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How Institutional Investors Frame Their Losses: Evidence on Dynamic Loss Aversion from Currency Portfolios

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Do institutional investors care about past losses? If so, how do they frame the past to inform subsequent decisions and what causes panic trading? The ability of investors to compartmentalize their losses and remain rational on their current investment decisions is an axiom of classical theory. Human nature suggests that we should place limits on this rationality and allow for the possibility that gain and losses affect future activity. This limited rationality allows not only for investors to be affected by their memory of past performance but for the impact to differ between gains and losses, between the performance of active and expired positions and the potential for losses in one asset to affect activity in another asset.

Behavioral finance offers two theories that frame and explain such behavior. Kahneman and Tversky [1979] outline the disposition effect where investors have a propensity to cut their gains and hold on to their losing positions. Odean [1998], Grinblatt and Keloharju [2001] and Seasholes and Feng [2005] document the presence of this effect in retail investors while Coval and Shumway [2005] and Locke and Mann [2005] document the disposition effect on the floor of the Chicago Board of Trade.

Barberis, Huang and Santos [2007] describe dynamic loss aversion where gains and losses directly affect an investor's utility and subsequent loss aversion. This is a plausible description for institutional investors, who may derive both pecuniary and non-pecuniary benefits from performance. Institutional investors scale back their risk as they experience losses. This pattern of behavior is observed among institutional investors by O'Connell and Teo [2009].[2]

In this article, we extend the notion of dynamic loss aversion to differentiate between position level, portfolio level and aggregate cross-portfolio losses in currency investments. We also develop a framework to disentangle the impact of

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[2] O'Connell and Teo (2009) also show that this relationship cannot result from a mechanical connection between risk and performance. Good performance may mechanically affect current, but not future, changes risk, given the near-zero autocorrelation in currency returns. Moreover, contemporaneous risk increases with gains on long positions but on *losses* on short positions. This invalidates even contemporaneous connections between risk and performance, provided shorts and longs are equally likely, which is the case in our data.

past losses on current trades from past losses on matured trades.

We find that investors experiencing losses have an increased propensity to cut risk (cutting back on both longs and shorts) and an asymmetrically weaker tendency to add risk after a gain. These results can be partially explained by constraints from client capital withdrawal. Manager preferences seem to have an effect as well. However, this effect does not appear to be the result of passive hedging transactions both because of the low correlation between underlying stocks and bonds and currencies, and also because our results apply to both longs and shorts.

Finally, by differentially weighting investors' losses on existing contracts and losses due to expired or closed positions, we show that, while there is a memory of past losses, the impact of a loss on current trading decisions declines significantly once the losing positions are removed.

REAL MONEY INVESTOR CURRENCY HOLDINGS AND TRADING ACTIVITY

Our sample is based on the transactions and holdings of 1,067 independent portfolios for the period Jan 1, 1997 to Mar 10, 2010. These investors represent an average aggregate absolute currency exposure of $200Bn across the 22 currencies listed in Exhibit 1.

Exhibit 1: Currencies covered in sample

Australian Dollar	Norwegian Krone
Brazilian Real	Polish Zloty
Canadian Dollar	Pound Sterling
Czech Koruna	Singapore Dollar
Euro	South African Rand
Hungarian Forint	South Korean Won
Indian Rupee	Swedish Krona
Indonesian Rupiah	Swiss Franc
Japanese Yen	Taiwanese Dollar
Mexican Peso	Turkish Lira
New Zealand Dollar	US Dollar

For each contract we observe the trade date, valuation date, forward exchange rate and currency pair. Each contract is separated into a buy component and sell component and aggregated with other contracts for a total of 10,936,703 unique fund, currency, date observations. Removal of net near-zero positions and sporadic positions reduces the effective sample size to 8,510,215 observations.

BREAKEVEN EXCHANGE RATES AND CUMULATIVE PROFIT AND LOSS

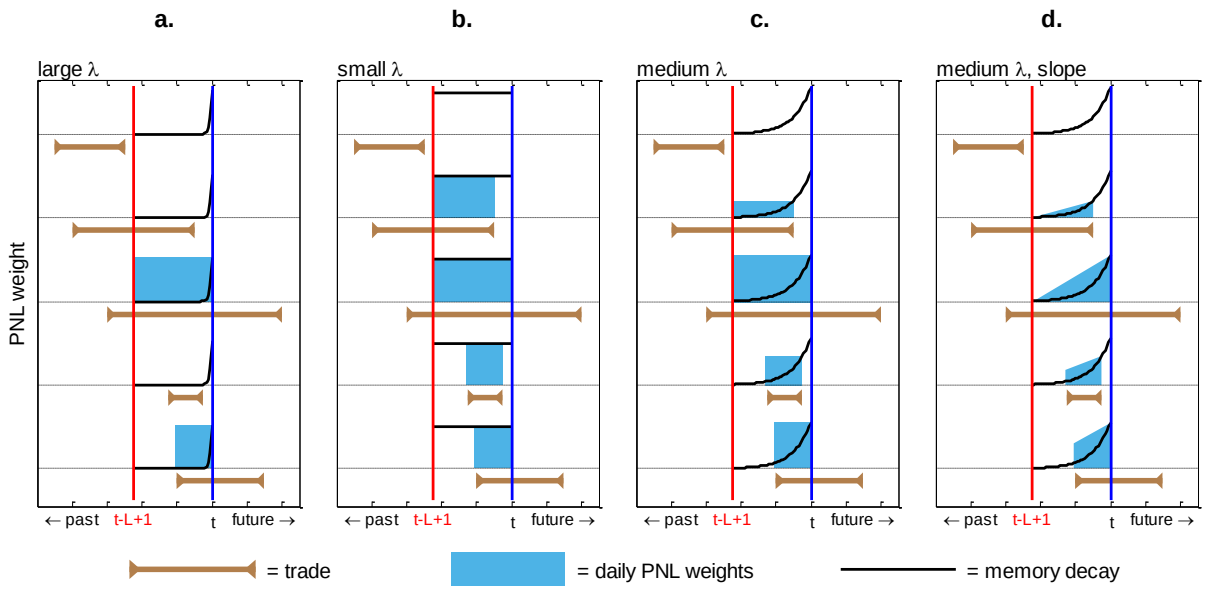
Individual trades or contracts may differ in their impact on subsequent behavior. To systematically test the effect of investment performance on risk taking activities, we develop a framework for aggregating transactions which allows us aggregate individual contracts and span the gap between two natural approaches to performance measurement: Breakeven exchange rates and cumulative profit and losses.

The breakeven exchange rate of a set of positions is defined as the spot exchange rate at which the profit and losses of all current positions nets out, subject to some maximum look-back window, L. A measure of profit and loss based on this concept puts zero weight on any contracts that have expired (See Exhibit 2a). Any expired contract is irrelevant regardless of how recently it expired, while the initial purchase price of an existing contract matters as long as it is in the investor's frame of reference (t-L+1 to t).

Cumulative profit and loss simply looks at the daily performance experienced by all contracts in the investor's frame of reference (See Exhibit 2b). As long as a contract exists in the look-back window its performance is relevant to today, regardless of its current status.

The importance of past losses is generalized through the introduction of two parameters. First, a memory decay parameter, λ, captures the importance of expired contracts by exponentially decaying a contract's profit and loss once it expires (See Exhibit 2c). Second, we provide an alternative profit and loss expression that incorporates a decay for all past performance (See Exhibit 2d). By including both a level and sloped measure of profit and loss in our analysis we can estimate the relative importance of past losses over recent losses

Exhibit 2: Definitions of breakeven exchange rate and profit and loss measures



a. Breakeven exchange rates only consider currently active contracts.
b. Cumulative profit and loss treat all contracts equally within the frame of reference.
c. The decay parameter λ generalizes between breakeven exchange rates and cumulative profit and loss.
d. The slope coefficients measure the extent to which more recent performance matters more, regardless of current contract status.

These profit and loss expressions can be written as:

$$PNL_{x,t} = \frac{\sum_{j\in X}\sum_{t'=t-L+1}^{t} w_{t-t',j} h_{t'-1,j}\, r_{t'-1,t'}^{i(j)}}{\sum_{j\in Y}\sum_{t'=t-L+1}^{t} w_{t-t',j} \left|h_{t'-1,j}\right|}$$

L is the look-back window; $h_{t'-1,j}$ is the value of contract *j* at time *t*'-1; $r_{t'-1,t'}^{i(j)}$ is the return over the subsequent day for a contract in currency *j* measured relative to the fund's currency of reference. The weight *w* assigned to a contract's daily profit and loss is:

$$w_{\tau,j} = \left(\frac{L-\tau}{L^2(L+1)}\right)\cdot(0.5)^{\lambda(t-\min(t,t_1(j))}$$

The first term in *w* is a linear decay function and is only present in the calculation of the sloped profit and loss. t_1 is the maturity date of contract *j*, so the decay only takes effect if the valuation date is greater than t_1.

In the above equation, *X* and *Y* represent the set of contracts considered for the various aggregations of profit and loss. We consider four aggregations of holdings:

1) Currency/Fund: Profit and loss for fund *k* in currency *i* as a fraction of total fund holdings. X is the set of all trades by fund *k* in currency *i*. Y is the set of all trades by fund *k*.
2) Fund: Profit and loss for fund *k* across all currencies as a fraction of total fund holdings. *X* and *Y* are the set of all trades by fund *k*.
3) Currency: Aggregate profit and loss at the currency level as a fraction of aggregate holdings. *X* is the set of all trades by all funds in currency *i*. *Y* is the set of all trades.
4) Universe: Aggregate profit and loss across all funds and currencies as a fraction of aggregate holdings. *X* and *Y* are the set of all trades.

Exhibit 3: Regression of the direction (sign) of change in risk on past profit and losses

		Currency/Fund PNL		Fund PNL		Currency PNL		Universe PNL	
		Level	Slope	Level	Slope	Level	Slope	Level	Slope
Univariate	β	1.84%	–1.08%	1.95%	–1.05%	1.47%	–0.86%	1.17%	–0.52%
	t-stat	31	–17	31	–17	9.0	–3.2	19	9
Multivariate	β	1.00%	–0.65%	1.26%	–0.63%	1.04%	–0.65%	0.61%	–0.20%
	t-stat	14	–9	17	–9	16	–10	9	–3

Regressions of the sign of change in risk appetite on past profit and loss, plus a constant term (not reported). Independent variables are volatility standardized prior to regression. Decay parameter for expired contracts, λ = 0.1. Number of observations: 8,510,215. R-squared for multivariate regression: 2.534 bps.

Exhibit 4: Decay impact for recently-closed contracts. Univariate regression

Λ	Half-Life (days)		Currency/Fund PNL		Fund PNL		Currency PNL		Universe PNL	
			Level	Slope	Level	Slope	Level	Slope	Level	Slope
0	∞	β	1.88%	–1.16%	1.93%	–1.03%	1.47%	–0.86%	1.19%	–0.55%
		t-stat	29	-18	31	-16	24	-14	19	-9
		R^2 (bps)	1.21		1.46		0.79		0.63	
0.01	100	β	1.87%	–1.15%	1.93%	–1.03%	1.47%	–0.86%	1.19%	–0.54%
		t-stat	30	-18	31	-16	24	-14	19	-9
		R^2 (bps)	1.21		1.46		0.79		0.63	
0.03	33	β	1.87%	–1.13%	1.94%	–1.03%	1.44%	–0.83%	1.18%	–0.54%
		t-stat	30	-18	31	-16	23	-14	19	-9
		R^2 (bps)	1.21		1.47		0.77		0.63	
0.1	10	β	1.84%	–1.08%	1.95%	–1.05%	1.47%	–0.86%	1.17%	–0.52%
		t-stat	30	-17	31	-17	24	-14	19	-9
		R^2 (bps)	1.23		1.49		0.79		0.63	
1	1	β	1.78%	–0.97%	2.15%	–1.37%	1.45%	–0.84%	1.12%	–0.47%
		t-stat	31	-17	36	-23	24	-14	19	-8
		R^2 (bps)	1.31		1.65		0.78		0.61	
3	0.33	β	1.75%	–0.96%	2.21%	–1.46%	1.44%	–0.84%	1.11%	–0.46%
		t-stat	31	-17	37	-24	23	-14	19	-8
		R^2 (bps)	1.31		1.70		0.78		0.61	
10	0.1	β	1.73%	–0.93%	2.20%	–1.46%	1.44%	–0.83%	1.10%	–0.45%
		t-stat	31	-17	37	-24	23	-14	19	-8
		R^2 (bps)	1.29		1.70		0.77		0.61	

Regressions of the sign of change in risk appetite on past profit and loss, plus a constant term (not reported). Independent variables are volatility standardized prior to regression. Number of observations: 8,510,215.

RISK APPETITE AS A FUNCTION OF PAST LOSSES

Profits and losses within the various frames outlined above are expected to result in changes in risk appetite.

Risk appetite is defined as the absolute fund exposure to a currency, multiplied by the volatility of that currency. The change in partial risk is defined as the change in risk appetite as a fraction of total fund holdings:

$$CPR_{i,k,t} = \frac{\sigma_{i,t-1}\Delta\left|h_{i,k,t}\right|}{\sum|h|}$$

Exhibit 3 presents the results from regressions of the sign of change in partial risk (CPR) on the various aggregations of profit and loss for a fixed decay parameter, λ.
The coefficient is positive at each aggregation of profit and loss, suggesting that investors have a tendency to cut (increase) their risk when they experience losses (gains). In the multivariate regression these coefficients remain positive and significant, implying that no one frame of reference dominates. In particular, fund/currency losses (gains) and fund losses (gains) both matter, which suggests that the effect may be partially explained by both manager preference with regard to currency positions and capital constraints on the fund (e.g. client withdrawals).

Slope coefficients are negative and smaller than the level coefficients. This implies that past losses are less important than recent losses.

Exhibits 4 and 5 present the results of univariate and multivariate regressions for various levels of decay of expired contracts, λ. R-squared values and coefficients show that at the position level, expired contracts are important and weigh heavily in the minds of investors while at the portfolio level, expired contracts are less relevant.

Exhibit 5: Decay impact for recently-closed contracts. Multivariate regression

λ	Half-Life (days)	Currency/Fund PNL		Fund PNL		Currency PNL		Universe PNL		R^2 (bps)
		Level	Slope	Level	Slope	Level	Slope	Level	Slope	
0	∞	1.05%	–0.73%	1.21%	–0.57%	1.04%	–0.65%	0.64%	–0.23%	2.506
0.01	100	1.04%	–0.72%	1.22%	–0.57%	1.04%	–0.65%	0.63%	–0.23%	2.509
0.03	33	1.03%	–0.70%	1.23%	–0.59%	1.01%	–0.64%	0.63%	–0.21%	2.504
0.1	10	1.00%	–0.65%	1.26%	–0.63%	1.04%	–0.65%	0.61%	–0.20%	2.534
1	1	0.88%	–0.43%	1.51%	–1.03%	1.03%	–0.66%	0.54%	–0.11%	2.682
3	0.33	0.84%	–0.39%	1.58%	–1.13%	1.03%	–0.65%	0.53%	–0.09%	2.725
10	0.1	0.82%	–0.37%	1.58%	–1.14%	1.03%	–0.65%	0.53%	–0.09%	2.712

Regressions of the sign of change in risk appetite on past profit and loss, plus a constant term (not reported). Independent variables are volatility standardized prior to regression. Number of observations: 8,510,215.

Exhibit 6: Look-back window sensitivity

Lag (days)		Currency/Fund PNL		Fund PNL		Currency PNL		Universe PNL		R^2 (bps)
		Level	Slope	Level	Slope	Level	Slope	Level	Slope	
5	β	0.81%	–0.31%	1.35%	–0.85%	1.02%	–0.60%	0.42%	–0.10%	2.48
	t-stat	12	–5	20	–13	17	–10	7	–2	
10	β	0.84%	–0.39%	1.58%	–1.13%	1.03%	–0.65%	0.53%	–0.09%	2.72
	t-stat	13	–6	22	–16	16	–10	8	–1	
20	β	0.76%	–0.44%	1.46%	–0.96%	0.98%	–0.80%	0.68%	–0.21%	2.47
	t-stat	12	–8	21	–15	15	–12	11	–3	

Regressions of the sign of change in risk appetite on past profit and loss, plus a constant term (not reported). Independent variables are volatility standardized prior to regression. Number of observations: 8,510,215.

Exhibit 7: End of quarter risk appetite effects

			Currency/Fund PNL		Fund PNL		Currency PNL		Universe PNL	
			Level	Slope	Level	Slope	Level	Slope	Level	Slope
Univariate	Unconditional	β	1.71%	–0.85%	2.12%	–1.36%	1.58%	–0.92%	1.09%	–0.35%
		t-stat	24	–12	28	–17	21	–12	15	–5.0
	End of quarter	β	0.07%	–0.17%	0.15%	–0.17%	–0.24%	0.14%	–0.01%	–0.17%
		t-stat	1.0	–2.4	2.0	–2.1	–3.3	1.9	–0.09	–2.5
Multivariate	Unconditional	β	0.81%	–0.29%	1.49%	–1.11%	1.17%	–0.79%	0.49%	–0.03%
		t-stat	9.9	–3.5	17	–12	15	–10	76.6	–0.38
	End of quarter	β	0.04%	–0.16%	0.16%	–0.07%	–0.24%	0.23%	0.03%	–0.21%
		t-stat	0.52	–2.0	1.8	–0.70	–3 .2	2.9	0.40	–2.9

Regressions of the sign of change in risk appetite on past profit and loss, plus a constant term and dummy term for end of quarter (not reported). End of quarter variables take on PNL value for March, June, September and December and zero otherwise. Independent variables are volatility standardized prior to regression. Number of observations: 8,510,215.

Exhibit 8: End of year risk appetite effects

		Currency/Fund PNL		Fund PNL		Currency PNL		Universe PNL	
		+ Level	– Level	+ Level	– Level	+ Level	– Level	+ Level	– Level
Unconditional	β	–0.07%	1.37%	0.13%	1.13%	0.41%	0.65%	0.45%	0.13%
	t-stat	–1.4	26	2.6	21	8.5	11	9.2	1.8
End of year	β	–0.10%	0.16%	–0.02%	0.06%	–0.13%	–0.02%	0.06%	0.35%
	t-stat	–2.0	3.0	–0.39	1.0	–2.6	–0.29	1.1	4.6
Unconditional	β	–0.28%	1.01%	0.15%	0.66%	0.34%	0.49%	0.42%	–0.28%
	t-stat	–5.1	17	2.9	10	6.8	8.0	8.3	–3.8
End of year	β	–0.09%	0.18%	0.10%	–0.12%	–0.12%	–0.18%	0.08%	0.38%
	t-stat	–1.6	2.9	1.8	–1.8	–2.5	–2.7	1.4	4.6

Regressions of the sign of change in risk appetite on past profit and loss, plus a constant term and dummy term for second half of year (not reported). End of year variables take on PNL value for July through December and zero otherwise. Independent variables are volatility standardized prior to regression. Number of observations: 8,510,215.

Different look-back window are compared in Exhibit 6. The default window of two weeks provides the best fit although the results are generally robust to the choice of window.

Studies such as Lakonishok et al. have found significant window dressing activities while O'Connell and Teo find increased intensity of dynamic loss aversion towards the end of the year. Exhibit 7 presents the results from regressions with dummies on the last month in each quarter while Exhibit 8 replicates the work of O'Connell and Teo with a dummy for the second half of the year and separate coefficients for losses and gains.

While the coefficient for the end of quarter effect is positive, suggesting increased intensity of dynamic loss aversion, the coefficient is only barely significant for fund level end of quarter effects.

The annual effect observed by O'Connell and Teo is also present in our methodology, with a strong dynamic risk aversion caused by losses at the position level.

CURRENCY LEVEL EFFECTS

Exhibit 9 presents the results from regressions run at the currency level rather than the fund position level.

Aggregation from the position level is done either by equally weighting profits and losses (to get an idea of the average fractional loss) or dollar weighting (which places more weight on larger positions). Changes in risk are measured as the change in absolute magnitude of net aggregate exposure to a given currency.

The net effects of currency level losses are weaker than those observed in the fund level regressions. The aggregate dollar weighted profit and losses of all investors across all currencies remains significantly tied to aggregate shifts in currency risk.

Exhibit 9: Currency level regression of the direction of change in risk on past profit and losses

		Equally Weighted Currency PNL		Equally Weighted Universe PNL		Dollar Weighted Currency PNL		Dollar Weighted Universe PNL	
		Level	Slope	Level	Slope	Level	Slope	Level	Slope
Univariate	β	0.89%	–0.21%	1.01%	0.33%	1.05%	–0.07%	4.82%	–1.70%
	t-stat	1.5	–0.35	1.8	0.58	1.7	–0.12	7.4	–2.6
Multivariate	β	0.40%	–0.40%	0.81%	0.52%				
	t-stat	0.58	–0.58	1.2	0.79				
						0.54%	0.04%	4.75%	–1.71%
						0.88	0.06	7.3	–2.6

Regressions of the sign of change in risk appetite on equally weighted and dollar weighted past profit and loss, plus a constant term (not reported). Currency change in risk is calculated as the change in risk of aggregate fund holdings. Independent variables are volatility standardized prior to regression. Number of observations: 71,769. R-squared for dollar weighted multivariate regressions: 12.989 bps.

Exhibit 10: Developed market currency level regression of the direction (sign) of change in risk on past profit and losses

		Equally Weighted Currency PNL		Equally Weighted Universe PNL		Dollar Weighted Currency PNL		Dollar Weighted Universe PNL	
		Level	Slope	Level	Slope	Level	Slope	Level	Slope
Univariate	β	4.12%	–3.30%	3.56%	–0.90%	11.13%	–7.08%	7.18%	–3.09%
	t-stat	4.5	–3.5	3.9	–0.99	11	–7.4	7.6	–3.3
Multivariate	β	3.33%	–3.42%	2.28%	0.41%				
	t-stat	3.3	–3.4	2.3	0.41				
						9.74%	–6.78%	3.74%	–0.76%
						9.5	–6.6	3.7	–0.75

Regressions of the sign of change in risk appetite on equally weighted and dollar weighted past profit and loss, plus a constant term (not reported). Currency change in risk is calculated as the change in risk of aggregate fund holdings. Independent variables are volatility standardized prior to regression. Number of observations: 33,807. R-squared for dollar weighted multivariate regressions: 52.67 bps.

Exhibit 11: Emerging market currency level regression of the direction (sign) of change in risk on past profit and losses

		Equally Weighted Currency PNL		Equally Weighted Universe PNL		Dollar Weighted Currency PNL		Dollar Weighted Universe PNL	
		Level	Slope	Level	Slope	Level	Slope	Level	Slope
Univariate	β	0.29%	0.48%	1.39%	0.12%	–0.33%	0.99%	2.69%	–0.41%
	t-stat	0.36	0.60	1.8	0.16	–0.40	1.2	3.0	–0.46
Multivariate	β	–0.77%	0.72%	1.78%	–0.22%				
	t-stat	–0.80	0.76	1.9	–0.25				
						–0.53%	1.00%	2.72%	–0.49%
						–0.63	1.2	3.0	–0.54

Regressions of the sign of change in risk appetite on equally weighted and dollar weighted past profit and loss, plus a constant term (not reported). Currency change in risk is calculated as the change in risk of aggregate fund holdings. Independent variables are volatility standardized prior to regression. Number of observations: 37,962. R-squared for dollar weighted multivariate regressions: 6.01 bps.

Aggregating to the currency level places a significantly larger weight in the regression on emerging markets than in previous regressions, so Exhibits 10 and 11 separate out the currency level regressions into developed and emerging markets, respectively.

The relationships between profit and loss and aggregate risk appetite are significantly stronger in developed markets than in emerging markets, with renewed significance for currency level profits and losses.

Separating aggregate (universe) profits and losses into developed and emerging series improves significance for both subsets, suggesting that the two groups of currencies are evaluated and traded separately.

LOGISTIC REGRESSIONS

The effect of profits and losses on risk appetite is further analyzed in Exhibit 12 through the use of logistic regressions. These regressions allow the change in risk to be modeled as a statistical event and estimate the likelihood of a risk increase or risk decrease given a change in profit and loss.

The unconditional baseline probability of a risk reduction is 12.3%. A one standard deviation shift in profit and loss increases this probability by 0.22% at the position level, 0.44% at the currency level and 0.63% at the aggregate (universe) level. These probabilities are all statistically significant and represent a sizeable change in the behavior of investors whose trades are typically driven by systematic investment objectives.

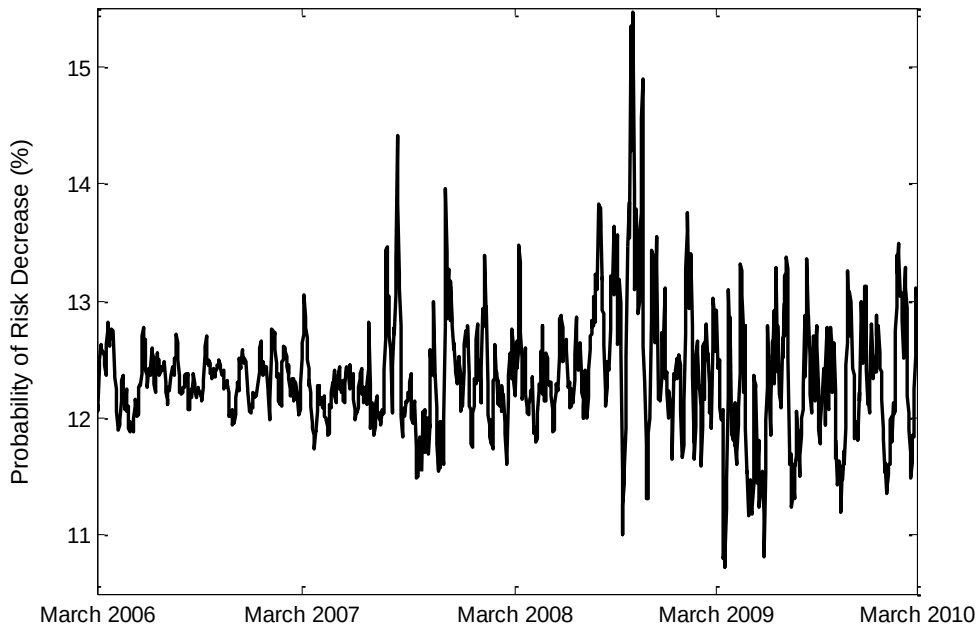
Exhibit 13 plots the global average probability of a risk reduction from 2006 to 2010. The typical probability of a risk reduction remains between 12 and 13 percent for most of the sample but jumps to over 15 percent during the height of the crisis.

Exhibit 12: Logistic regression of the direction (sign) of change in risk on past profit and losses

	Base Case Probability		Currency/Fund PNL		Fund PNL		Currency PNL		Universe PNL	
			Level	Slope	Level	Slope	Level	Slope	Level	Slope
Risk Increase	14.8%									
Univariate		Δ prob	+0.56%	–0.33%	+0.90%	–0.61%	+0.02%	–0.14%	–0.25%	+0.19%
		t-stat	26	–16	39	–27	1.1	–6.0	–11	8.4
Multivariate		Δ prob	+0.17%	–0.06%	+0.86%	–0.60%	+0.05%	–0.18%	–0.39%	+0.33%
		t-stat	6.9	–2.5	31	–22	1.9	–7.3	–17	14
Risk Reduction	12.3%									
Univariate		Δ prob	–0.28%	+0.12%	–0.18%	+0.09%	–0.66%	+0.27%	–0.76%	+0.41%
		t-stat	–14	6.1	–8.4	4.0	–31	12	–37	19
Multivariate		Δ prob	–0.22%	+0.11%	+0.08%	–0.06%	–0.44%	+0.14%	–0.63%	+0.37%
		t-stat	–9.4	4.9	3.3	–2.3	–20	6.0	–29	17

Three class (positive, negative, no change) logistic regressions of the sign of change in risk appetite on past profit and loss, plus a constant term (not reported). Independent variables are volatility standardized prior to regression. Number of observations: 8,510,215. Risk increase probability deltas indicate the change in the probability of an increase in risk appetite due to a positive PNL change. Risk decrease probability deltas indicate the change in the probability of a decrease in risk appetite due to a positive PNL change.

Exhibit 13: Global average probability of risk reduction



Plot of the mean of fund level logistic regression ŷ values.

CONCLUSION

There is significant evidence of dynamic loss aversion behavior among investors which can be characterized through a combination of position level, portfolio level and aggregate profit and loss.

Investors' memory of past losses results in a decreased risk appetite manifested by risk reducing trades. Trading activity is shaped by past profits and losses on the currency in question, aggregate portfolio performance and performance of real money investors on aggregate.

The memory effect for expired trades is weaker than that for current trades but can still have a strong influence on position level trading decisions.

These findings challenge not only the classical view that investors form fully rational decisions based only on their expectation of future returns, but also the notion that behavioral biases are encapsulated by a single frame of reference for past losses.

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