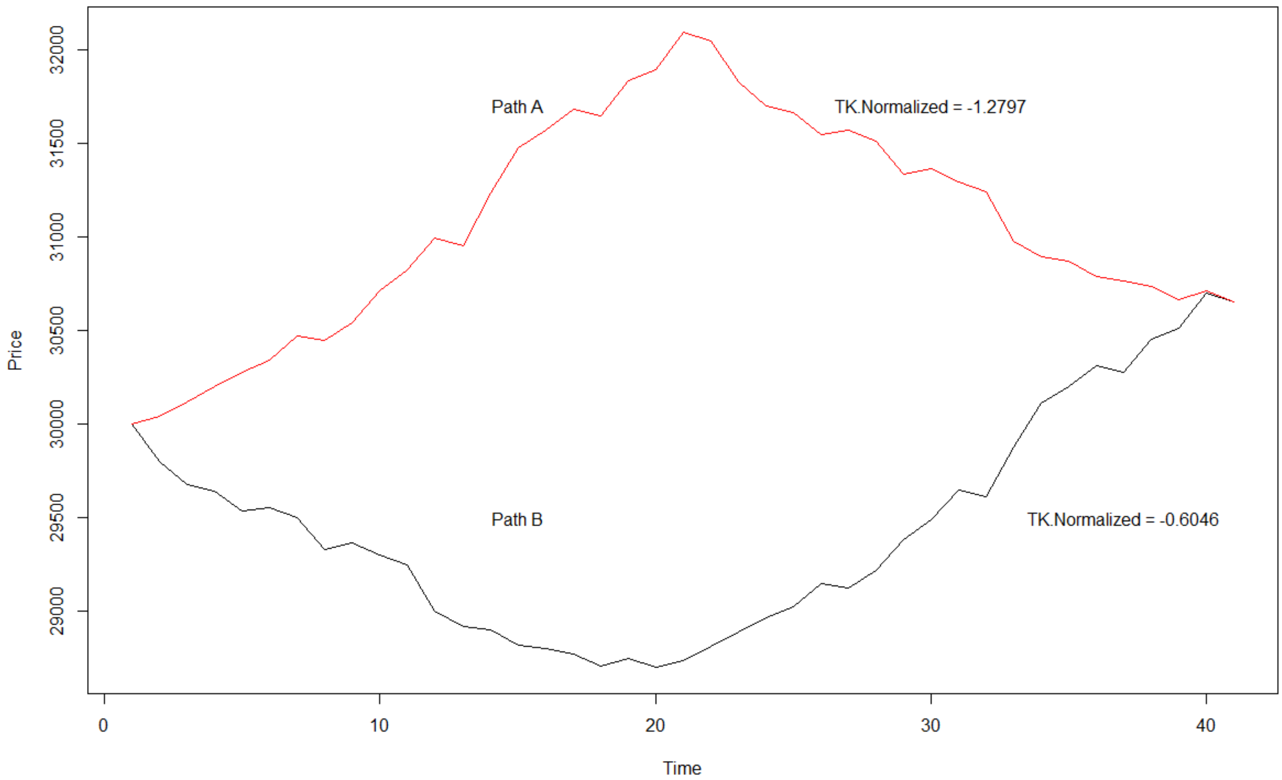

Figure 1: Positive Return: Up-Down versus Down-Up Path

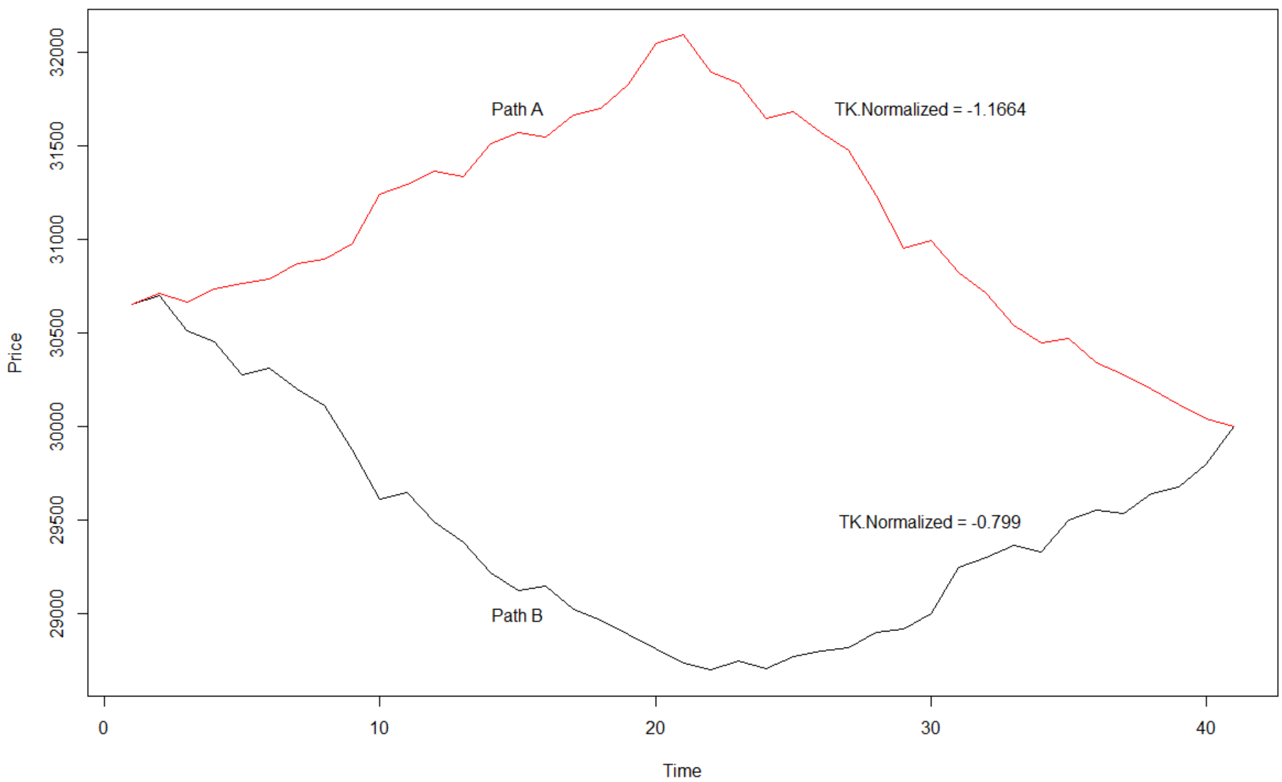

Figure 2: Negative Return: Up-Down versus Down-Up Path

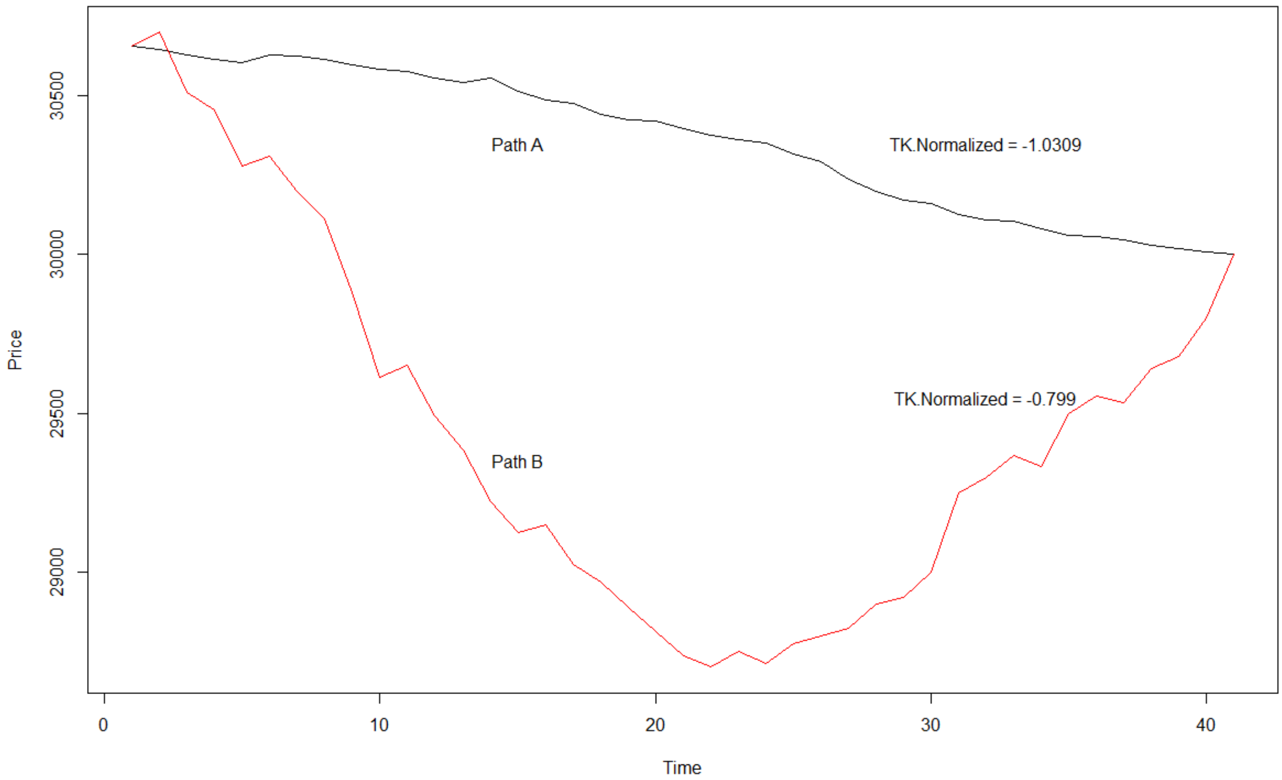

Figure 3: Negative Return: Straight Down versus Down-Up Path

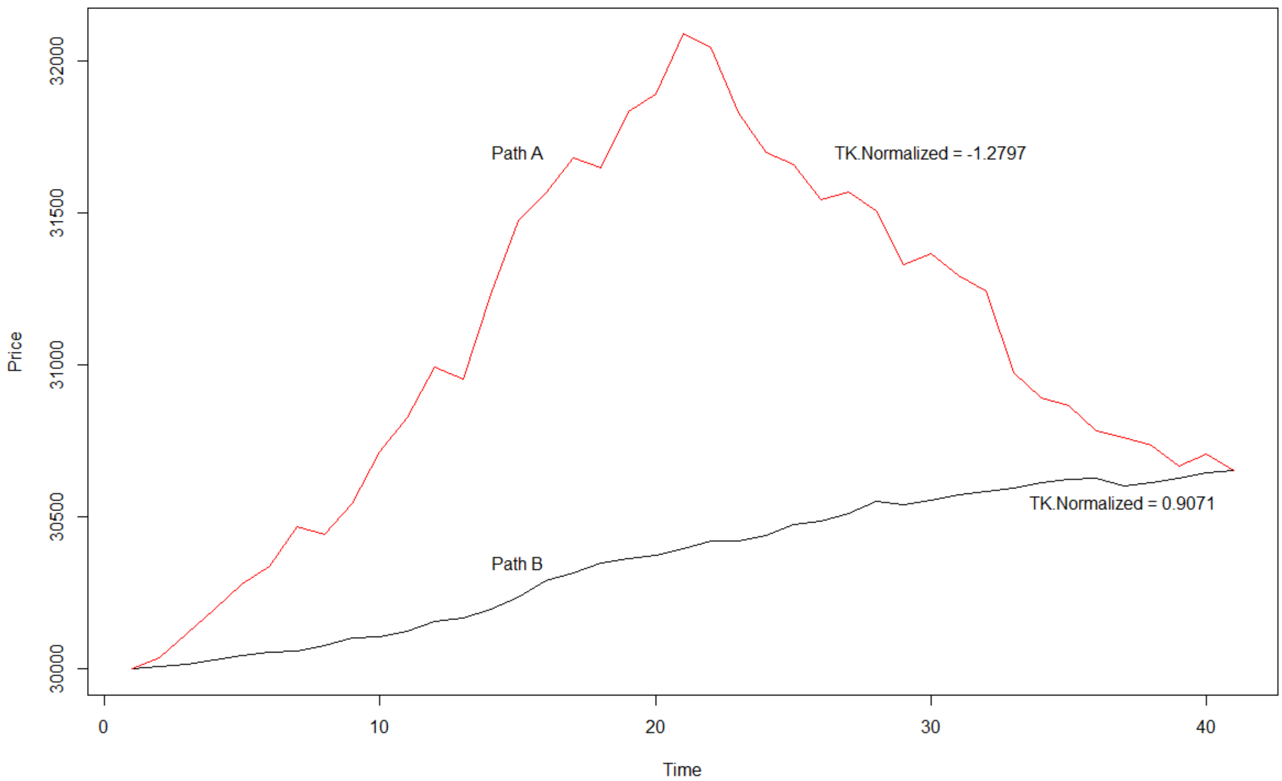

Figure 4: Negative Return: Up-Down versus Straight Up Path

Figure 5: Spot Prices of Gold (INR)

Figure 6: Spot Prices of CRUDEOIL (INR)

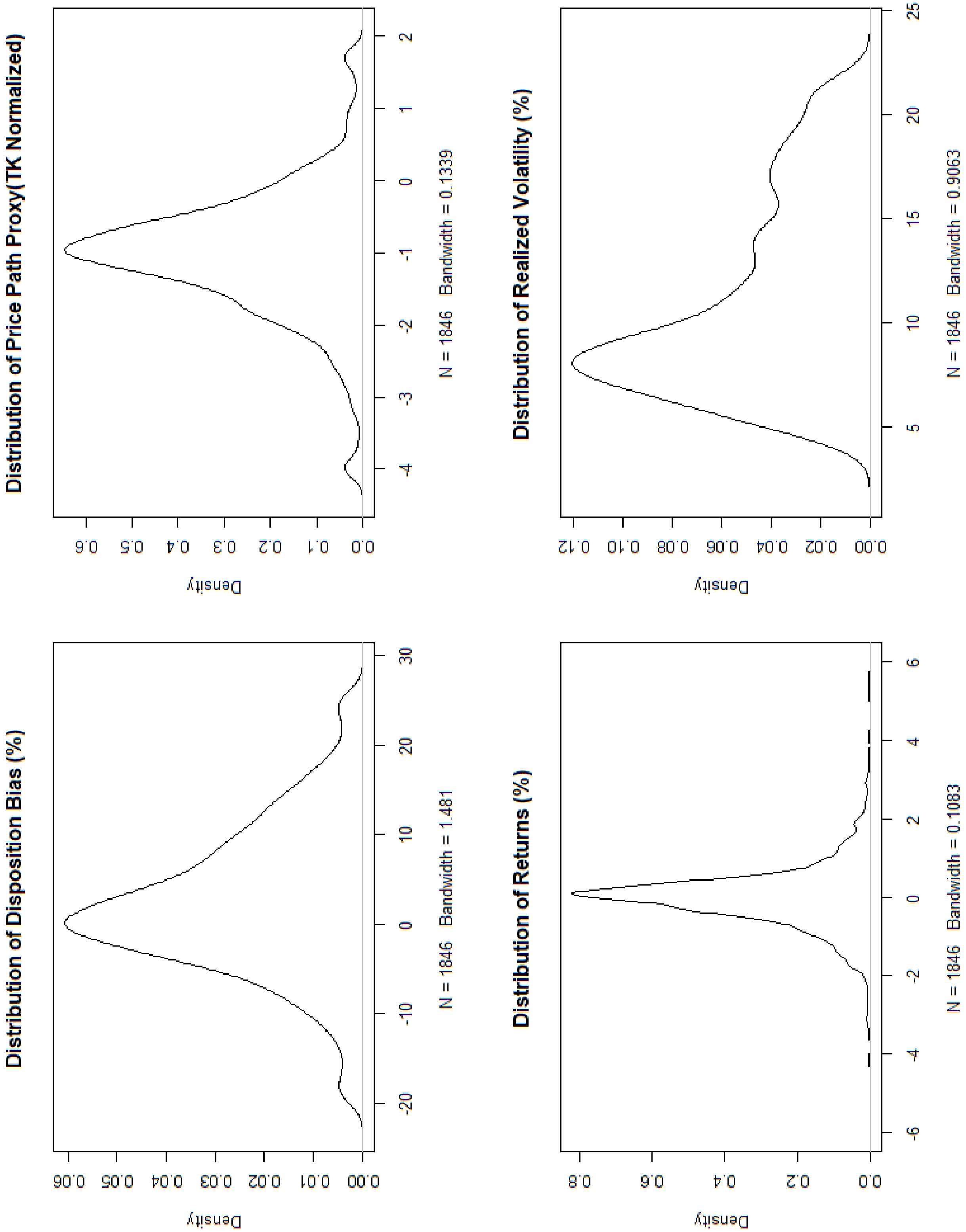

Figure 7: Density plot of Regression Variables - GOLD - Long

Table 1: Variable Description

Variable Name	Description
$DE_{i,t}$	Market-level disposition bias prevalent among traders in contract i on day t
$PGR_{i,t}$	Propensity for gain realization in contract i on day t
$PLR_{i,t}$	Propensity for loss realization in contract i on day t
$Days.to.Expiry_{i,t}$	Time to expiry of the derivative contract i measured in calendar days on day t
$r_{i,t}$	Return in contract i on day t
$r_{i,t-1}$	Return in contract i on day $t-1$
$r_{i,t-2}$	Return in contract i on day $t-2$
$TK_{norm_{i,1,t-1}}$	Proxy constructed to capture the nature of price path of contract i till day $t-1$
$r_{i,1,t}$	Cumulative Return in contract i till day t
$RV_{i,1,t}$	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
Feb 2012	1,229	15,228	0.68	1.23	195	6,483	9.81	1.25
Apr 2012	2,718	24,902	1.16	1.22	886	13,374	13.43	1.25
Jun 2012	2,605	24,678	1.29	1.20	721	13,754	14.22	1.20
Aug 2012	2,975	27,869	1.25	1.20	696	15,811	13.74	1.20
Oct 2012	2,643	27,789	1.47	1.21	669	15,305	15.39	1.21
Dec 2012	2,429	26,975	1.62	1.22	804	14,730	16.32	1.20
Feb 2013	2,620	28,591	1.66	1.22	865	16,432	17.23	1.22
Apr 2013	2,584	27,349	1.49	1.25	638	15,260	16.03	1.26
Jun 2013	3,220	25,533	1.10	1.31	720	12,979	15.16	1.28
Aug 2013	2,788	25,670	1.04	1.26	648	12,942	15.09	1.25
Oct 2013	1,698	19,174	0.99	1.18	342	9,002	15.20	1.18
Dec 2013	1,409	16,345	0.99	1.18	270	8,130	15.25	1.21
Feb 2014	1,249	17,022	1.08	1.19	234	8,648	14.79	1.24
Apr 2014	1,108	16,285	1.16	1.21	261	8,204	14.24	1.27
Jun 2014	985	15,090	1.31	1.22	275	7,700	14.69	1.29
Aug 2014	1,016	15,414	1.30	1.21	257	8,068	14.83	1.25
Oct 2014	1,022	13,785	1.31	1.25	218	6,871	15.51	1.29
Dec 2014	957	13,426	1.37	1.30	200	6,721	15.56	1.35
Feb 2015	541	9,343	0.81	1.25	101	3,500	11.16	1.32
Average	1,884	20,551	1.21	1.23	474	10,732	14.61	1.25

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 6 show the statistics for the entire dataset, and columns 6 to 10 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**

Contract Expiry	All Holding Periods: No. of Trades (000)	No. of Traders	Avg. Holding Period (days)	Avg. Trade Size	Holding Period $\geq$ 5 Days: No. of Trades (000)	No. of Traders	Avg. Holding Period (days)	Avg. Trade Size
Jan 2012	2,632	46,912	0.50	1.82	129	12,538	7.60	1.68
Feb 2012	3,467	59,943	0.95	1.72	623	29,201	11.26	1.75
Mar 2012	3,373	55,373	1.00	1.72	409	26,156	11.70	1.68
Apr 2012	3,738	56,202	0.98	1.79	443	28,523	11.22	1.69
May 2012	4,404	61,423	0.96	1.76	948	31,397	11.66	1.77
Jun 2012	5,281	67,012	0.84	1.79	841	33,242	11.63	1.87
Jul 2012	6,867	75,307	0.79	1.75	1,105	37,647	11.38	1.86
Aug 2012	5,947	75,756	0.97	1.77	999	41,466	11.18	1.80
Sep 2012	6,206	79,453	0.92	1.79	802	40,641	11.65	1.68
Oct 2012	6,147	81,799	0.99	1.80	1,097	46,059	11.62	1.77
Nov 2012	5,001	73,193	0.99	1.77	1,054	38,648	11.79	1.76
Dec 2012	6,023	81,430	1.00	1.83	906	45,286	11.57	1.74
Jan 2013	4,309	74,908	1.24	1.83	537	42,612	11.98	1.78
Feb 2013	4,327	71,558	1.17	1.94	916	37,739	12.17	1.99
Mar 2013	4,345	70,332	1.06	1.96	741	35,351	11.23	1.97
Apr 2013	4,589	68,250	1.00	1.98	756	36,021	11.05	1.98
May 2013	4,355	64,165	0.92	1.82	619	31,294	11.65	1.89
Jun 2013	5,247	70,481	0.94	1.79	1,022	37,967	11.49	1.84
Jul 2013	5,058	76,644	0.96	1.63	943	42,311	12.39	1.71
Aug 2013	3,878	68,323	1.05	1.46	765	37,038	13.18	1.56
Sep 2013	2,618	51,230	0.94	1.46	376	24,672	12.71	1.57
Oct 2013	2,207	38,180	0.77	1.41	248	16,550	13.16	1.49
Nov 2013	1,994	37,773	0.80	1.44	224	17,541	11.86	1.50
Dec 2013	2,001	42,423	0.86	1.45	225	19,383	11.59	1.52
Jan 2014	1,632	41,015	1.02	1.46	220	19,966	11.65	1.57
Feb 2014	1,973	42,621	0.86	1.47	226	19,291	11.55	1.55
Mar 2014	1,783	40,650	0.83	1.46	193	17,591	10.93	1.56
Apr 2014	1,826	39,146	0.85	1.47	223	18,344	10.49	1.64
May 2014	1,523	35,273	0.84	1.49	170	15,288	11.09	1.65
Jun 2014	1,659	39,196	0.91	1.56	219	18,534	10.71	1.77
Jul 2014	1,506	37,467	0.94	1.54	169	19,213	10.36	1.61
Aug 2014	1,679	36,153	0.84	1.57	225	16,354	10.70	1.77
Sep 2014	2,244	41,319	0.80	1.54	357	20,134	11.23	1.77
Oct 2014	2,548	41,212	0.75	1.59	403	20,812	10.66	1.86
Nov 2014	2,762	43,088	0.70	1.54	431	20,224	10.72	1.80
Dec 2014	3,664	50,193	0.62	1.64	712	21,847	11.17	1.97
Jan 2015	1,497	35,123	0.65	1.58	125	11,380	9.41	1.54
Average	3,522	55,960	0.90	1.66	551	27,791	11.34	1.73

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 6 show the statistics for the entire dataset, and columns 6 to 10 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 and CRUDEOIL

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Panel A: Long Traders - GOLD							
Disposition $\text{Bias}_{i,t}$ (%)	1,846	2.4	8.3	-18.9	-2.4	7.5	24.9
$r_{i,t}$(%)	1,846	0.004	0.9	-8.6	-0.4	0.4	5.6
$TK_{norm_{i,1,t-1}}$	1,846	-1.0	0.9	-4.0	-1.4	-0.5	1.7
$r_{i,1,t}$ (%)	1,846	-0.6	8.0	-24.2	-4.8	4.8	16.8
$\text{RV}_{i,1,t}$ (%)	1,846	11.2	4.5	4.3	7.7	14.4	21.5
Panel B: Short Traders - GOLD							
Disposition $\text{Bias}_{i,t}$ (%)	1,574	2.2	9.9	-17.9	-4.3	7.7	35.6
$r_{i,t}$(%)	1,574	0.01	0.9	-8.6	-0.4	0.4	5.6
$TK_{norm_{i,1,t-1}}$	1,574	-1.0	0.9	-3.9	-1.4	-0.5	1.8
$r_{i,1,t}$ (%)	1,574	-0.7	8.6	-24.2	-5.3	5.2	16.8
$\text{RV}_{i,1,t}$ (%)	1,574	11.7	4.3	5.4	8.1	14.7	21.5
Panel C: Long Traders - CRUDEOIL							
Disposition $\text{Bias}_{i,t}$ (%)	2,003	2.5	8.5	-17.7	-2.7	7.0	28.9
$r_{i,t}$(%)	2,003	-0.03	1.3	-6.5	-0.7	0.6	7.4
$TK_{norm_{i,1,t-1}}$	2,003	-1.1	0.9	-3.7	-1.6	-0.5	0.9
$r_{i,1,t}$ (%)	2,003	0.9	13.4	-50.3	-7.3	7.9	42.6
$\text{RV}_{i,1,t}$ (%)	2,003	12.5	2.3	5.8	10.9	14.0	22.1
Panel D: Short Traders - CRUDEOIL							
Disposition $\text{Bias}_{i,t}$ (%)	2,039	3.7	9.2	-16.7	-2.1	8.7	34.4
$r_{i,t}$(%)	2,039	-0.02	1.2	-6.5	-0.6	0.6	7.1
$TK_{norm_{i,1,t-1}}$	2,039	-1.1	0.9	-3.7	-1.6	-0.4	0.9
$r_{i,1,t}$(%)	2,039	1.2	13.0	-50.3	-6.6	7.9	42.6
$\text{RV}_{i,1,t}$ (%)	2,039	12.3	2.5	3.3	10.7	13.9	22.1

The table shows the summary statics of the regression variables. Disposition $\text{Bias}_{i,t}$ (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. $TK_{norm_{i,1,t-1}}$ (Equation 10) is the value of TK_{norm} in contract i on date $t-1$, computed using value of $\rho = 0.95$. $r_{i,1,t}$ is the cumulative return in the contract i from date 1 to date t. $\text{RV}_{i,1,t}$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. Disposition $\text{Bias}_{i,t}$ and TK_{norm} are winsorized at 1% level. In all the regression, we are considering only 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. We also exclude all the trades carried out by algorithmic traders.

Table 5: Comparison of disposition among different groups of traders

Panel A: Long Traders - GOLD	Overall Sample	Return Quartile			
		1	2	3	4
Overall	0.024	0.028	0.020	0.016	0.033
$TK_{norm_{i,1,t-1}}$ Below Median	0.034	0.040	0.027	0.025	0.045
$TK_{norm_{i,1,t-1}}$ Above Median	0.015	0.014	0.016	0.004	0.024
Difference	0.019	0.026	0.012	0.021	0.021
t-stat	(4.962)	(3.341)	(1.541)	(2.952)	(2.599)
Panel B: Short Traders - GOLD					
Overall	0.022	0.006	0.022	0.028	0.031
$TK_{norm_{i,1,t-1}}$ Below Median	0.006	-0.006	0.001	0.018	0.010
$TK_{norm_{i,1,t-1}}$ Above Median	0.038	0.022	0.038	0.043	0.046
Difference	-0.032	-0.028	-0.038	-0.025	-0.035
t-stat	(-6.517)	(-3.112)	(-3.750)	(-2.463)	(-3.407)
Panel C: Long Traders - CRUDEOIL					
Overall	0.025	0.030	0.029	0.019	0.021
$TK_{norm_{i,1,t-1}}$ Below Median	0.027	0.030	0.034	0.022	0.024
$TK_{norm_{i,1,t-1}}$ Above Median	0.022	0.030	0.025	0.017	0.018
Difference	0.005	0.001	0.008	0.005	0.006
t-stat	(1.347)	(0.075)	(1.107)	(0.599)	(0.810)
Panel D: Short Traders - CRUDEOIL					
Overall	0.037	0.035	0.037	0.040	0.034
$TK_{norm_{i,1,t-1}}$ Below Median	0.029	0.025	0.032	0.039	0.022
$TK_{norm_{i,1,t-1}}$ Above Median	0.044	0.047	0.043	0.041	0.046
Difference	-0.015	-0.022	-0.011	-0.002	-0.024
t-stat	(-3.743)	(-2.702)	(-1.389)	(-0.307)	(-2.926)

The table shows the average value of Disposition $\text{Bias}_{i,t}$ (Equation 2) within each quartile of cumulative return ($r_{i,1,t}$) and quantile of $TK_{norm_{i,1,t-1}}$ (Equation 10). 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 $TK_{norm_{i,1,t-1}}$ is below the median, the third row indicates the average disposition bias among the group when $TK_{norm_{i,1,t-1}}$ 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 $TK_{norm_{i,1,t-1}}$ (computed in fourth row). 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.

Table 6: Comparison of PGR and PLR

	GOLD	CRUDEOIL
Panel A: PGR - Long Traders		
Overall	0.091	0.100
$TK_{norm_{i,1,t-1}}$ Below Median	0.094	0.102
$TK_{norm_{i,1,t-1}}$ Above Median	0.088	0.098
Difference	0.005	0.004
t-stat	(1.414)	(1.058)
Panel B: PGR - Short Traders		
Overall	0.110	0.108
$TK_{norm_{i,1,t-1}}$ Below Median	0.095	0.101
$TK_{norm_{i,1,t-1}}$ Above Median	0.125	0.115
Difference	-0.030	-0.015
t-stat	(-5.997)	(-3.106)
Panel C: PLR - Long Traders		
Overall	0.067	0.076
$TK_{norm_{i,1,t-1}}$ Below Median	0.058	0.075
$TK_{norm_{i,1,t-1}}$ Above Median	0.075	0.077
Difference	-0.017	-0.002
t-stat	(-5.697)	(-0.618)
Panel D: PLR - Short Traders		
Overall	0.088	0.071
$TK_{norm_{i,1,t-1}}$ Below Median	0.090	0.072
$TK_{norm_{i,1,t-1}}$ Above Median	0.086	0.069
Difference	0.004	0.003
t-stat	(1.207)	(1.124)

The table shows the average value of PGR$_{i,t}$ (Equation 3) and PLR$_{i,t}$ (Equation 4) within the quantile of $TK_{norm_{i,t-1}}$ for GOLD and CRUDEOIL contracts. Panel A and B show the values of PGR$_{i,t}$ for long and short investors respectively. Panel C and D shows the values of PLR$_{i,t}$ for long and short investors respectively. In each Panel, the first row indicates the average value in the group, the second row indicates the average value among the group when $TK_{norm_{i,1,t-1}}$ is below the median, the third row indicates the average value among the group when $TK_{norm_{i,1,t-1}}$ 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 the values between quantiles of $TK_{norm_{i,1,t-1}}$ (computed in fourth row). 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.

Table 7: GOLD - Price path and disposition bias

	Disposition Bias$_{i,t}$			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_{i,t}$	-0.0002^{***}	-0.0002^{***}	0.0002^{**}	0.0002^{**}
	(-4.782)	(-5.474)	(2.129)	(2.228)
$r_{i,t}$	3.314^{***}	3.424^{***}	-3.900^{***}	-4.006^{***}
	(10.428)	(12.358)	(-7.512)	(-8.360)
$r_{i,t-1}$	1.948^{***}	2.528^{***}	-2.288^{***}	-2.804^{***}
	(6.225)	(8.893)	(-5.771)	(-7.230)
$r_{i,t-2}$	0.374	0.914^{***}	-0.193	-0.659^{**}
	(1.424)	(3.854)	(-0.635)	(-2.144)
$TK_{norm_{i,1,t-1}}$		-0.023^{***}		0.022^{***}
		(-9.998)		(5.051)
$r_{i,1,t}$	-0.051^{*}	-0.018	0.194^{***}	0.154^{***}
	(-1.703)	(-0.688)	(5.064)	(4.299)
RV$_{i,1,t}$	-0.122^{**}	-0.048	0.135^{*}	0.046
	(-2.174)	(-0.988)	(1.941)	(0.703)
Constant	0.058^{***}	0.028^{***}	-0.004	0.028^{**}
	(5.953)	(3.050)	(-0.299)	(2.035)
Adjusted R^2	0.172	0.223	0.182	0.212

The table reports the result from regression of Disposition Bias$_{i,t}$ for GOLD contract for both long and short investors. Models 1 and 2 depict the results for long investors and models 3 and 4 depict the results for the short investors. Disposition Bias$_{i,t}$ (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. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 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. Heteroskedasticity and autocorrelation consistent robust standard errors are computed in the regression and the t-statistics are reported in parenthesis. Disposition Bias$_{i,t}$ and TK_{norm} are winsorized at 1% level. 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.

Table 8: CRUDEOIL - Price path and disposition bias

	Disposition Bias$_{i,t}$			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_{i,t}$	-0.0002^{**}	-0.0002^{**}	-0.0001	-0.00005
	(-2.078)	(-2.271)	(-0.691)	(-0.500)
$r_{i,t}$	2.335^{***}	2.398^{***}	-2.956^{***}	-3.009^{***}
	(13.247)	(13.665)	(-12.744)	(-12.925)
$r_{i,t-1}$	1.423^{***}	1.720^{***}	-1.314^{***}	-1.669^{***}
	(7.465)	(8.577)	(-6.734)	(-8.247)
$r_{i,t-2}$	0.498^{***}	0.768^{***}	-0.363^{*}	-0.708^{***}
	(3.045)	(4.532)	(-1.723)	(-3.383)
$TK_{norm_{i,1,t-1}}$		-0.014^{***}		0.017^{***}
		(-5.417)		(6.443)
$r_{i,1,t}$	-0.082^{***}	-0.095^{***}	0.053^{***}	0.070^{***}
	(-4.241)	(-4.998)	(2.688)	(3.742)
RV$_{i,1,t}$	-0.249^{**}	-0.284^{***}	-0.205	-0.170
	(-2.276)	(-2.679)	(-1.564)	(-1.367)
Constant	0.068^{***}	0.057^{***}	0.064^{***}	0.077^{***}
	(4.118)	(3.669)	(3.146)	(3.907)
Adjusted R^2	0.173	0.191	0.184	0.207

The table reports the result from regression of Disposition Bias$_{i,t}$ for CRUDEOIL contract for both long and short investors. Models 1 and 2 depict the results for long investors and models 3 and 4 depict the results for the short investors. Disposition Bias$_{i,t}$ (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. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 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. Heteroskedasticity and autocorrelation consistent robust standard errors are computed in the regression and the t-statistics are reported in parenthesis. Disposition Bias$_{i,t}$ and TK_{norm} are winsorized at 1% level. 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.

Table 9: Price path and PGR

	$PGR_{i,t}$			
	GOLD		CRUDEOIL	
	Long	Short	Long	Short
	(1)	(2)	(3)	(4)
Days to $Expiry_{i,t}$	-0.001^{***}	-0.0005^{***}	-0.001^{***}	-0.001^{***}
	(-15.621)	(-6.295)	(-8.054)	(-5.328)
$r_{i,t}$	2.999^{***}	-3.337^{***}	2.415^{***}	-3.472^{***}
	(10.034)	(-5.204)	(11.061)	(-10.212)
$r_{i,t-1}$	1.608^{***}	-1.607^{***}	0.895^{***}	-1.294^{***}
	(5.498)	(-5.017)	(3.909)	(-5.618)
$r_{i,t-2}$	0.732^{***}	-0.013	0.340^{*}	-0.308
	(3.251)	(-0.039)	(1.755)	(-1.419)
$TK_{norm_{i,1,t-1}}$	-0.016^{***}	0.017^{***}	-0.007^{**}	0.017^{***}
	(-7.074)	(3.301)	(-2.512)	(5.518)
$r_{i,1,t}$	0.006	0.147^{***}	-0.101^{***}	0.030
	(0.226)	(3.361)	(-4.193)	(1.414)
$RV_{i,1,t}$	0.079^{*}	0.034	-0.185^{*}	-0.180
	(1.694)	(0.451)	(-1.649)	(-1.247)
Constant	0.124^{***}	0.158^{***}	0.153^{***}	0.184^{***}
	(14.081)	(9.733)	(9.404)	(7.990)
Adjusted R^2	0.282	0.155	0.185	0.217

The table reports the result from regression of PGR_{it} (Equation 3). Model 1 and 2 depict the result for long and short investors in the GOLD contract respectively. Model 3 and 4 depict the result for long and short investors in the CRUDEOIL contract respectively. $PGR_{i,t}$ is the propensity for gain realization among the traders in contract i on date t. $r_{i,t}$ is the return on contract i on date t. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 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. $TK_{norm_{i,1,t-1}}$ is winsorized at 1% level. Heteroskedasticity and autocorrelation consistent robust standard errors are computed and the t-statistics are in parenthesis. 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.

Table 10: Price path and PLR

	$PLR_{i,t}$			
	GOLD		CRUDEOIL	
	Long	Short	Long	Short
	(1)	(2)	(3)	(4)
Days to $Expiry_{i,t}$	-0.0004^{***}	-0.001^{***}	-0.0004^{***}	-0.001^{***}
	(-9.738)	(-13.755)	(-6.555)	(-9.661)
$r_{i,t}$	-0.654^{*}	0.845^{***}	-0.011	-0.321
	(-1.895)	(3.346)	(-0.059)	(-0.825)
$r_{i,t-1}$	-0.976^{***}	1.206^{***}	-0.803^{***}	0.432^{**}
	(-5.347)	(4.447)	(-5.368)	(2.442)
$r_{i,t-2}$	-0.124	0.577^{***}	-0.418^{***}	0.349^{**}
	(-0.559)	(2.928)	(-2.815)	(1.963)
$TK_{norm_{i,1,t-1}}$	0.010^{***}	-0.006^{***}	0.007^{***}	-0.001
	(3.965)	(-2.652)	(3.681)	(-0.545)
$r_{i,1,t}$	0.029	-0.020	-0.006	-0.043^{**}
	(1.134)	(-0.788)	(-0.405)	(-2.554)
$RV_{i,1,t}$	0.117^{**}	0.001	0.115	0.018
	(2.547)	(0.015)	(1.369)	(0.184)
Constant	0.098^{***}	0.128^{***}	0.094^{***}	0.105^{***}
	(10.107)	(14.209)	(7.115)	(6.662)
Adjusted R^2	0.140	0.149	0.091	0.102

The table reports the result from regression of PLR_{it} (Equation 4). Model 1 and 2 depict the result for long and short investors in the GOLD contract respectively. Model 3 and 4 depict the result for long and short investors in the CRUDEOIL contract respectively. $PLR_{i,t}$ is the propensity for loss realization among the traders in contract i on date t. $r_{i,t}$ is the return on contract i on date t. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 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. $TK_{norm_{i,1,t-1}}$ is winsorized at 1% level. Heteroskedasticity and autocorrelation consistent robust standard errors are computed and the t-statistics are in parenthesis. 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.

Appendix

A Addition information on data

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 1.884 million trades are carried out in each contract. There are 20,551 unique traders in the market including the day traders. The average quantity per trade is 1.23 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 3.5 million trades in each CRUDEOIL contract, carried out by about 56,000 unique traders. The average traded quantity is 1.66 contracts (corresponding to 166 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

Table A2: Price path and Disposition Bias - Full Sample

	Disposition Bias$_{i,t}$			
	GOLD		CRUDEOIL	
	Long	Short	Long	Short
	(1)	(2)	(3)	(4)
Days to Expiry$_{i,t}$	-0.0001	0.0005^{***}	0.00002	0.001^{***}
	(-1.393)	(7.465)	(0.200)	(7.576)
$r_{i,t}$	5.667^{***}	-5.929^{***}	4.804^{***}	-5.495^{***}
	(12.541)	(-10.053)	(24.275)	(-26.978)
$r_{i,t-1}$	3.576^{***}	-3.860^{***}	2.289^{***}	-2.410^{***}
	(11.361)	(-9.722)	(11.702)	(-12.938)
$r_{i,t-2}$	0.136	-0.182	0.231	-0.360^{*}
	(0.410)	(-0.449)	(1.213)	(-1.767)
$TK_{norm_{i,1,t-1}}$	-0.041^{***}	0.049^{***}	-0.037^{***}	0.040^{***}
	(-11.474)	(9.129)	(-12.239)	(14.879)
$r_{i,1,t}$	-0.044	0.206^{***}	-0.221^{***}	0.142^{***}
	(-1.142)	(5.014)	(-10.370)	(7.328)
RV$_{i,1,t}$	-0.052	-0.031	-0.317^{**}	-0.180
	(-0.772)	(-0.350)	(-2.221)	(-1.475)
Constant	0.014	0.047^{***}	0.044^{**}	0.078^{***}
	(1.206)	(3.172)	(2.033)	(4.083)
Adjusted R^2	0.255	0.278	0.278	0.323

The table reports the result from regression of DE_{it} (Equation 2). Model 1 and 2 depict the result for long and short investors in the GOLD contract respectively. Model 3 and 4 depict the result for long and short investors in the CRUDEOIL contract respectively. $DE_{i,t}$ is the disposition bias among the traders in contract i on date t. $r_{i,t}$ is the return on contract i on date t. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 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. $TK_{norm_{i,1,t-1}}$ is winsorized at 1% level. Heteroskedasticity and autocorrelation consistent robust standard errors are computed and the t-statistics are in parenthesis. In these four regressions, we are considering the full sample of traders except the trades made by the day traders.

Table A3: Price path and Disposition Bias - Holding Period at least 10 Days

	Disposition Bias$_{i,t}$			
	GOLD		CRUDEOIL	
	Long	Short	Long	Short
	(1)	(2)	(3)	(4)
Days to Expiry$_{i,t}$	-0.0001^{***}	0.0003^{***}	-0.0001^{*}	0.0001
	(-3.073)	(5.056)	(-1.723)	(0.787)
$r_{i,t}$	3.373^{***}	-3.757^{***}	2.292^{***}	-2.809^{***}
	(11.257)	(-8.897)	(17.002)	(-15.697)
$r_{i,t-1}$	2.876^{***}	-2.969^{***}	1.280^{***}	-1.419^{***}
	(7.673)	(-6.521)	(7.716)	(-9.193)
$r_{i,t-2}$	0.842^{***}	-0.730^{**}	0.326^{**}	-0.598^{***}
	(3.191)	(-2.430)	(2.206)	(-3.658)
$TK_{norm_{i,1,t-1}}$	-0.020^{***}	0.018^{***}	-0.010^{***}	0.010^{***}
	(-7.904)	(4.718)	(-3.856)	(3.713)
$r_{i,1,t}$	-0.004	0.112^{***}	-0.058^{***}	0.053^{***}
	(-0.144)	(3.233)	(-2.936)	(2.739)
RV$_{i,1,t}$	-0.061	0.093	-0.427^{***}	-0.155
	(-1.260)	(1.624)	(-3.388)	(-1.216)
Constant	0.021^{**}	0.005	0.077^{***}	0.056^{***}
	(2.388)	(0.440)	(4.023)	(2.787)
Adjusted R^2	0.188	0.201	0.133	0.159

The table reports the result from regression of DE_{it} (Equation 2). Model 1 and 2 depict the result for long and short investors in the GOLD contract respectively. Model 3 and 4 depict the result for long and short investors in the CRUDEOIL contract respectively. $DE_{i,t}$ is the disposition bias among the traders in contract i on date t. $r_{i,t}$ is the return on contract i on date t. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 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. $TK_{norm_{i,1,t-1}}$ is winsorized at 1% level. Heteroskedasticity and autocorrelation consistent robust standard errors are computed and the t-statistics are 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

Table A4: Gold - Comparison of disposition among investors with different trade value

	$DE_{i,t}$			
	Long		Short	
	Above Median Average Trade	Below Median Average Trade	Above Median Average Trade	Below Median Average Trade
	(1)	(2)	(3)	(4)
Days to $Expiry_{i,t}$	-0.001^{***}	0.0001	0.0005^{***}	-0.0001
	(-9.944)	(0.898)	(4.996)	(-0.648)
$r_{i,t}$	5.116^{***}	1.613^{***}	-5.378^{***}	-2.929^{***}
	(13.622)	(3.914)	(-8.482)	(-5.847)
$r_{i,t-1}$	3.364^{***}	1.492^{***}	-3.671^{***}	-2.064^{***}
	(7.309)	(4.984)	(-5.875)	(-6.108)
$r_{i,t-2}$	1.231^{***}	0.778^{***}	-1.166^{***}	-0.494
	(3.521)	(3.401)	(-2.900)	(-1.591)
$TK_{norm_{i,1,t-1}}$	-0.029^{***}	-0.024^{***}	0.030^{***}	0.025^{***}
	(-8.832)	(-6.329)	(6.088)	(5.368)
$r_{i,1,t}$	-0.020	0.029	0.147^{***}	0.132^{***}
	(-0.523)	(1.011)	(3.138)	(3.024)
$RV_{i,1,t}$	-0.050	-0.021	0.090	-0.010
	(-0.720)	(-0.359)	(1.024)	(-0.129)
Constant	0.088^{***}	-0.017	-0.017	0.060^{***}
	(6.751)	(-1.526)	(-0.969)	(4.030)
Adjusted R^2	0.288	0.089	0.257	0.142

The table reports the result from regression of Disposition $Bias_{i,t}$ for GOLD contract among the set of investors divided based on the average trade value. Models 1 and 2 depict the results for long investors and models 3 and 4 depict the results for the short investors. In model 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 model 2 and 4, the sample is the set of investors whose average trade value ($N_{contracts} \times Price$) is below the median trade value. Disposition $Bias_{i,t}$ (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. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 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. Heteroskedasticity and autocorrelation consistent robust standard errors are computed in the regression and the t-statistics are reported in parenthesis. Disposition $Bias_{i,t}$ and TK_{norm} are winsorized at 1% level. 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.

Table A5: CRUDEOIL - Comparison of disposition among investors with different trade value

	$DE_{i,t}$			
	Long		Short	
	Above Median Average Trade	Below Median Average Trade	Above Median Average Trade	Below Median Average Trade
	(1)	(2)	(3)	(4)
Days to $Expiry_{i,t}$	-0.001^{***}	0.0004^{***}	0.0004^{***}	-0.0002^{*}
	(-6.292)	(3.086)	(3.192)	(-1.841)
$r_{i,t}$	3.241^{***}	1.484^{***}	-3.569^{***}	-2.615^{***}
	(14.664)	(6.490)	(-13.244)	(-9.128)
$r_{i,t-1}$	2.080^{***}	1.493^{***}	-1.890^{***}	-1.428^{***}
	(8.821)	(7.121)	(-7.887)	(-5.632)
$r_{i,t-2}$	0.836^{***}	0.915^{***}	-0.463^{*}	-0.839^{***}
	(3.850)	(4.740)	(-1.920)	(-3.767)
$TK_{norm_{i,1,t-1}}$	-0.017^{***}	-0.012^{***}	0.025^{***}	0.012^{***}
	(-5.341)	(-3.535)	(6.566)	(4.055)
$r_{i,1,t}$	-0.120^{***}	-0.084^{***}	0.085^{***}	0.012
	(-4.747)	(-3.268)	(3.731)	(0.476)
$RV_{i,1,t}$	-0.279^{*}	-0.534^{***}	-0.260	-0.108
	(-1.803)	(-3.080)	(-1.624)	(-0.779)
Constant	0.105^{***}	0.043^{*}	0.062^{**}	0.078^{***}
	(4.686)	(1.767)	(2.435)	(3.552)
Adjusted R^2	0.227	0.155	0.225	0.177

The table reports the result from regression of Disposition $Bias_{i,t}$ for CRUDEOIL contract among the set of investors divided based on the average trade value. Models 1 and 2 depict the results for long investors and models 3 and 4 depict the results for the short investors. In model 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 model 2 and 4, the sample is the set of investors whose average trade value ($N_{contracts} \times Price$) is below the median trade value. Disposition $Bias_{i,t}$ (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. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 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. Heteroskedasticity and autocorrelation consistent robust standard errors are computed in the regression and the t-statistics are reported in parenthesis. Disposition $Bias_{i,t}$ and TK_{norm} are winsorized at 1% level. 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.

Table A6: GOLD - Price path and disposition bias, $\rho = 0.91$

	$\mathrm{DE}_{i,t}$			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to $\mathrm{Expiry}_{i,t}$	-0.0002^{***}	-0.0002^{***}	0.0002^{**}	0.0001^{**}
	(-4.782)	(-5.460)	(2.129)	(2.189)
$r_{i,t}$	3.314^{***}	3.420^{***}	-3.900^{***}	-4.032^{***}
	(10.428)	(12.027)	(-7.512)	(-8.476)
$r_{i,t-1}$	1.948^{***}	2.650^{***}	-2.288^{***}	-3.041^{***}
	(6.225)	(8.806)	(-5.771)	(-7.484)
$r_{i,t-2}$	0.374	1.013^{***}	-0.193	-0.863^{***}
	(1.424)	(4.093)	(-0.635)	(-2.768)
$TK_{norm_{i,1,t-1}}$		-0.015^{***}		0.017^{***}
		(-8.506)		(5.527)
$r_{i,1,t}$	-0.051^{*}	-0.029	0.194^{***}	0.162^{***}
	(-1.703)	(-1.084)	(5.064)	(4.525)
$\mathrm{RV}_{i,1,t}$	-0.122^{**}	-0.066	0.135^{*}	0.058
	(-2.174)	(-1.300)	(1.941)	(0.896)
Constant	0.058^{***}	0.040^{***}	-0.004	0.020
	(5.953)	(4.318)	(-0.299)	(1.561)
Adjusted R^2	0.172	0.211	0.182	0.213

The table reports the result from regression of Disposition $\mathrm{Bias}_{i,t}$ for GOLD contract for both long and short investors. Models 1 and 2 depict the results for long investors and models 3 and 4 depict the results for the short investors. Disposition $\mathrm{Bias}_{i,t}$ (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. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 in contract i on date $t-1$, using value of $\rho = 0.91$. $r_{i,1,t}$ is the cumulative return in the contract i from date 1 to date t. $\mathrm{RV}_{i,1,t}$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. Heteroskedasticity and autocorrelation consistent robust standard errors are computed in the regression and the t-statistics are reported in parenthesis. Disposition $\mathrm{Bias}_{i,t}$ and TK_{norm} are winsorized at 1% level. 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.

Table A7: GOLD - Price path and disposition bias, $\rho = 0.99$

	$\mathrm{DE}_{i,t}$			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_{i,t}$	-0.0002^{***}	-0.0002^{***}	0.0002^{**}	0.0002^{**}
	(-4.782)	(-5.146)	(2.129)	(2.209)
$r_{i,t}$	3.314^{***}	3.384^{***}	-3.900^{***}	-3.946^{***}
	(10.428)	(11.837)	(-7.512)	(-7.892)
$r_{i,t-1}$	1.948^{***}	2.195^{***}	-2.288^{***}	-2.439^{***}
	(6.225)	(7.595)	(-5.771)	(-6.311)
$r_{i,t-2}$	0.374	0.597^{**}	-0.193	-0.323
	(1.424)	(2.523)	(-0.635)	(-1.061)
$TK_{norm_{i,1,t-1}}$		-0.070^{***}		0.048^{***}
		(-8.664)		(3.515)
$r_{i,1,t}$	-0.051^{*}	-0.037	0.194^{***}	0.180^{***}
	(-1.703)	(-1.392)	(5.064)	(4.901)
$\mathrm{RV}_{i,1,t}$	-0.122^{**}	-0.096^{**}	0.135^{*}	0.104
	(-2.174)	(-1.985)	(1.941)	(1.570)
Constant	0.058^{***}	-0.016	-0.004	0.049^{**}
	(5.953)	(-1.301)	(-0.299)	(2.551)
Adjusted R^2	0.172	0.207	0.182	0.194

The table reports the result from regression of Disposition Bias$_{i,t}$ for GOLD contract for both long and short investors. Models 1 and 2 depict the results for long investors and models 3 and 4 depict the results for the short investors. Disposition Bias$_{i,t}$ (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. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 in contract i on date $t-1$, using value of $\rho = 0.99$. $r_{i,1,t}$ is the cumulative return in the contract i from date 1 to date t. $\mathrm{RV}_{i,1,t}$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. Heteroskedasticity and autocorrelation consistent robust standard errors are computed in the regression and the t-statistics are reported in parenthesis. $\mathrm{DE}_{i,t}$ and $TK_{norm_{i,1,t-1}}$ are winsorized at 1% level. 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.

Table A8: GOLD - Price path and disposition bias, $\rho = 0.95$, with contract and year fixed effects

	$\text{DE}_{i,t}$			
	Long		Short	
	(1)	(2)	(3)	(4)
Days to Expiry$_{i,t}$	-0.0004^{***}	-0.0004^{***}	0.0003^{*}	0.0002
	(-3.623)	(-3.543)	(1.895)	(1.599)
$r_{i,t}$	3.718^{***}	3.636^{***}	-4.260^{***}	-4.165^{***}
	(13.245)	(13.432)	(-8.661)	(-8.762)
$r_{i,t-1}$	2.199^{***}	2.532^{***}	-2.565^{***}	-2.886^{***}
	(8.043)	(9.397)	(-6.945)	(-7.773)
$r_{i,t-2}$	0.657^{***}	0.949^{***}	-0.486^{*}	-0.762^{***}
	(3.047)	(4.194)	(-1.664)	(-2.609)
$TK_{norm_{i,1,t-1}}$		-0.018^{***}		0.019^{***}
		(-5.379)		(3.733)
$r_{i,1,t}$	-0.474^{***}	-0.300^{***}	0.548^{***}	0.342^{***}
	(-9.437)	(-5.201)	(7.692)	(4.078)
$\text{RV}_{i,1,t}$	-1.059^{***}	-0.911^{**}	0.787	0.521
	(-2.738)	(-2.467)	(1.456)	(1.044)
Constant	0.208^{***}	0.152^{***}	-0.058	0.016
	(3.893)	(2.864)	(-0.728)	(0.213)
Adjusted R^2	0.245	0.261	0.267	0.278

The table reports the result from regression of Disposition Bias$_{i,t}$ for GOLD contract for both long and short investors. Models 1 and 2 depict the results for long investors and models 3 and 4 depict the results for the short investors. Disposition Bias$_{i,t}$ (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. $TK_{norm_{i,1,t-1}}$ is computed as per Equation 10 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. $\text{RV}_{i,1,t}$ is the cumulative 5 minute realized volatility of the contract i from date 1 to date t. Heteroskedasticity and autocorrelation consistent robust standard errors are computed in the regression and the t-statistics are reported in parenthesis. In all the models the analysis is run with contract and year level fixed effects. $\text{DE}_{i,t}$ and $TK_{norm_{i,1,t-1}}$ are winsorized at 1% level. 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.