DISPOSITION EFFECT – BEHAVIOURAL EVIDENCE FROM CONSECUTIVE TRADES WITHIN A DYNAMIC PANEL QUANTILE REGRESSION WITH ATTRITION

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Abstract
The disposition effect has been found in a wide range of investment fields, but the underlying causes remain unclear. This paper investigates the disposition effect in an under-researched but increasingly significant field: retail currency traders. The properties of the FX market allow us to use novel methods to measure and model the disposition effect, and the very short timescales typical of these currency trades allow us to identify differences in the degree of disposition effect over successive trading days. Using an innovative panel quantile regression with fixed effects and sample selection, we find that realizing a loss on one trading day significantly increases the disposition effect on the next trading day, as traders become even less likely to close a loss-making position. This is evidence that the disposition effect cannot be adequately explained by preference-based theories and must instead be attributed to behavioural effects such as depletion of self-control or realisation utility which becomes more negative following previous losses.

*Keywords:* disposition effect, foreign exchange, conditional skewness, quantile regression.

*JEL Classification:* G10, G11
DISPOSITION EFFECT - BEHAVIOURAL EVIDENCE FROM CONSECUTIVE TRADES WITHIN A DYNAMIC PANEL QUANTILE REGRESSION WITH ATTRITION

1. Introduction
The disposition effect is the tendency for investors to be quicker to sell winners (assets that have risen in price since they bought them) than losers (which have generated losses). The effect has been found among investors in a range of asset markets.

Identifying why the disposition effect comes about has been more challenging. The effect tends to increase downside volatility whilst limiting upside volatility, giving an increased negative skew to the distribution of investor wealth which would be welfare-reducing under many plausible utility functions. It also goes directly against the old investment adage: “cut your losses, but let your profits run”, often attributed to economist David Ricardo (1772-1823).

We investigate the disposition effect among retail FX traders. The contribution of this paper is threefold: (i) Using the unique properties of the FX market to introduce a new method for measuring the disposition effect by inferring it from the skew in the distribution of traders’ returns (Section 3); (ii) A novel econometric model using conditional quantiles in panel data (Section 5); (iii) Using the resulting empirical evidence to assess the competing behavioural hypotheses which might explain the disposition effect (Section 7).

Our empirical model introduces a novel robust measure of the disposition effect based on a dynamic panel quantile regression model, which accounts for (i) the panel characteristics of the data, (ii) unobserved trader heterogeneity, (iii) the potential endogeneity between the decision to quit trading and the disposition effect. Our approach allows us to investigate – at individual trader level – the impact of various trade characteristics on the dynamics of the disposition effect.
In particular, it allows for (iv) inference on both the conditional quantiles and skewness of the realized returns and (v) the investigation of how past losses shape the disposition effect over the profit and loss region.

Our empirical results show that the disposition effect becomes more pronounced following losses on preceding trades. This is very difficult to square with explanations (such as conventional prospect theory) which are based on an underlying utility function, since such preferences are generally assumed to be relatively stable. The disposition effect is instead best attributed to behavioural effects such as depletion of self-control or realisation utility which is exacerbated by previous losses.

2. Literature review

The disposition effect has been found among investors in many different markets: equities (Shefrin and Statman (1985), Grinblat and Keloharju, 2001, Seasholes and Feng, 2005, Cici, 2011); bonds (Coval and Shumway, 2005); foreign exchange (Nolte, 2012, Hayley and Marsh, 2016); real estate (Genesove and Mayer 2001, Crane and Hartzell, 2010); in experimental studies (Weber and Camerer, 1998, Fogel and Berry, 2006, Da Costa et al, 2013) and among futures traders (Locke and Mann, 2005, Choe and Eom, 2009).

Shefrin and Statman (1985) hypothesised four factors to explain why the disposition effect comes about: prospect theory, mental accounting, regret aversion and self-control. They argue that the shape of the prospect theory value function gives an incentive for investors to hold on to assets which have fallen in value (because of the convexity of the value function over losses), whilst the concavity of the section related to profitable positions would make traders risk averse, increasing their tendency to sell assets which have risen in price. This argument was widely adopted (e.g. Weber and Camerer, 1998, and Grinblatt and Han, 2005).
Subsequent research showed that the implications of prospect theory were not so straightforward. Barberis and Xiong (2009) demonstrated that for some parameter values prospect theory generates a disposition effect, but for other plausible parameter values it generates the opposite. Kaustia (2010) showed that for conventional parameters prospect theory predicts a gradual reduction in the incentive to sell a stock as the price moves in either direction from the purchase price, yet empirical data instead shows a sharp rise in the probability of liquidation at the break-even price, and little sensitivity to the price at other points. Hens and Vlcek (2011) showed that the parameters required for the prospect theory value function to generate a disposition effect are unlikely to be consistent with buying assets in the first place.

The wider literature on investor risk appetite helps explain the variance of investor returns. By contrast, the disposition effect suggests that investor risk-taking is asymmetric in the positive and negative parts of the return distribution. Risk appetite can be regarded as addressing the second moment of the return distribution, and the disposition effect the third moment. Indeed, we argue below that in the FX markets that we study, the skew of the return distribution can be regarded as a direct indication of the size of the disposition effect.

The disposition effect in FX markets has been subject to comparatively little study. O’Connell and Teo (2009) find no disposition effect among institutional FX traders. Nolte (2012) investigates retail FX traders similar to ours, but finds a reverse disposition effect (investors tending to close loss-making positions more rapidly than profitable ones) which can be attributed to the widespread use of pre-placed stop-loss orders. This is a confounding factor which is not found to be significant among the traders in our data. We discuss the interpretation of this factor further in section 7.3 below.
Odean (1998) and Barber and Odean (1999) considered a wide range of factors which might underlie the disposition effect, but reject explanations based on taxes (which give an incentive to realise losses rather than gains), portfolio rebalancing and transaction costs.

Aversion to emotional pain has also been hypothesised to play a role in driving the disposition effect. Shefrin and Statman (1985) suggest regret aversion as such a factor. Consistent with this, Strahilevitz et al. (2011) find that investors tend to avoid repurchasing stocks which they previously sold at a loss. This is argued to be because the memory of the emotional pain caused by the loss leaves the investor averse to holding these particular equities in the future. However, it could also be regarded as a rational response, as the losses made on stocks which unexpectedly fell in value could convince traders that they have limited ability to forecast returns for these stocks, so they choose different equities in future.

We study the disposition effect among retail traders in the foreign exchange (FX) markets. This is an increasingly important market and, as discussed below, the specific properties of the FX market allow us to take a very different approach to measuring and modelling the disposition effect. Furthermore, the disposition effect has mainly been explored in assets which are held over relatively long horizons, whereas our dataset covers short-term trades. This allows us to identify changes in the scale of the disposition effect over consecutive trades. This gives us new evidence on the plausibility of different possible underlying causes of the effect.

3. Measuring Disposition in FX Markets
The unique properties of the FX market allow us to measure the disposition effect in a new way. Previous research measured the effect using data on investors’ asset holdings and trades, either (i) by comparing the proportion of the portfolio assets which have risen in price that are subsequently sold with the corresponding proportion of the assets which have fallen in price (the proportion of gains realised versus the proportion of losses realised); or (ii) by comparing the
length of time that the investor holds profitable and unprofitable investments. The approach taken in this paper is entirely different, and relies on the properties which make FX trading very different from trading traditional asset classes.

For illustration, suppose that asset returns follow a random walk with zero drift, recording a return of \(+d\) or \(-d\) in each period and that the investor chooses to sell assets as soon as they record a profit of \(+d\), but continues to hold them if they record a corresponding loss. At the end of the first period a significant number of small profits are realised. The loss-making assets are retained: in future periods some of these will continue to fall and be realised at a larger loss, but a few will subsequently rebound and be realised at a profit. This results in a negatively skewed distribution of realised returns, with a relatively large number of small profits, but a smaller number of larger losses. Specifically, if the investor sold assets as soon as they reached \(+d\) or \(-2d\), then eventually (almost) all assets would have drifted to one or other of these limits and the investor would have realised a large number of holdings at a profit of \(+d\) and half that number at \(-2d\), giving a distribution of realised gains with a positive mode, but a substantial negative skew and zero mean (since in this random walk without drift investor behaviour has no effect on expected profits in any period).

This shows that the disposition effect tends to give rise to a negative skew in realised returns even if there is no such skew in the underlying asset return. For most asset classes we know that the underlying asset returns also have a negative skew, with crashes tending to be more sudden and severe than booms, but less frequent. The disposition effect will tend to result in an even larger skew in realised returns, but any empirical investigation will need to distinguish how much of this skew was due to the disposition effect and how much was inherent in the asset returns themselves.
This identification problem is not present in the FX markets. We can see empirically that there has been very little skew in the distribution of returns for exchange rates between the major currencies. There is also a more fundamental point: it is just as natural for traders to take a short position in an exchange rate as a long position. Indeed, the terms long and short are entirely arbitrary in FX markets. This means that even if, for example, the empirical distribution of returns for EUR/USD happened to be skewed, the distribution of possible trading returns available to traders on long and short positions in this market would nevertheless be symmetrical. By contrast, investors in other asset markets are overwhelmingly long, so the negative skew in asset returns will feed through into realised returns even if there is no disposition effect.

This gives a strong a priori case for regarding the underlying distribution of returns on the trades that could be opened by investors as symmetrical. When we observe that the distribution of the returns realised by investors is negatively skewed, this must instead be because investors tended to close profitable positions more rapidly than losses. Thus in FX trading, unlike traditional asset markets, a skew in the distribution of realised returns can be attributed directly to the disposition effect.

Finally, note that in the FX markets this skew in the distribution of realised returns can be expected to feed into the distribution of overall investor returns. If a trader immediately replaced each asset sold with a new asset with similar risk characteristics, then the disposition effect would lead the distribution of realised returns to differ from the distribution of unrealised returns, but the distribution of overall portfolio returns (realised or unrealised) is not affected. This would be the case for equity investors who swap one share for another whilst maintaining constant overall risk exposure, but is far from being true for FX traders. Equity investors might try to “pick winners”, but FX traders must choose from a much more limited number of distinct FX risks, and instead generally seek to generate returns by timing the market. Indeed the majority of trading in our dataset is in EUR/USD, and many individuals are pure day traders who return to zero
exposure at the end of each day. Thus for FX traders the disposition effect in realising returns should be expected to feed through into the distribution of overall trading returns.

The fact that FX positions are typically held over very short horizons gives us a large number of consecutive trades, where a new position is opened after the previous position is closed. This is in stark contrast to assets such as equities where holding periods are typically far longer, and different assets are typically held simultaneously. This means that a very natural question to address in our dataset is whether the scale of the disposition effect is affected by recent trading profits or losses. We find that it is affected, and this fact is very powerful in allowing us to assess the relative plausibility of the different behavioural factors which might be driving the disposition effect.

Preference-based explanations of the disposition effect (such as those based on prospect theory) assume that investors exhibit narrow framing: that rather than caring only about the profit/loss on their portfolio as a whole, the profit/loss on individual assets also has a direct impact on investor utility. This is a questionable assumption for equity assets which are held in a portfolio simultaneously. By contrast, FX trading is more often a sequence of individual trades, so narrow framing seems a more natural assumption

Finally, three possible underlying causes of the disposition effect can be readily rejected for our dataset:

(i) Transaction costs have been suggested as a possible cause (Harris 1988), since the reduced price of losing stocks is likely to result in transactions costs rising as a proportion of this lower price, which would rationally discourage their sale. However, our study finds a strong disposition effect even though FX trading costs are tiny (averaging just under 0.01% of trade volume) and holding periods typically very short.
(ii) No taxes are imposed.

(iii) Portfolio rebalancing had been suggested as a possible cause of the disposition effect, with investors selling some of their holding of stocks which have outperformed (and hence now have higher portfolio weight), whilst retaining those that have underperformed (Lakonishok and Shmidt, 1986). However, even on the questionable assumption that traders look at their FX positions in the context of their exposures to other asset markets, the short-term trades seen in our datasets would imply that any such rebalancing effects would be tiny.

4. Data
The data used in this study comes from a large online retail FX trading platform which wishes to remain anonymous. The dataset records for each trader: (i) the number of trades placed each day; (ii) the total daily trading volume (US dollar equivalent - multiple trades within a single trading day are not recorded separately), and (iii) the resulting daily profit/loss for each trader (open trades are marked to market at the end of each day, so this data aggregates both realised and unrealised returns). The platform allows trading in all major currencies, although most trades are in the euro-dollar exchange rate. All trading is for real money, and hence is potentially subject to the various behavioural factors underpinning risk aversion and disposition. After cleaning, this dataset contains data for over 70,000 traders between 4 January 2010 and 29 June 2012.

Trading is on margin, allowing traders to take substantial positions after depositing only limited funds. This suggests that trading is likely to be largely motivated by speculative motives. By contrast, trading in other asset markets is more likely to be affected by liquidity needs, as traders invest funds that have been saved, or draw down cash to fund income shortfalls. In principle, the closure of loss-making FX trades could be triggered if the trader is unwilling to fund a margin call. However, if this effect was significant it would tend to reduce the observed disposition effect. The fact that we nevertheless observe a substantial disposition effect – and one which is exacerbated
by prior losses – suggests that positions are seldom closed because of margin calls, and that the skew in the distribution of daily returns is instead largely driven by behavioural effects. Thus the relative absence of liquidity effects in FX trading helps us to identify the behavioural effects at work here.

Hayley & Marsh (2016) used same dataset, and found that the average trade loses an amount approximately equal to the spread, consistent with traders on average having no trading skill. Traders quit trading at a fairly rapid rate, with each trading loss increasing the probability of quitting. This is consistent with traders behaving fairly rationally as they learn from experience, quitting as they discover that trading is less profitable (and perhaps less enjoyable) than they had initially assumed. We model this quitting rate explicitly in order to avoid attrition bias.

5. Econometric Model
We measure the extent to which each trader exhibits the disposition effect by looking at the conditional skewness of his/her distribution of realized returns. Several measures and models of the conditional skewness have been proposed in the literature in the context of time series data, see for example Leon, Rubio and Serna (2004), White et al. (2008). We extend Bowley’s (1920) coefficient to a panel data setting using the following robust quantile-based measure of conditional skewness:

\[ SK = \frac{q_{3,t} - q_{1,t} - 2q_{2,t}}{q_{3,t} - q_{1,t}} \]  

(1)

Where \( q_{1,t}, q_{2,t} \) and \( q_{3,t} \) denote respectively the first, the second and third quantiles of the individual investors’ profit and loss conditional distribution. The use of conditional quantiles allows us to model the disposition effect exploiting the dynamic evolution of individuals’ trading performances and incorporating information on their characteristics. To model the evolution of the individual quantiles we propose a parametric dynamic panel quantile regression model with
fixed effect. Let $i=1,...,N$ denote the $i$th trader. The $\tau$-th conditional quantile function of the $t$-th observation on the $i$-th individual, $y_{i,t}$, can be represented as:

$$Q_{yt}(\tau|x_{it},\eta_i,y_{i,t-1}) = q_{t,i,t} = \eta_i + \theta'(\tau)y_{i,t-1} + \beta'(\tau)x_{it}$$

(2)

where $y'_{i,t-1} = (y^+_{i,t-1}, y^-_{i,t-1}, y^0_{i,t-1}, y^+_A, y^-_A, y^0_A)$ is a vector that contains information about the past trading performance of the $i$-th trader at time $t$, where $y^+_{i,t-1} = y_{i,t-1}1(y_{i,t-1} > 0)$, $y^-_{i,t-1} = y_{i,t-1}1(y_{i,t-1} < 0)$, $y^0_{i,t-1} = y_{i,t-1}1(y_{i,t-1} = 0)$ capture whether on the previous trading day the trader had a positive, negative or zero profit and $y^+_A, y^-_A, y^0_A$ indicate whether the average the previous five trading days from $t-2$ to $t-6$ brought a positive, negative or zero profit. This latter variable affects the trader’s perception of his/her own abilities. The vector $x_{it}$ contains exogenous variables, and $\eta_i$ identifies the individual fixed effect. The model should be seen as the reduced form approximation of the “true” conditional quantile function under the assumption that the conditional quantiles can be expressed as linear and separable functions of the covariates. The impacts of all the covariates varies across quantiles but we assume that the individual effect does not represent a distributional shift. In the model $\eta_i$ is a pure location shift effect on the conditional profit and loss distribution of the $i$-th trader. We impose that it is independent across quantiles by estimating model (2) for several quantiles simultaneously.

A source of concern in our application is the attrition in the panel. During our sample period some traders quit trading altogether, and the decision to quit might be driven by some or all of the factors in the reduced form quantile regression. Failure to account for this “non-ignorable” selection rule (Baltagi and Song, 2006) is well known to lead to endogeneity and inconsistent estimates of the parameters of interest, which are confounded with the parameters that determine the probability of attrition. We model the probability of each trader quitting using a first stage selection equation:

$$Q_{it} = 1(z'_{it}y + \alpha_i + \nu_{it} > 0)$$

(3)
where the decision of the $i$-th trader at time $t$ whether to quit or to continue trading, defined through the indicator function $1(.)$ in eq(3), depends on a linear index and an unobserved time constant additive individual effect. The vectors $x_{it}$ and $z_{it}$ are vectors of strictly exogenous explanatory variables which may contain common variables, however identification by exclusion restriction scheme requires equation (3) to contain at least one time variant variable which is not included in the main equation (Kyriziadou 2009). We follow Hayley and Marsh (2016) and use the proportion of traders in the trader in question’s city that trade on day $t$ ($PropActive_t$).

It is well known that identification and estimation of panel quantile regression models with unobserved heterogeneity are quite challenging. The standard methods of differencing out fixed effect are no longer applicable since quantiles are highly non-linear objects, i.e. the quantile of the differences is generally not equal to the difference in quantiles. Several estimation and identification strategies have been suggested in the static panel fixed effect quantile literature. Lamarche (2006) and Geraci and Bottai (2008) suggest a penalized quantile regression estimator that simultaneously estimates quantile regression coefficients and fixed effects. Canay (2010) introduces a two step procedure where the unobserved fixed effects are estimated at the first step. Ponomareva (2010) proposes a moment-based approach based on the random coefficient model (see Graham, Hahn and Powell, 2009). In the context of a dynamic data generating processes, under the assumption that fixed effects represent pure location shifts, we estimate the parameter of interest, namely $(\theta(\tau), \beta(\tau))$, using the quantile regression dynamic panel instrumental variable (PQRIV) estimator proposed by Galvao (2011), which adapts the instrumental variable estimator of Chernozhukov and Hansen (2008). The estimator corrects the bias induced by the unobservable initial conditions of the process using instruments from inside the model, i.e. using lagged values of the regressors which are correlated with the included regressors and uncorrelated with the disturbances. We instrument a positive/negative/zero profit at time $t-1$ for the $i$-th trader with the first positive/negative/zero lagged profit of the trader and
we select analogous internal instruments for the trader’s career success rate. All estimation is carried out in Matlab and codes are available upon request from the authors.

6. Results
Table 1 reports the results of the fixed effect panel Probit selection equation with the best predictive likelihood. Identification by exclusion restrictions is ensured by the presence of the variables PropActive, which displays significant time variability, and by a non-linear function of a significant regressor, the daily number of trades. The probability of quitting trading is estimated by quasi maximum likelihood methods. Equation (3) is a highly non-linear equation estimated to control for attrition in the panel, but it displays strong predictive power and its findings are in line with those in Hayley and Marsh (2016). The estimates suggest that the decision to quit is significantly influenced by performance on the most recent trading day; a loss on the most recent trading day significantly increases the probability of quitting trading. Similarly, the cumulative success rate to date exerts a negative influence – the better the success rate the less likely it is that the trader will quit. Exogenous controls number of trades and PropActive appear significant. Using the estimated probability of quitting from model (3), we construct the inverse Mills’ ratios:

\[ IM_{it} = \frac{\phi(z'_{it} \hat{y})}{1 - \Phi(z'_{it} \hat{y})} \] (4)

which are included as instruments in the main outcome equation. Estimation results for the reduced forms of the quantile functions are reported in Table 1 with bootstrapped p-values and post estimation diagnostic tests. The significance of the estimated coefficients of the inverse Mills’ ratios confirms the presence of attrition-type endogeneity. Estimation results show that the outcome of the most recent trade impacts significantly on all the quantiles: a recent loss reduces the first two quantiles and increases the third, a recent profit has opposite sign effect on the quantiles. A zero recent profit appears to have negligible influence on the conditional quantiles.
A similar pattern of influence is observed for the cumulative success rate to date. Our findings suggest that losses impact the conditional quantiles to a larger extent than profits and that recent trading performance has a stronger impact than cumulative performance to date. The results from Table 2 allow us to shed some light on the impact of the covariates on the conditional skewness of the trader’s profit and loss distribution. The marginal effect of each covariate on our measure of skewness is evaluated by the partial derivative of (1) with respect to the covariate of interest. For example, the impact of a negative recent trade on the conditional skewness (full derivations are reported in Appendix 1) is found as:

\[
\frac{1}{(q_{3,t} - q_{1,t})^2} \left[ (q_{3,t} - q_{1,t})(\theta_{31} + \theta_{11} - 2\theta_{21}) - (q_{3,t} + q_{1,t} - q_{2,t})(\theta_{31} + \theta_{11}) \right].
\]

Since the term \((q_{3,t} - q_{1,t})\) is positive and the term \((q_{3,t} + q_{1,t} - q_{2,t})\) is negative, the impact of the most recent trade loss on the disposition effect is estimated as negative. The overall calculations of the corresponding partial derivatives for all the controls show that (i) the outcome of the most recent trade impacts on conditional skewness more significantly than the career success rate; (ii) losses during the last trade significantly increase the disposition effects of those traders that do not quit trading; (iii) a profit in the most recent trades reduces the disposition effect but to a smaller degree than the increase brought by a loss.

7. Interpretation

Behavioural finance is a rich theoretical field, so we can identify several possible effects which might be candidates to explain the disposition effect. In this section we discuss the extent to which these different theories are consistent with our finding that the disposition effect is strongly increased by recent losses. We consider (i) the general process by which traders adjust their forecasts of future exchange rate movements in response to new information since the trade was placed (e.g. a belief in mean reversion), and adjust their confidence in their own
forecasts; (ii) the specific role which could be played by the gambler’s fallacy; (iii) realisation utility and depletion of self control; and (iv) dynamic loss aversion and dynamic realisation utility.

7.1 Mean Reversion and Updating of Forecasts
Previous studies have suggested a belief in “mean reversion” as a possible motive for investors to hold onto a loss-making position, believing that this loss will subsequently reverse itself. However, Odean (1998) found that equity investors who displayed the disposition effect tended to buy stocks which had recently outperformed. This would be inconsistent with a general belief in mean reversion. Odean (1998) also demonstrated that equity traders in his sample would not be justified in expecting mean reversion, since equities that were sold at a profit subsequently outperformed corresponding loss-making positions that were retained.

Furthermore, a wider effect must be at work here. Suppose that the decision to open a trade is motivated by the trader forecasting that the exchange rate would rise from its current level. If, after the position was opened, the exchange rate did indeed rise to the forecast level then the trader would happily close it at a profit. If instead the exchange rate fell, then the position would record a loss, and if the trader maintained his/her original forecast of where the exchange rate would end up then holding the position would now be even more attractive than it initially was, given the greater rise now anticipated from the current level to the forecast level.

This could explain the disposition effect without the trader believing that the exchange rate has any general tendency to mean revert. All that is required is for traders to maintain their conviction in the original forecasts that motivated them to open each position. Indeed, if traders really do maintain an unchanged level of conviction in their original forecasts then we would have an extreme version of the disposition effect where traders never choose to realise a loss.

This effect would be moderated to the extent that traders instead tend to lose conviction in their original forecast as a result of information revealed since the trade was opened, and in particular
the information that the exchange rate had actually moved in the opposite direction to forecast (this could take the form of Bayesian updating, where traders rationally adjust their level of belief in their forecasts in the light of subsequent evidence, or the updating process could be complicated by behavioural effects such as overconfidence, attribution bias and groupthink).

Traders’ willingness to close trades at a loss thus depends on the balance between these two effects: whether reduced confidence in the trader’s original forecast offsets the greater gains if the exchange rate did subsequently reach the level originally forecast (from the current loss-making level). This process could explain the disposition effect. However, it is hard to reconcile this with our finding that a loss on one day increases the disposition effect on subsequent trading days. By contrast, rational traders should be expected to respond to prior losses with reduced belief in their forecasting ability. This would make them more willing to realise a subsequent loss, rather than assume that price movements since opening the position will reverse, as originally forecast. However, we find the opposite (that prior losses increase the disposition effect), which suggests instead that some less rational behavioural effect is driving the disposition effect.

7.2 The Gambler’s fallacy
This is a widespread behavioural bias where an individual observing a sequence of one type of event (e.g. heads in a coin toss) concludes that the opposite outturn (tails) is more likely next time. This can be interpreted as a cognitive error where the law of large numbers (that the ratio of heads to tails is likely to converge to unity over time) is assumed also to apply to small samples.

This fallacy could be interpreted at an intellectual level (that a trader looking for a particular pattern of FX movements to occur will believe that it is more likely next time if it failed to take place at this time) or at a more emotional level: that loss-making traders regard themselves as having had bad luck so far, and hence conclude that they should expect better luck in future. Indeed at an emotional level they may feel they “deserve” better luck.
The gambler’s fallacy would imply that recent trading losses should be expected to increase the trader’s conviction that the next trade is likely to be profitable. Thus if this next trade also starts to record a loss, the trader is likely to hold it even longer before finally being willing to close it and realise the loss. Thus the gambler’s fallacy could explain why a loss increases the subsequent disposition effect, consistent with our findings. However, an increased conviction that the next trade will be profitable would also encourage the trader to trade again soon and in larger amounts, whereas our data shows the exact opposite: that a loss encourages traders to trade less frequently, in smaller amounts, or even to quit trading entirely.

In order to explain our findings we would need to assume that some other effect is at work which simultaneously reduces risk appetite. We cannot rule this out, but Occam’s razor should lead us to favour a simpler explanation.

7.3 Realisation Utility & Depleted Self Control

In addition to the negative utility resulting from accruing a loss, it has been argued that investors also suffer an immediate burst of negative utility when they realise the loss. This “realisation utility” can be regarded as coming about because of mental accounting, with the realisation of the position resulting in the loss being shifted from one account to another which is subject to a different utility function (Shefrin and Statman, 1985). Regret has long been hypothesised to be a key driver of the disposition effect (e.g. Shefrin and Statman, 1985, Fogel and Berry 2006) and realisation utility could be interpreted as representing the pain of regret when investors close a trade, since this is the moment that they admit to themselves that they made a mistake in opening it. Traders might well find it less painful to leave the position open and admit nothing. Barberis and Xiong (2012) point out that if the investor applies a high discount rate to expected future realisation utility then this effect could encourage risk-seeking behaviour. In effect the trader can choose whether to suffer the realisation utility now, or instead leave it to a highly discounted future. This choice gives the investor an option value which is utility-enhancing.
Realisation utility can explain the disposition effect, but in order to explain our observation that prior losses increase the disposition effect, we need to extend this idea to explore why investors would ever choose to realise a loss.

Closing such a position might require the trader to accept that an accrued loss is already evidence of poor forecasting skill. Indeed, unless the trader continues to have very high confidence in his/her original forecast (and so is confident that the loss will reverse itself), an accrued loss should be taken to imply that negative realisation utility should be expected either sooner or later, and it would be myopic to discount this disutility at an excessive rate. Alternatively, closing the position might require the trader to reject narrow mental accounting in favour of a broader framing, with financial gains and losses in different mental accounts regarded as equivalent. These possible explanations both involve the investor rejecting instinctive behavioural effects in favour of more rational decision-making. This is likely to require significant emotional effort: an exertion of willpower.

Some experimental studies argue that an individual’s self-control is a finite resource and hence is more likely to fail in decisions following previous acts of self-control (e.g. Baumeister et al., 1998). This depletion of self-control is an attractive explanation for our observed increase in the disposition effect following prior losses: realising a previous loss would weaken the trader’s remaining willpower, making it harder to exercise the self-control needed to realise a loss on the following trade, even though this might clearly be the sensible course.

The depletion effect as a general phenomenon is currently controversial, with meta-studies of the experimental evidence taking contrary views: Hagger, Wood, Stiff, and Chatzisarantis (2010) support the depletion effect, but Carter et al. (2015) argue that there is “very little evidence that the depletion effect is a real phenomenon”. However, there is specific evidence for investors that closing a loss-making trade inflicts psychological pain, supported by experimental data derived
using fMRI brain scans (Frydman et al. 2014). Consistent with this, Summers and Duxbury (2012) establish that the disposition effect is not observed in an experimental context unless individuals feel responsible for the decision to open the trading position. Standard prospect theory cannot in itself be an adequate explanation of these effects, since it assumes that utility is a stable function of the gain/loss on the asset, with no role for prior losses or a sense of responsibility and regret to enter into the value function.

There is evidence that more experienced traders exhibit a more modest disposition effect (Dar and Zhu (2006), Feng and Seasholes (2005), Seru Shumway and Stoffman (2010)). This would be consistent with these traders being better able to exert the necessary willpower to close loss-making positions.

It is also useful to consider the widespread use of stop-loss orders. These are limit orders which close a trade as soon as it reaches a pre-defined level of loss. Many traders set up such stop-loss orders as soon as they open a trade. This is consistent with the idea that realising a loss requires willpower, and indeed that traders themselves are aware of this fact. They could choose to close such trades manually, but set stop-loss orders in advance to pre-commit themselves, since they do not trust themselves to have the discipline required to close the trade when they are in a relatively emotional state after having accrued a loss (stop-loss orders might also be motivated by the desire to guarantee the maximum loss, rather than risk losing more than this before the trader is able to respond). Nolte (2012) finds that the widespread use of “special orders” such as stop-losses leads to a reverse disposition effect where many FX positions are closed when they record small losses. We do not see evidence of widespread use of stop loss orders in our own dataset.
7.4 Dynamic Loss Aversion/Dynamic Realisation Utility

Previous research has established that risk appetite varies, with investors tending to become more risk averse following recent losses/more risk loving following gains (Thaler and Johnson (1990) characterised this as the “house money” effect, and similar history-dependence has been found by Barberis et al. 2001, O’Connell and Teo 2009, Froot et al. 2011). It may seem intuitive to link this effect with our own finding that the disposition effect is similarly exacerbated by recent losses. However, even where risk preferences are affected asymmetrically by losses (with losses leading to greater loss aversion rather than simply greater risk aversion), we still face great difficulty in deriving a disposition effect from these preferences. Kaustia (2010) finds that risk aversion is at its greatest at the prospect theory reference point (because of the kink in the value function at this point as loss aversion kicks in), and declines as an asset shifts to either a profit or a loss. Thus it is very hard to use this value function to explain the disposition effect, nor why increased loss aversion should increase the disposition effect.

The more general point is that the disposition effect cannot easily be explained by preferences over accrued gains/losses, but can be readily explained by a separate realisation utility caused by the realisation of a loss which has already been accrued. We could plausibly hypothesise that the disutility associated with realising a loss of a given size is increased if this new loss is the latest of a sequence of recent losses, thus exacerbating the emotional pain and regret associated with this realisation.

However, this hypothesis would be very hard to distinguish from the hypothesis of depleted willpower in the previous section. We observe that traders are less willing to realise losses following prior losses. This might be due to traders having less of the willpower needed to endure the realisation disutility associated with a given loss, or willpower might not have changed, but the size of the realisation disutility itself increased. Given that we cannot observe realisation utility directly, these two hypothesis are to a large extent observationally equivalent.
8. Conclusion
The disposition effect has been identified in a wide range of investment fields, but the underlying causes remain unclear. This paper investigates the disposition effect among retail currency speculators. Unlike more traditional studies of equity investors, the very short timescales typical of these currency trades allow us to identify differences in the degree of disposition effect over successive trades.

Our method makes use of specific properties of the FX market to derive a novel way of measuring and modelling the disposition effect. Using an innovative panel quantile regression with fixed effects and sample selection, we find that realizing a loss on one trading day significantly increases the disposition effect on the next trading day, consistent with investors becoming even less likely to close a loss-making position.

This is further evidence that the disposition effect cannot be adequately explained by pure preference-based theories. We consider alternative behavioural effects and find that our findings are most consistent with a realisation utility which becomes more negative following earlier losses, or the depletion of willpower by earlier losses, leaving traders less able to exert the self-control needed to realise a loss-making position.
REFERENCES


Strahilevitz, M. A., Odean, T., & Barber, B. M. (2011). Once burned, twice shy: How naïve learning, counterfactuals, and regret affect the repurchase of stocks previously sold. Journal of Marketing Research, 48(SPL), S102-S120.


Table 1: Panel Probit Attrition Equation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimated Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_{t-1}$</td>
<td>0.177***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>$y_{t-1}^+$</td>
<td>-0.101**</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
</tr>
<tr>
<td>$y_{t-1}^0$</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
</tr>
<tr>
<td>$y_{tA}^-$</td>
<td>0.113**</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
</tr>
<tr>
<td>$y_{tA}^+$</td>
<td>-0.095**</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
</tr>
<tr>
<td>$y_{tA}^0$</td>
<td>-0.011</td>
</tr>
<tr>
<td></td>
<td>(0.102)</td>
</tr>
<tr>
<td>Number of trades$_{t-1}$</td>
<td>0.059*</td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
</tr>
<tr>
<td>Age</td>
<td>0.012*</td>
</tr>
<tr>
<td></td>
<td>(0.082)</td>
</tr>
<tr>
<td>PropActive$_{t}$</td>
<td>-0.048*</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
</tr>
</tbody>
</table>

| Individual fixed effet | Yes |
| Day dummies           | Yes |
| Pseudo $R^2$          | 0.9321 |
| LogLikelihood         | -17,564.233 |

The table reports the Quasi Maximum Likelihood estimates of the panel probit first stage attrition equation with fixed effects. Convergence is achieve at the 12th iteration. The covariance matrix used is sandwich and the quadrature method is Gaussian Quadrature with 26 points. The reported Log Likelihood value suggests that the first stage equation is highly significant as a predictive equation. The dependent variable takes value 1 if the i-th trader quits trading at trading day t, and 0 otherwise. P-values are reported in brackets. * denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1%.
Table 2: Dynamic Panel Quantile Regression System Estimation Results

<table>
<thead>
<tr>
<th>Variables</th>
<th>0.025</th>
<th>0.25</th>
<th>0.50</th>
<th>0.75</th>
<th>0.975</th>
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<tbody>
<tr>
<td>$y_{t-1}$</td>
<td>-0.158**</td>
<td>-0.168**</td>
<td>-0.045***</td>
<td>0.048***</td>
<td>0.096*</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.015)</td>
<td>(0.000)</td>
<td>(0.008)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>$y_{t+1}$</td>
<td>0.055*</td>
<td>0.021**</td>
<td>0.036**</td>
<td>-0.052**</td>
<td>-0.044**</td>
</tr>
<tr>
<td></td>
<td>(0.074)</td>
<td>(0.045)</td>
<td>(0.038)</td>
<td>(0.033)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>$y_{t-1}^0$</td>
<td>0.003</td>
<td>0.001</td>
<td>0.003</td>
<td>-0.008</td>
<td>-0.007</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.123)</td>
<td>(0.143)</td>
<td>(0.152)</td>
<td>(0.155)</td>
</tr>
<tr>
<td>$y_{i,t}$</td>
<td>-0.085*</td>
<td>-0.087**</td>
<td>-0.041*</td>
<td>0.038**</td>
<td>0.047*</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.044)</td>
<td>(0.057)</td>
<td>(0.039)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>$y_{i,t}^+$</td>
<td>0.052*</td>
<td>0.026*</td>
<td>0.034**</td>
<td>-0.028*</td>
<td>-0.031*</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.074)</td>
<td>(0.046)</td>
<td>(0.063)</td>
<td>(0.076)</td>
</tr>
<tr>
<td>$y_{i,t}^0$</td>
<td>0.011</td>
<td>0.005</td>
<td>0.013</td>
<td>-0.001</td>
<td>-0.025</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td>(0.156)</td>
<td>(0.101)</td>
<td>(0.124)</td>
<td>(0.111)</td>
</tr>
<tr>
<td>Number of trades</td>
<td>0.016*</td>
<td>0.017*</td>
<td>0.003**</td>
<td>-0.002**</td>
<td>-0.014**</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.081)</td>
<td>(0.043)</td>
<td>(0.048)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>$IMR_{t-1}$</td>
<td>-0.04***</td>
<td>-0.07***</td>
<td>-0.09***</td>
<td>-0.08***</td>
<td>-0.075**</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.023)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Sargan</td>
<td>0.902</td>
<td>0.887</td>
<td>0.836</td>
<td>0.951</td>
<td>0.794</td>
</tr>
<tr>
<td>Wald</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

This table reports the dynamic quantile instrumental variable estimator estimates for the parameters of interest. We report bootstrapped p-values in parentheses, using a bootstrap size of 20,000 and 1,000 bootstrap replications. * denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1%. The dependent variable is realised returns. $IMR_t$ denotes the inverse Mills’ ratio at time $t$ obtained from the first stage estimated equation. Explanatory variables are $y^+_{i,t-1} = y_{i,t-1}1(y_{i,t} > 0)$, $y^-_{i,t-1} = y_{i,t-1}1(y_{i,t} < 0)$, $y^0_{i,t-1} = y_{i,t-1}1(y_{i,t} = 0)$, the average of the most recent last trades between $t-2$ and $t-6$, and the daily number of trades per trader. Sargan reports the bootstrap-corrected p-values for the Sargan test of instruments overproliferation.